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Applying Analytics to Design Lung Transplant Allocation Policy

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Abstract. In 2019, the United Network for Sharing (UNOS), which has been operating the Organ Procurement and Transplantation Network (OPTN) in the United States since 1984, was seeking to design a new national lung transplant allocation policy. The goal was to develop a point system that would prioritize candidates on the waiting list in a way that would yield more efficient and equitable outcomes. Our joint Massachusetts Institute of Technology (MIT)/UNOS team joined forces with the OPTN Lung Transplantation Committee in these policy design efforts. We discuss how our team applied a novel analytical framework, which was developed at MIT and utilizes optimization, regression, and simulation techniques, to illuminate salient trade-offs among outcomes and guide the choice of how to weigh different point attributes in the allocation formula. The committee selected for the allocation formula weights that were highlighted in the team's analysis. The team's proposal was implemented as the national lung allocation policy on March 9, 2023 across the United States.

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Keywords: organ allocation • multiobjective optimization • lung transplantation

Introduction

Since the 1984 National Organ Transplant Act established the Organ Procurement and Transplantation Network (OPTN) to maintain a national registry for organ matching, the United Network for Organ Sharing (UNOS) has been operating the OPTN and coordinating transplantation activities in the United States. As such, UNOS manages the national transplant waiting list, matching donors to recipients 24 hours a day, 365 days a year. In addition to these operations, UNOS is tasked with developing national allocation policies that determine how candidates on the waiting list are prioritized.

Although donated organs are often lifesaving gifts, the grim reality is that the United States persistently faces an insufficient organ supply; as a result, thousands of candidates die each year while awaiting transplantation. In recent years, over 100,000 candidates have been registered on the waiting list at any point in time. Each year, approximately 65,000 new candidates are registered, and the number of transplants reached an all-time high of 41,354 in 2021.

In view of this scarcity, national transplant allocation policies have a profound impact on the welfare of the broader patient population. Consequently, when designing allocation policies, UNOS must balance multiple goals. On the one hand, policies need to be efficient and make the best use of the limited supply of organs. On the other hand, policies need to give all patients a fair chance at receiving the organ they need, regardless of factors such as age, sex, ethnicity, religion, lifestyle, and financial or social status. To accomplish this, the OPTN supports policy development by bringing together a diverse volunteer workforce from the clinical and patient communities, in partnership with professional staff, within constraints established in federal law.

Guided by its mission to continuously improve allocation outcomes and to ensure that policies meet its goals, UNOS decided in 2018 to redesign its allocation policies within a unifying framework it termed "continuous distribution" (CD) (Organ Procurement and Transplantation Network 2018).

Continuous Distribution

CD policies operate based on point systems. In particular, candidates are ranked based on points that they are awarded across specific relevant criteria or attributes;

examples include medical urgency, proximity to the donor hospital, and whether they are pediatric (Kasiske et al. 2020). The system also uses relative weights for the various attributes to combine the individual scores per attribute into a composite allocation score (CAS) that will ultimately be used for prioritization.

To exemplify, consider a point system that ranks patients based on three attributes: medical urgency, proximity to the donor hospital, and whether they are pediatric. The CAS for such a system would take the form

$$CAS = w_1 \cdot \text{urgency} + w_2 \cdot \text{proximity} + w_3 \cdot \text{pediatric},$$

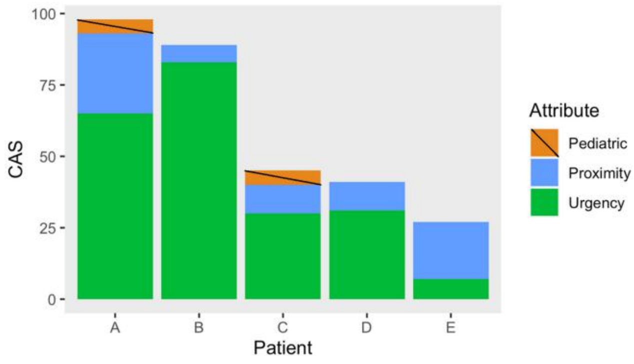
where urgency, proximity, and pediatric are the individual scores for the associated attributes and parameters w_1, w_2, and w_3 are the corresponding weights. Figure 1 provides an example in which such a point system is deployed, with the three attributes displayed. The figure shows the ranking of five patients, A–E, displayed on the x axis according to their CAS on the y axis. In this example, Patient A is ranked first. Notably, Patient A is not the most medically urgent patient (that ranking is likely given to Patient B); however, because Patient A earns relatively more points for the proximity and pediatric attributes, that patient is ranked first.

Although the impact that the choice of attributes can have on outcomes is clear, the example in Figure 1 highlights that the choice of weights can also be a first-order consideration in policy design because it can greatly influence allocation outcomes. In particular, in this example, had the weight on medical urgency been larger or the weights on proximity and pediatric been smaller, then Patient B might have been ranked first.

Application of Continuous Distribution: Designing a New Lung Allocation Policy

In 2019, UNOS decided to redesign its lung allocation policy by migrating it within the continuous distribution framework (Organ Procurement and Transplantation Network 2019). From 2019 to 2020, six attributes were

Figure 1. (Color online) The Chart Shows an Example of Patient Ranking Using a Sample Continuous Distribution Policy



identified, which are associated with points and contribute to the overall score for each candidate (Organ Procurement and Transplantation Network 2021d). These are as follows.

1. Posttransplant outcomes. Posttransplant area under (the survival) curve (PTAUC) measures a patient's life expectancy if that patient receives a transplant of median quality.
2. Medical urgency. Waiting list area under (the survival) curve (WLAUC) measures a patient's life expectancy if that patient does not receive a transplant and remains on the waiting list.
3. Placement efficiency measures the distance between the donor and recipient hospitals.
4. Biological disadvantages measure a patient's medical compatibility with donors.
5. Pediatric indicates if the patient is pediatric.
6. Prior living donor indicates if the patient had donated for solid organ transplant in the past (solid organ transplants include kidney, liver, intestines, heart, lung, and pancreas).

The challenge that we addressed was how to select the relative weights that would be used in the new lung allocation policy.

Materials and Methods

Data

Policy performance evaluation was based on the latest available version of the thoracic simulation allocation model (TSAM; version 2015), a program developed by the Scientific Registry of Transplant Recipients (SRTR) that uses historical real-world data from 2009 to 2011 to simulate the allocation of lung transplants to patients during that period. In particular, given a candidate allocation policy, TSAM simulates various aspects of the waiting list, the procurement, and the matching processes to estimate allocation outcomes of interest, such as the mortality of patients on the waiting list, median distance traveled per organ, and disparities and equity metrics across factors such as age, gender, and racial group. SRTR's simulation allocation models (SAMs), like TSAM, have been routinely used by OPTN committees over the past 15 years to evaluate policy proposals and therefore, have been a cornerstone in the policy design process for all organs, including lungs.

Outcome-Driven Policy Design

OPTN committees have usually designed new policies by following an iterative procedure in which they first select a few policy parameters and evaluate them using SAMs. If they identify undesirable outcomes in the simulation evaluation, they revise the policies and repeat the process.

In this application, we followed an outcome-driven design paradigm like the one first proposed by Bertsimas

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et al. (2013). According to this paradigm, the design process is flipped; that is, target outcomes are first debated, and then, analytics are used to identify a policy that best meets the target outcomes. As Papalexopoulos et al. (2022) argue, this flipped process has many advantages, including the following three. First, it accommodates the so-called ethics-by-design principle, in which equity and ethical considerations are embedded in the process from the onset rather than being treated as an afterthought. Second, the policy space is explored in a more rigorous and systematic way. Third, debating outcomes is typically more intuitive than debating policy parameters, such as weights in the CAS.

Furthermore, the process of focusing on outcomes allows a comprehensive exploration of trade-offs between the allocation outcomes of interest.

Trade-off Analysis

By varying target outcomes in the ethics-by-design process, important trade-offs can be explored. Trade-off analyses can assist the policy design process for lung allocation because associated weights for the CAS can be identified as those weights that strike the right balance between outcomes of interest. Therefore, in this application, we utilized trade-off analyses to recommend attribute weights to the OPTN Lung Transplantation Committee.

Analytical Framework

The analytical challenge in our approach is, given target outcomes, to find a policy that best meets them. This corresponds to a multidimensional inverse control problem. This problem in our application is made more challenging because outcome evaluation is costly given that it involves time-consuming simulations via TSAM.

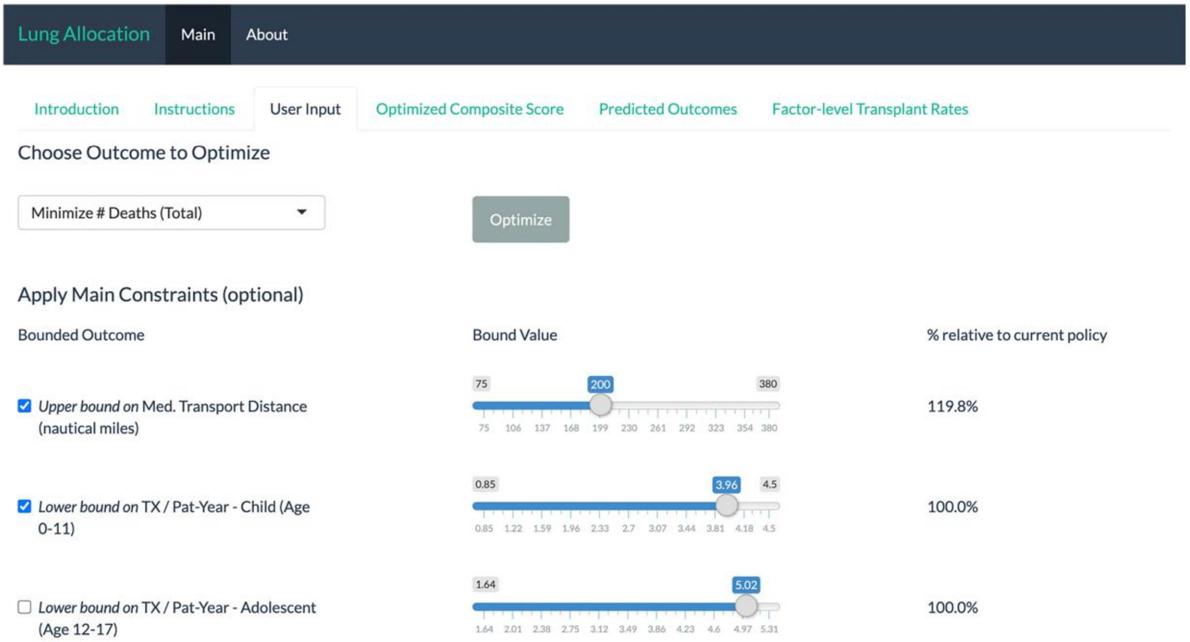
To address these challenges, we utilized a novel analytical framework that addresses general problems of this nature (Papalexopoulos et al. 2021, Papalexopoulos 2022). The framework, which employs machine learning and mathematical optimization to enable tractability, made the outcome-driven policy design process and trade-off analyses possible for our application. A description is provided in the Optimization Framework section after we present and discuss our results.

Interactive Dashboard

To facilitate the policy design process, we made the framework available to UNOS by developing an interactive dashboard. The dashboard enabled users to specify targets for all outcomes of interest to the OPTN Lung Transplantation Committee; examples include numbers of waiting list and posttransplant deaths; average transplant net benefit (i.e., posttransplant life expectancy minus life expectancy on the waiting list); median transport distance and estimated transport cost; transplant rates for children and adolescents; and transplant rate disparities by age group, sex, height, and blood group. Then, the embedded algorithm produced the attribute weights for a CAS that would achieve the target outcomes. If the target outcomes were not achievable, then the algorithm produced the attribute weights for a CAS that would minimize the expected aggregate relative violations of the targets.

To exemplify, Figure 2 depicts a snapshot of the dashboard's user input tab. The user input depicted for this

Figure 2. (Color online) This Example Shows a Use Case of the Dashboard's User Input Tab



example use case has set three targets for illustrative purposes: first, to minimize the total number of expected deaths as displayed in the drop-down menu on the upper left; second, to limit the median transport distance to 200 nautical miles as displayed by the top checked box; and third, to ensure that the transplant rate for children ages 0–11 was at least as large as with current policy: that is, 3.96 transplants per patient-year (TX/Pat-Year) as displayed by the other checked box. Another target displayed but not selected on this particular occasion included a lower bound on transplant rates of adolescent patients. As we remark, the dashboard included several other targets, which we do not display in Figure 2.

Upon selecting the "optimize" option in the user input tab, the user could obtain, within seconds, detailed results. In particular, Figure 3 depicts the optimized composite score tab of the dashboard, which includes the six attribute weights that the algorithm produces. In this example, the algorithm chose to assign weights to the PTAUC, WLAUC, proximity, and pediatric attributes. The first two attributes have a direct effect on mortality and were accordingly weighed by the algorithm because a target of minimizing mortality was chosen. Similarly, the third and fourth attributes have direct effects on median transport distance and pediatric transplant rates, respectively; therefore, they were appropriately weighed and calibrated to achieve the corresponding targets of 200 nautical miles and 3.96 transplant rate set.

Figure 4 depicts a snapshot of the predicted outcomes tab of the dashboard. This tab includes values for a range of expected outcomes in simulation of the newly designed policies. Figure 4 depicts a subset of the outcomes considered, which we describe in the first column and report their values under the current policy in the second column and under the newly designed CD policy in the third column for this example. The fourth column indicates if an outcome was associated with a target in the user input tab upon the design phase. Of note, the values for the targeted outcomes are also highlighted so that the user can readily determine whether they were achieved or not. On this particular occasion, we can see that the designed policy indeed achieved its targets; it minimized mortality by reducing deaths from 1,077 to 932, maintained transport distance at 200 nautical miles, and achieved a pediatric transplant rate of at least 3.96.

Figures 5 and 6 depict snapshots of the factor-level transplant rates tab of the dashboard by age and blood group, respectively. The tables show the number of candidates in each age or blood group and their associated simulated transplant rates under the current policy and the CD policy designed using the dashboard.

Disclaimer

This study used data from the SRTR. The SRTR data system includes data on all donors, wait-listed candidates, and transplant recipients in the United States submitted by the members of the OPTN. The Health Resources and Services Administration, U.S. Department of Health and Human Services provides oversight of the activities of the OPTN and SRTR contractors.

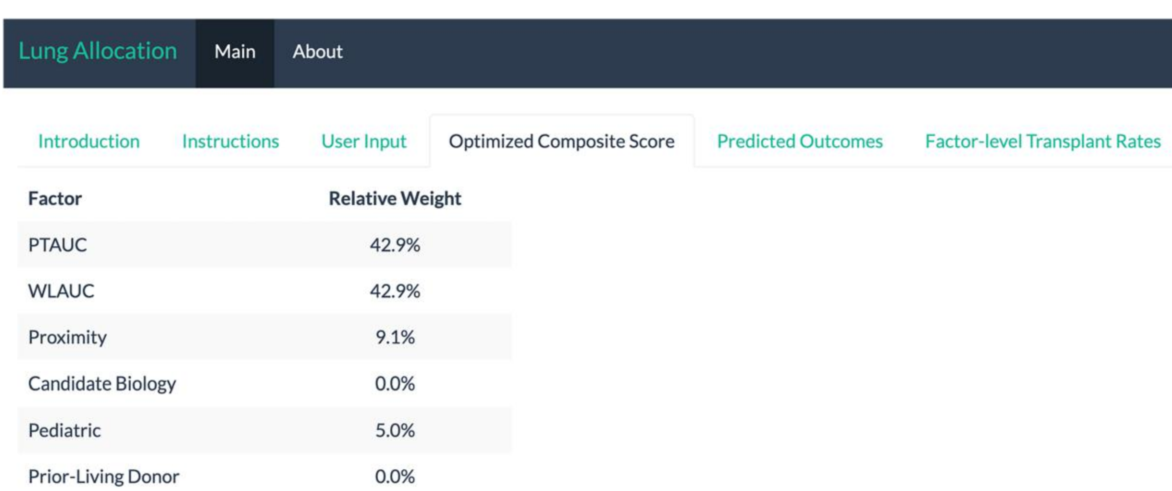
Results

The use of the dashboard highlighted various important analyses of interest that we conducted. One of them related to the trade-off between mortality and transport distance. Another related to the transplant rates by blood group as the biological disadvantages attribute weights were varied.

Mortality and Transport Distance Trade-off

As transport distance increased, mortality was expected to decrease but at diminishing returns. Figure 7 depicts the analysis conducted to quantify this trade-off. The x axis measures median transport distance in nautical miles; the y axis measures the number of simulated waiting list deaths. At the top, the associated placement

Figure 3. (Color online) This Example Shows a Use Case of the Dashboard's Optimized Composite Score Tab



Factor	Relative Weight
PTAUC	42.9%
WLAUC	42.9%
Proximity	9.1%
Candidate Biology	0.0%
Pediatric	5.0%
Prior-Living Donor	0.0%

Figure 4. (Color online) This Example Shows a Use Case of the Dashboard's Predicted Outcomes Tab

Lung Allocation Main About

Introduction Instructions User Input Optimized Composite Score Predicted Outcomes Factor-level Transplant Rates

	Current Policy	Continuous Distribution	User Input	R2
# Deaths (Total)	1,077	934	min	0.98
# Deaths (Waitlist)	553	420		0.98
# Deaths (Post-TX)	524	514		0.92
Avg. Transplant Net-Benefit (PTAUC - WLAUC)	39.9	56.6		0.99
Med. Transport Distance (nautical miles)	167	200	<= 200	0.99
Estimated Transport Cost (rel. Current Policy)	100%	113%		0.98
TX / Pat-Year - Child (Age 0-11)	3.96	3.96	>= 3.96	0.91
TX / Pat-Year - Adolescent (Age 12-17)	5.02	26.95		0.94
Transplant Rate Disparities by Age Group - Adults (TX / Pat-Year)	0.36	0.28		0.95
Transplant Rate Disparities by Gender (TX / Pat-Year)	0.38	0.23		0.85
Transplant Rate Disparities by Height Group (TX / Pat-Year)	0.32	0.17		0.95
Transplant Rate Disparities by ABO (TX / Pat-Year)	0.12	0.10		0.98

efficiency weight is depicted. To generate the graph, we used the framework to design multiple CD policies with the target of minimizing waiting list mortality subject to all transplant rate disparities discussed while retaining the same or lower values compared with the current policy subject to a varying upper bound on transport distance. Each dot corresponds to the outcomes of each such designed policy for varying transport distance. The labeled dot illustrates the outcomes of the current policy.

The results in Figure 7 show that CD policies, particularly those rigorously designed using our framework, dominated the current policy and were able to greatly reduce mortality without increasing transport distance if desired. For example, Figure 7 depicts CD policies that achieve the same median transport distance as the current policy but result in a mortality reduction of more than 100 deaths per year.

Furthermore, the results show that a placement efficiency weight of approximately 10% appeared to be an "inflection point." Weights lower than 10% appeared to increase transport distance without offering mortality reductions of significance; weights higher than 10% appeared to reduce transport distance but increased mortality at a significant rate.

Based on this analysis, the committee selected for its CAS proposal a placement efficiency weight of 10%. The

Figure 5. (Color online) This Example Shows a Use Case of the Dashboard's Factor-Level Transplant Rates Tab by Age Group

Lung Allocation Main About

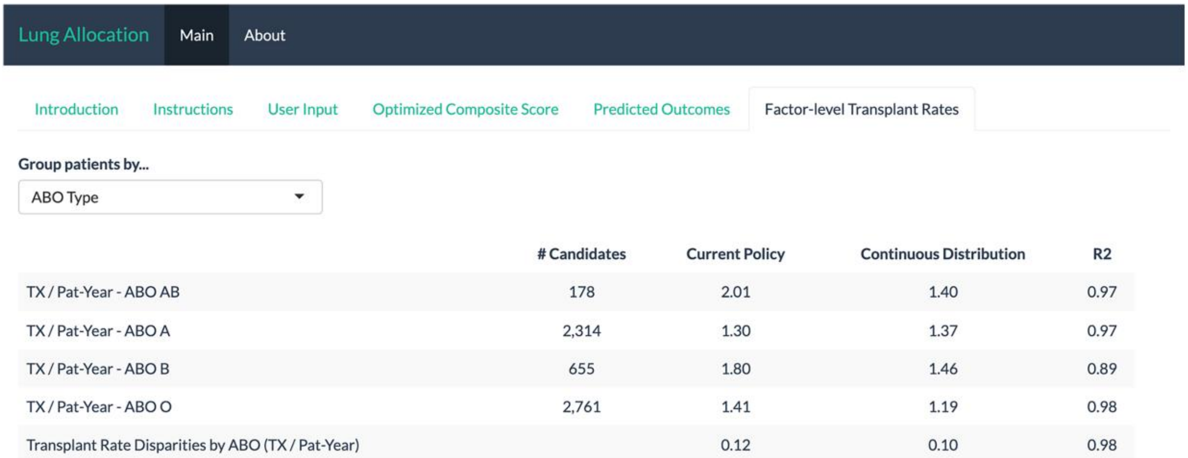
Introduction Instructions User Input Optimized Composite Score Predicted Outcomes Factor-level Transplant Rates

Group patients by...

Age Group

	# Candidates	Current Policy	Continuous Distribution	R2
TX / Pat-Year - Child (Age 0-11)	96	3.96	3.96	0.91
TX / Pat-Year - Adolescent (Age 12-17)	121	5.02	26.95	0.94
TX / Pat-Year - Age 18-34	692	1.27	1.69	0.97
TX / Pat-Year - Age 35-50	899	1.27	1.75	0.98
TX / Pat-Year - Age 51-65	2,901	1.16	0.98	0.97
TX / Pat-Year - Age 66+	1,199	2.28	1.28	0.92
Transplant Rate Disparities by Age Group - Adults (TX / Pat-Year)		0.36	0.28	0.95

Figure 6. (Color online) This Example Shows a Use Case of the Dashboard's Factor-Level Transplant Rates Tab by Blood Group or ABO Type


Lung Allocation Main About

Introduction Instructions User Input Optimized Composite Score Predicted Outcomes Factor-level Transplant Rates

Group patients by...

ABO Type

	# Candidates	Current Policy	Continuous Distribution	R2
TX / Pat-Year - ABO AB	178	2.01	1.40	0.97
TX / Pat-Year - ABO A	2,314	1.30	1.37	0.97
TX / Pat-Year - ABO B	655	1.80	1.46	0.89
TX / Pat-Year - ABO O	2,761	1.41	1.19	0.98
Transplant Rate Disparities by ABO (TX / Pat-Year)		0.12	0.10	0.98

proposal was approved by the OPTN board of directors and was implemented as the national lung allocation policy on March 9, 2023 across the United States (Organ Procurement and Transplantation Network 2021a, b, c).

Transplant Rates by Blood Group

As the biological disadvantages weight increased, transplant rates for blood group O candidates were expected to increase, and transplant rates for all remaining candidates were expected to decrease. Although some increase in the number of blood group O candidate transplant rates might be desirable, an excessively large weight might accentuate transplant rate disparities across blood groups by a significant amount.

To quantify the increase of blood group O candidate transplant rates vis-à-vis transplant rate disparities across blood groups, we considered 10,000 different CD policies that we generated by randomly sampling all attribute weights. The transplant rates for each blood group that resulted from these policies were produced using our framework.

Figure 7. (Color online) The Graph Illustrates the Mortality and Transport Distance Trade-off Analysis

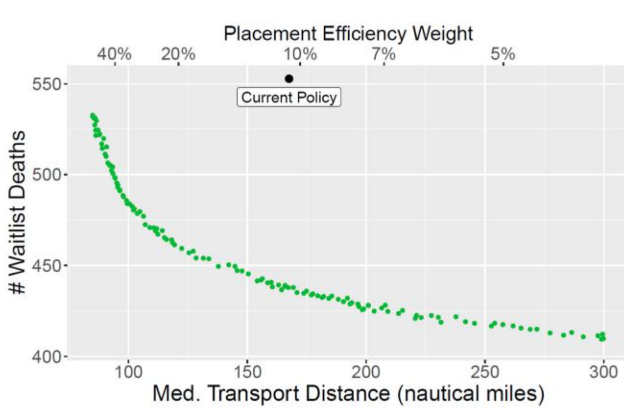
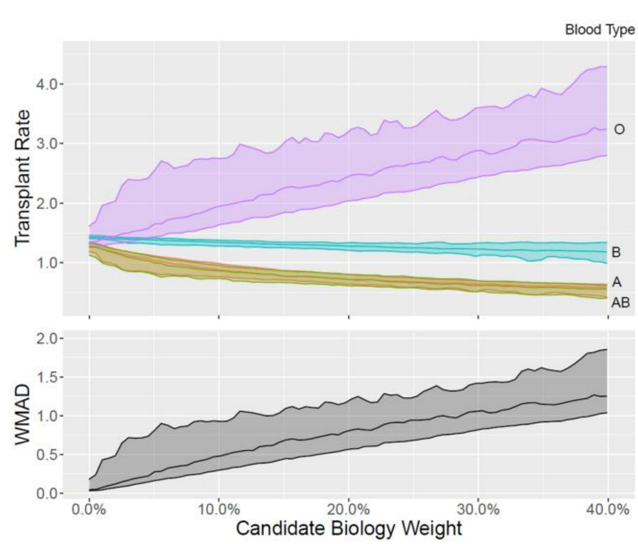


Figure 8 depicts the results of the analysis. The x axis measures the biological disadvantages weight of the policies analyzed. In the upper panel, the y axis measures the transplant rate for each blood group; in the lower panel, it measures the weighted mean absolute deviation (WMAD) of the transplant rates across the blood groups. For each biological disadvantages weight, the figure plots the range of transplant rates for each blood group (upper panel) and the range of their WMAD (lower panel) across the policies considered. Within each range, the median is also plotted with a solid line.

The results in Figure 8 quantify the rates at which blood group O candidate transplant rates and disparities across blood groups increase as the weight increases. The committee used the analysis to help justify keeping the blood type weight fairly low; a blood type weight of 5% was selected, and a biological disadvantages weight of

Figure 8. (Color online) The Graph Illustrates Transplant Rates by Blood Group Analysis



15% shared with two other biological compatibility attributes, height and Calculated Panel Reactive Antibody, was selected. These weights were selected by the committee for its CAS proposal. The proposal was approved by the OPTN board of directors and was implemented as national lung allocation policy on March 9, 2023 across the United States (Organ Procurement and Transplantation Network 2021a, b, c).

Discussion

The OPTN represents the largest organ allocation system in the world. For more than 30 years, OPTN organ allocation policies have been developed by a volunteer workforce from the clinical and patient communities, in partnership with professional staff, within constraints established by federal law. Despite frequent policy revisions and improvements, organ allocation is so complex that potential inefficiencies and inequities often arise as patient needs change. Among others, geographic disparities have been documented for liver and kidney allocation (Lynch and Patzer 2019), and sex disparities have recently been documented for liver allocation (Allen et al. 2018). In response and in the spirit of continuous improvement, the OPTN contractor, UNOS, launched a major overhaul of its policies with the intention of migrating them into the continuous distribution framework.

In this paper, we demonstrated the use of analytics to aid the design process of CD policies. In collaboration with the OPTN Lung Transplantation Committee, we applied a novel analytical policy design methodology we developed to inform the design of a new CD allocation policy for lungs. For the allocation formula, the committee ultimately selected weights that were highlighted in our analysis. The formula was implemented as the national lung allocation policy on March 9, 2023 across the United States.

The analysis demonstrated the potential gains that the CD framework provides. CD policies that were rigorously constructed using our methodology significantly outperformed extant allocation policies in simulation, delivering gains both in terms of reducing mortality (i.e., utility) and in reducing disparities in access (i.e., equity).

Relative to the policy design process, the application we presented demonstrates the value of using analytics and mathematical optimization to illuminate trade-offs and focuses the discussion on resolving them. The application of our methodology created a committee discussion framework that was able to change what could have been a contentious conversation into a civil, evidence-based, collegial, and consensus-based discussion.

An important enabler of the application's success was the deployment of the interactive dashboard we presented. Making the methodology available to various stakeholders in an intuitive way makes it transparent and enables rapid experimentation and feedback loops. Consequently, our work eventually also helped to reduce the policy development cycle time.

Notably, as factors such as patient needs, therapies, and disease burdens change, policies need to be revisited and adjusted to ensure that they best serve the community in an efficient and equitable manner. Faster and more efficient policy development processes of the kind we utilized in the application are key in such continuous improvement efforts.

Optimization Framework

In this section, we present the technical implementation details of our methods. To ease exposition, we present an example of how to conduct a trade-off analysis, like the ones that were conducted for the OPTN Lung Transplantation Committee. In particular, in our example we will consider a trade-off analysis between overall patient mortality and pediatric transplant rates for children. All analyses discussed in the paper entail appropriate modifications of the discussed methodology.

The building block of the trade-off analysis we consider is the design of a particular CD policy with the following desiderata.

- First, the policy needs to minimize mortality.
- Second, because of fairness considerations, the policy needs to perform "no worse" than the current allocation policy in key transplant rate disparity metrics. The latter included transplant rate disparities by age groups, transplant rate disparities by gender, transplant rate disparities by height group, and transplant rate disparities by blood group. To be precise, the transplant rate of a patient group is measured as the number of transplants that the group receives divided by the total accumulated time on the waiting list by the candidates in the group over the simulation horizon (therefore, the transplant rate is measured in TX/Pat-Year). The disparity among certain groups is then measured as the maximum difference between transplant rates among the groups, i.e., if t_i is the transplant rate of the ith group, the disparity among groups in set G is given by

$$\max_{i,j \in G} |t_i - t_j|.$$

- Third, the policy needs to achieve a median transport distance that is no longer than the current policy.
- Fourth, the policy needs to achieve transplant rates for children that are at least a certain multiple, say $(1+\alpha)$, of the transplant rates for children of the current policy. The parameter α can be varied, with negative values corresponding to a potential decrease in transplant rates for children and positive values corresponding to a potential increase in transplant rates for children compared with the current policy.

By varying the parameter α in the constraints, one can conduct a trade-off analysis; for a certain "budget" of transplant rates for children controlled by the parameter α, we record the ensuing minimum waiting list mortality that can be achieved subject to the rest of the constraints.

One can formulate the aforementioned design problem as the following mathematical optimization problem:

$$
\begin{aligned}
\text{minimize} \quad & \text{MORTALITY}(w_1, \ldots, w_6) \\
\text{subject to} \quad & \text{RATE DISPARITY BY AGE} \\
& \quad (w_1, \ldots, w_6) \le 0.36 \\
& \text{RATE DISPARITY BY GENDER} \\
& \quad (w_1, \ldots, w_6) \le 0.38 \\
& \text{RATE DISPARITY BY HEIGHT} \\
& \quad (w_1, \ldots, w_6) \le 0.32 \\
& \text{RATE DISPARITY BY ABO} \\
& \quad (w_1, \ldots, w_6) \le 0.12 \\
& \text{TRAVEL DISTANCE} \\
& \quad (w_1, \ldots, w_6) \le 167 \\
& \text{CHILD RATE} \\
& \quad (w_1, \ldots, w_6) \ge (1 + \alpha)3.96.
\end{aligned}
$$

In the formulation, variables $(w_1, \ldots, w_6)$ correspond to the weights associated with the attributes of the CD policy we seek to design as described in the main paper. For example, w_1 would correspond to the weight associated with the first attribute, namely PTAUC; w_2 would correspond to the weight associated with the second attribute, WLAUC; and so on. The constraints and objective are readily derived from the discussed desiderata. Finally, the right-hand side values correspond to the observed values of the associated quantities under the current policy. For example, the transplant rate disparity by age group of the current policy is 0.36.

Notably, the outcomes of interest that appear in capital letters in the objective and constraints of the formulation are functions of $(w_1, \ldots, w_6)$. As we discuss in the paper, evaluation of these outcomes for a fixed set of $(w_1, \ldots, w_6)$ is costly and conducted only via time-consuming simulation.

A first approach to solve the optimization problem that we face is to use well-studied simulation-optimization approaches. At a high level, these approaches employ iterative gradient descent methods. At each step, repeated calls to the underlying simulation model are made in order to approximate the local gradient. Consequently, the *run time per instance* to solve a single instance of the optimization problem we face can be significant, and such approaches would work well only when solving a small number of problem instances.

For our application, because trade-off analyses need to be conducted, one has to solve a rather large number of problem instances like the one we describe. To accommodate this, we can borrow from the methodology introduced by Papalexopoulos et al. (2021). Concretely, the idea would be to substitute the functions that require simulation in the optimization problem with approximations thereof, which can take the form of affine functions for example. The latter choice would mean that the resulting problem, after the substitution, would reduce to a convex optimization problem, namely a linear optimization, which would be very efficient to solve. The net result would be that, on the one hand, we will have a method to approximate the original optimization problem that would have "minimal" run time requirements per instance. On the other hand, some fixed setup time might be involved when calculating the affine approximations. Given the large number of instances that one would need to solve in practice, the fixed setup time would be sufficiently amortized, and the shorter run time of the approximation scheme would prevail.

To introduce some notation, let the outcomes written in lowercase be the approximations we consider to the true outcomes (e.g., mortality $(w_1, \ldots, w_6)$ is the approximation we consider to MORTALITY$(w_1, \ldots, w_6)$). We consider the following functional forms for the approximations:

$$
\begin{aligned}
\text{mortality}(w_1, \ldots, w_6) &= \sum_{i=1}^{6} \beta_{0i} w_i + \gamma_0 \\
\text{rate disparity by age}(w_1, \ldots, w_6) &= \sum_{i=1}^{6} \beta_{1i} w_i + \gamma_1 \\
\vdots \qquad &= \qquad \vdots \\
\text{child rate}(w_1, \ldots, w_6) &= \sum_{i=1}^{6} \beta_{6i} w_i + \gamma_6,
\end{aligned}
$$

where β_{ij} and γ_i are parameters to be learned.

To learn the parameters, we generate K policies by randomly sampling weights $(w_1, \ldots, w_6)$ from the six-dimensional simplex. Let $(w_1^s, \ldots, w_6^s)$ denote the weights of the sth sample. Next, we simulate these K policies to generate MORTALITY$(w_1^s, \ldots, w_6^s)$, …, CHILD RATE $(w_1^s, \ldots, w_6^s)$. Then, we determine the parameters by solving a regression-style problem in which we pick parameters β_{ij} and γ_i that minimize the mean square error between MORTALITY$(w_1^s, \ldots, w_6^s)$ and $\sum_{i=1}^{6} \beta_{0i} w_i^s + \gamma_0$, …, CHILD RATE$(w_1^s, \ldots, w_6^s)$ and $\sum_{i=1}^{6} \beta_{6i} w_i^s + \gamma_6$ across all sampled policies.

Having learned the parameters, we can then reformulate the original problem we sought to solve as the following linear optimization problem:

$$
\begin{aligned}
\text{minimize} \quad & \sum_{i=1}^{6} \beta_{0i} w_i + \gamma_0 \\
\text{subject to} \quad & \sum_{i=1}^{6} \beta_{1i} w_i + \gamma_1 \le 0.36 \\
& \qquad \vdots
\end{aligned}
$$

$$\sum_{i=1}^{6} \beta_{5i} w_i + \gamma_5 \leq 167$$

$$\sum_{i=1}^{6} \beta_{6i} w_i + \gamma_6 \geq (1+\alpha)3.96,$$

with $(w_1, \ldots, w_6)$ as the decision variables.

Solving the linear optimization problem provides us with a policy that would approximately satisfy our desiderata. By varying the parameter α, we can then obtain the minimum mortality that can be achieved (i.e., produced as the optimal value of the linear optimization problem) as a function of the child transplant rate (i.e., produced as the right-hand side of the last constraint), which is the trade-off curve we sought to analyze.

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