The SEArch for a task to measure TIME preference in EQ-5D valuation (SEATIME)

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Funding sources

This study was made possible through funding provided by the EuroQol Research Foundation (project number: 245-2020RA).

Acknowledgements

The authors gratefully acknowledge the guidance of a team of experts that advised on this project, consisting of Han Bleichrodt, Benjamin Craig, Michal Jakubczyk, Kirsten Rohde and Marjon van der Pol The views expressed by the authors do not necessarily reflect the views of the EuroQol group or the expert group.

Conflicts of interest:

Marcel Jonker is a member of the EuroQol Group. All authors have received research grants from the EuroQol Research Foundation for work outside the scope of the submitted work.

Abstract (500 words)

Objectives: There is ample evidence that time preference, i.e. the importance individuals assign to health now and in the future, can influence EQ-5D valuation. In particular, time preference affect time trade-off utilities in EQ-VT and will also be modelled in the upcoming stand-alone DCE protocol. There is, however, no consensus on how time preference could and should be measured in valuation of EQ-5D, with different solutions suggested for EQ-VT and stand-alone DCE. In this project, we aimed to contribute to that discussion by reviewing the existing methods for measuring time preferences, as well as identifying which appear promising for complementing the current procedures used in EQ-5D valuation.

Methods: Our project commenced with a systematic literature review using Web of Science, PsychInfo and Scopus in order to identify and describe all unique methods for measuring time preference. A panel of experts was formed to review the extraction forms and give feedback on the systematic review results. Our goal with this review was to characterize differences between existing methods as these may inform us about the methods that may be introduced to EQ-VT and how the current approach suggested for the stand-alone DCE protocol may be modified.

Results: After deduplication, 4976 records were included for abstract and title review. At this stage, the team is working on data extraction for the 201 records identified for full-text review (data extraction scheduled between April-August). Preliminary results suggest that methods for measuring time preference differ systematically on the following domains: outcome domain (e.g. health/money), reference-dependence (i.e. are gains and losses separated, the parametric forms they allow (e.g. constant discounting, quasi-hyperbolic discounting), and time needed for completion.

Conclusion: Currently, EQ-VT includes no measurement of time preference and the stand-alone DCE protocol estimates time preference concurrently with EQ-5D utilities with a single parameter capturing average time preferences for the sample. The latter approach differs from existing approaches in psychology and behavioural economics – with the key difference being that most literature estimates time preferences at the individual level. We suggest to expand the stand-alone DCE protocol to also estimate time preference individually. Although the existing modelling approach can straightforwardly be extended for this purpose, we discuss the potential of using a separate, dedicated task instead. Our review identified several tasks that could serve that purpose but may need adaptation to EQ-5D contexts. The use of such separate, dedicated tasks introduce ways to model individuals' time preferences more accurately in several ways, i.e. i) by allowing more flexibility in the functional form of the discount function, ii) by measuring time preferences separately for gains and losses, or iii) by allowing negative time preferences. Although such accuracy helps with better identification of time preferences, it is unclear if introducing additional complexity and realism in measurement of time preference will affect the efficiency and outcomes of stand-alone DCE valuation.

1. Introduction

The current EQ-5D valuation protocols use a mix of composite time trade-off (TTO) and discrete choice experiment (DCE) methods (1, 2). In valuation of EQ-5D-5L with EuroQol Valuation Technology (EQ-VT), it is recommended that both tasks are completed by a single sample with trained interviewers present (2), whereas for EQ-5D-Y-3L valuation protocol a decoupling of cTTO and DCE was recommended. That is, Ramos-Goni et al. (1) recommend that a sample of 200 respondents value EQ-5D-Y-3L states with cTTO, which is used to anchor utilities obtained with DCE in a sample of 1000 respondents. Notably, the DCE component of EQ-5D-Y valuation is completed online and without interviewers present, as is often the case for health state valuation with DCE (3).

Given the significant costs associated with interviewer-supported EQ-5D valuation, as well as potential benefits in terms of geographical reach of online data collection, alternative modes of EQ-5D valuation have been explored (4, 5). For example, online interviewer-assisted cTTO interviews may save costs and offer flexibility at little to no decrement in data quality (4, 6). Other teams have explored approaches that do away with cTTO completely, estimating value sets based on DCE data exclusively (e.g. 7, 8-10). Yet, to date no EQ-5D valuation protocols have been released that recommend the use of only DCE data.

Such a stand-alone DCE protocol has been in development, i.e. Pullenayegum et al. (11) presented a draft protocol in which EQ-5D value sets are generated based on online data collected with DCE exclusively. In this protocol, respondent complete choice tasks with three alternatives: two health profiles (with various durations) and either immediate death or full health for some duration. The protocol is, furthermore, set-up with an efficient design, optimized taking into account severity balance (12), colour coding and attribute overlap (13, 14). The authors suggest a range of analytical models that should be presented (11), which relax the various assumptions often applied to DCE data, e.g. models that take into account preference heterogeneity. Another key change with respect to earlier EQ-5D valuation protocol is that the authors suggest to include a model that models non-linear utility of life duration, or in other words, they recommend a model that relaxes the assumption of no time preferences that has typically been applied in EQ-5D valuation.

Linear utility of life duration (or constant proportional trade-offs) is one of the key assumptions of the QALY model as applied in EQ-5D valuation (15). It implies that respondents consider each year of equivalent value as the next, i.e. no time preferences for life duration are assumed. It has long been recognized that if utility of life duration is non-linear, TTO methods will yield biased results (16-20). Typically, utility of life duration is concave (i.e. positive time preference), which means that the value of life duration decreases over time (e.g. 17, 21, 22). If one incorrectly (e.g. as in all TTO-based valuation protocols) assumes that respondents completing TTO have linear utility functions instead, TTO results will be too low (16, 20). Note that this is only true for states better than dead, when composite TTO (i.e. which includes lead-time TTO) is used for valuation of states worse than dead a bias in the opposite direction occurs (23). Although it has become standard practice to apply discount factors to QALYs to capture societal time preferences in health technology assessment (24), correction for *individual* time preference is not typically applied to TTO utilities.

The stand-alone DCE protocol involves discrete choices between EQ-5D profiles that, in contrast to the EQ-VT protocol, include a duration element (25). Although the use of such DCE task with duration allow transforming the latent scale to QALYs, correction for time preferences is necessary (26). It may even be argued that the effect of time preferences on DCE with duration will likely be larger than that of time preferences in composite TTO (26). That is, in DCE with duration utility for worse than dead health states is typically obtained by extrapolating trade-offs to the point of zero duration. Incorrectly assuming linear time preferences will therefore not only result in biased estimates of relative health preferences but also overstate the proportion of states considered WTD. The latter is not the case in composite TTO valuation, where one can directly observe whether health states are considered better or worse than dead. Furthermore, Craig et al. (27) show that straightforwardly extrapolating trade-offs to short (or zero) durations may not be warranted, as disutility associated with impaired health depends on their duration. For example, some states may be considered worse than dead when experienced for a few days or months, better than dead when experienced for a year, but worse than dead for a duration of 10 years.

Therefore, Pullenayegum et al's (11) recommendation of modelling DCE data without assuming constant proportionality or linear utility of life duration is an important step in the direction of the paradigm shift argued for by Jonker et al. (26). That is, although various approaches have been developed for TTO data (28-30), the draft stand-alone DCE protocol is the first EQ-5D valuation protocol to implement some procedure that corrects for bias related to violations of linear utility. Importantly, the authors acknowledge that their draft protocol is a working model, with subsequent discussion feeding into its' further development. Therefore, it seems worthwhile to discuss ways in which the modelling strategy proposed in the protocol (11), or related work on time preference in DCE health state valuation (7, 8, 26, 27, 31), differs from previous work on time preferences in health and health state valuation.

Hence, the main motivation of this paper is to identify key differences between how time preferences are modelled in the stand-alone DCE protocol (and related DCE studies) and existing work in this area in other disciplines, e.g. behavioural (health) economics, psychology and marketing. To this end, we begin with elaborating on the approach used for modelling time preferences in DCE valuation in Section 2. In Section 3 we (briefly) discuss the strategy used for a systematic review we are conducting, in which we are reviewing *all* existing methods for measuring time preferences. Although the review is not complete, in Section 4, we can identify a set of differences between DCE valuation literature and the existing literature on time preferences. In Section 5, we discuss a set of potential changes to the stand-alone DCE protocol that may be considered.

2. Time preferences in DCE valuation

The existence of and bias related to time preferences in (EQ-5D) health state valuation has been a topic of discussion for decades. Yet, even though discrete choice tasks have been frequently used for estimation of time preferences in various contexts (32-34), the first studies modelling time preferences in DCE valuation data were published only fairly recently (26, 27). Subsequently, the insights generated in these papers have been applied in valuation studies for e.g. a wellbeing instrument for older people (31) and valuation of EQ-5D-5L in the United States (8) and Peru (7).

Preferences in DCE valuation tasks with duration are typically evaluated with a multiplicative utility function. That is, when using the notational conventions used in Pullenayegum et al. (11), before taking into account time preferences, the utility (U) an individual i assigns to health state j in choice task k with duration T is expressed as:

$$U_{ijk} = H_{ijk} \times T + \varepsilon_{ijk}. \quad (1)$$

In other words, utility consists of a systematic component ($H_{ijk} \times T$) and unobserved error, that is (typically) assumed to be independently and identically distributed. H_{ijk} describes utility of health status, and is obtained by taking N dummy variables ($X_{ijk1} \dots X_{ijkN}$) reflecting health state attributes and multiplying them with a vector of associated regression coefficients ($\beta_{i1} \dots \beta_{iN}$) that capture the utility associated with dimensions of quality of life, e.g. the 5 dimension captures in EQ-5D. Formally:

$$H_{ijk} = \sum_{n=1}^{N} (\beta_{in} \times X_{ijkn}). \qquad (2)$$

The model applied in Equation 1 assumes utility is proportional to the time spent in health states, or in other words, linear utility of health status. Time preferences are typically modelled by replacing T in Eq. 1 with a function that captures the net-present value of T years, e.g. as below:

$$U_{ijk} = H_{ijk} \times NPV_{ijk}(T) + \varepsilon_{ijk}. \qquad (2)$$

Here, for simplicity, we immediately present a set of discounting families used in this general framework. Traditionally, time preferences are modelled with exponential discounting (i.e. constant discounting). In our notation, applied to DCE valuation, as shown in (26, 27) this implies that non-linear utility of life duration is modelled as:

$$U_{ijk} = H_{ijk} \times \frac{1-\exp(-rT)}{\exp(r)-1} + \varepsilon_{ijk}, \quad \text{with } r \neq 0. \qquad (4)$$

Note that equation (4) reduces to linear discounting as in equation (1) when $r = 0$. Other functions have also been used. Two studies (7, 8) used power discounting, which in this notation can be expressed as:

$$U_{ijk} = H_{ijk} \times T^{\alpha} + \varepsilon_{ijk}, \quad \text{with } \alpha \leq 1. \qquad (5)$$

That is, a power α is applied to durations, with $\alpha = 1$ capturing linear utility of life duration and $\alpha < 1$ capturing concave utility of life duration. Note that power discounting is only adequately identified when many small durations are included in the experimental design, and tends to be difficult to fit when longer durations of life are used (as is typical in EQ-5D trade-off tasks).

Finally, different types of hyperbolic discounting functions have been used, which capture a tendency of discounting being strongest for outcomes closer to the present but decreasing over time. In DCE valuation, this implies that discounting is stronger for lower durations T, but the net present value of T falls in value slower for larger T. Although different specifications have been proposed (26, 27), typically logarithmic functions are proposed, e.g. (7):

$$U_{ijk} = H_{ijk} \times \frac{\ln(1+\rho T)}{\ln(1+\rho)} + \varepsilon_{ijk}, \qquad \text{with } \rho \neq 0. \tag{6}$$

Estimates for the parameters introduced in Eq. 4 to 6 differed between studies. For example, point estimates for exponential discount rate r ranged from $r = 0.057$ (26) to $r = 0.173$ (31), the power discount parameter (for T in years) ranged from $\alpha = 0.277$ (35) to $\alpha = 0.654$ (27). Note that Augustovski et al. (7) used the hyperbolic formulation in Eq. 5 but found no evidence that this model fit the data better than assuming linear utility of life duration. Jonker et al. (26), using a related formulation, point out that negative parameter values of ρ are not supported. Appendix A shows the net present value of 30 years in perfect health (i.e. $H_{ijk} = 1$) for a set of parametric specifications per discounting function described. At this stage, there is no consensus on which discounting function should be used in this context.

As such, the strategy for modelling time preferences in DCE valuation can be summarized as capturing non-linear utility of life duration by introducing a single parameter that describes curvature of the utility function in either power, exponential or hyperbolic functions. Jonker and Bliemer (36) describe how DCE with duration task designs can be optimized for estimating this single parameter as well as H_{ijk} under different specifications. Their work shows that traditional designs (e.g. optimized for estimating Eq. 1) are inefficient for estimating models that take into account time preferences, and therefore require considerable sample sizes (for power and hyperbolic functions in particular). Interestingly, any designs optimized to take into account time preferences with one function (e.g. exponential) performs well for other discount functions.

3. Systematic review on methods for measuring time preference

This paper is the first output to result from research program on methods for measuring time preference funded by the EuroQol research foundation (245-2020RA). The first stage of this program of work involved a systematic review of the existing literature of measurement of time preference. In particular, our goal was to identify *all* unique methods for measuring time preferences regardless of the outcome for which the method was designed. That is, time preferences in EQ-5D valuation characterize non-linear utility of *life duration,* but methodology for measurement of time preference has typically been developed for monetary outcomes (37). In that domain, time preference capture the temporal discounting of utility associated with money rather than life duration. Such temporal discounting is also understood to be a character trait associated with a wide array of addictive behaviours (38), and as such its' measurement is also important in treatment and prevention of addiction.

With this systematic review, besides providing a valuable overview of measurement methods with relevance in multiple fields, we aimed to identify methods that could have strategic relevance for EQ-5D valuation. Note that the goal of the current manuscript is to reflect on differences between the literature we identified and the current DCE valuation literature. Hence, a complete and elaborate description of the strategy used for this systematic review as well as presenting all data extracted from identified records is beyond the scope of the current manuscript – this will be reported in a subsequent manuscript once data extraction is complete. The systematic review was conducted in line with the following steps: i) develop search strategy, ii) implement search in Scopus, PsychInfo and Web of Science, iii) title and abstract screening (with two screeners), iv) development of extraction strategy with expert group, v) data extraction (currently ongoing), each of which is briefly outlined below.

3.1. Development and implementation of search strategy

In collaboration with Erasmus Library Services we developed a search strategy for a total of three databases. We selected PsychInfo, as we expected the psychological literature would contain many studies on time preferences, as well as two multidisciplinary search engines: Scopus and Web of Science. The search string was specified to combine search terms that describe time preference (e.g. patience, delay discounting, time discounting) and measurement methods (e.g. preference measure, questionnaire, measurement method). The full search string per database is found in Appendix A. Implementing the search strategy in June 2021 yielded 2297, 2664, and 3675 documents for PsychInfo, Web of Science and Scopus respectively. After deduplication, a total of 4976 records were identified for title and abstract screening.

3.2.Title and abstract screening

All titles and abstracts were blind-screened by the first two authors of this manuscript using the Rayyan.ai application. Before commencing the screening, all authors met to discuss criteria for inclusion and exclusion. Seeing as our goal was to include all unique methods inclusion criteria involved: i) titles or abstracts clearly signaling the use of a new method, ii) the use of an existing method with a new domain (e.g. using methods developed for monetary outcomes for health outcomes), ii) papers we knew proposed new methods for measuring time preference and iv) papers other authors based their methodology on. If we were unsure if papers proposed a new method, studies were set to potential inclusion. Exclusion criteria involved: i) no abstracts available, ii) if documents were non-peer reviewed PhD dissertations, iii) non-English documents, iv) the use of non-human respondents, and v) signals that suggested use of existing tasks (i.e. naming existing methods). After the blind screening by the first two authors, 148 documents were included based on positive inclusion decisions by both authors. A total of 596 articles were flagged for potential inclusion. The first author screened the full-text of these potential inclusions to render a definitive inclusion decision. Any remaining disagreement between both blind-screeners was resolved in a separate discussion. The total number of included documents after title and abstract screening was 201.

3.3.Extraction strategy

After title and abstract screening was completed, we developed a strategy and form for extracting relevant characteristics of each unique method. This strategy was co-developed with a team of experts on time preference and DCE valuation, that advised on the type of information extracted. We decided to extract information on: i) *Bibliographics and general characteristics* (e.g. abstract, titled, the domain the method was operationalized in), ii) *Theoretical framework of the method* (e.g. information the discount fuction, utility function, whether the method included risk and if it allowed negative discounting), and iii) *Operationalization of the method* (e.g. the units used to describe (life) durations or other outcomes, characteristics of the elicitation process). For the sake of completeness, we included the description of the information extracted in Appendix B.

3.4.Data extraction

In order to efficiently extract all relevant information from 201 records, the first two authors blind-extracted the first 50 document in three rounds of 25, 10 and 15 documents respectively. After the first round, several changes were made to the form used for data extraction in order to promote more consistency between screeners, as well as extract additional sources of information (e.g. additional fields describing the parametric forms of the discount/utility function). The second and third round were followed up by discussion on subsequent extraction and inclusion decisions. The remaining 151 documents, as well as any additional references that would be identified during full-text screening were divided between the first two authors of this paper. At the time of writing of this manuscript, data extraction for these records is still ongoing.

4. Differences between DCE valuation and existing literature on time preference

Based on our discussions about the information that needed to be extracted from the existing literature, as well as the partially completed data extraction of the systematic review, we can identify a set of differences between time preferences as modelled in DCE valuation and the measurement and modelling strategies used in other literatures. In some cases, such differences are trivial. For example, the existing literature has estimated time preference for a plethora of outcomes with little relevance to EQ-5D valuation, such as pieces of candy (39) or time spent playing video games (40). However, we identified a single key difference: Pullenayegum et al. (11) recommend modelling time preferences with a single parameter, that captures the *whole sample's* tendency to discount life duration. Although not technically necessary, every DCE valuation study modelling time preference to date has made this simplifying assumption (7, 8, 26, 27, 31). Our ongoing review of existing methods shows that the majority of methods (~75%) are designed to model time preferences with *individual-level parameters*. Such studies typically identify considerable heterogeneity in time preferences (23, 41). Furthermore, when heterogeneity in time preferences is explored, as in much of the existing literature, additional differences between time preferences as modelled in DCE valuation and the measurement and modelling strategies used in other literatures are discovered, of which some with potential relevance for EQ-5D valuation are explored in some detail below. In particular:

i. time preferences are typically measured separately from other (e.g. health state) preferences with a separate task,
ii. many discounting models are used, and it is not clear how to determine which works best for whom,
iii. time preferences are modelled reference-dependently, with potential for negative time preferences

4.1. The use of separate tasks

In the current stand-alone DCE protocol (11), as well as related DCE literature (7, 8, 26, 27, 31), time preferences are estimated from the same choice data as health state preferences. This has the consequence that the DCE design needs to be optimized for *both* purposes (36), and may require increasing the sample size or amount of questions asked compared to designs in which only health state preferences are estimated. In contrast, earlier work on correcting QALYs for time preference has typically included separate tasks for measuring time preferences for health (20, 29, 30, 42). In these studies, correcting for time preferences involves three steps. First, time preferences for health are measured, as well as tasks estimating health preferences (e.g. TTO tasks). The estimates of the former task are used to correct the latter, ex-post (43).

4.2. Flexible discounting models

Although the stand-alone DCE protocol does not specify the discount function to be used, Section 2 shows that the type of functions considered so far are either exponential, power or hyperbolic discounting. The commitment to a single function implies that the same discounting model should be applied to all respondents' data, whereas some studies in the existing literature have shown that the type of discounting model that fits individuals' data best may differ between respondents (e.g. 44). Also, more flexible discounting models have been introduced, e.g. Loewenstein and Prelec (45) introduce generalized hyperbolic discounting, a two-parameter discounting model. Other two-parameter discounting models are also popular, e.g. quasi-hyperbolic discounting (46) and constant-sensitivity discounting (47). Such two-parameter models, by definition, allow more flexible modelling of time preferences. Furthermore, there is even a range of methods developed that require no a priori assumptions about the type of discounting model (48, 49). In the ongoing review, ~25% of methods used such non-parametric measurement approaches.

4.3.Negative time preference and reference-dependence

Both Craig et al, (27) and Jonker et al, (26) for hyperbolic find average discount rates are strictly positive. Such positive time preference capture the intuitive assumption that health today is of higher value than health in the future – *in the majority of most samples*. Yet, negative time preference has been identified in several studies (50), for health in particular (23, 30, 51). As such, when modelling or measuring time preferences at the individual level, it may be important to use methods that allow negative time preferences. Note that the existing methods reviewed so far also only allow for negative time preferences in a minority of cases (~28%). Yet, when they do, many studies find evidence for negative time preference. In particular, negative time preference for health is often observed in two contexts. First, whenever non-constant health profiles are used, many individuals prefer profiles with time in impaired health sooner rather than later (23, 30) (e.g. prefer 10 years in wheelchair followed by 10 years in full health over the reverse profile). Second, negative time preference can be observed when a distinction is made between gains and losses in health (29, 41) (i.e. reference-dependence). Our (ongoing) review showed that a minority of existing methods (~20%) model time preferences separately for gains and losses. Positive time preference would imply that losing health is worse now than in the future and people would rather postpone a loss of health. Yet, several studies identified negative discounting of health losses in at least a considerable minority of the sample (29, 41, 52). In both cases, these preferences reflect a tendency to want to 'get the worst over with', leading to negative time preferences.

Summarizing, as opposed to the DCE valuation literature, the existing literature reviewed so far appears focused on uncovering heterogeneity in time preferences in various ways, often with a separate decision task designed for this purpose.

5. Potential changes to the stand-alone DCE protocol

The key difference our ongoing review identified between the DCE valuation literature and other existing literature on time preferences is that literature's focus on measuring and modelling heterogeneity in time preference. Although existing work has not done so, expanding the Pullenayegum et al. (11) framework, i.e. based on a mixed logit specification allowing for individual-level parameters capturing such heterogeneity in time preference, is relatively straight-forward. Instead of a fixed parameter, a random discounting parameter could be specified in each of the functions discussed, which would allow for respondent-specific discounting parameter estimates[1]. Accommodating preference heterogeneity, for both health and time, will require estimating designs that are able to estimate both efficiently, i.e. the approach by Jonker and Bliemer (36) would need to be modified. Moving beyond such practical considerations, two questions remain crucial when considering implementing this change to the stand-alone DCE protocol: i) why is modelling heterogeneity in time preference

[1] It can be questioned, however, if such preference heterogeneity can be accommodated in the Craig et al. 8. Craig BM, Rand K. Choice Defines QALYs: A US Valuation of the EQ-5D-5L. Medical Care. 2018; 56: 529-36. modelling strategy, that relies on Zermelo-Bradley-Terry models.

relevant for EQ-5D valuation? ii) would modelling heterogeneity in time preference also have an impact on the population (mean) health preferences and estimated QALY tariffs? Conceptually, we believe the answer to the former lies within the increased recognized need as well as degree of sophistication applied to modelling preference heterogeneity in EQ-5D valuation (53, 54). Recognizing that individuals, just as is now common practice for health state preferences, differ in the utility assigned to life duration requires modelling such heterogeneity. Besides being consistent across in the modelling of the core components of the utility function (i.e. both H_{ijk} and ε_{ijk} are estimated at the individual level), this also introduces additional realism in the modelling approach applied – as there is no mistaking that time preferences differ substantially between individuals (23, 41). The second question (i.e. the effect on QALY tariffs) requires experimentation with DCE valuation approaches that accommodate preference heterogeneity, which is our key recommendation for future research and for consideration in the stand-alone DCE protocol (11).

When, as we recommend, heterogeneity in time preference is accounted for in the DCE valuation literature, this opens up a set of additional areas of research, which align with other differences between the DCE valuation literature and the existing literature on time preference. At this stage, we form no recommendations for the stand-alone DCE protocol based on these differences with existing literature, but rather suggest further study in three key areas: i) the use of separate, dedicated tasks for measuring heterogeneity in time preference, ii) the use of flexible discounting functions, and iii) negative (and reference-dependent) time preferences. Note that if heterogeneity in time preferences is considered irrelevant for EQ-5D valuation, none of the areas of future study would be of strategic relevance.

First, it may be investigated if heterogeneity in time preferences can be more efficiently or accurately measured with a separate, dedicated task. In particular, non-parametric tasks, which measure discounting without committing to a single discount function could have relevance. For example, the direct method (48) measures utility of life duration by asking respondents to choose between different profiles in which they receive health impairments either earlier or later, until indifference is reached. Lipman et al. (30), for example, elicited five such indifferences in personal interviews, elicited in approximately 10 minutes including instruction. The main advantage of using separate, dedicated task is that they allow precise and typically flexible (e.g. the direct method is non-parametric and does not require any discount function to be selected a-priori) identification of heterogeneity in time preferences.

As such, the use of separate, dedicated tasks could enable the use of a relatively simple DCE design, focused on identifying heterogeneity in health state preferences, with identification of heterogeneity in time preferences left to the separate task. Yet, a few important, unanswered questions remain. For example, the feasibility and efficiency of existing methods is unclear, particularly for online data collection as in the stand-alone DCE protocol. Note, however, that our review already identified a set of highly efficient methods (55, 56) that may be adapted for valuation of EQ-5D. More importantly, it is unclear what exactly is gained (i.e. in terms of DCE design efficiency) by identifying heterogeneity in time preference with a separate task, and at what cost that identification would come (e.g. separate tasks introduce a separate error distribution that needs to be accounted for).

Second, when heterogeneity in time preference is investigated the question remains whether respondents only differ in the strength of discounting, or also in type of discounting function that best describes their preferences itself. Although there is evidence that the use of (some forms of) hyperbolic discounting may not describe some individuals' preferences well (44), it is unclear how impactful the use of discount functions with suboptimal fit is on QALY tariffs. Furthermore, it is unclear which set of tasks to use to identify the best fitting discount function in the first place. When no consensus can be reached on which single-parameter discounting function performs best, more flexible, two-parameter discount functions may be considered (45, 47), which does introduce an additional challenge to DCE design optimisation.

Third, when the parameter(s) that describe discounting are estimated or measured for each individual, we should consider how to deal with the substantial minority of respondents that discounts negatively. In particular, care should be taken to ensure that the design, task structure, and discounting function allows negative time preference – which may require new types of tasks to be used. When homogeneity of time preferences is assumed, this of little strategic relevance, as on average positive time preferences are typically observed (23, 26, 27, 30). A related area for future study is the existence of reference-dependence in discounting, as negative discounting is particularly prevalent for losses (in health) (29, 41). Jonker et al. (57) have already shown that preference for health profiles may depend on reference-points: health profiles better than current health are valued differently than profiles worse than current health. Other work has argued that TTO valuation is subject to reference-dependence, people may experience the short durations consider in EQ-5D valuation as losses compared to their subjective life expectancy (58) and loss aversion affects preferences when respondents asked to give up time in impaired health (29, 59). Seeing as conceptually the choice tasks Pulleneyagum et al. (11) recommend for stand-alone DCE valuation resemble TTO valuation (albeit without eliciting direct indifferences), reference-dependence in stand-alone DCE valuation may be expected. Nonetheless, beyond the Jonker et al. (57) study, there is little work on reference-points in DCE valuation, which is an important caveat. Hence, before further exploring how to expand the DCE valuation protocol to accommodate reference-dependent discounting (i.e. separately estimating discounting for gains and losses), a case should be made on why reference-dependence (in time preference) is relevant for EQ-5D valuation and how it can be studied in DCE valuation.

In conclusion, based on an ongoing review of *all* existing literature on measuring time preferences, our recommendation is to expand the stand-alone DCE protocol to estimate heterogeneity in time preferences. Our review also suggests that when heterogeneity in time preference is taken seriously, a set of areas of future study open up that will help in the search for a task to measure time preferences in EQ-5D.

6. References

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Appendix A. Net present value for durations up to 30 year for each discounting function under different parametric specifications

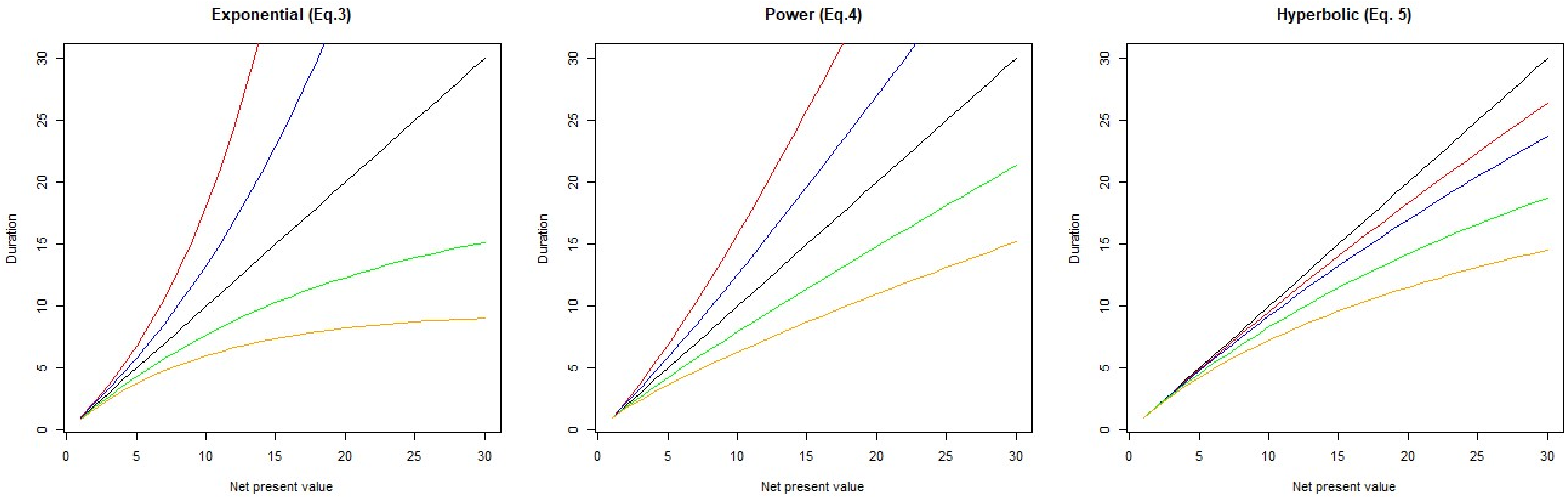

Figure A1. Net present values for durations between 1 and 30 years in full health generated for exponential, power and hyperbolic discounting. Note that black lines represent no time preferences, and red, blue, green and orange lines represent $r = -0.10, -0.05, 0.5, 0.10$, $a = 1.2, 1.1, 0.9, 0.8$ and $\rho = 0.01, 0.02, 0.05, 0.10$ respectively.

Appendix B: Search strings used per database

Web of Science

TS=("decision-making" OR "choice behavio*" OR "intertemporal choice" OR "measurement method*" OR "preference measure*" OR questionnaire* OR survey*)

- Results: 2,255,558

TS=("time preference*" OR "time discount*" OR "delay discount*" OR "utility of life duration*" OR "*patience")

- Results: 9,625
- Combining #1 and #2 results in 2,664 documents

Scopus

TITLE-ABS-KEY("decision-making" OR "choice behavio*" OR "intertemporal choice" OR "measurement method*" OR "preference measure*" OR questionnaire* OR survey*)

- Results: 4,258,670

TITLE-ABS-KEY("time preference*" OR "time discount*" OR "delay discount*" OR "utility of life duration*" OR "*patience")

- Results: 13,137
- Combining #1 and #2 resulted in 3,675 documents

PsycINFO

decision making OR measurement method* OR choice behavio?r OR intertemporal choice OR preference measure* OR questionnaire* OR survey*

- Results: 890,665

time preference* OR time discount* OR delay discount* OR utility of life duration OR patience OR impatience

- Results: 5,639
- Combining #1 and #2 resulted in 2,638 documents
- Limiting to humans resulted in 2297 documents

Appendix B. All information extracted in full text review

Table B1

Attribute	Explanation
Bibliographics	
#NR	Record number
First author	For easy indexing
Year	Year of publication
Journal	Include full journal name
General	
Name method	If the authors have used a name for their approach, include it.
Domain used	Which outcome type is the method used or designed for
Existing categories	A priori we can already distinguish a set of families of methods the identified method could fit: • Multiple price list • DCE • Kirby • Convex time budget
Theoretical framework	
Discount function	
Non-parametric	Boolean (Yes/No) that indexes if the method is introduced as being implemented without parametric assumptions for discounting
Parametric forms used	Selection from discrete categories below: • Constant discounting $d_t= (1+\delta)^{-t}$ • Quasi-hyperbolic discounting $d_t= \beta(1+\delta)^{-t}$ for $t>0$ and 1 for $t=0$. • Power discounting $d_t= (1+t)^{-\beta}$ • Proportional discounting $d_t= (1+\alpha t)^{-1}$ ○ This includes Mazur discounting • Generalized hyperbolic discounting $d_t= (1+\alpha t)^{-\beta/\alpha}$ • Constant sensitivity $\exp((-at)^{b})$

	• Other • No parametric assumptions needed
Parametric notes	Open text field to add notes about parametric form (e.g. if slight modifications were made)
Reference-dependence	Boolean (Yes/No) that indexes if the method is introduced as being implemented with reference-dependent discount functions (i.e. discounting separately estimated for gains/losses)
Utility function	
Non-parametric	Boolean (Yes/No) that indexes if the method is introduced as being implemented without parametric assumptions for discounting. Also write no if the method requires no measurement of utility.
Parametric forms used	Selection from: • Linear utility • Power utility/CRRA • Exponential utility/CARA • Other
Parametric notes	Open text field to add notes about parametric form (e.g. if slight modifications were made)
Reference-dependence	Boolean (Yes/No) that indexes if the method is introduced as being implemented with reference-dependent utility function.
Single/Flow outcome	Does the method involve outcomes at a single point in time or outcome that consists of a sequence of different outcomes at different timepoints (i.e. a flow). Index as Single/Flow
Negative discount rates	Boolean (Yes/No) that tracks whether or not negative discount rates can be estimated with the method.
Risk involved	Boolean (Yes/No) that tracks if the method includes risks
Probability weighting	Boolean that tracks if (when risks were involved) probability weighting was measured or corrected for.

Gains/losses	Does the method involve gains, losses or both?
Operationalisation	
Outcome unit	What unit are outcomes expressed in?
Time unit	What unit is time expressed in?
Outcomes bounded	Are outcomes bounded (i.e. they have a fixed minimum and maximum or do these differ between respondents)? Index as: Yes (min/max) or No
Durations bounded	Are durations bounded (i.e. they have a fixed minimum and maximum or do these differ between respondents)? Index as: Yes (min/max) or No
Finite questions	Is a fixed amount of questions used (or does this differ between respondents/operationalisations)? Index as: Yes or No
Number of tasks	Number of questions/decision tasks (how many data points are obtained)
Iterations per task	Number of iterations per task (e.g. if a bisection is used with 5 choices write 5, DCE gives 1).
Population	Which population was used?
Country	Which country was data collected? Index as: Country name
Sample size	Numeric
Lab/field	Was data collected in the lab or field? Index as: Lab or Field
Duration	How much time (indexed in minutes) did data collection take (per respondents) in the study. Note that this may also include additional data collected for other purposes.
Mode	How was the method implemented (CAPI-personal interview, CAPI-group-interview, CAPI-self-completed, Online, Pen and Paper).

Direct choice	Is the method based on direct choices between options (or rather based on fill-in-the-blank)? Extracted as: Yes or No
Indifference based	Is the method based on direct elicitation of indifferences, e.g. bisection/titration. Extracted as: Yes (time/outcome/both) or No. The qualifier in brackets indicates whether indifferences are elicited for durations, outcomes or both
Search procedure	If indifferences are elicited through choice, which search procedure is used: • Titration • Bisection • Ping-pong • Random • Choice list
Chaining indifferences	Is the method dependent on chaining of multiple indifferences? Extracted as: Yes or No
Incentive compatible	Is the method implemented with incentives compatible with preferences? Extracted as Yes or No
Individual estimation	Is the data collected with the method used for estimating discount rates at the individual level? Extracted as: Yes or No