The Development of a prediction model for early hospital readmission after kidney transplantation using Machine Learning

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Abstract

Background: Early hospital readmission (EHR) after kidney transplantation is a prevalent and preventable issue that poses ean conomic burden to both patients and the healthcare system and has been associated with poor outcomes.

Objective: This retrospective observational study aimed to develop and validate machine learning-based prediction models, each using a different approach, to predict risk factors associated with early hospital readmission (EHR) following kidney transplantation.

Methods: The study was conducted at the organ transplantation center of a university hospital in South Korea. Electronic health records of 470 kidney transplant recipients were used. The original imbalanced samples were upsampled using the random oversampling example method. We built and trained four machine learning models and tested them to identify the most appropriate EHR predictors. Predictive performance was evaluated using confusion matrices and the area under the receiver operating characteristic curve.

Results: Among 470 patients with a mean age of 46 years, 246 (52.3%) were men, and 74 (15.7%) were readmitted within 30 days after kidney transplantation. After applying the random oversampling example method, 241 (51.2%) patients were found to have experienced EHR. The random forest model achieved the best performance with an area under the receiver operating characteristic curve of 0.824 and accuracies of 0.787 (validation set) and 0.791 (test set). The 15 most important features were steroid pulse therapy (recipient), cerebrovascular accident (donor), heart failure (recipient), male sex (donor), cardiovascular disease (recipi-ent), weekend discharge (recipient), cerebrovascular accident as the cause of brain death (donor), tobacco (recipient), cardiopulmonary resuscitation (donor), previous kidney trans-plantation (recipient), age (donor), hypertension (donor), male sex (recipient), and duration of dialysis (recipient).

Conclusions: The machine learning model identified the top 15 strongest predictors for identifying recipients at high risk of EHR after kidney transplantation. Our framework can achieve reasonable predictive interpretation and support effective and appropriate clinical decision-making.

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Original Manuscript

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heart failure (recipient), male sex (donor), cardiovascular disease (recipient), weekend discharge (recipient), cerebrovascular accident as the cause of brain death (donor), tobacco (recipient), cardiopulmonary resuscitation (donor), previous kidney transplantation (recipient), age (donor), hypertension (donor), male sex (recipient), and duration of dialysis (recipient).

Conclusion: The machine learning model identified the top 15 strongest predictors for identifying recipients at high risk of EHR after kidney transplantation. Our framework can achieve good predictive interpretation and support effective and appropriate clinical decision-making.

Keywords: Machine Learning; Decision Support; Kidney Transplantations; Clinical Decision-making; Patient Readmission

Introduction

Kidney transplantation (KT) is the optimal renal replacement therapy option for patients with end-stage renal disease (ESRD) compared with dialysis [1]. Successful KT reduces morbidity and mortality in patients with ESRD, improves their quality of life, and is a cost-effective alternative to dialysis [2].

Early hospital readmission (EHR) is defined as hospitalization within 30 days of discharge following KT [3]. It is associated with increased medical costs, higher graft loss, higher mortality rates, and lower quality of life [4,5]. EHR is one of the major issues encountered by patients and transplant healthcare professionals following KT [6]. Approximately 30% of patients are readmitted within 30 days after discharge from the hospital following KT in the United States and Korea [7,8], which is a significantly higher proportion than the patients readmitted for other types of surgeries (4–15%) [9]. In patients with KT, EHR is associated with a two-fold increase in graft failure, a three-fold increase in future readmission, and a 50–75% increase in mortality [6,9,10]. Furthermore, patients with KT exhibit an elevated risk of readmission because of their poor health status when KT is performed for end-stage organ failure, sensitivity to complications due to pre-existing comorbidities, and cumulative burden of years of chronic disease (e.g., diabetes, hypertension, and vascular disease) [11,12]. Additionally, patients with KT are discharged with complex immunosuppressive regimens, posing a risk of multiple types of toxicities, and these patients also experience numerous significant metabolic and lifestyle changes following KT [11].

Policymakers and health insurance review and assessment services generally use the 30-day EHR

rate as an important proxy for evaluating hospital quality owing to its strong association with mortality [13]. Notably, previous research has revealed that up to 50% of readmissions are preventable [14]. Considering the high proportion of preventable readmissions and the demonstrated ability of early post KT interventions to reduce EHR [15], reducing the frequency of preventable EHRs and the associated costs are crucial for improving the quality of the healthcare system [16]. Consequently, the development of reliable tools for predicting EHR following KT is imperative to identify at risk patients who may benefit from interventions. Furthermore, the risk factors associated with EHR remain ambiguous, and findings from studies conducted in different healthcare systems vary across countries [17]. Although EHR implementation has been widely elucidated in American transplant centers, comparable data from the Korean transplant population remain lacking. Generalizing the results of American studies to the Korean context is not feasible owing to the significant variations in healthcare delivery and patient outcomes between American and Korean transplant settings. Therefore, identifying EHR-related risk factors is crucial in Korean patients with KT who may benefit from enhanced post-transplant surveillance and for developing strategies to reduce EHR-related risks and outcomes.

Over the past few decades, prediction models have been employed as risk assessment tools in various healthcare settings [6]. These models facilitate the early identification of individuals at risk of illness or adverse events, enabling effective interventions for those who could benefit the most from identifying specific risk factors. However, few studies have attempted to predict EHR after KT, demonstrating a low accuracy of 0.61–0.69 [16]. Furthermore, these data are frequently restricted to surveillance datasets of varying quality and limited granularity. Additionally, prior studies have focused only on isolated variables associated with EHR following KT, limiting their scope and impact [18,19].

Machine learning (ML) methods can be suitably applied for predicting outcomes and constructing decision support systems using clinical data [20]. ML methods are frequently employed for prediction or classification in acute settings and have demonstrated better forecasts than logistic regression for readmission and worsening conditions. Furthermore, ML is a highly useful approach for uncovering otherwise difficult-to-identify patterns between variables and investigating optimal models to explain data using algorithmic methods [21]. Additionally, ML presents several valuable advantages [22]. First, numerous individual patient features and variables can be incorporated into ML predictive models [23], whereas traditional statistical methods primarily focus on a few preselected variables, assuming linear relationships. ML automatically detects and integrates nonlinear relationships and complex interactions among variables in the model, facilitating the development of a more accurate predictive model considering multiple patient characteristics. Second, ML can detect patterns in EHR and can discover hidden patterns and relationships within data [24]. Conversely, conventional statistical analyses, such as hypothesis testing, often emphasize data analysis based on prior assumptions. However, ML is adept at revealing complex patterns and trends within data, which can be leveraged in predictive models to increase the predictive accuracy, especially when multiple factors interact, such as in the EHR following KT. Finally, ML can handle large-scale complex data [25]. Data related to EHR following KT can be complicated, with numerous variables collected from hundreds of patients, each with unique characteristics. ML excels in processing and effectively utilizes extensive datasets with complex structures, thereby improving the performance of the predictive models. Consequently, ML models exhibit increased accuracy for EHR predictions following KT.

This study aimed to overcome the limitations of previous research on the determinants of readmission in KT recipients based on existing linear models and to predict EHR risk using ML in Korean patients with KT. We explored the interactions among complex factors using ML algorithms such as decision tree (DT), random forest (RF), extreme gradient boosting (XG boost), and support vector machine (SVM). Notably, the RF and XGBoost models offered more stable and crucial predictors than logistic regression, thereby increasing the accuracy of identifying patients at high risk for EHR.

Research on EHR is essential for the continuous improvement of patient care processes, including the prevention of premature discharge and inadequate outpatient follow-up [26]. The models developed in this study may provide practical and specific guidance for the early identification of EHR risk and prevention among patients with KT.

Methods

Study setting and participants

This retrospective observational study used data collected at a university hospital in South Korea. It included 650 patients with KT aged ≥18 years who received KT between January 1, 2000 and December 31, 2022 and received follow-up care at the study hospital.

We adopted a prospective cohort study. Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guidelines for cohort studies were followed.

Data sources

We extracted data sources from the Electronic Medical Record (EMR) system from April 1 to August 31, 2024. The electronic medical records of the KT recipients, including data from the pretransplant and perioperative (i.e., shortly after surgery but before discharge) periods, were analyzed. Data were categorized as related to the donor, recipient, or transplant process (e.g., transplant surgery). We excluded participants with >10% missing data. Ultimately, 470 KT recipients were included in the primary analysis. Clinical notes during the pretransplant evaluation process and index transplant hospitalization data (before discharge) were collected to develop a predictive model for EHR that would be useful to hospital personnel before the recipient's discharge.

Variables

The outcome of interest was rehospitalization within 30 days after transplant discharge. This variable was defined as the first unplanned hospital admission after the patient was discharged from the index hospitalization when KT was performed. Admission to the emergency room was considered unexpected hospitalization. The variables were selected based on our clinical experience and prior

research indicating the risk factors for readmission among the patients with KT [3,6,27-29]. Data on the variables collected from the hospital's electronic medical records are presented in Table 1.

Statistical analysis

All statistical analyses were performed using STATA 18.0 (StataCorp. 2023. *Stata Statistical Software: Release 18*. College Station, TX, USA; StataCorp LLC) and R software, version 4.3.2 (R Core Team 2023, R: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria; https://www.R-project.org/). To compare the predictive variables between patients readmitted within 30 days after KT and those not readmitted within 30 days, the t-test was used for continuous variables and the chi-square test was employed for categorical variables. The threshold of significance was set at $p < 0.05$ for all statistical tests, and all reported *p*-values were two-sided.

Data pre-processing

We implemented an upsampling technique to address the issue of data imbalance where the readmission cases were significantly fewer than non-readmission cases using the random oversampling example (ROSE) method. ROSE helps alleviate the imbalance by augmenting the data of the minority class, thereby enhancing the model's ability to learn effectively from these cases [30,31]. It resamples the data points using a bootstrap method based on kernel techniques [32].

ROSE creates synthetic data points, unlike mere duplication of existing minority class data points, thus preventing overfitting [33]. This strategy is particularly advantageous in situations where the minority class is very small, which is a common issue in healthcare data [30,31].

Model construction via supervised ML

This study used ML algorithms to predict EHR following KT. ML approaches are advantageous owing to their robustness against the issues of overfitting and collinearity [34]. Initially, the dataset was split into training and temporary datasets in an 80:20 ratio to ensure a reliable evaluation of the model's performance. During this phase, stratified sampling was utilized based on readmission status to preserve the original distribution of the target variable. Subsequently, the temporary dataset was divided into validation and test sets using stratified sampling to ensure that each set represented 10% of the total dataset. This methodological approach allocated 80% of the data for training, with the remaining 20% equally divided between validation and testing. Additionally, cross-validation was conducted for each model to increase the sophistication of the developed models.

Evaluation methods

This study developed and evaluated four ML models—DT, RF, XGBoost, and SVM—to predict readmission after kidney transplantation. The optimal model was selected by evaluating various hyperparameter combinations or other models through cross-validation. Parameter sensitivity

analysis was conducted during cross-validation to optimize the performance of each model. The DT model was tested with different complexity parameters (CP), RF with varying numbers of variables randomly sampled as candidates at each split (mtry), and SVM with different cost values (C) while maintaining a fixed sigma. For XGBoost, multiple parameters, including learning rate (eta), maximum tree depth, and sampling ratios, were evaluated to uncover the optimal combination. Detailed cross-validation results are presented in Supplementary Table 1 and Supplementary Figure 1. The evaluation metrics encompassed accuracy, F1-score, sensitivity, specificity, ROC AUC, and precision-recall curve (PRC) with bootstrap analysis.

Feature ranking

The significance of each permutation feature was assessed using the final model, which calculated the importance of each factor to determine their respective weights to identify the major predictors.

Ethical considerations

This study was approved by the Institutional Review Board (No. 2024-01-057-002). The Institutional Review Board (IRB) approved a waiver of informed consent for this retrospective study as it involved the use of existing data, with no direct interaction with or additional risk to the participants. Also, this study relied on retrospective de-identified data.

Results

Demographic and clinical characteristics

Among the 470 identified patients, 74 (15.7%) were readmitted within 30 days following KT. In this study, the original imbalanced samples were upsampled using the ROSE method, resulting in 241 readmitted (51.2%) and 229 non-readmitted (48.7%) patients.

The mean readmission day was day 19, and 92.34% of patients were discharged on weekdays (Table 1). Baseline characteristics were compared between the two groups according to the EHR status (Table 1). Differences were observed between the groups in terms of recipient discharge days (weekdays or weekends), duration of intensive care stay following KT surgery, and administration of steroid pulse therapy (all $p < 0.05$).

Model comparison

Table 2 and Figure 1 present the performance of each model evaluated using both validation and test datasets. The RF and XGBoost models were most effective, demonstrating consistently strong performance across all metrics in predicting EHR following KT.

The RF model achieved the highest accuracy of 0.787 (95% CI: 0.643–0.893) on the validation set and maintained robust performance on the test set, with an accuracy of 0.791 (95% CI: 0.650–0.895). It exhibited balanced sensitivity (0.833) and specificity (0.739) on the validation set, with a strong ROC AUC of 0.824. The reliability of this model was further evidenced by its high PRC value of 0.897 (95% CI: 0.783–0.974), indicating an excellent precision-recall trade-off.

The XGBoost model performed similarly to the RF model, particularly in test set metrics. Although its validation set accuracy was 0.702 (95% CI: 0.551–0.826), it achieved identical test set accuracy to the RF model at 0.791 (95% CI: 0.650–0.895). The model demonstrated strong discriminative ability, with an ROC AUC of 0.807 and a PRC of 0.815 (95% CI: 0.663–0.924), suggesting robust predictive performance.

The SVM model showed moderate performance, with validation set accuracy of 0.659 (95% CI: 0.506–0.791) and test set accuracy of 0.666 (95% CI: 0.515–0.796). Although it maintained consistent sensitivity across validation (0.708) and test (0.680) sets, its PRC value of 0.760 (95% CI: 0.561–0.903) indicated reasonable but lower predictive capability than RF and XGBoost.

Despite achieving moderate validation set accuracy of 0.723 (95% CI: 0.573–0.843), the DT model showed considerable performance deterioration on the test set (accuracy: 0.604, 95% CI: 0.452–0.742). Its low sensitivity on the test set (0.400) and ROC AUC (0.607) suggested limited

generalizability, although it maintained the highest specificity (0.826) among all models. The PRC value of this model (0.736, 95% CI: 0.534–0.898) confirmed its inferior performance relative to other models.

These results provide strong evidence against overfitting in the RF and XGBoost models. This is demonstrated by several key observations. First, both models maintained consistent performance between validation and test sets, with nearly identical accuracy measures [35,36]. Second, the stability of performance metrics across different evaluation sets was supported by tight 95% confidence intervals, obtained through rigorous 10-fold cross-validation and bootstrap analysis [36]. Third, the balanced performance across multiple metrics (sensitivity, specificity, and F1-score) in validation and test sets indicated robust generalization capability. The comprehensive parameter sensitivity analysis conducted during cross-validation, including optimization of key parameters, reinforced the resistance of these models to overfitting [36].

Comparative analysis across all metrics indicates that RF and XGBoost models demonstrated the most robust and generalizable performance for predicting post-kidney transplantation readmission. The stability of their performance metrics between validation and test sets, coupled with superior PRC values and tight confidence intervals, suggests their greater reliability for clinical implementation [35,37].

Model performance

In this study, the DT model was used to predict the readmission status of the KT recipients (Figure 2). DT predicted the likelihood of EHR based on various factors, and the final predictions were derived based on the importance of each variable. This approach elucidates the impact of specific conditions on the probability of patient readmission. Within the model, each node processes data according to specific variables, and the leaf nodes display the final prediction outcomes, indicating the readmission status with “Yes.”

The first criterion was whether the patient had received pulse steroid therapy or not. If a patient did not receive this therapy (value of 0), the probability of not being readmitted was 44%, representing 85% of the sample. However, if a patient received steroid pulse therapy (value of 1), the probability of readmission increased to 90%, representing 15% of the sample. The second criterion was the presence of a donor with cerebral vascular accident (CVA). Among patients who did not receive steroid pulse therapy, those with a donor CVA value of 0 exhibited a 38% probability of not being readmitted, representing 63% of the sample. Conversely, if the donor CVA was 1, the probability of readmission was 64%. The third criterion was the donor sex. For donors with a CVA value of 1, if the donor was male (male donor = 0), the probability of readmission was 83%, representing 13% of the sample. If the donor was a female (male donor = 1), the probability of not being readmitted was 34%. The fourth criterion was the recipient discharge status. If the recipient’s discharge status was 1, the probability of readmission was 34%. If the recipient’s discharge status was not 1, the probability of readmission was 69%. For cases in which the recipient’s discharge status was 1, the DT was moved to the following criterion: heart failure. If the recipient had heart failure (heart failure ≠ 0), the probability of readmission was 61%. If there was no heart failure (heart failure = 0), the DT advanced to the next criterion, and the probability of readmission increased to 65% if the value for

peritoneal dialysis was not zero.

In this study, we analyzed the importance of various variables using the RF and XGBoost models, both of which demonstrated relatively high accuracy in predicting EHR following KT. Figure 3 illustrates the importance of the best-performing RF and XGBoost models. Analysis of variable importance in the RF model indicated that steroid pulse therapy was the most significant variable, substantially influencing the model's predictions. Other critical variables included CVA (donor), heart failure (recipient), male sex (donor), and cardiovascular disease (recipient), all of which played a vital role in predicting readmission. As RF assesses variable importance by evaluating numerous DTs, these variables could be key decision points across multiple trees. Similarly, analysis of the XGBoost model identified steroid pulse therapy as the most influential variable, aligning with the findings of the RF model. In the XGBoost model, the importance of steroid pulse therapy was even more pronounced, underscoring its pivotal role in model prediction. Additional significant variables included comorbid conditions (recipient), cold ischemic time, age (recipient), and dialysis duration (recipient). The XGBoost model, which utilizes a boosting algorithm, builds trees iteratively by correcting errors from previous iterations, resulting in a higher importance being assigned to certain variables.

Collectively, the results of the variable importance analysis from both models suggested that key variables, such as steroid pulse therapy, play a critical role in predicting readmission following KT. Although RF and XGBoost assess variable importance differently, both models identified the similar important variables. Notably, a detailed analysis of specific variables may further aid in improving the performance of the developed models.

Discussion

Many countries, including the United States, Australia, Canada, Denmark, England, and Germany, have developed their own readmission strategies. This is especially important as healthcare systems worldwide grapple with readmissions driven by an aging population and the increasing burden of chronic illnesses [38]. Therefore, assessing clinical risk early during hospitalization may enable clinicians to identify key indicators from EMRs, facilitating early intervention programs and supporting clinical decision-making, which are essential components of patient-centered discharge planning [39].

In this study involving patients with KT, EHR occurred in 15.7% of our cohort, a rate slightly lower than that reported in other studies in the United States (18–47%) [8,11,16,40,41], Canada (22.4%) [42], and Korea (approximately 30%) [7,8]. Although direct comparisons of results may not be practical owing to the different health system settings across countries, these findings are likely attributable to the strict definition of EHR adopted in our study, defined as a patient's first unplanned hospital admission after discharge from the index admission during KT.

To the best of our knowledge, this is the first study to use ML to create prediction models based on the data of Korean patients with KT to identify those at risk for EHR, achieving an area under the ROC curve of 0.82 and accuracy of 0.787 and 0.791 for the validation and test datasets, respectively.

This result is encouraging because our models demonstrated better predictive performance than those in previous studies [6,16]. In this study, an integrated algorithm was developed to achieve good prediction performance on the KT dataset. Specifically, ML algorithms, such as DT, RF, XGBoost, and SVM, have been recognized for their advantages in designing systems for clinical decision support because of their potential for evaluating intricate and large datasets [20,43]. For example, DT provides a straightforward and precise examination of various data formats [44], and RF and XGBoost create numerous DTs that sort and select significant predictive factors [45,46]. Therefore, these methods are valuable for predicting outcomes.

KT recipients often experience multiple readmissions [6]. Therefore, developing an analytical approach capable of identifying the risk factors considering their complex interaction is crucial for EHR following KT rather than utilizing a typical linear model such as logistic regression. RF and XG Boost ML methods can identify predictors of EHR. Moreover, unlike logistic models, ML approaches capture predictors without assumptions, misspecifications, or bias. An RF model produces a more stable and significant ranking of factors than a logistic regression [47]. Therefore, predictive models generated using ML methods can improve the prediction of risk categories for EHR. Consequently, EHR can be prevented by providing appropriate interventions to KT recipients who were not previously considered to be at high risk for EHR.

To date, previous studies investigating readmission among KT recipients have mostly identified risk factors including demographic factors (e.g., older age) [40], socioeconomic factors (lower education levels and Medicaid insurance) [48], clinical factors (high body mass index and various comorbidities), surgical factors (longer length of stay, receipt of a transplant from a deceased donor,

older age of the donor, and surgical complications), utilization-related factors (pretransplant hospitalization), and medication adherence [4,5]. In the present study, several risk factors were validated using structured data. In particular, transplantation factors are powerful predictors of EHR, as illustrated by the finding that surgical complications are the most common cause of EHR following KT, accounting for 36% of all readmissions [40]. Therefore, efforts to develop a prediction model for EHR should focus on integrating information related to transplant characteristics [6]. This finding was confirmed by the inclusion of 38 transplant-related indicators in the EHR prediction model. Additionally, although previous studies have revealed that the risk of EHR is influenced by variables, no studies have used an EHR cutoff or reference point to commence preventive care. DT analysis facilitates the derivation of splitting criteria, enhancing the evaluation of the need for preventive management of EHR. Moreover, the application of ML algorithms facilitates the inclusion of a significantly larger number of variables in the modeling process. The robustness of these algorithms enables the construction of complex models, thereby improving decision-making within large and complex datasets [49].

In our study, feature importance analysis identified the top 15 EHR predictors in the highest-performing RF model. These predictors included steroid pulse therapy (recipient), CVA (donor), heart failure (recipient), male sex (donor), cardiovascular disease (recipient), weekend discharge (recipient), cause of brain death due to CVA (donor), tobacco use (recipient), cardiopulmonary resuscitation (donor), previous kidney transplant (recipient), age (donor), hypertension (donor), male sex (recipient), and dialysis duration (recipient). This EHR prediction model underscores the value of EHR in risk prediction by integrating variables related to transplant complications, such as the use of steroid pulse therapy. It also includes recipient-specific factors such as pre-existing conditions (e.g., heart failure and cardiovascular disease), demographic information (e.g., age and sex), smoking

status, and aspects of hospital management such as discharge timing (e.g., weekend discharges). Additionally, donor-related characteristics (e.g., age and sex), cause of brain death (e.g., cerebrovascular accidents), and underlying conditions (e.g., hypertension), were also incorporated to improve predictive accuracy.

As EHR affects key surgical outcomes in KT, such as graft function, recipient survival, and quality of life of the recipient, performing individualized risk assessments to identify patients at the highest risk for EHR is essential. A systematic review reported 3–12% incidence of acute rejection within the first year after KT. Furthermore, most studies focusing on death-censored graft failure have identified acute rejection as an independent risk factor [50]. Notably, steroid pulse therapy is a useful treatment for such complications. Nevertheless, preventing rejection episodes remains a significant challenge despite the development of transplant immunotherapy drugs [51]. Similarly, a recent Canadian study [42] concluded that patients in the EHR group were more likely to have a history of acute rejection, which has been previously associated to mortality, graft failure, and hospitalization following KT [40]. Moreover, the rate of hospital discharge has outpaced the increase in KT procedures over time, whereas the frequency and rate of emergency department visits have remained constant [52]. Notably, rejection contributes to the largest proportion of hospitalizations associated with post-transplant complications [52]. Therefore, implementing strategies to prevent and accurately identify these episodes is crucial to enhancing graft survival outcomes.

Donor characteristics, such as donor age or type (e.g., living donor versus deceased donor and donation after brain death versus donation after circulatory death), are strongly associated with rehospitalization [6]. However, the recipient characteristics were the most important predictors using

the RF model in our study. Notably, these findings may not be applicable to other countries owing to disparities in organ acceptance policies and healthcare delivery systems [11,40,53]. Consequently, additional studies considering regional factors, such as socioeconomic conditions, epidemiology, endemic diseases, and mobility, are needed. Nevertheless, transplant programs worldwide, including in Korea, have expanded their recipient and donor pools in recent years to encompass more medically complex individuals, such as those classified as expanded criteria donors [54]. Accordingly, studies have indicated that patients undergoing transplantation in a more recent period are more prone to experiencing EHR than those who underwent transplantation in earlier years [17]. Therefore, comprehensive history-taking to assess the characteristics of the matched donor is vital, particularly in cases where KT was performed from a brain-dead donor.

Additionally, consistent with the results of studies from other countries, such as the United States and Canada, our model also identified the recipient's age and pre-existing comorbidities (e.g., heart disease) to be associated with EHR post-transplantation. This aspect is likely to become increasingly significant as the KT recipient population ages and presents with a higher prevalence of comorbid conditions [55]. In particular, in Korea, which represents an era of super-aging, this is an important factor to consider in the future.

Unlike the results of a study in the United States [56], our RF model did not indicate delayed graft function as a significant factor in EHR. This dissimilarity may be attributed to cultural and geographical differences in the definitions of cardiac death between Korea and the United States. Organ donation after cardiac arrest associated with delayed graft function is accepted and understood differently in each country or culture, and organ donation after cardiac death is performed in various

categories [57,58]. However, owing to the serious organ shortage, Korea is gradually following Western countries, which are already actively implementing KT with a donor after cardiac death and are increasingly using kidneys from expanded criteria donors after cardiac death [59]. Consequently, additional research on this topic in Korea is necessary.

In our RF model, weekend discharge was included as a risk factor for EHR. Similarly, a meta-analysis in the United States [60] revealed that the 30-day readmission rate was higher in patients who were discharged on weekends than on weekdays among the general patients.

Considering the financial and operational risks associated with EHRs, significant attention has been directed toward clinical oversight and the mitigation of EHR-related challenges. However, explicit clinical guidelines addressing the management and surveillance of KT risks in the context of EHR remain lacking [17]. Although general standard KT risk management practices exist, gaps in the implementation of EHR management may highlight deficiencies in discharge planning and present opportunities for enhancing post-transplant care practices [10]. Further interventions for discharge planning should be developed to eliminate healthcare inequalities within the healthcare system.

Early risk prediction is essential for effectively preventing readmission. Ideally, preventive measures should be implemented prior to discharge. The models in our study aimed to predict the risk of EHR in KT recipients at an early stage. Our results will contribute to individualized evaluations, education, and treatment of KT recipients. Our study builds on existing predictive factors and offers new insights that can improve KT outcomes and enhance the quality of life of Korean patients with

KT. The integration of EHR risk assessment systems into electronic health record platforms can be achieved by developing prediction models based on medical records. Additionally, EHR alert systems can be designed for transplant nursing, enabling healthcare professionals, including transplant specialists, nurses, and physicians, to effectively allocate preventive interventions to KT recipients identified as exhibiting high risk for EHR [61].

Future studies should assess the usefulness and predictability of our models for discharge plans and interventions targeting KT recipients. These findings may contribute to the development of an evaluation instrument and intervention program to promote the early detection of EHR risk, facilitating EHR prevention. Additionally, future studies should provide an evaluation strategy or intervention program that focuses on the factors identified in the prediction models presented herein.

This study has some limitations. First, our data were obtained from a single university hospital, and we did not have an external dataset for model validation. Therefore, the efficacy of this model to data from different institutions remains unclear. Notably, we established a method for building a prediction model using electronic medical records and ML techniques. Second, improvements over logistic regression models demonstrate the strength of the ML approaches. However, conducting a more in-depth examination is important to determine the consistency of the model with those in the previous studies using data from various domains. Therefore, further research is required to investigate the other potentially relevant determinants of readmission.

Conclusions

The early identification of EHR following KT is critical for its prevention and may represent the most effective approach for initiating care in high risk KT recipients. In this study, we developed a ML-based prediction model for EHR among KT recipients, which demonstrated high predictive accuracy. Such models have the potential to facilitate targeted EHR prevention strategies in KT recipients. The top 15 risk predictors identified by the model can assist in clinical decision-making and improve KT outcomes by enabling personalized discharge planning tailored to the unique needs and characteristics of each patient, thereby improving the overall quality of life of KT recipients.

We propose the integration of supervised ML-based clinical decision support systems into electronic medical record systems. Further research is required to validate the characteristics identified in this study, which may serve as indicators for identifying high risk EHR groups across different healthcare settings through longitudinal monitoring. The models developed in this study have the potential to assist healthcare professionals in implementing early interventions to prevent EHR in KT recipients, particularly in the context of transplant nursing care. This algorithm facilitates the enrollment of patients in EHR prevention programs and provides targeted interventions for various cohorts of patients with KT. Additionally, we recommend incorporating data from these computer-based models at the beginning of hospitalization, in conjunction with ongoing assessments, throughout the patient's stay.

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Author Contributions

Hye Jin Chong: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Writing – original draft, Writing – review & editing, Validation, Visualization,

Ji-hyun Yeom: Data curation, Project administration, Resources, Writing – review & editing.

Statements and declarations+

Not applicable

Ethical considerations

This study was approved by the Institutional Review Board of Jeonbuk National University Hospital (No. 2024-01-057-002).

Consent to participate

The Institutional Review Board (IRB) approved a waiver of informed consent for this retrospective study as it involved the use of existing data, with no direct interaction with or additional risk to the participants. Also, this study relied on retrospective de-identified data.

Consent for publication

Not applicable

Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Data Availability Statement

The data that support the findings of this study are available on reasonable request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Tables

Table 1. Comparison between patients requiring and not requiring early hospital readmission

Characteristics	Total (N = 470)	Readmission within 30 days (N = 74)	No readmission within 30 days (N = 396)	*p*-value
Donor				
Body mass index				
Mean (SD)	24.23 (3.14)	23.76 (2.95)	24.31 (3.17)	0.144
Age (years)				
Mean (SD)	46.14 (15.29)	48.45 (15.80)	45.74 (15.18)	0.170
Gender				
Male (%)	246 (52.34)	42 (56.75)	204 (51.51)	0.482
Female (%)	224 (47.65)	32 (43.24)	192 (48.48)	
Cardiac arrest				0.343
No (%)	142 (30.21)	28 (37.83)	114 (28.78)	
Yes (%)	72 (15.31)	11 (14.86)	61 (15.40)	
Unknown	256 (54.48)	35 (47.31)	221 (55.82)	
Cause of brain death				
Accident (%)	121 (25.74)	18 (24.32)	103 (26.01)	0.061
Cerebral vascular accident (%)	104 (22.12)	25 (33.78)	79 (19.94)	
Others (%)	245 (52.14)	31 (41.89)	214 (0.25)	
Diabetes mellitus				
No (%)	422 (89.78)	66 (89.18)	356 (89.89)	0.103
Yes (%)	22 (14.68)	1 (1.35)	21 (5.30)	
Unknown	26 (5.53)	7 (9.45)	19 (4.79)	
Hypertension				
No (%)	375 (79.78)	55 (74.32)	320 (80.80)	0.232
Yes (%)	69 (14.68)	12 (16.21)	57 (14.39)	
Unknown	26 (5.53)	7 (9.45)	19 (4.79)	
Creatinine				
Mean (SD)	1.07 (0.71)	1.13 (0.65)	1.06 (0.72)	0.453
Cold ischemic time (min)				
Mean (SD)	113.73 (111.69)	122.39 (122.19)	112.12 (111.67)	0.471
Recipient				

Duration of dialysis (years)				
Mean (SD)	3.60 (4.29)	3.85 (3.88)	3.56 (4.37)	0.562
Human leukocyte antigen mismatch				
Mean (SD)	3.56 (1.39)	3.63 (1.42)	3.55 (1.39)	0.639
Body mass index				
Mean (SD)	22.55 (4.43)	22.84 (3.60)	22.50 (4.57)	0.471
Post KT admission day				
Mean (SD)	19.00 (7.84)	19.35 (10.56)	18.93 (7.24)	0.747
Discharge				
Weekday (%)	434 (92.34)	62 (83.78)	372 (93.93)	0.005
Weekend (%)	36 (7.65)	12 (16.21)	24 (6.06)	
Age (years)				
Mean (SD)	47.06 (11.98)	49.48 (12.69)	46.61 (11.81)	0.074
Sex				
Male (%)	322 (68.51)	48 (64.86)	274 (69.19)	0.549
Female (%)	148 (31.48)	26 (35.13)	122 (30.80)	
KT Type				
Deceased donor KT (%)	312 (66.38)	48 (64.86)	264 (66.66)	0.867
Living donor KT (%)	158 (33.6)	26 (35.13)	132 (3.33)	
ABO-incompatible transplantation				
No (%)	426 (90.63)	70 (94.59)	356 (89.89)	0.291
Yes (%)	44 (9.36)	4 (5.40)	40 (10.10)	
Heart failure				
No (%)	412 (87.65)	61 (82.43)	351 (88.63)	0.194
Yes (%)	58 (12.34)	13 (17.56)	45 (11.36)	
Lung disease				
No (%)	445 (94.68)	71 (95.94)	374 (94.44)	0.805
Yes (%)	25 (5.31)	3 (4.05)	22 (5.55)	
Cardiovascular disease				
No (%)	445 (94.68)	74 (100)	371 (93.68)	0.052
Yes (%)	25 (5.31)	0 (0)	25 (6.31)	
Peripheral vascular disease				

No (%)	443 (94.25)	71 (95.94)	372 (93.93)	0.682
Yes (%)	27 (5.74)	3 (4.05)	24 (6.06)	
History of orthopedic surgery				
No (%)	450 (95.74)	71 (95.94)	379 (95.70)	1.00
Yes (%)	20 (4.25)	3 (4.05)	17 (4.29)	
Any comorbid condition (number)				
0 (%)	340 (72.34)	49 (66.21)	291 (73.48)	0.661
1 (%)	120 (25.53)	23 (31.08)	97 (24.49)	
2 (%)	8 (1.70)	2 (2.70)	6 (15.15)	
3 (%)	1 (0.21)	0 (0)	1 (0.25)	
4 over (%)	1 (0.21)	0 (0)	1 (0.25)	
Hypertension				
No (%)	65 (13.82)	15 (20.27)	50 (12.62)	0.117
Yes (%)	405 (86.17)	59 (79.72)	346 (87.37)	
Smoking habit				
Do not smoke (%)	343 (72.97)	51 (68.91)	292 (73.73)	0.629
History of smoking (%)	78 (16.59)	15 (20.27)	63 (15.90)	
Current smoking (%)	49 (10.42)	8 (10.81)	41 (10.35)	
Drinking habit				
Do not drink alcohol (%)	371 (78.93)	57 (77.02)	314 (79.29)	0.902
History of drinking (%)	71 (15.10)	12 (16.21)	59 (14.89)	
Current drinking (%)	28 (5.95)	5 (6.75)	23 (5.80)	
Diabetes mellitus				
No (%)	305 (64.89)	44 (59.45)	261 (65.90)	0.350
Yes (%)	165 (35.10)	30 (40.54)	135 (34.09)	
Hepatitis B				
No (%)	437 (92.97)	70 (94.59)	367 (92.67)	0.652
Yes (%)	29 (6.17)	4 (5.40)	25 (6.31)	
Unknown	4 (0.85)	0 (0)	4 (1.01)	
Cancer				
No (%)	441 (93.82)	70 (94.59)	371 (93.68)	0.972
Yes (%)	29 (6.17)	4 (5.40)	25 (6.31)	
Dialysis type				
Hemodialysis (%)	429 (91.27)	65 (87.83)	364 (91.91)	0.358

Peritoneal dialysis (%)	41 (8.72)	9 (12.16)	32 (8.08)	
Panel reactive antibody ≥50%				
No (%)	311 (66.17)	42 (56.75)	269 (67.92)	0.173
Yes (%)	53 (11.2)	11 (14.86)	42 (10.60)	
Unknown (%)	106 (22.5)	21 (28.37)	85 (21.46)	
Delayed graft function				
No (%)	438 (93.19)	65 (87.83)	373 (94.19)	0.081
Yes (%)	32 (6.80)	9 (12.16)	23 (5.80)	
Previous KT				
No (%)	427 (90.85)	66 (89.18)	361 (91.16)	0.748
Yes (%)	43 (9.14)	8 (10.81)	35 (8.83)	
Induction treatment				
Bacilimab (%)	411 (87.44)	65 (87.83)	346 (87.37)	1.00
Anti-thyroglobulin (%)	59 (12.55)	9 (12.16)	50 (12.62)	
Intensive care unit stay day				
Mean (SD)	4.65 (2.25)	4.06 (2.38)	4.76 (2.21)	0.021
Creatinine at discharge				
Mean (SD)	1.51 (1.29)	1.54 (1.07)	1.51 (1.32)	0.808
Steroid pulse therapy				
No (%)	436 (92.76)	57 (77.02)	379 (95.70)	<0.001
Yes (%)	34 (7.23)	17 (22.97)	17 (4.29)	

KT, kidney transplantation; SD, standard deviation

Table 2. Model evaluation via cross-validation

		Accuracy (95% CI)	F1-score	Sensitivity	Specificity	ROC AUC	PRC (95% CI)*
Decision Tree	Validation set	0.723 (0.573–0.843)	0.512	0.625	0.826	0.731	0.736 (0.534–0.898)
	Test set	0.604 (0.452–0.742)	0.512	0.400	0.826	0.607	
Random Forest	Validation set	0.787 (0.643–0.893)	0.791	0.833	0.739	0.871	0.897 (0.783–0.974)
	Test set	0.791 (0.650–0.895)	0.791	0.760	0.826	0.824	
XGBoost	Validation set	0.702 (0.551–0.826)	0.791	0.791	0.608	0.786	0.815 (0.663–0.924)
	Test set	0.791 (0.650–0.895)	0.791	0.760	0.826	0.807	
Support Vector Machine	Validation set	0.659 (0.506–0.791)	0.680	0.708	0.608	0.735	0.760 (0.561–0.903)
	Test set	0.666 (0.515–0.796)	0.680	0.680	0.652	0.718	

* PRC 95% Interval results come from bootstrap (1000 repetitions)

Figure legends

Figure 1. Receiver operating characteristic curves of different cross-validation models.

XG boost, extreme gradient boosting; SVM, support vector machine

Figure 2. Decision tree.

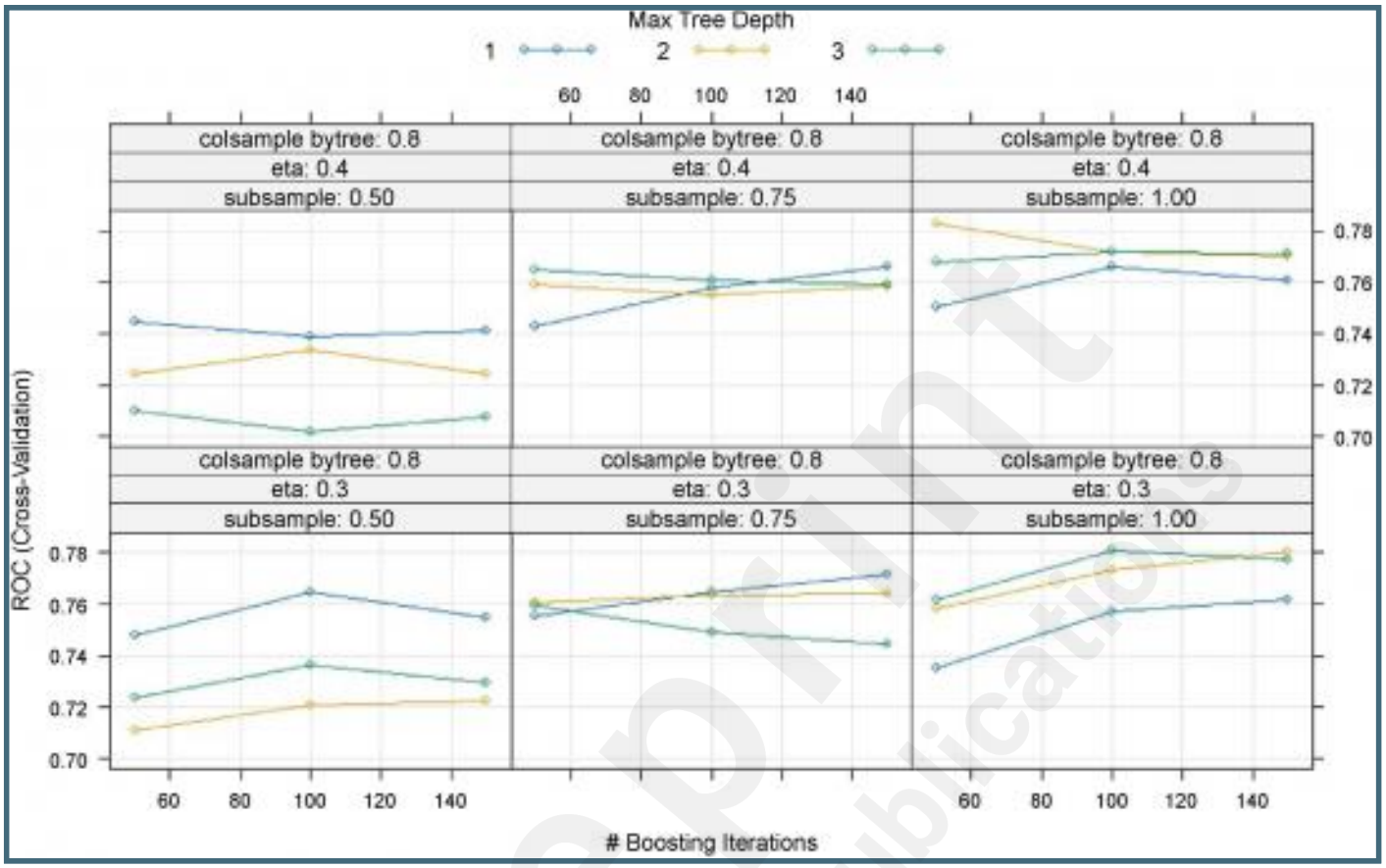
Yes: admitted within 30 days, 1 = yes, 0 = no. CVA, cerebral vascular accident; PD, peritoneal dialysis

Figure 3. Analysis of the importance of variables through cross-validation (top 15).

Tx, therapy; CVA, cerebrovascular accident; CVD, cardiovascular disease; KT, kidney transplantation; HTN, hypertension; CIT; cold ischemic time; BMI, body mass index; ICU, intensive care unit; HLA, human leukocyte antigen

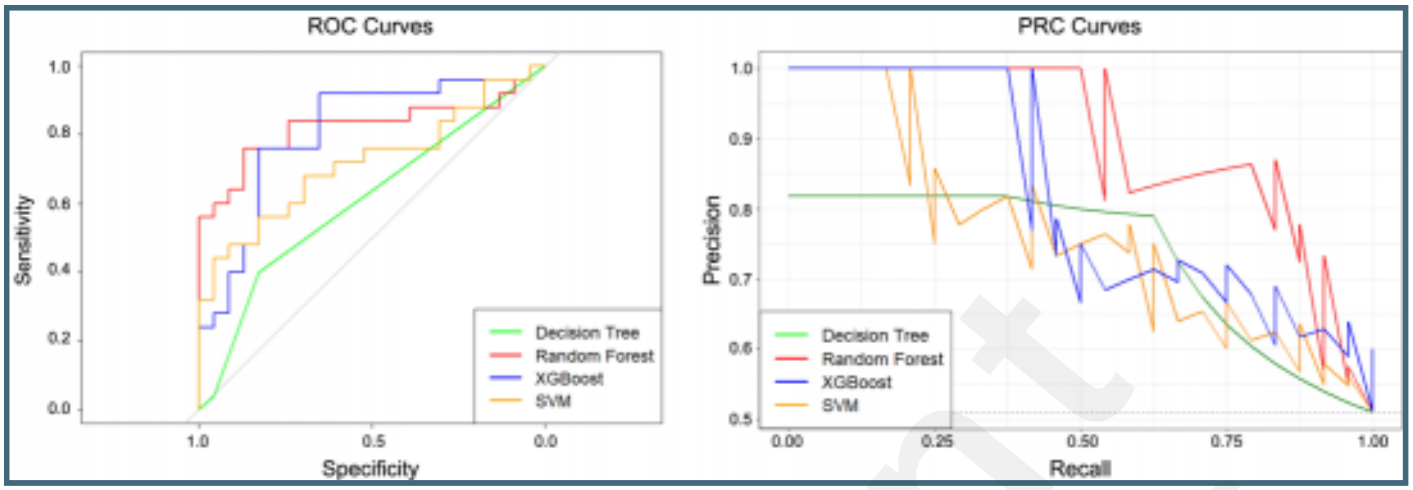
Supplementary Files

The evaluation metrics encompassed accuracy, F1-score, sensitivity, specificity, ROC AUC, and precision-recall curve (PRC) with bootstrap analysis.

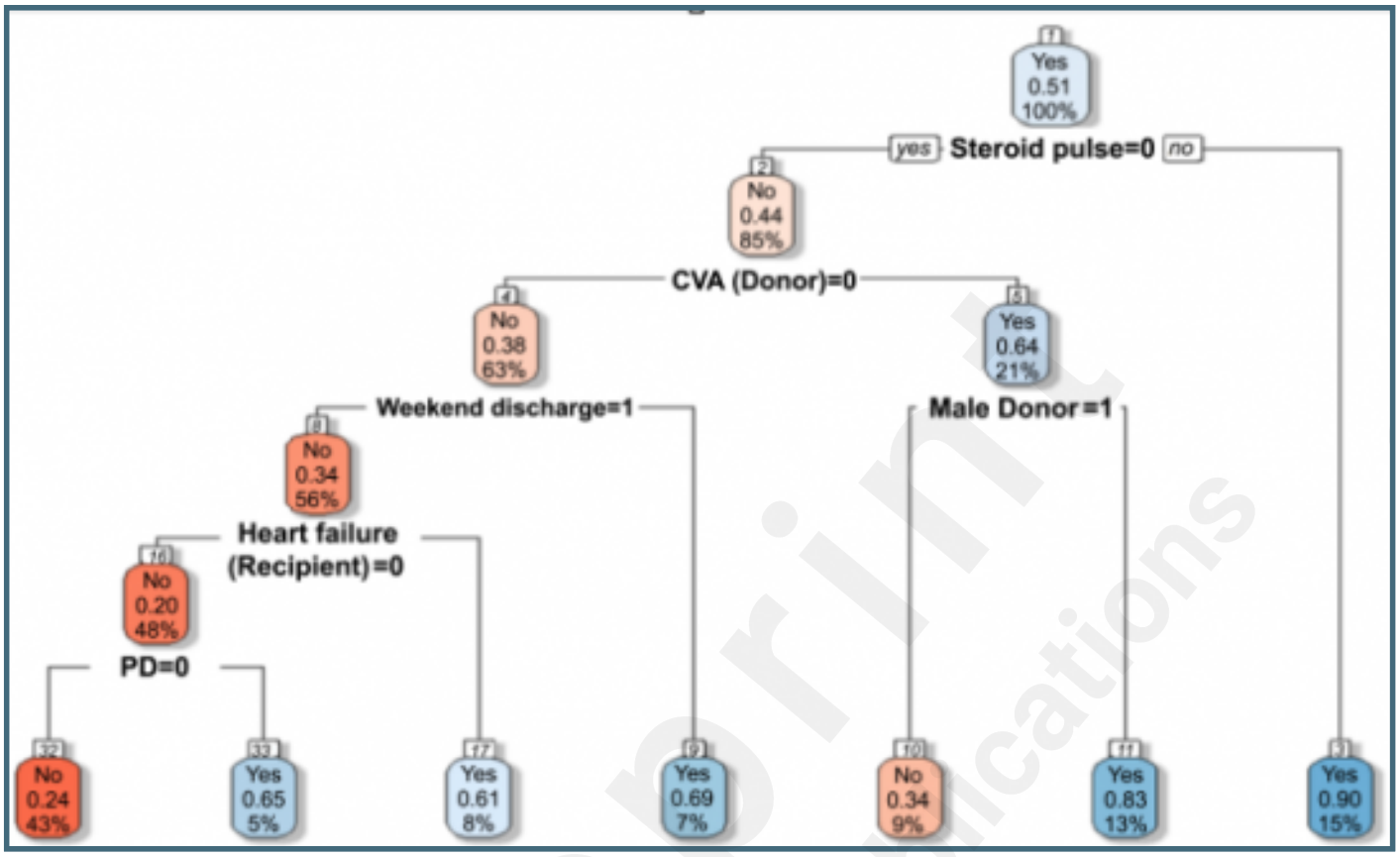


Figures

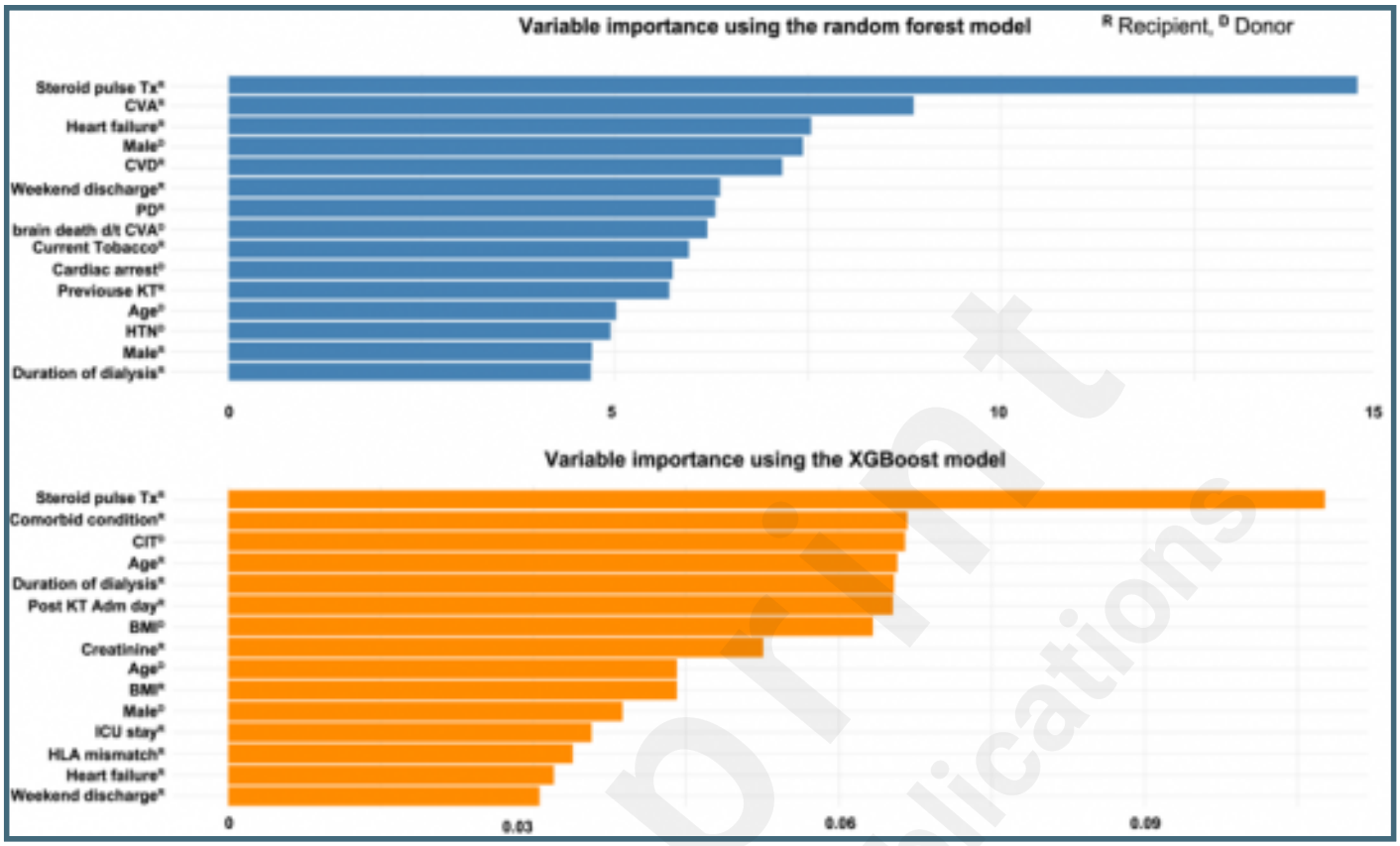
Receiver operating characteristic curves of different cross-validation models.



Receiver operating characteristic curves of different cross-validation models.



Analysis of the importance of variables through cross-validation (top 15).



Multimedia Appendixes

Cross-validation results for each model.
URL: http://asset.jmir.pub/assets/3b146ad6935d4a5bbbb4fe69de85a94b.pdf