Valuing the EQ-5D-Y-5L using DCE methods that account for nonlinear time preferences

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Abstract

Objectives

The development of a valuation protocol for the EQ-5D-Y-5L is underway. This will be informed by evidence relating to key features of the valuation method, including the preference elicitation task, perspective taken in valuation, and the sample frame for the sample valuing the health states. Discrete choice experiments (DCEs) have grown in popularity as a valuation approach and may be a suitable approach for valuation of the youth instrument. Recent evidence from DCE valuation for adult instruments has found that respondents may exhibit nonlinear time preferences. This requires testing for the youth measures. The aims of this study were to test the feasibility of using DCE approaches which allow for nonlinear preferences for duration for the valuation of the EQ-5D-Y-5L in an adult sample, and, further, to explore the impact of perspective i.e. valuing health states on behalf of a 10-year-old or 'self', on the modelled nonlinear preferences and the value sets produced.

Methods

A representative Australian adult general population sample completed an online survey which included 15 DCE split triplet tasks and background questions. There were two arms, conducted consecutively. In the first arm respondents were asked to imagine themselves when choosing between health states. This was followed by data collection of the second arm where respondents were asked to respond on behalf of an imagined '10-year-old' when answering the questions. In each arm, data collection was staggered to allow for periodic updates to the DCE choice task design. For both arms, initial priors were taken from the Australian population EQ-5D-5L value set to create the first 150 choice tasks. There were 3 updates to the DCE choice task design, resulting in 600 choice tasks in total per arm. Approximately 200 respondents were collected each time (the aim was for 1000 respondents per arm). Data were analysed in OpenBUGS.

Results

Data collection commenced in December 2023 and was completed by June 2024. There were 955 respondents in the 'self' arm and 947 respondents in the '10-year-old' arm included for analysis. In both arms, significant nonlinear time preferences were detected with a discount rate of 17% in the 'self' arm and 15% in the '10-year-old' arm. When imagining a '10-year-old', experience of pain and discomfort and feeling worried, sad and unhappy comparatively had larger overall decrements (a proxy for importance). The scale of health state utilities was also noted to be longer in the '10-year-old' arm with a utility of the worst health state (55555) at -1.42 as opposed to -1.1 in the 'self' arm. Sensitivity analysis also revealed that whether a respondent was a parent or non-parent did not matter as much to the valuation of health states for a '10-year-old', but it did matter when imagining 'self'.

Conclusion

This is the first study to use a nonlinear DCE approach in the valuation of the EQ-5D-Y-5L. Consistent with other EQ-5D-Y valuation studies, pain and discomfort was the most important dimension to respondents for a 10-year-old. It was also found that respondents do discount future years, in valuing states for themselves and a 10-year-old, indicating that nonlinear modelling methods are suitable in the valuation of the EQ-5D-Y-5L. Information from this study provides crucial evidence to inform the development of the EQ-5D-Y-5L valuation protocol.

Introduction

Economic evaluation methods, such as cost utility analyses (CUA), are used by many health technology assessment (HTA) agencies to inform the allocation of health resources. Benefits of health technologies are often measured by quality adjusted life years (QALYs), which is a measure of outcome that accounts for both quality and quantity of life. Health related quality of life (HRQoL) instruments can be used to measure and value health benefits and estimate the quality weight of the QALY. (also referred to as health utilities in this paper). To calculate QALYs, HRQoL values anchored at 1 (perfect health) and 0 (dead) are required, with values less than 0 representing health states considered worse than dead.

For adult populations, detailed guidelines for economic evaluation are available from major HTA agencies (1) such as the Pharmaceutical Benefits Advisory Committee (PBAC) in Australia (2), the National Institute for Health and Care Excellence (NICE) in the UK (3), the Institute for Quality and Efficiency in Health Care (IQWiG) in Germany (4). While many emerging health technologies are targeted towards children and adolescents (5), to evaluate technologies for paediatric populations, including about how HRQoL is measured and valued (1). Major HTA agencies have been observed to use evidence based on valuations of adult HRQoL in paediatric specific technology assessments. For instance, a 2020 review by (6) found that of 40 evaluations of technology by NICE for people aged 18 and younger, 16 generated HRQoL valuations using the adult version of the EQ-5D to reflect paediatric health. Similar issues were observed in PBAC assessments of paediatric interventions (7).

The EQ-5D is the most common HRQoL instrument cited in national HTA guidelines (8). A key advantage of the EQ-5D is the availability of a wide range of country specific value sets, i.e. a set of preference weights ('values') for HRQoL states, that can be used in the estimation of QALYs (9). The EQ-5D-Y-3L was developed for use in paediatric populations in 2010 (10). An international valuation protocol for the EQ-5D-Y-3L was published in 2020 (11) leading to a rapid increase in the number of country specific value sets available (5). This has also led to exploratory research to understand whether paediatric and adult HRQoL have similar values in 'comparable' health states described by adult and child instruments (9).

Expanding on the EQ-5D-Y-3L, the five-level version, the EQ-5D-Y-5L, is soon to become an approved instrument. Recent evidence has suggested that the EQ-5D-Y-5L has been shown to have better sensitivity in measuring moderate to severe problems and performs better in longitudinal study designs (12) compared to the EQ-5D-Y-3L. The EQ-5D-Y-5L has the potential to be a widely used paediatric HRQoL measure. Research is underway to test different valuation methods to inform a protocol for valuing the EQ-5D-Y-5L. There continues to be debate in the literature about the best approach to the valuation of paediatric HRQoL instruments. This includes debate about framing issues such as perspective and the type of valuation method (7).

Regarding perspective, there is evidence to suggest that that adults value HRQoL differently when asked about themselves in comparison to valuing health for someone from the paediatric population. For instance, Powell et al. (13) in a qualitative study, demonstrate that adults view the impact of EQ-5D-Y-3L health states on HRQoL differently for a 10-year-old versus an adult. There was no consensus on whether health states were considered worse, just as bad or better for children to live in than adults. However, it was found that for the more 'physical' states of ill health, respondents were less willing to trade off life years for a child. Respondents were willing to trade off life years to shorten suffering of the child when it came to dimensions like worried, sad or unhappy or experience of pain or discomfort. Age of the child can also impact on the valuation of HRQoL. Reckers-Droog, Karimi (14) provide evidence that adults prioritise different EQ-5D-Y-3L dimension levels for a 10-year-old versus a 15-year-old. For instance, feelings of worried, sad or unhappy were believed to have less impact on a 10-year-old as it was often short lived. In comparison, these same feelings were believed to have a much bigger impact on a 15-year-old adolescent, although it was also considered normal to have such feelings during puberty. There was also a belief a 10-year-old would be more accepting of help with any problems with mobility, self-care and usual activities whereas a 15-year-old would find this unacceptable, especially when it came to self-care. There is also evidence to suggest that there are fundamental differences in value sets for the EQ-5D-Y-3L compared to the adult EQ-5D instruments (9). As such, it is questionable whether it is appropriate for HTA agencies to use adult HRQoL to reflect paediatric HRQoL. Hence, it is important for HTA agencies to provide clearer guidance on the perspective to use in paediatric HRQoL instruments to encourage their use in economic evaluations of paediatric health technologies.

There are a range of completed and ongoing studies that could inform a potential EQ-5D-Y-5L valuation protocol. One such programme of work is the Australian QUOKKA project (https://www.quokkaresearchprogram.org/) which is a mixed methods study exploring the measurement and valuation of health-related quality of life for use in HTA. A major component of QUOKKA has explored the valuation of the EQ-5D-Y-5L by both adults and adolescents using DCE approaches. This has provided evidence that DCE with duration approaches are feasible in both adults and adolescents, and the different samples and perspectives results in different patterns of preferences (15, 16).

Separately, there is emerging evidence that respondents in valuation studies exhibit nonlinear time preferences in valuation tasks for adult instruments (17-20). Jonker et al. (17) found evidence for nonlinear time preferences by estimating a discount rate directly in the valuation of the Dutch SF-6D. That is, nonlinear time preferences were detected through models that can accommodate respondent consideration of years further in the future to have less value right now i.e. are discounted. Jonker and Bliemer (18) introduced the Time Preference Corrected (TPC)-QALY software package, also used in Jonker et al. (17), that can be used to the obtain Bayesian D-efficient designs that account for nonlinear time preferences. These designs take into account that respondents may discount future years when selecting durations in the choice tasks.

Nonlinear time preferences have been explored in the context of valuing adult measures such as the EQ-5D-5L but has not been explored for paediatric HRQoL measures. A common choice task format seen in DCE studies that account for nonlinear time preferences are split triplets or DCE choice tasks with full health (17, 21, 22). In these DCE choice tasks, respondents are firstly asked to choose between health state A and B, where duration is always the same for both health states. They are then asked to choose between health state B and C, where health state C is always full health for a shorter duration than health state B. Using a single valuation approach may have advantages over more complex protocols that combine data from different methods (e.g. cTTO tasks and DCE choice tasks without duration (11), for the EQ-5D-Y-3L). This choice task format can generate HRQoL values that allow QALY estimates accounting for nonlinear time preferences exhibited by respondents (20). Recent evidence also supports the notion that in terms of scale and importance of dimensions for the EQ-5D-5L, valuation using cTTO and DCE choice tasks with duration are the same as DCE choice tasks with full health once they account for nonlinear time preferences (23). This suggests that different methods of valuation (and anchoring) can still capture similar concepts and lead to consistent results.

It is unknown how time preferences might affect adult valuation of paediatric health states. So far, valuation studies of nonlinear time preferences have only been for adult instruments where adults value health states from a 'self' perspective. Such responses are affected by individual rates of personal time preferences. In the case where adults are asked to value health states for a 10-year-old child, it is not clear that the same time preferences would apply. For example, would respondents discount time differently for 'self' versus a '10-year-old'?

In order to investigate this, we report a study valuing the EQ-5D-Y-5L using a DCE modelling approach that allows for nonlinear time preferences amongst the Australian adult population.

The aims of this study are:

1. To explore whether and how adult respondents discount time when valuing EQ-5D-Y-5L health states,
2. To understand the impact of asking adult respondents to imagine themselves versus a 10-year-old on the values for EQ-5D-Y-5L obtained using nonlinear DCE with duration, and
3. To explore whether adult respondents value EQ-5D-Y-5L health states differently if they are a parent/caregiver or someone without children (non-parent).

Methods

Recruitment and arms of study

This study focused on the stated preferences of the Australian adult population (i.e. 18 years or older). There were two arms in this study. In arm 1, respondents were asked to imagine themselves as they completed the DCE choice tasks and to select the EQ-5D-Y-5L state they would prefer to live in. In arm 2, respondents were asked to imagine a 10-year-old child and to select the health state they would prefer for the child. Data collection occurred consecutively, with data for Arm 1 collected first, followed by Arm 2.

A representative sample of the adult Australian population in terms of age, gender and state was used for each arm. Respondents were recruited from a major panel provider in Australia, PureProfile (https://www.pureprofile.com/). It was planned to recruit 1000 respondents per arm. This sample size allows for the periodic updates required to the DCE choice tasks (see below for more information about the construction of DCE choice tasks).

Survey overview

When respondents entered the survey, they were provided with information about the study, and asked to consent to participate. Those who consented were then asked about their age, gender and postcode to determine their eligibility for the study as quotas were in place to ensure a representative Australian sample. Respondents were also asked about whether they have ever had children although this was not used for the quotas. This was followed by self-reporting their health on the EQ-5D-Y-5L questionnaire prior to a short tutorial on the DCE choice tasks. Respondents were then shown a short tutorial on the DCE choice tasks, before being asked to complete DCE choice tasks. The perspective respondents saw in the tutorial and DCE choice tasks depended on whether they were part of Arm 1 or Arm 2. After completion of the DCE choice tasks, respondents were asked some further follow up questions about the DCE choice tasks, and additional demographic and health questions. They were also asked to complete the EQ-5D-5L questionnaire. Respondents were given space to provide free text comments before the conclusion of the survey. A copy of the survey is available upon request. Maths in Health (https://www.mathsinhealth.com/) programmed and hosted the survey.

DCE choice tasks

Each respondent was shown 15 DCE choice tasks (with two choices per task), where each DCE choice task entailed considering 3 health states. Each health state was described by a combination of EQ-5D-Y-5L dimension levels and a duration attribute which described the number of years the health state would be experienced for before dying. Duration levels used were 0.25, 0.5 and all integers from 1 to 15 years. Overlap of up to two dimensions was also allowed in DCE choice tasks, to increase the ease of decision making for respondents.

Each choice task is divided into 2-parts. In part 1, respondents were asked to choose between health states A and B, where the duration specified is the same. In part 2, respondents were asked to choose between health states B and C, where health state C is always full health (i.e. ‘no problems’ on each dimension) for a shorter duration than that of health states A and B. This is the ‘matched’ pairwise’ choice format that has been used in previous studies (17, 19, 21).

Figure 1 and Figure 2 provides an example choice task. To help respondents differentiate between levels, a blue gradient has also been used to indicate the severity of the level, with a darker shade of blue indicating a more severe level.

Figure 1 Example choice task with 10-year-old perspective: part 1

Please read each health state closely and imagine **10-year-old child** living in each one. Then select the health state you would prefer for the child.

What do you prefer for the child, health state A or health state B?

Task 1 of 15: Part 1

Health State A	Health State B	Health State C
10 years in this health state, followed by death	**10 years** in this health state, followed by death	**4 years** in this health state, followed by death
Some problems walking around	A lot of problems walking around	No problems walking around
Cannot wash or dress (self)	A little of a problem washing or dressing	No problems washing or dressing
A little bit of a problem doing usual activities	Some problems doing usual activities	No problems doing usual activities
Extreme pain or discomfort	Extreme pain or discomfort	No pain or discomfort
Not worried, sad or unhappy	Not worried, sad or unhappy	Not worried, sad or unhappy

Figure 2 Example choice task with 10-year-old perspective: part 2

Please read each health state closely and imagine **10-year-old child** living in each one. Then select the health state you would prefer for the child.

What do you prefer for the child, health state B or health state C?

Task 1 of 15: Part 2

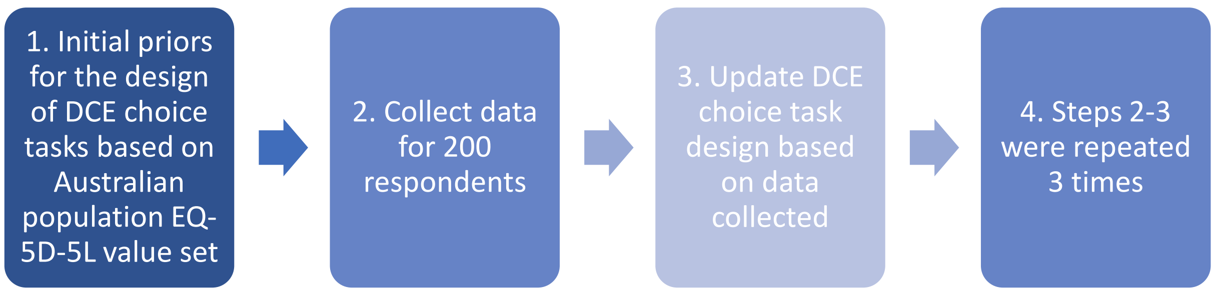
Health State A	Health State B	Health State C
10 years in this health state, followed by death	**10 years** in this health state, followed by death	**4 years** in this health state, followed by death
Some problems walking around	A lot of problems walking around	No problems walking around
Cannot wash or dress (self)	A little of a problem washing or dressing	No problems washing or dressing
A little bit of a problem doing usual activities	Some problems doing usual activities	No problems doing usual activities
Extreme pain or discomfort	Extreme pain or discomfort	No pain or discomfort
Not worried, sad or unhappy	Not worried, sad or unhappy	Not worried, sad or unhappy

Method of constructing DCE choice tasks

A Bayesian efficient design was used to construct the DCE choice tasks. These were constructed in the Time Preferences Corrected QALY Design (TPC-QD) software with customised code that has been used in previous studies (17, 18). The Bayesian efficient design was optimised for a discount rate using an exponential function i.e. nonlinear preferences for time were explicitly considered in the design of the DCE choice tasks. Each Bayesian efficient design included 10 sub-designs i.e. 10 versions each of 15 DCE choice tasks, with respondents randomly assigned to one sub-design. The use of sub-designs increases the robustness and efficiency of the overall DCE design (17, 24). The selection of DCE choice task health states and durations were based on minimising the weighted average Bayesian D-efficiency of the design, with one quarter of the weight assigned to the combined D-efficiency and three quarters of the weight assigned to the individual D-efficiencies of the sub-designs. More weight was given to the D-efficiencies of the sub-designs to ensure more power at the individual level rather than the aggregate levels. This is relevant for mixed logit (MXL) models where individual parameters are estimated.

The Bayesian efficient design requires priors for the model parameters. For both arms, initial priors were taken from the Australian population EQ-5D-5L value set (25) to create the design of 150 DCE choice tasks for the initial recruitment of 200 respondents. Upon collecting this sample of 200 respondents, the data were analysed, and a new design generated using as priors the results of the analyses of the collected data. Subsequently, a new sample of 200 respondents was collected, and the combined data were again analysed, with the results serving as the prior for a newly updated design. This was repeated until the results of the analysis roughly matched the previously used priors for the last design update, or until the data collection was completed. In total, 1000 respondents were planned to be collected per arm, with recruitment proceeding in approximate increments of 200 respondents at a time, anticipating 3 design updates per arm. This means the final designs include 600 choice sets per arm. This process is illustrated in Figure 3.

Figure 3 DCE Choice Task Design Update Process



Data analysis

Quality checks

The final sample of respondents was determined based on a set of data quality criteria, largely motivated by issues experienced during the initial stages of recruitment (see Appendix A). Respondents were included only if they consented to participate and completed the whole survey. Respondents also had to meet a series of predefined quality criteria to be considered valid respondents. This included a measure for capturing bots, where responses were excluded if the measure gave a probability of greater than 25% that the response was from a bot. Respondents were only included if they had a median response time of 12.5 seconds per DCE choice task i.e. more than 6 seconds per choice between the health state pairs A/B and B/C. Respondents also had to pass an inverse VAS traffic light task, where they are asked to order red, orange and green traffic lights along a VAS scale in reverse order. This has been used in a previous valuation study for the EQ-5D-Y-5L (26). An example of this task is available in the surveys on request.

As a further consistency check, respondents who said they had children at the beginning of the survey were also asked the same question after the completion of the DCE choice tasks. They were also asked to restate how many children they had and the age of their child or oldest child at their last birthday. For respondents who indicated they had no children at the beginning of the survey, they were instead asked about their age on their last birthday, again after the completion of the DCE choice tasks.

Modelling nonlinear time preferences

Choice information was from the initial DCE choice task design plus 3 updates of the design. This resulted in information from 600 choice tasks in total (4 x 150 choice sets) per arm. For the initial choice set design, priors for the 20 interaction terms between EQ-5D-Y-5L dimension levels and duration were based on the anchored coefficients from the Australian population EQ-5D-5L value set (25). The initial prior for parameter ‘perfect health’ was set to have mean of 1 and a standard deviation of 0.2. For the discount rate parameter, an initial prior value of 0.075 was selected, with a standard deviation of 0.02. Initial prior for the discount rate parameter was motivated by a need to provide broad enough coverage for a first estimate but also to set to be not too high as it may cause life years to start dominating. For each design update, priors for the parameters perfect health and the discount rate were based on model parameter estimates. For the first update, a conditional logit model with a discount rate was used. Subsequent data collections were sufficiently powered to estimate mixed logit models (MXL), so for subsequent updates, MXL estimates were used as priors.

The final models were based on data from all respondents in each arm who passed the data quality checks. The correlated MXL model was estimated. This model was chosen due to its flexibility. The correlated MXL model collapses to an uncorrelated MXL if no statistically significant correlation is present, which in turn collapses to a conditional logit model if there are no statistically significant differences between respondents. Analyses were conducted in OpenBUGS (27). The model specification is based on Jonker, Donkers (17) which allows for linear time preference as a special case. For the MXL model, utility *U* for individual i for alternative n in choice set j is specified as:

$$U_{inj} = (\beta_i X_{inj})NPV_{inj} + \varepsilon_{inj}, \qquad \beta_i \sim MVN(\beta, \Sigma) \quad (1)$$

where β_i are the preference parameters associated with individual i that are assumed to be multivariate normal distributed with population mean β and covariance matrix $\sum$. X_{inj} are the attribute levels shown to individual i in alternative n of choice set j. Net present value NPV_{inj} is the sum of the present value of future life years ($TIME_{inj}$). In this case, net present value, NPV_{inj}, is discounted using the standard exponential function. The standard exponential function allows for linear time preference as a special case when the discount rate (*r*) is equal to zero. This can be expressed as:

$$NPV_{inj} = TIME_{inj}, \qquad if\ r = 0, \quad (2)$$

And the more general case where the discount rate is not zero, can be expressed as:

$$NPV_{inj} = ((1 - e^{(-r)TIME_{inj}}))/(e^{r} - 1)), \text{ if } r \neq 0. \quad (3)$$

Reporting of results

Results are reported on the QALY scale i.e. scale anchored at 1 for perfect health and 0 for death, with the associated 95% confidence intervals. QALY scale estimates were obtained by dividing the estimate of the mean $\hat{\beta}$, by the first element of $\hat{\beta}$ i.e. the perfect health intercept, $\hat{\beta}_1$. This can be expressed as:

$$QALY_{decrement} = \hat{\beta}/\hat{\beta}_1. \quad (4)$$

QALY scale parameters were estimated directly in OpenBugs (27) along with the raw parameter estimates. Raw parameter estimates are available in Appendix B.

Results

Recruitment and final sample for analysis

A representative Australian adult population sample was recruited. Pure Profile was the panel provider that was ultimately used for recruitment. Data quality issues were experienced with an initial provider (details can be found in Appendix A).

A summary of respondent numbers by round of data collection has been provided in Table 1. The aim was for about 200 respondents per round of data collection. During the collection of Round 2 for the 'self' arm, more than 200 respondents were collected due to a technical error in the survey platform. Due to a technical error during data collection, some respondents who did not pass the inverse VAS traffic light test (VAS test) were mistakenly recorded as having passed; this has been recorded in Table 1.

The decision process for the final sample is summarised in Table 2. In total, 955 respondents in the 'self' arm and 947 respondents in the '10-year-old' arm were included for analysis. Respondents who provided inconsistent responses to the repeated question about their age or their parental status were excluded from final analysis.

Table 1 Summary of data collection dates

Data collection		No. of days	No.	No. failed VAS test but included in round
'Self' arm (n = 1004)	Round 1	5	211	46
	Round 2	3	322	73
	Round 3	4	205	52
	Round 4	6	266	72
'10 year old' arm (n = 1011)	Round 1	6	218	N/A
	Round 2	1	202	N/A
	Round 3	4	195	N/A
	Round 4	7	396	N/A

Table 2 Decision process to final sample

Decision process	'Self' arm	'10 year old' arm
Completed whole survey	3274	3824
Passed reCAPTCHA test (<25% chance of being a bot)	1268	1782
Passed speed test (> 12.5 seconds/choice task)	1004	1351
Passed inverse VAS traffic light test (VAS test)	Error*	1011
Passed age/ child response consistency check	955	947

*see Table 1

Respondent characteristics

Table 3 provides a summary of respondent demographics. Respondents were generally representative of the Australian population in terms of gender and state. There was underrepresentation of respondents between the ages of 18-24, largely due to the difficulty in recruiting males in this age group. The vast majority of respondents spoke English as their main language at home. There were also a higher number of respondents who were parents/caregivers in the 'self' arm (63%) and the '10-year-old' arm (64%) arms compared to respondents with no children. This is higher than the national figure of 43.7% of couples with children (28). Respondents were generally well educated, with a large minority holding a Bachelor's degree or higher (47% in 'self' arm and 44% in 10-year old arm). This is in comparison to the Australian population where 26% of the labour force hold a Bachelor's degree or higher (29). About half of respondents lived in a household that earnt AUD1, 500 or more per week, this is comparable to the Australian median household income of AUD1,770 per week (30).

Table 3 Basic demographics

Basic demographics	'Self' arm No. (%)	'10-year-old' arm No. (%)	Population %
Gender			
Male	462 (49%)	431 (46%)	49%
Female	485 (50%)	515 (54%)	51%
Non-binary	4 (0%)	1 (0%)	
Prefer not to say	4 (0%)	N/A	
Age Group			
18-24	70 (7%)	82 (9%)	12%
25-39	244 (26%)	262 (28%)	28%
40-59	334 (35%)	321 (33%)	32%
60+	307 (32%)	282 (30%)	27%
State			
ACT	18 (2%)	20 (2%)	2%
NSW	272 (28%)	280 (30%)	31%
NT	3 (0%)	6 (1%)	1%
QLD	198 (21%)	195 (20%)	20%
SA	75 (8%)	67 (7%)	7%
TAS	22 (2%)	21 (2%)	2%
VIC	258 (27%)	247 (26%)	26%
WA	109 (11%)	111 (11%)	11%
Parental/caregiver status			
Yes	611 (63%)	592 (64%)	44%
No	344 (37%)	354 (36%)	56%
N/A		1 (0%)	

DCE choice task difficulty

Table 4 provides a summary of how respondents rated the DCE choice tasks. For the 'self' arm, some respondents found the DCE choice task difficult with 44% agreeing or strongly agreeing with the statement 'I found the choice task difficult'. However, 68% of respondents disagreed or strongly disagreed with the statement that they found it difficult to tell the difference between health states i.e. they did not find it difficult although some respondents (46%) agreed or strongly agreed that it was difficult to choose between health states.

In contrast to the 'self' arm, many more respondents in the '10-year-old' arm, found the DCE choice task difficult with 66% agreeing or strongly agreeing that 'I found the choice task difficult'. Similar to the 'self' arm, while most respondents did not find it difficult to tell the difference between health states (61%), it was difficult to choose between them (67%).

Chi-square tests were performed to test for differences by arm. It was found that respondents in the ’10-year-old’ arm were significantly more likely to find DCE choice tasks challenging across all 3 questions. They were more likely to find the choice tasks difficult ($p < 0.01$), found it more difficult to tell difference between health states ($p < 0.01$) and found it more difficult to choose between health states ($p < 0.01$).

Table 4 Ratings of DCE choice tasks

Rating (%)	Choice task difficult		Difficult to tell difference betwe health states		Difficult to choose between health state	
	‘Self' Arm	‘10-year-old' arm	‘Self' Arm	‘10-year-old' arm	‘Self' Arm	‘10-year-old' arm
Strongly agree	10%	25%	4%	4%	9%	21%
Agree	34%	42%	10%	16%	37%	46%
Neutral	19%	14%	18%	20%	20%	14%
Disagree	30%	16%	51%	48%	26%	16%
Strongly Disagree	8%	4%	18%	13%	8%	3%

Reported health and well-being

Most respondents described their own health as good or better than good, 74% in the ‘self’ arm and 77% in the ’10-year-old’ arm. Most respondents would also describe themselves as usually happy or very happy, 67% in the ‘self’ arm and 69% in the ’10-year-old’ arm.

Model results

Discount rates

The estimated discount rates are significant, indicating respondents exhibited nonlinear time preferences. For the ‘self’ arm, respondents and a discount rate of 17%; this was slightly lower at 15% in the ’10-year-old’ arm (see Table 5).

QALY estimates

In both arms, all QALY parameter estimates were significant at the 95% confidence level with no disordering of QALY decrements (see Table 5). This indicates that respondents had ordered preferences and would significantly prefer the baseline, i.e. level 1, compared to the more severe levels of 2-5 in each dimension.

Figure 4 provides a visual representation of QALY decrements. The dimension PD i.e. pain and discomfort, was most important to respondents in both arms. However, pain and discomfort was associated with higher QALY decrements when imagining a 10 year old versus self (i.e. yielding lower values in states considered for a 10 year old).

Table 5 QALY scale MXL parameter estimates

QALY parameter estimates	'Self' arm (N = 955)				'10-year-old' arm (N = 947)			
	Mean	SD	L95%CI	U95%CI	Mean	SD	L95%CI	U 95%CI
MO2	-0.06	0.01	-0.07	-0.04	-0.06	0.01	-0.08	-0.05
MO3	-0.09	0.01	-0.1	-0.07	-0.09	0.01	-0.11	-0.07
MO4	-0.22	0.01	-0.24	-0.19	-0.23	0.01	-0.25	-0.2
MO5	-0.43	0.02	-0.47	-0.39	-0.35	0.02	-0.39	-0.32
SC2	-0.05	0.01	-0.06	-0.04	-0.02	0.01	-0.04	-0.01
SC3	-0.07	0.01	-0.08	-0.05	-0.06	0.01	-0.08	-0.04
SC4	-0.2	0.01	-0.22	-0.18	-0.15	0.01	-0.17	-0.13
SC5	-0.41	0.02	-0.44	-0.37	-0.27	0.02	-0.3	-0.24
UA2	-0.03	0.01	-0.04	-0.01	-0.03	0.01	-0.05	-0.02
UA3	-0.06	0.01	-0.07	-0.04	-0.07	0.01	-0.09	-0.05
UA4	-0.16	0.01	-0.19	-0.14	-0.19	0.01	-0.21	-0.17
UA5	-0.3	0.01	-0.33	-0.27	-0.31	0.02	-0.35	-0.28
PD2	-0.05	0.01	-0.07	-0.04	-0.09	0.01	-0.11	-0.07
PD3	-0.09	0.01	-0.11	-0.08	-0.14	0.01	-0.16	-0.12
PD4	-0.29	0.01	-0.32	-0.26	-0.44	0.02	-0.49	-0.4
PD5	-0.58	0.03	-0.63	-0.53	-0.89	0.04	-0.98	-0.81
AD2	-0.06	0.01	-0.08	-0.05	-0.11	0.01	-0.13	-0.09
AD3	-0.17	0.01	-0.19	-0.15	-0.26	0.02	-0.3	-0.24
AD4	-0.24	0.01	-0.27	-0.21	-0.39	0.02	-0.43	-0.35
AD5	-0.39	0.02	-0.43	-0.35	-0.6	0.03	-0.66	-0.54
Discount rate	0.17	0.01	0.15	0.18	0.15	0.01	0.13	0.16
Log likelihood	-9982	109.3	-10200	-9768	-9813	119.4	-10040	-9576

After the dimension of pain and discomfort, feelings of worried, sad or unhappy (AD) were also relatively more important to respondents in both arms. It was noted that for the 'self' arm, a change from level 2 to 3 i.e. 'a little bit' to 'quite worried, sad or unhappy', had a higher utility decrement than changes from levels 2-3 on other dimensions. Respondents that were asked to imagine a 10-year-old generally had higher utility decrements when moving from level 3-5 (quite/really/extremely worried, sad or unhappy) compared to those that were asked to imagine themselves. Feelings of worried, sad or unhappy were seen as more serious for a 10-year-old when compared against the same feelings for respondents themselves.

Figure 4 Plot of HRQoL utility decrements

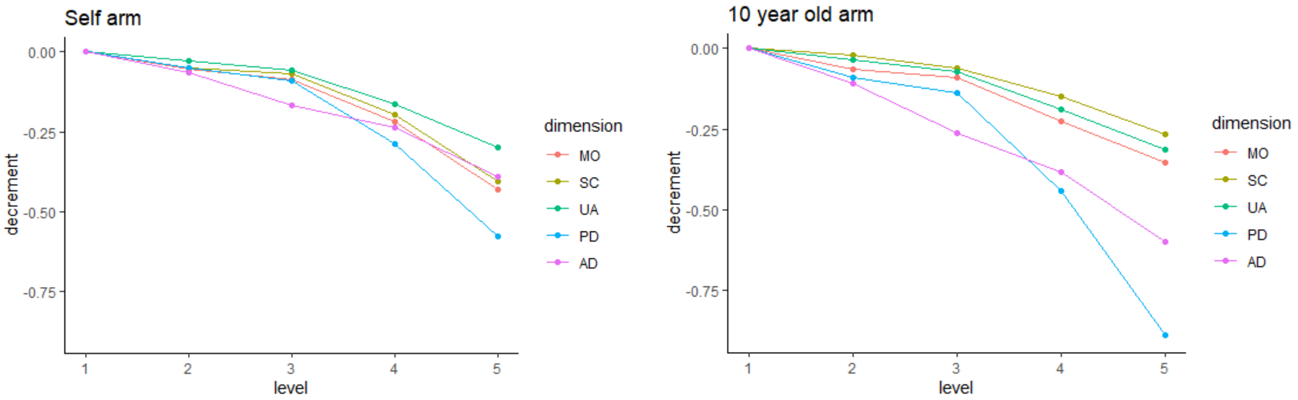


Table 6 Summary of health state utilities

State	'Self' Arm	'10-year-old' arm
11111	1.00	1.00
11211	0.97	0.97
22222	0.75	0.68
33333	0.53	0.38
44444	-0.11	-0.39
55555	-1.10	-1.42
% <0	26%	42%

Figure 5 Kernel density plot of health state utilities

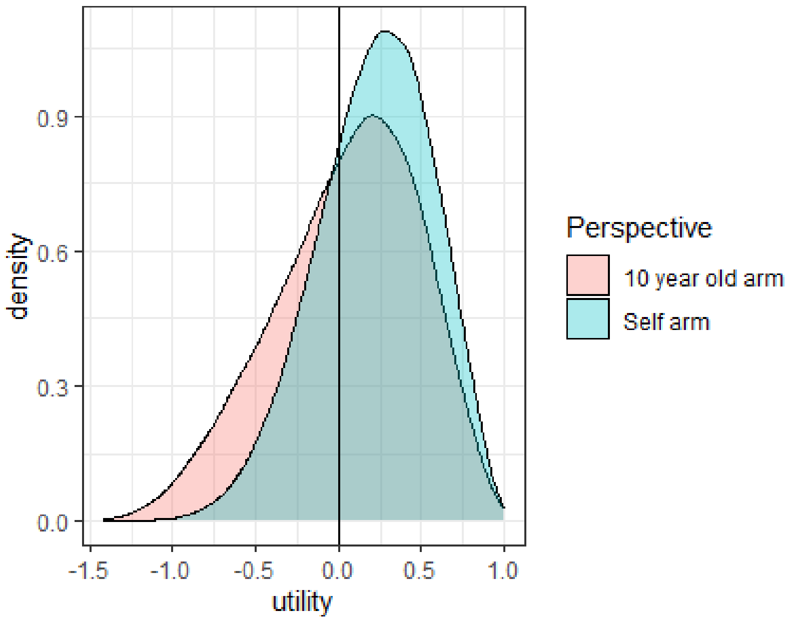
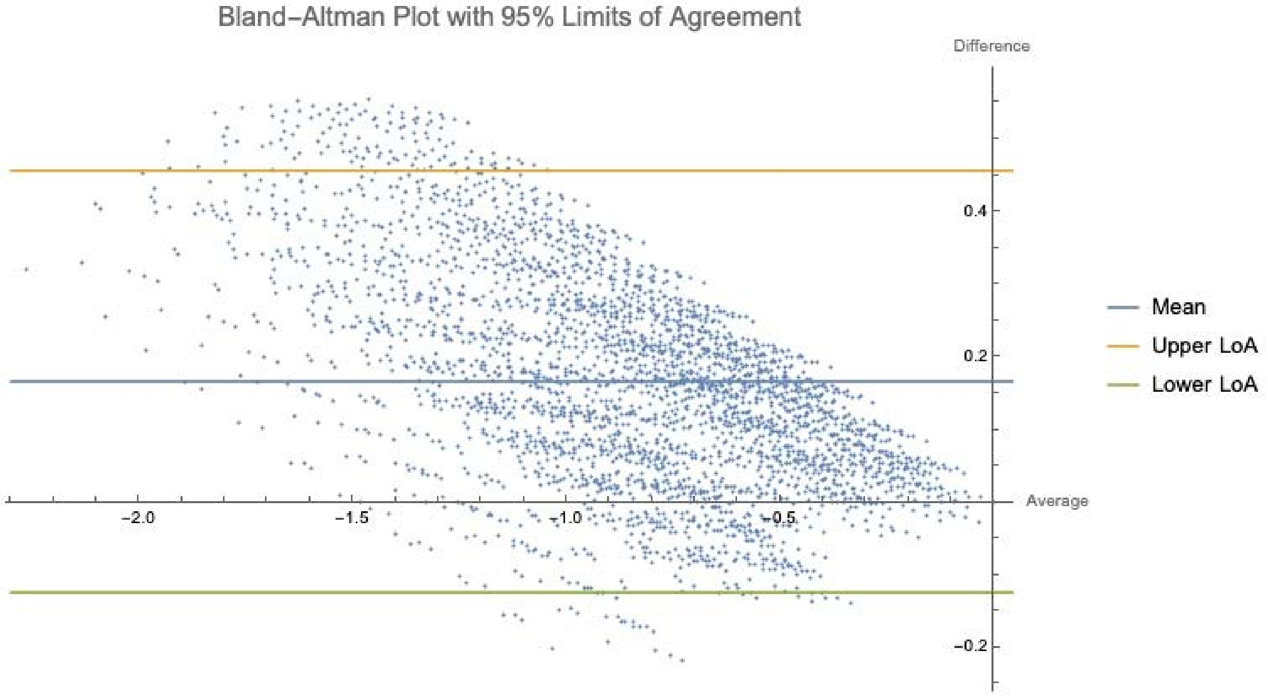


Table 6 provides some basic summary statistics of the calculated health state utilities from the QALY estimates, while Figure 5 provides a kernel density plot of the calculated health utilities. The worst state i.e. 55555, was lower for the 10-year-old child arm at -1.42 as opposed to -1.10 for the 'self' arm. It was also of note that more health states were valued as worse than dead when respondents were asked to imagine a 10-year-old (42%) compared to when they were asked to imagine themselves (26%). This is reflected in Figure 5 where a distinctly larger proportion of the curve is below 0 for the 10-year-old perspective.

Comparison of health state utilities

A Bland-Altman plot of the 3125 health state utilities was used to explore differences between the two arms, featured in Figure 6. A Bland-Altman plot can be used to compare two methods of measurement e.g. utility of health states from each of the arms (31). The difference in utility of each health state in the two arms is calculated and this difference is then plotted (vertical axis) against the average of the utility of each health state (horizontal axis) from the two arms. The mean of the differences is plotted in the middle and can be used as the reference line. Lines in Figure 6 are for the upper and lower 95% limits of agreement and the mean differences. As can be seen, the majority of the 3125 data points, representing the health state utilities, fall within the 95% limits of agreement, indicating acceptable agreement between the two arms in terms of measuring utility of health states. This suggests that the two arms are measuring utility in similar ways.

Figure 6 Bland-Altman plot with upper and lower 95% limits and the mean



There were 125 health states above the upper 95% limit of agreement. These health states all included level 5 of pain and discomfort followed by level 5 of feelings of worried, sad or unhappy in 84 out of 125 health states. 33 health states were below the 95% limit of agreement. 32/33 of these health states included level 5 of self-care (looking after myself) while 24/33 of these health states included level 5 of mobility.

Parents vs non-parent valuation of health states

There was an overrepresentation of parents/caregivers (over 60%) in both arms. Thus, sensitivity analysis was undertaken to see how results differ if arms are separated into respondents that identified as parents/caregivers versus respondents with no children (referred to as parents versus non-parents henceforth). Correlated MXL models were estimated separately for parents and non-parents in each arm. Key health state utilities, percentage of health states worse than dead and discount rate for each group have been summarised in Table 7.

Results were relatively similar for parents versus non-parents in the '10-year-old' arm. The greatest contrast is seen in results for the 'self' arm. The length of the utility scale for parents was much shorter compared to non-parents. This is also reflected in non-parents considering a higher number of health states to be worse than dead compared to parents in the 'self 'arm. This suggests that being a parent may not be a relevant factor in valuing a child's health but may be relevant when valuing your own health. Discount rates were significant at the 5% level for all four groups, indicating that both parents and non-parents discount time regardless of perspective.

Table 7 Summary of results by parents versus non-parents

Health state utility	'Self' arm		'10-year-old' arm	
	Parents (N= 611)	Non-parents (N = 344)	Parents (N= 592)	Non-parents (N = 354)
11111	1	1	1	1
11211	0.97	1.00	0.97	0.98
22222	0.77	0.75	0.68	0.73
33333	0.59	0.46	0.39	0.42
44444	0.00	-0.25	-0.37	-0.35
55555	-0.86	-1.48	-1.33	-1.48
%<0	17%	39%	39%	41%
Discount rate	24%	16%	20%	17%

Discussion

This is the first study to apply nonlinear DCE methods to the valuation of paediatric HRQoL. In this study, respondents were asked to imagine themselves or imagine a 10-year-old when completing EQ-5D-Y-5L valuation tasks. Respondents exhibited significant nonlinear preferences for time in both arms, indicating that respondents do perceive future years in health state as being less valuable than time now for themselves and when valuing health states on behalf of children/younger people. It was noted that the discount rate was similar between the two arms, suggesting that discounting of time is not that different when completing valuation tasks for themselves versus on behalf of a 10-year-old. Experience of pain and discomfort and feelings of worried, sad or unhappy were of much higher importance for a 10-year-old with less importance placed on other dimensions of mobility, self-care (looking after self) and usual activities. Most notably, respondents were much more sensitive to a 10-year-old experiencing worse health states, with many more health states considered worse than dead, compared to respondents that valued health states for themselves.

These results contrast with those from a recent study, also undertaken in Australia as part of the QUOKKA Research Program, looking at the impact of perspective on the valuation of the EQ-5D-Y-5L but using *linear* DCE methods with duration (see poster by Luo et al. at thi plenary, 16). Similar to the current study, respondents were split into arms where they were asked to imagine themselves or a 10-year-old when completing valuation tasks. Both an adult and adolescent sample were used. Results from that work shows comparatively shorter utility scales overall, regardless of perspective, compared to the current study. The worst health state (55555) was valued between -0.412 to -0.588, depending on assigned perspective and sample type. It was also noted that there were substantially fewer health states considered worse than death, 8% and 15% of health states in the adolescent '10-year-old' arm and adult '10-year-old' arm, respectively. This contrasts with 40% of health states considered worse than death in the '10-year-old' arm in this study. These differences could be due to how DCE choice task are presented and modelled. The linear DCE study uses DCE choice tasks with duration, where respondents are asked to choose between two health states at a time (A and B). Each health state is described by EQ-5D-Y-5L dimension levels that vary, but also have an additional duration attribute which can be different for health state A and B. This is different from how duration is presented to respondents in this study, where respondents are asked to compare health state B to full health for a shorter duration. Despite these differences, it was noted that consistent with this study, findings also found pain and discomfort to be the important dimension. Latent class analysis for the linear DCE study also revealed that there was a class of respondents, that completed the '10-year-old' perspective arm, that placed the most importance on dimensions pain and discomfort and feelings of worried, sad or unhappy (39% of 3 class model). This is consistent with findings in the current study of these two dimensions being most important to respondents for a 10-year-old.

There is also a stark contrast between the characteristics reported here for EQ-5D-Y-5L and the characteristics of value sets for the EQ-5D-Y-3L, produced using the EQ-VT protocol. EQ-5D-Y-3L values – produced using a combination of latent scale DCE and TTO – have tended to produce values for the worst health state much closer to 0 and the length of the value scale is therefore shorter. For instance, while the current study finds about 40% of health states were considered worse than dead in the '10-year-old' arm, this is in contrast to the Australian EQ-5D-Y-3L value set for Pan et al. (32) where *no* health states were considered worse than dead. Similarly, in the EQ-5D-Y-3L Brazilian value set (33), had only the worst health state (i.e. 33333) considered worse than dead, at -0.006. Our results also show the utility scale is also comparatively longer for the '10-year-old' arm, with the value for 55555 at -1.42. This contrasts with other recent EQ-5D-Y-3L value set such as in Hungary (34) where the value for the worst state i.e. 33333, was -0.485. and for China (35), where the value of 33333 was -0.089 for the model with the lowest mean absolute error.

These differences could be due to a number of factors. For this study and EQ-5D-Y-3L valuation studies, adults complete valuation tasks while imagining a 10-year old. However, the way duration is used to anchor value sets is different. The EQ-5D-Y-3L protocol uses cTTO to anchor value sets and nonlinear time preferences are not considered. cTTO produces 'direct' values and has a very different process to DCE choice tasks. In cTTO, respondents are asked directly whether they wish a 10-year-old child to die. This may keep the values of health states higher than when this question is not asked. There is evidence that the way in which health state valuation is framed can affect the proportion of health states considered better or worse than death. Jakubczyk et al. (36) note that comparisons to immediate death reduces the number of health states considered worse than death, while comparisons in terms of prolonging life in a given health state increases it. Type of DCE task shown to respondents also differs. The EQ-5D-Y-3L protocol requires respondents to complete DCE choice tasks without duration, whereas this study uses the format of DCE choice tasks with full health. Despite these differences, it was noted that consistently, across this study and the EQ-5D-Y-3L valuation studies mentioned, pain and discomfort was found to be the most important dimension.

There are some limitations to note for this study. In the 'self' arm, about 24% of respondents over the 4 rounds of data collection were accidently included even though they did not pass 1 of the quality checks. These may have inadvertently affected the DCE choice task updates and ultimately on the obtained results. As such, results from the 'self' arm should be interpreted with a degree of caution, even though these respondents did pass the other two quality checks. A further limitation is that the VAS traffic light task may not be intuitive to all respondents and hence may be considered a very conservative (strict) quality control task. It was included in this study to address quality issues with data during the initial recruitment and data collection. In future valuation studies for paediatric HRQoL instruments this quality control task may not be necessary or may be modified or replaced by other measures to ensure respondents are truly engaged.

The proportion of respondents who identified as parents/caregivers in this sample was also higher than would be expected in the Australian adult population. This may be due to the nature of the study or of those who choose to participate in survey panels. Sensitivity analysis conducted suggests that parents and non-parents provide similar valuations for a 10-year-old.

It is also important to be cautious in interpretation of the discount rate. There is some evidence to suggest that the discount rate does not only capture time preferences but also some forms of heteroskedasticity, as the error term is assumed to be similar in size between choice tasks with different durations, which may not be realistic. In addition, the time preferences exhibited may be influenced by the nature of the task (choosing durations of survival) and by the range of durations presented.

The contrast in findings between the current study and EQ-5D-Y-3L valuation studies represents a challenge users and decision makers choosing which value sets should be used in policy settings, and sensitivity analysis across value sets may be required in evaluation of new technologies or in comparisons of population health. This study demonstrated that nonlinear DCE modelling methods produce utility decrements that are consistent across dimensions/levels. This suggests respondents are readily able to understand and differentiate between EQ-5D-Y-5L level labels. Consistency was also noted in terms of pain and discomfort being the most important dimension to respondents when comparing study results with those of other EQ-5D-Y value sets. This suggests that despite differences in methods, what is most important to respondents is still being reflected in results. These findings will be valuable in informing a valuation protocol for the EQ-5D-Y-5L.

This study provides evidence that nonlinear methods are feasible to be used for the valuation of paediatric HRQoL, and also that respondents do have nonlinear time preferences when valuing paediatric health states for the EQ-5D-Y-5L. Future studies could investigate whether this finding generalises to valuation of other paediatric HRQoL instruments.

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Appendix A Panel provider and data quality issues

Pure Profile was the panel provider that was ultimately used for recruitment. This was after significant quality issues and delays from the use of panel provider, Cint. There were concerns about data quality issues after the analysis of the first 200 respondents. It was found that while the conditional logit model was able to run, extreme scaling was noted when running MXL models e.g. values of around -4 for state 55555. Strange patterns were also noted in the data. A third of respondents always chose health state C when choosing between health state B and C i.e. flatliners. This could be valid preferences by respondents however, it was noted that 80% of flatliners were from computer/tablet device users while 20% were from mobile device users. This is a large proportion considering a third of respondents were mobile device users.

As a result, more stringent data quality checks were put in place (see description of quality checks). Cint also increased their internal quality criteria to the highest level for recruitment. The next 200 respondents were recruited, but this took 3 weeks to collect. Estimation of the MXL model was still problematic based on the new set of data. It was also not considered feasible in terms of timelines for collection of 2000 respondents in total if the collection of 200 respondents were to take 3 weeks.

The lack of confidence in data collected led the team to the decision to terminate recruitment with Cint and move to a new panel provider. Pure Profile was chosen and results from the first 200 respondents proved to be fruitful. The MXL model was showing reasonable estimations. Recruitment time was also much more reasonable for 200 respondents, taking a couple of days to recruit as opposed to weeks.

Appendix B Correlated MXL Model Raw Parameter Estimates

Raw Parameter Estimates	Self' arm (N = 955)				10-year-old' arm (N = 947)			
	Mean	SD	L95%CI	U95%CI	Mean	SD	L95%CI	U95%CI
Full Health	1.95	0.1	1.76	2.14	1.56	0.08	1.39	1.72
MO2xFull Health	-0.11	0.01	-0.14	-0.08	-0.1	0.01	-0.12	-0.07
MO3xFull Health	-0.17	0.02	-0.2	-0.14	-0.14	0.01	-0.17	-0.11
MO4xFull Health	-0.42	0.02	-0.47	-0.38	-0.35	0.02	-0.39	-0.31
MO5xFull Health	-0.84	0.03	-0.91	-0.77	-0.55	0.02	-0.6	-0.5
SC2xFull Health	-0.1	0.01	-0.12	-0.07	-0.03	0.01	-0.06	-0.01
SC3xFull Health	-0.13	0.01	-0.16	-0.1	-0.09	0.01	-0.12	-0.07
SC4xFull Health	-0.39	0.02	-0.43	-0.35	-0.23	0.02	-0.26	-0.2
SC5xFull Health	-0.79	0.03	-0.85	-0.73	-0.41	0.02	-0.45	-0.37
UA2xFull Health	-0.05	0.01	-0.08	-0.03	-0.05	0.01	-0.08	-0.03
UA3xFull Health	-0.11	0.01	-0.14	-0.08	-0.11	0.01	-0.14	-0.08
UA4xFull Health	-0.32	0.02	-0.36	-0.28	-0.29	0.02	-0.33	-0.26
UA5xFull Health	-0.58	0.03	-0.63	-0.53	-0.49	0.02	-0.53	-0.45
PD2xFull Health	-0.1	0.01	-0.13	-0.07	-0.14	0.01	-0.16	-0.11
PD3xFull Health	-0.18	0.02	-0.21	-0.15	-0.21	0.02	-0.24	-0.18
PD4xFull Health	-0.56	0.03	-0.61	-0.51	-0.69	0.03	-0.75	-0.63
PD5xFull Health	-1.13	0.04	-1.22	-1.04	-1.38	0.06	-1.49	-1.28
AD2xFull Health	-0.12	0.01	-0.15	-0.09	-0.17	0.01	-0.2	-0.14
AD3xFull Health	-0.32	0.02	-0.36	-0.29	-0.41	0.02	-0.45	-0.37
AD4xFull Health	-0.46	0.02	-0.51	-0.42	-0.6	0.03	-0.65	-0.55
AD5xFull Health	-0.76	0.03	-0.83	-0.69	-0.93	0.04	-1.01	-0.85
Discount rate	0.17	0.01	0.15	0.18	0.15	0.01	0.13	0.16
Log likelihood	-9982	109.3	-10200	-9768	-9813	119.4	-10040	-9576