Understanding Patient Preferences for Kidney Transplants

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Abstract

Kidney transplantation is the most effective treatment option for end-stage kidney disease. In the United States, Organ procurement organizations (OPOs) are responsible for recovering these organs from deceased donors and offering them to patients that need transplants. However, the current kidney transplant process is suffering from many frictions and inefficiencies. In the US, most patients wait three to five years for a kidney transplant while an average of 3,500 kidneys are discarded each year. And, unfortunately, around 5,000 patients per year die while waiting for a kidney transplant. One cause of these frictions is the lack of patient involvement in the organ allocation process. Surgeons typically accept organs, not only kidneys, for their patients without consulting them. In order to get patients involved, it is important that they understand the different factors that go into organ allocation.

We analyzed data from the Organ Procurement and Transplantation Network to gain insight on exactly what factors affect a patient's waiting time, specifically for kidneys. Looking into exploiting variability in transplant centers' decision, the allocation process, and historical data, we can accurately provide patients with predictions regarding waiting time which would help them make informed decisions on their transplant.

Background

The organ allocation system in the United States is confronted with numerous inefficiencies, which pose significant challenges for individuals in need of an organ transplant. Among these inefficiencies, the demand for kidneys far exceeds the supply provided by Organ Procurement Organizations (OPOs). Despite the pressing demand, a startling number of kidney organs, approximately 3,500, are discarded each year. It is very possible that some of these discarded kidneys if the allocation process had less frictions.

Extensive waiting times for organs are another issue in the allocation process. Patients awaiting kidney transplants in the US generally wait three to five years and this number in places like California is doubled to five to ten years. This problem is the result of a combination of factors, one of them being the lack of patient involvement in the decision of what type of kidney they will receive. Not every patient wants to wait many years for a high quality kidney and suffer through dialysis procedures. Several patients prefer waiting a short time for a low quality kidney so they can resume with their daily lives. However, because their preferences are not voiced in the allocation process and surgeons generally choose their organs, patients are forced to wait and many even die while doing so. Every year, around 5,000 patients lose their lives awaiting a kidney transplant.

To combat high patient mortality rates, increased kidney discards, and, most importantly, long patient waiting times, we analyzed STAR data files from the OPTN. Looking specifically into factors that affect waiting times for the Stanford and UCSF transplant centers, there were shocking insights on what certain groups of patients preferred in their organ.

Methods

In this study, we conducted an extensive analysis utilizing the Scientific Registry of Transplant Recipients (STAR) data files from the Organ Procurement and Transplantation Network (OPTN). The dataset included over a million records of patient and donor data from the US, enabling a thorough investigation of the influences on the kidney allocation process.

To analyze characteristics of patients and donors such as age, CPRA, gender, ethnicity, KDPI, and cold ischemic time, we utilized the Python language and various packages. Commonly known packages such as matplotlib, pandas, numpy, and seaborn were used to work with datasets and create visualizations that would help us compare factors for certain groups of patients and take a closer look at different regions' and hospitals' data. We built machine learning models using scikit-learn to investigate relationships between patients and donors, therefore advancing our understanding of the outcomes of transplantation. Additionally, we conducted survival analysis using the lifelines program, which allowed us to evaluate the time-dependent factors that affect the success of organ donation.

Upon getting the data, we started by creating summary statistics in order to get an understanding of the factors that affected patient waiting times based on age, CPRA, KDPI, etc. With each member of the team looking at different portions of the data, we were able to identify anomalies and frictions in the kidney allocation system. The team focused on digging deeper at these abnormal occurrences in order to get an understanding of the situation and what can be changed in order to make kidney allocation a smoother process. From then, we utilized ML models to assist us in our analysis process. The next section, results, will further explain our process and include visuals created through these methods.

Results

The first results that we found were insights from graphs based on kidney data from the OPTN. Much of the results are based on data from 2014-2018.

Many past papers relating to this topic reveal that too many kidneys are discarded. Thus, we created some graphs looking into this issue (Figures 1-3). They revealed that there were 3000+ kidneys that were discarded since 2015 simply because recipients couldn't be found. This solidifies that there are great inefficiencies in the kidney allocation process, since finding a recipient in such a large waiting list shouldn't be an issue.

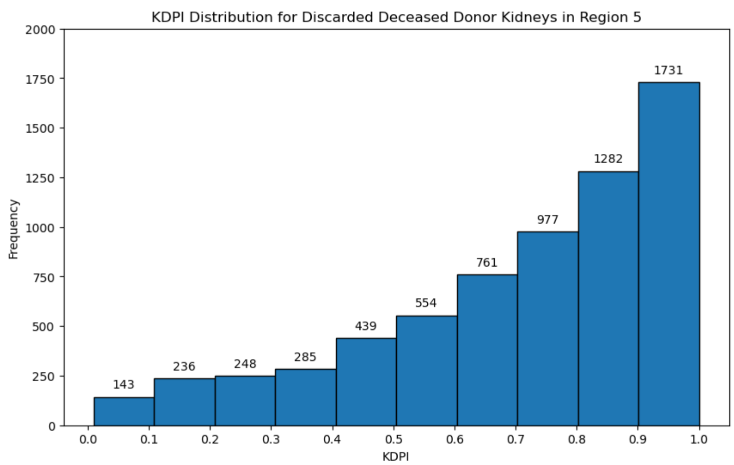

Figure 1

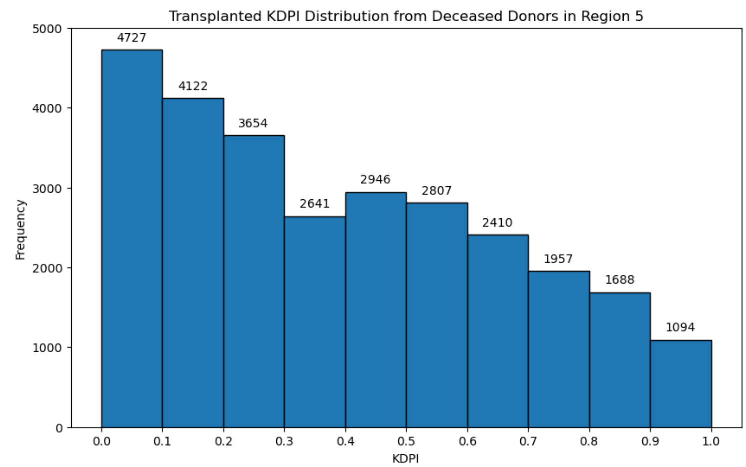

Figure 2

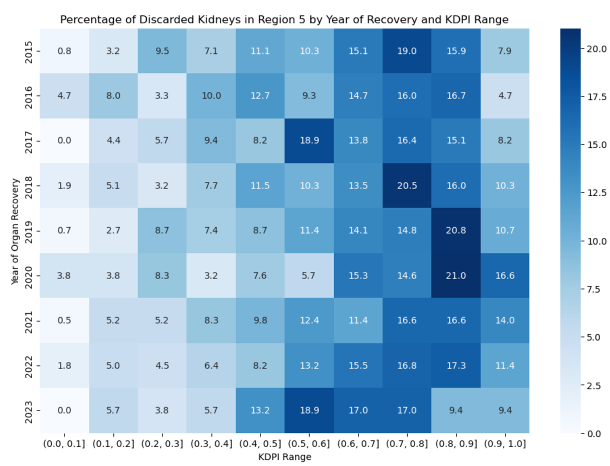

Figure 3

Visualization regarding waitlist times based on basic patient clinical information (blood type, age, etc.) were conducted (Figure 4). The main insight from these graphs is that there are large outliers (as seen in Figure 4). This suggests that the waiting times were highly dependent on a case by case basis, since no clear pattern was found.

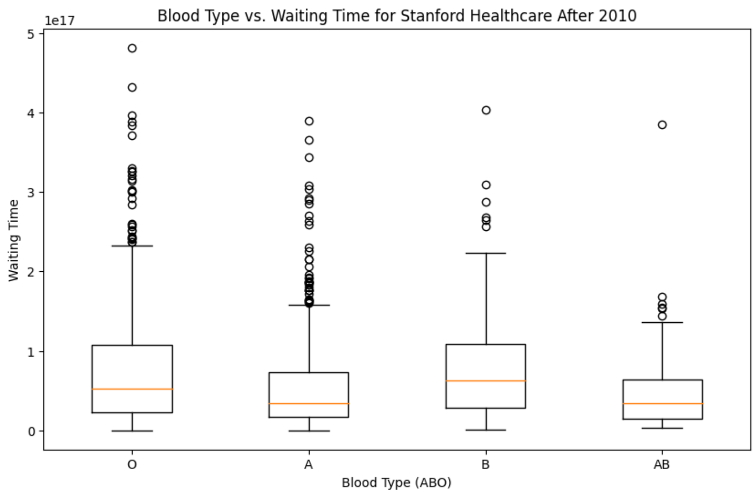

Figure 4

Additional research was conducted with specific hospitals (in this case Stanford Healthcare and UCSF), with the hope of finding differences between the patterns of kidney transplants in each hospital. Insights in this area would help patients decide on the best facility to get their treatment. It is evident that Stanford is more selective about their kidneys and usually transplant kidneys with higher quality (Figures 5-6).

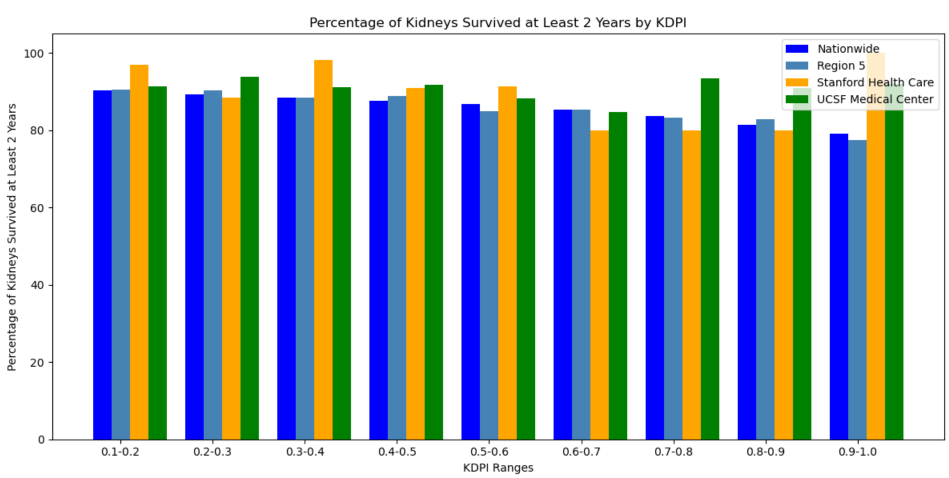

Figure 5

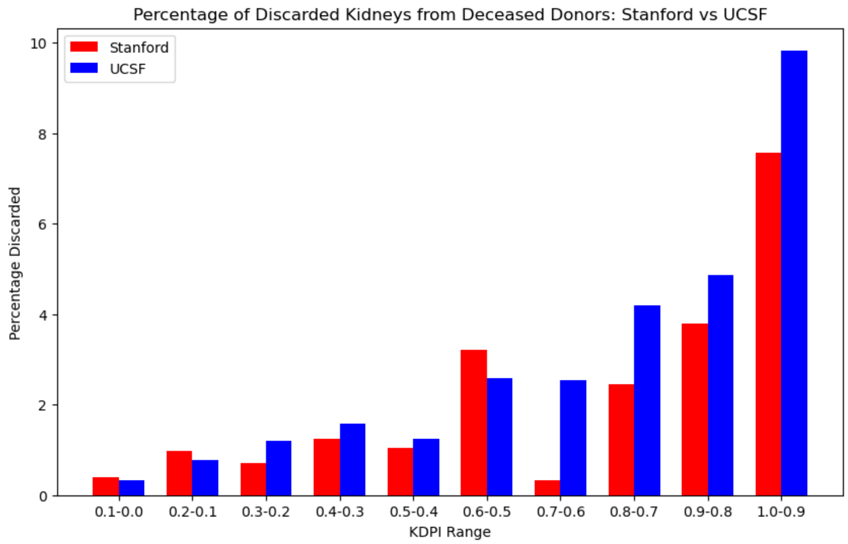

Figure 6

More visualizations were conducted regarding average distances for each KDPI (kidney quality) range. UCSF Healthcare had considerable spikes in these visualizations (Figure 7), and there was clear variability from facility to facility, despite the all the facilities being compared were in the same region.

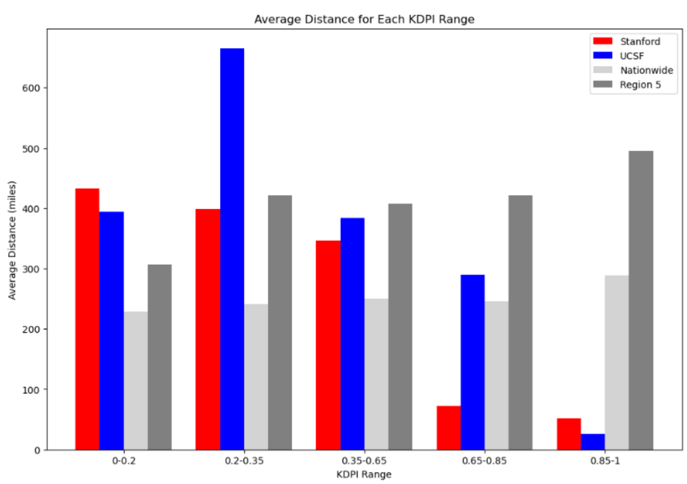

Figure 7

The second part of results that were collected were with machine learning models. Two ML models were created: one model predicted patient waiting times based on patient clinical information (blood type, patient EPTS score, diabetic status, age, etc.). This model (gradient boosting algorithm) was able to predict waiting times within 100 days accuracy 17% of the time, and patient waiting times within 1 year about 45% of the time. Although it wasn't very accurate, the results are promising. The second model was a Cox proportional-hazard model, with a graph of its predictions shown in Figure 8. This was used to develop the Estimated Waitlist Survival Score (EWLS), which helps inform patients how urgently they need a new kidney.

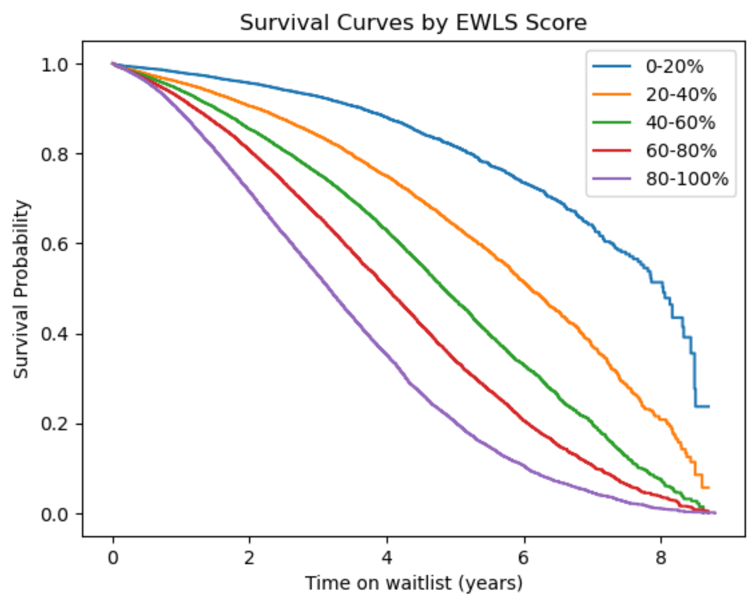

Figure 8

Conclusion

This research aimed to provide insight into the kidney allocation process, specifically understanding how patients can optimize their chances of getting a kidney transplant within reasonable time. As discussed in the background, the kidney allocation process in the United States is heavily flawed and inefficient. By tackling one of the smaller issues within this large problem, we aimed to become one step closer to improving the system.

By looking into the kidney data provided by the OPTN, we were able to make insightful graphs (as seen in results) that help shed light on the underlying problems in the current kidney allocation system. Many of these visualizations, such as the graphs regarding kidney discard rates, revealed concrete evidence for the current system's inefficiencies. Most of this research was heavily focused on Region 5 of the OPTN, but it is safe to infer that these inefficiencies are present in other regions in the United States. Furthermore, the insights into specific transplant facilities, such as Stanford Healthcare, can help patients decide on what healthcare facilities to do their treatment at (if they want a facility with more strict rules on kidney quality, a facility that has a high number of incoming kidneys, etc.).

The machine learning models were also very significant parts of this project, as well as the current kidney allocation process in general. These models can be used by patients, who can gain a new understanding of their survival probabilities and their times on the waitlist. Based on these factors, they can decide on a specific treatment center, or whether or not to accept a lower quality kidney (since those are more readily available). For instance, if the model predicts a patient's waitlist time to be 4 years, and the patient cannot wait that long, they may opt for a lower quality kidney which they could get in a smaller period of time. This way, they would be making a more informed decision, rather than accepting or denying a kidney without knowing how long it would be until they get the best kidney for them.

However, the model that predicted waiting times wasn't very accurate. The Cox proportional-hazard model also could have performed better. However, the results were promising, and with more resources, these models could be improved and can be implemented in the real-world. This ties in with the significance of this paper— eventually, both the ML models and data insights can be used by transplant centers around the United States to help patients accurately define their preferences for treatment, kidney quality, etc.

Future Directions

Moving forward, building upon our current findings and models, we aim to continue to refine our machine learning models to increase a consistent level of accuracy. The goal is to eventually have these ML models be used as a rough estimate regarding patient health and urgency; this would be helpful to both patients and hospitals. We will continue to use current data to train the models to increase their accuracy.

Future work will also contain a further analysis regarding offers, once that data is acquired. Analyzing offers on the OPO and patient level can help reveal insights about how accepting certain patients and OPOs tend to be.

To put it all together, a website or application is atop our priorities for the future. This interface would allow patients to access helpful metrics that would help them decide on which OPO to choose, as well as, which kidneys to consider given their situation. This system would enable accessibility of important information to patients and can serve as a genuinely helpful tool for patients who are considering multiple recovery options.

Finally, we believe that we can create medical and political change within the inefficient kidney allocation system. Our analysis has revealed that an unnecessarily large amount of kidneys are being discarded due to a recipient not being located or transportation issues, among other insights. Taking these findings to executives and officials within the kidney transplantation network could result in countless lives changed.

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