CONCLUSION: ICT is associated with stabilization of eGFR, thereby reducing need for future kidney transplantation and improving long-term survival.

Socioeconomic Factors Impacting Organ

Transplantation on the National Level



Wali Rashad Johnson, MD, Seth J Karp, MD, FACS Vanderbilt University Medical Center, Nashville, TN

INTRODUCTION: Transplantation revolutionized treatment for organ failure. However, access to transplantation is difficult for patients due to factors including sex, ethnicity, location, income, and insurance coverage. In this study, we aim to identify how socioeconomic factors impact waitlist access to identify areas for policy improvement at the local, state, and national levels.

METHODS: 2017 national waitlisted kidney and liver characteristics were identified with United Network for Organ Sharing (UNOS), the Scientific Registry of Transplant Recipients (SRTR), US Census, and County Health Rankings & Roadmap reports. Patients were grouped by state of residence. Waitlist additions were converted into proportions based on state population and correlated with state-based socio-economic variables using simple and multiple linear regression. Lowess regression was performed to validate linear regression models.

RESULTS: By state, significant correlations were found between waitlist additions and minority population (p<0.0001, kidney), available transplant centers (p=0.004, kidney; p=0.009, lung), household median income (p = 0.05, kidney; p = 0.041, liver), and private insurance coverage (p = 0.05, kidney; p = 0.004, liver). The coefficients for kidney and liver remained significant after multiple linear regression, with reliable lowess regressions.

CONCLUSION: States with significant minority populations, fewer available transplant centers, less private insurance, and low median household income waitlist fewer patients for various types of transplants. Future studies will attempt to identify how socioeconomic status affects other transplant milestones and areas in which policy can increase access in states where access to health care is limited.

Successful Long-Term Outcomes in HIV-Infected Transplant Recipients: Overcoming Hepatitis C



Arya Zarinsefat, MD, Arushi Gulati, BS, Ryutaro Hirose, MD, FACS, Nancy L Ascher, MD, PhD, Mehdi Tavakol, MD, Rodney Rogers, BA, Peter G Stock, MD, FACS University of California, San Francisco, San Francisco, CA

INTRODUCTION: Initial trials looking at the efficacy of kidney (KT) and liver transplantation (LT) in HIV-infected patients showed early graft and patient survival outcomes comparable to those in noninfected patients, except for patients with HCV co-infection. We hypothesized comparable long-term outcomes in the post-HCV direct acting agent (DAA) era.

METHODS: We performed a single-center review of consecutive HIV-infected patients who underwent KT (N=122) and/or LT

(N=85) from 2000-2019. We analyzed acute rejection (AR), graft loss, death, and surgical complications, using Kaplan-Meier and Cox proportional-hazards regression. Survival analyses used our HIV-noninfected cohort from the same period (KT, N=7,818; LT, N=3,265), with log-rank test for comparison. Surgical complications were compared to our center's ACS NSQIP transplant data for HIV-noninfected patients. AR incidence was compared to Scientific Registry of Transplant Recipients (SRTR) national data for all transplant centers.

RESULTS: Surgical complications were comparable to HIVnoninfected patients, but with higher rates of KT wound infections (5.7% vs 1.0%) and biliary complications (27.1% vs 16%). Oneyear incidence of AR in KT (25.6%) and LT (27.8%) were nearly 3 times higher than in HIV-noninfected recipients. In HIVinfected KT, AR increased the risk of graft loss (hazard ratio [HR] 29.6, p=0.001), although overall KT graft survival was comparable to HIV-noninfected recipients (p=0.81). For both KT and LT, the post-DAA era resulted in improved survival in HIV/HCV co-infection (Figure).



CONCLUSION: Despite higher rejection rates, KT graft survival is comparable to HIV-noninfected patients. The negative impact of HCV co-infection on transplant patient survival has been abrogated by anti-HCV DAA. Transplantation of HIV-infected recipients is an appropriate use of medical resources.

Using Artificial Intelligence to Improve Post-Transplant Survival Predictions Rowland W Pettit, BS, Stuart Corr, PhD, Jim Havelka, MBA, Abbas A Rana, MD, FACS Baylor College of Medicine, Houston, TX InformAI, Houston, TX

INTRODUCTION: Modeling is essential for regulatory oversight and risk stratification in clinical practice. Our hypothesis was that machine learning models would prove superior to currently accepted linear models (AUC \sim 0.70) in predicting mortality after liver transplantation.

METHODS: We created 4 machine learning predictive models, a Random Forest (RF), an AdaBoost (AB) ensemble-based model, a Naïve Bayes (NB) model, and a logistic regression (LR) model. We selected all 109,742 adult patients from the UNOS database who underwent 1 recorded orthotopic liver transplantation. All transplantation parameters that would be known at the time of transplant discharge were included, totaling 324 features. We performed 10-fold cross-validation. This involved random sampling, dividing our data into training (66%) and test (34%) sets 10 times. Each iteration, we trained our models on the training data and tested the predictive power of these models on their respective test set. We measured the average 10-fold cross-validated model performance with classification accuracy (CA), and area under the receiver operator curve (AUC) metrics.

RESULTS: For mortality predictions, the RF and AdaBoost models proved superior to LR and NB methods. For the prediction of 1-month post-transplantation survival, the RF model had a classification accuracy (CA) of 0.950 and an AUC of 0.830, while the AB achieved a 0.949 and 0.773, the NB 0.741 and 0.708, and the LR marked 0.943 and 0.654, respectively.

CONCLUSION: Machine learning methods produce accurate and precise models for post-transplantation survival. We should consider incorporating machine learning methods into the construction of our transplant outcome models.