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Using discrete choice experiments within a cost-utility analysis framework

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Abstract

This study considers the application of discrete choice experiments (DCEs) for estimating utility scores which can be incorporated into a CUA/CEA framework. The aim is to estimate 'cost-utility' ratios that go beyond health outcomes, and take account of user preferences. The application is the provision of genetic counselling services in Scotland. Utility scores, akin to the 'attractiveness index' developed in environmental economics, based on results from DCEs, are estimated for different ways of providing genetics counselling services in Scotland. These utility scores are then combined with costs to estimate cost-utility ratios. Consideration is given to issues raised concerning the interpretation and application of such ratios at a decision making level as well as issues around the use of such scores within an allocative efficiency framework.

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Introduction

Economic evaluation in health care has used three main frameworks within which to combine costs and benefits to make decisions on the cost-effectiveness of goods and services and hence the best way to allocate scarce health care resources. The most commonly used method of economic evaluation is cost-effectiveness analysis (CEA) where the measures of benefit are usually fairly narrow, uni-dimensional clinical outcomes such as pain scores. Cost utility analysis (CUA) has become synonymous with the use of Quality Adjusted Life Years (QALYs) as the measure of benefit. Such use of QALYs can help to address questions of technical efficiency as well as allocative efficiency when a generic form of the QALY is used, such as the EuroQol (EuroQol, 1990). Cost benefit analysis (CBA) has become synonymous with the use of willingness-to-pay (WTP) to obtain welfare estimates using open-ended, closed–ended or payment card techniques.

During recent years choice experiments have grown in popularity as a method to estimate welfare gains resulting from given policy changes. Such welfare measures have mainly been monetary, thus fitting into the framework of a CBA (Ryan, 1999). However, a number of studies have conducted choice experiments without including cost as an attribute (Ryan et al, 1998; Bate and Ryan, 1998; Ryan and Farrar, 2000). This raises the question of how the output of such experiments can be used within the framework of an economic evaluation. This study directly addresses this question. It uses an approach developed in environmental economics (known as an attractiveness index) to derive a 'utility index' as a measure of value when cost is not included as an attribute in a choice experiment (Adamovicz 1999; Opulach et al, 1993). This index is then combined with costing information to produce cost-effectiveness ratios. The application is genetic counselling.

Application: genetic counselling

It is estimated that 5-10% of cancers occur as a result of genetic predisposition (Go 1983; Williams and Anderson 1984; Newman *et al* 1988). The genetic basis of these dispositions is rapidly becoming understood (Claus *et al* 1991; Houlston *et al.* 1992). Many regional genetics units currently offer risk assessment for individuals within high-risk cancer families. This may involve genetic counselling and selective mutation testing (if available), with a view to improving risk prediction, preventive management and informed decision making by patients and their families (Murday, 1994). This, coupled with the availability of new technologies and the high levels of awareness amongst potentially susceptible families and their general practitioners (Struewing *et al*. 1995;Lerman *et al*. 1994), suggest the trend towards expansion of such services will not reverse. This has enormous resource implications for the NHS in Scotland, and in the context of such rapidly increasing demand, it is essential that the service provided is cost effective.

The need to reconsider the delivery of genetic counselling services in the light of expanding technology has been recognised in Scotland and Europe more broadly (DOH 1995, 1996). In particular there is interest in expanding the role of general practitioners and the primary care team to include genetic counselling for cancer (Kay *et al.*1996). Some regional genetics units now employ non-medical genetics associates or specialist nurses who may carry clinical responsibility, under the overall supervision of a medical specialist. Whilst there is a lot of literature on the psychosocial consequences of genetic counselling (Lerman *et al.*1994; Lerman *et al.*1995), little is known about costs and benefits of pre-symptomatic testing (Clarke 1995).

Methodology

The study consisted of a discrete choice experiment to establish utility scores for different ways of proving the service and a costing exercise to estimate costs to the NHS in Scotland (NHSiS) of familial cancer genetic counselling services. Following this, benefits and costs were combined within the framework of a CUA.

Discrete choice experiment

Setting and subjects

Adults (aged over 18) who had attended one of the four specialist genetic centres in Scotland (Aberdeen, Dundee, Edinburgh and Glasgow) for genetics counselling in the previous 2 years were eligible for inclusion in the experiment. Potential subjects were randomly selected from the each centre's database. A pilot questionnaire was mailed to a random sample of 30 patients from Aberdeen to test whether individuals would complete the questionnaire, and to see if trading was taking place among the chosen levels of the attributes in the discrete choice experiment. For the main study, a letter was sent to potential participants' general practitioners (GPs) to inform them of the study and provide them with an opportunity to exclude their patients from the study. Patients included in the study (i.e. those who passed the inclusion criteria and had the consent of their GP) were sent a covering letter from their consultant and a questionnaire. Nine hundred and thirty eight patients were identified as potential respondents. Two reminders were sent. Ethical committee approval was gained from both the Multi-Centre Research Ethics Committee for Scotland and the relevant local ethics committee.

Discrete choice experiment

Within the postal questionnaire a DCE was used to establish utility scores for different ways of providing the service. The attributes included in this study were taken from a pre-pilot study which had consulted patients on factors important in the provision of the service (O'Neill, 1998), current policy issues (GRAG 1995, Harper and Clarke 1997), consultations with providers of the service, and a pilot study. The attributes, and levels assigned to them, are shown in Table 1. Levels were based on current service provision and what was considered realistic within a policy context.

Table 1 Attributes and levels used in the discrete choice conjoint analysis experiment

Attributes	Levels	Regression Coding
Staff seen at the appointment	Genetics Associate, Genetics Nurse, Consultant	1,2,3
Waiting time till appointment	1 month, 4 months, 8 months, 12 months	1,4,8,12
Distance to appointment	1 mile, 5 miles, 15 miles, 30 miles	1,5,15,30

Duration of appointment	15 minutes, 30 minutes, 45 minutes, 60 minutes	15,30,45,60

These attributes and levels gave rise to 192 possible configurations of clinics ($4^3 * 3^1$). Statistical design software was used to reduce these scenarios to a manageable level whilst still being able to infer utility scores for all possible scenarios (Bradley, 1991). Sixteen scenarios were produced. These were paired into eight choices in such a way as to maintain the orthogonal properties of the statistical design, figure 1 shows an example of the type of choice individuals were presented with. In addition, three dominant tests were included to check that individuals understood the questionnaire and were answering it in a rational way (see section below on '*rationality of responses*').

Figure 1 Example of a choice

• **Appointment 1**	**A**	**B**
Who you see at the appointment	Specialist Nurse	Specialist Doctor
How long you wait for the appointment	8 months	8 months
Distance to appointment	30 miles	15 miles
Duration of appointment	60 minutes	15 minutes

Which option would you prefer? (*tick one box only*)	Prefer appointment A ❒	Prefer appointment B ❒

Since each individual respondent could provide up to ten responses, a random effects probit model was used to analyse the data (Propper, 1995). Given the categorical nature of the staffing variable, no pre-defined order preference could be assumed. To assist in the specification of the model additional information was collected on the staffing preference structure. Respondents were asked to rank their preferred counsellor (consultant, genetic associate or genetic nurse), where 1=most preferred and 3=least preferred. A linear additive model was assumed, the basic model estimated for the aggregate sample was specified as:

$$U = \beta_1(Staff_B - Staff_A) + \beta_2(Wait_B - Wait_A)\ \beta_3(Dist - Dist_A) + \beta_4(Dur_B - Dur_A) + e + u \quad (1)$$

which is equal to:

$$\Delta U = \beta_1 Difstaff + \beta_2 Difwait + \beta_3 Difdist + \beta_4 Difdur + e + u \quad (2)$$

where ΔU is the change in utility or satisfaction in moving Appointment A to Appointment B. 'Difstaff' is the difference in staff category between the two appointments, 'Difwait' is the difference in waiting times, 'Difdist' is the difference in distance and 'Difdur' is the distance in duration of appointment. *e* and *u* are the unobservable error terms where, e is the error term due to differences amongst observations and u is the error term due to differences amongst respondents.[1] The coefficients β_1 to β_4 are the parameters of the model to be estimated from the instrument. They indicate the relative importance, or weight, of a unit change in that attribute on overall utility.

Following estimation of equation (2), the relative importance of counselling staff, waiting time, distance to appointment and duration of appointment, as indicated by the significance of the coefficients $\beta_{1,}\beta_{2,}\ \beta_{3,}\beta_4$ and their relative size, can be estimated. Based on these marginal effects or 'weights', utility scores for different ways of providing the service can be derived. The following section deals with this in more depth.

Utility scores

The inclusion of cost as an attribute within DCEs provides a measure of relative WTP for individual attributes and hence provides an overall measure of welfare for changes in service configurations. In doing so, it is possible to examine the monetary impact of a quality change and compare service configurations before and after the change in terms of welfare gained/lost. However, when cost is *not* included as an attribute within a DCE, this begs the question – what measure of welfare/benefit is being estimated? Environmental economists have developed a scoring method, originally termed the 'attractiveness index', based on the summation of DCE marginal effects when cost is not included as an attribute. In doing so, they are able to estimate potential welfare gains and losses from various changes in service provision.

The estimation of such scores is facilitated by the random utility framework as the model provides a natural index of value. In a multiple alternative case one can use the expected value of the maximum utility (which has a closed form expression when a probit/logit model is used). This is a theoretically consistent and appealing way to create an index. The original applications of this index approach were in the area of damage assessment in environmental economics, in which the amount of resource improvement required to offset damages (from toxic spills for example) were computed using a utility index derived from the estimation of a random utility model (Adamovicz 1999; Opulach *et al* 1993). The index was originally termed an index of 'attractiveness'. A study by Adamovicz (1999) looked at angler's preferences for different fishing sites and estimated an index of attractiveness for individual sites. The 'attractiveness' for all sites across all anglers were summed to devise an 'existing angler satisfaction index' which reflected the overall level of satisfaction anglers had for current fishing

[1] Given that respondents were told to assume that all aspects of the service, other than those specified in the questionnaire, were identical, there was no constant term in the estimated regression equation (Ryan and Hughes, 1997).

opportunities. The index estimated included all existing site characteristics and their importance to anglers. The summed attractiveness scores provided an overall measure of utility with the current fishing opportunities. In this study, the discounted utility gains and losses from different configurations of fishing scenarios were estimated to observe the impact of any policy changes on the utility of anglers.

This study aims to use this ‘utility index’ approach to estimate the utility of various genetic counselling scenarios. This paper estimates utility scores for all configurations presented and combines these scores with the actual costs of each of the scenarios within an economic evaluation framework.

Segmented model

To allow for non-random variation in coefficients (i.e. preferences for individual attributes may vary across sub-populations) segmentation analysis was carried out. Three hypotheses were tested:

Hypothesis 1 – preferences vary according to experience of service. To test this the data was analysed by the centre respondents attended, and dummy variable interaction terms were created for centre-specific preferences.

Hypothesis 2 - preferences vary according risk status. To test this information was collected on respondent’s own risk of cancer. Respondents were asked to state the level of risk they were told they had at their counselling appointment. Possible responses were: much less than the general population; a little less than the general population; much the same as the general population; a little more than the general population; and a lot more than the general population. Three ‘risk’ groups were then created using dummy variable interaction terms.

Hypothesis 3 – preferences vary according to type of cancer. To test this information was collected on the type of cancer respondents were concerned about, with possible types of cancer being breast, breast/ovarian, colon and other.

The Wald statistic (Kennedy 1995) was used to test for statistically significant differences between the coefficients of the segmented models. The null hypothesis was that the coefficients in each subgroup were not significantly different from each other i.e. preferences did not vary across these sub-groups.

Rationality of responses

When using surveys it is important to include tests of whether individuals understand the questionnaire and are taking it seriously. This study tested for rationality of responses in two ways: dominance tests and transitivity tests.

- Dominance tests involve including scenarios that are 'better' or equal on all attributes in one scenario when compared to another. Respondents who are responding rationally are expected to choose the better option. Three dominant test were included in the questionnaire. Given that individuals may fail a test by chance, only those who failed at least 2 of the 3 dominance tests were dropped from the regression analysis.
- Economic theory postulates that rational individuals have transitive preferences. Such a preference structure implies that is if alternative A_1 is preferred to B_1, and B_1 to B_2, then A_1 should be preferred to $B_{2.}$ Within the choices presented in the questionnaire, Appointments 6 and 9 provided an opportunity to test for transitive preferences. Here, if the respondent prefers A in Appointment 6, A should also be preferred to B in Appointment 9 (since clinic B in Appointment 6 is better than clinic B in Appointment 9). For those who preferred B in Appointment 6, no conclusions could be reached concerning a transitive preference structure. Individuals who failed this test were dropped from the regression analysis.

Respondents were also asked how difficult/easy they found the 10 discrete choices on a scale of 1 to 10, where 1 represented very difficult and 10 very easy.

NHSiS costing exercise

Costs of the service were collected from the 4 centres participating in the study. The following resources were identified and measured: staff costs (including time spent in consultation with the patient and preparation time in assessing risk status and secretarial costs); room costs; and equipment (e.g. computers and specialised software packages). Staff costs were valued at the actual salary where known plus employer's on-costs (ranged from 11%-15%). Where salary costs were not available mid-points for the given grade were used. Room costs included capital costs of the building and overheads. Equivalent annual costs were estimated for equipment. A life span of 5 years was assumed, and a discount rate of 6% applied.

Bringing benefits and costs together into a cost-utility analysis framework

Following collection of utility scores and costing estimates, these data were brought together within the framework of a cost-utility analysis. The costs of each scenario presented in the choice experiment were estimated using the costs collected from each centre. This cost comprised both variable and fixed components. The variable component was based on the type staff seen at each ‘scenario’ and the duration of appointment, both of which were a function of the specific centre (Edinburgh, Glasgow, Dundee, Aberdeen). The fixed component comprised costs that were not a function of type of appointment e.g. room costs and equipment charges. From this data set it was possible to model the cost for each scenario by centre. This costing data was combined with utility scores for each of the four centres to estimate a cost-utility score for each scenario by centre. This provides an indicator of the most ‘cost-effective’ scenarios in each centre, taking account of patient preferences. For this part of the study only the costs for staff time and duration were included. Future analysis will incorporate the costs of changing the other attributes waiting time and distance by examining the cost implications of reducing waiting time and the provision of local clinics.

Results

Following feedback from GPs, 857 questionnaires were mailed. Of these, 86 patients were excluded from the study because they had either moved away or had not had counselling. Of the 771 eligible cases, 695 were returned. Of these, 538 were usable and 157 were blank. The response rate, adjusting for excluded patients, was 70% (538/771).

Discrete choice experiment

Respondents found the choice questions relatively easy to complete, with the mean response being 7 (where 1 represented very difficult and 10 very easy). Results from the dominance tests were encouraging, with only 4% (n=21) of respondents failing at least two of the three tests. In the transitivity test, of the 13 respondents who chose clinic A in Appointment 6, 5 exhibited a intransitive preference structure by choosing clinic B in Appointment 9. These 26 ‘irrational’ respondents were removed from further analysis. Because there were so few ‘irrational’ responses, it was not possible to carry out statistical tests to see if such responses came from a particular group or population. Segmented results indicated no significant differences in preferences according to risk status and type of cancer. Differences were however observed according to experience of service. In what remains the results are presented for respondents from Edinburgh (since the aim of this paper is to explore the use of utility scores).[2] These results are shown in Table 2. All coefficients have the expected sign and are significant at the 1% level. This suggests that all chosen attributes are important in the provision of

[2] Respondents attending clinics at Dundee and Glasgow place a significantly higher importance on waiting time than those attending Aberdeen; respondents attending Dundee clinic place significantly more importance on reducing distance to appointment than those attending Aberdeen and Edinburgh; respondents attending clinics in Aberdeen and Edinburgh place a significantly higher importance on increasing the duration of their appointment than those attending Dundee. There does not appear to be any obvious relationship with actual experience. More details of these results are reported elsewhere (CSO Final Report, 2000).

genetic counselling services. The positive sign on staff and duration of appointment indicate that the higher the attributes, the more likely the individual is to choose the clinic. For staff, given the coding, this can be interpreted as a doctor being preferred to a nurse being preferred to an associate. The negative sign on waiting time and distance to appointment suggests that the lower the level of these attributes, the more likely the individual to choose that clinic. These results are in line with a priori expectations, providing support for the theoretical validity of choice based conjoint analysis experiments.

Table 2 Random effects probit regression model – Edinburgh sub-group

Attributes	Levels	Coefficient (weight)	SE	P
Staff*	1=Associate 2=Nurse 3=Doctor	0.124	0.011	0.000
Waiting time	1,4,8,12 months	-0.106	0.003	0.000
Distance to appointment	1,5,15,30 miles	-0.012	0.001	0.000
Duration of appointment	15,30,45,60 minutes	0.005	0.0004	0.000

n = 507
Log-likelihood: -1791.703
Restricted log likelihood: -1795.456
Correct predictions = 83%
Chi-squared: 7.50
McFadden R^2: 0.002

* Coding based on results from ranking exercise and by testing alternative model specifications.

Utility scores

Since the utility scores are estimated from a linear model, the marginal effects estimated can be interpreted as values for a change in one unit of the attribute from *any* level. As a result of this, it is possible to interpret them as the mean value for any unit of the attribute. Based on this a composite utility score was estimated for each scenario presented in the questionnaire, see Table 3. This was carried out by multiplying the marginal effect of each attribute by the corresponding level of that attribute (where the segmented model showed significant differences between centres for attributes, the centre-specific marginal effects were used). Whilst patients would prefer to see a doctor, improvements in other aspects of the service can more than compensate for not seeing preferred staff. For example, clinic 3, which involves the patient seeing a nurse, yields more benefit than clinics 4, 8, 9, 11, 12 and 15, all of which involve seeing the doctor. This indicates that patients can be compensated for not seeing their staff by improvements in the levels of other attributes. So, comparing clinics 3 and 4, respondents would prefer to see a nurse for 15 minutes and wait 1 month for the appointment as opposed to waiting 4 months and seeing a doctor for 45 minutes. Using the results from the model in this way allows the ranking of scenarios according to their utility or benefit.

Table 3 Utility scores for clinic configurations provided in the questionnaire

Genetics Clinic	Staff	Wait	Distance	Duration	Edinburgh Utility score	Utility Ranking
1	Doctor	1	5	60	**2.640**	**1**
2	Doctor	1	15	30	**2.390**	**2**
3	Nurse	1	1	15	**2.331**	**3**
4	Doctor	4	1	45	**2.287**	**4**
5	Nurse	4	5	30	**2.048**	**5**
6	Associate	1	30	45	**2.066**	**6**
7	Associate	4	15	60	**1.973**	**7**
8	Doctor	4	30	15	**1.847**	**8**
9	Doctor	8	5	45	**1.823**	**9**
10	Associate	8	1	30	**1.539**	**10**
11	Doctor	8	15	15	**1.573**	**11**
12	Doctor	12	1	60	**1.514**	**12**
13	Nurse	8	30	60	**1.524**	**13**
14	Nurse	12	15	45	**1.175**	**14**
15	Doctor	12	30	30	**1.074**	**15**
16	Associate	12	5	15	**1.000**	**16**

Costs to the NHSiS of familial cancer genetic counselling services

Table 4 provides a summary of the mean cost to the NHSiS of providing genetic counselling services. The different costs at the 3 centres are reflective of the different skill mixes, and thus staffing costs. For example, whilst Aberdeen staff mix involves 60% of a whole time equivalent (wte) consultant and genetics nurse, 50% wte of an associate registrar, specialist registrar, and staff doctor, and 100% wte of both a receptionist/secretary and administrator, Edinburgh involves only 20% wte of a consultant and the remaining staffing is at a lower grade, thus resulting in lower staff costs. This raises important issues concerning the optimal staffing mix in the provision of genetic counselling services. From an economic perspective, the important question is whether different skill mixes result in different benefits (this is addressed in the next section). Centre-specific costs per patient were estimated for each scenario in the discrete choice experiment. These costs were a function of staff type and duration of appointment. The costs for the discrete choice scenarios based on Edinburgh costs are shown in Table 6.

Table 4 **Average cost per patient to the NHSiS of providing genetic counselling services**

Centre	Staff Costs (£)	Room Costs (£)	Equipment Costs (£)	Total Costs (£)	**Average per patient cost (£)**
Aberdeen	144,309	7,172	1,858	153,340	**192**
Dundee			**Dundee cost information pending.**		
Edinburgh	68,688	9,251	4,508	82,447	**86**
Glasgow	214,434	11,103	2,910	228,4474	**136**

Costs are reported in 1999/2000 prices.

Bringing utility scores and costs together within a cost-utility analysis framework

The utility scores estimated were combined with costing data for each of the scenarios at each of the centres to provide cost-effectiveness estimates for each of the individual scenarios presented in the questionnaire. These cost-utility ratios then provided a new ranking of scenarios, compared to that given in Table 3, this time according to cost-effectiveness. These ratios provide an indicator of whether the extra cost incurred by moving from one clinic configuration to another is justified in terms of the extra benefit (or utility). The five most cost-effective clinic configurations are highlighted. Whilst there is some variation across the centres, provision of the service by either a nurse of genetics associate appears in the top 5 across all centres (although only the results from Edinburgh are shown). The results indicate that, for the scenarios shown, whilst the doctor is preferred in terms of utility (as shown in Table 3), the additional cost of this may not be justified by the additional benefits.

Table 5 **Cost-utility ratios based on Edinburgh costs and utility scores** [1]

Genetic Clinic	Staff	Wait	Distance	Duration	Utility score	Utility Ranking	Cost per patient	Cost-utility ratio	CU ranking
1	**Doctor**	**1**	**5**	**60**	**2.640**	**1**	**86.92**	**32.93**	**11**
2	**Doctor**	**1**	**15**	**30**	**2.390**	**2**	**66.25**	**27.72**	**7**
3	**Nurse**	**1**	**1**	**15**	**2.331**	**3**	**28.87**	**12.39**	**1**
4	**Doctor**	**4**	**1**	**45**	**2.287**	**4**	**76.58**	**33.49**	**12**
5	**Nurse**	**4**	**5**	**30**	**2.048**	**5**	**32.44**	**15.84**	**2**
6	**Associate**	**1**	**30**	**45**	**2.066**	**6**	**36.00**	**17.42**	**3**
7	**Associate**	**4**	**15**	**60**	**1.973**	**7**	**39.56**	**20.05**	**4**
8	**Doctor**	**4**	**30**	**15**	**1.847**	**8**	**55.92**	**30.28**	**10**
9	**Doctor**	**8**	**5**	**45**	**1.823**	**9**	**76.58**	**42.01**	**14**
10	**Associate**	**8**	**1**	**30**	**1.539**	**10**	**32.43**	**21.07**	**5**
11	**Doctor**	**8**	**15**	**15**	**1.573**	**11**	**55.92**	**35.55**	**13**
12	**Doctor**	**12**	**1**	**60**	**1.514**	**12**	**86.92**	**57.41**	**15**
13	**Nurse**	**8**	**30**	**60**	**1.524**	**13**	**35.96**	**25.96**	**6**
14	**Nurse**	**12**	**15**	**45**	**1.175**	**14**	**35.00**	**29.80**	**9**
15	**Doctor**	**12**	**30**	**30**	**1.074**	**15**	**66.25**	**61.69**	**16**
16	**Associate**	**12**	**5**	**15**	**1.000**	**16**	**28.87**	**28.86**	**8**

[1]Top 5 most cost-effective configurations shaded

Discussion

Within health economics, the traditional approach to measuring benefits has been to assume that some measure of health outcome is the only important factor. Thus, cost-utility analysis (CUA) has become synonymous with Quality Adjusted Life Years (QALYs) and cost-effectiveness analysis (CEA) has become synonymous with the use of some clinically-derived measure of effectiveness. However, there is evidence that, in the provision of genetic counselling services, patients are concerned with the process of care (Harper and Clarke, 1997; Lenaghan, 1998). Lenaghan (1998) points out that 'The traditional approach of measuring what is clinically and cost-effective is clearly too narrow for the assessment of the new genetic services'. This means that some measure of benefit is required which is neither a QALY nor some narrowly defined clinical measure of effectiveness. This study went beyond the traditional approaches and valued the process of care using a theoretically-based utility index approach derived from a DCE.

Whilst DCEs are being increasingly used in health economics (Ryan, 1999), this was the first study to link the output of such a study with costs within a 'CUA/CEA' framework. Utility scores were linked directly to cost data to estimate the cost-effectiveness of alternative service configurations. The results indicate that a counselling service provided by specialist genetic nurses or genetic associates rather than doctors is a cost-effective option provided that improvements, such as either reduced waiting time or longer duration of appointment, are provided. The adaptation of the random utility model to estimate a natural index of value i.e. an 'attractiveness index' as of the kind developed in environmental economics has proved to be of use in this project and has permitted the ranking of scenarios by utility score. Such a theoretically consistent way to derive such an index for use in the economic evaluation of health care is very appealing.

This study estimated utility scores within a hypothetical fixed budget for the provision of genetics counselling services and as a result, the scores estimated were specific to the attributes and levels used to provide a specific counselling service. This raises the question of the appropriateness of such scores within a broader, allocative framework for the provision of competing alternatives. Given the existence of generic attributes such as those used in the EuroQol, it would be possible to obtain weights for such generic attributes using DCEs and compile a generic utility index such as that matrix already used for this purpose (Dolan *et al.*1995).

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