

# Statistical Methods in Organ Failure and Transplantation

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The special issue contains ten stimulating articles which feature the development of novel statistical methodology applied to important issues in organ failure and transplantation. Several of the articles feature survival analysis, which has a long history in the organ failure setting, dating back to (at least) the seminal analysis of the Stanford heart transplant data by Crowley and Hu [1]. Fields such as end-stage renal disease (ESRD) and end-stage liver disease (ESLD) are among the many areas of medicine which have been particularly receptive to (and, as a result, heavily influenced by) innovative statistical techniques.

This issue spans several domains with respect to statistical methodology and areas of application, including instrumental variables, competing risks, recurrent events, gap times, landmark analysis, dynamic prediction of outcomes, joint modeling of longitudinal and time-to-event data, and variable selection. Methodologists and practitioners whose area of application is outside the organ failure setting will find plenty of stimulating material in this issue.

Lehmann et al. [2] propose a weighting approach for instrumental variable (IV) analysis, designed to make the IV more robust to the critical assumption of random assignment. Using data obtained from the United States Renal Data System (USRDS), the proposed methods are used to compare mortality on hemodialysis versus peritoneal dialysis, a long-standing yet unresolved issue in ESRD treatment. The increasingly important topic of kidney paired donation (KPD) is studied by Wang et al. [3], who develop a novel multiple-look-ahead decision strategy to select transplant chains.

Huang et al. [4] consider recurrent event data and, in particular, the setting where each recurrent event is subject to competing risks. Subdistribution hazard regres-

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sion methods are proposed and applied to analyze shunt thrombosis events among Taiwanese dialysis patients. Competing risks are also considered by Yang et al. [5] who jointly model repeated measures and competing failure events. The methods are applied to the Chronic Renal Insufficiency Cohort (CRIC) study to determine risk factors for progression from chronic kidney disease (CKD) to ESRD.

A general framework for landmark analysis is developed by Li et al. [6]. The methods are used to dynamically project ESRD and death among CKD patients. Putter and van Houwelingen [7] establish connections between landmark analysis and time-dependent Cox regression, both theoretically and empirically.

Penalized variable selection techniques are proposed for the competing risks setting in the article by Fu et al. [8]. The methods are applied to data clustered by center and are used to determine risk factors for adverse post-transplant outcomes. We return to variable selection in the article by Zhou et al. [9]. The authors apply a LASSO machine learning algorithm in the context of Cox regression, with the goal being to identify proteins associated with graft failure among kidney transplant patients.

Nguyen and Gillen [10] propose a survival-tree approach to identify group-specific censoring patterns in order to estimate the average hazard ratio under a misspecified proportional hazards model. The methods are motivated by estimating the effect of vascular access type with respect to time until access revision among hemodialysis patients. Methods for comparing gap times are proposed by Shu and Schaubel [11]. The authors develop techniques for estimating the gap time hazard ratio, with the application being to compare primary versus repeat liver transplant survival.

I would like to thank the authors of the exciting articles appearing in this issue for their interesting and important contributions. On behalf of the authors, I thank Mei-Cheng Wang, Co-Editor-in-Chief of Statistics in Biosciences, for her encouragement to assemble a special issue dedicated to transplantation. I also wish to thank Mei-Cheng for giving me the opportunity and honor to serve as Guest Editor for this issue.

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