Medication Adherence and Cost Exposure: A Story in Heterogeneity

Abstract

A gap exists in understanding how causes of medication non-adherence differ across sub-groups of patients, in particular which patients' adherence is most sensitive to cost-exposure. In our study, we use statistical machine learning methods to propose patient groups whose non-adherence we predict will be strongly impacted by changes in cost-exposure, a data-driven strategy to generate hypotheses about heterogeneous treatment effects prior to running an experiment. This is in contrast to the large body of work done in the domain of heterogeneous treatment effects, either based only on observational data using strong assumptions or where heterogeneity is observed following an experiment, which then needs to be tested further. We use 2013 claims data for a sample of patients suffering from four chronic conditions (diabetes, asthma, hypertension, and coronary heart disease), and use agglomerative hierarchical cluster analysis, based on patients' clinical and demographic features, to identify patient clusters. We test for heterogeneous associations of cost-exposure - the amount that patients incur out-of-pocket for medications - with adherence across the clusters. We compare this approach with an alternative model-based recursive partitioning method for directly identifying clusters with distinctive cost and adherence relationships, and evaluate the most relevant partitioning features and their clinical implications. We validate and compare the two approaches by running them on 'test' patients from 2012 claims data. We also compare our machine learning approaches to traditional econometric patient matching strategies. Our study serves to demonstrate how machine learning tools can be applied to identifying potentially 'high-impact' patient sub-groups, which can be oversampled for inclusion in future experiments to test this a priori heterogeneity hypothesis