Review of methods for mapping between measures of health related quality of life onto generic preference-based measures: a road to nowhere?

John Brazier*, Yaling Yang, Aki Tsuchiya
School of Health and Related Research, University of Sheffield

* Corresponding author John Brazier <J.E.Brazier@sheffield.ac.uk>

INTRODUCTION

A common approach to assessing the outcomes of health care is to obtain patient reported descriptions of health status across various dimensions and then to apply a standardised numerical scoring system. There are many different measures of health, including several hundred condition specific measures of health designed for use in specific medical conditions or groups of condition (Spilker et al, 1990). There are also generic measures designed to cover the core dimensions of health that are relevant across all medical conditions. Health measures are distinguished in terms of whether they generate a profile of dimension scores or a single index and if they produce a single index, whether or not the index has been derived using simple summation of item scores or by using preference weights obtained from patients or the general public. These patient reported measures of health can be administered by self-completion, proxy completion or by interview.

There are many different potential uses of these types of measures of health. One has been in clinical trials as a primary or secondary outcome measure. For this purpose condition specific measures are typically applied since trials are limited to making comparisons within a patient group. Preference-based measures of health are necessary to generate the health state utility values required to calculate QALYs for assessing the cost effectiveness of interventions. These are usually based on generic instruments that permit comparisons between patient groups (e.g. EQ-5D), though there are examples of condition specific preference-based measures (Revicki et al 1998). Even for assessing clinical effectiveness, it could be argued that a preference-based index is necessary to deal with trade-offs made between outcomes. A further use is to compare performance, such as between acute hospitals or clinicians and has been less common to date.

There is little agreement on which specific instruments should be used for these purposes. For assessing clinical efficacy, there is disagreement on whether to use a generic or condition specific measure, and between condition specific measures there is often disagreement amongst clinical researchers on the most appropriate instrument. As a result clinical trials around the world often use different measures for the same patient groups. This presents a substantial barrier to the synthesis of evidence. Similarly, there has been

a lively debate amongst health economists about the most appropriate preference-based generic measure to use in cost effectiveness analyses. Whilst the EQ-5D is the most widely applied in recent years, the HUI3, QWB, SF-6D and others continue to be used. However, different preference-based measures have been shown to generate different values on the same sample of patients (Marra et al, 2005; Feeny et al, 2004; Barton et al, 2004). Furthermore, many key clinical trials on the efficacy of new interventions do not have a generic measure. This presents a barrier to populating economic models with the best evidence on effectiveness. A comparison of hospital performance would also be severely inhibited by the use of different measures both within and across specialities, medical conditions or age groups. If policy makers want to compare performance, then it seems necessary to get clinicians to agree to use the same preference-based instrument and this seems unlikely in the near future.

One solution to the problem of having different measures of health has been to try to map between measures using judgement or statistical inference. Mapping between measures enables researchers to predict the value of one measure from another. This paper presents a review of methods of mapping between measures of health and includes a systematic review of the examples of empirical mapping studies. The aim is to address the following questions:

1) Whether mapping between condition specific and generic measures is a viable approach.
2) If it is a viable approach, the circumstances in which mapping can be used.
3) How it should be done.
4) How mappings should be reported.

The next section describes the different approaches to mapping and the way empirical mappings have been specified, estimated and their performance assessed. This is followed by a systematic review of empirical mapping studies. The final section is a discussion that addresses the above questions and avenues for further research.

BACKGOUND

There are two approaches to mapping. One uses judgement to undertake the mapping (e.g. using panels of experts) and the other is done empirically using a data set with the two measures administered on the same patients.

Mapping using judgement

In this approach components of a non-preference based measure of health or quality of life would be assigned by judgement to specific domains and levels of a generic preference-based measure (such as the EQ-5D) (e.g. Coast, 1992). For a valid translation process to be possible, the non-preference based measure must include the dimensions of the preference-based measure (though it may have more) and to have items which readily equate to the dimension levels of it. The process can be based on the judgements of professionals or researchers. It can involve the development of an explicit set of decision rules or simply be an aggregation of expert opinion (Bryan and Longworth, 2005).

This mapping can be undertaken by dimension or by item. By dimension, a score range would be judged to be equivalent to a given level on a given domain of EQ-5D. For instance, scores in the range 30 to 50 on the SF-36 pain dimension might be mapped to level 2 on the pain dimension of EQ-5D, or levels 4 and 5 of the SF-6D pain dimension might be mapped onto EQ-5D pain/discomfort level 3. Mapping by dimension scores assumes that the items within a given dimension carry equal weight.

The main criticism for this approach is its arbitrariness. Furthermore, it does not involve any attempt to estimate the uncertainty around the mapping. The validity of the mappings are questionable and the only way to test the validity of the mappings is by empirically comparing the judgements against real data to see whether or not patients who score between 30 to 50 on the pain dimension of the SF-36 report themselves as being on level 2 for pain in EQ-5D (Brazier et al, 2007). Ultimately a much better approach is to estimate the relationship between the measures empirically by statistical inference.

Empirical mapping

The approach of empirically mapping a health measure onto a (usually) generic preference-based measure is also known as 'cross walking' or estimating exchange rates between instruments. It requires the two measures to be administered on the same population. The population should cover the range of clinical and demographic characteristics of the sample on whom the mapping function is ultimately going to be applied. Having obtained the data there are a number of choices regarding the possible specification, the statistical technique for estimating the mapping function and how performance should be assessed. These are now discussed in turn.

Specification

The different possible specifications for the mapping function are presented in order of increasing sophistication in Table 1 (adapted from Tsuchiya et al, 2002). The simplest additive model (1) is to regress the target measure (such as the EQ-5D) onto the total score of the starting measure (e.g. SF-36, HAQ, HAD etc.). This is the most limiting specification, since it makes the following assumptions: the dimensions of the starting measure are equally important (since they are typically scored the same way, say out of 100); all items carry equal weight; and response choices to each item lie on an interval scale (so for example the intervals between 'all of the time', 'most of the time', 'some of the time', 'a little of the time' and 'none of the time' are equal). It is possible to relax these assumptions by modelling the following as independent variables: dimension scores (model 2), item scores (model 3) or item responses (model 4). Dimension and item scores are treated as continuous variables and item responses are modelled as discrete dummy variables (e.g. 'all the time' is one, other wise zero, and so forth). A more sophisticated approach to modelling the relationship between measures is to regress separate models for each dimension of the target instrument (such as the 5 EQ-5D dimensions) (i.e. models 5 and 6). For the EQ-5D this creates a dependent variable that can be treated as continuous (model 5), but is more accurately treated as a discrete variable (model 6) (e.g. Tsuchiya *et al*, 2002; Gray *et al*, 2006). The dimension level models can be estimated from any of the previous 4 specifications.

Using item scores categorically can result in a large number of independent variables (over 100 for SF-36) and so some researchers have been selective in the items included in the model. Items are often excluded for having coefficients that are non-significant or counter-intuitive in their sign prior to estimating a model with item responses (model 4).

The assumptions of a simple additive model can be further relaxed by including squared terms for dimension or item scores and interaction terms. Again these can generate a large number of variables and so researchers may also limit them to variables with significant main effects, at least for the item level models. The progression from model (1) to (4) may be expected to result in an improvement to the fit of a simple additive model. The introduction of squared and interaction terms dispels any prior expectation regarding the sign of the regression coefficients.

Given the aim is to be able to predict one measure from another, any means of improving the prediction should be considered. One method for doing this would be to include additional variables, such as other measures of health. Two (or more) measures may be better than one in situations where a condition specific measure only covers some of the dimensions of the generic measure. It may also be worth considering adding clinical indicators where these predict the dependent variable and likewise demographic variables (Brazier et al, 2004).

Estimation and model performance

Most mapping functions have been estimated by OLS, though some researchers have explored Generalised Linear Models with random effects, Adjusted Least Square Regression Model (ALS), Tobit Model, Censored Least Absolute Deviation Model (CLAD) and non-linear models. For models with a discrete dependent variable (e.g. EQ-5D dimension level) then researchers have used Ordinal Logit and Multi-nomial Logit regression models. These latter models generate a probability distribution across dimension levels and there is a subsequent stage of imputing a single level for calculating a single index value for the respondent. One way for doing this has been to choose the highest probability level (Tsuchiya et al, 2002). In a recent study, researchers used a Monte Carlo procedure to select from the distribution (Gray et al, 2006).

The performance of models can be assessed in a number of ways in the literature. It is common to report explanatory power in terms of adjusted R-Squared, but this has limited value for comparing models estimated using different methods of estimation. Models have also been assessed in terms of the sign, significance and consistency of the estimated coefficients. With higher values indicating preferred health states, coefficients should be negative and the more severe the health problem the larger the negative coefficient. However, for some descriptive systems there might be some ambiguity regarding the ordering of statements (e.g. between ‘your health limits you a little in bathing and dressing’ versus ‘your health limits you a lot in moderate activities’ in the SF-6D). Furthermore, interaction terms would interfere with these orderings.

Ultimately the purpose of modelling these data is to predict values in other data sets. One way to evaluate models has been to examine the difference between predicted and

observed values at either the aggregate level by calculating Mean Error (ME); or the individual level by calculating the Mean Absolute Error (MAE) or the Root Mean Squared Error (RMSE). Models can also be compared in terms of the numbers or the proportion of absolute errors greater than some cut-off (e.g. 0.05 or 0.10) or within 5% or 10% of the observed value at the individual level. A key concern is the appropriate level for estimating these statistics, since these mapping functions are not usually being undertaken to make predictions at the individual or across entire groups of patients. Usually, the aim is to predict differences in values across sub-groups of patients, such as between arm of a trial or over time. This issue will be discussed further below.

Bias in predictions can be assessed using a *t*-test and the normality of prediction errors by the Jarque-Bera test, but this is little used in assessing OLS models since these are unbiased by definition. What is potentially more important is the pattern of errors across the range of the dependent variable. It is therefore important to estimate mean error by severity of health problem or to examine the plots of observed against predicted values in the dependent variable.

Model performance is often assessed on the same data set as used to estimate the model and referred to in the literature as within-sample testing. Another strategy is to estimate the model on a sub-sample of the full data (the 'estimation' sample) and then test the model on the remaining sample (the 'validation' sample). These strategies provide only limited information on how the model would perform with respect to the data set to which it is going to be applied. This requires an independent data set.

LITERATURE REVIEW

Search

A systematic literature search strategy has been carried out in four parts:

(1) Citation search

Based on a few core papers identified by the research group a citation search was carried out using the Science Citation Index, Social Science Citation Index and Web of Science citation database. The citation search was undertaken both forwards and backwards. The forward search ensures that all papers that cite the core papers are reviewed. The backwards search ensures that all papers cited by the core papers are reviewed.

(2) Key word search

A narrowly defined key words search was undertaken using titles and abstracts in 15 electronic bibliographic databases as shown below, covering biomedical and health-related sciences, social science, and the grey literature. Key words were combinations of: mapping/cross walking and EQ-5D/SF-36/HUI/QWB/NHP/SIP/health status/health profile/HUI.

The following data bases were searched: Cinahl, Cochrane Central Database of Controlled Trials (CENTRAL), Cochrane Database of Systematic Reviews (CDSR), DH-Data, Embase, Kings Fund, Medline, Medline Plus, NHS Database of Abstracts of Reviews of Effectiveness (DARE), NHS Economic Evaluations Database (NHS EED),

NHS Health Technology Assessment (HTA) Database, OHE Health Economic Evaluations Database (HEED), Science Citation Index, Scopus, Social Sciences Citation Index, HESG.

Where possible, the searches were not restricted by publication type, language, or date of publication.

(3) Experts contacted
The following experts were contacted regarding possible published and unpublished work that had not been found using electronic searching methods: Nick Bansback, Alan Brennan, Andy Briggs, Stirling Bryan, Martin Buxton, Simon Dixon, Richard Edlin, Denny Fryback, Alastair Gray, Carlo Marra, Jeff Richardson, and Katherine Stevens. We also contacted: the HUI group, QWB group and EuroQol Group; the six NICE TAG leaders and all members of the UK Health Economist's Study Group.

Review
The review aimed to address the following questions:

- What instruments have been used in existing mapping studies?
- What medical conditions/diseases are covered by existing mapping studies?
- What methods have been employed to undertake the mappings?
- How have the mapping functions been assessed in terms of statistical performance?

Specifically, data were extracted from each mapping study using the items list in Table 2. Data were extracted on 56 items covering: description of the study, model specification, model fit and predictive performance within and outside the estimation sample. In addition any important comments from the author(s) were noted. These data were extracted for each of the regression models estimated within a study.

Findings
Description of studies
One thousand two hundred and seventy nine papers were identified from strategies (1) and (20, while 32 papers from strategy (3). All papers were put into a Reference Manager database for further screening. The number of relevant papers was reduced to 227 based on the title and then to 34 based on the abstract. Among the 34 papers, three papers were excluded as only conference abstracts could be found even after contacting the authors. Another three papers were excluded because they were not based on empirical methods. This left a total of 28 papers for the review (See Table 3). These 28 papers covered 119 different estimation models. [A further 30-page Appendix tabulating the 119 estimation models is available on request from the corresponding author.]

Data extraction on all 28 papers was undertaken by a member of the research team and summarized in Excel using headings shown in table 2 that had been agreed by all team members. Details of the 28 studies are presented in Table 3.

Mapping between HRQoL measures is a new research area with most papers (26 out of 28) published or produced after 2000, with the remaining 2 papers published in 1997 and

1998. Out of the 28 papers, 20 have been published in scientific journals including: *Medical Decision Making* (6 papers), *Value in Health* (3 papers), *Health Economics* (2 papers), *Medical Care* (2 papers), *Quality of Life Research* (2 papers); and the others (5 papers) were published in specific clinical journals. Of the remaining eight, three are project reports and have not been published and five are unpublished manuscripts with 3 presented at the HESG conference and 2 as HEDS Discussion Paper (University of Sheffield).

Data sets

Twenty-seven out of the 28 studies involved the mapping of a non-preference based measure of health (the "starting measure") onto to a preference-based measure of health (the "target measure"); the exception being one study between two preference-based measures (SF-6D to EQ-5D). The most popular target measure used for mapping was the EQ-5D with 16 studies (15 used the UK MVH value set and one used the US value set), followed by HUI2/HUI3 with 6 studies, SF-6D with 5 studies, and QWB with one study. On the right hand side of the mapping equation, the most widely used starting measures were SF-12 (n=7) and SF-36 (n=5), and the remainder consisted of various condition specific HRQoL instruments covering asthma, overactive-bladder, obesity, cancer and heart disease. One study mapped clinical measures onto EQ-5D in angina patients.

The sample size (number of people giving responses) used in the mapping studies ranged from 98 to 23,547. Clinical trials were the most common source of data. Respondents were also recruited from populations in the community, hospital and primary care. Six studies used large panel survey data, such as the US Medical Expenditure Panel Survey data and the Health Survey for England data (and these studies all involved mapping from one of the non-preference based generic instruments).

Specifications

Most studies used the index generated by the preference-based target measure as the dependent variable and estimated models using OLS. Some explored Maximum Likelihood, Adjusted Least Square Regression Model (ALS), Tobit Model, Censored Least Absolute Deviation Model (CLAD) and non-linear models. Only four studies had dimension scores as the target measure and in all cases these were the 5 dimensions of the EQ-5D (Tsuchiya et al, 2002; Edlin et al, 2002, Gray et al, 2004; 2006).

Most studies used total, dimension and item scores as the independent variables and some entered dummy variables representing the level of each item. Out of the 119 models reviewed, 33 models included interaction terms, 19 models incorporated transformation of main effect such as square terms, six models included other health measures and 15 models included clinical measure; 34 models considered respondents' personal characteristics, such as age, gender, race and income. There was no agreement on how to assess improvements to the model by introducing these additional variables. Generally, judgements were made arbitrarily, based on R^2 improvement, prediction (i.e. MAE, RMSE), statistical significance of the additional coefficients and influence on main effects coefficients (e.g. where these became non-significant or inconsistent with the

inclusion of the additional variable then the latter was dropped). Quite modest or negligible improvement was achieved at the price of model complexity.

Performance
Overall, models mapping a generic onto a generic preference-based measure (e.g. SF-12/36 to EQ-5D, NHP to SF-6D, and SF-36 to QWB) achieve R^2 or adjusted R^2 of more than 0.5 within sample. There was little reduction in the goodness of fit from testing the mapping function on samples randomly selected from the same data set as the estimation samples. The fit of mapping functions from condition specific to generic measures is more variable. One of the poorest fitting models was from the Overactive Bladder Questionnaire (OABq) onto the SF-6D which achieved an adjusted R^2 of 0.17. One of the best models was between the International Weight Quality of Life Questionnaire (IWQoL) and the SF-6D that managed 0.51. Figure 1 shows the distribution of R^2 statistics for generic to generic measures and condition-specific to generic measures.

Mean error across the entire sample of each study for the 119 models reviewed ranged from 0.0007 to 0.042 and was nearly zero for the OLS models (as would be predicted). MAE at the individual level ranged from 0.0011 to 0.19 and RMSE ranged from 0.084 to 0.2. These typically represented a percentage error of up to 15% of the overall scale of the dependent variable.

A number of studies have noted that the degree of error is not evenly distributed across the scale of the dependent variable. This problem was shown using condition specific measures (Tsuchiya et al, 2002) and generic measures (Gray et al, 2006) as the start measures. Overall, the level of error is far greater at the lower end. Gray et al (2006), for example, found that the MAE varied from 0.065 to 0.109 for EQ-5D range 0.7 to 1.00, but for less than 0.7 the MAE was over 0.30. A few researches presented plots for their preferred models to demonstrate error between observed and predicted values and found that there was a tendency for EQ-5D models to over predict values at the lower end and under predict at the upper end of the EQ-5D. The papers also reveal something important about the prediction of the degree of error around the mean estimates. The predicted values from the mapping functions tend to have lower levels of variance than the original observed values.

DISCUSSION

All mapping studies to date have been onto preference-based measures, with a view to assist in estimating QALYs for use in economic evaluations conducted alongside trials or decision analytic models. This reflects a very pragmatic need for health state values for this purpose. This may limit its value for other purposes. Nonetheless there are important lessons to be drawn from the literature. This section addresses the questions presented earlier above.

Is mapping a viable approach and in what circumstances?

The question of whether mapping is a viable approach is difficult to gauge without having clear cut criteria for assessing adequate performance. One useful distinction is

between two situations. One is 'ex post' where the analyst has no other data, and the second situation is where a decision is being made 'ex ante'.

In the ex post situation of the analyst not having any other data, some of the poorer models might still be acceptable. This may happen in economic evaluations alongside clinical trials where a non-preference-based condition specific measure has been used or where an analyst is seeking to synthesise data across studies and does not want to limit the evidence base to those studies using a particular preference-based measure. The concern relates to the degree of error that is acceptable. At the individual level, the mean absolute error was often quite high and larger than published minimally important differences for these measures (Walters and Brazier, 2004). However, the purpose of mapping functions is to predict differences across groups of patients in a trial or synthesis of evidence and not at the individual level. What is important is the distribution of that error by severity and in those studies that have actually examined this, the findings seem to suggest that these models tend to over predict at the lower end and under predict at the upper end. While at the mean level this may not seem to matter, it could lead to important errors, such as in estimated differences over time, since those with severe problem will have the gain under estimated. This may have important implications for cost effectiveness.

Few studies examined external validity by assessing predictive performance in other data sets. This is important in order to gauge the likely importance of this error in practice. Furthermore, these tests need to be undertaken in studies that have used the two instruments and examine differences between arms and over time, to test whether there are any significant differences between predicted and observed in the estimates of gain (and ultimately cost effectiveness). This is currently being examined by Ara and Brazier (2007).

For ex ante, prospective decisions about the instruments to use in future studies or other planned applications (such as performance assessment between hospitals), similar questions need to be addressed. However, the decision maker needs an estimate of the error relevant to the population of interest (e.g. disease, severity and size of sample) to decide whether the error in these models is acceptable. The likely implications of any error in the estimation of differences or changes over time must be weighed against the additional cost of using the favoured generic preference-based measure directly in the study or application being considered.

For mapping from conditions specific measures the degree of error tended to be larger, though it varies across patient groups. However, the use of mapping to derive a preference-based generic value from condition specific measures raises a more fundamental concern. Mapping assumes that the preference-based target measure covers all important aspects of health of the non-preference-based start measure. In other words, the strength of the mapping function depends on the degree of overlap between the two descriptive systems. Where there are important dimensions of one instrument not covered by the other, then this may undermine the model. Where the generic measure does not cover certain dimensions of the non-preference based condition specific

measures that are regarded as important, then this could be a weakness. The same applies to the degree of health problem covered by the two instruments. Even the mapping of two generic measures provides examples of this problem. EQ-5D does not, for example, contain a dimension for energy or vitality. So it is not surprising that in published mapping functions from any of the SF instruments to EQ-5D, energy has a small and non-significant coefficient. Another source of weakness can arise from differences in the severity range covered for given health dimension. The SF-36 physical functioning dimension, for example, has been demonstrated to suffer from floor effects (i.e. lager number of patients have, or are near, the lowest score) and so it is not likely to be as good at predicting at the lower end. These problems can be more dramatic in condition specific measures.

Mapping of any kind is only ever a second best solution to using the generic preference-based measure in the study in the first place. It has been argued in the context of economic evaluation that it is also second best to estimating preference weights for the non-preference based measure (as was done for the SF-36, Brazier ***et al***, 2002; or the condition specific Asthma Quality of Life Questionnaire, Yang et al, 2007). However, this raises additional concerns about achieving comparability between instruments that lie beyond the scope of this paper. (As a result of this concern two of the authors have embarked on an MRC funded methodological study to examine the scope of mapping between measures using preferences. This avoids compromising the descriptive system of these instruments and yet achieves comparability between measures.)

The bottom line is that mapping is viable, but whether the levels of error found for these mappings functions is ***acceptable*** requires careful assessment in the right context (in terms of patient group and application).

How should mappings be done?

The background section set out the process of mapping between instruments in terms of specification and estimation. Most studies tended to start with a simple additive model with main effects of either total or dimension scores as independent variables and an index score as the dependent variable, then increased in its complexity. Moving from total to dimension usually improved the fit of the model. Moving to item level models also improved the model fit, but these were not compared to models using dimension scores that also contained squared terms and interactions. However, the overall differences between models of different complexity tended to be very modest. Greater complexity came with little gain in most cases, though small gains come at little cost in terms of computer time. In some circumstances there was an important impact on the range of scores being predicted and large improvement in fit. One example is the mapping between IBDQ to EQ-5D where R^2 increased from 0.45 to 0.69 after incorporating squared terms of dimension scores (Buxton, et al, 2007).

The most common method of estimation was OLS. There is a concern in the literature that the standard OLS regression models under-estimate the level of uncertainty in the estimates (Briggs et al, 2004). This results from a centering around the mean, since it assumes that all respondents who complete the start measure (e.g. SF-36) in the same

way would also complete target instrument in the same way (EQ-5D). The result is a lower variance around the mean estimates. Again, the importance of this problem really depends on the way the data are going to be used. In large pooled analysis this may have little importance. More of a problem is the systematic pattern referred to earlier of over predicting at the lower end and under predicting at the upper end may be partly a result of this. One solution to this has been to use multinomial model that predicts the probability across the dimension levels of the EQ-5D. Gray and colleagues have used Monte Carlo methods to select a level for each respondent. This should partly solve the problem, though their model is still subject to the same systematic pattern of values. There may be other solutions to the problem, including the development of a Bayesian approach such as the successful application in modelling health state values (Kharroubi et al, 2007).

How should mapping functions be presented in published paper?

The reporting of mapping functions in the literature has been variable. It is not sufficient to simply report the goodness of fit of the model (e.g. adjusted R^2). To understand how well a mapping function performs, it is necessary to have the degree of error presented in the mean error, MAE and RMSE. However, these may not reflect what matters to the potential user. ME is too aggregated in many cases and the MAE and RMSE reflect error at the level of the individual. A more helpful way of presenting a model is in terms of the relationship between error and severity, either through tabulation or plotting predicted mean values against observed. An assessment of the importance of any error must be tested in a relevant application of the mapping function to an independent data set, such as estimates of differences between arms of trials or changes over time.

Future research

1. There is always scope for improving the statistical models and work exploring the use of Bayesian methods may help to reduce the current systematic errors found in mapping functions.
2. The performance of mapping functions varies considerably between instruments. For any proposed application it is important to estimate mapping functions and to fully test their performance.
3. The testing of performance must be extended to considering potential applications and may need to include the use of simulation methods.

Conclusion

This review addresses a number of questions about the use of mapping between condition specific measures and generic measures. It found a surprisingly large body of literature. The performance of the mappings functions in terms of goodness of fit and prediction was variable and so it is not possible to generalise across instruments. Performance is related to the degree of overlap in content between the instruments being mapped. The current literature is also limited in the way these models have been tested, since most testing has focused on their use at the individual level and yet most uses of these mappings functions are likely to be on subgroups of patients (such as arms of trials or diagnostic group in hospital). Further work is required to test the accuracy of these functions in more relevant contexts and over a larger range of instruments. The use of mapping functions is always a second best solution to using the generic measure in the

first place (or arguably using preference-weighted condition specific measure), but it is often necessary for pragmatic ex post reasons and so this remains an important of area of research.

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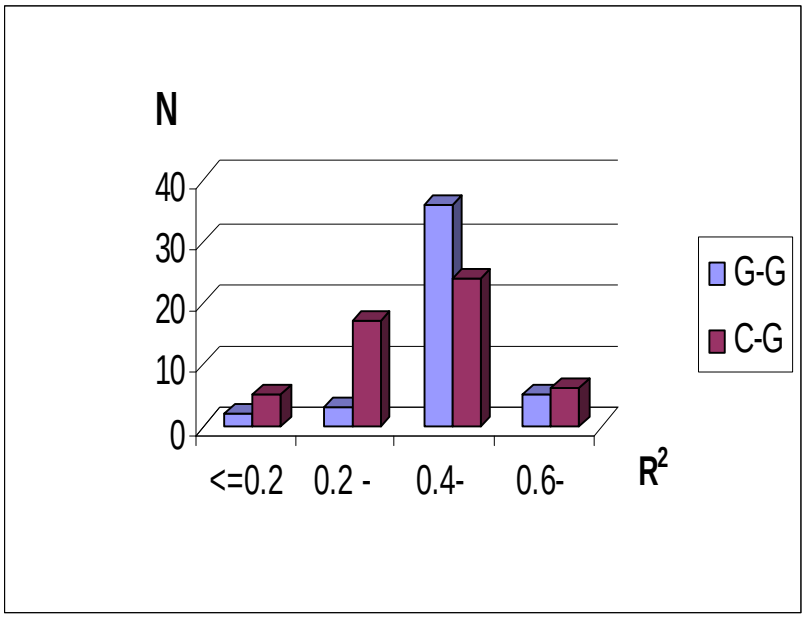
Figure 1 Distribution of R^2 of mapping models by type of start measure



N: Number of models relevant
G-G: Mapping from a generic health measure to another generic measure
C-G: Mapping from a condition-specific measure to a generic health measures

Table 1: Alternative specifications of mapping functions

Model	dependent variable	D/C †	independent variables			
			Main effects	D/C †	Interactions	Other measures
(1)	index	C	overall score	C		For any model: squared terms, other health measures, clinical measures, demographics
(2)	index	C	dimension scores	C	dimensions	
(3)	index	C	item levels	C	items	
(4)	index	C	item levels	D	items level	
(5)	Dimension level	C	Models 1-4	C/D	Models 1-4	
(6)	Dimension level	D	Models 1-4	C/D	Models 1-4	

† C, continuous; D, discrete

Table 2 : Items extracted from papers

Author name
Start Measure
Target Measure
Population, method of recruitment and setting
Estimation sample size
Estimation method
Dependent variable (C/D)
Main effects independent variable(C/D)
Method of selection of main effects variable
Main effects interactions
Transformations
Other measures
Independent variables in model (βs)
Proportion of βs (P<0.1)
Proportion of βs unexp. sign (P<0.1)
Proportion of Inconsistent βs (P<0.1)
R^2 and Adjusted R2
Uncertainty
In-sample tests: Mean error
Mean absolute error (MAE) (95% CI)
Proportion MAE>0.05
Proportion MAE>0.10
MAE by sev./cat.
MAE /obs (%)
RMSE
Maximum predicted score compared to observed
Minimum predicted score compared to observed
Correlation
Intra class correlation
Use of plots
External-sample size
Source
Setting
R^2 and Adjusted R2
Mean error
MAE (95% CI)
Prop. MAE>0.05
Prop. MAE>0.10
MAE /obs (%)
RMSE(95%CI)
Max. pred vs./ obs
Min pred vS. obs
MAE by severity group or category
Correlation
Intraclass correlation coefficient
Plots
Authors' comments on the study

Table 3: Summary of mapping studies

ID	First Author	Year	Journal	Start Measure	Target	Population	Sample size [3]
1	Bansback N	2007	*Arthritis Care Research*	HAQ-DI (Health Assessment Questionnaire Disability Index)	EQ-5D	Rheumy Arthritis (RA) patients	923
2	Bartman BA	1998	*Quality of Life Research*	SF-36	HUI3	Older patients with intermittent claudication (>=55)	510
3	Brazier J	2004	*Value in Health*	BI (Barthel Index)	EQ-5D	Oder patients of intermediate care - admission	964
4	Brazier J	2004	*Health Economics*	IWQOL- Lite	SF-6D	1. Community volunteers; 2. Participants in clinical trials for obesity; 3.gastric bypass surgery taker	468
5	Brennan DS	2006	*BMC Health Services Research*	SF-6D	EQ-5D	7 samples of patients with different diseases	2192
6	Buxton MJ	2007	*Value in Health*	OHIP-14 (14 item version of the oral Health Impact Profile)	EQ-5D	Dental patients	248
7	Dixon S	2003	*Journal of Outcomes Research*	IBDQ (Inflammatory Bowel Disease Questionnaire)	SF-6D	Moderate to severe Crohn's disease patients	905
8	Dobrez D	2007	*Value in Health (In press)*	NHP (Nottingham Health Profile)	SF-6D	Primary care patients	1327
9	Dooslaser E	2003	*Journal of Health Economics*	FACR-G (Functional Assessment of Cancer Therapy - General)	TTO utilities	Cancer patients	717
10	Edlin R	2002	Unpublished manuscript	SAH (self-assessed health question)	HUI3	General public >=12	15539
11	Edlin R	2002	Unpublished manuscript	NDI (Nepean Dyspepsia Index)	SF-6D	Dyspepsia patients	271
12	Franks P	2004	*Medical Decision Making*	MLWHF (Minnesota Living with Heart Failure Questionnaire)	EQ-5D	Heart patients	3000
13	Franks P	2003	*Medical Care*	SF-12	EQ-5D	General public (>=18)	12988
14	Fryback DG	1997	*Medical Decision Making*	SF-12	EQ-5D	Patients >=18	240

15	Gray A	2006	*Medical Decision Making*	SF-36	QWB	General public >=45 years	1356
16	Gray A	2004	HESG[1], January 2004, Paris	SF-12	EQ-5D	General public adults >=18	12967
17	Grootendorst P	2007	*The journal of Rheumatology*	SF-36	EQ-5D	General public adults >=18	12753
18	Kaambwa B	2006	HESG[1], July 2006, York	WOMAC(Western Ontario and McMaster University Osteoarthritis Index)	HUI3	Knee Osteoarthritis (OA) patients	168
19	Lauridsen J	2004	*Health Economics*	SAH (self-assessed health question)	15D	Finnish General public >=15	2697
20	Lawrence WF	2004	*Medical Decision Making*	SF-12	EQ-5D	General public (>=18)	7313
21	Longo M	2000	HESG[1], July 2000, Nottingham	SF-36	EQ-5D	Women with breast disorder	271
22	Longworth L	2005	*European Journal of Health Economics*	CCS (Canadian Cardiovascular Society Score) & the Breathlessness Grade	EQ-5D	Patients with stable angina	533
23	Nichol MB	2001	*Medical Decision Making*	SF-36	HUI2	Managed care patients with at least 1 prescription in the previous year, >18	6921
24	Roberts J	2005	Unpublished manuscript	OABQ (Overactive-bladder Questionnaire)	SF-6D	Over Active Bladder patients	688
25	Sengupta N	2004	*Medical Care*	SF-12	HUI3	Managed care patients,>18, with at least one prescription in the previous year	6323
26	Sullivan PW	2006	*Medical Decision Making*	SF-12	EQ-5D (US)	Representative sample of US population >=18	23647
27	Tsuchiya A	2006	HEDS[2] discussion paper	AQLQ (Asthma Quality of Life Questionnaire)	EQ-5D	Asthma patients	3059 - 6939
28	Tsuchiya A	2002	HEDS[2] discussion paper	IBS_QoL (Irritable Bowel Syndrome questionnaire)	EQ-5D	IBS patients	121

1. Health Economists' Study Group meeting;
2. Health Economics and Decision Science unit, University of Sheffield
3. Sample size is the respondents included in the dataset. The number of observations used for model estimation may vary if repeated observations are used.