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Anticipating the Unexpected: A Predictive Model for Early Hospital Readmissions in Kidney Transplant Recipients Using Machine Learning

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Abstract

Background: Early hospital readmissions (EHR) within 30 days after kidney transplantation are common and add clinical and financial burden. Early identification of high-risk recipients can guide post-discharge care. We aimed to develop a machine learning model to predict 30-day hospital readmission in adult kidney transplant recipients.

Methods: We conducted a retrospective cohort study of 2,110 adult kidney transplant recipients treated at Colombiana de Trasplantes between July 2008 and December 2023. Patients with allograft thrombosis at the time of transplantation were excluded. Clinical and demographic data were extracted from electronic records. Missing values were imputed using multivariate imputation by chained equations with classification and regression trees (MICE-CART). We then implemented a 10-fold cross-validation framework, restricting oversampling to the training folds to prevent data leakage. Two machine learning models (Random Forest and XGBoost) were trained and compared against a baseline logistic regression model on both discrimination and calibration metrics.

Results: Overall, 14.5% of patients were readmitted within 30 days. Readmitted recipients more often had diabetes mellitus, longer pre-transplant dialysis, delayed graft function, and surgical complications. Evaluated via 10-

fold cross-validation, XGBoost yielded the highest discrimination (AUC 0.750; 95% CI 0.722–0.778). Random Forest (AUC 0.744) and baseline logistic regression (AUC 0.747) performed comparably. Both algorithms identified initial hospitalization length, dialysis duration, GFR at day 7, recipient age, and surgical reintervention as the most important predictors.

Conclusions: A machine learning model that combines pre- and early post-transplant variables can identify kidney transplant recipients at higher risk of 30-day readmission. Based on this model, we developed a web-based risk calculator that returns individualized risk estimates to support discharge planning and follow-up. External validation in independent cohorts is needed before clinical adoption.

Keywords: Kidney Transplantation; Patient Readmission; Machine Learning; Risk Assessment; Decision Support Systems, Clinical.

List of abbreviations

AUC, area under the curve; BMI, body mass index; CART, classification and regression trees; CI, confidence interval; CKD-EPI, Chronic Kidney Disease Epidemiology Collaboration; DCA, decision curve analysis; DGF, delayed graft function; EHR, early hospital readmission; GFR, glomerular filtration rate; GVIF, generalized variance inflation factor; ICU, intensive care unit; LR, logistic regression; MICE, multiple imputation by chained equations; RF, Random Forest; ROC, receiver operating characteristic; ROSE, Random Over-Sampling Examples; VIF, variance inflation factor; XGBoost, Extreme Gradient Boosting.

1.1.1. Background

Early hospital readmissions (EHR) within 30 days of kidney transplantation represent a major clinical concern, as they are closely linked to complications, graft loss, and mortality [1,2]. While these events are common, their reported frequency varies significantly in the literature, ranging from 20% to 31% across different transplant centers [1,3–5]. This wide variation is largely driven by differences in patient risk profiles and institutional discharge protocols. Beyond their clinical impact, these readmissions also drive up healthcare costs and serve as a key quality metric that directly affects hospital reimbursement [4,6].

Extensive research has identified several predictors of early hospital readmission. Regarding recipient characteristics, factors such as older age, diabetes, and prolonged pre-transplant dialysis are consistently linked to a higher risk. Donor factors, particularly advanced age, and transplant-related variables like delayed graft function and prolonged initial hospitalization also contribute to this risk [1,4,5]. At the time of discharge, conditions such as electrolyte imbalances and active comorbidities further increase vulnerability, making discharge planning and outpatient follow-up essential targets for preventive interventions [7].

Although recipient demographics and clinical profiles have evolved, EHR rates have remained remarkably stable over time, suggesting that core risk determinants persist across cohorts [3]. Most existing predictive models are

based on North American and European registries, making their generalizability to Latin American populations largely unknown. To address this geographic gap, we developed and validated a machine learning model to predict 30-day readmissions in a large adult kidney transplant cohort from Colombia, establishing a predictive tool tailored to our healthcare context.

1.1.2. Methods

Study Design and Patient Population

We conducted a retrospective cohort study of consecutive adult kidney transplantations performed at Colombiana de Trasplantes between July 2008 and December 2023. Out of 2,143 transplantations performed during this period, 33 recipients were excluded due to hyperacute allograft thrombosis at implantation, leaving a final cohort of 2,110 patients. Because this early complication leads to immediate graft loss and transplantectomy during the index stay, these patients were never candidates for post-discharge planning [8,9]. Demographic and clinical characteristics from both recipients and donors, along with perioperative variables, were extracted from electronic medical records.

Data Preprocessing and Handling of Missing Data

All statistical analyses were conducted using R software version 4.4.2 [10]. Missing values were observed in nine candidate predictors, with dialysis duration (29.9%) and glomerular filtration rate on day 7 (15.7%) exhibiting the

highest rates of missingness (Supplementary Table 1). Missing data were handled using multiple imputation by chained equations with classification and regression trees (MICE-CART) [11,12]. We generated five imputed datasets over five iterations and confirmed convergence using trace plots of means and variances. To ensure a consistent analytical sample for downstream modeling, the fifth imputed dataset was selected. To address class imbalance in the primary outcome, the ROSE algorithm [13] was applied.

Predictor Variable Definitions and Functional Forms

To ensure clinical utility as a discharge planning tool, we selected 14 candidate predictors routinely available at the time of initial post-transplant discharge. These variables comprised recipient demographics (age and biological sex), pre-transplant clinical status (diabetes mellitus, dialysis modality, and dialysis duration), donor characteristics (transplant type and expanded criteria donor status), and index hospitalization events (delayed graft function, day 7 glomerular filtration rate, urinary tract infection, surgical site infection, unplanned ICU admission, surgical reintervention, and length of post-transplant stay). All clinical events and complications were limited to the index transplant hospitalization. Expanded criteria donor was defined by standard clinical criteria (donor age ≥60 years, or 50–59 years with at least two of: terminal creatinine ≥1.5 mg/dL, cerebrovascular cause of death, or history of hypertension) [14]. Delayed graft function was defined as the requirement for dialysis within the first seven days post-transplant [15], and estimated GFR

was calculated using the CKD-EPI equation on post-operative day 7 [16] as a dynamic marker of early graft recovery.

Descriptive Baseline Analysis

Descriptive baseline analyses summarized recipient demographics, comorbidities, donor characteristics, and perioperative variables, comparing distributions between readmitted and non-readmitted recipients. These comparisons are descriptive and intended to characterize the study population, not to establish formal predictive associations.

Appropriate statistical tests were selected based on variable type and distribution. For continuous variables, normality within groups was assessed using the Shapiro–Wilk test. Depending on the results, either a Student's t-test (for normally distributed data) or a Mann–Whitney U test (for non-normal distributions) was applied. For categorical variables, chi-square test was used when expected values were ≥5; otherwise, Fisher's exact test with Monte Carlo simulation was conducted. Statistical significance was defined as two-sided p-value ≤ 0.05.

Stratified analyses examined GFR on day 7 across donor type, DGF status, and 30-day readmission outcome. Furthermore, readmission-specific characteristics were evaluated, including the duration of rehospitalization, frequency of multiple readmissions, primary causes of hospitalization, and the need for surgical intervention.

Multicollinearity Evaluation

Prior to predictive modeling, multicollinearity among the 14 candidate predictors was evaluated on the complete imputed dataset. Variance Inflation Factors (VIF) and Generalized VIF (GVIF) were computed from a logistic regression model using the car package [17]. A VIF threshold of 5.0 was set a priori as the criterion for significant multicollinearity. All GVIF values fell well below this threshold (range: 1.02 to 1.42). No variables were excluded, and all 14 clinical features were retained for model training.

Development of Machine Learning Models

To predict 30-day hospital readmission after kidney transplantation, we developed Random Forest and XGBoost models alongside a traditional multivariable logistic regression baseline, adhering to reporting guidelines for clinical artificial intelligence [18,19]. Predictive performance was evaluated using a unified 10-fold cross-validation framework on the full cohort of 2,110 patients, maximizing sample size while preventing data leakage. The cohort was partitioned into ten stratified folds, where each fold served sequentially as the validation set while the remaining nine folds were used for model training. To address class imbalance, the ROSE algorithm [13] was applied strictly within the training folds to generate synthetic observations, while the validation folds retained the true, unaltered readmission prevalence, ensuring unbiased out-of-fold performance estimates.

All models were implemented in R using standard packages. The Random Forest model was trained using the randomForest package [20] with 200 trees

and an optimal mtry parameter of 3 determined via internal grid search. The XGBoost model was developed using the xgboost package [21] with hyperparameter tuning, establishing a maximum depth of 4, a learning rate (eta) of 0.1, a subsample of 0.8, a colsample_bytree of 0.8, and a minimum loss reduction (gamma) of 1. To optimize the number of boosting rounds and prevent overfitting, early stopping was configured with a nested 80/20 split within the training folds; training was halted if the validation log-loss did not decrease for 15 consecutive rounds, yielding an average of 60 rounds across folds (Supplementary Table 2). The baseline logistic regression model was fitted using standard maximum likelihood estimation. Following the cross-validation loop, out-of-fold predictions were pooled into a single predicted probability per patient for downstream performance evaluation.

Model Evaluation and Selection

Model performance was evaluated on out-of-fold predictions using both discriminative and classification metrics. Discrimination was quantified by the area under the receiver operating characteristic curve (AUC-ROC) for all three models, with 95% confidence intervals estimated using DeLong's method [22,23]. To determine optimal classification thresholds under class imbalance, we applied Youden’s J statistic to the pooled out-of-fold predictions. Unbiased 95% confidence intervals for accuracy, sensitivity, specificity, precision, balanced accuracy, and F1-score were obtained through bootstrap resampling with 1,000 iterations.

Model calibration was assessed by plotting predicted out-of-fold probabilities against observed readmission rates across deciles of risk, while overall model fit was quantified using McFadden's pseudo-R^2. These discrimination and calibration measures collectively guided final model selection. To evaluate the clinical applicability of the models beyond statistical performance, we conducted a Decision Curve Analysis (DCA) [24], which quantifies the net clinical benefit across a spectrum of decision-threshold probabilities.

Interactive Risk Calculator

To translate the predictive model into a clinical decision support tool, we developed an interactive, web-based risk calculator using the Shiny package in R [25]. The tool allows clinicians to input patient-specific predictor values at discharge to generate individualized risk estimates that inform post-discharge planning.

Ethical Considerations

The study protocol was approved by the institutional ethics committee, which waived the requirement for written informed consent due to its retrospective, observational design. All patient data were fully anonymized to safeguard confidentiality, and the study was conducted in strict accordance with the Declaration of Helsinki.

1.1.3. Results

The overall 30-day rehospitalization rate among kidney transplant recipients was 14.5%, with 306 out of 2,110 patients requiring readmission. Baseline characteristics for rehospitalized and non-rehospitalized patients are summarized in Table 1. Rehospitalized patients were older (median age: 47 vs. 43 years, $p = 0.0019$), had a higher prevalence of diabetes mellitus (25.2% vs. 16.7%, $p < 0.001$), and were more likely to experience delayed graft function (15.0% vs. 6.4%, $p < 0.001$). Complications during the index stay, such as urinary tract infections (12.7% vs. 7.3%, $p = 0.0017$) and surgical site infections (18.6% vs. 4.7%, $p < 0.001$), were significantly more common in rehospitalized patients. Additionally, they had significantly longer dialysis times before transplantation (median: 59.6 vs. 42.5 months, $p < 0.001$) and lower GFR at day 7 (median: 25.4 vs. 45.5 mL/min/1.73 m^2, $p < 0.001$).

Baseline Characteristics of Kidney Transplant Recipients

To account for the distinct immunological and surgical profiles inherent to donor source, the baseline characteristics of the 2,110 kidney transplant recipients are stratified by graft type in Table 1. Of the total cohort, 1,399 patients (66.3%) received a deceased-donor kidney and 711 (33.7%) received a living-donor kidney, with corresponding 30-day readmission rates of 14.8% (207 patients) and 13.9% (99 patients); the overall readmission rate was 14.5% (306 patients). These unadjusted descriptive comparisons serve to

characterize the study population, whereas formal predictive associations are evaluated within the multivariable machine learning framework.

Readmitted living-donor recipients had a higher proportion of female patients than their non-readmitted counterparts (54.5% vs. 42.2%, p = 0.028), whereas gender distribution did not significantly differ by readmission status in the deceased-donor cohort (Female: 41.1% vs. 38.9%, p = 0.614). Regarding age, readmitted deceased-donor recipients were significantly older than those who were not readmitted (median: 51.0 vs. 47.0 years, p = 0.005), while age did not significantly differ among living-donor recipients (median: 40.0 vs. 36.0 years, p = 0.102). Pre-existing diabetes mellitus was more prevalent among readmitted patients in both the deceased-donor (26.1% vs. 18.7%, p = 0.018) and living-donor cohorts (23.2% vs. 12.7%, p = 0.009).

Regarding pre-transplant characteristics, pre-transplant dialysis duration and modality showed distinct patterns of association across the stratified cohorts. Among deceased-donor recipients, readmitted patients had a significantly longer dialysis duration than those who were not readmitted (median: 71.7 vs. 52.7 months, p < 0.001), while no significant difference was observed in the living-donor cohort (median: 34.9 vs. 26.2 months, p = 0.126). In terms of dialysis modality, living-donor recipients requiring readmission were more likely to have undergone pre-transplant peritoneal dialysis (55.6% vs. 39.4%) and less likely to have been in predialysis (7.1% vs. 18.0%) compared to non-readmitted patients (p = 0.002); no significant association with dialysis modality was found in the deceased-donor group (p = 0.913). Additionally, the

use of deceased donors meeting expanded criteria was significantly more frequent in the readmitted group compared to the non-readmitted group (34.8% vs. 25.2%, p = 0.005).

During the index hospitalization, early post-transplant complications and hospital stay patterns varied significantly between the groups. Among deceased-donor recipients, readmitted patients experienced significantly higher rates of urinary tract infections (14.5% vs. 8.2%, p = 0.006), surgical site infections (20.8% vs. 4.7%, p < 0.001), intensive care unit admissions (5.8% vs. 1.7%, p < 0.001), and surgical reinterventions (40.1% vs. 13.8%, p < 0.001). For living-donor recipients, readmitted patients also showed significantly higher rates of surgical site infections (14.1% vs. 4.7%, p < 0.001) and surgical reinterventions (38.4% vs. 17.0%, p < 0.001), whereas the rates of urinary tract infections (9.1% vs. 5.4%, p = 0.223) and intensive care unit admissions (3.0% vs. 1.6%, p = 0.407) did not differ significantly. Finally, the mean length of index hospitalization was significantly shorter in readmitted patients across both the deceased-donor (mean: 2.36 ± 2.89 vs. 2.96 ± 2.65 days, p < 0.001) and living-donor cohorts (mean: 1.70 ± 1.74 vs. 2.35 ± 1.77 days, p < 0.001).

Table 1. Baseline Characteristics of Kidney Transplant Recipients According to Donor Type and Readmission Status. This table summarizes recipient, dialysis-related, hospitalization-related, and donor characteristics stratified by donor type (deceased or living) and 30-day readmission status. The recipient variables included demographics,

comorbidities, kidney disease etiology, and immunosuppressive induction. Dialysis-related data includes information on the modality and duration of dialysis. Hospitalization-related variables included surgical complications, ICU admission, and length of hospital stay. Donor characteristics included sex, age, BMI, and expanded criteria status. Comparisons were conducted between recipients who were readmitted and those who were not classified by donor type. Continuous variables are expressed as median [interquartile range] or mean ± SD depending on distribution; categorical variables are expressed as counts and percentages. P-values reflect between-group comparisons by readmission status within each donor type stratum. Abbreviations: BMI, Body Mass Index; DGF, Delayed Graft Function; GFR, Glomerular Filtration Rate; ICU, Intensive Care Unit.

Variable	**Deceased Donor - No (N, %)**	**Deceased Donor - Yes (N, %)**	**P-value (Deceased)**	**Living Donor - No (N, %)**	**Living Donor - Yes (N, %)**	**P-value (Living)**
	(N=1192)	(N=207)		(N=612)	(N=99)	
Recipient Gender			0.614			0.028*
Female	464 (38.9%)	85 (41.1%)		258 (42.2%)	54 (54.5%)	
Male	728 (61.1%)	122 (58.9%)		354 (57.8%)	45 (45.5%)	
Age at Transplant (years)			0.005**			0.102

Variable	Deceased Donor - No (N, %)	Deceased Donor - Yes (N, %)	P-value (Deceased)	Living Donor - No (N, %)	Living Donor - Yes (N, %)	P-value (Living)
Mean (SD)	46.7 (12.6)	49.2 (12.9)		38.0 (12.7)	40.3 (12.9)	
Median [Min, Max]	47.0 [18.0, 77.0]	51.0 [18.0, 72.0]		36.0 [18.0, 78.0]	40.0 [18.0, 72.0]	
BMI at Transplant			0.232			0.93
Underweight	63 (5.3%)	17 (8.2%)		51 (8.3%)	9 (9.1%)	
Normal weight	706 (59.2%)	110 (53.1%)		369 (60.3%)	62 (62.6%)	
Overweight	347 (29.1%)	65 (31.4%)		147 (24.0%)	22 (22.2%)	
Obesity	76 (6.4%)	15 (7.2%)		45 (7.4%)	6 (6.1%)	
Diabetes Mellitus			0.018*			0.009**
No	969 (81.3%)	153 (73.9%)		534 (87.3%)	76 (76.8%)	
Yes	223 (18.7%)	54 (26.1%)		78 (12.7%)	23 (23.2%)	
Type of Dialysis			0.913			0.002**
Hemodialysis	649 (54.4%)	116 (56.0%)		261 (42.6%)	37 (37.4%)	
Peritoneal Dialysis	447 (37.5%)	75 (36.2%)		241 (39.4%)	55 (55.6%)	

Variable	Deceased Donor - No (N, %)	Deceased Donor - Yes (N, %)	P-value (Deceased)	Living Donor - No (N, %)	Living Donor - Yes (N, %)	P-value (Living)
Predialysis	96 (8.1%)	16 (7.7%)		110 (18.0%)	7 (7.1%)	
Dialysis Time (months)			<0.001***			0.126
Mean (SD)	62.7 (43.4)	80.0 (51.9)		40.9 (39.2)	48.5 (45.3)	
Median [Min, Max]	52.7 [1.43, 313]	71.7 [1.58, 249]		26.2 [0.968, 233]	34.9 [1.58, 233]	
Expanded Donor Criteria			0.005**			1
No	892 (74.8%)	135 (65.2%)		612 (100%)	99 (100%)	
Yes	300 (25.2%)	72 (34.8%)		0 (0%)	0 (0%)	
Delayed Graft Function			<0.001***			0.478
No	1090 (91.4%)	164 (79.2%)		599 (97.9%)	96 (97.0%)	
Yes	102 (8.6%)	43 (20.8%)		13 (2.1%)	3 (3.0%)	
GFR at Day 7 (mL/min/1.73m²) (mL/min/1.73m^2)			<0.001***			0.005**
Mean (SD)	41.5 (25.1)	26.7 (20.8)		55.8 (26.0)	47.3 (26.7)	

Variable	Deceased Donor - No (N, %)	Deceased Donor - Yes (N, %)	P-value (Deceased)	Living Donor - No (N, %)	Living Donor - Yes (N, %)	P-value (Living)
Median [Min, Max]	40.1 [0.620, 136]	17.1 [1.28, 89.1]		57.2 [0.729, 134]	50.1 [0.290, 113]	
Urinary Tract Infection			0.006**			0.223
No	1094 (91.8%)	177 (85.5%)		579 (94.6%)	90 (90.9%)	
Yes	98 (8.2%)	30 (14.5%)		33 (5.4%)	9 (9.1%)	
Surgical Site Infection			<0.001***			<0.001***
No	1136 (95.3%)	164 (79.2%)		583 (95.3%)	85 (85.9%)	
Yes	56 (4.7%)	43 (20.8%)		29 (4.7%)	14 (14.1%)	
ICU Admission			<0.001***			0.407
No	1172 (98.3%)	195 (94.2%)		602 (98.4%)	96 (97.0%)	
Yes	20 (1.7%)	12 (5.8%)		10 (1.6%)	3 (3.0%)	
Surgical Reintervention			<0.001***			<0.001***
No	1028 (86.2%)	124 (59.9%)		508 (83.0%)	61 (61.6%)	
Yes	164 (13.8%)	83 (40.1%)		104 (17.0%)	38 (38.4%)	

Variable	Deceased Donor - No (N, %)	Deceased Donor - Yes (N, %)	P-value (Deceased)	Living Donor - No (N, %)	Living Donor - Yes (N, %)	P-value (Living)
Length of Hospitalization (days)			<0.001***			<0.001***
Mean (SD)	2.96 (2.65)	2.36 (2.89)		2.35 (1.77)	1.70 (1.74)	
Median [Min, Max]	2.00 [0, 21.0]	2.00 [1.00, 24.0]		2.00 [0, 14.0]	1.00 [1.00, 12.0]	

Early Graft Function and Readmission

Early graft function, measured by the estimated glomerular filtration rate on postoperative day 7, was further analyzed across key clinical strata. Figure 1 displays day 7 glomerular filtration rate distributions stratified by donor type, delayed graft function status, and 30-day readmission outcome. Among deceased-donor recipients, readmitted patients had significantly lower day 7 function compared to those who were not readmitted, both in the presence of delayed graft function (median: 11.8 vs. 20.9 mL/min/1.73 m^2, $p = 0.002$) and in its absence (median: 20.8 vs. 41.5 mL/min/1.73 m^2, $p < 0.001$). Similarly, readmitted living-donor recipients without delayed graft function exhibited significantly lower early clearance capacity compared to non-readmitted patients (median: 50.8 vs. 57.5 mL/min/1.73 m^2, $p = 0.006$). Within the living-donor group with delayed graft function, no statistically significant difference

was observed (median: 11.3 vs. 21.4 mL/min/1.73 m², p = 0.364); however, due to the very small size of this subgroup (n = 13 for non-readmitted and n = 3 for readmitted patients), this specific comparison has limited statistical power and must be interpreted with caution.

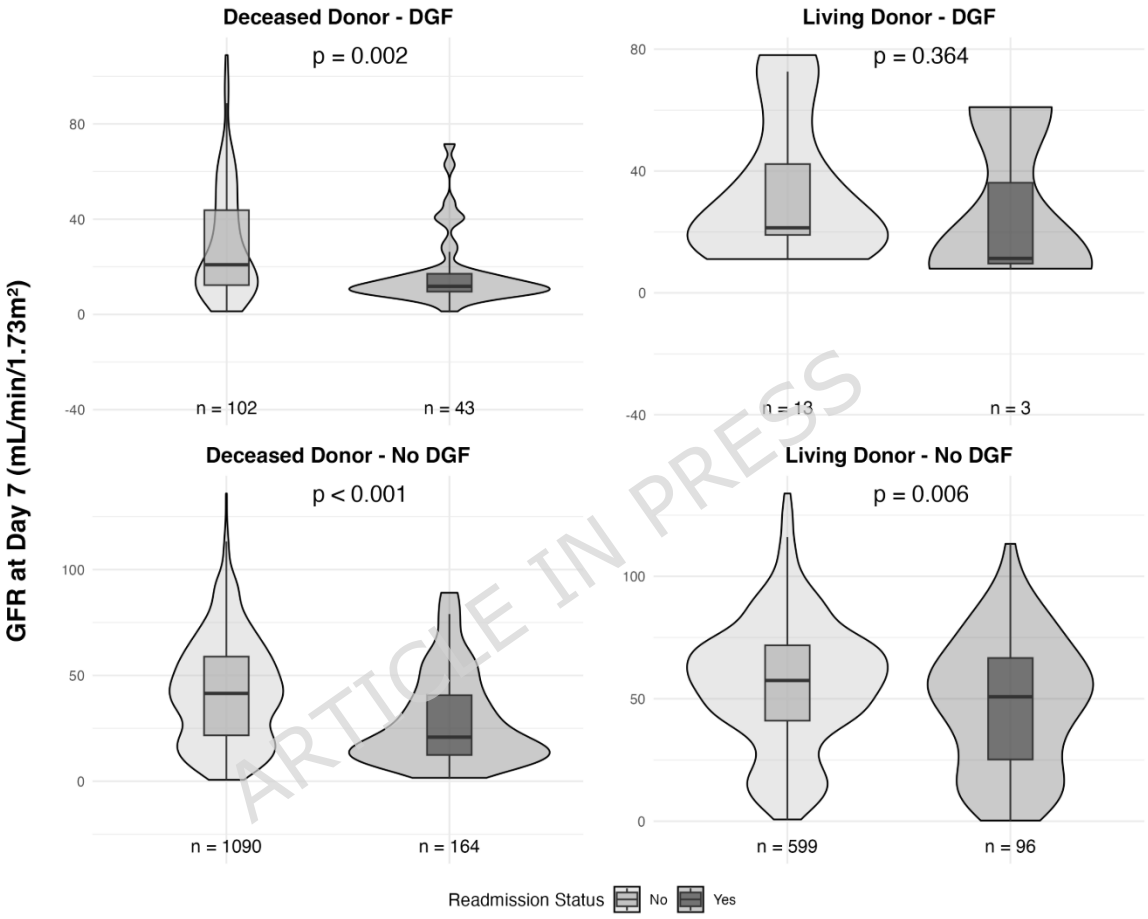

Figure 1. Distribution of Glomerular Filtration Rate at Day 7 Post-Transplant, Stratified by Donor Type, Delayed Graft Function, and 30-Day Readmission Status. The figure illustrates the distribution of glomerular filtration rate (GFR) on day 7 post-transplantation, stratified by donor type (deceased vs. living), presence or absence of delayed graft function (DGF), and 30-day readmission status. Violin plots combined with

boxplots display the distribution and central tendency of GFR across subgroups. The p-values correspond to the statistical comparisons between readmitted and non-readmitted recipients within each subgroup. Note: Certain subgroups, specifically living donor recipients with delayed graft function, have small sample sizes (n = 13 for non-readmitted and n = 3 for readmitted), which restricts the statistical power of this specific comparison. DGF, Delayed Graft Function; GFR, Glomerular Filtration Rate.

Characteristics of 30-Day Hospital Readmissions

Among patients requiring 30-day readmission, the clinical characteristics and course of the rehospitalization episodes showed notable variations when stratified by donor type, as summarized in Table 2. Deceased-donor recipients had a significantly longer duration of rehospitalization compared to living-donor recipients (median: 5.0 [range: 1.0–34.0] vs. 3.0 [range: 1.0–32.0] days, $p = 0.019$). Furthermore, deceased-donor recipients exhibited a significantly higher rate of intensive care unit admission during readmission (8.7% vs. 2.0%, $p = 0.027$) and required hemodialysis during readmission more frequently (38.2% vs. 11.1%, $p < 0.001$). Consequently, the total cumulative length of stay, combining the index hospitalization and the readmission stay, was significantly longer for deceased-donor recipients (median: 6.0 [range: 1.0–70.0] vs. 4.0 [range: 1.0–42.0] days, $p = 0.001$). In contrast, there were no statistically significant differences between deceased-donor and living-donor cohorts regarding the proportion of patients with a single readmission episode (52.7% vs. 49.5%, $p = 0.756$), the primary causes of readmission

(where infections predominated in both groups: 42.0% vs. 49.5%, p = 0.488), the requirement for surgical treatment during readmission (p = 0.179), the rate of graft biopsies (17.9% vs. 11.1%, p = 0.176), or the use of outpatient parenteral treatment (44.4% vs. 40.4%, p = 0.586).

Table 2. Clinical Characteristics of 30-Day Hospital Readmissions by Donor Type. This table summarizes the clinical characteristics and hospital course of rehospitalization episodes among patients requiring 30-day readmission, stratified by donor type (deceased vs. living). The variables analyzed include the length of rehospitalization, the frequency of multiple readmission episodes, the primary causes of readmission, the discharge diagnosis categories, and clinical interventions required during rehospitalization (such as surgical treatment, ICU admission, hemodialysis, and graft biopsy). The total cumulative length of hospitalization (combining index and readmission stays) is also presented. Continuous variables are expressed as median [minimum, maximum] or mean (SD); categorical variables are expressed as counts and percentages. P-values reflect between-group comparisons by donor type. Abbreviations: ICU, Intensive Care Unit.

	Deceased Donor	Living Donor	P-value
	(N=207)	(N=99)	
Length of Rehospitalization (days)			0.019
Mean (SD)	7.24 (7.20)	5.47 (5.81)	
Median [Min, Max]	5.00 [1.00, 34.0]	3.00 [1.00, 32.0]	
Number of Readmissions			0.756

	Deceased Donor	Living Donor	P-value
1	109 (52.7%)	49 (49.5%)	
>1	98 (47.3%)	49 (49.5%)	
Missing	0 (0%)	1 (1.0%)	
Cause of Readmission			0.488
Graft-related issues	27 (13.0%)	10 (10.1%)	
Infections	87 (42.0%)	49 (49.5%)	
Surgical/urinary complications	21 (10.1%)	12 (12.1%)	
Other causes	72 (34.8%)	28 (28.3%)	
Required Surgical Treatment			0.179
Drainage and cleaning	27 (13.0%)	6 (6.1%)	
Reconstruction/repair	23 (11.1%)	15 (15.2%)	
Minor interventions	5 (2.4%)	5 (5.1%)	
Graft nephrectomy	7 (3.4%)	2 (2.0%)	
Others	4 (1.9%)	0 (0%)	
No surgery	141 (68.1%)	71 (71.7%)	
Required ICU Admission			0.027
No	189 (91.3%)	97 (98.0%)	
Yes	18 (8.7%)	2 (2.0%)	
Required Hemodialysis			<0.001
No	128 (61.8%)	88 (88.9%)	
Yes	79 (38.2%)	11 (11.1%)	
Required Graft Biopsy			0.176
No	170 (82.1%)	88 (88.9%)	
Yes	37 (17.9%)	11 (11.1%)	

	Deceased Donor	Living Donor	P-value
Discharge Diagnosis Category			0.506
Renal and transplant-related issues	24 (11.6%)	7 (7.1%)	
Infections	0 (0%)	0 (0%)	
Surgical complications	26 (12.6%)	15 (15.2%)	
Metabolic or cardiovascular disorders	0 (0%)	0 (0%)	
Other issues	18 (8.7%)	6 (6.1%)	
Not registered	139 (67.1%)	71 (71.7%)	
Outpatient Parenteral Treatment			0.586
No	115 (55.6%)	59 (59.6%)	
Yes	92 (44.4%)	40 (40.4%)	
Total Days of Hospitalization			0.001
Mean (SD)	9.07 (9.62)	6.27 (6.54)	
Median [Min, Max]	6.00 [1.00, 70.0]	4.00 [1.00, 42.0]	

Predictive Model Performance for 30-Day Readmission

The out-of-fold performance metrics of the three predictive models on the full cohort (N = 2,110) are presented in Table 3, and their ROC curves are compared in Figure 2. XGBoost achieved an area under the ROC curve of 0.750 (95% CI: 0.722–0.778), while baseline logistic regression and Random Forest yielded AUC values of 0.747 (95% CI: 0.717–0.778) and 0.744 (95% CI: 0.715–0.773), respectively. Regarding classification, Random Forest exhibited the highest sensitivity at 0.746 (95% CI: 0.699–0.791) and a specificity of 0.625 (95% CI: 0.603–0.648). In contrast, XGBoost and logistic regression showed

higher specificity (0.703 [95% CI: 0.682–0.723] and 0.718 [95% CI: 0.697–0.739]) and moderate sensitivity (0.683 [95% CI: 0.635–0.732] and 0.674 [95% CI: 0.625–0.724]). Balanced accuracy was similar across the three models, ranging from 0.686 to 0.696. Finally, precision ranged from 0.253 to 0.289, and F1-scores ranged from 0.378 to 0.404.

Table 3. Performance Metrics of Predictor Models for Predicting 30-Day Hospital Readmission. This table summarizes the out-of-fold predictive performance of the developed models (Random Forest, XGBoost, and the baseline Logistic Regression model) evaluated on the full cohort of 2,110 patients via 10-fold cross-validation. The performance metrics reported include the Area Under the Receiver Operating Characteristic curve (AUC-ROC), classification accuracy, sensitivity, specificity, precision, balanced accuracy, and F1-score. For each metric, the point estimate and the corresponding 95% confidence interval are presented. Confidence intervals for AUC-ROC were estimated using DeLong's method, while intervals for classification metrics were obtained through bootstrap resampling with 1,000 iterations. Abbreviations: CI, Confidence Interval; AUC-ROC, Area Under the Receiver Operating Characteristic Curve; RF, Random Forest; XGB, XGBoost; LR, Logistic Regression.

Metric	Random Forest (95% CI)	XGBoost (95% CI)	Baseline Logistic Regression (95% CI)
Accuracy	0.643 (0.623-0.664)	0.700 (0.679-0.719)	0.712 (0.692-0.731)

Metric	Random Forest (95% CI)	XGBoost (95% CI)	Baseline Logistic Regression (95% CI)
Sensitivity	0.746 (0.699-0.791)	0.683 (0.635-0.732)	0.674 (0.625-0.724)
Specificity	0.625 (0.603-0.648)	0.703 (0.682-0.723)	0.718 (0.697-0.739)
Balanced Accuracy	0.686 (0.659-0.712)	0.693 (0.665-0.721)	0.696 (0.668-0.724)
Precision	0.253 (0.224-0.280)	0.281 (0.249-0.312)	0.289 (0.256-0.320)
F1-Score	0.378 (0.342-0.410)	0.398 (0.359-0.434)	0.404 (0.367-0.440)
ROC AUC	0.744 (0.715-0.773)	0.750 (0.722-0.778)	0.747 (0.717-0.778)

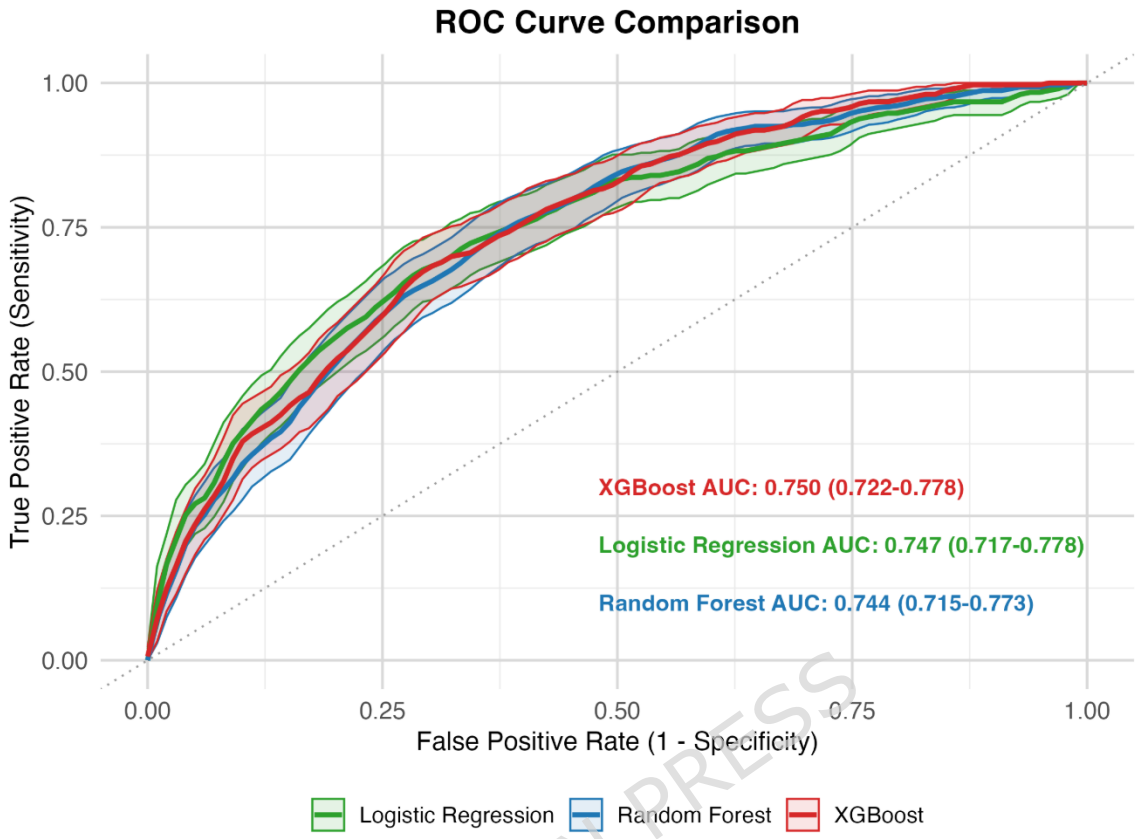

Figure 2. Receiver Operating Characteristic Curve Comparison Between Predictor Models. The figure displays the receiver operating characteristic (ROC) curves for the Random Forest, XGBoost, and baseline Logistic Regression models developed to predict 30-day hospital readmission among kidney transplant recipients (N = 2,110). The shaded areas represent 95% confidence intervals. Empirical (unsmoothed) ROC curves and their out-of-fold confidence bands are displayed. The area under the ROC curve (AUC) values and their corresponding 95% confidence intervals are shown for each model. ROC, Receiver Operating Characteristic; AUC, Area Under the Curve; RF, Random Forest; XGB, XGBoost; LR, Logistic Regression.

The out-of-fold calibration curves of the three models are illustrated in Figure 3A. Across all three algorithms, the curves lie below the 45-degree diagonal, indicating a systematic overestimation of readmission risk, particularly in the higher-risk deciles. In the highest decile, mean predicted probabilities of 0.782 for Random Forest, 0.791 for XGBoost, and 0.831 for baseline logistic regression corresponded to actual observed readmission rates of 0.406, 0.403, and 0.427, respectively. McFadden pseudo-R^2 values were 0.121 for XGBoost, 0.114 for Random Forest, and 0.129 for baseline logistic regression. Figure 3B displays the Decision Curve Analysis. Each model demonstrated clinical utility (defined as a higher net benefit than both the 'treat all' and 'treat none' strategies) within specific threshold probability ranges. Specifically, the clinical utility range was 0.01 to 0.18 for Random Forest, 0.05 to 0.16 for XGBoost, and 0.03 to 0.14 for baseline logistic regression. Within these utility windows, Random Forest consistently achieved the highest net clinical benefit.

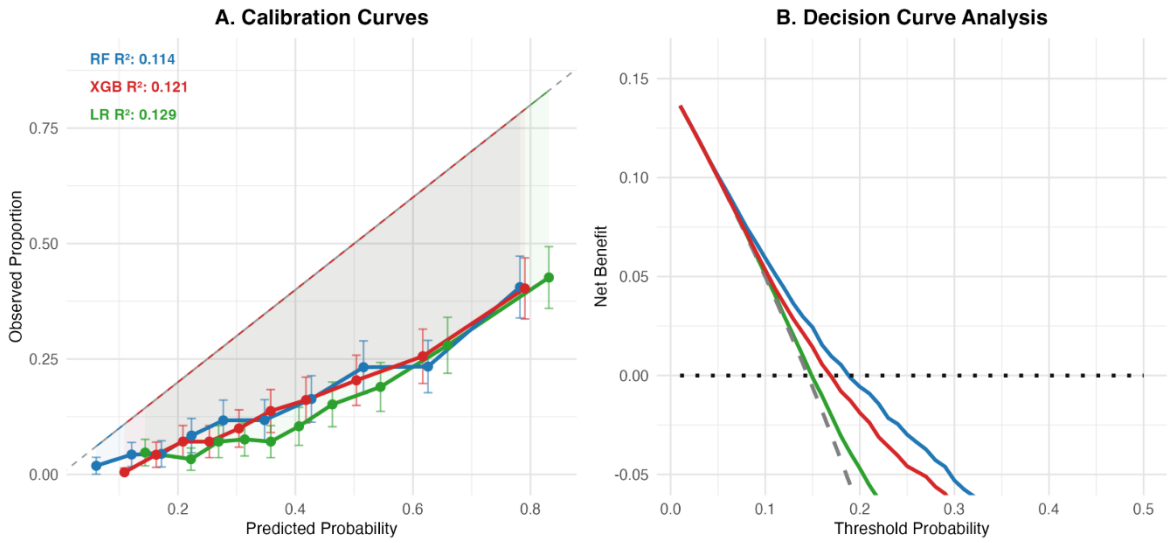

Figure 3. Model Calibration and Decision Curve Analysis (DCA) for 30-Day Hospital Readmission. The figure displays: (A) Calibration curves, and (B) Decision Curve Analysis (DCA) for the Random Forest, XGBoost, and baseline Logistic Regression models used to predict 30-day hospital readmission among kidney transplant recipients (N = 2,110). In (A), predicted probabilities are plotted against observed proportions across deciles of risk, with the dashed diagonal line representing perfect calibration, and McFadden's pseudo-R^2 values indicating overall model fit. In (B), the net clinical benefit of applying each model is plotted across a range of decision threshold probabilities (0% to 50%), demonstrating positive net benefit for all models compared to the default clinical strategies of "treat all" (gray dashed line) and "treat none" (black dotted horizontal line). RF, Random Forest; XGB, XGBoost; LR, Logistic Regression; R^2, McFadden's pseudo-R^2 Coefficient of Determination; DCA, Decision Curve Analysis.

Figure 4 displays the normalized variable importance for the Random Forest and XGBoost models. Importance was computed on the final models fit to the ROSE-balanced full cohort (N = 2,110) to obtain stable, global rankings. Post-transplant length of hospitalization was the top-ranked predictor in both algorithms, serving as the reference standard (normalized importance: 1.00) for relative feature comparison. For Random Forest, the subsequent most influential predictors were GFR at day 7 (0.93), pre-transplant dialysis duration (0.86), and recipient age (0.75). For XGBoost, the subsequent top predictors were GFR at day 7 (0.73), surgical reintervention (0.66), pre-transplant dialysis duration (0.63), and recipient age (0.45). Among multi-level categorical features, Random Forest reported a normalized importance of 0.25 for dialysis type and 0.13 for transplant type, whereas XGBoost reported a normalized importance of 0.13 for peritoneal dialysis, 0.11 for predialysis, and 0.09 for living donor.

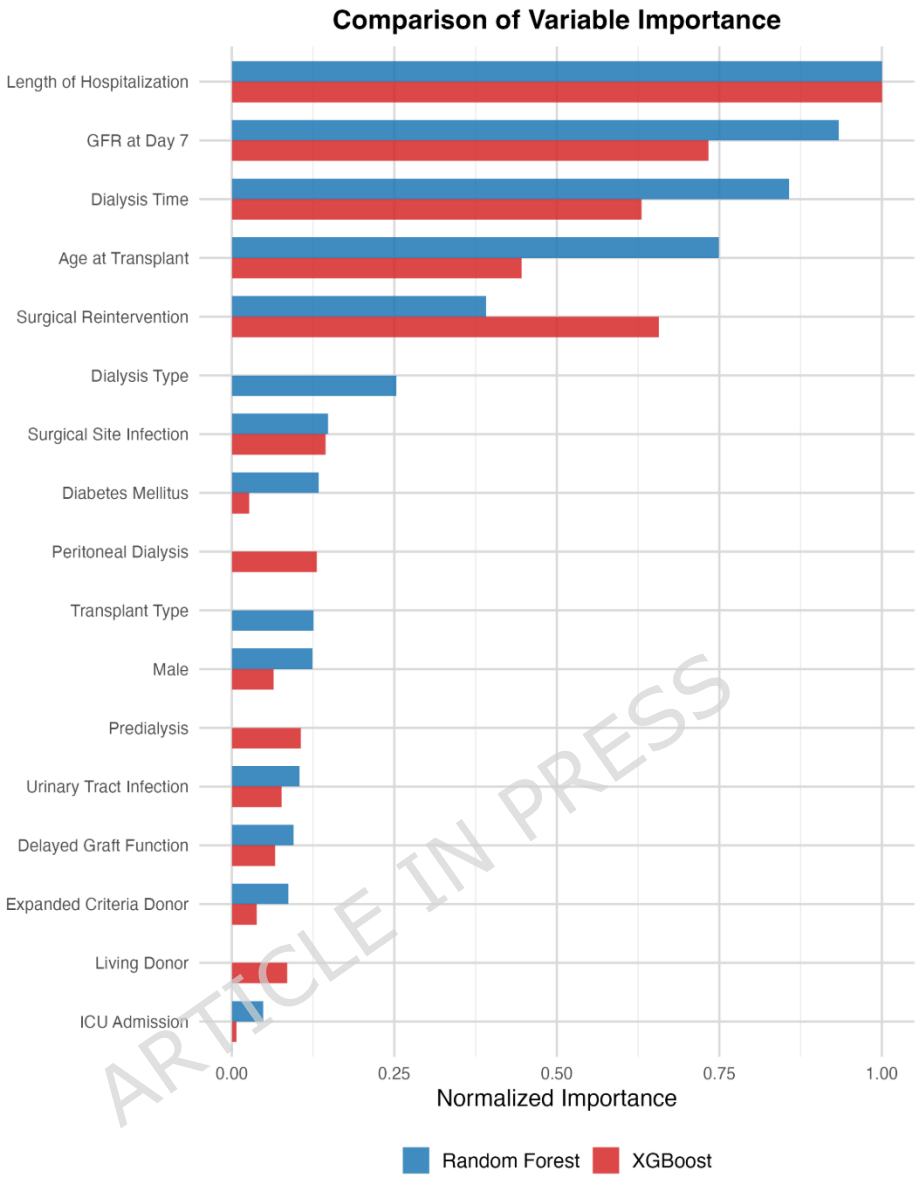

Figure 4. Normalized Variable Importance in Random Forest and XGBoost Models. The figure presents the normalized importance of the variables used in the Random Forest and XGBoost models to predict 30-day hospital readmission among kidney transplant recipients (N = 2,110). Importance values reflect each variable's relative contribution to model performance, scaled from 0 to 1 within each model. The variables are ordered

by average importance across both models. GFR, Glomerular Filtration Rate; ICU, Intensive Care Unit.

1.1.4. Discussion

Predicting early hospital readmission after kidney transplantation requires an integrated assessment that bridges pre-transplant clinical history with dynamic postoperative markers. In this study, we demonstrated that a machine learning framework relying entirely on routinely collected clinical data can effectively stratify this risk during the discharge planning window. Our findings indicate that the predictive signal is dominated by a combination of the patient's cumulative pre-transplant physiological stress and their dynamic early post-transplant recovery course, rather than static baseline characteristics alone. By internally validating our models under a strict, leakage-free pipeline, we established that a clinically-driven gradient boosting algorithm can provide highly calibrated, patient-level risk estimates. This computational foundation enables the translation of complex electronic health record data into an actionable decision-support tool to guide targeted post-discharge surveillance in the clinic.

To translate these patient-level risk estimates into clinical utility, recipients flagged as high risk can be prioritized for a structured Transition-of-Care Surveillance Bundle at the time of discharge. This clinical protocol comprises: (1) early outpatient follow-up within 3 to 5 days of discharge [26]; (2) nurse-led telephone surveillance within 24 to 48 hours post-discharge to assess

clinical stability, medication adherence, and fluid balance; (3) clinical pharmacist-led medication reconciliation of complex immunosuppressive and prophylactic regimens to prevent dosing errors [27–29]; and (4) standardized patient education focusing on early red-flag symptoms. The clinical efficacy of such multimodal transition programs is supported by a randomized controlled trial of 220 kidney transplant recipients, which demonstrated a significant reduction in hospital readmissions at both 30 days ($p = 0.033$) and 90 days ($p = 0.013$) compared to standard care [30].

Beyond the immediate post-discharge period, the clinical significance of predicting and preventing 30-day readmissions is underscored by its profound impact on long-term allograft survival and patient mortality. Although long-term time-to-event survival data were not available for our specific cohort, extensive national registry data from 56,076 kidney transplant recipients demonstrate that early hospital readmission is a potent independent risk factor for subsequent graft failure. Indeed, previous registry analyses reported adjusted hazard ratios for graft loss of 2.40 for deceased-donor recipients and 2.50 for living-donor recipients following an early readmission event, with this excess hazard persisting and attenuating by 14% to 19% annually [31]. Multicenter cohorts consistently corroborate these findings, establishing a strong link between early post-transplant hospitalization and long-term mortality [1,2]. Latin American evidence is highly concordant with these international patterns; a Brazilian cohort study reported a four-fold higher odds of one-year mortality among recipients experiencing early readmissions

(OR 4.01, 95% CI 2.13–7.54) [32]. Consequently, implementing targeted post-discharge surveillance is not merely an administrative strategy to reduce short-term healthcare utilization, but a critical clinical pathway to preserve long-term graft viability and patient survival.

Our modeling strategy aligns with prior work demonstrating that integrating static baseline patient characteristics with dynamic, index-stay perioperative data significantly improves the accuracy of post-transplant risk stratification [33]. Comorbidities, delayed graft function, and early postoperative clinical progress have been consistently reported to improve risk stratification for early readmission [1,34]. Among these features, the length of the index transplant hospitalization emerged as the primary predictive signal across both model architectures. Rather than reflecting a direct causal relationship, length of stay serves as a proximal surrogate for the recipient's overall clinical complexity, surgical stability, and acute recovery course. While shorter hospitalizations typically correspond to uncomplicated postoperative courses, prolonged index stays capture the cumulative downstream effects of subclinical complications or extended clinical observation. Consequently, the length of the index hospitalization should be interpreted as an informative, high-level prognostic marker that identifies clinically vulnerable recipients requiring intensive post-discharge monitoring, rather than acting as a target for direct therapeutic intervention.

Pre-transplant dialysis duration and modality constitute another key predictor domain, capturing the cumulative physiological stress and cardiovascular

burden of end-stage renal disease before transplantation. Our finding that longer dialysis duration strongly predicts early readmission is highly consistent with multicenter analyses demonstrating that chronic uremic exposure compromises vascular compliance and immune responsiveness, predisposing patients to post-discharge complications [1,35,36]. Although some registry studies have reported inconsistent associations for dialysis vintage [37], our results confirm its role as a proxy for pre-transplant clinical vulnerability. Furthermore, regarding dialysis modality, peritoneal dialysis has been associated in some cohorts with distinct early readmission patterns compared to hemodialysis [38], possibly due to variations in fluid volume shifts or baseline cardiovascular burden. Our model successfully integrates both duration and modality to capture this pre-transplant physiological baseline without requiring separate clinical stratifications.

Transitioning from pre-transplant history to early post-transplant physiological markers, early graft function, represented by estimated GFR on postoperative day 7, was strongly associated with 30-day readmission across all model architectures. Notably, even among recipients who did not experience delayed graft function, lower day-7 GFR values corresponded to significantly higher readmission rates, indicating that subtle impairments in early renal recovery signal clinical vulnerability and a more complicated post-transplant course. Previous studies have identified early graft function as a sensitive predictor of short-term transplant outcomes [1,5,39], and our findings support its utility in discharge risk assessment. However, an important physiological caveat must

be applied to GFR estimation at this early stage. During the first postoperative week, serum creatinine levels fluctuate dynamically and have not yet reached a stable steady state; therefore, standard filtration equations do not reflect mature or permanent clearance capacity. Instead, Day-7 GFR is better interpreted as a dynamic proxy for allograft clearance velocity and recovery from ischemia-reperfusion injury. Its strong predictive value in our models suggests that the speed of early allograft creatinine clearance, rather than stable long-term function, is a highly informative prognostic signal.

Regarding recipient demographic characteristics, recipient age emerged as a notable prognostic factor across both machine learning models, whereas recipient sex exhibited negligible predictive influence. Advanced age likely captures the cumulative burden of subclinical cardiovascular comorbidities, physical frailty, and diminished physiological reserve, which collectively lower the threshold for early acute decompensation and subsequent hospitalization following the stress of transplantation. This finding aligns with extensive multicenter evidence linking older age to increased early post-discharge utilization [1,2,40]. Conversely, the minor predictive contribution of recipient sex in our cohort is consistent with the highly divergent literature on gender-based readmission risk. While some registries report slightly elevated risks among female recipients [35], other major cohorts find no significant gender associations [1,41]. These discrepancies likely arise from variations in institutional discharge protocols, regional socioeconomic barriers, and

differences in baseline registry demographics, confirming that sex is a weak, non-generalizable independent predictor of early rehospitalization.

Postoperative complications, infectious events, and baseline metabolic comorbidities represent another closely aligned predictor domain. Surgical reinterventions during the index hospitalization, typically prompted by acute vascular thrombosis, major hematomas, or urologic complications, strongly elevate the risk of early readmission by disrupting the recovery trajectory and extending clinical vulnerability. This finding is highly consistent with previous multicenter analyses demonstrating that early surgical revisions compromise short-term graft stability and predict readmission [7,41], while also predicting worse overall patient survival [1]. Similarly, infectious complications such as urinary tract infections and surgical site infections contributed notably to our model's predictions. Infections are widely documented as a leading cause of early post-transplant hospitalization [42,43], with surgical site infections significantly compounding the likelihood of readmission and predicting worse long-term allograft survival [41,44,45]. Finally, our model successfully incorporated pre-existing diabetes mellitus as a key metabolic contributor. Diabetes mellitus compromises systemic vascular health and wound healing, thereby directly increasing the risk of post-transplant surgical site infections [46]. Moreover, early post-transplant hyperglycemia, which is highly prevalent in diabetic recipients and those under high-dose glucocorticoid therapy, has been shown to significantly elevate the risk of opportunistic infections, acute allograft rejection, and early rehospitalization [47].

This study has several methodological strengths. The dataset systematically captures granular variables across multiple clinical phases of the transplant process, and the deployment of non-parametric machine learning models enables the identification of complex, non-linear relationships and high-order clinical interactions without restrictive assumptions. Furthermore, rigorous internal validation using 10-fold cross-validation, with minority class oversampling isolated strictly within the training folds, ensures robust model stability and prevents optimistic performance bias.

Several limitations of this study must be acknowledged, primary among which are its retrospective design and single-center nature. Retrospective analysis constrains data quality and completeness, making our findings susceptible to unmeasured confounding, while the single-center cohort limits the immediate geographic and institutional generalizability of our predictive metrics. Furthermore, several candidate day-0 immunological predictors, such as HLA mismatches, panel-reactive antibody levels, donor-specific antibodies, and cold ischemia times, alongside detailed immunosuppressive induction and maintenance regimens, were not included in our models. Although documented in our clinical registries, we prioritized routinely available, dynamic post-transplant markers to ensure clinical utility in daily workflows, particularly since immunosuppression protocols are highly standardized within our clinical network, which limits their predictive variability. Clinical indicators such as delayed graft function and postoperative day-7 GFR capture much of the downstream physiological impact of these initial immunological and

ischemic insults, functioning as practical clinical proxies for these parameters. Future multicenter studies should prospectively investigate whether the addition of granular day-0 variables provides incremental predictive value beyond these clinical proxies.

Our modeling choices also reflect deliberate trade-offs regarding validation and cohort segmentation. Restricting minority class oversampling exclusively to training folds prevented data leakage and provided unbiased validation, explaining why our performance metrics are more conservative than those in prior studies where leakage was inadvertently introduced. Furthermore, we intentionally avoided fitting separate models per clinical subgroup. Splitting our cohort by age or donor type would have severely reduced statistical power and heightened the risk of overfitting in small, underrepresented strata. Instead, incorporating recipient age and donor type as candidate predictors in global, non-parametric models allowed the algorithms to learn complex, high-order interactions across the entire clinical spectrum.

While traditional parametric regression provides direct coefficients, non-parametric algorithms like Random Forest and XGBoost operate as black boxes [19]. We address this limitation by reporting global feature importance alongside the local patient-level predictions of our online calculator, available at https://colombianadetrasplantes.shinyapps.io/readmission-risk-calc/ [48]. Global feature importance, illustrated in Figure 4, shows that index hospitalization length and early graft function are key predictive signals. The web-based calculator translates these patterns into a personalized

readmission probability to guide post-discharge surveillance. This deployment aligns with the emerging TRIPOD-AI and PROBAST-AI reporting standards [18], which provide a framework for responsible clinical integration of artificial intelligence [49].

1.1.5. Conclusions

A machine learning model combining pre-transplant and perioperative variables successfully identifies kidney transplant recipients at high risk of 30-day readmission. The dominant predictive signals include index hospitalization length and early graft function. The XGBoost algorithm outperformed alternative machine learning and traditional regression models in both discrimination and calibration. Delivered as a web-based calculator, this tool offers practical decision support to guide discharge planning and post-transplant surveillance. Prospective external validation in independent cohorts is required to confirm generalizability before clinical adoption.

1.1.6. Declarations

Ethics approval and consent to participate

The study adhered to the Declaration of Helsinki and Colombian Resolution 8430 of 1993. It was classified as risk-free research, not requiring informed consent, and was approved by the ethics committee of DEXA DIAB (CIE-CC-01477 2022).

Consent for publication

Not applicable

Availability of data and materials

The datasets generated and/or analyzed during the current study are not publicly available due to ethical and privacy considerations involving patient information. Access to the data may be granted upon reasonable request, subject to approval and the signing of a data use agreement. Interested researchers may contact the corresponding author at aegarcia@colombianadetrasplantes.com.

Competing interests

The authors declare no financial or non-financial competing interests directly or indirectly related to the work submitted for publication.

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Authors' contributions

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Data analysis and interpretation: Santiago Cabas, Andrea Garcia-Lopez, Juan García

Manuscript drafting: Santiago Cabas, Andrea Garcia-Lopez, Jessica Pinto-Ramírez

Critical revision of the manuscript: Fernando Girón-Luque, Jessica Pinto-Ramírez, Yenny Báez-Suarez, Néstor Pedraza

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1.1.7. References

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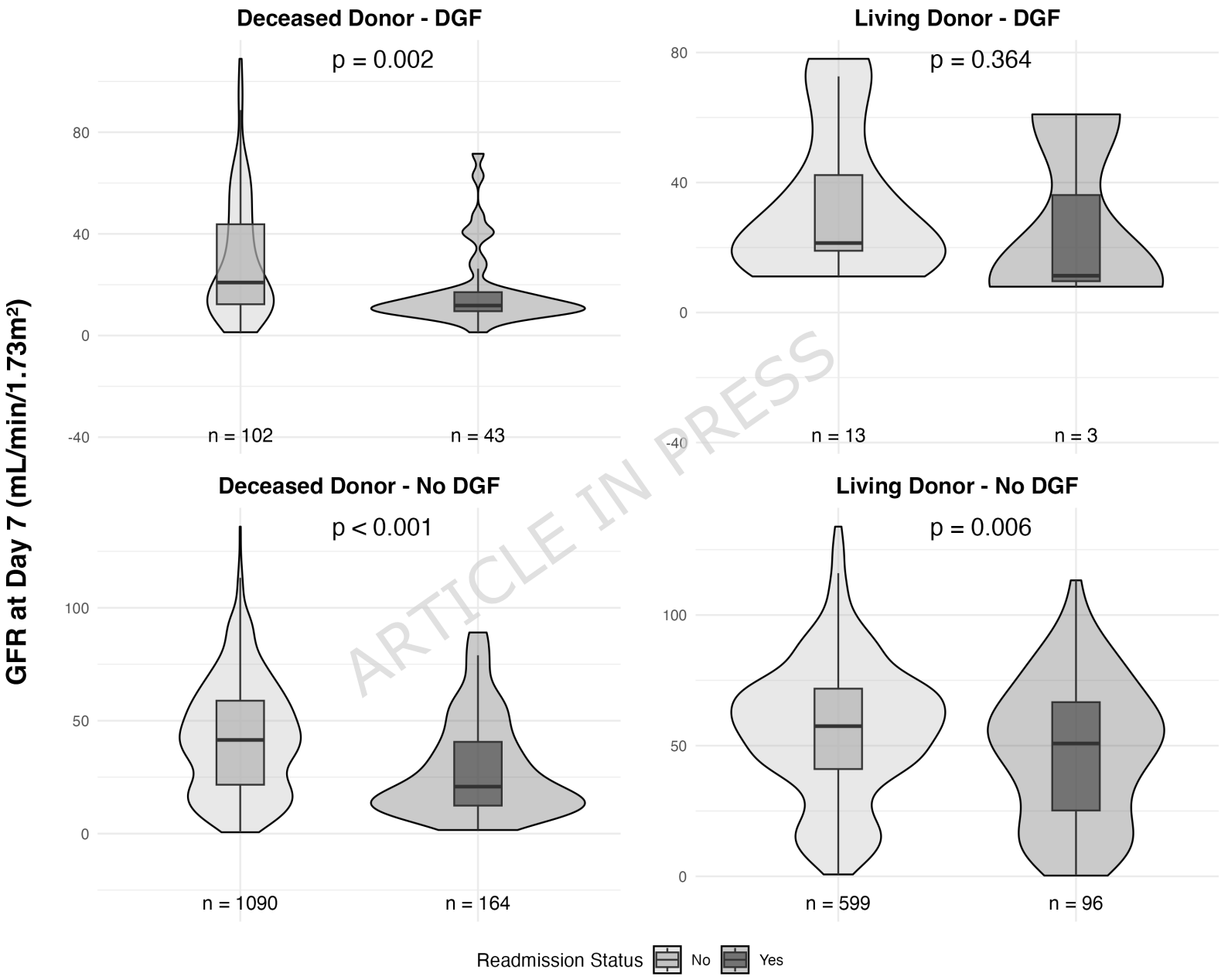

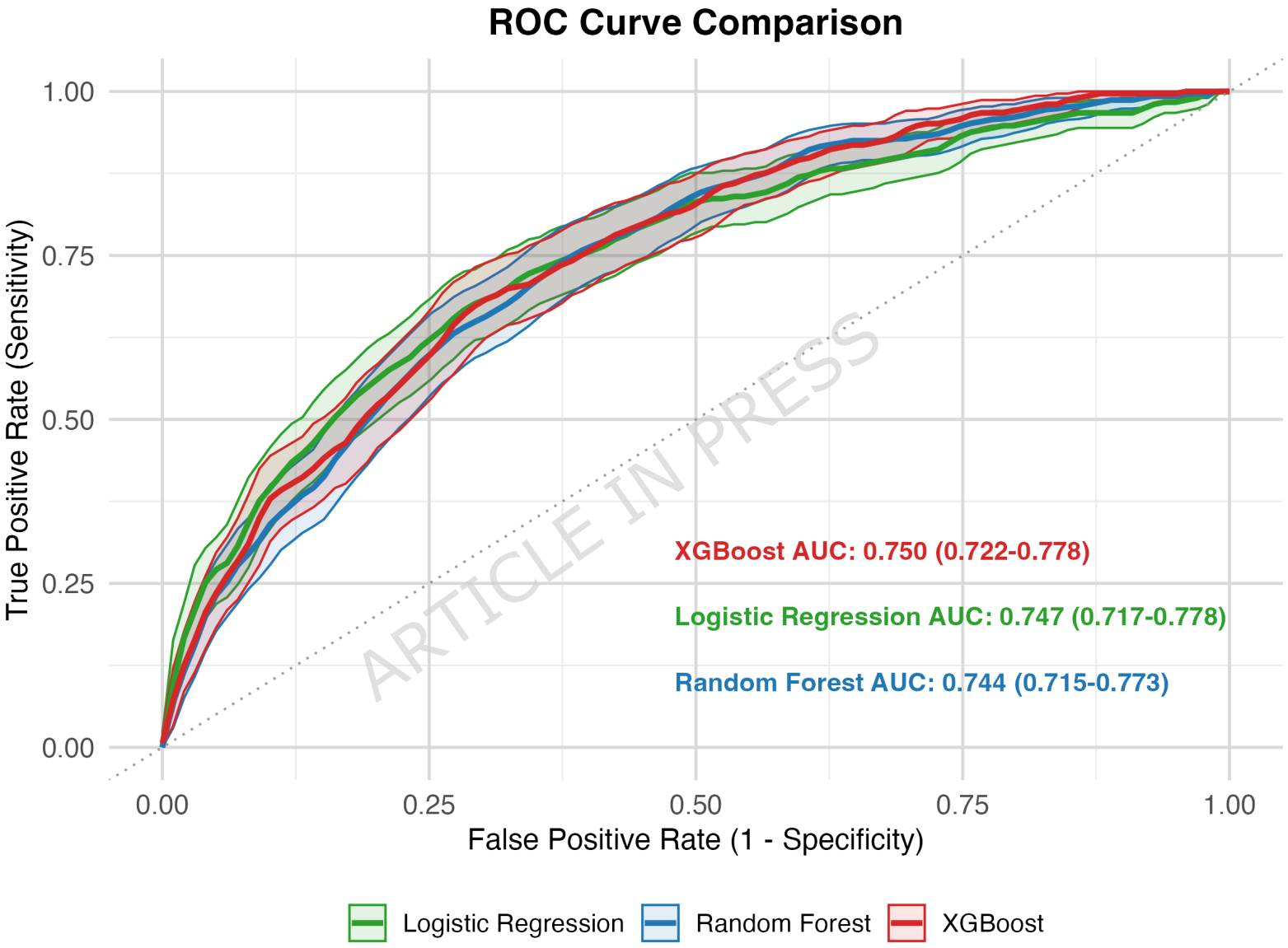

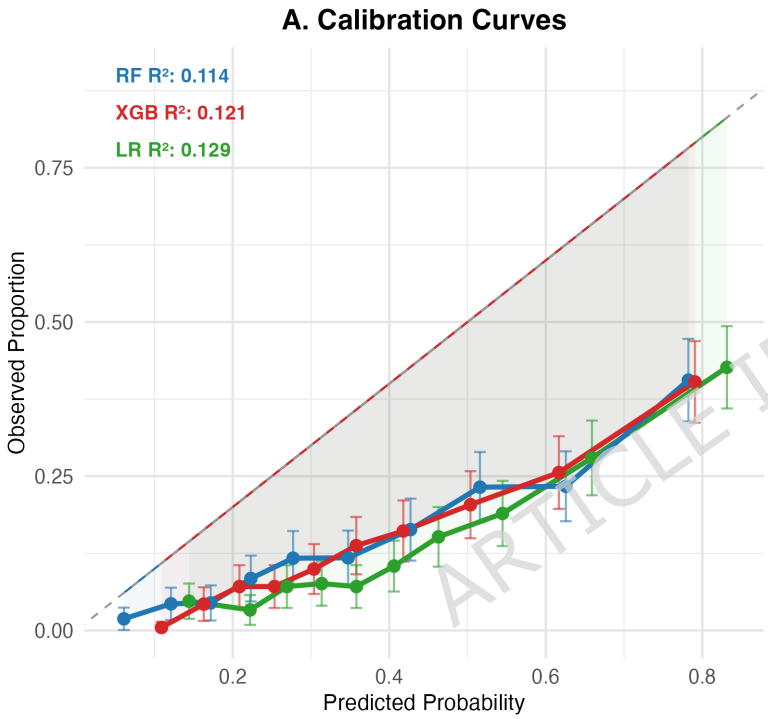

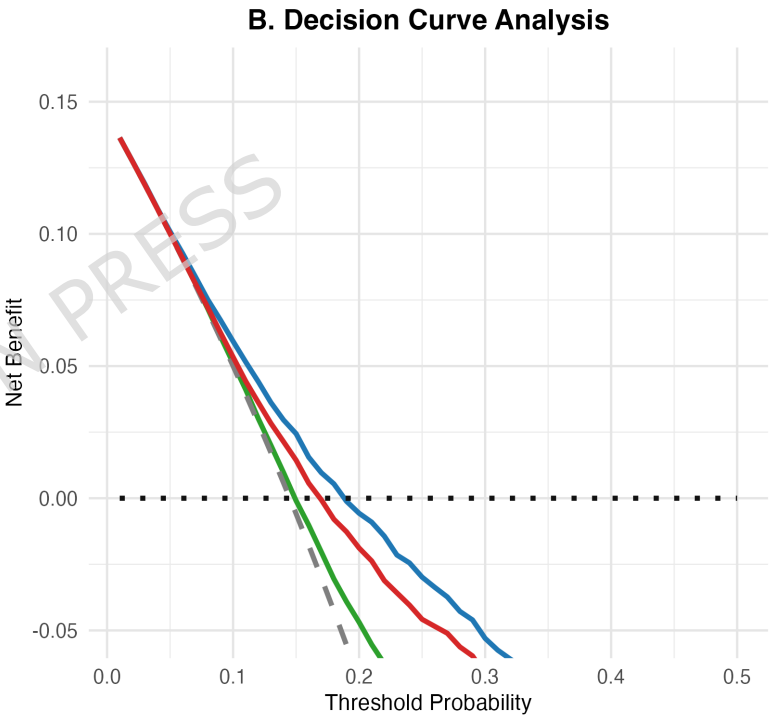

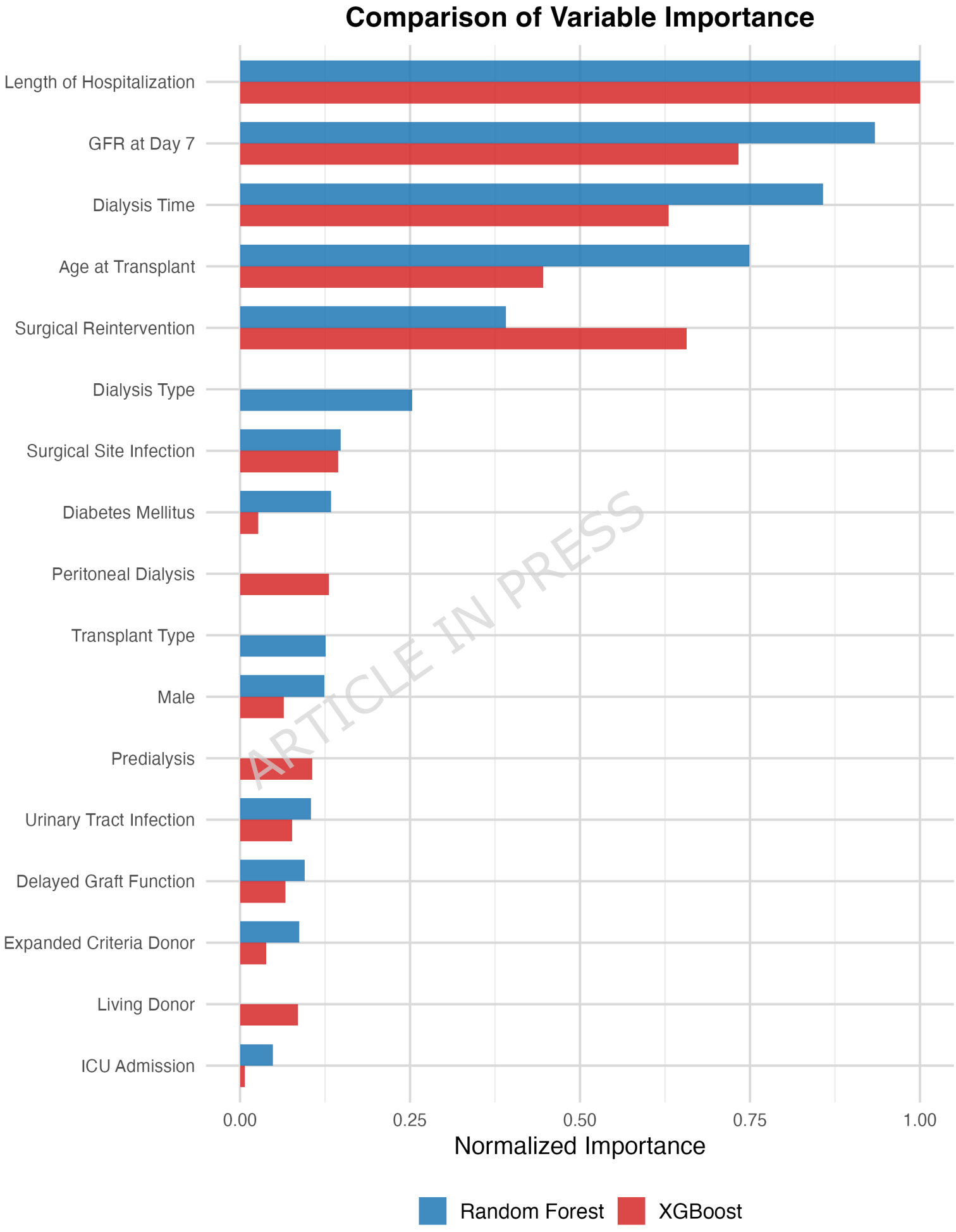

Variable	Donor - Deceased (N=1192)	Donor - Value (Deceased)	Donor - Living (N=612)	Donor - Value (Living)
Recipient Gender		0.614		0.028*
Female	464 (38.8	5 (41.1%)	258 (42.1	54 (54.5%)
Male	728 (61.1	22 (58.9%)	354 (57.8	45 (45.5%)
Age at Transplant (year		0.005**		0.102
Mean (SD)	46.7 (12.2)	49.2 (12.9)	38.0 (12.2)	40.3 (12.9)
Median [Min, Max]	47.0 [18.0, 81.0]	51.0 [18.0, 72.0]	36.0 [18.0, 81.0]	40.0 [18.0, 72.0]
BMI at Transplant		0.232		0.93
Underweight	63 (5.3%)	17 (8.2%)	51 (8.3%)	9 (9.1%)
Normal	706 (59.1	10 (53.1%)	369 (60.2	62 (62.6%)
Overweight	347 (29.1	65 (31.4%)	147 (24.0	22 (22.2%)
Obesity	76 (6.4%)	15 (7.2%)	45 (7.4%)	6 (6.1%)
Diabetes Mellitus		0.018*		0.009**
No	969 (81.1	53 (73.9%)	534 (87.2	76 (76.8%)
Yes	223 (18.7	54 (26.1%)	78 (12.8	23 (23.2%)
Type of Dialysis		0.913		0.002**
Hemodialysis	649 (54.4	16 (56.0%)	261 (42.6	37 (37.4%)
Peritoneal	447 (37.5	75 (36.2%)	241 (39.4	55 (55.6%)
Predialysis	96 (8.1%)	16 (7.7%)	110 (18.0	7 (7.1%)
Dialysis Time (months)		<0.001***		0.126
Mean (SD)	62.7 (48.3)	80.0 (51.9)	40.9 (39.8)	48.5 (45.3)
Median [Min, Max]	52.7 [1.58, 249]	71.7 [1.58, 249]	26.2 [0.34, 233]	34.9 [1.58, 233]
Expanded Donor Criteria		0.005**		1
No	892 (74.8	135 (65.2%)	612 (100	99 (100%)
Yes	300 (25.2	72 (34.8%)	0 (0%)	0 (0%)
Delayed Graft Function		<0.001***		0.478
No	1090 (91.4	164 (79.2%)	599 (97.9	96 (97.0%)
Yes	102 (8.6%)	43 (20.8%)	13 (2.1%)	3 (3.0%)
GFR at Day 7 (mL/min/1.		<0.001***		0.005**
Mean (SD)	41.5 (25.5)	26.7 (20.8)	55.8 (26.6)	47.3 (26.7)
Median [Min, Max]	40.1 [0.17, 113]	17.1 [1.28, 89.3]	57.2 [0.50, 113]	50.1 [0.290, 113]
Urinary Tract Infection		0.006**		0.223
No	1094 (91.8	177 (85.5%)	579 (94.6	90 (90.9%)
Yes	98 (8.2%)	30 (14.5%)	33 (5.4%)	9 (9.1%)
Surgical Site Infection		<0.001***		<0.001***
No	1136 (95.3	164 (79.2%)	583 (95.2	85 (85.9%)
Yes	56 (4.7%)	43 (20.8%)	29 (4.7%)	14 (14.1%)
ICU Admission		<0.001***		0.407
No	1172 (98.3	195 (94.2%)	602 (98.3	96 (97.0%)
Yes	20 (1.7%)	12 (5.8%)	10 (1.6%)	3 (3.0%)
Surgical Reintervention		<0.001***		<0.001***
No	1028 (86.2	124 (59.9%)	508 (83.0	61 (61.6%)
Yes	164 (13.8	83 (40.1%)	104 (17.0	38 (38.4%)
Length of Hospitalizati		<0.001***		<0.001***
Mean (SD)	2.96 (2.36	2.89)	2.35 (1.70	1.74)
Median [Min, Max]	2.00 [0, 24.0]	2.00 [1.00, 24.0]	2.00 [0, 12.0]	1.00 [1.00, 12.0]

	eased Doving Don	P-value
	(N=207)	(N=99)
Length of Rehospitaliza		0.019
Mean (	7.24 (	7.5.47 (5.81)
Mediar	5.00 [1.	3.00 [1.00, 32.(
Number of Readmissions		0.756
1	109 (52.	49 (49.5%)
>1	98 (47.3	49 (49.5%)
Missir	0 (0%)	1 (1.0%)
Cause of Readmission		0.488
Graft-	27 (13.(	10 (10.1%)
Infect	87 (42.(	49 (49.5%)
Surgic	21 (10.1	12 (12.1%)
Other	72 (34.8	28 (28.3%)
Required Surgical Treat		0.179
Drain	27 (13.(	6 (6.1%)
Recons	23 (11.1	15 (15.2%)
Minor	5 (2.4%)	5 (5.1%)
Graft	7 (3.4%)	2 (2.0%)
Others	4 (1.9%)	0 (0%)
No sur	141 (68.7	71 (71.7%)
Required ICU Admission		0.027
No	189 (91.	97 (98.0%)
Yes	18 (8.7%	2 (2.0%)
Required Hemodialysis		<0.001
No	128 (61.	88 (88.9%)
Yes	79 (38.2	11 (11.1%)
Required Graft Biopsy		0.176
No	170 (82.	88 (88.9%)
Yes	37 (17.9	11 (11.1%)
Discharge Diagnosis Cat		0.506
Renal	24 (11.(	7 (7.1%)
Infect	0 (0%)	0 (0%)
Surgic	26 (12.(	15 (15.2%)
Metabc	0 (0%)	0 (0%)
Other	18 (8.7%	6 (6.1%)
Not re	139 (67.7	71 (71.7%)
Outpatient Parenteral T		0.586
No	115 (55.	59 (59.6%)
Yes	92 (44.4	40 (40.4%)
Total Days of Hospitali		0.001
Mean (	9.07 (9.6	27 (6.54)
Mediar	6.00 [1.	4.00 [1.00, 42.(

Metric	Forest (ost (95%	ic Regression (95% CI)
Accuracy	0.643 (0	0.700 (0	0.712 (0.692-0.731)
Sensitiv	0.746 (0	0.683 (0	0.674 (0.625-0.724)
Specific	0.625 (0	0.703 (0	0.718 (0.697-0.739)
Balanced	0.686 (0	0.693 (0	0.696 (0.668-0.724)
Precisio	0.253 (0	0.281 (0	0.289 (0.256-0.320)
F1-Score	0.378 (0	0.398 (0	0.404 (0.367-0.440)
ROC AUC	0.744 (0	0.750 (0	0.747 (0.717-0.778)