Cost-effective personalised treatment recommendations: An example in depression treatments

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Objective: To develop a generalised method of identifying personalised cost-effective interventions based on clinical and demographic characteristics and test it on recent depression studies.

Methods: A dataset including individual-patient data pooled from three randomised controlled-trials comparing internet-based treatment (IBT) and usual care (UC) for depression was used. Costs and QALYs were measured at 1-year. Statistical approaches (linear regression, generalised additive models, support vector machine, lasso regression, random forest, and neural networks) were used to predict costs and QALYs for all patients, separately for IBT and UC. We calculated the net-monetary benefit (NMB) for patients based on their predicted costs and QALYs for each treatment. When NMB was positive, IBT was recommended, otherwise UC was. We compared the observed mean costs and QALYs for all patients with the predicted mean costs and QALYs after assigning the recommended treatment.

Results: The IBT group included 443 and the UC group 449 patients. The observed mean QALYs at 1 year were the same between the two groups (0.74), whereas the mean costs for the IBT group were €8,230 (SD= 9,244) and for the UC group €8,079 (SD= 8,541). Random forest performed better than the other techniques based on two error measures (RMSE and MAE). For 24% of the total cohort of

patients both the recommended and observed treatments were IBT, and for 26% they were both UC. For the rest of the patients (50%), the recommended treatment was different from the observed. In comparison with the observed mean costs and QALYs, assigning interventions based on predicted treatment led to an 8.8% reduction of mean costs and a 2.4% increase in mean QALYs. Predicted QALYs at 12 months were 0.76 for both IBT and UC (SD= 0.09 and 0.06 respectively), and predicted costs €6,897 (SD= 2,502) for the IBT group and €7,934 (SD= 2,559) for UC.

Discussion: We showed that it is feasible to identify cost-effective personalised treatments based on patients' clinical and demographic characteristics, which can form the basis of treatment recommendations. Simulating the provision of personalised recommendations based on patient-level cost-effective treatments resulted in reduced mean costs and increased mean QALYs compared to mean costs and QALYs derived from the observed allocation.