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Comans, T.A., Nguyen, K.-H., Ratcliffe, J. et al. (2 more authors) (2020) Valuing the AD-5D dementia utility instrument : an estimation of a general population tariff. PharmacoEconomics, 38 (8). pp. 871-881. ISSN 1170-7690

https://doi.org/10.1007/s40273-020-00913-7

This is a post-peer-review, pre-copyedit version of an article published in PharmacoEconomics. The final authenticated version is available online at: http://dx.doi.org/10.1007/s40273-020-00913-7.

Valuing the AD-5D dementia utility instrument: an estimation of a general population tariff

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Compliance with Ethical Standards

Ethical approval for this study was granted from Griffith University Human Research and Ethics Committee (approval number 2016/626) and University of Queensland Human Research and Ethics Committee (approval number 2017001481).

Funding Statement

This study was supported by funding provided by the National Health and Medical Research Council (NHMRC) Partnership Centre on Dealing with Cognitive and Related Functional Decline in Older People (grant no. GNT9100000). A/Prof Tracy Comans is supported by a NHMRC Boosting Dementia Research Fellowship. The contents of the published materials are solely the responsibility of the University of Queensland and the individual authors identified, and do not reflect the views of the NHMRC or any other funding bodies or the funding partners.

Conflicts of interest: Tracy Comans, Kim-Huong Nguyen, Julie Ratcliffe declare they have no conflicts of interest relevant to this manuscript. Brendan Mulhern and Donna Rowen were involved in the development of the DEMQOL-U, a utility instrument for dementia.

Contributions

TC conceived the study, all authors contributed to the overall study design. KHN and BM designed the DCE, KHN analysed the data, all authors made the decisions on direction of data analysis and final models to use. The first draft manuscript was written by KHN and TC, all authors contributed to writing and editing draft manuscripts and approved the final version.

Keywords: dementia, utility weight, preference, quality adjusted life year, discrete choice experiment, health economics, economic evaluation

Acknowledgements: We would like to acknowledge the contributions of the AD5D project team, the project manager Alyssa Welch and participants of the online survey.

Abstract

Objective: This paper reports on the valuation of AD-5D quality of life states with a representative sample of the general population in Australia using the discrete choice experiment with duration DCE_{TTO} elicitation technique.

Method: A DCE with 200 choice sets of two quality of life state-duration combinations blocked into 20 survey versions, with 10 choice sets in each version, was designed and administered to an online sample representative of the Australian population. Two additional choice sets comprising internal consistency and dominance checks were included in each survey version. A range of model specifications investigating preferences with respect to duration and interactions between AD-5D dimension levels were estimated. Utility weights were developed, with estimated coefficients transformed to the 0 (being dead) to 1 (full health) scale, suitable for the calculation of quality-adjusted life-year (QALY) weights for use in economic evaluation.

Results: 1999 respondents completed the choice experiment. Overall, respondents were slightly better educated and with higher annual incomes than the Australian general population. The estimation results from different specifications and models were broadly consistent with the monotonic nature of the AD-5D: utility increases with increased life expectancy and decreases as the severity level for each dimension worsens. A utility value set was generated for the calculation of utilities for all quality of life states defined by AD-5D descriptive system.

Conclusion: The DCE-based utility value set is now available to use to generate QALYs for the economic evaluation of treatments and interventions targeting people with dementia and/or their family caregivers.

Key Points

1. Economic evaluation for dementia interventions has commonly used generic multi attribute utility instruments that may not capture dimensions of quality of life important for people living with dementia.
2. We present the first tariff set for the AD-5D, a multi attribute utility instrument derived from the Quality of Life-Alzheimer's Disease instrument that incorporates the domains of mood, memory, physical health, living situation, and doing things for fun.
3. Of the 5 dimensions, participants rated "memory" the least important attribute for quality of life, while "physical health" and "living situation" rated highest.

1. Introduction

The increasing number of people with dementia is a world-wide challenge driven by the ageing of the population [1]. The development of new dementia-modifying treatments and interventions to maintain patient daily functioning and quality of life (QoL) has been a key research and practice priority in many countries. In a context of constrained health and social care budgets and increasing pressures from new and expensive treatment options, it is vitally important to assess which dementia interventions or treatments offer good value for money. [2]–[6]

It is a common practice to use generic preference-based instruments of health-related quality of life to generate utility weights and subsequently quality-adjusted life-years (QALYs) for use in economic evaluation [2]–[6]. The most commonly used instruments include the EQ-5D (3L and 5L versions)[7], SF6D [8], and Health Utility Index HUI2 [9] and HUI3 [10]–[12]. A systematic review on preference-based instruments for dementia [13] found that the EQ-5D was most widely used (45/64 included studies) followed by the HUI3 (10/64 studies) and HUI2 (5/64 studies). It also highlighted significant variations between utility values generated by different instruments and by type of respondents (patient self-reporting versus proxy completion), leading to potentially wide variations in estimated QALYs. Additionally, while generic instruments are designed to measure QoL weights for all health conditions, concerns remain around their ability to capture aspects of health-related QoL relevant to specific conditions. For instance, for people with dementia, the QoL dimensions that have found to be important to people with dementia, such as memory and cognition, relationship with family and friends, and living conditions [14]–

[19], are often outside the health-related dimensions on which most generic instruments focus [8], [9], [12].

Condition-specific QoL instruments that capture dimensions relevant to people living with dementia have been developed, such as Quality of Life in Alzheimer's Disease (QoL-AD) [20], [21], dementia-specific health-related quality of life instrument (DEMQOL and DEMQOL-Proxy) [22], [23], quality of life questionnaire for dementia (QOL-D) [24] and Dementia Quality-of-life Instrument (DQI) [25]. Of those, DEMQOL has preference-based instruments – the DEMQOL-U and DEMQOL-Proxy-U – to generate utility weights for QALY calculation [26]; and the DQI is itself a preference-based instrument. Neither of these have been used widely in clinical trials and/or observational studies [26], [27]. The DEMQOL-U may also be limited due to its lack of direct measurement of physical health, while the DQI has not been psychometrically validated. Detailed discussions of those instruments can be found in Nguyen et al 2017 and Comans et al 2018. Of the other non-preference based instruments, the QoL-AD is a well-validated instrument [28] and has been widely used in clinical and observational studies [29] and translated into many languages. However, there exists no utility value set that allows the conversion of the raw QoL-AD scores into utility weights. Therefore, in its original form, the QoL-AD cannot be used directly in economic evaluations.

The QoL-AD was originally developed as a 13-item instrument to collect QoL information of the person with dementia using a simple summative scoring system [20], [21]. It evaluates the patient's physical condition, mood, interpersonal relationships, ability to participate in meaningful activities, and financial situation. These dimensions have previously been identified and validated as important in cognitively impaired adults [29], [30]. All QoL-AD items have four possible levels ranging from “poor” to “excellent”, giving a range of total scores for the questionnaire of 13 to 52. An adaption with 15 items was developed for use in long-term care facilities / nursing homes [31]. This version shares 10 items with the original version and includes five new items that reflect the institutionalisation environment: patient relationships with staff, living with others, ability to make choices, keeping busy, and self-care. Comparison of the community and nursing home surveys is presented elsewhere (Nguyen et al 2017). Each adaptation of the QoL-AD has two versions: one is completed by the patient (self-rated), and one by the caregiver (proxy-rated). When both patient and caregiver instruments are used, a weighted composite score is calculated. The patient’s rating is often given higher weight relative to the caregiver’s.

Combining the need for a better dementia-specific preference-based instrument and the fact that QoL-AD has desirable properties in measuring QoL in populations with cognitive impairment, the AD-5D project was initiated [32]. We previously developed the AD-5D classification system, including five QoL dimensions from the QoL-AD nursing home version [33].

This paper reports the valuation of the AD-5D classification system using a discrete choice experiment with duration (DCE_{TTO}) method with a representative sample of the Australian general population. An AD-5D utility value set was derived from the valuation results to generate utility weights for all responses to the QoL-AD self-complete and proxy-complete versions.

2. Method

2.1. Discrete choice experiment with duration

Discrete choice experiment (DCE) is a method of preference elicitation that has gained increasing popularity over the last decade with health practitioners and researchers [34], [35]. The theoretical foundations of DCE are grounded in random utility theory [36], which assumes that people generally choose the option that provides them with the highest level of utility and that any amount of deviation from that choice can be explained by random factors. Following the theory, a random utility model (RUM) aims at modelling the choices of individuals among discrete sets of alternatives [36], [37]. In its simplest form, a DCE presents individuals with two alternative scenarios (e.g., health and/or quality of life states), each containing a number of attributes, between which individuals are asked to choose their preferred scenario. While this form of DCE can provide information on the relative preference of one alternative over others, its derived values are not anchored on the zero–one scale, which is required to produce a utility scale. Therefore, it cannot be used directly for QALY calculation. The DCE_{TTO} (DCE + time trade off) method was developed to directly anchor relative preferences to the utility scale through the inclusion of a survival/duration attribute [38].

We based the DCE_{TTO} task on the five dimensions of the AD-5D classification system, as summarised in **Error! Reference source not found.** (detailed discussion of the system development can be found in Nguyen et al.'s study [33]). In the valuation exercise, respondents were presented with a set of DCE_{TTO} tasks, each of which contains a pair of QoL states with an associated duration, and asked to choose the state they considered to be better. Each QoL state consists of five AD-5D dimensions (physical health, mood, memory, living situation and ability to do things for fun), with each attribute set at a particular level (excellent, good, fair or poor), and a survival attribute (duration), taking a value of 1, 4, 7 or 10 years. The choice of duration levels was determined with consideration of previous DCE_{TTO} work, durations used in other valuation methods, and taking into account trading across health state dimension levels and duration [39], [40]. Ten years was chosen as the most commonly used duration in health state valuation studies (e.g. TTO). One year was chosen as the lowest whole year value, and four and seven years were chosen as intervals within the overall range to encourage respondents to trade both health state dimensions and duration when presented with different combinations. This design means that the four duration levels used result in possible differences between scenarios of nine, six and three years. The states within a DCE_{TTO} task were labelled A (on the left) or B (on the right), without any description of dementia or any other diseases/conditions (see Table 2). There was no mention of the condition or condition labelling, since previous research has found that the inclusion of a condition label can impact the results [41].

TABLE 1: The AD-5D classification system (reproduced from Table 5, Nguyen et al. [34])

Quality of life domains	**Descriptions**
Physical Health	You have **excellent** physical health
	You have **good** physical health
	You have **fair** physical health
	You have **poor** physical health
Mood	You have **excellent** mood
	You have **good** mood
	You have **fair** mood
	You have **poor** mood
Memory	You have **excellent** memory
	You have **good** memory

Quality of life domains	Descriptions
	You have **fair** memory
	You have **poor** memory
Living situation	You have **excellent** living situation
	You have **good** living situation
	You have **fair** living situation
	You have **poor** living situation
Ability to do things for fun	You have **excellent** ability to do things for fun
	You have **good** ability to do things for fun
	You have **fair** ability to do things for fun
	You have **poor** ability to do things for fun

2.2. Experimental design

Given six attributes (five AD-5D dimensions and one survival attribute) and four levels each, it was not feasible to provide respondents with the full factorial combinations (i.e., $4^6(4^6 - 1)/2$ or 8,386,560 possible combinations). To generate the experimental design, we used a D-efficient design using a swapping algorithm, as implemented in the design software NGene [42]. The design included 200 choice sets (or tasks), which was substantially more than the number of parameters that were estimated in the model (16). The set of parameters consists of 15 for the interaction terms between duration and 15 AD-5D dimension-levels (5 dimensions, 3 levels each: good, fair, and poor, compared to excellent as the base), and one parameter for the continuous variable of duration. The full design was then blocked into 20 blocks of 10 choice sets using the NGene blocking function that aims to minimise the average correlation between the blocking columns and all other design columns.

For each standard 10-choice-set block, we added two additional DCE tasks. The first (appearing as the eleventh task) was a dominant task containing a QoL state that is clearly worse than the alternative (poor mood, memory, living situation and ability to do fun things and one remaining life year versus excellent in three dimensions, fair or good in the other two, and seven remaining life years). The second was a repeated task (appearing as the twelfth task), which was identical to the task appearing second. These additions were designed to check whether or not respondents have logical and consistent preferences, which are key assumptions of choice modelling. Each respondent therefore answered 12 DCE_{TTO} choice sets, meeting the recommendation that survey participants can efficiently handle 9 to 15 choice sets at a time if they do not have cognitive problems [43]. An example of a DCE_{TTO} task is presented in **Error! Reference source not found.**.

In order to maximise the statistical power of the estimated models and allow for complex modelling procedures (e.g., generalised multinomial logistic models developed by [44], [45]), the target sample was 2,000 adults who are representative of the Australian population.

TABLE 2: A sample question of a discrete choice experiment with duration

Quality of life state A	Quality of life state B
You have **poor** physical health	You have **excellent** physical health
You have **good** mood	You have **fair** mood
You have **fair** memory	You have **fair** memory
You have **good** living situation	You have **good** living situation
You have **good** ability to do things for fun	You have **fair** ability to do things for fun
You live in this situation for **4 years** and then you die	You live in this situation for **4 years** and then you die
☒	☑

2.3. Data collection

Data collection for the Australian general population sample was conducted using an online survey. The survey was powered by LimeSurvey, designed and coded by the AD-5D research team, and administered by Pureprofile – an online participant panel widely used in previous research studies in Australia [32]. This panel was drawn from volunteers (aged 18+ and able to give consent) in the general population who were paid a small amount by the panel administrators for completion of the survey. The incentive was independent of the time they spent answering the survey. Quotas were set for age, gender and geographic area during recruitment to ensure the sample was representative of the Australian population. Potential respondents who met the quota criteria were invited by email and used a web link and token to access the survey webpage where the project details (including the consent form) were presented. Those who consented to participate proceeded to the full survey.

The survey contained three modules: (1) a series of sociodemographic questions, self-reported health-related quality of life using the EQ-5D-5L and the QoL-AD 13-item (community version); (2) the DCE_{TTO} block of 12 choice sets including questions about difficulty of the task and difficulty to understand; and (3) a best–worst scaling (BWS) block of six choice sets (details are described elsewhere [32]). Each participant was randomly allocated one of the 200 survey versions using a computerised number generation process. The survey started with the sociodemographic and quality of life questions, followed by either the DCE_{TTO} or the BWS modules, which were randomly and independently allocated such that approximately half would see the DCE_{TTO} before the BWS module. Each module was preceded with a practice question, and followed by a series of feedback questions asking participants to rate the overall difficulty of the valuation task with respect to understanding and ability to complete the task.

The survey was conducted in two parts. The survey was initially capped at 200 participants to allow the research team to check the data quality, including the representativeness of the pool compared to the Australian general population in relation to age, gender and residential location. Once we were satisfied with the quality of the data, the survey was reopened until the set sample quota was met.

2.4. Statistical analyses

We followed the good practice recommendations for analysing DCE in the literature [46]–[48] and considered two appropriate models for the estimation of utility values, the conditional logit and the scale multinomial logit models. Sensitivity analyses were also conducted with a variety of estimation approaches (including more flexible models such as heteroscedastic logit, random parameter logit and generalised multinomial logit models), and on different sub-samples (such as those excluding people who reported having dementia, those who failed the dominant task, those who failed the repeated task, and those who failed both). All estimations were performed in Stata 15 (StataCorp LLC) using one built-in command (clogit) and other user-written commands (clogithet, mixlogit, gmnl) [43].

For each estimated model, there are 16 dimension-level coefficients: one for duration and 15 for duration interacting with AD-5D dimensions (see Equation 1, PH = physical health, MD = mood, MM = memory, LS = living situation, FT = ability to do things for fun; U is the latent utility that consists of two component: the deterministic utility component V and the stochastic/random error ε; i represents individual and j choice sets). The magnitude of each coefficient reflects the relative value decrement by deviating from the best state of "excellent". As such, it is expected that the coefficients would be negative, and we would observe a logical order of absolute decrement values (good < fair < poor). Statistical significance levels were assessed at 1%, 5% and 10%. Estimation results for the basic models are presented in the Web Appendix.

$$
\begin{aligned}
U_{ij} &= V_{ij} + \varepsilon_{ij} \\
V_{ij} &= \alpha_{ij}T_{ij} + \beta_{11}PH_{good,ij}T_{ij} + \beta_{12}PH_{fair,ij}T_{ij} + \beta_{13}PH_{poor,ij}T_{ij} \\
&\quad + \beta_{21}MD_{good,ij}T_{ij} + \beta_{22}MD_{fair,ij}T_{ij} + \beta_{23}MD_{poor,ij}T_{ij} \\
&\quad + \beta_{31}MM_{good,ij}T_{ij} + \beta_{32}MM_{fair,ij}T_{ij} + \beta_{33}MM_{poor,ij}T_{ij} \\
&\quad + \beta_{41}LS_{good,ij}T_{ij} + \beta_{42}LS_{fair,ij}T_{ij} + \beta_{43}LS_{poor,ij}T_{ij} \\
&\quad + \beta_{51}FT_{good,ij}T_{ij} + \beta_{52}FT_{fair,ij}T_{ij} + \beta_{53}FT_{poor,ij}T_{ij}
\end{aligned}
\qquad \text{(Equation 1)}
$$

Model selection: An estimated model is preferred (over the other alternatives) when it is the most parsimonious model, and (1) its estimated coefficients are in logical order (i.e., there are consistent absolute decrements from excellent to good, to fair, and to poor) and statistically significant, (2) its log-likelihood value, information criteria of AIC and BIC are smallest or comparable to others, and (3) the utility value ranges are logical. All these statistics are summarised in the Web Appendix, together with the model estimates.

Anchoring to the utility scale: While the estimated coefficients (from the logit models) reflect the relative importance of each AD-5D's dimensions, their values are not anchored onto the utility scale. After the estimation, we adjusted the coefficients using the anchoring formulae developed for the DCE$_{\text{TTO}}$ method to obtain the relative weight for each level of each quality of life dimension (the proof is described in detail in [38]) and the formulae is as follows:

$$\hat{\beta}_{dl,ij} = \frac{\beta_{dl,ij}}{T_{ij}}; d = [1, 5]; l = [1, 3];$$

In which, $\hat{\beta}_{dl,ij}$ is the anchored values of $\beta_{dl,ij}$ – the estimated coefficients in Equation 1, and T_{ij} is the respective duration of option j^{th} faced by individual i^{th}; d is the index for the five AD-5D quality of life dimensions (physical health, mood, memory, living situation, do things for fun) and l is the index for quality of life level (good, fair, poor).

3. Results

3.1. Summary of statistics

There were 2,003 respondents who completed the online survey. Basic demographics are summarised in **Error! Reference source not found.**. The cohort is broadly representative of the Australian population, matching closely for gender, age, location and marital status, however the cohort generally displays a higher education level according to published census data by the Australian Bureau of Statistics [49]. Of 2,003 completions, four responses were discarded as their reported ages were less than 18 years, leaving the final analysis sample of 1,999.

TABLE 3: Summary of individual characteristics of respondents (N=1,999)

	N (%)	**Australian Bureau of Statistics data (%)**
Gender		
Female	991 (49.57)	50.7
Male	1,005 (50.28)	49.3
Not specified	3 (0.15)	
Age group		
24 years and below	222 (11.11)	11.79
25-34 years	387 (19.36)	18.51
35-44 years	368 (18.41)	17.29
45-54 years	312 (15.61)	17.06
55-64 years	311 (15.56)	15.13

	N (%)	Australian Bureau of Statistics data (%)
65 years and above	399 (19.96)	20.22
State of residence		
Australia Capital Territory	37 (1.85)	1.67
New South Wales	649 (32.47)	31.98
Victoria	532 (26.61)	25.61
Queensland	367 (18.36)	20.03
South Australia	141 (7.05)	7.04
Western Australia	209 (10.46)	10.53
Tasmania	46 (2.30)	2.14
Northern Territory	16 (0.80)	1.00
Others	2 (0.10)	
Marital status		
Never married	489 (24.46)	35.00
Widowed	45 (2.25)	5.20
Divorced	167 (8.35)	8.50
Separated	48 (2.40)	3.20
Married/De facto	1,250 (62.53)	47.70
Highest level of education		
Primary school	11 (0.55)	7.80
Year 8 and 9	60 (3.00)	-
Year 10 (junior)	221 (11.06)	11.50
Year 12 (senior)	433 (21.66)	23.50
Other post-school qualification	559 (27.96)	27.90
Bachelor degree or higher	715 (35.77)	26.90
Employment		
Full-time	611 (30.57)	
Part-time	362 (18.11)	
Not working and looking for work	130 (6.50)	
Not working and currently not looking for work	141 (7.05)	

	N (%)	**Australian Bureau of Statistics data (%)**
Retired	422 (21.11)	
Student	97 (4.85)	
Self-employed	136 (6.80)	
Unable to work	100 (5.00)	
Income		
Q1: poverty line (below A$ 20,000)	489 (28.75)	29.30
Q2: poverty to median (A$ 20,000 – A$ 50,000)	611 (35.92)	31.40
Q3: median (A$ 50,000)	300 (17.64)	15.20
Q4+5: above median	301 (17.70)	15.10
Prefer not to say	-	9.00

Of 1,999 valid responses, 36 individuals indicated that they currently had dementia, 27 individuals always chose the same alternative throughout (A – on the left; or B – on the right), which is an indicator that they may not have paid full attention to the DCE$_{TTO}$ task. The number of participants who failed the dominant task (question DCE12; 138 failed) was lower than those who failed the repeated task (DCE11; 370 failed); and 51 participants failed both tasks. We included the whole sample (N=1,999) in the base case analysis and sub-samples (e.g., exclusion of participants who failed dominant, and/or those who failed repeat, or those who always chosen the same side) in sensitivity analyses.

The mean completion time for the entire survey (including the demographic and quality of life module) was 16 minutes (SD=36 minutes; range: 2 – 678 minutes) while the median was 11 minutes. Specifically, the median completion time for the group of 27 individuals who consistently picked only left or the right answers was very short (1.33 minutes). For the DCE$_{TTO}$ block, the mean completion time was 6 minutes (SD=14 minutes; range: 1 – 330 minutes) and heavily right skewed with 95% respondents completing the block within 12 minutes. When asked about the clarity (whether or not the task is easy to understand) and difficulty (whether or not it is easy to make a choice between the two options) of the task, only 5% of the respondents found the $\mathrm{DCE}_{\mathrm{TTO}}$ task either unclear or very unclear, and 13% of respondents found the task either difficult or very difficult. Around 27% of respondents found it difficult or very difficult to choose between options.

3.2. Model results

The results of estimated models consistently reflected the monotonic nature of the five AD-5D dimensions: most coefficients follow a logical order with correct sign (negative sign, indicating consistent absolute decrements) and statistically significant. Out of the five AD-5D dimensions, impairment in “physical health” generates the highest utility decrements, followed by the reduction in “living situation” and “mood”. Across all models, “memory” is associated with the smallest (relative) decrement gaps. The “duration” coefficient was positive and statistically significant (p-value <1%), indicating that utility increases with life expectancy. The estimated coefficients, statistics and anchored values of all models are presented in Tables 1 and 2 of the Web Appendix.

We selected the conditional logit model as the final model to develop the AD5D utility algorithm using the selection criteria (see estimated coefficients and anchored values for use in utility estimation in TABLE 4). For all models, most estimated coefficients satisfied criteria 1 (correct signed, ordered and statistically significant), with very similar goodness of it statistics (log likelihood, BIC and AIC). All models achieved very similar magnitude of estimated coefficients (after anchored) and level of significance. The conditional logit model was the most parsimonious, thus its coefficients were selected to calculate the final utility value set for the AD5D. The relative utility weights of the five AD-5D dimensions of the conditional logit model (i.e., adjusted coefficients using the anchoring formula) are presented in TABLE 4**: Estimated coefficients, conditional and scale logit model (N=1,999)**

	Conditional logit		**Scale logit**	
	Coefficient	**Std. Err**	**Coefficient**	**Std. Err**
Duration (*T*)	**0.3996**	0.0138	**0.5981**	0.0545
Physical health (base = excellent)				
β_{11} Good × duration	-0.0022	0.0058	0.0223	0.0150
β_{12} Fair × duration	**-0.0516**	0.0056	**-0.0915**	0.0154
β_{13} Poor × duration	**-0.1793**	0.0070	**-0.3500**	0.0613
Mood (base = excellent)				
β_{21} Good × duration	**-0.0200**	0.0076	**-0.0568**	0.0199
β_{22} Fair × duration	**-0.0498**	0.0072	**-0.0904**	0.0204
β_{23} Poor × duration	**-0.1412**	0.0077	**-0.2597**	0.0455
Memory (base = excellent)				
β_{31} Good × duration	-0.0038	0.0065	-0.0030	0.0135
β_{32} Fair × duration	**-0.0170**	0.0064	**-0.0587**	0.0155
β_{33} Poor × duration	**-0.0992**	0.0068	**-0.1868**	0.0255
Living situation (base = excellent)				
β_{41} Good × duration	-0.0021	0.0066	-0.0181	0.0139
β_{42} Fair × duration	**-0.0369**	0.0067	**-0.0959**	0.0247
β_{43} Poor × duration	**-0.1255**	0.0068	**-0.2474**	0.0484
Ability to do things for fun (base = excellent)				
β_{51} Good × duration	**-0.0323**	0.0063	**-0.0552**	0.0194
β_{52} Fair × duration	**-0.0495**	0.0058	**-0.0867**	0.0199
β_{53} Poor × duration	**-0.1263**	0.0066	**-0.2512**	0.0475
Estimation statistics				
Tau (τ) – *scale logit model only*			**1.1448**	0.1651

Log pseudo-likelihood (LL)	-11311	-11218
AIC	22654	22469
BIC	22792	22615

Note: bold indicates statistically significant at 5% level

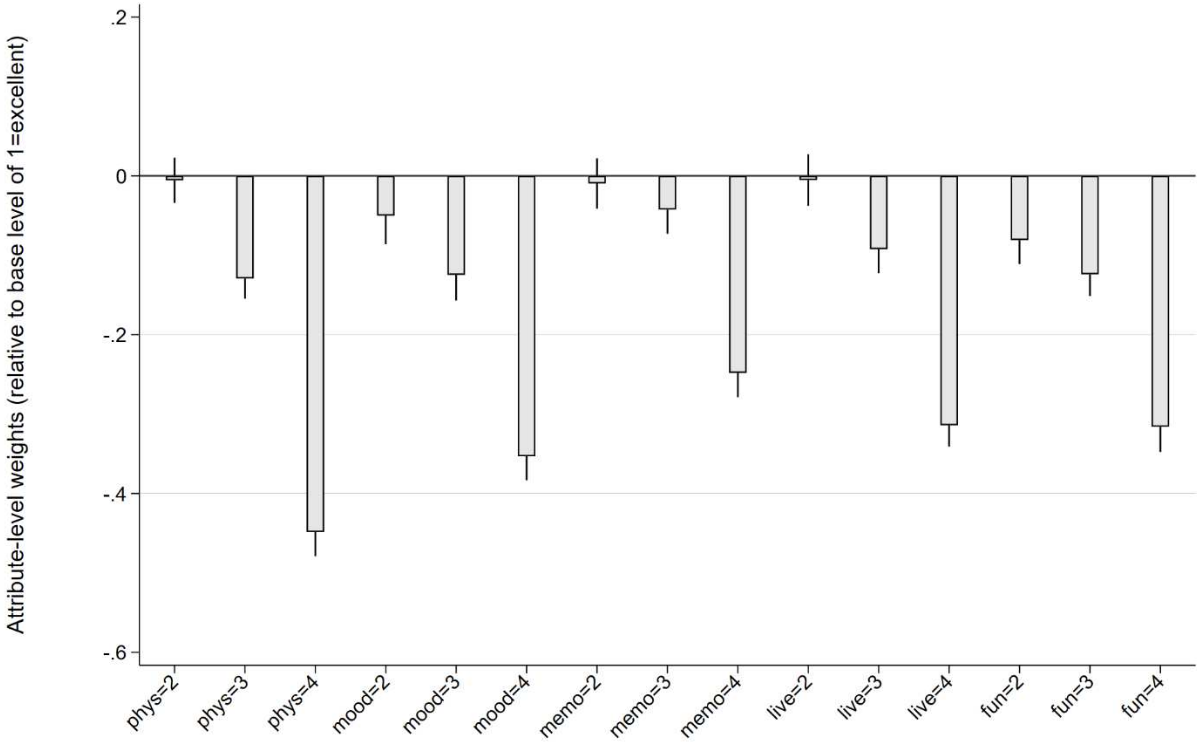

FIGURE 1.

TABLE 4: Estimated coefficients, conditional and scale logit model (N=1,999)

	Conditional logit		Scale logit	
	Coefficient	**Std. Err**	**Coefficient**	**Std. Err**
Duration (T)	**0.3996**	0.0138	**0.5981**	0.0545
Physical health (base = excellent)				
β_{11} Good × duration	-0.0022	0.0058	0.0223	0.0150
β_{12} Fair × duration	**-0.0516**	0.0056	**-0.0915**	0.0154

β_{13} Poor × duration	**-0.1793**	0.0070	**-0.3500**	0.0613
Mood (base = excellent)				
β_{21} Good × duration	**-0.0200**	0.0076	**-0.0568**	0.0199
β_{22} Fair × duration	**-0.0498**	0.0072	**-0.0904**	0.0204
β_{23} Poor × duration	**-0.1412**	0.0077	**-0.2597**	0.0455
Memory (base = excellent)				
β_{31} Good × duration	-0.0038	0.0065	-0.0030	0.0135
β_{32} Fair × duration	**-0.0170**	0.0064	**-0.0587**	0.0155
β_{33} Poor × duration	**-0.0992**	0.0068	**-0.1868**	0.0255
Living situation (base = excellent)				
β_{41} Good × duration	-0.0021	0.0066	-0.0181	0.0139
β_{42} Fair × duration	**-0.0369**	0.0067	**-0.0959**	0.0247
β_{43} Poor × duration	**-0.1255**	0.0068	**-0.2474**	0.0484
Ability to do things for fun (base = excellent)				
β_{51} Good × duration	**-0.0323**	0.0063	**-0.0552**	0.0194
β_{52} Fair × duration	**-0.0495**	0.0058	**-0.0867**	0.0199
β_{53} Poor × duration	**-0.1263**	0.0066	**-0.2512**	0.0475
Estimation statistics				
Tau (τ) – *scale logit model only*			**1.1448**	0.1651
Log pseudo-likelihood (LL)	-11311		-11218	
AIC	22654		22469	
BIC	22792		22615	

Note: bold indicates statistically significant at 5% level

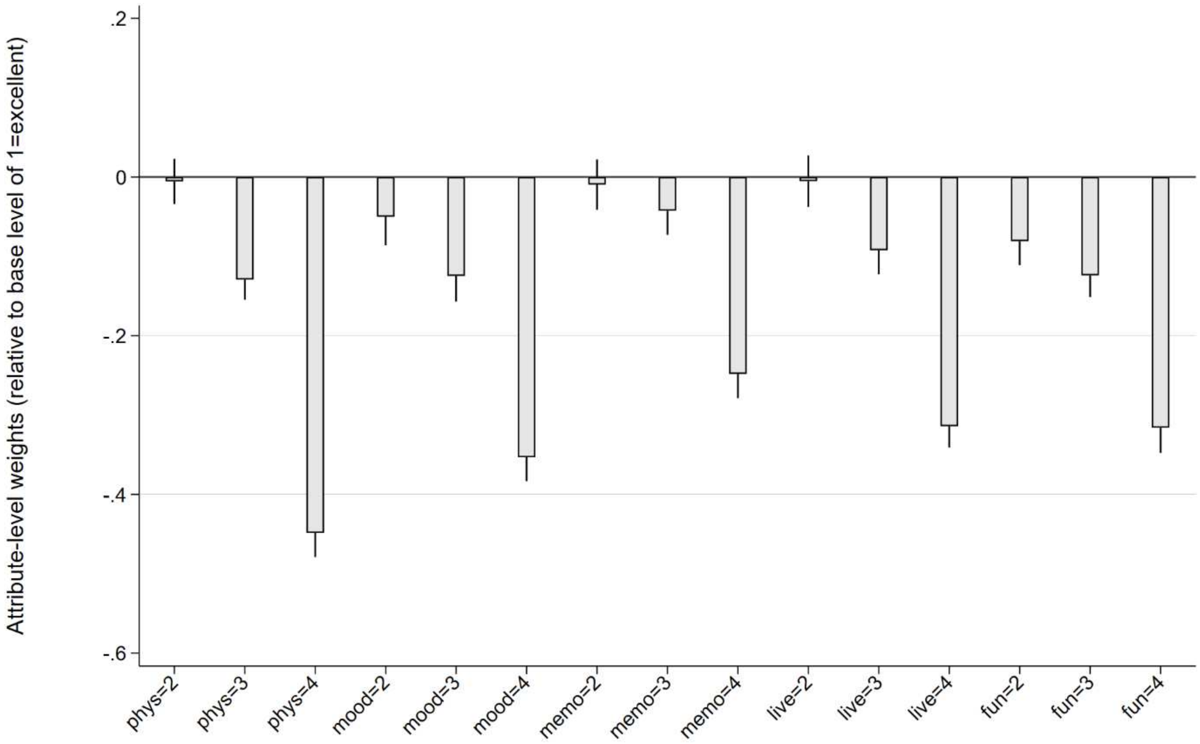

FIGURE 1 Anchored coefficients of the conditional logit model (N=1,999)

We repeated the estimations on different sub-samples using the conditional logit model for the purpose of comparison with the base case (conditional logit model, N=1,999). These sub-samples excludes participants who either (1) stated they had dementia, or (2) picked only left (A) or right (B) for all choices, or (3) failed dominant tasks. (Detailed results of these models are available upon request). Overall, the (estimated) adjusted coefficients are highly robust across different sub-samples, especially with respect to their logical orderings and magnitudes.

3.3. AD-5D utility weights

The full sample of 1,999 respondents were used to generate the full set of utility values for all 1,024 AD-5D QoL states (combination of the five dimensions with four levels each). The utility value distribution is presented in FIGURE 2. The distribution is right skewed, with a mean of

0.41 (SD = 0.30, range = [-0.68; 1.00]). Approximately 10% of QoL states (101 states) have negative values, indicating that they are worse than death. Most of these states have at least three dimensions at the most severe level (poor).

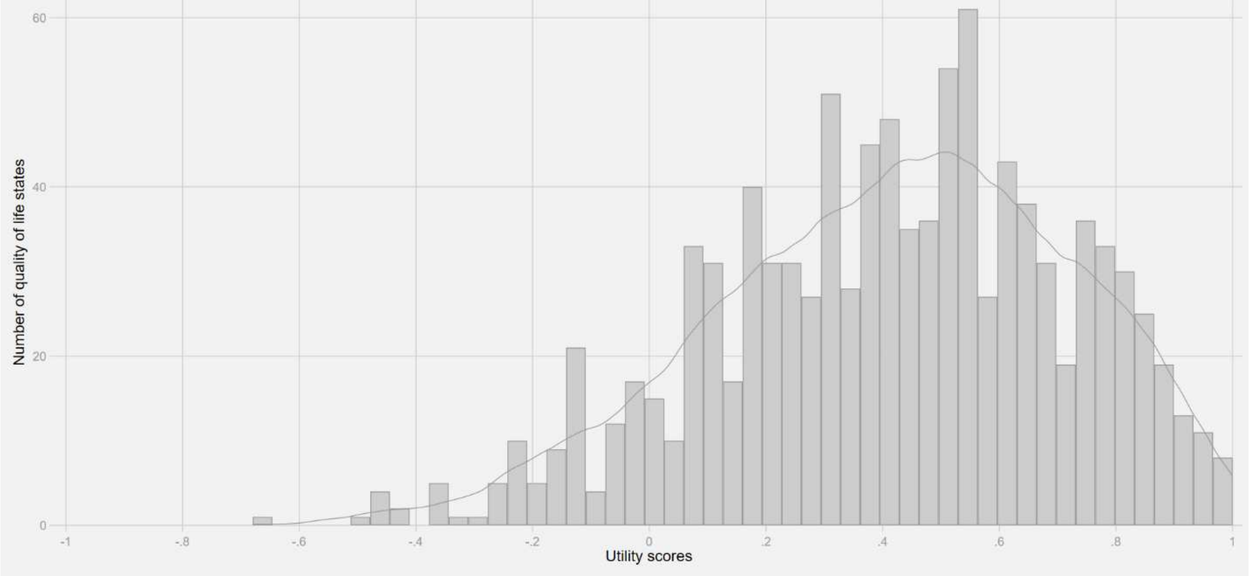

FIGURE 2 Distribution of AD5D utility values

4. Discussion

In this paper, we reported the valuation of the AD-5D classification system to generate a utility value set to form the new dementia-specific preference-based measure for use in cost–utility analysis. Each time the QoL-AD is administered to a person living with dementia, a utility value can be generated and observations over time can in turn be used to generate QALYs. The valuation exercise followed recommended practice [46]–[48], from the experimental design to the sampling and administration of the survey and the econometric analyses of the collected data. The anchored values provided in Table 4 can now be used to generate utility values from QOL-AD datasets.

The AD-5D utility value set, based on the estimated coefficients of the conditional logit model using the Australian general population sample, was chosen from a number of estimated models. The model showed satisfactory fit statistics, reasonable range of values, and insights of choice behaviour, and was derived from a large sample size in line with other DCE_{TTO} studies [34]. The estimated coefficients of the model were stable across different sample sizes, including those that excluded the sub-group who failed the dominant task and/or repeated task.

While memory loss is often considered the signature characteristic of dementia, it is strongly suggested in our estimation that individuals consider “memory” a less important contributing factor to QoL than dimensions such as “physical health” and “living situation”. There are a few potential explanations for this finding. First, participants may not have had sufficient direct or family experience of cognitive decline and memory loss to imagine what it would be like to have dementia-related memory problems, whereas physical health and living situation are more readily identifiable for most people. Second, the survey was blinded to condition. If people understood that dementia was the condition leading to memory decline, they may have stated different preferences in their choices. Third, it might be due to the discrepancy in the interpretation of excellent/good/fair/poor “memory”. For instance, some respondents might refer to poor memory as “forgetfulness” while the question intends to understand the ability to remember important aspects in life, such as family members, life events or even language. However, this finding is consistent with the results of a qualitative study conducted to confirm the content validity of the AD-5D dimensions. Focus group participants were asked to identify and prioritise activities contributing to their quality of life and allocate them to an AD-5D dimension [50]. For all three groups (comprising people with dementia, caregivers and community members), memory was identified as the least important dimension for good quality of life, and people with dementia identified living situation as the most important dimension. During the focus group discussions, participants had opportunities to discuss what each QoL dimensions meant for them, where good memory was understood as the ability to remember/recall important life events. Consistent findings across both studies therefore increase our confidence in the validity of the AD-5D utility values.

The AD-5D value set enables the inclusion of QoL dimensions central to the evaluation of many social interventions for people with dementia (such as relationships with family and caregivers, or living conditions) rather than relying on those most important for pharmaceutical interventions (memory and cognitive decline). Most economic evaluations of pharmaceutical and non-pharmaceutical interventions for people with dementia have used the EQ-5D-3L and the health utility index (HUI2 and HUI3) [13]. While both EQ-5D-3L and HUI2/3 are the most frequently used utility instruments, their measurement focus is health-related quality of life. The EQ-5D-3L classification contains five health dimensions of mobility, self-care, usual activity, pain/discomfort, and anxiety/depression; and each has three levels (no problem, some problem, unable). The HUI3 classification system includes eight dimensions of vision, hearing, speech, dexterity, ambulation, cognition, emotion, and pain; each has five or six severity levels. Both systems do not explicitly cover some quality of life dimensions that are the primary outcomes of many social interventions for people with dementia (e.g., relationships with family and caregivers in both systems, or living conditions or activities of daily living in HUI2/3) [51].

Given the wider experience of quality of life captured by the QoL-AD for people with dementia, it is expected that the availability of the AD-5D algorithm to convert the QoL-AD scores collected in clinical trials to utility values may improve the ability to detect meaningful change for dementia interventions, and hence provide more accurate information for cost-effectiveness analyses. This may be particularly relevant for those interventions focussed on the care of people with dementia. However, until further validation work is conducted, we suggest that the QoL-AD be collected alongside a generic instrument such as the EQ-5D.

Limitations

The sampling method used an online sample that may not broadly represent population values. It is also acknowledged that internet-stated preference values can differ from other modes of delivery [52]. However, the sample was large and matched to population characteristics, a method that is known to improve accuracy of panel surveys [53]. Non-response or invalid surveys were very low in this sample, increasing the confidence in the representativeness of the cohort. The sample covers the Australian population only and further valuation is suggested to understand if preferences differ by country as is commonly found in other quality of life state valuation tasks [54].

5. Conclusion

The AD-5D utility value set is now available for use in economic evaluation of programs for dementia when the QoL-AD instrument is used to assess quality of life. The DCE-based utility value set for the AD-5D classification system will have wide applicability in facilitating QALY calculations for the economic evaluation of treatments and interventions targeting people with dementia and/or their family caregivers. This value set will enable trials and clinical studies of dementia interventions that have used and will use the QoL-AD instrument, both community and nursing home versions, to convert responses into utility values for the evaluation of the benefits of interventions. This approach removes the need for additional data collection and enables comparative evaluation of interventions for which QoL-AD data has been collected. The AD-5D utility value set presented here can be applied to all future and existing QoL-AD datasets for use to inform future planning and resource allocation for dementia care.

6. Data Availability Statement

The dataset used to generate the algorithm is available for reuse with commercial restriction in The University of Queensland, eSpace repository [55].

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