

Development of a value-based scoring system for the WAIte using the OPUF in a sample of adults

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Abstract

Background: Online personal utility functions (OPUF) present a new method for eliciting preferences. In this study we used the OPUF to elicit a health state utility value set for the Weight-specific Adolescent Instrument for Economic-evaluation (WAIte) with a representative sample of the UK adult population.

Methods: WAIte OPUF survey design was informed by prior qualitative work. The survey consisted of the WAIte descriptive system, attribute weighting, level rating (per attribute) and a VAS anchoring task. Personal utility functions were estimated on the individual level for all participants. Personal utility functions were aggregated and combined with the anchoring factor to give the social utility function and utility value set. Preference heterogeneity was assessed using Euclidean distance and PERMANOVA to explore preference variation within the sample. An experimental sensitivity analysis dichotomised preference heterogeneity into anchoring variation and attribute weighting/level rating variation.

Results: A total of 300 participants completed the WAIte OPUF survey. The sample was broadly representative of the UK adult population. Participants, on average, took less than 10 minutes to complete the survey. The most important attributes were tiredness and unhappiness, while least important attributes were sports and embarrassment. Social utility values and the anchoring utility value estimated were comparable to previous studies. Preferences generally were heterogeneous, especially among different ages. Younger participants assigned lower utility values to WAIte health states and provided significantly lower scores on the VAS anchoring task compared to older participants.

Conclusion: This study successfully elicited health state utility values for the WAIte using the OPUF. Preference heterogeneity analysis identified differences in preferences for different age groups and a further valuation study is ongoing to explore whether this heterogeneity exists between adults and adolescents.

Keywords: Health state valuation, preference elicitation, quality of life

Disclaimer: This is a work-in-progress, please do not redistribute or cite without the authors permission. This work was supported by the NIHR-ARC and Newcastle University.

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Code availability: An interactive document (HTML) which includes the live survey is available [here](#). Source code for the analysis and this Quarto generated PDF are available [here](#).

1. Introduction

1.1. Compositional preference elicitation methods

Preference elicitation methods typically, fall into two categories: compositional and decompositional [1, 2, 3]. That is, methods such as DCE, BWS and TTO elicit preference orderings from individuals for an entire health state (composed of a combination of attributes and levels) and then responses are

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decomposed to identify marginal contributions of each attribute and level in each health state. Models like multinomial logit, mixed logit and latent class are frequently used to decompose responses to decomposition preference elicitation tasks [4]. Coefficients estimated in these models form the basis of dis/utility values for each attribute and level in a descriptive system.

Conversely, compositional methods seek to identify preferences for each attribute weighting and level rating individually for the number of attributes and levels in a given descriptive system. Therefore, statistical models to elicit coefficients for each individual attribute and level are not required and responses to each attribute weighting and level rating are combined (in addition to an anchoring factor) to yield dis/utility values for each attribute and level in the descriptive system. Compositional approaches can take many forms from simple VAS scores to using semantic categories and ranking methods [5, 6, 7]. These approaches have previously been used successfully in multi-criteria decision analysis (MCDA), but have been used less extensively in the preference elicitation space. Since the development of the OPUF, compositional approaches to elicit preferences have become more commonplace and a number of countries are using the OPUF to elicit value sets specific to their population [8].

1.2. From PUF to OPUF

Personal utility functions (PUF) were first used in the context of preference elicitation by Devlin et al. (2019) [9] to estimate the feasibility for using this approach to estimate a value set for the EQ-5D-5L. Since the feasibility for the underlying PUF methods were established, the approach has been expanded by Schneider and colleagues [10] and converted into an online personal utility functions (OPUF) survey built initially using RShiny and subsequently using Javascript (available [here](#)). Since the development of the OPUF, a number of descriptive systems and different research teams have begun using this method to elicit value sets [11, 8].

1.3. An overview of the OPUF structure

1.3.1. Attribute weighting

This section is composed of two parts. First, attribute ranking is completed where participants identify their most important attribute (Figure 1a). Second, respondents complete the attribute weighting (swing weighting) where the relative importance of other attributes is ascertained using their most important attribute as a reference point (Figure 1b). These questions are presented in Figure 1.

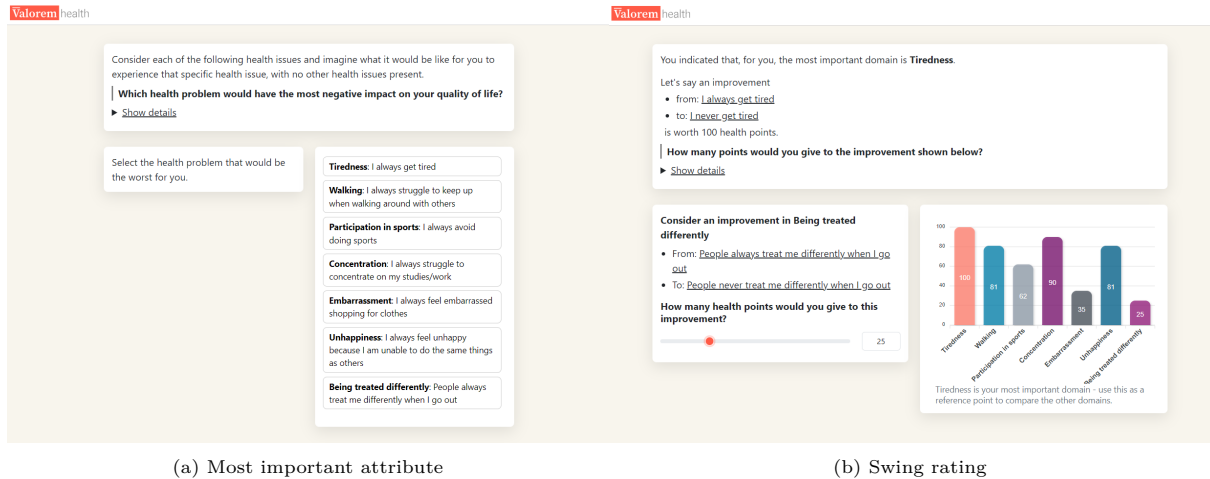


Figure 1: Attribute weighting

1.3.2. Level ratings

This element of the OPUF has varied across different iterations of the survey. Schnieder et al. (2022) [10] asked participants to rank the levels within the descriptive system generally (i.e. for any given attribute), while other iterations have administered separate level rating questions for each attribute in the descriptive system [11]. Selection of method requires a trade-off between participant burden and sensitivity of level ratings to each attribute. Figure 2 presents the level rating question for the tiredness and treated differently attributes of the WAItE.

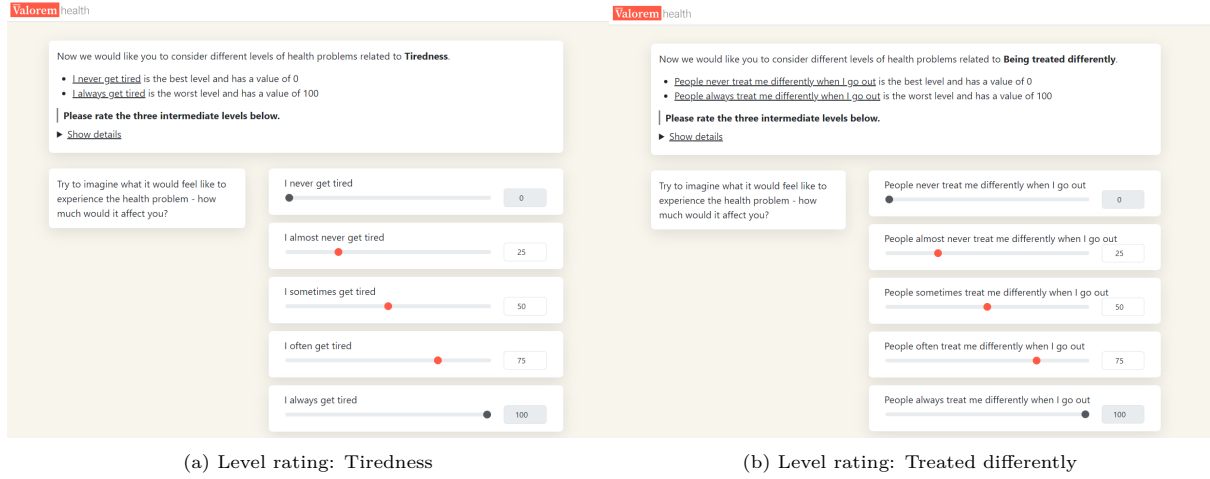


Figure 2: Level rating

1.3.3. Anchoring factor

A task is required to rescale the latent coefficients estimated via combining level ratings and attribute weights onto the QALY scale. Participants are presented with a binary choice between the PITS state (or another state) of a given descriptive system and “being dead” (Figure 3a). If the PITS state is chosen, participants are asked to rank the PITS state on a VAS from 1 (full health) to 0 (dead). If “being dead” is chosen, participants are asked to rank “being dead” on a VAS from 1 (full health) to 0 (PITS state) (Figure 3b). Responses to these respective questions provide the anchoring factor. Anchoring questions, such that PITS is preferred to dead, are presented in Figure 3.

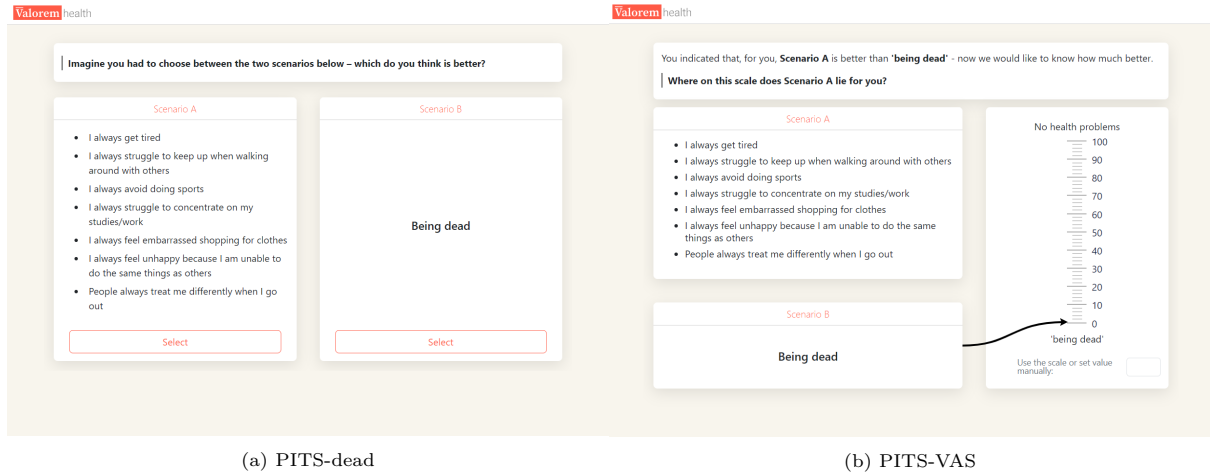


Figure 3: Anchoring factor

1.4. OPUF logic and mathematics

This section presents the logic and underlying mathematics required to convert the raw OPUF responses from one person into an anchored value set for the WAItE descriptive system. This example assumes that level ratings are obtained for each attribute separately, therefore the mathematics presented here differs to those presented elsewhere [10]. Example response data are used for demonstration in this section and are presented in Table 1.

1.4.1. Example responses

Table 1: Example individual responses to the OPUF

Response	Tired	Walking	Sports	Concentration	Embarrassed	Unhappiness	Treated
Level rating: Never	0	0	0	0	0	0	0
Level rating: Almost Never	14	26	21	15	16	12	19
Level rating: Sometimes	57	55	63	54	38	26	66
Level rating: Often	83	82	85	86	64	38	91
Level rating: Always	100	100	100	100	100	100	100
Attribute Weighting	28	33	36	45	100	34	56

Level ratings (presented in Table 1) are converted to coefficients bounded between 0-1 (shown in Equation 1). Level rating coefficients are presented in Equation 2. Attribute weights (presented in Table 1) are then normalised to sum to the value of 1 by dividing each weight by the sum of all weights (shown in Equation 3). Normalised attribute weights are presented in Equation 4.

$$L_{ij} \cdot 0.01 \quad (1)$$

$$L_{ij} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.14 & 0.26 & 0.21 & 0.15 & 0.16 & 0.12 & 0.19 \\ 0.57 & 0.55 & 0.63 & 0.54 & 0.38 & 0.26 & 0.66 \\ 0.83 & 0.82 & 0.85 & 0.86 & 0.64 & 0.38 & 0.91 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} \quad (2)$$

$$\frac{w_j}{\sum w_j} \quad (3)$$

$$w_j = [0.08 \quad 0.10 \quad 0.11 \quad 0.14 \quad 0.30 \quad 0.10 \quad 0.17] \quad (4)$$

Combining the attribute weights (Equation 4) with the level coefficients (Equation 2) via element-wise multiplication (shown in Equation 5) gives the coefficient matrix presented in Equation 6. Once the coefficient matrix has been estimated, preference values can be estimated on the 0-1 QALY scale where the worst health state (PITS state denoted 5555555) is zero and the best health state (denoted 1111111) is one. These latent coefficients must now be rescaled to incorporate the results from the PITS anchoring task so that the minimum utility value possible is equal to the PITS value.

$$L_{ij} \cdot w_j = M_{ij} \quad (5)$$

$$M_{ij} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.01 & 0.03 & 0.02 & 0.02 & 0.05 & 0.01 & 0.03 \\ 0.05 & 0.05 & 0.07 & 0.07 & 0.11 & 0.03 & 0.11 \\ 0.07 & 0.08 & 0.09 & 0.12 & 0.19 & 0.04 & 0.15 \\ 0.08 & 0.10 & 0.11 & 0.14 & 0.30 & 0.10 & 0.17 \end{bmatrix} \quad (6)$$

To rescale the latent coefficient matrix to incorporate the anchoring task, the coefficient matrix is multiplied by the compliment of the PITS value (shown in Equation 7) to give the anchored coefficient matrix presented in Equation 8.

$$M_{ij} \cdot (1 - P) \quad P = 0.2 \quad (7)$$

$$V_{ij} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.01 & 0.02 & 0.02 & 0.02 & 0.04 & 0.01 & 0.02 \\ 0.04 & 0.04 & 0.06 & 0.06 & 0.09 & 0.02 & 0.09 \\ 0.06 & 0.06 & 0.07 & 0.10 & 0.15 & 0.03 & 0.12 \\ 0.06 & 0.08 & 0.09 & 0.11 & 0.24 & 0.08 & 0.14 \end{bmatrix} \quad (8)$$

Once the attribute and level labels are reintroduced to the anchored coefficient matrix this forms the value set which presents the disutility corresponding to each attribute level combination presented in the WAIte. Table 2 presents the WAIte example PUF value set. Equation 9 provides examples of how to estimate a utility value given a specific WAIte health state.

Table 2: WAIte example PUF value set

Attribute level	Tired	Walking	Sports	Concentration	Embarrassed	Unhappiness	Treated
Never	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Almost Never	0.01	0.02	0.02	0.02	0.04	0.01	0.02
Sometimes	0.04	0.04	0.06	0.06	0.09	0.02	0.09
Often	0.06	0.06	0.07	0.10	0.15	0.03	0.12
Always	0.06	0.08	0.09	0.11	0.24	0.08	0.14

$$\text{Health State [5555555]} \Rightarrow 1 - (0.06 + 0.08 + 0.09 + 0.11 + 0.24 + 0.08 + 0.14) = 0.20$$

$$\text{Health State [5223445]} \Rightarrow 1 - (0.06 + 0.02 + 0.02 + 0.06 + 0.15 + 0.03 + 0.14) = 0.52 \quad (9)$$

$$\text{Health State [2222222]} \Rightarrow 1 - (0.03 + 0.02 + 0.01 + 0.01 + 0.02 + 0.02 + 0.04) = 0.85$$

1.5. Aggregation to social utility function

The OPUF is designed to be able to estimate personal utility functions and so estimation occurs on an individual basis. Aggregating personal utility functions to a social utility function (SUF) takes place by taking a mean of all the individual personal utility functions from your sample. This operation is presented in Equation 10.

$$\bar{V}_{ij} = \frac{\sum V_{ij}}{N} \quad (10)$$

2. Methods

2.1. Recruitment

This study recruited 300 adults to respond to a quality-of-life survey hosted online. Study participants were recruited based on specific quotas (age, ethnicity and gender) to form a representative sample based on UK census data. The survey was hosted on the [Prolific](#) platform which invited paid respondents to complete the WAIte version of the OPUF survey. A demonstration of the OPUF survey and questions is available [here](#). Informed consent was obtained at the outset of the survey and participants reserved the right to withdraw at any point without giving a reason. Participants who withdrew were not paid and their data deleted. Participation in this survey was estimated to take approximately fifteen minutes to complete and participants received £2.50 as a payment upon completion. This is in line with reimbursements rates from other OPUF studies [10, 11] and is in line with recommended reimbursement rates from [Prolific](#). The survey was designed to be an unassisted survey administered online (no face-to-face contact) and no identifiable data was collected. Statistical analysis was conducted on the survey data. Newcastle University Medical School Ethics Committee approved this study (reference 49737/2023). The survey structure is detailed in Section 2.2.

2.2. Survey structure

1. Consent and Prolific ID: Participants were asked to consent to participate and enter their unique Prolific ID. This enables demographic information held by Prolific on their participants to be linked to each respondent.
2. WAItE descriptive system: Participants were asked to complete the WAItE descriptive system (presented in Figure 4) to describe their current health state.
3. Attribute selection: Participants were presented with the worst level for each WAItE attribute and asked to choose which health problem would have the most negative impact on their quality of life. The attribute chosen is then used in the subsequent attribute swing weighting task.
4. Attribute swing weighting: Participants were presented with each attribute in the WAItE and asked to consider an improvement from the worst level of that attribute to the best level of that attribute. Participants were asked to rank this improvement on a visual slider from 0-100 where the most important attribute (chosen in the previous task) is fixed at 100. Participants were reminded to use their most important attribute as a reference point.
5. Level rating: Participants were presented with a specific attribute of the WAItE and shown each level within that attribute. Levels best and worst (never and always) were fixed at 0 and 100 respectively. Participants were asked to rank the intermediate levels within each attribute using the fixed levels as a reference point.
6. Anchoring: Participants were presented with a binary choice asking whether they prefer the worst state of the WAItE (PITS state) or death. If participants choose the worst state of the WAItE, a second question is asked which asks them to rank the WAItE PITS state on a visual analogue scale where zero is labelled as being dead and one hundred is labelled as no health problems. If participants choose death in the binary choice, they were asked to rank being dead on a visual analogue scale where zero is labelled as the WAItE PITS state and one hundred is labelled as no health problems.
7. Survey feedback and demographic questions: Participants were asked about how difficult they found the task to complete and demographic information on age, gender, ethnicity, education, employment and weight status.

INSTRUCTIONS:

The questions below ask about different things in your life. Read through each question carefully and **TICK ONE RESPONSE THAT BEST DESCRIBES YOU AT THE MOMENT**

EXAMPLE:

If you 'sometimes' have body pain then you should tick this box:

	Never	Almost Never	Sometimes	Often	Always
I have body pain			✓		

Now please read through each of the 7 questions below and choose ONE answer that best describes you at the moment

	Never	Almost Never	Sometimes	Often	Always
1. I get tired					
2. I struggle to keep up when I am walking around with others					
3. I avoid doing sports					
4. I struggle to concentrate on my studies/work					
5. I feel embarrassed shopping for clothes					
6. I feel unhappy because I am unable to do the same things as others					
7. People treat me differently when I go out					

Figure 4: WAItE descriptive system

2.3. Missing data

Through the survey design process, the potential for large amounts of missing data was mitigated by ensuring responses were compulsory to certain questions. However for ethical reasons, we allowed participants to not answer the questions relating to death. For participants who do not provide responses to the anchoring questions, their responses were imputed using multiple imputation by chained equations (MICE) [12] which were informed by demographic information and attribute weighting responses.

2.4. Preference heterogeneity

As PUFs are estimated on an individual basis, exploring preference heterogeneity between individuals in the sample is straightforward. Investigating the heterogeneity of preferences between individuals, requires a measure of dis/similarity to quantify how far apart two PUFs are [13]. The measurement and estimation of preference heterogeneity in this section will follow methods detailed by Schneider et al. (2024) [13]. Each PUF estimated in this study was represented by a vector of 78,125 health state utility values for each respondent in the sample. In order to assess the dis/similarity between these PUFs, we used the euclidean difference measure (EUD). Analogous to a line between two points on a two dimensional plane, the EUD between two PUFs denotes the shortest path length in a 78,125 dimensional space. It is computed as the square root of the sum of the squared differences between the PUFs of individuals i and j (presented in Equation 11). Once PUFs have been estimated for all individuals in the sample, pairwise EUD was estimated for all possible pairwise combinations within the sample. Pairwise EUD was stored in an $[N \times N]$ distance matrix.

$$d_{EUD}(i, j) = \sqrt{\sum_{s \in \{1111111, 2111111, \dots, 5555555\}} (u_i(s_1) - u_j(s_1))^2 + \dots + (u_i(s_{78125}) - u_j(s_{78125}))^2} \quad (11)$$

2.5. Permutational analysis of variance

Permutational analysis of variance (PERMANOVA), analogous to analysis of variance, is a geometric partitioning of variation across a multivariate data cloud, defined in the space of any given dissimilarity measure, in response to one or more groups [14, 15]. This method of statistical testing has been used most commonly in ecological research to test for population dispersion among different subgroups [16]. PERMANOVA decomposes the total distances between observations (SS_T) into within-groups (SS_W) and between groups sum-of-squares (SS_B). Equation 12 details the estimation of total and within-groups sum-of-squares. Mathematical notation presented here is reproduced from Schneider et al. (2024) [13] for consistency.

$$SS_T = \frac{1}{N} \sum_{i=1}^{N-1} \sum_{j=i+1}^N d(i, j)^2; \quad SS_W = \sum_{i=1}^{N-1} \sum_{j=i+1}^N d(i, j)^2 \epsilon_{ij}^\ell / n_\ell \quad (12)$$

where N is the total sample size ($=300$), $d(i, j)^2$ is the squared distance between the PUFs of participants i and j , $\epsilon_{i,j}$ indicator which is 1, if participants i and j belong to the same group, and 0 if they do not, and n_ℓ is the size for group ℓ . Then, SS_B can then be calculated as $SS_B = SS_T - SS_W$, which allows calculating the pseudo F statistic for p groups:

$$F = \frac{(\frac{SS_B}{p-1})}{(\frac{SS_W}{N-p})} \quad (13)$$

Further details about the mathematical and statistical properties of PERMANOVA are available elsewhere [13, 14, 15]. In this study, we used PERMANOVA to explore the variability in WAItE health state preferences (individual value sets) between various subgroups. A multivariate PERMANOVA model was estimated with subgroups of: age, gender, self-reported weight status, education, employment status and ethnicity.

2.6. Sensitivity analysis

In an experimental sensitivity analysis, preference heterogeneity was assessed using EUD estimated based on individual’s personal utility functions anchored using the social PITS utility value (henceforth referred to as EUD2). This differed to prior preference heterogeneity estimation as individual variation in PITS utility values were not included in the EUD2 estimation. EUD2 was entirely composed by differences in level ratings and attribute weights. Further details on the derivation of EUD2 are presented in the online [Appendix](#).

An additional analysis of preference heterogeneity in anchoring values was conducted using a generalised linear model. A multivariate Gamma GLM (with log-link function) was constructed to explore the relationship between PITS utility values and demographic information. This facilitated exploration into how anchoring preferences differed among different demographic subgroups in our sample.

3. Results

3.1. Study participants

A sample of 334 individuals were approached to participate in the study via the survey company [Prolific](#). Individuals that successfully inputted their unique Prolific ID and obtained a correct completion code from the end of the study were included in the analysis sample and received a small payment (£2.50) for their participation. Seven participants were excluded from the study as they had an incorrect completion code and did not enter the correct unique Prolific ID. Therefore, no data was available on those seven participants and they were excluded from the analysis. An additional participant was excluded from the analysis due to completing the survey in eighteen seconds (well under the pre-specified minimum time limit of 2 minutes). Two respondents timed-out while completing the survey and were therefore not included. Twenty-four individuals chose not complete the study (referred to by Prolific as ‘returned’ participants). This left an analysis sample of N=300 participants who successfully completed the survey. The sample was representative of the UK based on age, gender and ethnicity. A summary of demographic information collected in the OPUF are presented in Table 4.

3.2. Survey duration

The mean (SD) and median (IQR) survey completion time in minutes was 9.66 (5.85) and 8.15 (5.88; 11.89). Table 3 summarises how much time was spent completing each individual section of the survey.

Table 3: Survey completion times (secs)

Section	Mean (SD)	Median (Q1; Q3)	Min	Max
WAItE	73.0 (90.1)	53.0 (38.0; 77.0)	10.0	1066.0
Attribute ranking	35.4 (50.6)	26.0 (16.0; 40.0)	2.0	741.0
Attribute weighting	115.7 (94.9)	91.5 (69.8; 142.2)	18.0	1380.0
Level rating	220.5 (206.4)	171.0 (119.0; 249.0)	34.0	2158.0
PITS vs death	25.5 (45.4)	16.5 (11.0; 25.2)	4.0	620.0
PITS-VAS	37.3 (39.2)	29.0 (21.0; 45.0)	5.0	605.0
Total (secs)	579.5 (351.1)	489.2 (352.5; 713.4)	126.7	3738.2
Total (mins)	9.66 (5.85)	8.15 (5.88; 11.89)	2.11	62.30

3.3. WAItE descriptive system

Responses to the WAItE descriptive system are presented in Table 4. Feeling tired and avoiding doing sport were the attributes that were most frequently experienced by participants in our analysis sample. WAItE summary statistics were in line with results from previous studies [17].

3.4. Level ratings

Level ratings are presented individually for each different attribute in Table 5. The best and worst levels (*Always* and *Never*) were fixed at 0 and 100 respectively. The second best level (*Almost never*) had the lowest VAS score in the Sports and Embarrassment attribute, while the second worst level (*Often*) had the highest VAS score in the Concentration attribute. In this question, higher VAS scores indicate worse states of health.

Table 5: Summary of OPUF level ratings by attribute

Section	Mean (SD)	Median (Q1; Q3)	Min	Max
Tired				
Almost never	20.3 (23.2)	10.0 (5.0; 25.0)	0	100
Sometimes	36.3 (19.2)	33.5 (20.0; 50.0)	0	100
Often	62.2 (23.9)	70.0 (50.0; 80.0)	0	100
Walking				
Almost never	19.4 (21.8)	10.0 (6.0; 21.0)	0	100
Sometimes	37.7 (19.4)	40.0 (24.0; 50.0)	0	100
Often	63.0 (26.2)	71.0 (50.0; 80.0)	0	100
Sports				
Almost never	16.6 (21.0)	10.0 (5.0; 20.0)	0	100
Sometimes	29.5 (22.0)	25.0 (10.0; 45.0)	0	100
Often	49.8 (29.6)	50.5 (24.5; 75.0)	0	100
Concentration				
Almost never	21.4 (22.1)	14.0 (7.0; 25.0)	0	100
Sometimes	41.6 (20.1)	40.0 (25.8; 53.2)	0	100
Often	64.5 (26.2)	73.0 (50.0; 80.2)	0	100
Embarrassment				
Almost never	16.6 (22.3)	10.0 (4.0; 20.0)	0	100
Sometimes	29.4 (21.6)	25.0 (10.0; 50.0)	0	100
Often	47.9 (30.4)	50.0 (20.0; 75.0)	0	100
Unhappiness				
Almost never	21.1 (22.2)	13.0 (6.0; 25.0)	0	100
Sometimes	41.4 (22.1)	41.5 (25.0; 56.0)	0	100
Often	63.6 (28.2)	75.0 (50.0; 85.0)	0	100
Treated differently				
Almost never	20.9 (24.4)	11.0 (5.0; 25.0)	0	100
Sometimes	35.5 (22.8)	34.5 (19.8; 50.0)	0	100
Often	55.9 (30.6)	60.5 (31.0; 80.0)	0	100

3.5. Attribute weights

Summary statistics of attribute weightings are presented in Table 6. On average, Tiredness (76.5) and Unhappiness (70) were considered to be more important to participants than Embarrassment (40.1) and Sports (42.3). There was less variability in attribute weighting responses to Tiredness than responses to Treated differently or Embarrassment. Figure 5 illustrates the relative attribute importance (RAI) among WAItE attributes.

Table 6: Summary of OPUF attribute weights and anchoring responses

Section	Mean (SD)	Median (Q1; Q3)	Min	Max
Tired	76.5 (28.4)	90.0 (60.0; 100.0)	1	100
Walking	65.5 (32.5)	75.0 (40.0; 100.0)	0	100
Sports	42.3 (32.8)	35.0 (11.0; 70.0)	0	100
Concentration	67.9 (30.9)	80.0 (44.0; 99.2)	0	100
Embarrassment	40.1 (34.3)	30.0 (9.0; 70.0)	0	100
Unhappiness	70.0 (31.9)	80.0 (50.0; 100.0)	0	100
Treated differently	52.1 (35.6)	50.0 (15.8; 86.0)	0	100
Anchoring				
PITS preferred to death	0.9 (0.3)	1.0 (1.0; 1.0)	0	1
PITS-VAS	56.1 (31.3)	54.0 (30.0; 85.0)	0	100
Dead-VAS	42.5 (31.6)	38.5 (13.2; 63.5)	1	100
PITS VAS uncensored	-0.025 (5.950)	0.500 (0.200; 0.800)	-99	1
PITS VAS censored	0.431 (0.485)	0.500 (0.200; 0.800)	-1	1
PITS Utility Value	0.282 (1.456)	0.500 (0.200; 0.800)	-14.3	1

Table 4: Summary of demographic information collected in the OPUF

Participant Characteristics (N=300)	N (%)
Age	
18-24	32 (10.9%)
25-34	50 (17%)
35-44	48 (16.3%)
45-54	49 (16.7%)
55-64	81 (27.6%)
65-90	34 (11.6%)
Not Stated	6 (2.0%)
Gender	
Female	154 (51%)
Male	144 (48%)
Non-binary	1 (0%)
Ethnicity	
White	251 (84%)
Asian	23 (8%)
Black	11 (4%)
Mixed	10 (3%)
Other	5 (2%)
Weight Status	
Normal	154 (51%)
Overweight	104 (35%)
Obese	30 (10%)
Underweight	8 (3%)
Prefer not to say	4 (1%)
Education	
Degree	147 (49%)
A Level	64 (21%)
Higher Education	46 (15%)
Other	20 (7%)
GCSE A-C	18 (6%)
GCSE D-G	5 (2%)
Occupation	
Full-time	130 (43%)
Part-time	62 (21%)
Not Paid	30 (10%)
Other	31 (10%)
Student	17 (6%)
Unemployed	18 (6%)
Not Stated	9 (3%)
Starting a New Job	3 (1%)
WAItE	Mean (SD)
Tiredness	3.4 (0.8)
Walking	2.1 (1.1)
Sport	3.3 (1.3)
Concentration	2.7 (1.0)
Embarrassment	2.2 (1.2)
Unhappiness	2.3 (1.0)
Treated differently	1.9 (0.9)
Total	17.8 (4.8)

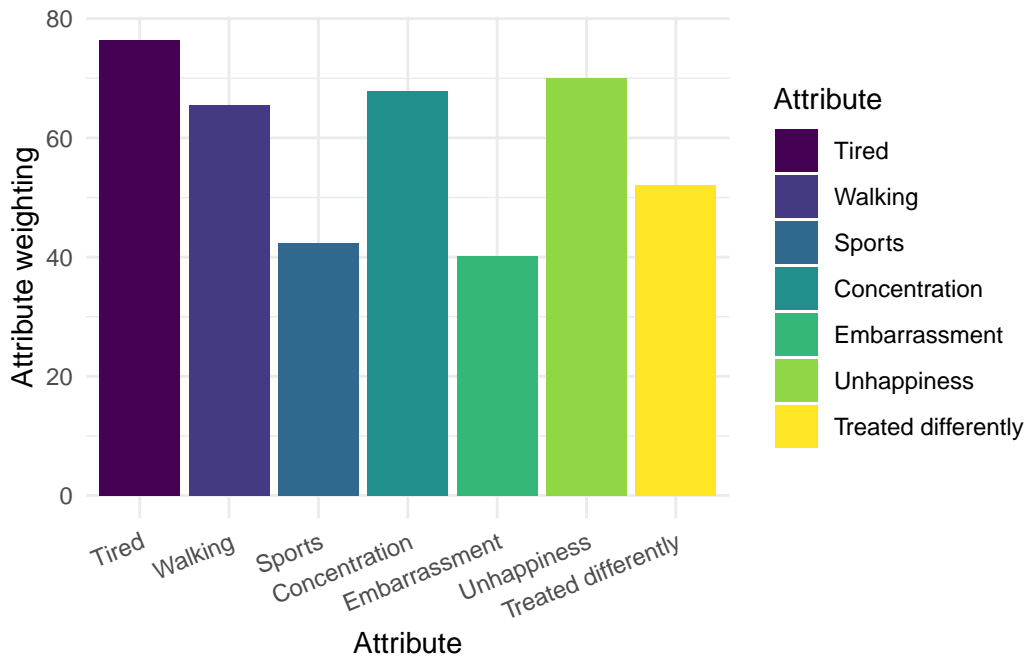


Figure 5: Relative attribute importance

3.6. Anchoring

The majority of respondents in the sample preferred the WAItE PITS state to being dead (87%). Therefore, 13% of participants answered the dead-VAS and 87% answered the PITS-VAS. A proportion of participants did not answer the anchoring task (1.67%). After winsorizing extreme values (top and bottom 0.1%) [18] and conducting multiple imputation by chained equations on the missing values, the mean (SD) and median (IQR) PITS utility value was 0.282 (1.456) and 0.5 (0.6). The distribution of WAItE PITS utility values (after winsorizing and imputation) is presented in Figure 6.

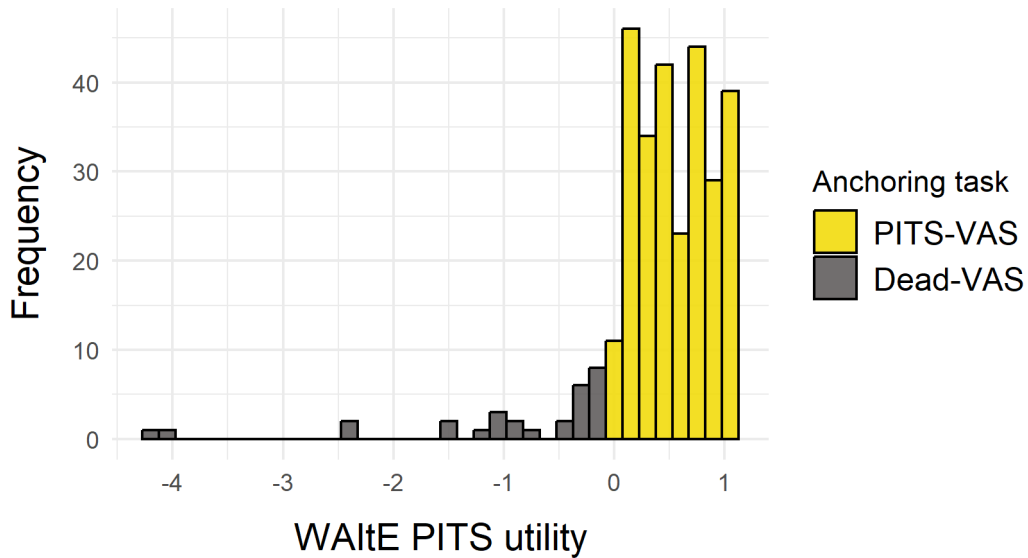


Figure 6: Distribution of PITS utility values

3.7. Social utility function estimation

Personal utility functions were estimated individually for each participant in our analysis sample via methods outlined in Section 1.4. After this, individual PUFs were aggregated into a group utility function and anchored using the group PITS utility value (0.282) to give the social utility function. Descriptive statistics from the social utility function are presented in Table 7 whereby the mean values can be used to estimate utility values for WAIte health states. Confidence intervals were estimated from bootstrap resampling with 10,000 iterations.

Figure 7 presents the mean social utility function (thick line) alongside individual personal utility functions (thin lines) for a selection of 100 WAIte health states ordered from high to low utility according to the social preference. Deviations of individual utility functions from the social preference illustrate the heterogeneity of preference within our analysis sample. Individual personal utility functions shown in Figure 7 are anchored using individual PITS utility values rather than the social PITS utility value.

Table 7: Social utility function based on 300 PUFs

Attribute Level	Mean (95% CI)	Median (Q1; Q3)	Min	Max
Tired				
Almost never	0.029 (0.025; 0.033)	0.016 (0.007; 0.033)	0	0.279
Sometimes	0.052 (0.048; 0.057)	0.043 (0.024; 0.070)	0	0.311
Often	0.088 (0.082; 0.094)	0.086 (0.052; 0.112)	0	0.359
Always	0.140 (0.133; 0.148)	0.126 (0.101; 0.161)	0.006	0.479
Walking				
Almost never	0.021 (0.018; 0.024)	0.013 (0.006; 0.026)	0	0.179
Sometimes	0.045 (0.041; 0.049)	0.040 (0.019; 0.062)	0	0.192
Often	0.075 (0.069; 0.082)	0.074 (0.028; 0.102)	0	0.428
Always	0.116 (0.108; 0.124)	0.110 (0.084; 0.141)	0	0.570
Sports				
Almost never	0.012 (0.010; 0.015)	0.006 (0.001; 0.016)	0	0.127
Sometimes	0.023 (0.020; 0.025)	0.015 (0.004; 0.036)	0	0.126
Often	0.038 (0.034; 0.044)	0.026 (0.008; 0.059)	0	0.461
Always	0.069 (0.063; 0.076)	0.064 (0.029; 0.103)	0	0.524
Concentration				
Almost never	0.026 (0.023; 0.030)	0.014 (0.006; 0.032)	0	0.229
Sometimes	0.051 (0.047; 0.055)	0.044 (0.024; 0.068)	0	0.261
Often	0.080 (0.074; 0.086)	0.076 (0.039; 0.107)	0	0.280
Always	0.121 (0.114; 0.128)	0.113 (0.088; 0.142)	0	0.532
Embarrassment				
Almost never	0.012 (0.010; 0.014)	0.004 (0.000; 0.013)	0	0.138
Sometimes	0.022 (0.019; 0.025)	0.012 (0.002; 0.031)	0	0.180
Often	0.034 (0.030; 0.038)	0.019 (0.004; 0.053)	0	0.359
Always	0.061 (0.056; 0.067)	0.053 (0.019; 0.100)	0	0.359
Unhappiness				
Almost never	0.025 (0.022; 0.029)	0.015 (0.006; 0.031)	0	0.208
Sometimes	0.054 (0.049; 0.059)	0.044 (0.022; 0.073)	0	0.371
Often	0.083 (0.076; 0.090)	0.081 (0.036; 0.112)	0	0.368
Always	0.124 (0.117; 0.133)	0.117 (0.087; 0.146)	0	0.463
Treated differently				
Almost never	0.019 (0.016; 0.022)	0.010 (0.002; 0.022)	0	0.157
Sometimes	0.035 (0.030; 0.039)	0.025 (0.006; 0.051)	0	0.359
Often	0.052 (0.047; 0.058)	0.040 (0.009; 0.082)	0	0.376
Always	0.087 (0.079; 0.095)	0.085 (0.038; 0.117)	0	0.553

3.8. Preference heterogeneity

After estimating individual PUFs for all participants, pairwise EUD was estimated between all participants. This yielded a $[300 \times 300]$ distance matrix with 44,850 unique pairwise comparisons. The mean (SD) and median (IQR) EUD were 115.73 (253.07) and 61.08 (33.17; 100.31). The highest and lowest

observed EUD were 2150.75 and 0. Figure 8 illustrates the relationship between EUD and WAItE health states. EUD tends to increase as WAItE health states worsen. That is, as the severity of WAItE health states increases, the more heterogeneous preferences become among our sample.

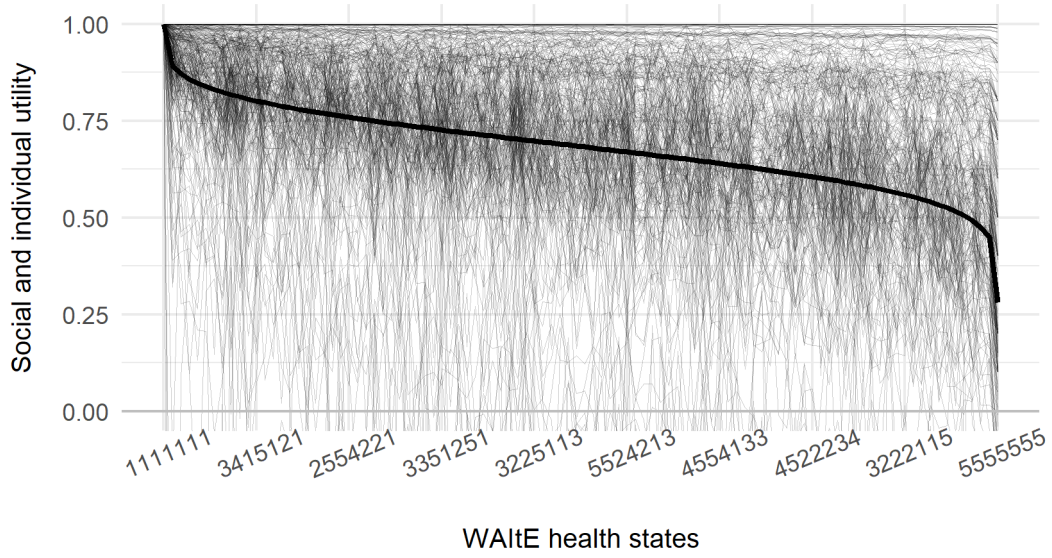


Figure 7: Social and individual utility functions

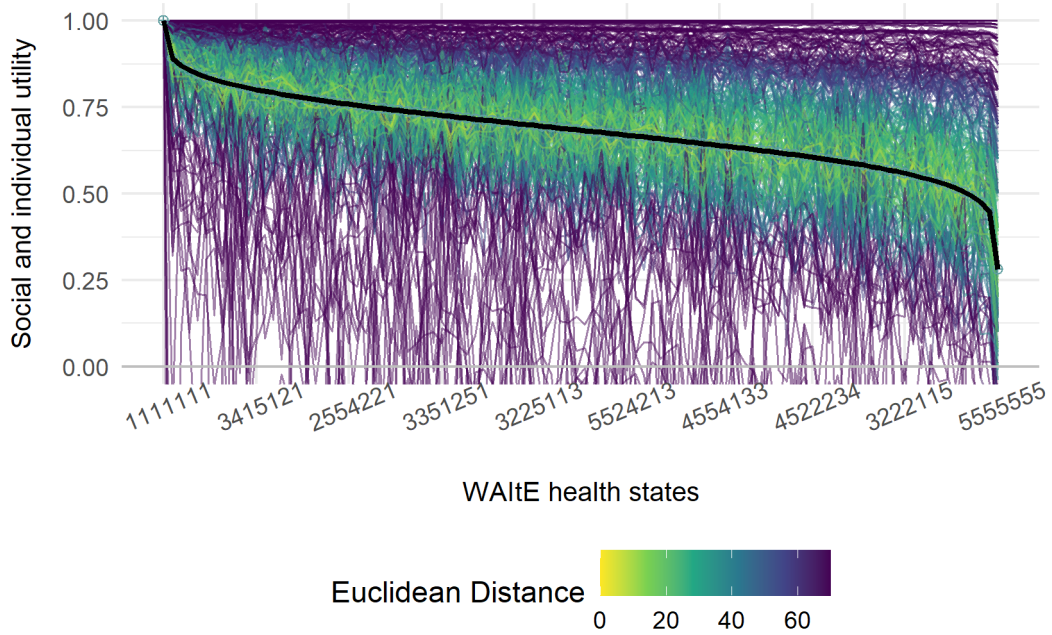


Figure 8: Social and individual utility functions coloured by EUD

3.9. PERMANOVA

Table 8 presents the PERMANOVA model results. Presented are within-group sum-of-squares (SS_W) for each group individually and for all groups combined, and the corresponding R^2 , pseudo F , and p values. Preference heterogeneity was significantly affected by age ($p = 0.03$), though the amount of variability in preferences that could be explained by age was relatively small ($R^2 = 5.7\%$). Figure 9 presents the difference in preferences between different age groups. Generally, as age increases, health state utility values for each given WAItE health state are higher. That is, younger populations tend to place more disutility on WAItE health problems than older populations. While weight status was not significantly related to preference heterogeneity according to the PERMANOVA model, given the WAItE

is a weight-specific measure, it was informative to explore the relationship between preferences and weight status. Though not statistically significant, we can observe a difference in preferences between normal weight and overweight individuals in Figure 10. For a given WAIte health state, overweight individuals in our sample placed less disutility on that state than did normal weight individuals.

Table 8: Results of PERMANOVA – testing for differences in WAIte health state preferences between group characteristics

Variable	df	SS_W	R^2	F	Pr(>F)
Age	6	663590.648	0.057	3.018	0.030
Weight status	1	6892.412	0.001	0.188	0.724
Education	5	33542.464	0.003	0.183	0.968
Occupation	7	290563.598	0.025	1.133	0.270
Gender	3	57313.577	0.005	0.521	0.361
Ethnicity	4	521334.829	0.045	3.557	0.056
Residual	273	10003165.515	0.864		
Total	299	11576403.042	1.000		

3.10. Sensitivity analysis

3.10.1. Attribute weighting and level rating preference heterogeneity

EUD2 was estimated for each pairwise comparison of individuals in our study. The mean (SD) and median (IQR) EUD were 34.30 (13.82) and 32.25 (24.54; 41.27). Results from the PERMANOVA2 analysis are presented in Table 9. After exclusion of individual variation in anchoring responses, weight status and age had a significant impact upon heterogeneity within our sample; though the amount of heterogeneity that was explained by these variables was fairly small (4.9%).

Table 9: PERMANOVA2 – testing for differences in level rating and attribute weighting preferences between group characteristics

Variable	df	SS_W	R^2	F	Pr(>F)
Age	6	8103.932	0.040	2.021	0.001
Weight status	1	1928.488	0.009	2.885	0.011
Education	5	4105.321	0.020	1.228	0.175
Occupation	7	4031.824	0.020	0.862	0.707
Gender	3	751.841	0.004	0.375	0.983
Ethnicity	4	3077.187	0.015	1.151	0.265
Residual	273	182464.444	0.892		
Total	299	204463.039	1.000		

3.10.2. Anchoring preference heterogeneity

A multivariate Gamma GLM model was estimated to explore preference heterogeneity in anchoring values (presented in Table 10). Demographic characteristics were regressed on PITS utility values to examine how demographic information was related to anchoring values. Age, had a significant impact on anchoring preference heterogeneity ($p = 0.003$), though the point estimate indicated a relatively small effect size.

Table 10: Multivariate Gamma GLM Model – exploring the relationship between PITS utility value and demographic characteristics

Variable	β	SE	t	Pr(> t)
Intercept	2.696	0.031	88.072	0.000
Age	0.001	0.000	3.007	0.003
Education	-0.001	0.004	-0.186	0.853
Occupation	-0.002	0.002	-0.979	0.329
Gender	-0.012	0.011	-1.143	0.254
Ethnicity	0.006	0.005	1.268	0.206

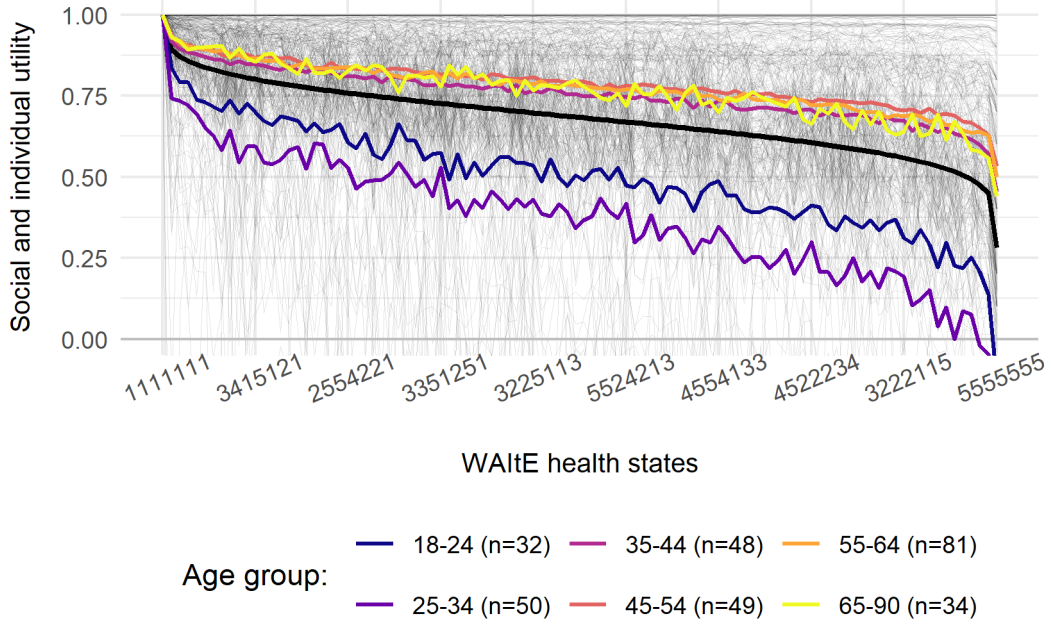


Figure 9: Social and individual utility functions grouped by age status

4. Discussion

This study is the first time that the OPUF has been used to estimate health state utility values for the WAIte. We obtained a representative sample of high quality data from Prolific, a survey company known for their high quality respondents [19]. Our average attribute weightings and implied ordering were similar to those exhibited in Robinson et al. (2024) [20].

Anchoring of the WAIte PITS state was a difficult procedure that required a number of methodological decisions. We decided to use uncensored responses to the Dead-VAS task which meant that data from one respondent (-99) skewed the mean PITS utility value quite substantially. To mitigate the impact of extreme values on the mean, we conducted winsorization of values lying in the outer 0.1% of the distribution. This practice, while effective at limiting the influence of extreme values on the mean, could understate the genuine variability in the data. However, winsorization would likely have had less of a distributional effect than exclusion altogether.

The social utility function elicited through this study, and underlying utility value set, present monotonic preferences which behave as one would have expected ex-ante (based on qualitative piloting work). Tiredness and Unhappiness were considered the most important attributes while Embarrassment and Sports the least important. As well as concurring with previous qualitative work, this is also in accordance with previous valuation work done with the WAIte [20]. Prior valuation work, which used a DCE to elicit preferences, yielded latent coefficients which violated the rational choice axiom of monotonicity. In the OPUF, monotonicity is essentially forced through the choice architecture of the level rating and the additional prompt to reconsider responses that are not monotonic. Forced monotonicity, in this context, could be problematic for eliciting unbiased preferences if preferences for certain health states are truly not monotonic. For example, prior qualitative work has suggested that “I almost never get tired” might be preferable to “I never get tired” in some circumstances where respondents are thinking about experiencing insomnia and sleep quality. This being said, the WAIte descriptive system was designed to be a monotonic descriptive system, validated using Rasch analysis, and so having a monotonic utility value set makes logical sense.

Preferences elicited through this study were considerably heterogeneous. This can be understood through the mean EUD value (47.6) but also illustrated in Figure 7 through the deviations of individual PUFs from the social utility function. Following on from prior work [13], we estimated EUD by calculating a distance matrix between each pairwise comparison of individual value sets for all 78125 WAIte health states. The implication of estimating distance (preference heterogeneity) by using individual value sets allows for much of the preference heterogeneity that exists to be composed of differences in

individual anchoring values (PITS state responses) rather than differences in level ratings and attribute weightings. This methodological decision, ultimately, results in the majority of EUD being composed of differences in anchoring values and this finding is important to acknowledge. Anchoring differences are important to present and explore, though in this preference heterogeneity analysis could be drowning out the heterogeneity in level ratings and attribute weighting. An example of this can be shown through the age preference heterogeneity in Figure 9 and Table 10. Preference heterogeneity is evident between individuals above and below age 35 and if we consider the mean PITS values for those two subgroups (age < 35 = -0.281; age > 34 = 0.487) we can see that a clear difference in anchoring responses is evident.

A methodological exploration was conducted as a sensitivity analysis to limit the influence that anchoring variation has on the overall preference heterogeneity. We considered this to be a strength of the research as it offers a new approach to decompose preference heterogeneity into anchoring variation and the difference in level ratings and attribute weightings. After exclusion of individual variation in anchoring responses, weight status and age were found to have a significant impact on preference heterogeneity within our sample; though the amount of variation that could be explained was limited. Preference heterogeneity between those of normal weight and those who were overweight is illustrated in Figure 10.

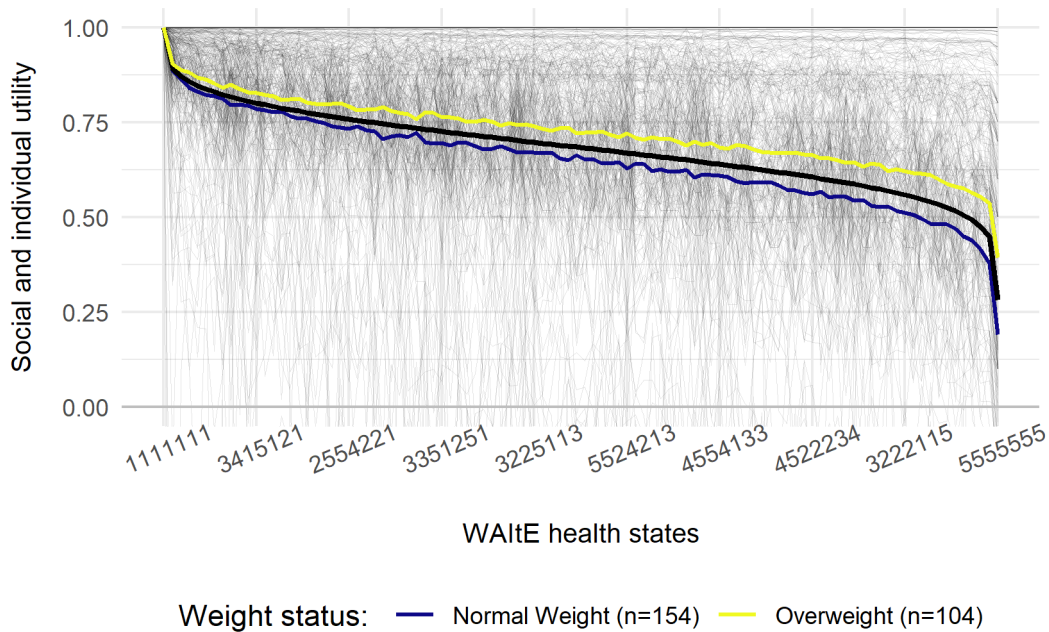


Figure 10: Social and individual utility functions grouped by weight status

This method of estimating preference heterogeneity should not be considered the gold standard, as only part of the variation in preferences is explored here. It can however be considered an additional option for future researchers that wish to isolate the effect of anchoring responses on overall preference heterogeneity. It is also, to our knowledge, the first time preference heterogeneity has been decomposed in this way with the OPUF.

The value set estimated here offers an alternative choice of preference values to the existing value sets estimated using DCE (shown in Table 11). When comparing the anchored coefficients between value sets, one of the key areas of divergence is where levels have been collapsed in the DCE value set. In the OPUF, “I almost never get tired” is given 0.029 compared to 0.064 in the DCE due to collapsing levels. Generally the difference between coefficients that have not been ‘collapsed’ between the value sets is small suggesting that there is comparability to an extent between the value sets. Anchoring values were broadly similar between studies too. The mean PITS utility values between studies were broadly comparable with a maximum range of 0.059. Interestingly, the EQ-VAS [21] anchoring task mean (0.289) was notably similar to the OPUF VAS anchoring task mean (0.282) again supporting the use of VAS for elicitation of PITS utility values.

Table 11: Comparison of WAItE utility value sets

Attribute Level	OPUF	DCE-TTO	DCE-VAS
Tired			
Almost never	0.029	0.064	0.059
Sometimes	0.052	0.064	0.059
Often	0.088	0.064	0.059
Always	0.140	0.148	0.137
Walking			
Almost never	0.021	0.015	0.013
Sometimes	0.045	0.015	0.013
Often	0.075	0.054	0.050
Always	0.116	0.106	0.098
Sports			
Almost never	0.012	0.021	0.019
Sometimes	0.023	0.021	0.019
Often	0.038	0.021	0.019
Always	0.069	0.058	0.053
Concentration			
Almost never	0.026	0.009	0.008
Sometimes	0.051	0.053	0.049
Often	0.080	0.067	0.062
Always	0.121	0.130	0.120
Embarrassment			
Almost never	0.012	0.007	0.007
Sometimes	0.022	0.025	0.023
Often	0.034	0.056	0.051
Always	0.061	0.069	0.064
Unhappiness			
Almost never	0.025	0.001	0.001
Sometimes	0.054	0.039	0.036
Often	0.083	0.076	0.070
Always	0.124	0.145	0.134
Treated differently			
Almost never	0.019	0.010	0.009
Sometimes	0.035	0.030	0.028
Often	0.052	0.075	0.069
Always	0.087	0.114	0.105

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