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EVALUATING LIVER GRAFT ACCEPTANCE POLICIES USING A CONTINUOUS-TIME MARKOV CHAIN SIMULATION FRAMEWORK

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ABSTRACT

Liver transplantation is the second most common transplant procedure in the United States and the only curative treatment for patients with end-stage liver disease, which is one of the leading causes of death nationwide. The United Network for Organ Sharing operates the national liver transplant waiting list and allocates organs under a complex priority system based on medical urgency, geography, and waiting time. Healthcare providers accept or refuse liver offers based on transplant candidates' medical needs and donor quality, among other factors. We develop a simulation environment to assess current acceptance practices based on a Markov reward process. Our simulation framework models organ arrivals and patients' health progression as continuous-time processes and mimics how decisions are made in practice using a randomized policy. Based on our simulation framework, we provide insights and identify areas for enhancing patient management and liver offer acceptance.

1 INTRODUCTION

End-stage liver disease is a life-threatening clinical condition, being one of the leading causes of death in the United States (Ahmad et al. 2024). Liver transplantation represents the only curative treatment for patients with end-stage liver disease, with grafts obtained either from living or deceased donors. As the number of living donors is limited (Kaplan et al. 2022), most patients are treated using deceased liver transplantation. In 2024 alone, over 41,000 deceased donor transplants were performed in the U.S., making it the second most common organ transplant procedure (UNOS 2025). However, the persistent shortage of donor organs remains a critical challenge, and ongoing population growth is expected to exacerbate this scarcity, further straining the liver transplantation system (Parikh et al. 2015).

The United Network for Organ Sharing (UNOS), a nonprofit organization that manages the Organ Procurement and Transplantation Network (OPTN) under contract with the federal government, maintains the national deceased liver transplant waiting list. This organization allocates organs based on a complex priority system by medical urgency, geographic restriction, and waiting time (UNOS 2025). When an organ becomes available, it is sequentially offered to suitable candidates on the waiting list. However, the final decision to accept or refuse a liver offer mainly relies on individual transplant centers and clinicians, who consider clinical and organ quality factors.

Ideally, this decision-making process should optimize candidate outcomes. Nonetheless, it remains complex and variable across centers in reality (Goldberg et al. 2016). Current liver graft acceptance practices may be influenced by the effects of health progression, offer arrival timing, and organ quality, among other factors. All of them are inherently stochastic and generate uncertainty, which makes the process highly complex. Consequently, the acceptance rate for the first ten deceased donor liver offers is

just above 14%, dropping to approximately 1% for later offers (Wey et al. 2018), emphasizing the need for strategic decision-making in liver acceptance.

Simulation is often a preferred practical approach when analytical solutions are difficult or intractable (Ross 2022). Most existing simulation models in liver transplantation assess waiting list dynamics, patient survival rates, and organ utilization through discrete-event simulations. These models incorporate biological factors, disease progression, and natural history of patients independent of allocation policies (Kreke et al. 2002; Iyer et al. 2011). They also evaluate various allocation strategies to optimize cost-effectiveness and improve overall outcomes (Vanness 2002). The Liver Simulated Allocation Model has been used to predict the effects of policy changes on organ offers, acceptance rates, waitlist survival, and post-transplant survival (Goel et al. 2018). Discrete-event and the Liver Simulated Allocation Model-based simulations detail survival trajectories and estimate benefits in life-years gained (Schaubel et al. 2009). Chang et al. (2014) presents a discrete-time Markov model to compare patient survival under different transplant strategies. Pritsker et al. (1995) also builds a simulation model called the UNOS Liver Allocation Model to compare various allocation policies. Organ utilization effectiveness appears less frequently in the literature. Still, it is measured in terms of increased transplant rates, the number of livers used, and shifts in travel distances, as reported by Toro-Díaz et al. (2015) and Schaubel et al. (2009). All these models capture survival outcomes, waiting list behavior, and aspects of transplant capacity to support policy evaluation in liver transplantation. However, they rely on discrete-time models to approximate a continuous-time process and fail to capture the ongoing evolution of health progression and organ arrival dynamics.

In this study, we develop a simulation environment to assess acceptance policies using a continuous-time Markov reward process (MRP) framework. Unlike discrete-time models, our approach allows for a more precise joint representation of health progressions and organ arrivals. Using real-world clinical data, we estimate organ acceptance rates by patient health condition and organ quality. We simulate liver offer arrivals and candidate health trajectories and incorporate current acceptance practices through a randomized policy rather than assuming a theoretical or idealized acceptance strategy. Instead of using a fixed time window for all patients, we also personalize the simulation by using individualized mortality estimates to set each patient's planning horizon. Our simulation framework identifies opportunities to improve patient management and offer acceptance.

The remainder of this paper is organized as follows. In Section 2, we describe the simulation framework and our approach to evaluating liver acceptance policies. Section 3 summarizes model parameterization, including a detailed overview of the data sources and the current liver acceptance practices. In Section 4, we present the key results of our simulation experiments. Finally, Section 5 concludes the paper with a discussion of the main findings, their implications for clinical practice and policy, and potential directions for future research.

2 SIMULATION FRAMEWORK

We model the health progression and organ arrivals for each candidate $i = 1,2,...,I$ in the waiting list as a simulation Markov model (Sonnenberg and Beck 1993). Once a liver offer arrives, each state in the model represents the combination of a candidate's health condition and the quality of a liver offer received. Given an initial health condition, we simulate the candidate's state trajectory over a finite planning horizon, capturing changes in health and offer quality over time. The trajectory of a single candidate in our simulation framework is summarized in Figure 1.

Before the start of the simulation, we estimate the current liver acceptance practices and calculate candidates' expected pre-transplant survival time based on their initial health condition, denoted by $T \in \mathbb{R}_{\geq 0}$. We then estimate health progression rates and liver offer arrival rates from historical data. For each candidate, we simulate the decision-making process across $N \in \mathbb{N}_{>0}$ replications over a continuous-time interval $t \in [0,T]$. In each replication $n = 1,2,\ldots,N$, liver offer arrivals are simulated based on the estimated offer arrival rate. When an offer is received after waiting time $\Delta_t \in \mathbb{R}_{\geq 0}$, we evaluate the quality of the offer and update the candidate's health condition according to the modeled progression dynamics. At each

decision epoch t, the candidate's healthcare provider may choose to accept or decline the offer based on the current health condition and the quality of the liver. If the offer is rejected, the simulation proceeds to the next potential offer. If the offer is accepted, the simulation replicate terminates, and the candidate's 1-year post-transplant survival probability is calculated and recorded. The full simulation concludes once each candidate's health progression has been replicated N times.

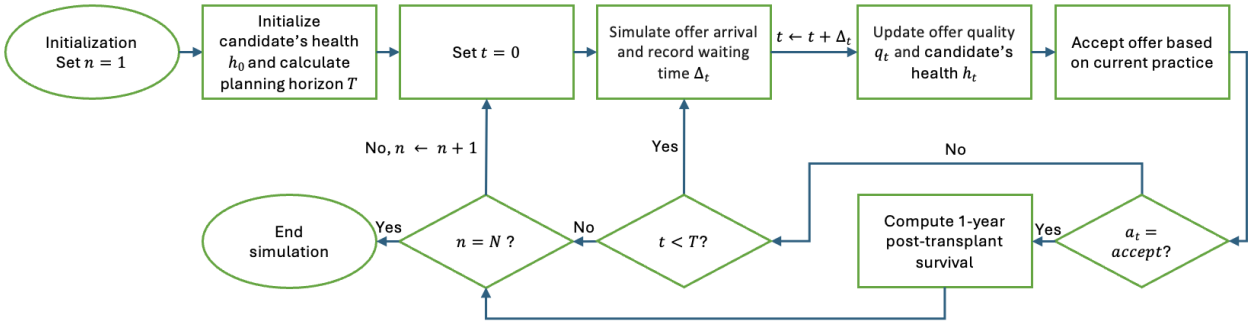

Figure 1: Summary of simulation framework for a single candidate.

We provide more details about candidates' health condition and progression, organ quality, offer arrival, and survival rate estimation in the following subsections.

2.1 Health State Definition and Progression

We use the Model for End-Stage Liver Disease (MELD) score to represent candidates' evolving health status. This score is a clinical metric used to assess the severity of chronic liver disease and predict short-term mortality risk (Kamath et al. 2001). The MELD score is calculated based on serum bilirubin, serum creatinine, and international normalized ratio of prothrombin time. According to OPTN, it serves as the primary tool for prioritizing most candidates on the liver transplant waiting list who are aged 12 and older based on their medical urgency. Higher MELD scores indicate more severe liver dysfunction and greater urgency for transplantation.

As a dynamic clinical metric that reflects liver function and the urgency of transplantation (Kamath and Kim 2007), the MELD score changes over time and thus provides a natural framework for modeling health state transitions. To capture patient-level variation with greater precision, we group the MELD score into individual categories: $S_H = \{<15, 15, 16, ..., 39, 40, >40, UC\}$, constructing a finite set of health states through which candidates can transition over time. Here, UC represents unsuitable condition for transplant. This categorization enables the formulation of a continuous-time Markov process to simulate patient deterioration or improvement while awaiting transplantation. Candidates with higher MELD scores are in more compromised health, facing increased mortality risk without transplantation.

To model health progression over time, we assume that transitions between MELD states follow an exponential distribution, a standard and well-established choice for representing memoryless transitions in continuous-time models. This assumption captures the inherently unpredictable timing of health progressions and enables tractable modeling within a continuous-time Markov chain framework (Masanet et al. 2023; Meyer et al. 2023). Nonetheless, we validate this assumption in our numerical study in Section 3.1. We denote the rates as $\lambda_H(h, h')$, indicating transitions from health state $h \in S_H$ to the next health state $h' \in S_H$.

2.2 Organ Quality and Arrivals

To assess the quality of organ offers, we incorporate the Donor Risk Index (DRI) — a composite measure developed to quantify the expected risk associated with an organ from a deceased donor. The DRI

aggregates multiple donor-specific characteristics, such as age, cause of death, organ preservation time, and other clinical attributes, into a single index (Feng et al. 2006). A higher DRI indicates a higher relative risk of graft failure after transplant and thus reflects a lower-quality organ. In our model, the DRI is used to stratify incoming organ offers by quality. By discretizing the DRI into 10 intervals: $S_Q = \{(0,1.1],(1.1,1.2],(1.2,1.3],(1.3,1.4],(1.4,1.5],(1.5,1.6],(1.6,1.7],(1.7,1.8],(1.8,2],(2,\infty)\}$, we capture heterogeneity in organ quality and its influence on post-transplant outcomes. This discretization results a similar number of donors per interval in our data while providing clinically meaningful differences in donor quality across intervals. This stratification allows us to model the variability in organ quality more precisely and evaluate its effect on liver acceptance outcomes.

In a continuous-time Markov process, the time between decision epochs is assumed to be exponentially distributed (Ibe 2013). Within our context, this assumption implies that the arrival of liver offers follows an exponential distribution, a common choice for modeling memoryless arrival processes in continuous time (Kong et al. 2010; Feng et al. 2013; Li and Mehrotra 2023). For example, Davis et al. (2013) adopts exponential distribution assumptions while modeling the time between organ offers. Given the evidence in the literature, we also adopt exponential distributions to represent liver offer inter-arrival times in our simulation framework. Nevertheless, we verify this assumption in our numerical study in Section 3.1

We parameterize a different exponential distribution for each candidate's health condition using the maximum likelihood estimation method (Rossi 2018). For each liver quality $q \in S_Q$ and patient health condition $h \in S_H$, we estimate the liver offer arrival rate $\lambda_Q(q,h)$ using:

$$\hat{\lambda}_Q(q,h) = \frac{1}{\bar{\Delta}_t(q,h)} = \frac{I_h O_q}{\sum_{i=1}^{I_h}\sum_{o=1}^{O_q}\Delta_t^{i,o}(q,h)},$$

where $\bar{\Delta}_t(q,h)$ denotes the average inter-arrival time across I_h candidates with health condition $h \in S_H$ and O_q liver offers with quality $q \in S_Q$. This estimation procedure is conducted across the inter-arrival times $\Delta_t^{i,o}(q,h)$ of candidates $i = 1,2,...,I_h$ receiving organ offers $o = 1,2,...,O_q$. The fitted exponential distributions are the basis for simulating offer arrivals in the liver transplantation model.

With the health progression model and the offer arrival model, we simulate realistic candidate trajectories on the waiting list, capturing changes in the timing of liver offers and health status. These components are critical to evaluating liver acceptance practices under our continuous-time liver acceptance framework.

2.3 Candidate Survival Estimation

Given their ability to handle censored time-to-event data and estimate relative risk, Cox proportional hazards models have become a standard choice in clinical survival analysis (Cox 1972). In this study, we use a Cox model to estimate each candidate's expected survival time without transplantation based on their MELD score. This estimate defines the planning horizon for each candidate. Additionally, we estimate candidates' 1-year post-transplant survival by incorporating their MELD score and their organ offer's DRI into a Cox proportional hazards model.

2.4 Model Formulation

We model the decision-making process of accepting or refusing liver offers for candidates on the waiting list as a continuous-time, finite-horizon MRP. This framework captures the evolution of outcomes under a fixed policy (Li 2010), the current liver acceptance practices. Since individuals may not always make decisions rationally and can respond differently even under identical circumstances (Simon 1955), we model organ acceptance practices as randomized policies to reflect the variability in decision-making behavior (see Section 3.2). The key components of an MRP include the following elements: time horizon, states, rewards, and a transition rate function. In addition, we incorporate actions into our MRP to quantify the impact of the current acceptance practices as rewards. Our formulation is as follows:

- $\mathscr{T} = [0,T]$: time horizon. Each decision epoch $t \in T$ corresponds to a point in time when a liver offer is received, and a decision must be made. If the current offer is declined, the candidate continues to wait, and the interval until the next decision epoch is denoted by the waiting time Δ_t. The time until the candidate's expected removal from the waiting list due to death or an unsuitable health condition T is the planning horizon.
- $S_H = \{<15, 15, 16, ..., 39, 40, >40, UC\}$: candidate's health state space. The higher the candidate's MELD score is, the sicker they are. We use UC to represent the absorbing state where a candidate is dead or in unsuitable condition for transplant.
- $S_Q = \{(0,1.1], (1.1,1.2], (1.2,1.3], (1.3,1.4], (1.4,1.5], (1.5,1.6], (1.6,1.7], (1.7,1.8], (1.8,2], (2,\infty)\}$: liver quality state space. Higher DRI values indicate lower-quality livers.
- $\mathscr{A} = \{W, A\}$: action space. The action $a \in \mathscr{A}$ represents either accepting or declining a liver offer.
- $r_t((q,h),a)$: candidates' rewards in state (q,h) according to their action a at time t. The outcomes of actions are quantified in terms of the probability of 1-year survival. If the current offer is accepted, a candidate receives the post-transplant probability of 1-year survival. Conversely, if they choose to wait, they receive no reward.
- $\lambda_H(h,h')$: health progression rate. We use this term to denote the transition rate from health state $h \in S_H$ to the next health state $h' \in S_H$.
- $\lambda_Q(q,h)$: liver offer arrival rate. This term represents the rate at which liver offers of quality $q \in S_Q$ arrive for a candidate in health state $h \in S_H$.

2.4.1 Transition Rate Function

Our transition rate function is built based on the rates $\lambda_H(h,h')$ and $\lambda_Q(q,h)$. We simulate liver arrivals and health conditions every time a liver is offered. This procedure determines the updated state (h_{τ^*}, q_{τ^*}) given an organ offer at time $\tau^* \in [0,T]$, and is presented in Algorithm 1. Our algorithm has two main steps:

Step 1: Organ Quality Simulation. Given the current health state of a candidate h, we simulate an exponential random variate $\Delta_t(q,h) \sim \text{Exp}(\lambda_Q(q,h))$ for each liver quality level $q \in S_Q$. These random variates represent the time until an organ of each quality arrives. The first arriving liver at time $\tau^* = t + \Delta_t^*$ defines the quality of the next offer, where $\Delta_t^* := \min_q\{\Delta_t(q,h) : q \in S_Q\}$ and $q_{\tau^*} = \arg\min_q\{\Delta_t(q,h) : q \in S_Q\}$.

Step 2: Health State Progression. We model health state progression using exponentially distributed waiting times for each potential next state. For health condition $h \in S_H$, we simulate a random variate $\rho_h \sim \text{Exp}(\lambda_H(h,h'))$ representing the time until a candidate with health state h transitions to health state h'. The health state at the time of organ arrival is the last state reached before Δ_t^*: $h_{\tau^*} = \max\{h \in S_H : \rho_h \leq \Delta_t^*\}$.

2.5 Policy Evaluation

We evaluate current liver graft acceptance policies using our MRP simulation framework. Each policy defines the probability of accepting a liver offer with quality q based on a candidate's current health state h. Given a fixed policy from current acceptance practices, we simulate candidate trajectories over a planning horizon $\mathscr{T}$, incorporating liver offer arrivals and health state transitions. We use the value function $V_t(h)$ to represent the expected total rewards starting from a health state $h \in S_H$, assuming the candidate follows the fixed acceptance policy throughout the simulation process. In our framework, the expected cumulative reward corresponds to the expected 1-year post-transplant survival from a liver offer. The expected total reward for our model under the fixed policy is:

$$V_0(h) = \mathbb{E}\left[\sum_{t=0}^{T} r_t((q_t,h_t),a_t) \,\middle|\, h_0 = h\right],$$

where q_t, h_t, and a_t represent the liver offer quality, the candidate's health condition, and the acceptance or rejection action at decision epoch t. For each candidate, we perform N replications, and compute the average cumulative reward across the simulated trajectories through:

Algorithm 1: Simulate state transition at each decision epoch.

Input: Current health state h, organ arrival rates λ_Q, health progression rates λ_H
Output: Updated state (h_{τ^*}, q_{τ^*}) at time τ^*

Step 1: Simulate liver offer arrival time and quality
for $q \in S_Q$ **do**
  Simulate $\Delta_t(q,h) \sim \text{Exp}(\lambda_Q(q,h))$;
Set $\Delta_t^* \leftarrow \min_q\{\Delta_t(q,h) : q \in S_Q\}$;
Set $\tau^* \leftarrow t + \Delta_t^*$;
Set $q_{\tau^*} \leftarrow \arg\min_q\{\Delta_t(q,h) : q \in S_Q\}$;
Step 2: Simulate health progression up to time τ^*
for $h \in S_H$ **do**
  Simulate $\rho_h \sim \text{Exp}(\lambda_H(h,h'))$;
Set $h_{\tau^*} \leftarrow \max\{h \in S_H : \rho_h \leq \Delta_t^*\}$;
Step 3: Return new state and time
return $\tau^*, (h_{\tau^*}, q_{\tau^*})$.

$$\hat{V}_0(h) = \frac{1}{N}\sum_{n=1}^{N}\sum_{t=0}^{T} r_t^n((q_t,h_t),a_t),$$

where $r_t^n((q_t,h_t),a_t)$ denotes the reward received at time t in replication n, given health state h_t, liver quality state q_t, and action a_t.

3 NUMERICAL STUDY

3.1 Data

We analyze data from the OPTN database from 2010 to 2023. Specifically, we examine the following datasets: (1) the liver data, which includes donor and candidate demographics (e.g., age, race, sex) and physical characteristics (e.g., blood type, height, weight, and body mass index), along with other relevant information like survival time and status; (2) the liver waiting list history data from the Standard Transplant Analysis and Research files, which detail modifications to waiting list records, such as changes in medical urgency status and MELD score inputs; and (3) the potential transplant recipient data, which contains information on all liver offers made to candidates, including their responses, reasons for refusal, and the associated match and response dates.

1. Using the liver data, we calculate DRI to represent organ quality and predict candidates' 1-year survival with and without a transplant based on MELD and DRI.
2. The liver waiting list history data is employed to characterize the longitudinal progression of candidates' MELD scores. This dataset provides time-stamped records of MELD score updates for each candidate, allowing us to observe transitions between different MELD categories over time. We estimate $\lambda_H(h,h')$ between MELD states by analyzing observed transitions in the data.
3. The potential transplant recipient data is used to model the arrival process of liver offers for waitlisted candidates. Each record in the data represents a liver offer made to a candidate, including the timestamp of the offer and associated liver characteristics. This data allows us to estimate the inter-arrival rates $\lambda_Q(q,h)$ of liver offers for individual candidates.

To ensure the appropriateness of the exponential distribution to model health transitions and liver inter-arrival times, we compare their fit against several alternative parametric models, including the Weibull, gamma, and log-normal distributions. For each health condition and year combination, the best fitting distribution of health transitions is the exponential distribution. Similar to the prior work by Davis et al. (2013), we find that the exponential distribution provides the best fit for liver inter-arrival times for each combination of health condition, liver quality, and year. We cannot reject the null hypothesis that the observations come from an exponential distribution for the majority of the combinations in Kolmogorov–Smirnov goodness-of-fit tests (Massey 1951). Furthermore, we visualize the empirical distributions using histograms overlaid with fitted probability density functions for each health condition and liver quality, confirming that the exponential distribution closely matches our empirical data.

3.2 Current Liver Acceptance Practices

To characterize the current liver acceptance practices, we derive acceptance probabilities from the potential transplant recipient data. We begin by categorizing all transplant candidates into one of our 28 predefined MELD score groups, representing health states. Simultaneously, we divide all liver offers into the 10 designed DRI intervals, which reflect different organ quality states.

The acceptance rate for a given (MELD, DRI) pair is then computed as the ratio of accepted offers to total offers observed in that group. For example, to determine the acceptance rate for candidates with a MELD score of 26 receiving offers with a DRI between 1.5 and 1.6, we identify all such instances in the data, count how many offers are made and how many are accepted, and compute the acceptance probability as the fraction of offers accepted.

This acceptance matrix, representing acceptance probabilities across all (MELD, DRI) combinations, serves as the basis for defining a randomized policy in our simulation framework. Under this policy, a candidate with a given health state who receives a liver offer of a specific quality will accept the offer with a probability equal to the observed acceptance rate for that health-quality combination.

Our analysis reveals distinct patterns in liver offer acceptance behavior across candidate health conditions and organ quality levels. From our data, we notice that within each MELD category, candidates are more likely to accept high-quality liver offers with low DRI. When comparing across MELD categories, acceptance rates for low-quality offers tend to be higher among high MELD groups (more severe candidates). In contrast, acceptance rates for high-quality offers are higher within low MELD groups (healthier candidates). These patterns suggest that healthier candidates are more willing to wait for scarce, high-quality liver offers. Due to their health acuity, sicker candidates are more inclined to accept available offers despite being in low-quality categories. This behavior also reflects clinical decisions to defer marginal organs for less urgent candidates, reserving riskier organs for sicker candidates with fewer alternatives. A plot illustrating the acceptance practices in the U.S. is presented in Figure 2. The overall acceptance rates remain relatively low across all groups in the U.S., aligning with previous research findings (Howard 2002; Wey et al. 2018) and highlighting the need for potential improvement in current acceptance practices.

3.3 Analysis

We use the following metrics to assess policy performance. First, the expected value function $V_0(h)$ represents the expected 1-year post-transplant survival probability starting from health state h. Second, the expected survival time estimates the average survival time following liver offer acceptance, conditional on the candidate's current health state and the quality of the accepted offer. Finally, the waiting list time captures the total expected waiting time for each candidate on the liver transplant waiting list. In the latter two scenarios, declining a liver offer leads to a reward $r_t((q,h),W) > 0$ corresponding to the time between organ offers.

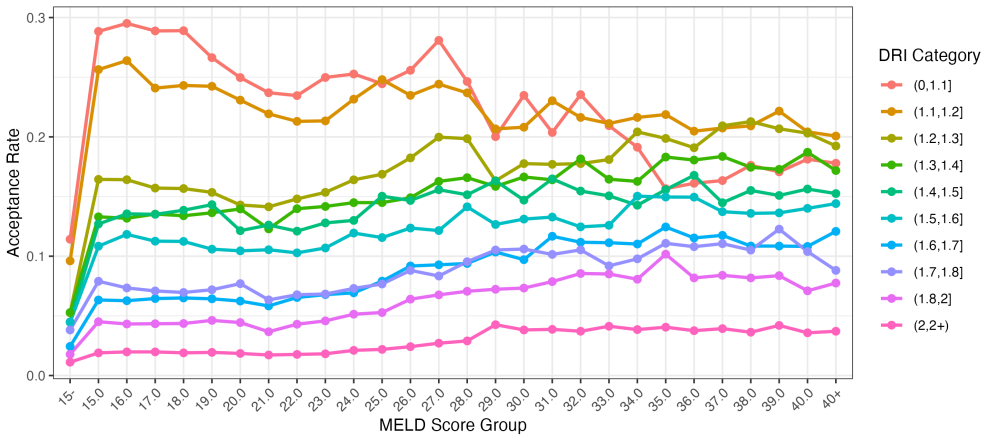

Figure 2: Current liver acceptance practices in the U.S.

3.3.1 Sensitivity Analysis

To assess the robustness of our simulation outcomes, we also evaluate how changes in offer acceptance behavior and organ arrivals impact the outcomes of our study population.

First, we modify acceptance rates across different quantiles of organ quality and evaluate how variation in candidate selectivity affects our outcomes of interest. Organs are classified into three quality groups based on their DRI: (1) Q25: High-quality organs (around the 25th percentile of DRI); (2) Q50: Median-quality organs (around the 50th percentile of DRI); and (3) Q75: Low-quality organs (around the 75th percentile of DRI). We sequentially increase the acceptance rates by 25% for different quality groups: first for high-quality organs (Q25), then for both high- and median-quality organs (Q25 and Q50), followed by inclusion of up to the 75th percentile (Q25, Q50, and Q75), and finally for all organs. In addition, we change organ arrival rates and assess how organ arrivals influence our outcomes. We increase and decrease the arrival rates by 25% relative to the baseline.

4 RESULTS

We evaluate patient outcomes across every combination of health state and organ quality under the current liver acceptance practices. Figure 3 displays heatmaps of (a) 1-year post-transplant survival probability, (b) average post-transplant survival time, and (c) average waiting list time. Our findings show that candidates with lower MELD scores have the highest 1-year survival proportion and average survival time after a transplant for any DRI score while experiencing the longest waiting list time. In addition, candidates transplanted with high-quality organs have higher 1-year survival proportion and survival time.

1-Year Post-Transplant Survival Probability: The 1-year survival probability decreases as MELD and DRI scores increase (i.e., as health conditions decline and organ quality worsens). Candidates with lower MELD scores and lower DRI offers have the highest short-term post-transplant survival, reaching above 92%. In contrast, candidates with MELD scores above 33 receiving organ offer with higher DRI have notably reduced survival probabilities, approximately 88%.

Average Post-Transplant Survival Time: The average post-transplant survival time shows a similar pattern to the 1-year survival proportion. Survival time declines with deteriorating health conditions and worsening organ quality. Candidates transplanted with high-quality organs while having healthier conditions are projected to live longer post-transplant than candidates with higher MELD scores transplanted with organs of low DRI.

Average Waiting List Time: With increasing MELD scores, average waiting times decrease, showing higher prioritization for candidates with urgent health conditions. Candidates with MELD scores below

23 typically face average wait times of over 100 days, while those with MELD scores above 33 have significantly shorter waiting times, averaging about 6 days.

These results also highlight the trade-off between waiting for better-quality organs while having risks for health deterioration versus accepting earlier offers of lower quality. Candidates with higher MELD scores have shorter waiting times but face reduced post-transplant outcomes. Notably, the quality of liver offers plays a critical role in patient survival, underscoring the necessity of enhancing both the supply and equitable access to high-quality organs.

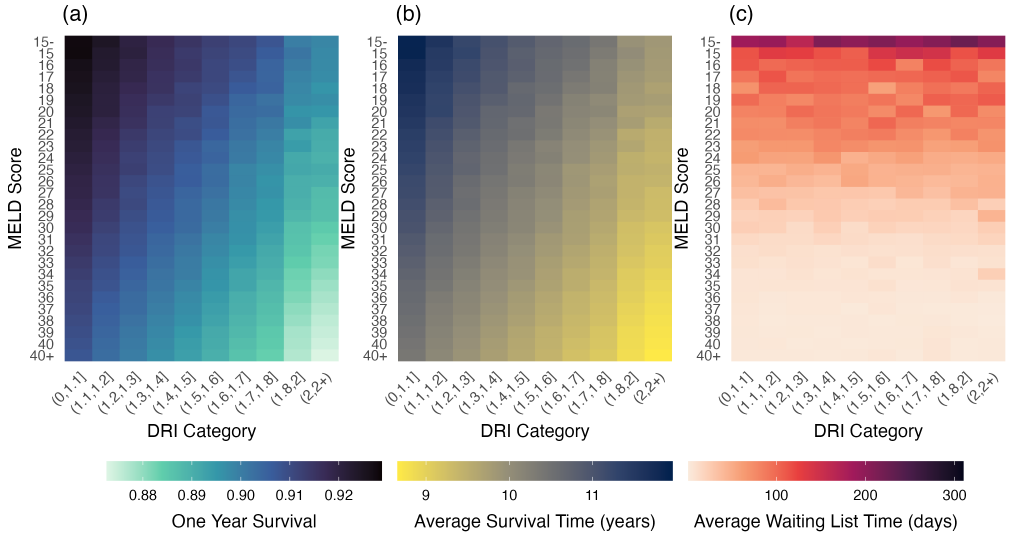

Figure 3: Simulation Outcomes by MELD Score and DRI. The panels show the following information: (a) 1-year post-transplant survival probability, (b) average post-transplant survival time, and (c) average waiting list time.

4.1 Sensitivity Analysis Results

To assess the robustness of our findings, we conducted a sensitivity analysis by varying organ acceptance behavior and organ arrival rates. Table 1 summarizes outcomes across six scenarios, each changing key model parameters while tracking our metrics of interest. The "Baseline" row represents the outcomes under current acceptance practices without any adjustments. In Scenario 1, we increase the acceptance rates by 25% for high-quality organs (Q25). In Scenario 2, acceptance rates are increased by 25% for high- and median-quality organs (Q25 and Q50). Scenario 3 applies the increase to all but the lowest-quality organs(Q25, Q50, and Q75). Scenario 4 increases acceptance rates by 25% for all organs. In contrast, Scenario 5 and Scenario 6 increase and decrease the organ arrival rates by 25%, respectively. We exclude the average survival times from our results since there were no considerable differences across scenarios. All scenarios displayed an average survival time of approximately 10.3 years.

We observe consistent trends across scenarios 1 to 4: slight increases in both 1-year survival probability (from 90.5% to 90.6%) with decreases in average waiting list time (from 73.0 to as low as 60.7 days). These results show that increased acceptance of higher-quality organs leads to improved survival outcomes and reduced waiting list time.

Scenarios 5 and 6 further indicate the importance of organ availability. In Scenario 6, we decrease organ arrival rates by 25%; this change results in the longest average waiting list time (92.0 days), while Scenario 5 achieves the shortest waiting list time (60.7 days) with a 25% increase in organ arrivals. Notably, Scenario 6 shows a slight decline in survival probability, illustrating the compounded impact of longer waiting on health outcomes.

Table 1: Simulation outcomes across sensitivity analysis scenarios.

Scenario Description	1-Year Survival (%)	Waiting List Time (days)
Baseline: current practices	90.5	73.0
Scenario 1: +25% accept Q25	90.5	66.4
Scenario 2: +25% accept Q25, Q50	90.5	64.1
Scenario 3: +25% accept Q25, Q50, Q75	90.6	61.9
Scenario 4: +25% accept all organs	90.6	60.9
Scenario 5: +25% organ arrival	90.6	60.7
Scenario 6: -25% organ arrival	90.5	92.0

5 CONCLUSIONS AND FUTURE WORK

In this paper, we introduced a continuous-time Markov chain simulation framework that models the liver transplantation decision-making process at the candidate level. We modeled the process as an MRP using a randomized policy informed by real-world acceptance practices. By using historical data from OPTN, we parameterized offer arrival and health progression rates from exponential distributions to simulate candidate trajectories and post-transplant outcomes. Our simulation incorporated all dynamics between candidate health, organ quality, and decision time.

Future work may extend this framework in several directions. First, broader simulations on policy interventions may be considered. For example, changes in offer-sharing regions could be evaluated in terms of equity and efficiency. Second, incorporating machine learning techniques into our framework may more accurately capture complex decision-making patterns and interactions among clinical factors. Third, the use of time-varying parameters may effectively account for evolving medical practices and technologies over time. Finally, our framework could be expanded to optimize personalized data-driven decision-making policies to balance the trade-off between waiting and accepting a liver offer. We believe such a framework will provide guidance and support on liver transplantation decision-making.

In conclusion, our findings highlighted that, although the overall scarcity of donor livers remained a major challenge, the more acute obstacle was the limited number of high-quality organs and the highly selective current acceptance behavior. Current acceptance patterns showed a strong preference for only the highest-quality grafts, resulting in markedly higher acceptance rates for these organs. Our simulations indicated that incremental differences in organ quality had only relatively modest effects on post-transplant outcomes. Candidates who accepted a medically suitable offer shortened their waiting-list exposure and notably improved their prognosis. From our sensitivity analysis, we noticed that expanding acceptance criteria and organ arrivals can increase organ availability, translating into higher survival rates and shorter waiting times. Encouraging broader acceptance of clinically appropriate organs, rather than only the highest-quality organs, is essential for maximizing the lifesaving potential of the donor pool. Greater acceptance would also enhance the overall efficiency and effectiveness of the transplant system due to the reduced waiting times for candidates, thereby allowing more transplants and improving overall survival.

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