Pan *et al. Health and Quality of Life Outcomes* (2025) 23:72
https://doi.org/10.1186/s12955-025-02402-x

Health and Quality of Life Outcomes

RESEARCH Open Access

An Australian Value Set for the EQ-5D-Y-3L

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Abstract

Background Australia has a well-established health technology assessment process and there is extensive use of generic health related quality of life (HRQoL) instruments in evidence presented to it. However, there are gaps in tools and evidence available to support evaluation of paediatric health. The aim of this paper is to produce an Australian EQ-5D-Y-3L (Y-3L) value set.

Methods The methods follow the international Y-3L valuation protocol, but with an expanded design. Data were collected using Composite Time Trade Off (cTTO) and Discrete Choice Experiment (DCE) data from two independent samples of adult members of the Australian general public. In total, 52 Y-3L health states, assigned into four blocks of 14 health states each containing health state 33333, were valued using cTTO. cTTO data were collected via videoconferencing interview and each respondent valued 14 health states. Mean observed cTTO values were adjusted for censoring at -1 using a Tobit model. For the DCE component, 150 latent scale DCE choice pairs were collected via an online survey with each participant completing 15 pairs. DCE data were modelled using a garbage class mixed logit model. Two approaches to anchor DCE data to the Quality Adjusted Life Years (QALYs) scale were explored: anchoring on the value for the worst health state (33333); and mapping DCE data onto the mean cTTO values using all 52 health states. Two evaluation criteria were used to select the final value set: (1) coefficient significance and logical consistency; (2) prediction accuracy of the mean observed cTTO values.

Results In total, 268 individuals participated in the cTTO interviews, and 1002 completed the DCE. The linear mapping without intercept performed best and was selected as the final value set. Health state values ranged between 0.142 and 1. The relative importance of domains by level 3 coefficients (ordered from most to least important) was: pain/discomfort, then feeling worried, sad or unhappy, usual activities, looking after myself, and mobility.

Conclusion This study reports an Australian value set for the Y-3L, which enables the calculation of QALYs for use in the economic evaluation of paediatric interventions and can support evidence development and decision making.

Key points

Employing the international EQ-5D-Y-3L (Y-3L) valuation protocol, this study developed an Australian Y-3 L value set, which enables the calculation of QALYs for use in the economic evaluation of paediatric interventions and can support evidence development and decision making.

Pain/discomfort was considered as the most important domain, followed by feeling worried, sad or unhappy, usual activities, looking after myself, and mobility.

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In the value set, the worst health state is valued as being better than being dead, which is not the case for most other Y-3L value sets and adult EQ-5D-3L value sets. This reflects the unwillingness of adults to trade off life years in cTTO when considering children's health states.

Keywords EQ-5D-Y-3L, EQ-5D-Y, Value set, utilities, Australia, Paediatrics, preferences, time Trade-Off, Discrete choice experiment

Introduction

Many Health Technology Assessment (HTA) organisations prefer economic evaluations reporting incremental cost per Quality-Adjusted Life Year (QALY) [1–3], including Australia's Pharmaceutical Benefits Advisory Committee [3]. Instruments exist to measure health-related quality of life (HRQoL) in children [4, 5], and there is growing evidence on the psychometric performance of these instruments [6–9]. However, until recently, there was little evidence providing preference weights for paediatric HRQoL required to allow estimation of QALYs. In the absence of these preference weights, decisions around paediatric interventions are being made with sub-optimal evidence, potentially leading to barriers to funding for high-quality services in these younger age groups [10].

For adults, the most widely used measure of HRQoL used to support QALY estimation is the EQ-5D [11, 12], including EQ-5D-3L [13] and EQ-5D-5L [14]. The EQ-5D-Y-3L (Y-3L) was adapted from the EQ-5D-3L for use in children [4]. A protocol for valuing Y-3L health states is available [15]. Adoption of this protocol has been rapid [16], illustrating the demand for paediatric HRQoL values in HTA.

There are numerous methodological challenges in valuing paediatric HRQoL [17, 18]. The Y-3L valuation protocol elicits preferences from a sample of adults from the general population and ask them to value Y-3L health states considering a hypothetical 10-year-old child. It uses a two-step approach using two valuation methods via two independent surveys and samples. A discrete choice experiment (DCE) is the key method to determine relative importance of dimensions and levels. The composite time trade-off (cTTO) is then used to anchor the latent scale DCE results to a dead = 0 and full health = 1 scale to be used to construct QALYs. The protocol suggests the use of ten health states in the overall cTTO design as the minimum requirement.

While the protocol reflected an important step forward in valuing the Y-3L, a number of issues require further exploration. Results from published Y-3L valuation studies show that the DCE is working well as the key valuation method to determine the preferences for dimensions and levels [16]. However, the optimal way to anchor DCE values on the QALY scale remains unclear. Solutions include introducing an attribute in DCEs (such as time or risk of death) which can be used as a numeraire to allow direct anchoring on to the 0–1 scale, or using data obtained from other methods to anchor the DCE data. If we are to adopt the standard valuation approach for the EQ-5D-Y-3L, using cTTO as that external anchor, then strengthening the cTTO design has been identified as the first step [16]. In this study, we address this by using an expanded cTTO design, as described below.

The current study aimed to develop an Australian value set for the Y-3L based on preferences of the general adult population.

Methods

General approach

Our study mostly follows the Y-3L international valuation protocol [15]. We elicited preferences from a sample of adults from the general population in Australia. Respondents were asked to value Y-3L health states considering their views about a hypothetical 10-year-old child.

To ensure completeness in reporting, we followed the RETRIEVE checklist for reporting the elicitation of stated preferences for child health related quality of life [19] (reported in the electronic supplementary material (ESM) 1). The study was approved by Curtin University Human Research Ethics Committee (approval number HRE2021-0723).

The instrument

The official Australian (English) Y-3L instrument was used. The Y-3L descriptive system comprises five dimensions: mobility (walking about) [MO], looking after myself (washing or dressing) [SC], doing usual activities (going to school, hobbies, sports, playing, doing things with family or friends) [UA], having pain or discomfort [PD], and feeling worried, sad or unhappy [WSU]. Each dimension has 3 levels: (level 1 = no problems/no pain or discomfort/ not worried, sad or unhappy; level 2 = some problems/some pain or discomfort/a bit worried, sad or unhappy; and level 3 = a lot of problems/a lot of pain or discomfort/very worried, sad or unhappy) [20]. The health state measured by the Y-3L descriptive system can be summarized using a five-digit string, with each digit being the levels in the dimension order presented in the questionnaire. The best health state is therefore 11111 with the worst being 33333.

Valuation methods

The DCE task used pairwise comparisons, with each choice pair including two health profiles defined by the Y-3L descriptive system. The respondent was asked to consider which of two health states, A and B, they preferred for a hypothetical 10-year-old child. The duration of life in each health state was not included. The DCE design was D-efficient and consisted of 150 DCE pairs separated across ten blocks of 15 choices tasks per respondent. A target sample size of 1000 participants was followed, as suggested in the protocol [15].

The cTTO tasks comprised a traditional TTO to derive values for states considered better than dead and a lead-time TTO for states which were considered worse than dead. The respondent was asked to select between two lives for a hypothetical 10-year-old child, A and B, or they could state that they are indifferent. For health states considered as being better than dead, life A was a number between 0 and 10 of life-years in full health and life B was 10 years in a specific Y-3L state. The length of life in Life A was varied until the respondent stated they were indifferent. For health states that were considered as worse than dead, life A still equalled a number between 0 and 10 of life-years in full health whereas life B referred to 10 years in full health followed by 10 years in a Y-3L state. Detailed information on the composite TTO has been described elsewhere [21, 22]. The cTTO produces health state values on a scale between −1 and 1. After completing all the cTTO tasks, respondents were given the opportunity to review their responses, and to flag responses they felt should be reconsidered in the Feedback Module. Details about the feedback module can be found elsewhere [23].

We used an expanded cTTO design of 52 health states, including 50 health states obtained from an orthogonal array [24], and two additional states (i.e., the worst state '33333' and one intermediate state '22222'). The orthogonal array included 10 states with a level sum score (LSS) of 7 and 9 respectively, and 30 states with a LSS of 11. The 52 states were assigned into four blocks of 14 health states, with the state 33333 included in each block and state 22222 included in two of the four blocks. We have provided the distribution of the 52 health states by block in Table S1 in ESM2.

As we included a larger number of states than required by the protocol, we estimated that 70 observations per state would be needed, and we estimated the sample size of respondents required to be 260. Details on sample size calculation is provided in ESM2.

Sampling and data collection

The target sample size for the DCE and cTTO survey was 1000 respondents and 260 respondents respectively. Members of the general population (aged 18 years or above) who provided informed consent were included. For the DCE survey, participants were recruited through a market research company (Survey Engine) to complete DCE tasks online through self-completion. Participants were randomly assigned to one of the ten blocks. Quota-based sampling on sex, age, and whether the respondent had ever been a parent was applied. The DCE survey took place between Dec 2021 and Jan 2022.

For the cTTO interviews, respondents were recruited by another market research agency (CRNRSTONE). We used 'soft' quotas for age, sex and education– that is, we monitored recruitment continuously in an attempt to achieve a sample which broadly approximated the composition of the adult Australian population, according to census data, as much as possible. Interviewers talked with the respondents through videoconferencing software, sharing their screens to show respondents the tasks to be completed. Studies have demonstrated equivalence in TTO values between in person and online face-to-face interviews [25, 26]. Participants were randomly assigned to one of the four blocks. Detailed information on cTTO survey procedure was reported in ESM2. The cTTO data were collected by three interviewers using the EQ-VT platform between February and May 2023.

Quality control

The DCE tasks followed the design used in the protocol [15]. We did not add repeated pairs or logically dominant pairs in the tasks as Jonker et al. [27] found that these were unreliable screening tests and poor indicators of response quality. Instead, we applied a garbage class mixed logit model (described below) to identify and account for the respondents with low data quality in DCE [28]. Details are provided in Sect. 2.6.

Standard quality control (QC) processes established by the EuroQol Group were used to evaluate the cTTO interviewers' compliance with the protocol and interviewer effects [29]. Detailed information of the QC process and criteria are reported in ESM2.

Data analysis

All data analyses were performed using Stata (Version 14.2 MP; StataCorp). We reported the descriptive statistics of the respondents' sociodemographic characteristics for the DCE and cTTO samples respectively.

We modelled the latent scale DCE data using a garbage class mixed-logit model (MIXL) with a linear, additive utility function, with 10 dummy variables representing the two levels beyond level 1 (i.e. level 2 and level 3) for each of the five dimensions. We allowed for correlation between the estimated parameters of the variance-covariance matrix. Garbage class models have been used in latent class logit models to identify respondents with low data quality [30]. Recently, researchers have included a

garbage class in the MIXL which estimates the garbage class share, also providing an estimate of the number of low-quality respondents, and accounts for the influences of low quality responses [28]. The garbage class MIXL was estimated using Bayesian methods. The relative importance of dimensions was determined by the size of the level 3 coefficients. As mentioned above, we did not exclude any respondents or responses from the analysis of DCE data.

Mean observed cTTO values were adjusted for censoring at -1 using a Tobit model, given that the cTTO task does not allow for utilities below −1. No respondents were excluded from the analysis of cTTO data. We did not exclude non-traders (i.e., those who valued all health states = 1) as it could reflect true preferences. However, following literature [31], responses flagged by respondents in the feedback module during cTTO interviews were excluded from the cTTO data analysis. These states were flagged by respondents as those they felt needed reconsideration, but the states were not re-valued.

We explored two methods to anchor the DCE data to the QALY scale: (1) anchoring using the worst health state, where we rescaled the DCE model coefficients by the ratio of the mean cTTO value for 33333 to the predicted DCE value for 33333; (2) mapping by modelling the relationship between predicted DCE values and mean observed cTTO values for the 52 health states included in the cTTO design. We explored linear mapping with and without specifying an intercept.

Two criteria were used to select the best anchoring approach and final value set, including logical consistency, prediction accuracy (R-squared, mean absolute error (MAE) and root mean square error (RMSE) for the 52 health states included in the cTTO design and mild health states.

Table 1 Sample characteristics

	DCE *N* = 1002	cTTO *N* = 268	2021 census
Age			
18–29 years	215 (21.5%)	19 (7.1%)	17.8%
30–39 years	185 (18.5%)	54 (20.2%)	19.7%
40–49 years	174 (17.4%)	59 (22%)	17.1%
50–59 years	155 (15.5%)	49 (18.3%)	16.4%
60–69 years	151 (15.1%)	49 (18.3%)	14.3%
70 + years	122 (12.2%)	38 (14.2%)	16.2%
Gender			
Male	481 (48%)	138 (51.5%)	50.7%
Female	516 (51.5%)	130 (48.5%)	49.3%
Diverse	3 (0.3%)		
Prefer not to say	2 (0.2%)		
Have/Ever had children			
Yes	638 (63.7%)	180 (67.2%)	NA
No	364 (36.3%)	88 (32.8%)	
Country of Birth			
Australia	811 (80.9%)	187 (69.8%)	70.9%
Other English speaking countries	103 (10.3%)	40 (14.9%)	29.1%
Non- English speaking countries	88 (8.8%)	41 (15.3%)	
Education			
Years 11 or below	165 (16.5%)	9 (3.4%)	24.2%
Year 12	209 (20.9%)	21 (7.8%)	15.2%
Trade certificate	136 (13.6%)	49 (18.3%)	5.9%
Diploma	136 (13.6%)	53 (19.8%)	15.5%
Bachelor's degree	264 (26.3%)	91 (34%)	15.3%
Higher degree	92 (9.2%)	45 (16.8%)	6.3%

DCE: discrete choice experiment; TTO: Time Trade Off

* Population norms sourced from Australian Bureau of Statistics (ABS)

https://www.abs.gov.au/statistics/people/population

https://www.abs.gov.au/statistics/people/education/education-and-training-census/2021

Results

Sample characteristics

1002 respondents completed the DCE survey, and 268 completed the cTTO interview. Table 1 reports sociodemographic characteristics for both samples. The DCE sample is similar to the Australian general population in terms of age, gender, and education, but overrepresented respondents born in Australia. The cTTO sample underrepresented respondents aged under 30, and lower educated respondents.

cTTO data

The 268 respondents provided 3752 cTTO observations. Among them, 10 respondents were identified as non-traders. In the feedback module, 685 (18.3%) responses were flagged by the respondents that they felt did not represent their preferences. Figure 1 reports the distribution of cTTO responses.

Among the remaining 3067 responses (after excluding the flagged responses), 197 (6.4%) were negative values. The raw mean observed cTTO values of the 52 health states ranged from 0.099 for state 33333 to 0.933 for state 12211. Figure 2 shows the mean observed value (raw data and data adjusted for censoring at -1); The means and standard deviations of the 52 states are reported in Table S2 in ESM2.

DCE model results

Table 2 reports the modelling results of DCE data from the garbage class MIXL and rescaled coefficients after anchoring of these on to the QALY scale. All the coefficients were negative and monotonically ordered by problem level. Based on level 3 coefficients, PD received the largest weight, followed by WSU, UA, SC and MO.

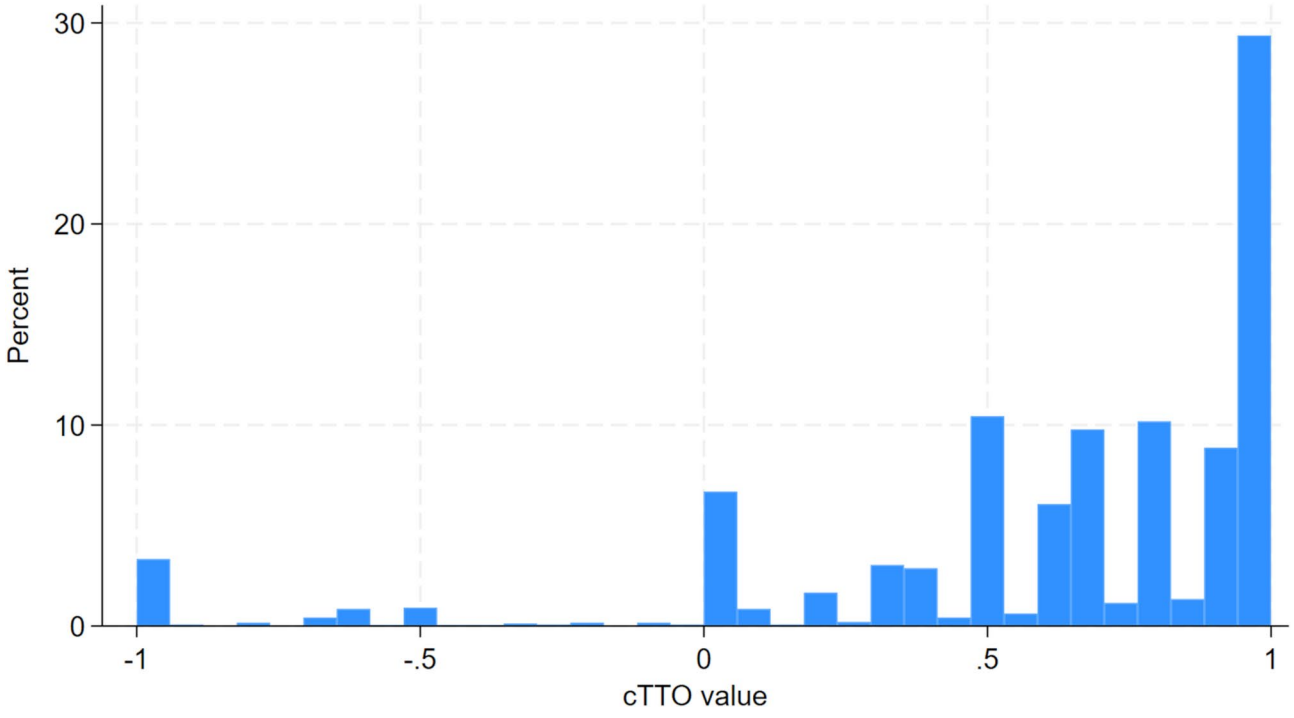

Fig. 1 cTTO value distribution. Figure legend: Distribution of all cTTO responses over the range of possible values (raw observed data without excluding flagged responses and censoring). cTTO: composite Time Trade Off

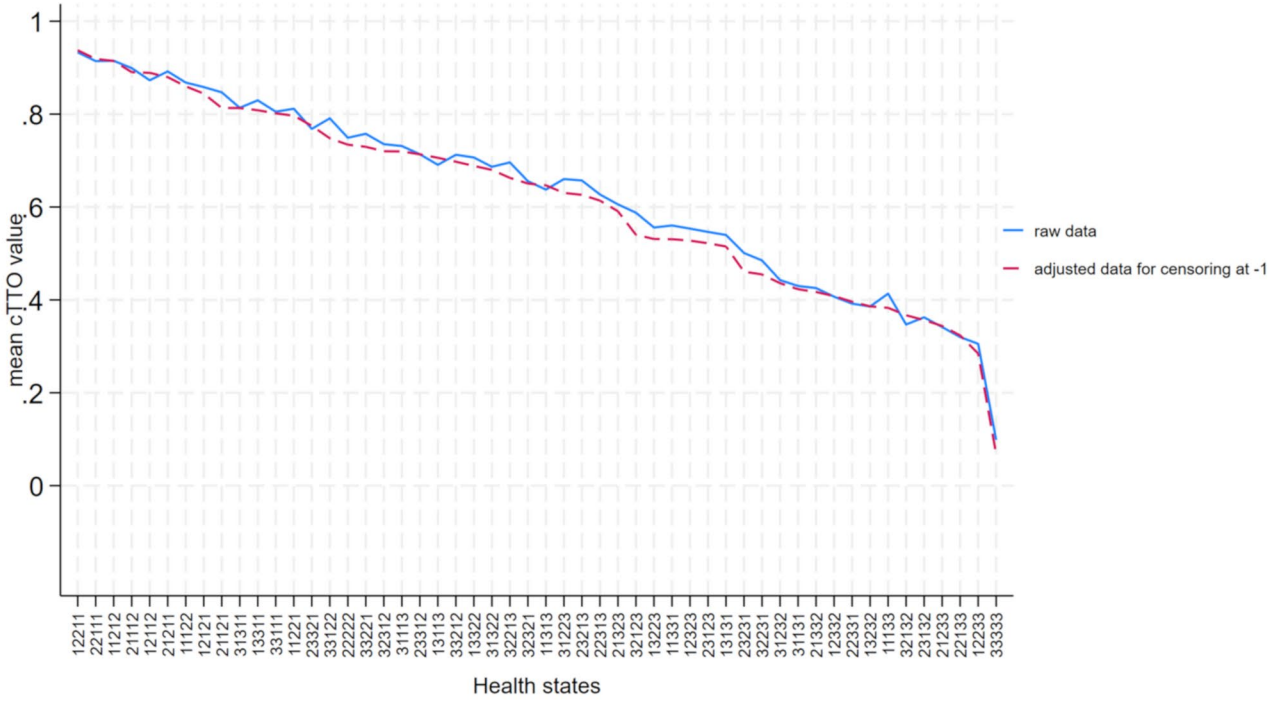

Fig. 2 Mean observed cTTO value (raw data and data adjusted for censoring at -1) of the 52 health states included in cTTO design. Figure legend: Mean observed value (raw data and adjusted data for censoring at -1) for the 52 states included in the cTTO design. cTTO: composite Time Trade Off

Table 2 Modelling results of DCE data using garbage class mixed logit model

Level	Coefficients	SD	Rescaled final value set
MO2	-0.447 ***	1.099***	-0.025
MO3	-1.279***	1.969***	-0.071
SC2	-0.409***	0.807***	-0.023
SC3	-1.422***	1.316***	-0.079
UA2	-0.936***	0.348***	-0.052
UA3	-2.615***	0.920***	-0.146
PD2	-2.211***	0.889***	-0.123
PD3	-5.339***	1.674***	-0.298
WSU2	-1.731***	0.936***	-0.097
WSU3	-4.730***	2.245***	-0.264
Garbage class share	35.4%		

DCE: discrete choice experiment. SD: standard deviation. MO: Mobility. SC: Self-care. UA: usual activity. PD: Pain/discomfort. WSU: worried, sad, unhappy.

The rows represent the coefficient level dimensions (e.g. MO2 represents mobility level 2)

Coefficients estimated from the garbage class mixed logit model. We allowed for correlation between the estimated parameters of the variance-covariance matrix.

*** indicates significance at the 1% level

Rescaling factor: 0.0558, based on linear mappings without constant

Table 3 Estimation results for different anchoring approaches

	Rescaling on mean value state 33333	Linear mapping	Linear mapping (no constant)
Intercept	0.0606	-0.0257	
Coefficient	-	0.0589	0.0558
R-squared	-	0.8392	0.9653
Root MSE	0.0885	0.0808	0.0807
MAE (means 52 states)	0.0703	0.0645	0.0656
MAE (mild states)	0.0342	0.0386	0.0328
Value (22222)	0.653	0.688	0.680
Value (33333)	0.068	0.119	0.142

MSE mean square error. MAE mean absolute error.

MAEs are calculated on the mean cTTO values for the 52 health states in the health state design and the means for 25 mild health states included in our study, which have a level sum score of 7

Anchoring and final value set

Table 3 reports the model and performance results from the different anchoring approaches used. Figure 3 shows the relationship between predicted DCE values and mean cTTO values for these different anchoring approaches.

Directly rescaling on the value for the worst health state (33333) resulted in larger MAEs and RMSEs than those from mapping. The linear mapping (without a constant) produced the highest R-squared; it showed marginally higher MAEs and RMSEs for the mean values of the 52 health states, but a smaller MAEs for mild states. Milder health states are more prevalent in the general population and patient groups, therefore precise estimation of values for milder health states was considered more important compared to values for the less common very severe states. Therefore, we recommend the linear mapping without a constant for the Australian Y-3L value set. This means that the coefficients of the garbage class MIXL were multiplied by 0.0558. The utility decrements of the final value set are provided in the final column of Table 2, and the model is represented as:

$U(HS) = 1 - 0.025 * MO2 - 0.071 * MO3 - 0.023 * SC2 - 0.079 * SC3 - 0.052 * UA2 - 0.146 * UA3 - 0.123 * PD2 - 0.298 * PD3 - 0.097 * WSU2 - 0.264 * WSU3.$

To illustrate, the value of health state 12321 would be: $Value = 1 - 0.023 - 0.146 - 0.123 = 0.708$.

For the preferred value set, values for Y-3L health states ranged from 0.142 (33333) to 1 (11111), with the value of 0.188 for the second worst health state (23333) and 0.977 for the mildest impaired state (12111). Figure 4 shows the distribution of values.

Discussion

The study reports an Australian value set for the Y-3L, allowing use of the instrument in both Australian cost-utility analysis, and other applications where health state values might support the use of Y-3L in decision making and evidence development regarding paediatric health care.

The value set notably has a narrower range of values than those from the Australian adult EQ-5D-3L value set [32, 33]. The implication is that, all other things being equal, cost-utility analysis performed using this value set will produce relatively high estimates of QALY gains from interventions that extend child survival, and relatively low estimates of QALY gains for interventions that improve HRQOL, compared to adults. The Australian adult EQ-5D-3L value set developed using solely a Time-Trade Off reported a minimum value of −0.217 [32], while a DCE-only study reported a minimum value of −0.516 [33]. However, direct comparisons between these ranges from adult and paediatric value sets are difficult, because of different valuation methods used, differences in the health states described by adult EQ-5D-3L and Y-3L, and different perspective being adopted in the valuation tasks [34].

Potentially, a more interesting comparison is with Y-3L value sets in other countries, conducted using the same instrument and similar valuation methods [16, 35]. Our dimension importance ordering appears more similar to countries such as Germany, the Netherlands and Belgium, in which PD, WSU and UA are most highly valued [36–38]. However, the scale length of the value set appears closer to Japan, China and Indonesia, which tended to have no or much fewer health states valued below 0 [39–41]. The shorter range for the value set reflects adults' relative unwillingness to trade time for improved health in children in TTO tasks [42, 43]. This

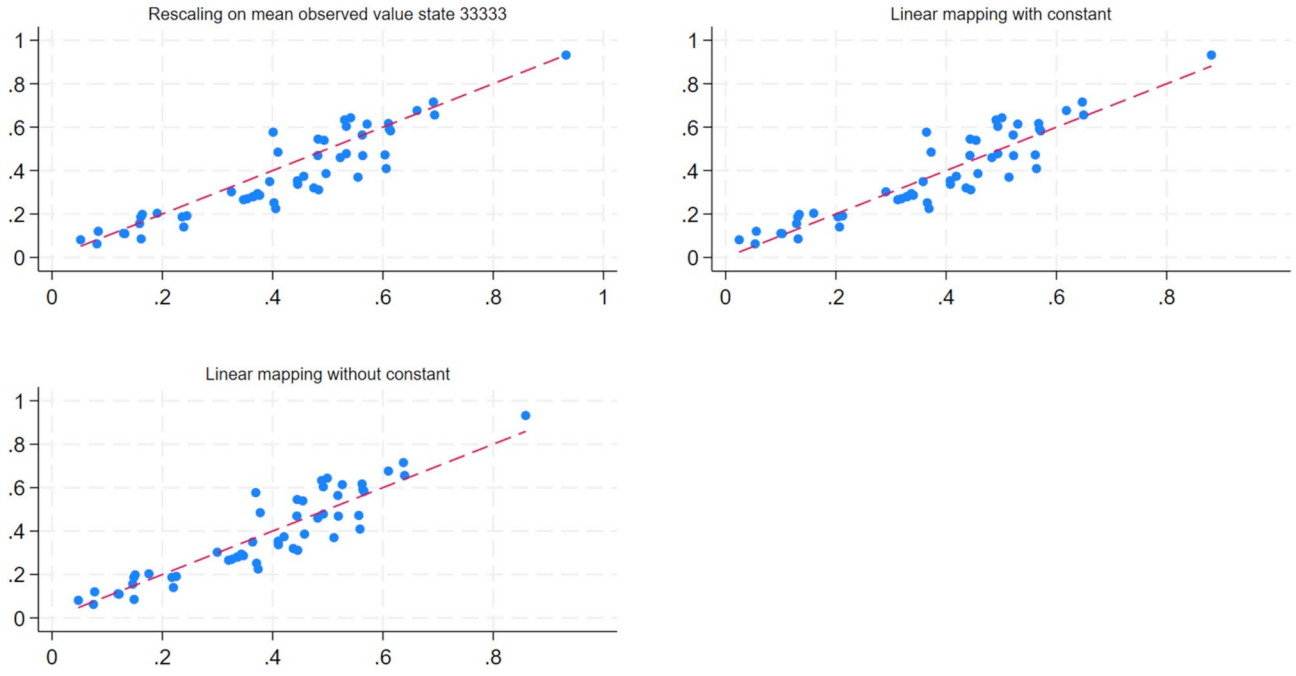

Fig. 3 Predicted DCE values and mean observed cTTO values (disutility, 52 states), from different anchoring approaches. Figure legend: Scatter plots for the predicted DCE values (x-axis) and the mean observed cTTO values (y-axis) for the 52 health states included in the health state design, for different anchoring strategies. cTTO: composite Time Trade Off. DCE: DCE: discrete choice experiment

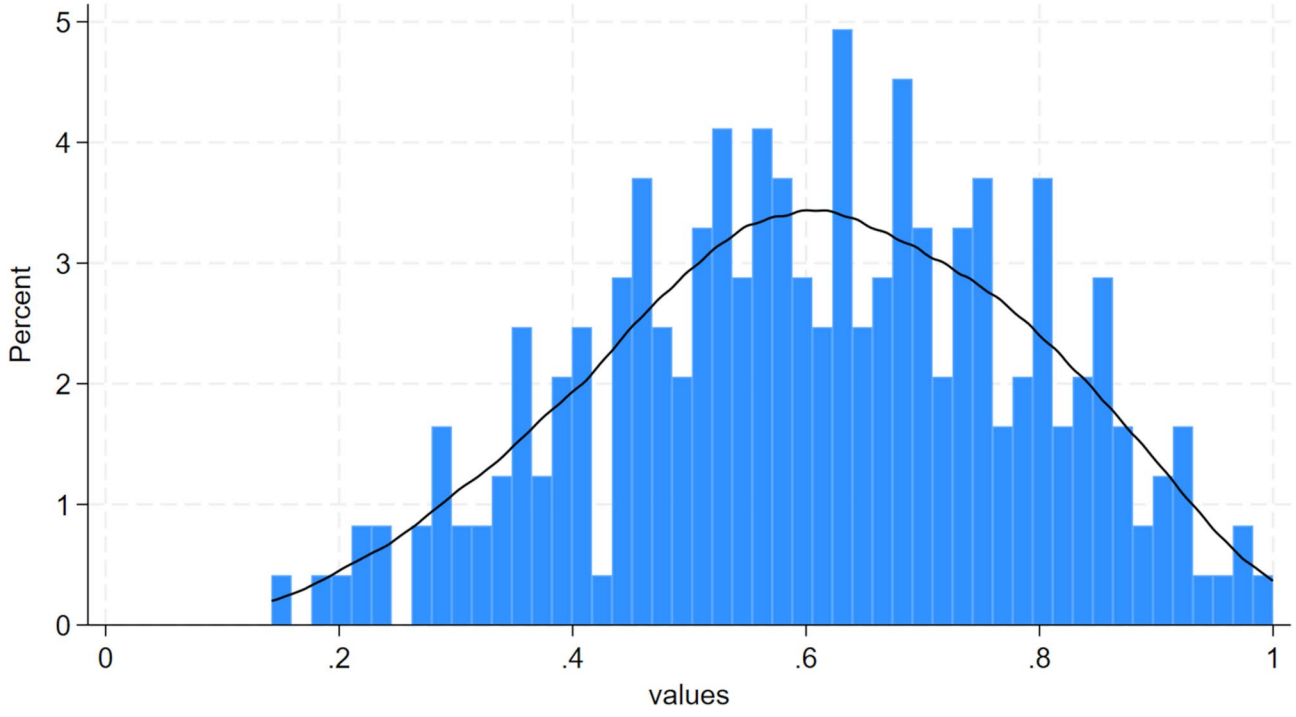

Fig. 4 Distribution of the Australian EQ-5D-Y-3L value set. Figure legend: Distribution of the Australian EQ-5D-Y-3L value set

pattern is reasonable, but might lead to a situation where the importance of child HRQoL is obscured [34].

The value set we report is based on an adult sample valuing health given their views about a 10-year-old child, which contrasts with the approach for valuing adult instruments where respondents answer on their own behalf. While this is in alignment with the valuation protocol for the Y-3L [15], it entails value judgements which

decision makers may reject. For example, some decision makers may prefer values to be based on the stated preferences of children or adolescents themselves [44, 45]. This makes the task more similar to the task used to value the adult EQ-5D, but involves further ethical and feasibility considerations regarding eliciting preferences from children, given we are asking respondents to consider trade-offs involving life and death. On the other hand, stakeholders may have different expectations and mixed opinion about the 'correct' valuation approach and whether any single approach could be recommended for future valuation of paediatric HRQOL instrument.

In analysing the DCE data, we used the garbage class approach. When presenting difficult tasks, particularly in an online setting, there is a broad acceptance that we risk poor engagement and/or understanding. There is no perfect solution to this problem, and our view is that best practice is to apply a series of approaches in survey design and presentation, recruitment, and analysis to minimise and remove data that can be reasonably flagged as problematic. The garbage class approach does not perfectly identify such responses, but it significantly improved the quality of resultant data in most cases. In our analysis, 35% of the respondents were identified with a random choice pattern. In sensitivity analysis, we modelled the DCE data using a standard MIXL (Table S3 in ESM2) and compared with our main results. The relative importance of dimensions did not change much but the garbage class approach increased the scale length by 65%, indicating a substantial increase in choice consistency.

Part of the cTTO approach used here (and in most other valuation studies) is permitting respondents to flag problematic responses for removal using a feedback module after the valuation task. This opportunity to reflect on the relative scores assigned to different health states is likely to lead to greater internal validity of responses from each individual. However, it might be argued that exclusion of data is not appropriate. While we believe it is a valuable component of the valuation survey, we conducted a robustness check to explore whether the results differed if such data were not excluded. When including all cTTO responses, the overall results were similar to our preferred analysis, with a minimum value of 0.174 (Figure S1 & Table S4 in ESM2).

Among the two anchoring strategies, the linear mapping approach exhibited good predictive performance but over-predicted the value of the worst health state (33333), resulting in a value set with a smaller range. A similar pattern has also been observed in studies exploring different anchoring approaches [39, 46, 47]. Of relevance here is that, relative to the cTTO design suggested in the protocol, our design was larger but included only one very severe state (33333). Including a broader range of poor health states might mitigate the over-prediction of the worst states associated with the linear mapping approach.

One limitation of the study is that, while we spent significant time seeking a representative sample, our cTTO data had relatively few respondents aged under 30, and few people with lower levels of education. To explore this, we compared observed cTTO mean values by age group and education groups and we did not find statistically significant differences across age and education groups. Another limitation of our study was a delay in cTTO data collection; our DCE survey was conducted in Dec 2021 and Jan 2022, while cTTO interviews occurred between Feb and May 2023. The delays in cTTO interviews occurred due to the COVID-19 pandemic, requiring a switch to online administration. There is evidence that health preferences do not differ by mode of administration [25]. However, we acknowledge that COVID-19 remained a major and ongoing public health concern over that period and may have had some impact on the cTTO results. A further limitation was that we did not consider the possibility of non-linear time preference in the DCE design and analysis [48], as these are not addressed in the Y-3L valuation protocol.

Despite these potential limitations, we believe that our value set has significant strengths. The availability of the Australian Y-3L value set enables the calculation of QALYs for use in the economic evaluation of paediatric interventions. While we are aware of the recent launch of the EQ-5D-Y-5L (Y-5L) [49], which has the same five dimensions as the Y-3L but with expanded response options from three to five, the protocol to develop Y-5L value sets is not yet available. Value sets for the Y-3 L therefore remain highly relevant to users, both to support the use of data collected using the Y-3L and to provide an interim means of preference weighting Y-5L data, via a crosswalk (research underway) [50]. Furthermore, to our knowledge, it is the first paediatric HRQoL value set reported using the RETRIEVE checklist [19]. This is important as the valuation of paediatric health poses a series of methodological and practical considerations (e.g. involving adolescents in valuation tasks [51], alternative valuations methods [52, 53]). Clearly reporting the methods used, and the justification for doing so, is extremely important as the field lacks consensus in how these valuation studies should be conducted and used.

Conclusion

This study reports an Australian Y-3L value set. Pain/discomfort was considered as the most important domain, followed by feeling worried, sad or unhappy, usual activities, looking after myself and mobility. Health state values ranged from 0.142 to 1, which is narrower than the range of values in the Australian adult EQ-5D-3L value set. This may reflect the unwillingness of adult respondents

to trade off children's life years when completing TTO tasks. The implication is that, all other things being equal, cost-utility analysis performed using this value set will produce relatively high estimates of QALY gains from interventions that extend child survival, and relatively low estimates of QALY gains for interventions that improve HRQOL, compared to adults. The availability of the Australian Y-3L value set enables the calculation of QALYs for use in the economic evaluation of paediatric interventions and can support evidence development and decision making.

Abbreviations

HRQoL	Health related quality of life
Y-3L	EQ-5D-Y-3L
Ctto	Composite Time Trade Off
DCE	Discrete Choice Experiment
HTA	Health Technology Assessment
QALY	Quality-Adjusted Life Year
ESM	Electronic supplementary material
MO	Mobility (walking about)
SC	Looking after myself
UA	Doing usual activities
PD	Having pain or discomfort
WSU	Feeling worried, sad or unhappy
QC	Quality control
MIXL	Mixed-logit model
MEA	Mean absolute error
RMSE	Root mean square error

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12955-025-02402-x.

Supplementary Material 1

Acknowledgements
The authors thank the survey participants. The authors also thank Maths in Health for their work supporting the data collection. The authors also thank the interviewers, Ashwini Da Silva, Akanksha Akanksha, Elia Bidgood, Gayanda Madurapperuma, for their dedicated work.

Author contributions
Concept and design: RN, ND, BM, TP. Acquisition of data: RN. Analysis and interpretation of data: all authors. Drafting of the manuscript: TP, RN. Critical revision of the paper for important intellectual content: all co-authors. Statistical analysis: TP, BR. Obtaining funding: RN, BM, ND, TP.

Funding
This study was funded by the EuroQol Research Foundation (EQ Project 83-2020VS). The funding agreement ensured the authors' independence in designing the study, interpreting the data, writing, and publishing the report.

Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethics approval
The study was approved by Curtin University Human Research Ethics Committee (approval number HRE2021-0723). The study was performed in accordance with the Declaration of Helsinki.

Consent to participate
Informed consent was obtained from all individual participants included in the study.

Consent for publication
Not applicable.

Competing interests
TP, BR, ND, BM and RN are members of the EuroQol Group. All authors reported receiving grants from the EuroQol Research Foundation during the conduct of the study. BR is employed by the EuroQol Research Foundation.

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Received: 9 April 2025 / Accepted: 1 July 2025
Published online: 15 July 2025

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