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SIMULATING DONOR HEART ALLOCATION USING PREDICTIVE ANALYTICS

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ABSTRACT

In the U.S., only about one-third of donor hearts were transplanted, largely due to concerns over organ quality or matching delays. To improve organ utilization rate and outcomes, a discrete-event simulation model was developed to evaluate the use of predictive models in organ transplant decision making. In the simulation, a donor organ is accepted when the post-transplant one-year mortality risk of a candidate is predicted to be lower than the predicted risk of staying on the waitlist. Simulation using U.S. 2006-2018 data showed a 33% increase in heart utilization rate and a 90% reduction in average waiting time.

1 INTRODUCTION

The Organ Procurement and Transplantation Network (OPTN) is the US national system that manages organ donation and transplantation. OPTN maintains the national transplant waiting list and matches donor organs to recipients based on its allocation policies. Despite its coordinated effort, donor heart utilization rate is only about one-third (Israni et al. 2023), largely due to concerns over organ quality or matching delays. This underutilization contributes to longer wait times and increased mortality among patients on the heart transplant waiting list.

We develop a discrete-event simulation model to evaluate the effect of using explainable predictive models as a decision-support tool for transplant centers to decide whether to accept a donor heart. We simulate the OPTN heart transplantation system between January 2006 and October 2018. A donor heart is accepted when the predicted risk of the transplant is lower than the predicted risk of waiting for a new donor heart. Figure 1 shows the simulation flowchart. The explainable models offer transparency and computational efficiency, preparing them for potential clinical implementation.

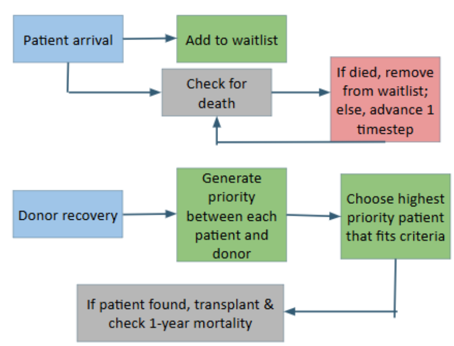

Figure 1: Transplant simulation flowchart.

2 METHODS

The simulation model simulates the allocation of organs by OPTN, the decisions made by transplant centers, and the addition and removal of patients from the waitlist due to transplant and death. Donor and candidate data were imported from the Scientific Registry of Transplant Recipients (SRTR) Standard Analytics File (SAF) and match run dataset. Missing values were handled by Multiple Imputations by Chained Equations (MICE), using Bayesian ridge regression for numerical variables and random forest classifiers with numerical labels for categorical variables.

The logistic regression model to predict post-transplant one-year mortality risk was based on the model by Xu et al. (2023). It was trained on a balanced dataset between 2006 to 2016 and validated on 2017-2018 data with an AUC of 0.642. The model had input from licensed cardiologists. The risk of patient dying within one year on the waiting list was predicted by a Cox proportional hazards model. The model was fit on patient data from 2006 to 2018, with the baseline risk over time estimated using the Breslow estimator. The trained model achieved a concordance of 0.65 and a log-likelihood ratio test of 1326.72 on 25 covariates.

For each organ, the wait list is sorted by priority, which is generated according to OPTN policy. Subsequently, each transplant center on the match list applies the logistics regression model and the Cox proportional hazard model. The donor heart is accepted if the predicted risk of transplantation is lower than that of staying on the wait list. The donor heart is then allocated to the highest-priority patient who accepts the donor heart. The simulation ran over a twelve-year period from 2006 to 2018 using SRTR data.

3 RESULTS & DISCUSSION

Figure 2 compares the donor heart utilization rate in reality and in simulation. We observe that using predictive models to help transplant center make organ acceptance decisions increased utilization from around 30% to 40%, which then led to a drastic 90% reduction in average waiting times.

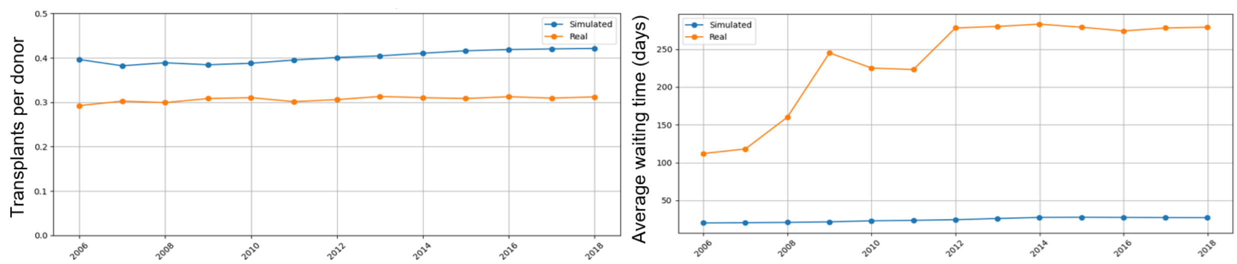

Figure 2: Annual heart utilization rate (left) and average waiting days (right) in reality and simulation.

Figure 3 reported patient outcomes in reality and simulation. Patients with better/worse outcomes in simulation are marked in green/red. In the simulation, 36.8% of patients had better outcomes. Those patients either did not receive transplants or received a poor transplant in reality. In the simulation, they received transplants and were predicted to survive at least one year. Only 2% of patients had worse outcomes in simulation. These results are dependent upon the predictive accuracy of models used.

Simulation / Reality		Transplanted		Not Transplanted
		Survived 1 year	Died within 1 year	
Transplanted	Survived 1 year	29979 (59.9%)	**815 (1.6%)**	**203 (0.4%)**
	Died within 1 year	**3092 (6.2%)**	107 (0.2%)	95 (0.2%)
Not Transplanted		**15316 (30.6%)**	436 (0.9%)	37 (0.1%)

Figure 3: Comparison of patient outcomes in reality and in simulation.

In conclusion, the developed heart transplant simulation model uses data-driven simulation to evaluate the use of predictive models as decision support tools in the heart matching process. Simulation results showed the system-wide benefits of the predictive modeling approach.

REFERENCES

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