Mapping three commonly used heart disease-related quality of life instruments to MacNew 7D

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BACKGROUND

Cost-utility analysis, one of the accepted methods for economic evaluation, relies on quality-adjusted life years (QALYs) as a measure of outcome. It allows comparisons across diseases and interventions by capturing the quality and quantity of life changes. The utility measures the quality component of QALY. Utility represents the preference of the general population for a given health state. The multi-attribute utility instruments (MAUI) classification systems are used to define these health states. MacNew 7D is a cardiac-specific MAUI. Mapping algorithms can convert scores from a non-preference-based instrument to health utilities of an MAUI.

The objective of this study was to develop mapping algorithms that will enable Kansas City Cardiomyopathy (KCCQ), Seattle Angina (SAQ)and Minnesota Living with Heart Failure (MLHFQ) questionnaire scores to be converted into MacNew 7D utility scores that can be used in cost-utility studies.

Methods

Patients with heart disease were recruited from Australia. Two model specifications were considered to predict the MacNew 7D utility score using the three instruments' total scores (Model 1) and domain scores (Model 2). Four regression techniques (i.e. Gamma GLM, Bayesian GLM, Linear regression and Random forest), each of which can cope with either skewness, heteroscedasticity and ceiling effects were used to identify the optimal mapping functions for each of the two models. In the absence of an external validation dataset, the predictive performance was assessed using three-fold cross-validation. The Goodness of fit of the models was assessed using root mean square (RMSD), R-squared value, and mean absolute error (MAE). Greater preference was put on MAE performance as it is less sensitive to outliers and easy to interpret.

RESULTS

493 participants participated in the study and were divided into two samples. Sample one included patients diagnosed with heart failure (n=180), and sample two included patients diagnosed with angina (n=313). Sample one completed the KCCQ & MLHFQ, and sample two completed the SAQ. The mean age of the study participants for sample one was 60.8 (SD 14.2), and more than half (68%) were males. The mean MacNew 7D utility was 0.726 (SD 0.196), and the median was 0.720 (IQR 0.622 – 0.899).

The lowest mean absolute error (MAE) was from the Random Forest model in model one (prediction using total scores) of all three instruments. The lowest MAE of model two of MLHFQ and SAQ were from Bayesian GLM and Linear regression, respectively (Table 1).

Table 1: Goodness of results from three-fold cross-validation

Prediction using item scores							
Instrument	Method	Mean utility	Min utility	Max utility	RMSD	R-squared	MAE
KCC (n=180)	Observed	0.7264	0.0159	1.0000			
	Gamma GLM (link = identity)	0.7408	0.0179	1.0491	0.1498	0.5237	0.1148
	Bayesian GLM	0.7264	0.2720	0.9509	0.1323	0.5573	0.0991
	Linear regression	0.7264	0.2625	0.9569	0.1459	0.4798	0.1091
	Random forest	0.7274	0.1956	0.9800	0.1272	0.5961	**0.0929**
MLHFQ (n=180)	Observed	0.7264	0.0159	1.0000			
	Gamma GLM (link = identity)	0.7378	0.0184	1.0657	0.1299	0.6082	0.0990
	Bayesian GLM	0.7264	0.2741	0.9256	0.1090	0.7001	0.0861
	Linear regression	0.7264	0.2512	0.9513	0.1414	0.5480	0.1058
	Random forest	0.7265	0.2931	0.9334	0.1144	0.6686	**0.0818**
SAQ (n=317)	Observed	0.7351	0.1373	1.0000			
	Gamma GLM (link = identity)	0.7353	0.1869	0.9681	0.1455	0.4924	0.1108
	Bayesian GLM	0.7351	0.2599	0.9710	0.1435	0.4993	0.1080
	Linear regression	0.7351	0.3425	1.0131	0.1610	0.4130	0.1163
	Random forest	0.7357	0.3524	0.9431	0.1346	0.5617	**0.0993**

Prediction using domain scores							
Instrument	Method	Mean utility	Min utility	Max utility	RMSD	R-squared	MAE
KCC (n=180)	Observed	0.7314	0.0159	1.0000			
	Gamma GLM (link = identity)	0.7364	0.1895	1.0567	0.1538	0.5192	0.1168
	Bayesian GLM	0.7314	0.2468	0.9522	0.1245	0.6003	0.0955
	Linear regression	0.7314	0.2757	0.9673	0.1373	0.5298	0.1024
	Random forest	0.7317	0.2523	0.9498	0.1275	0.5799	**0.0939**
MLHFQ (n=180)	Observed	0.7264	0.0159	1.0000			
	Gamma GLM (link = identity)	NA	NA	NA	NA	NA	NA
	Bayesian GLM	0.7264	0.2702	0.9393	0.1097	0.6928	**0.0828**
	Linear regression	0.7264	0.2702	0.9393	0.1137	0.6675	0.0855
	Random forest	0.7269	0.2490	0.9440	0.1149	0.6691	0.0834
SAQ (n=317)	Observed	0.7355	0.1373	1.0000			
	Gamma GLM (link = identity)	0.7351	0.3467	0.9380	0.1379	0.5391	0.1012
	Bayesian GLM	0.7355	0.3299	0.9431	0.1403	0.5199	0.1024
	Linear regression	0.7355	0.3970	0.9677	0.1377	0.5396	**0.0995**
	Random forest	0.7354	0.3598	0.9450	0.1397	0.5278	0.1027

RMSD-Root mean square; MAE-Mean absolute error; GLM-Generalised Linear Model; KCCQ-Kansas City Cardiomyopathy; SAQ-Seattle Angina; MLHFQ-Minnesota Living with Heart Failure

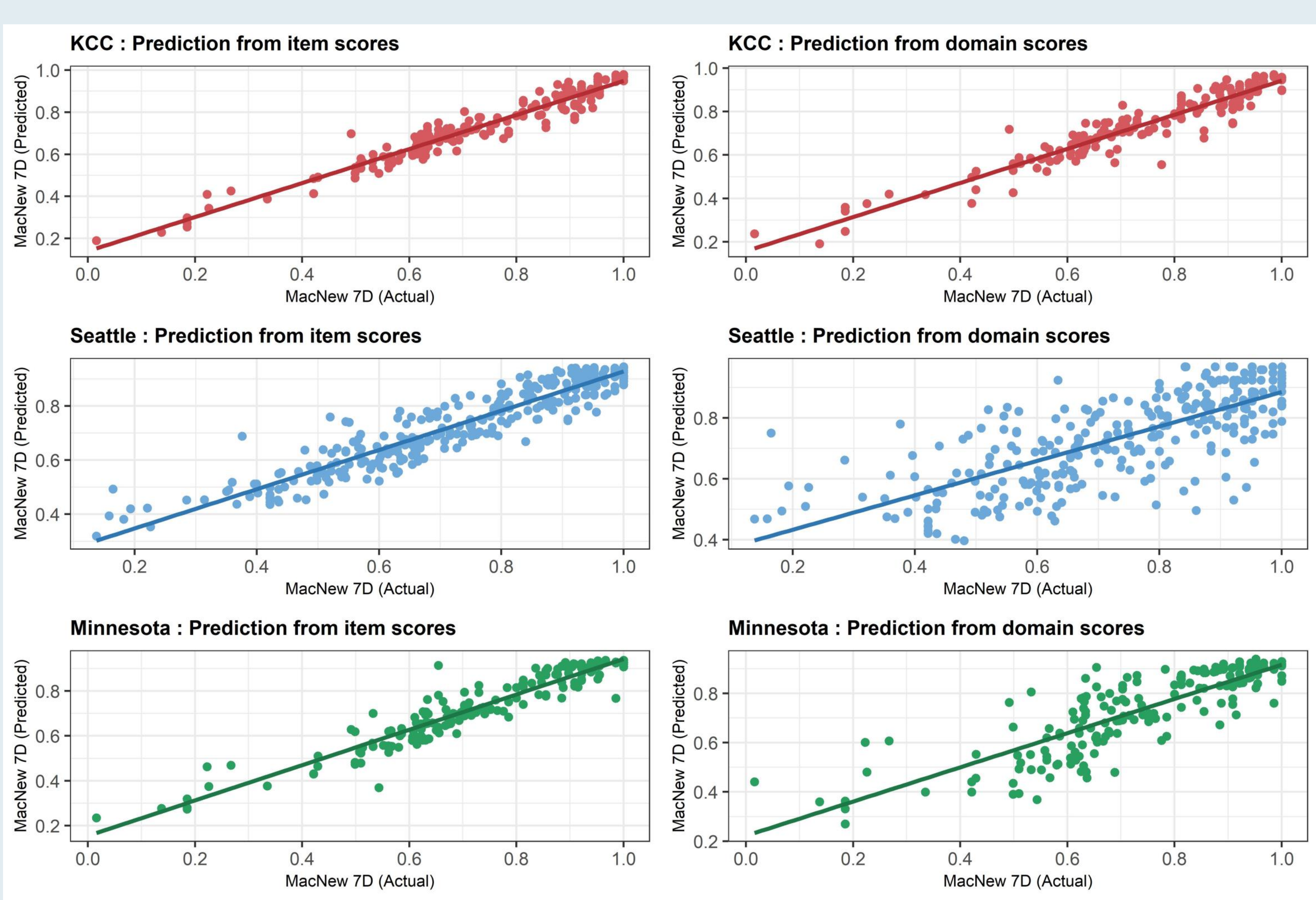

Figure 1: Scatter plot of observed versus predicted Mac New 7D. Line of equality between observed and predicted values (solid line)

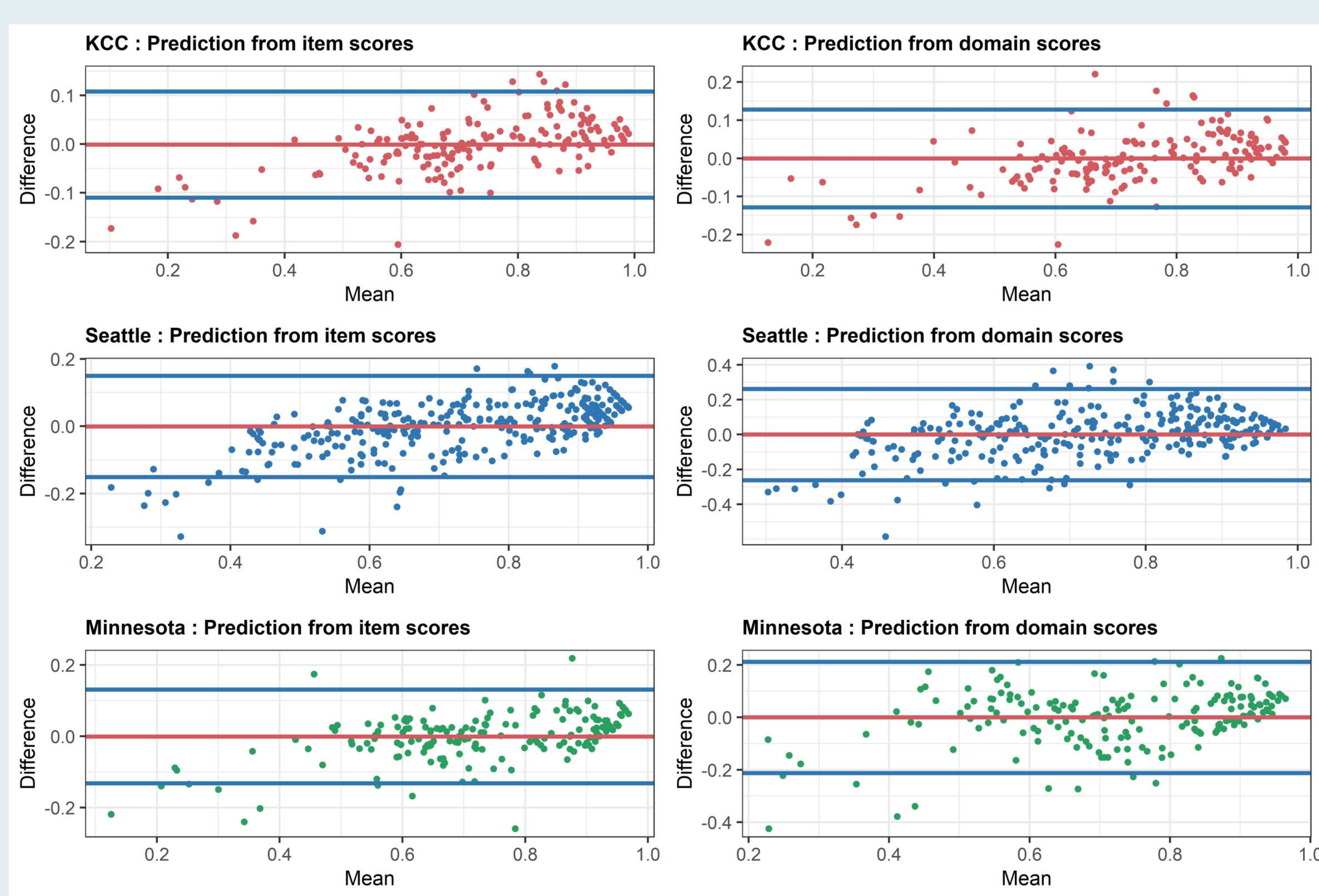

Figure 2: Bland and Altman plot of differences between the actual and the predicted Mac Ned 7D utility scores

Both figures 1 and 2 indicate that there is good agreement between the actual and the predicted MacNew 7D utility scores.

CONCLUSION

KCCQ, SAQ and MLHFQ can be mapped onto MacNew 7D utilities with good predictive accuracy. The reported mapping algorithms would facilitate the calculation of health utility for economic evaluations related to heart disease.

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