American Journal of Transplantation xxx (xxxx) xxx

Contents lists available at ScienceDirect

American Journal of Transplantation

journal homepage: www.amjtransplant.org

Original Article

An experiment on the impact of predictive analytics on kidney offers acceptance decisions

Ian McCulloh [1,2,*], Darren Stewart [3], Kevin Kiernan [1], Ferben Yazicioglu [1], Heather Patsolic [1], Christopher Zinner [1], Sumit Mohan [4], Laura Cartwright [3]

[1] Discovery Lab, Applied Intelligence, Accenture, Washington, DC, USA
[2] Bloomberg School of Public Health, Johns Hopkins University, Baltimore, Maryland, USA
[3] United Network for Organ Sharing, Richmond, Virginia, USA
[4] Department of Medicine, Vagelos College of Physicians and Surgeons and Department of Epidemiology, Mailman School of Public Health, Columbia University, New York, USA

ARTICLE INFO

Keywords:
clinical decision making
organ procurement transplantation network
time-to-next offer
kidney
UNOS

ABSTRACT

Because of the breadth of factors that might affect kidney transplant decisions to accept an organ or wait for another, presumably "better" offer, a high degree of heterogeneity in decision making exists among transplant surgeons and hospitals. These decisions do not typically include objective predictions regarding the future availability of equivalent or better-quality organs or the likelihood of patient death while waiting for another organ. To investigate the impact of displaying such predictions on organ donation decision making, we conducted a statistically designed experiment involving 53 kidney transplant professionals, in which kidney offers were presented via an online application and systematically altered to observe the effects on decision making. We found that providing predictive analytics for time-to-better offers and patient mortality improved decision consensus and decision-maker confidence in their decisions. Providing a visual display of the patient's mortality slope under accept/reject conditions shortened the time-to-decide but did not have an impact on the decision itself. Presenting the risk of death in a loss frame as opposed to a gain frame improved decision consensus and decision confidence. Patient-specific predictions surrounding future organ offers and mortality may improve decision quality, confidence, and expediency while improving organ utilization and patient outcomes.

Introduction

The complex decision to accept or reject a deceased donor kidney includes numerous clinical, logistical, and regulatory considerations,[1] but presumably is also driven primarily by whether another, better organ offer is likely to occur for the intended recipient. During the organ allocation process, cold ischemia time is accruing, making the organ less desirable over time, thus forcing the need to enforce strict time limits on the decision-making process.[2] The combination of complexity and time urgency creates a high-pressure condition for both the intended recipient and the next patients in line if the organ offer is declined.

Decision making under these conditions is not consistent. Organ offer decisions appear to be influenced by many factors beyond the quality of the organ in question, with variations being noted across nights and weekends.[3-6] Many surgeons may experience optimism bias, where they believe that a better-matched organ will be available and offered sooner than it will in reality.[7,8] There is also a risk-aversion bias where decision-makers are biased toward refusal in the spirit of "do no harm," yet refusal decisions may actually do harm by negatively affecting a patient's survival likelihood.[8] As a result, there is a high rate of organ offer declines, with 85% of kidneys being declined at least once, which has resulted in a concerningly high nonutilization rate that appears to be steadily increasing over time.[3,9-13] Providing more information about the consequences of declining an organ with more precise estimates of patient prognosis and time-to-subsequent offers may help to create more objective assessments of the consequences of an organ offer refusal and thereby reduce optimism bias and uncertainty among decision-makers.

Abbreviations: DMS, DonorNet Mobile Simulator; KDPI, kidney donor profile index; OPTN, Organ Procurement and Transplantation Network; TTBO, time-to-better offer.

* Corresponding author. Bloomberg School of Public Health, Johns Hopkins University, Baltimore, MD, United States.
E-mail address: imccull4@jhu.edu (I. McCulloh).

https://doi.org/10.1016/j.ajt.2023.03.010
Received 23 February 2023; Accepted 8 March 2023
Available online xxxx

Please cite this article as: McCulloh I et al., An experiment on the impact of predictive analytics on kidney offers acceptance decisions, American Journal of Transplantation, https://doi.org/10.1016/j.ajt.2023.03.010

In the USA, organ transplant offers are managed through DonorNet, an online system that matches available organs with medically suitable recipients. When patients are offered a kidney from a deceased donor, the organ procurement organization notifies their transplant care teams via DonorNet. For each offer, DonorNet provides decision-makers with hundreds of clinical, social, and physiological data points in addition to matching scores to assess the quality of the available kidney for the patient. Since the introduction of DonorNet (2007), which allowed organ procurement organizations to send electronic offers to multiple transplant centers simultaneously, its effectiveness has been questioned.[14,15] Meanwhile, organ nonutilization rates have continued to rise,[8,12,16-18], suggesting the need for improved decision-support to help clinicians evaluate the multitude of factors that could affect patient outcomes.

Behavioral studies conducted by the United Network for Organ Sharing have demonstrated that alterations in the presentation of certain clinical data can dramatically influence acceptance decisions and that decision making is highly heterogeneous among surgeons and physicians, even at the same transplant center.[19] Schnier et al[1] found that simply altering the frame in which an offer is presented can have a profound effect on an organ offer decision. In some clinical contexts, presenting the offer in a loss frame (ie,"years lost") instead of a gain frame (ie, "years gained") can increase treatment acceptance rates. Tversky and Kahneman[20] found that with decisions for radiation or surgery in cancer treatment, a loss frame almost doubled treatment acceptance rates and reduced risk aversion, thus improving health outcomes.

We present a novel behavioral study that investigates how changes in the presentation of deceased donor organ offers may speed time-to-decision, increase acceptance likelihood, or improve decision consistency through evidence-based medicine. Specifically, we tested the impact of presenting new predictive analytics consisting of 3 components: the predicted time to the next, better kidney offer; the risk of patient death without a transplant until that time; and a visual representation of the patient's survival probability over time without a transplant. By testing the impact of these predictive analytics in a hypothetical offer environment, we aimed to pave the way toward displaying these types of predictions for real organ offers to help overcome known biases and ultimately reduce organ nonutilization rates while improving patient outcomes.

Materials and methods

We conducted a multiresponse, human subjects, statistically designed experiment using an organ offer simulator tool. The limited objectives were to determine and validate key factors affecting transplant decision-making to inform the future design of the DonorNet application's user interface. Participants for the study were recruited to opt-in via e-mail and through presentations at Organ Procurement and Transplantation Network (OPTN) professional meetings. Individual e-mails containing a unique link to the study were sent to potentially eligible participants, identified using the OPTN membership database. Approximately 3000 initial e-mail invitations were sent. Interested participants were screened for eligibility criteria of being involved in responding to adult deceased donor kidney offers. Two follow-up e-mails were sent to participants who had not completed the study before the final submission deadline, and the deadline was extended by 1 week. Participants were effectively given 2 weeks to complete their responses for the study. Fifty-three participants completed the full study (mean years of experience 11.8, standard deviation 4.1), including 24 surgeons, 4 nephrologists, and 25 transplant coordinators.

Each participant rendered a decision on 16 simulated kidney offers presented sequentially via the DonorNet Mobile Simulator (DMS). All participants provided informed consent, and the study was approved by an institutional review board Protocol#21ACFS102.

The following 3 dependent variables were investigated: (1) accept/decline decisions; (2) decisions; (2) decision confidence; and (3) time-to-decide. Decision consensus also referred to as doctor-to-doctor agreement/consistency, was measured using Fleiss's Kappa,[21] a generalization of interrater reliability for a fixed number of raters assessing categorical data (organ accept/reject) and ranging from 0 (complete disagreement) to 1 (complete agreement). To measure the confidence a decision-maker has in their decision for the patient, we use an anchored 5-point Likert scale where 1 is "not confident," 2 is "somewhat confident," 3 is "confident," 4 is "very confident," and 5 is "perfectly confident" in response to the following question: "*Based on the data reviewed, how confident are you that this is the best decision for this patient?*" The time-to-decide was measured in seconds from the time a simulated offer was displayed on the web application until the subject selected accepted or rejected the offer after reviewing it. Outlier durations were removed to account for subjects that may have been distracted or walked away from the application in the middle of a case.

Experimental factors were features that were systematically altered to understand their impact on response variables (Table). We identified 5 experimental factors, 2 of which were variations in the type of offer presented to subjects, and 3 were data presented to inform evidence-based decisions. The first factor was the ease-of-decision. There were 2 levels for this factor: easy and borderline. The determination of easy or borderline was based on the kidney donor profile index (KDPI), which ranges from 0 (highest quality) to 100 (lowest quality). Offers having KDPI of <20 or ≤ 95 were hypothesized to be relatively "easy" decisions.

Table
Experimental design.

Case number	Ease-of-decision	KDPI	Numeric predictions	Mortality slope viz	Framing effect	Predicted time-to-better offer (TTBO)	Predicted probability of death before next offer	Predicted survival probability
1	Easier	16	−	+				
2	Easier	14	+	−	−	10 mos	5%	
3	Easier	16	−	−				
4	Easier	17	+	+	+	1.1 yrs		94.7%
5	Borderline	52	−	−				
6	Borderline	54	+	+	−	1.3 yrs	13%	
7	Borderline	53	−	+				
8	Borderline	51	+	−	+	1.3 yrs		88%
9	Borderline	68	−	+				
10	Borderline	69	+	−	−	5 mos	5%	
11	Borderline	67	−	−				
12	Borderline	68	+	+	+	7 mos		93.5%
13	Easier	97	−	−				
14	Easier	96	+	+	−	2 mos	1.9%	
15	Easier	98	−	+				
16	Easier	95	+	–	+	3 mos		97.8%

+ indicates the presence of a factor, whereas − indicates absence.
KDPI, Kidney donor profile index.

Cases ranging between a KDPI of 50 and 70 were considered of borderline difficulty. Simulated offers were reviewed to ensure clinical plausibility, and KDPI was only one donor factor among many. We used KDPI as our proxy for organ quality for the purpose of this study.

The second factor was lower or higher KDPI. A low KDPI was defined as those KDPI <55. A high KDPI was defined as ≥67. These 2 factors create the following 4 quadrants for analysis: (1) easier decision, low KDPI; (2) borderline decision, low KDPI; (3) borderline decision, high KDPI; and (4) easier decision, high KDPI.

The remaining 3 experimental factors represented differences in how predictive analytics were presented to the subjects and were the primary focus of the study. The third factor was the display of a predicted time-to-better offer (TTBO). For this study, a "better offer" was defined as an organ with a KDPI that is at least 20 points lower than the offered deceased donor organ. Because this behavioral study was conducted as a preliminary phase of a broader project that included building statistical models to predict TTBO, model-based predictions were not available. Instead, because the purpose of this study was to learn how different values of TTBO would impact offer decisions if displayed (vs hidden), we strategically assigned the specific TTBO values are shown in the Table. These TTBO choices allowed us to test the impact of relatively long (approximately 1 year), short (approximately 2-3 months), and moderate (approximately 5-7 months) TTBOs on offer decision-making in different offer contexts (eg, KDPI). We considered historical kidney offer rates (eg, offers received per year, on average, and by candidate characteristics), as well as the KDPI of the given offer, to avoid assigning clinically implausible TTBOs. The illustration of TTBO is provided in Figure 1.

The fourth factor was a binary variable indicating whether a patient mortality slope was displayed or not. The mortality slope, as shown in Figure 2, is a visual representation of the patient's predicted survival probability over time on the waitlist in the absence of a transplant. Although strategically chosen for the purposes of this study, patient-specific mortality predictions were selected to be realistic based on the candidates' EPTS scores and published algorithms.[22] The x-axis is time in years starting from the time of the present offer. The y-axis is the survival probability. The red line represents the predicted patient survival probability over time. Superimposed on the graphic is the TTBO. The patient's risk of mortality (Fig. 1) is equal to one minus the survival probability associated with this predicted time.

The fifth factor, the "frame effect," presents the mortality prediction as an advantage/gain or a disadvantage/loss. This factor, based on prospect theory,[20] was either presented as a gain or loss condition. Under prospect theory, decision-makers are not considered fully rational actors but instead assess losses and gains differently and are more inclined to be loss-averse when making decisions. When the "frame effect" was set to the gain condition, the prediction was presented in terms of the advantage of an offer decline decision in the following manner, eg, "76% probability of survival until a better offer." In the loss condition, the identical prediction was presented in terms of the disadvantage of an offer decline decision in the following manner, eg, "24% probability of death before a better offer." The clinical data presented about the donor and potential recipient were essentially the same for each condition.

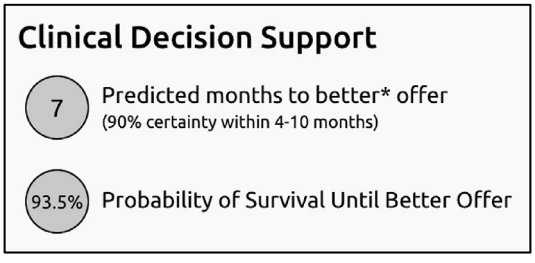

Figure 1. Example TTBO display. TTBO, time-to-better offer.

The statistically designed experiment[23] consisted of 16 factor combinations, ie, 16 simulated offer scenarios for each subject to review, systematically varied to ensure that none of the factors were confounded with each other or any 2-factor, ie, with an estimated 4 to 5 minutes to review an offer, subjects spent between 1 and 1½ hours reviewing these simulated offers. With 53 subjects participating in this study, we had 848 data points for the analysis.

Simulated offers were derived from 4 real offers drawn from the OPTN database such that they represented the 4 quadrants defined by the easy/borderline decision and high/low KDPI factors. These 4 offers consisted of most of the clinical data normally presented for an OPTN organ offer, and the data were slightly perturbed, ie, changing donor age by 1 to 2 years, KDPI by 1 to 2 points, and a few other clinical variables, to avoid subjects recognizing that essentially the same 4 cases were repeated 4 times each. Using essentially the same clinical conditions across the experimental conditions prevents unaccounted-for clinical variables from being confounded with changes to the predictive analytics and visuals provided to decision-makers. Personally identifiable offer data were anonymized to present realistic yet nonattributable data for the study.

Each participant was provided 16 offers via a unique URL to the DMS, which displayed donor and potential recipient data and predictive analytics according to the experimental design (Fig. 3), while capturing the participants' decisions to accept or refuse the offer. DMS also recorded the time to make the decision and participants' reported confidence in each decision. Each of the 16 offers included clinical data commonly provided to inform offer decisions, such as donor and candidate ages, comorbidities, and measures of organ function status. such as donor serum creatinine levels.

Response variables were modeled with multiple regression using the R statistical environment. The proposed experimental design created orthogonal factor combinations that reduce or eliminate leverage or variance inflation in the estimation. In factor combinations where the frame effect would be varied, but the TTBO is not displayed, there would effectively be no difference in the evidence provided to the subject. Thus, a frame effect without a TTBO is not meaningful. The frame effect is only relevant within the context of a 2-factor interaction with TTBO. We further anticipate interactions between ease-of-decision and the 3 experimental factors, where evidence has a greater impact on informing borderline cases.

To construct the mock organ offers, this study used data from the OPTN, which includes data on all donors, waitlisted candidates, and transplant recipients in the USA. The Health Resources and Services Administration, US Department of Health and Human Services provides oversight of the OPTN contractor.

Results

Overall, the study showed high consensus, where decision-makers agreed on 716 (84.4%) out of 848 offers. The most significant variable affecting decision consensus was the display of the "TTBO" ($T = 4.42$; $P < .0001$), where displaying the predictive analytics-improved consensus with an effect size of 5.4% increase in overall decision quality. This model included a control for ease-of-decision to account for improved consensus on easy accept/reject decisions. The frame effect was also significant ($T = 2.12$; $P = .03$), whereby presenting the TTBO data as a loss frame improved consensus. The display of the mortality slope did not have any measurable effect on consensus. The findings were consistent in terms of P value and effect size when controlled for each quadrant.

The most significant variable affecting decision confidence was the frame effect ($T = 2.16$; $P < .02$), where a loss frame improved confidence. The display of TTBO was also significant ($T = 1.93$; $P < .03$), where the display of TTBO data improved confidence. As expected, providing TTBO predictions improved confidence.

Approximately 83% of case decisions were made within 3 to 7.5 minutes of the offer presentation, with an average time of 5.6 minutes

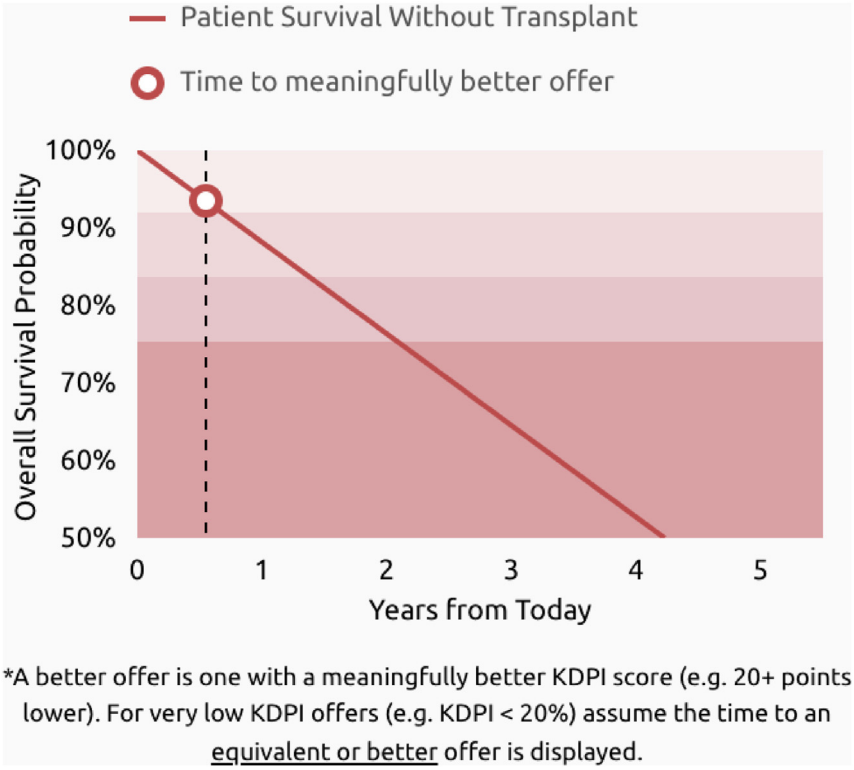

Figure 2. Visual display of patient mortality slope. KDPI, Kidney donor profile index

(338 seconds). There were 147 (17%) decisions that exceeded 15 minutes, and were deemed outliers, because no data existed between 7.5 and 15 minutes, suggesting that these subjects were distracted or interrupted when responding to a case. To avoid misleading results, these outliers were removed from the time-to-decision analysis.

The only significant variable affecting time-to-decision was the display of the mortality slope ($T = 2.19$; $P < .03$). Providing the mortality slope reduced the time-to-decision with a small effect size of 21 seconds (6%) reduction in time.

The observed impact of predictive analytics and the frame effect varied based on the type of offer, as shown in Figure 4. Most notable are the offers shown in panels B and D with KDPI ranging from 50 to 55 or those with KDPI >95. Displaying the numerical predictions of TTBO and mortality risk improves consensus in the direction of a priori medical judgment, which suggests improved decisions in the presence of predictive analytics. Although the frame effect was also significant, it is important to note that providing numerical predictions was the most impactful in supporting decisions, with the frame effect providing marginal improvement in consensus.

Notably, for the KDPI 50 to 55 offer, when predictive analytics—TTBO of 1.3 years; mortality risk of 13%; mortality slope—was displayed, the acceptance rate increased from 87% to 95% (Fig. 4, panel B). By contrast, for the KDPI >95% offer, when predictive analytics—TTBO of 2 months; mortality risk of 1.9%; mortality slope—was displayed, the acceptance rate decreased sharply, falling from 41% to 9% (Fig. 4, panel D).

Discussion

At present, the overwhelming majority of deceased donor kidney offers are declined by transplant centers for their patients.[8] This phenomenon often results in organs being accepted at other centers for patients with lower priority for the organs who are lower on the match run.[16] Alternatively, this frequently results in the eventual nonutilization of the deceased donor kidney as a result of accrual of excessive cold ischemia whereas attempting to identify a transplant center that would be willing to accept the organ for a patient.[8,16]

One factor affecting offer acceptance decisions might be the belief that the patient ought to continue to wait for a better organ offer, which they would anticipate would become available in relatively short order. However, the relative timing of the next offer can be highly variable depending on the patient's level of priority in the allocation system, degree of biological compatibility with the donor pool, randomness in the occurrence of deceased donors becoming available, and the number of patients/centers ahead of them that need to decline an organ, with no certainty that the subsequent offer that does come will be of a significantly better quality to offset the negative consequence of increasing time on dialysis in the interim. Finally, waitlisted patients with end-stage kidney disease have a high annualized mortality rate and are also at risk of being delisted for a variety of medical reasons while awaiting that future better organ offer.

As a result, clinicians have a large number of clinical variables of both the donor and the potential recipient to consider at the time of the organ offer, increasing the risk of cognitive overload. Framing the decision by providing more precise estimates of the TTBO and the risk of patient mortality while on dialysis may help lower the cognitive load and improve decision making.

Our results demonstrate that when made aware of a relatively long predicted TTBO (eg, >1 year) along with a relatively high mortality risk waiting for that offer (eg, 13%), clinicians' acceptance rates increased. Ostensibly, these predictions dampen the willingness of clinicians to wait for a subsequent offer, thereby helping to overcome the optimism bias that a meaningfully better offer is imminent for the candidate, and that the candidate will survive long enough to receive the transplant.

This study demonstrates that providing TTBO data, visual mortality slope, and framing patients' mortality risk in a loss frame may improve evidence-based clinical decision making for deceased donor organ offers, although increasing the confidence that clinicians have that they are making the appropriate choice for their patients.

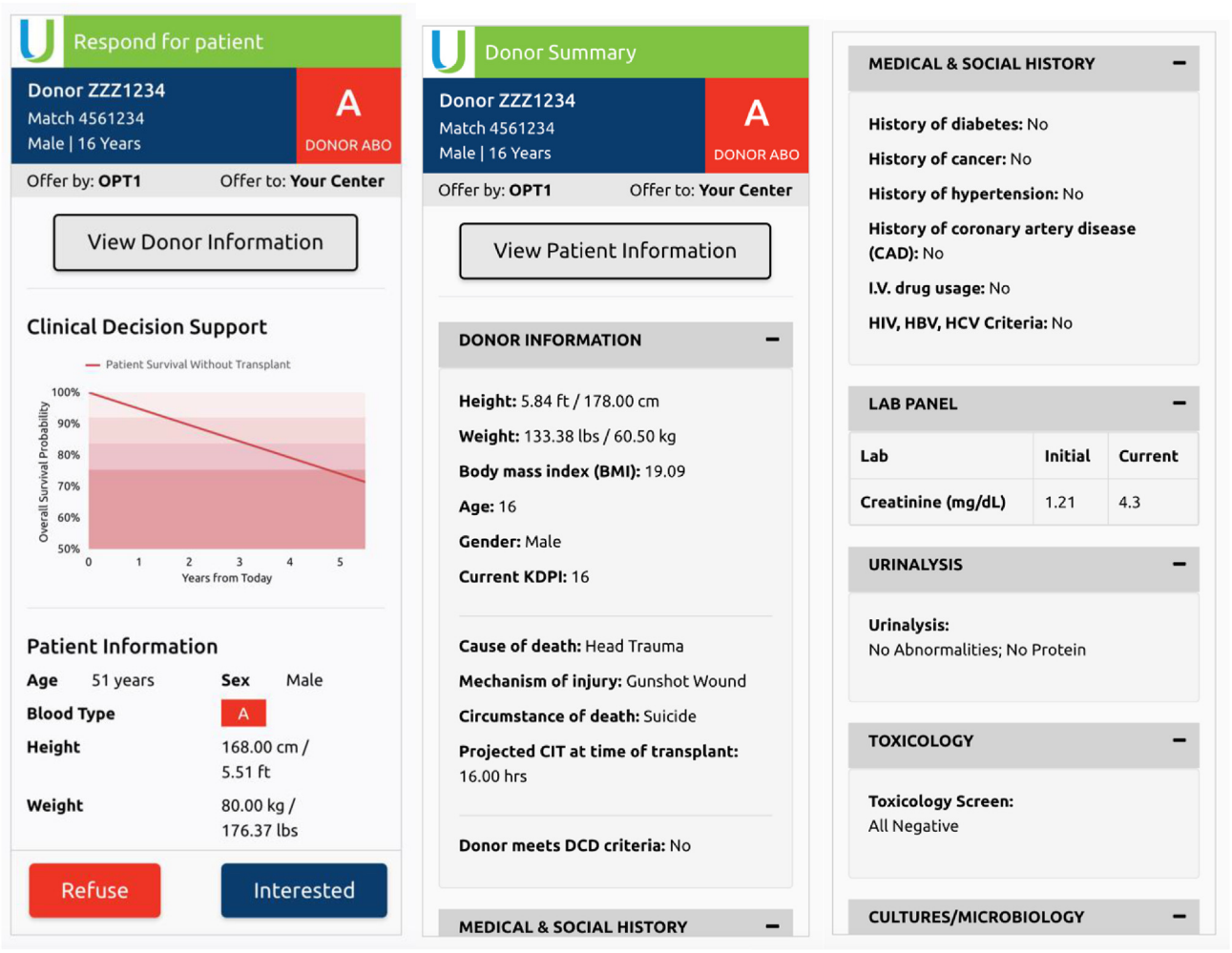

Figure 3. Screen shot example for a simulated offer.

Adding predictive analytics may increase offer acceptance in clinically suitable patients who stand to benefit from the kidney, compared with remaining on dialysis and waiting for another one. Predictive analytics has the potential to reduce both kidney nonutilization and waiting list mortality rates. Considering the even higher mortality risk for candidates waiting for a deceased donor liver, lung, or heart, the potential impact may be even greater in other transplant contexts.

Interestingly, our study also showed that predictive analytics with very low TTBO, eg, 2 to 3 months, dramatically *decreased* the offer acceptance rate (from 41%-9%) for a high-KDPI kidney (Fig. 4). Although this might seem problematic at first glance, declining an organ offer when a truly better near-term offer is realistic, may very well be the right decision for that patient. Although this might seem counterintuitive for the allocation system, these offer declines, if done rapidly, would still facilitate getting the organ to a patient who is likely to benefit from it the most whereas contributing to increased efficiency of the system. However, we should note that the TTBO is merely a statistical estimate that may change over time, and in practice, it will be essential to provide a measure of uncertainty around the point estimate so the extent of the imprecision is apparent.

We did not attempt to assess decision quality, ie, whether or not each acceptance or decline decision was "correct" (in the patient's best interest from a survival perspective), in this study. It is difficult to assess decision quality in a study, such as this, where medical judgment can differ. Just because most decision-makers agree on a decision it does not imply that it is the right decision. Future studies are needed to evaluate the impact of decisions on medical outcomes.

Several additional limitations apply. The study used only 16 cases, one for each combination of factors. Ideally, a study would include replications with different cases, but our study was intentionally limited to prevent task overload among the participants. Furthermore, although designed based on expert opinion and historical data to be clinically realistic, the TTBO and mortality slopes were artificially created for this study and may deviate from real-world predictions, which could impact our findings' generalizability. Short TTBOs were intentionally chosen for high KDPI offers (and vice versa) to reduce factor discordance; additional experiments would be needed to assess the impact of displaying predictions for offers with discordant TTBO and KDPI.

Participants knew that they were participating in a study, which may have impacted their time-to-decision either to be more careful in reviewing features or hastier in that real lives are not at stake.

Our statistical findings were robust. Several regression models (results not shown) were fitted to these data, including random and mixed-effect models and logistic and general linear models. All combinations of variables were fitted to identify the best fit models. All findings were consistent across all the models.

The impact of prospect theory (the "frame effect") on decisions suggests that objective assessment of data alone is not responsible for clinical decisions. In our study, to examine the "frame effect" on transplant decision making, the same predictions were reported via 2 different experimental conditions: either "probability of survival until" or "probability of death before" a better offer. Consistent with other decision-making contexts,[20] the loss frame of "probability of death" was found to be more likely to result in a decision to treat (ie, offer acceptance). It is

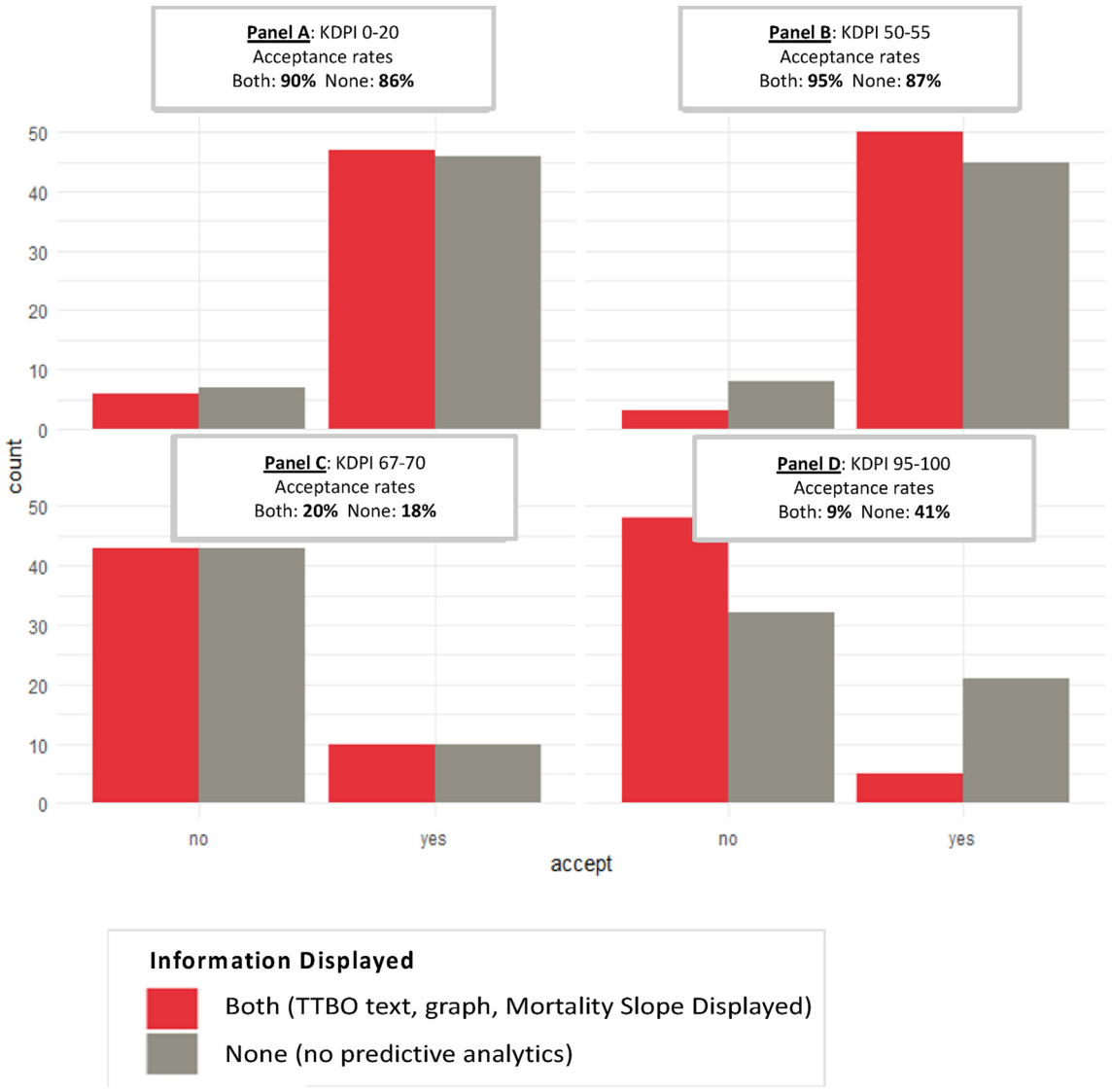

Figure 4. Accept/reject decision by offer conditions. Red bars represent decisions where TTBO and mortality slope were both displayed vs. no predictive analytics displayed. KDPI, Kidney donor profile index; TTBO, time-to-better offer.

interesting that prospect theory provides an even greater contribution to decision confidence than predictive analytics alone. When medical decisions can be affected by the way in which data are presented, this may suggest that other biases exist.[17,24-26] Might a drive toward more evidence-based decision-making reduce human bias and improve health outcomes? This study suggests that it is important to not only ask decision-makers what data they require, but also to test how the data are presented, to evaluate not only which data to present, but also how it should be presented using a systematic and objective approach.

Distilling numerous data elements into predictions tailored to address the most relevant clinical questions at the time of offer—should this particular organ be accepted for this particular patient, or is it in the patient's best interest to wait for another, better offer?—has the potential to take some of the guesswork out of what is arguably the most challenging decision-making context in all medicine.[1] The development of new, data-informed predictive analytics and the robust behavioral testing of such interventions prior to implementation have the potential to improve outcomes for patients on organ transplant waiting lists, increase organ utilization, and improve equity by reducing variation in transplant center decision making.[17]

Funding

This work was funded by the US Department of Health and Human Services, the Health Resources and Services Administration, the Health Systems Bureau, and the Division of Transplantation under contract number HHSH250201900001C and was conducted under the auspices of the United Network for Organ Sharing (UNOS), the contractor for the Organ Procurement and Transplantation Network (OPTN). The interpretation and reporting of these data are the responsibility of the author(s) and in no way should be seen as an official policy or interpretation by the OPTN or the US Government.

Disclosure

The authors of this manuscript have conflicts of interest to disclose as described by the American Journal of Transplantation. S. Mohan reported grant funding from the NIH and Angion Biomedica and personal fees from Kidney International Reports and HSAG. S. Mohan is also the vice chair of the UNOS data advisory committee and

the national faculty chair of the ESRD Treatment Choices Learning Collaborative.

Data Availability

Potential Transplant Recipient (PTR) data are available on request from the OPTN.

ORCiD

Ian McCulloh https://orcid.org/0000-0003-2916-3914
Darren Stewart https://orcid.org/0000-0002-6764-4842
Ferben Yazicioglu https://orcid.org/0000-0002-4040-5120
Christopher Zinner https://orcid.org/0000-0001-8005-5455
Sumit Mohan https://orcid.org/0000-0002-5305-9685
Laura Cartwright https://orcid.org/0000-0003-2370-1494

References

1. Schnier KE, Cox JC, McIntyre C, Ruhil R, Sadiraj V, Turgeon N. Transplantation at the nexus of behavioral economics and health care delivery. *Am J Transplant*. 2013; 13(1):31–35. https://doi.org/10.1111/j.1600-6143.2012.04343.x.
2. Debout A, Foucher Y, Trebern-Launay K, et al. Each additional hour of cold ischemia time significantly increases the risk of graft failure and mortality following renal transplantation. *Kidney Int*. 2015;87(2):343–349. https://doi.org/10.1038/ki.2014.304.
3. Li MT, King KL, Husain SA, Schold JD, Mohan S. Deceased donor kidneys utilization and discard rates during COVID-19 pandemic in the United States. *Kidney Int Rep*. 2021;6(9):2463–2467. https://doi.org/10.1016/j.ekir.2021.06.002.
4. Brennan C, Husain SA, King KL, et al. A donor utilization index to assess the utilization and discard of deceased donor kidneys perceived as high risk. *Clin J Am Soc Nephrol*. 2019;14(11):1634–1641. https://doi.org/10.2215/CJN.02770319.
5. Carpenter DJ, Chiles MC, Verna EC, et al. Deceased brain dead donor liver transplantation and utilization in the United States: nighttime and weekend effects. *Transplantation*. 2019;103(7):1392–1404. https://doi.org/10.1097/TP.0000000000002533.
6. Mohan S, Foley K, Chiles MC, et al. The weekend effect alters the procurement and discard rates of deceased donor kidneys in the United States. *Kidney Int*. 2016;90(1): 157–163. https://doi.org/10.1016/j.kint.2016.03.007.
7. Heilman RL, Green EP, Reddy KS, Moss A, Kaplan B. Potential impact of risk and loss aversion on the process of accepting kidneys for transplantation. *Transplantation*. 2017;101(7):1514–1517. https://doi.org/10.1097/TP.0000000000001715.
8. Husain SA, King KL, Pastan S, et al. Association between declined offers of deceased donor kidney allograft and outcomes in kidney transplant candidates. *JAMA Netw Open*. 2019;2(8), e1910312. https://doi.org/10.1001/jamanetworkopen.2019.10312, 2.
9. Ibrahim M, Vece G, Mehew J, et al. An international comparison of deceased donor kidney utilization: what can the United States and the United Kingdom learn from each other? *Am J Transplant*. 2020;20(5):1309–1322. https://doi.org/10.1111/ajt.15719.
10. Mohan S, Chiles MC, Patzer RE, et al. Factors leading to the discard of deceased donor kidneys in the United States. *Kidney Int*. 2018;94(1):187–198. https://doi.org/10.1016/j.kint.2018.02.016.
11. Mittal S, Adamusiak A, Horsfield C, et al. A re-evaluation of discarded deceased donor kidneys in the UK: are usable organs still being discarded? *Transplantation*. 2017;101(7):1698–1703. https://doi.org/10.1097/TP.0000000000001542.
12. Reese PP, Harhay MN, Abt PL, Levine MH, Halpern SD. New solutions to reduce discard of kidneys donated for transplantation. *J Am Soc Nephrol*. 2016;27(4): 973–980. https://doi.org/10.1681/ASN.2015010023.
13. Vinkers MT, Smits JM, Tieken IC, de Boer J, Ysebaert D, Rahmel AO. Kidney donation and transplantation in Eurotransplant 2006-2007: minimizing discard rates by using a rescue allocation policy. *Prog Transplant*. 2009;19(4):365–370. https://doi.org/10.1177/152692480901900414.
14. Massie AB, Zeger SL, Montgomery RA, Segev DL. The effects of DonorNet 2007 on kidney distribution equity and efficiency. *Am J Transplant*. 2009;9(7):1550–1557. https://doi.org/10.1111/j.1600-6143.2009.02670.x.
15. Kayler LK, Schold JD, Magliocca JF. Response: DonorNet and the potential effects on organ utilization. *Am J Transplant*. 2010;10(10):2376. https://doi.org/10.1111/j.1600-6143.2010.03197.x. author reply 2377.
16. Mohan S, Chiles MC. Achieving equity through reducing variability in accepting deceased donor kidney offers. *Clin J Am Soc Nephrol*. 2017;12(8):1212–1214. https://doi.org/10.2215/CJN.06220617.
17. Cohen JB, Shults J, Goldberg DS, Abt PL, Sawinski DL, Reese PP. Kidney allograft offers: predictors of turndown and the impact of late organ acceptance on allograft survival. *Am J Transplant*. 2018;18(2):391–401. https://doi.org/10.1111/ajt.14449.
18. Cooper M, Formica R, Friedewald J, et al. Report of National Kidney Foundation Consensus Conference to Decrease Kidney Discards. *Clin Transplant*. 2019;33(1), e13419. https://doi.org/10.1111/ctr.13419.
19. Stewart D, Shepard B, Rosendale J, et al. Can behavioral research improve transplant decision-making? A mock offer study on the role of biopsies. *Kidney360*. 2020;1(1): 36–37. https://doi.org/10.34067/KID.0000212019.
20. Tversky A, Kahneman D. The framing of decisions and the psychology of choice. *Science*. 1981;211(4481):453–458. https://doi.org/10.1126/science.7455683.
21. Fleiss JL. Measuring nominal scale agreement among many raters. *Psychol Bull*. 1971; 76(5):378–382. https://doi.org/10.1037/h0031619.
22. Bae S, Massie AB, Luo X, Anjum S, Desai NM, Segev DL. Changes in discard rate after the introduction of the Kidney Donor Profile Index (KDPI). *Am J Transplant*. 2016; 16(7):2202–2207. https://doi.org/10.1111/ajt.13769.
23. Montgomery DC. *Design and analysis of experiments*. John Wiley & Sons; 2017.
24. Husain SA, King KL, Mohan S. Left-digit bias and deceased donor kidney utilization. *Clin Transplant*. 2021;35(6), e14284. https://doi.org/10.1111/ctr.14284.
25. Stewart DE, Garcia VC, Aeder MI, Klassen DK. New insights into the alleged kidney donor profile index labeling effect on kidney utilization. *Am J Transplant*. 2017; 17(10):2696–2704. https://doi.org/10.1111/ajt.14379.
26. Bowring MG, Holscher CM, Zhou S, et al. Turn down for what? Patient outcomes associated with declining increased infectious risk kidneys. *Am J Transplant*. 2018; 18(3):617–624. https://doi.org/10.1111/ajt.14577.