A systematic review of unique methods for measuring discount rates

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Title

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A systematic review of unique methods for measuring discount rates

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Abstract (300 words)

Objective: Measures of discount rates have an important role in many fields, as they describe how individuals (or society) trade-off between now and the future and predict a variety of unhealthy or addictive behaviors. Yet, discount rates differ substantially between studies, methods and individuals. We aimed to provide a systematic overview of the many unique methods developed to measure discount rates.

Methods: We conducted a multi-database systematic literature review to identify and describe all unique methods for measuring discount rates. The review aimed to include published English studies that introduced and used methods for measuring discounting in human subjects. Titles and abstracts were screened by two authors, full-text review was divided between authors. For all included studies, data was extracted on bibliographics (e.g. journal), theoretical characteristics (e.g. discount function used), and operational characteristics (e.g. elicitation procedure).

Results: After deduplication, 4976, 218 and 83 records were identified for title and abstract screening, full-text screening and inclusion, respectively. Most methods were developed for measuring discounting of money (75%) and health (22%). A network analysis on the citations of the included studies suggests limited overlap between disciplines. Only approximately one fourth, one third, and one third of the methods had the following theoretically appealing characteristics, respectively: i) allowing negative discount rates, ii) applying multiple discount functions and iii) correcting for non-linearity in utility of outcomes.

Discussion: Many different methods for measuring discounting exist, with a wide array of theoretical and operational characteristics. These differences in characteristics may be a result of differences between the many fields (e.g. psychology, experimental economics, health economics) in which they have been developed in relative isolation. The results of our systematic review could help readers determine which method to use, depending on what characteristics they find most important when measuring discount rates.

Keywords: Time preferences; discounting; health; systematic review; measurement methods

1. Introduction

Many of life's important decisions are intertemporal: they involve trade-offs between the present and the future. For example, we may sacrifice leisure time today to go the gym and reap (potential) health benefits of being in better shape in the future, or we spend our salary on videogames today rather than saving for retirement. Since Samuelson (1937), these types of inter-temporal decision have been studied using models of time preference that involve discounting. In their traditional form, these models use a constant, positive discount rate (Koopmans, 1960). Similar to annual interest rates, constant (positive) discount rates capture that the value of outcomes depreciates when they are received later in time. As a result, individuals are impatient; they would rather receive benefits earlier and incur costs later.

Individuals may differ substantially from each other in this regard. That is, some individuals are strongly impatient and others not so much (Andersen et al., 2008), with some studies even finding negative time preference (Van der Pol and Cairns, 2000, Loewenstein and Prelec, 1991), i.e. individuals preferring to defer benefits to the future and incur costs earlier. To get insight into this heterogeneity, discount rates may be measured using various methods. Such measures of discounting are used in various fields for different purposes. For example, discount rates are studied for their association with many types of addiction (Amlung et al., 2017) and (the social rate of) discounting is an important consideration when investigating cost and benefits that can span generations (Groom et al., 2022) or in evaluation of new health technologies (Attema et al., 2018b). Given this widespread area of application, it is perhaps unsurprising that many different methods have been developed for measuring discount rates, both inside and outside the economics literature. To our knowledge, however, no up-to-date review of the methods used in this interdisciplinary field exists, which is a gap this paper aims to fill.

Several narrative and systematic literature reviews of studies on time preference or discounting have been conducted. These studies typically also review some aspects of the methodology, but restrict their literature search in one of multiple ways. Several studies restricted their search by reviewing the evidence for associations between discounting and specific health behaviours or health outcomes. For example, reviews have been conducted on the association between discount rates and addictive behaviours (Barlow et al., 2017, Cheng et al., 2021, Strickland et al., 2021), unhealthy behaviours (Story et al., 2014, Lawless et al., 2013), sexual behaviours (Johnson et al., 2021), eating disorders and obesity (McClelland et al., 2016) or diabetes self-management (Madsen et al., 2019). Clearly, this signals that studying discounting of future rewards is important in many different contexts. Indeed, a meta-analysis by Amlung et al (2019) suggested that discounting may be understood as a transdiagnostic process relevant to a wide array of psychiatric disorders. Other reviews have restricted their literature search to specific methodological concerns, such as discounting across different outcomes, e.g. money and primary rewards (Odum et al., 2020), time preference in medical decision-making (Attema, 2012), or the neural correlates of discounting (Carter et al., 2010, Frost and McNaughton, 2017).

Additionally, a set of review papers exist that provide an overview of the models and methodologies used for measuring time preference or discounting. Frederick et al. (2002) provided an early review of the literature on time preference, discussing the developments in measuring and modelling in this field since the seminal publication of Samuelson (1937). In particular, their work reviews a set of anomalies that violate constant discounting models, as well as alternative models that may be used (see section 2). Table 1 in their paper includes all published studies measuring discounting; approximately 40 studies published between 1978 and 2002 (also see the meta-analysis of these studies by Percoco and Nijkamp (2009)). Yet, two decades later, the literature on time preference has grown substantially, suggesting that the seminal review by Frederick et al. (2002) needed updating. Indeed, in such an updated review, Cohen et al. (2020) include 222 publications extracted from a single database.

Our systematic review distinguishes itself from earlier bibliographic work in this area, and as such our contribution to the literature is threefold. First, we developed an exhaustive, multi-database search strategy. In this way, our study differs from Matousek et al (2022), who recently published a meta-analysis of elicited discount rates, but included only the first 300 papers their query identified, or Cohen et al. (2020), who relied on a Google Scholar Search (in 2014). This paper, hence, aimed to provide a complete and up-to-date overview of methods for measuring discount rates. Second, we attempted to develop a search strategy that was sufficiently broad to identify papers on discounting across most relevant fields, by including synonymous terms for discounting used across fields (see section 3 for details on search strategy), as earlier work has shown a disconnect between work on discounting across fields (Barlow et al., 2017). Finally, rather than attempting to include all studies that published discount rates, our review aimed to identify *unique methodologies* for measuring discount rates. As such, our bibliographic work has excluded studies that are included in some of the reviews cited above, because the authors of those studies reused methods developed elsewhere.

The remainder of this paper is structured as follows. In section 2 we provide an overview of models of discounting and the discount rates (i.e. parameters quantifying time preference) they include, as well as challenges surrounding the measurement of such discount rates. In Section 3 we outline the methods used for the systematic review. Section 4 presents details on the unique methods for measuring discount rates identified and summarizes the characteristics of the methods. In Section 5, we discuss the results of the systematic review, as well as go through a set of challenges that arise when trying to identify if methods are ‘unique’.

2. Theoretical background

In this section we provide an overview of different functional forms used for modelling discounting and the discount rates implied in these functions, and discuss a set of theoretical and methodological considerations when measuring discounting.

2.1. Modelling discounting

Generally, studies on intertemporal choice presume additively separable preferences, which means that trade-offs between consumption in two different time periods are not affected by consumption in any other time period. Alongside some other basic assumptions, it results in the following discounted utility (DU) formulation for outcome *x* received at time *t* (Koopmans, 1960):

$$DU(x,t)=D(t)*U(x). \quad (1)$$

Here, D(t) is a discount function assigning a weight between 0 and 1 (or >1 in case of negative time preference) to the utility U of outcome x received at time point t. Usually, D(t) is monotonically decreasing in t.

The traditional form of D(t) used in neoclassical economic paradigm is exponential – or constant – discounting (Samuelson, 1937): $D(t)=e^{-rt}$ in a continuous format and $D(t)=(1+r)^{-t}$ in a discrete format, where *r* represents the discount rate. The central axiom of this model is stationarity, which says that if a particular common outcome is shifted from the last to the first period and all other outcomes are shifted one period ahead in time, then preferences are unaffected (Bleichrodt and Johannesson, 2001). In other words, the trade-off between two outcomes occurring at different points in time depends only on the difference in time of occurrence between these outcomes and not on the exact point in time at which they occur (Bleichrodt and Gafni, 1996).

However, many empirical studies have shown that constant discounting does not adequately represent intertemporal preferences (Frederick et al., 2002). Instead, many respondents have shown a tendency to be impatient for outcomes received in the near future but more patient for outcomes in the far future, or in other words decreasingly impatient. Such a preference can be modeled by hyperbolic discounting functions, which can accommodate decreasing discount rates over time. Decreasing impatience can result in time-inconsistency, where people make plans for the future, but do not execute these plans when the future arrives, even when no other factors, other than time passing, have changed (Prelec, 2004, Rohde, 2019). Such postponement of (usually) unpleasant tasks is called procrastination. Examples include postponing the decision to quit smoking, or to start exercising or studying for an exam.

The most popular hyperbolic discounting specification in psychological studies, is the proportional discounting function popularized by Mazur (1987):

$$D(t)=(1+kt)^{-1}. \tag{2}$$

Psychologists often simply refer to this function as ‘hyperbolic discounting’. In this discount function, parameter *k* represents the discount rate. To avoid confusion between this type of discounting and the set of potential models in which the discount function takes a hyperbolic form, we name it *Mazur discounting* throughout this paper. Some studies use a generalization of Mazur’s discounting function as proposed by Rachlin (2006), which adds a power *s* to the parameter *k* to allow for more flexibility: $D(t) =(1+kt^s)^{-1}$. This generalization is referred to as *Rachlin discounting.*

Another one-parameter hyperbolic discounting function is the model proposed by Harvey (1986):

$$D(t)=(1+t)^{-m}. \tag{3}$$

This form is sometimes called ‘power discounting’, where the discount rate is reflected by parameter *m*, but to be consistent with the other terminology, we refer to it as *Harvey discounting*.

The most popular hyperbolic model in economic studies is the *quasi-hyperbolic discounting model*, originally proposed by Phelps and Pollak (1968) and later popularized by Laibson (1997):

$$D(t)=1 \text{ for } t=0 \text{ and}$$

$$D(t)=\beta(1+r)^{-t} \text{ for } t>0, \text{ with } \beta\leq 1. \tag{4}$$

The main idea of this model is that any outcome not received at present (i.e. t>0) is given a penalty (β), the size of which being independent of the amount of the delay. Consequently, the factor β is often referred to as the *present bias* or *immediacy effect*, which is decreasing in the size of β. Another reason for the present getting a disproportionately higher weight than the future in this model is that transaction costs are frequently attached to a later outcome no matter how far in the future it occurs, while these costs are not incurred when the outcome is received immediately. The quasi-hyperbolic discounting model has become very popular in economics, mainly because of its analytic convenience, and its functional form showing close resemblance to the constant discounting function, which is a special case of this model if β=1. Moreover, whenever the present is involved in an intertemporal trade-off, this model has similar properties as the more general hyperbolic discounting functions in terms of a violation of stationarity and the possibility of time-inconsistencies and procrastination.

Loewenstein and Prelec (1992) derived a more general two-parameter hyperbolic discounting function. This function has also been dubbed 'generalized hyperbolic discounting', but because this term is again not universal, we term it *Loewenstein/Prelec (LP) discounting*.

$$D(t)=(1+kt)^{-m/k}. \quad (5)$$

The parameter k in this function reflects the departure from constant discounting, while the parameter m is an index of impatience. When k tends to 0, the function approaches constant discounting. One can easily see that the Mazur model is a special case of this function if m=k, and Harvey discounting is a special case for k=1.

Another class of models attributes decreasing impatience to a transformation of time rather than the discount function. That is, these models capture the idea that individuals have a subjective, nonlinear, time perception – similar to nonlinear probability weighting in decision under risk – that may result in decreasing impatience even if their discount function is exponential (Attema, 2012, Baucells and Heukamp, 2012, Zauberman et al., 2009). For example. Ebert and Prelec (2007) derived the constant sensitivity model which reflects the effect of different time perceptions:

$$D(t)=e^{-(at)^{\wedge}b}. \quad (6)$$

In this function, the parameter a represents impatience and the parameter b captures sensitivity to time.

Besides the 7 discount functions summarized above (i.e. constant, Mazur, Rachlin, Harvey, quasi-hyperbolic, Loewenstein-Prelec and constant-sensitivity), a substantial number of alternative models have been developed. Yet, many of these have been applied rarely, so we do not discuss all of them in detail[1].

2.2. Measuring discounting

Several methodological and theoretical considerations complicate the measurement of discount rates, which we will briefly summarize below (excellent reviews of these challenges can be found in e.g. Cohen et al. (2020) and Frederick et al. (2002)).

Perhaps unsurprisingly, given that models of discounted utility were first introduced in traditional economics (Koopmans, 1960, Samuelson, 1937), discount rates are often measured for monetary outcomes, i.e. individuals trade-off money or income received earlier or later. Yet, as discussed extensively in Cohen et al. (2020), income is not equal to or the only outcome that contributes to *utility* – which is typically understood as *consumption* (unless one applies the strong assumption that the monetary amounts traded off are directly consumed). Some authors have, instead, explored non-monetary discounting, e.g. discounting

[1] *A full overview of the discount functions applied by unique methods (including those not summarized above) can be found in the results section in Table 2*

for directly consumable goods such as effort (Augenblick et al., 2015) or food (McClure et al., 2007). Other authors (e.g. Fuchs, 1982), as a source of input for the discount rates in cost-effectiveness analyses of health technology, have studied discounting for health outcomes (e.g. years in good health, or lives saved). We will refer to these different outcomes for which discount rates are measured as *outcome domains.* Typically studies find some overlap between discount rates elicited in different outcome domains, but differences exist (e.g. Cairns, 1992, Chapman and Elstein, 1995, Bleichrodt et al., 2016, Attema et al., 2018a), see also the review by Odum et al. (2020). In their meta-analysis Matousek et al (2022) find evidence for such *domain independence,* they conclude that individuals tend to have higher discount rates for health than when it concerns money. Given that the domain used will likely influence the measured discount rates, the domain for which methods have been developed is an important methodological consideration. As a consequence, many studies have extended methods developed for monetary outcomes to other domains (Attema and Lipman, 2018, Lipman et al., 2019, Tompkins et al., 2016).

Another important consideration is (the flexibility of) the discounting function(s) that are used when measuring discount rates. As section 2.1 shows, many different discounting functions exist, with different parameters to capture the discount rate. The choice of discount function does not require to define a method, as in principle intertemporal trade-off data can be fit to many different functional forms, see e.g. Abdellaoui et al. (2013). Hence, many studies focus on comparing the fit of different discount functions, e.g. estimating discount rates using methods that enabled comparing the fit of constant and hyperbolic discount rates (Coller et al., 2003, Kirby and Maraković, 1995, Madden et al., 1999). Yet, some methods assume a single discount function applies a priori. For example, Kirby and Maraković (1995)'s widely used monetary choice questionnaire (MCQ) is used to estimate the *k* parameter in Mazur discounting. Such a loss in flexibility enables efficient estimation of discount rates, e.g. using prespecified calculations (Kaplan et al., 2016) or Bayesian adaptive procedures as in Toubia et al. (2013) and Pooseh et al. (2018). In contrast, there is also a range of methods developed that require no a priori assumptions about the type of discounting model (Attema et al., 2012, Blavatskyy and Maafi, 2018). Such *non-parametric methods* allow conclusions about discounting without assuming a specific discounting function, and can be used to estimate any discount rate.

Methods for measuring discount rates are also often applied with a set of restricting assumptions that will bias the estimated discount rates. In particular, some methods are only developed for estimating positive discount rates (i.e. for measuring D(t) monotonically decreasing in t). Such methods will therefore yield biased estimates of discounting whenever individuals are *patient* instead of impatient. Patience, i.e. deferring receipt of rewards and speeding up receipt of punishments, seems counterintuitive. Yet, *negative discount rates* been identified in several studies (Loewenstein and Prelec, 1991), for health in particular (Van der Pol and Cairns, 2000, Lipman et al., 2022a, Lipman et al., 2022c). If methods are used in which measuring negative discount rates is impossible, one would incorrectly conclude those with negative time preference as having zero or even (small) positive discount rates, leading to upwards bias on discount rates estimated on the population level. Bias may also result due to assumptions about the *shape of the utility function* U(x) in Eq.1. Many studies measure discounting whilst assuming U(x) is linear. For example, Mazur discounting is traditionally applied under this assumption. Typically, U(x) takes a concave shape, implying that $U(x)<x$ for $x\geq 1$ (regardless of how x is normalized). Hence, if the method does not include a procedure to take the shape of U(x) into account (e.g. Andersen et al., 2008, Attema et al., 2012), measures of discounting will typically be biased upwards. Some authors solve this issue by simultaneously estimating discounting and utility functions, where often utility is

estimated using *risk-based methods* (Andersen et al., 2008). Yet, such methods may be sensitive to biases in risk preferences, e.g. probability weighting (Gonzalez and Wu, 1999). It may also be relevant to consider using methods that allow *reference-dependent* discount rates or utility functions, i.e. separately measured or estimated for gain outcomes and loss outcomes, as earlier work has consistently shown differences in discounting and/or utility of gains and losses (MacKeigan et al., 1993, Abdellaoui et al., 2010, Shiba and Shimizu, 2019, Tversky and Kahneman, 1992)

Methods for measuring discount rates also differ in how they elicit intertemporal trade-offs, and the way in which such elicitations are operationalized may exert an influence on (the interpretation of) the outcomes of those tasks (Cohen et al., 2020, Frederick et al., 2002). In particular, the *elicitation procedure* has been shown to influence discount rates, with (the consistency of) trade-offs or preferences elicited differing between choice and non-choice-based elicitation procedures (Read and Roelofsma, 2003, Attema and Brouwer, 2013, Neumann-Böhme et al., 2021). Choice-based procedures refer to approaches in which individuals face intertemporal trade-offs through (series of) choices between outcomes now and later, e.g. (random) binary choice (Van der Pol and Cairns, 2001, Johnson and Bickel, 2002), bisection (Du et al., 2002), titration (Rachlin et al., 1991), and (multiple) price lists (Coller and Williams, 1999). Non-choice-based procedures refer to approaches where respondents are asked to state the outcome or time they would be willing to trade-off (or would make them indifferent), e.g. matching (Thaler, 1981) or bidding procedures (Olivola and Wang, 2016). Besides (potentially) influencing the measured discount rates, the choice for an elicitation procedure could also depend on whether discount rates should be elicited using real *incentives*. Little to no differences are typically found between discount rates elicited for hypothetical and real outcomes (Johnson and Bickel, 2002, Madden et al., 2003), although estimates appear more noisy for hypothetical outcomes (Coller and Williams, 1999). Yet, incentive compatibility remains an important methodological consideration in experimental economics, but of limited importance in other social sciences (Hertwig and Ortmann, 2003). Note that it is often impossible to use incentive compatible approaches when eliciting health trade-offs (Galizzi and Wiesen, 2018).

3. **Methods**

The systematic review was conducted in line with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009). Note that PRISMA is most often used for bibliographic work evaluating interventions (as opposed to our focus on unique methods), i.e. we followed the best practices outlined in these guidelines where relevant. In addition to the PRISMA guidelines this systematic review was performed in collaboration with a library spokesperson (specializing in bibliographics) and a panel of 7 experts on measuring (time) preferences. Our expectation beforehand was that the strategy for selection and extraction would be subject to changes informed by our experience during the process, hence we did not register a protocol for this review.

3.1. Eligibility Criteria

Rather than identifying every application of a specific methodology, our review aimed to identify unique methods for measuring discount rates. Whether or not a method is unique requires some value judgments (see also section 5), but we aimed to include studies that were the first to develop *and* apply a method or framework for measuring discount rates (in humans). This means that we include reports that propose new methods or developed new methods for a specific application, where new is defined chronologically in terms of date of publication. The type of studies included are published papers with empirical estimates of discount rates based on preference data obtained from human participants. We a priori excluded: i) papers collecting data from animal participants, ii) unpublished work (e.g. non-published dissertation chapters), iii) non-English publications, iv) studies that used pre-existing data to estimate discounting, v) theoretical contributions or contributions without data collection.

3.2. 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 discounting, as well as two multidisciplinary search engines: Scopus and Web of Science. The search string (see Appendix A) combined search terms that describe time preference (e.g. impatience, delay discounting, time discounting) and measurement methods (e.g. preference measure, questionnaire, measurement method). Implementing the search strategy in June 2021 (by the first author) yielded 2297, 2664, and 3675 documents for PsychInfo, Web of Science and Scopus, respectively. After deduplication, a total of 4976 records were identified for further screening (see Figure 1).

3.3. Title and abstract screening

All titles and abstracts were blind-screened by both authors of this manuscript using the Rayyan.ai application. Before commencing the screening, the 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 (e.g. using words as: 'novel', 'new', 'adapted'), ii) the use of an existing method with a new domain (e.g. using methods developed for monetary outcomes or health outcomes), iii) papers we knew proposed new methods for measuring discount rates 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). Rayyan.ai also allows screeners to identify papers for potential inclusion, i.e. a 'Maybe' category. Blind screening was performed by both authors of this manuscript, who discussed and finalized the screening and inclusion criteria after screening the first 500 records. After the blind screening by both authors, 148 documents were included based on positive inclusion decisions by both authors. A total of 596 articles were flagged for potential inclusion ('Yes' or 'Maybe' by one of the authors). The first author screened the full text of these potential inclusions to render a definitive inclusion decision (positive or negative). Any remaining disagreement inclusion decisions between both blind-screeners was resolved in a separate discussion through consensus. The total number of included documents after title and abstract screening was 202, which included 193 documents identified through the search strategy and 9 relevant documents identified when screening articles for potential inclusion that were not identified by the search strategy.

3.4. Data extraction: strategy and process

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 the expert panel, that advised on the type of information to be extracted. We decided to extract information on: i) Bibliographics and general characteristics (e.g. abstract, title, the domain the method was operationalized in), ii) Theoretical framework of the method (e.g. information the discount function, 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). The form was further finetuned through two rounds of pilot full text review. In the first pilot round, both authors of the manuscript used the form to review and extract information for included methods for the first 10 records identified (sorted alphabetically). After discussing and comparing extracted information, the form was revised. Revisions included greater detail about the utility function assumed in discounting methods and creating separate extraction categories for the number of tasks and number of choices per task (i.e. iterations). For the sake of completeness, we included the final description of the information extracted in Appendix B. In order to efficiently extract all relevant information using the final form from the large number of records identified after screening, both authors blind-extracted the first 50 documents in three rounds of 25, 10 and 15 documents, respectively. Each round was followed up by discussion on subsequent extraction and inclusion decisions. The remaining documents, as well as any additional references that would be identified during full-text screening were divided between both authors of this paper. After full text review and data extraction was completed, the authors discussed issues that arose during the extraction of data in the papers they each individually extracted. Inclusion and data extraction was finalized by the first author, who reorganized the list of included methods chronologically and checked if any duplicate methods were included (i.e. methods that had been used by other teams earlier), to finally check if extracted data was labelled uniformly across raters. Note that if a single publication used more than one method for measuring discounting, we extracted data for every new method (i.e. if an existing method was used as a benchmark, no data was extracted about the existing method). No quality or risk of bias assessment was performed, although raters used open text fields to verbalize thoughts they had about the methods. After the final inclusion decision and extraction was complete, the list of included papers was shared with the expert panel, who identified missing papers.

4. Results

Full-text review of the 202 records (of which 5 were excluded because full texts could not be retrieved) identified an additional 23 papers were identified for potential inclusion in the review. Review of the initial list of included papers by the expert panel resulted in one additional paper to be included (van der Pol and Cairns, 1999), as well as re-evaluation of 3 papers identified through the search strategy. After discussion between both authors, these papers were not included. Hence, a total of 85 papers were selected for inclusion in the review (see also Figure 1). Given the large number of unique methodologies identified, providing information on each of them within this paper would be infeasible, but the extracted data for each included paper can be viewed in an interactive table available online: https://referencepoints.shinyapps.io/SEATIMEtable/. The full list of included articles is also included in Appendix C.

4.1. Bibliographics and trends across fields

The first paper including a unique method for measuring discount rates was published in 1981 (Thaler, 1981). Our review identified 18 papers published between 1981 and 2000; the remaining 67 papers were published in the 20 years that followed, suggesting that the field of measuring discounting has expanded. Table 1 shows that most methods identified were published in journals we considered to be economics (n=39) and psychology (n=19) journals. Journal of Risk and Uncertainty (n=10), Health Economics (n=5), Behavioural Processes (n=5), Management Science (n=4) and Journal of the Experimental Analysis of Behavior (n=4) were the five journals most published in. Table 1 also shows the most frequently studied outcome domains, suggesting that domain studied differs somewhat between fields. For example, methods for measuring discount rates in the health domain have rarely been published outside of economics and health policy/medicine.

Table 1. Frequency of methods published per field and studied outcome domain.

Field **Domain**	Economics	Psychology	Health Policy/Medicine	Other	**Total**
Money	27	19	2	15	**62**
Health	11	1	4	1	**17**
Food/drink	1	2	1	1	**4**
Other	1	1	2	2	**6**
Total	**39**	**21**	**7**	**18**	

Note: Column totals are not the sum of the cells as some methods included multiple domains.

To further substantiate the dispersion of methods for measuring discount rates across fields we also performed a network analysis using VOSViewer of all papers that cited the 84 out of 85 included documents (11835 articles after deduplication). Note that the method developed in Fuchs (1982) was not included as it was not available in Dimensions, where we collected citations data. Figure 2 shows this citation network defined at the source-level (i.e. by journal), which for the sake of interpretability was limited to sources with at least 20 entries. Citation links are treated as undirected (i.e. it is not clear in which direction citations are taking place). Node size reflects the number of citations, proximity approximates the relatedness in citations. VOSviewer divides the journals citing the 84 methods included in our review into 5 clusters, which we provided with a label. We classified the clusters, in order of the number of documents they contained, as follows: Neuroscience (in red, e.g. Neuroimage, Journal of Neuroscience), Economics & Marketing (in green, e.g. American Economic Review, Journal of Marketing Research), Addiction & Psychopharmacology (in blue, e.g. Drug & Alcohol Dependence, Psychopharmacology), Health Economics and Policy (in yellow, e.g. Health Economics, Social Science & Medicine) and Psychology (in purple, e.g. Psychological Science, Journal of the Experimental Analysis of Behavior). The network analysis demonstrates a degree of separation between (neuro)psychology and (health) economics.

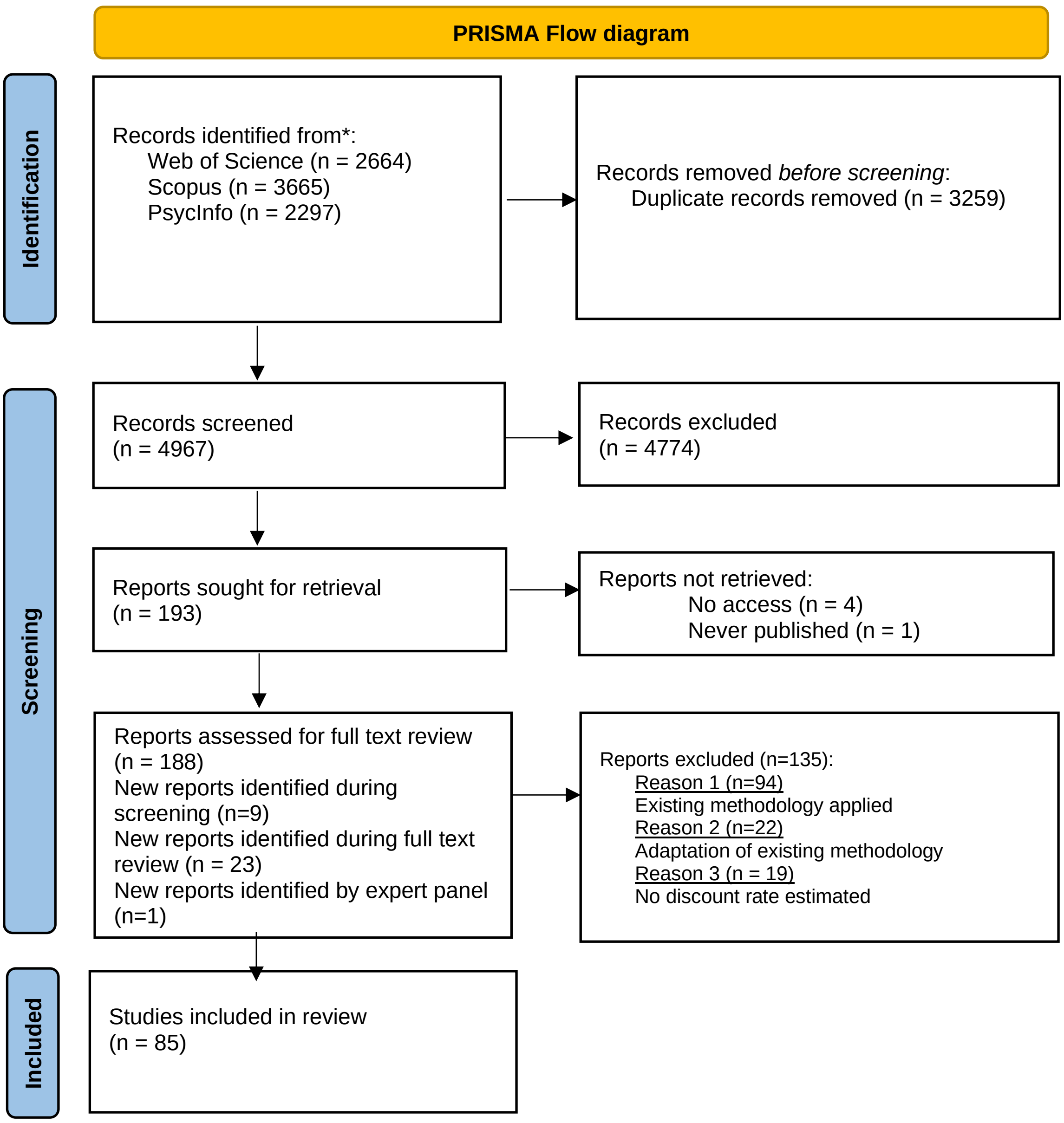

Figure 1. Prisma Flow diagram for the systematic review

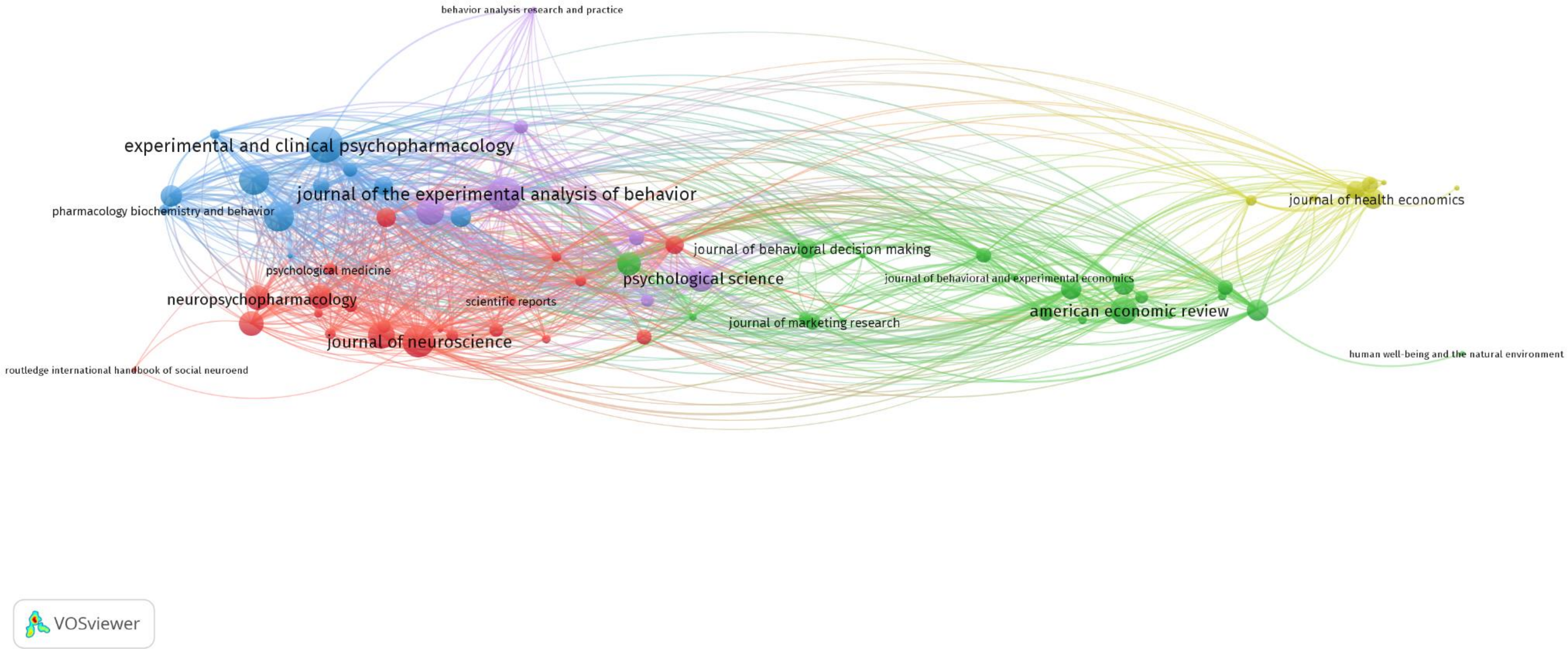

Figure 2. VOSViewer network visualisation for citations of the 11836 citations of 84 out of 85 studies included in our review (threshold set at 20 documents per source).

Table 2. Overview of discounting models used in included papers

Model name	**Functional form**	**Authors**	**Used by *n* methods**
Constant discounting	$D(t)=(1+r)^{-t}$	Samuelson (1937)	*N=47*
Mazur discounting	$D(t)=(1+kt)^{-1}$	Mazur (1987)	*N=39*
Rachlin discounting	$D(t) =(1+kt^{s})^{-1}$	Rachlin (2006)	*N=5*
Harvey discounting	$D(t)=(1+t)^{-m}$	Harvey (1986)	*N=4*
Quasi-hyperbolic discounting	$D(t)=1$ for $t=0$ and $D(t)=\beta(1+r)^{-t}$ for $t>0$	Laibson (1997)	*N=11*
Loewenstein-Prelec discounting	$D(t)=(1+kt)^{-m/k}$	Loewenstein and Prelec (1992)	*N=9*
Constant sensitivity	$D(t)=e^{-(at)^{\wedge}b}$	Ebert and Prelec (2007)	*N=5*
Constant absolute decreasing impatience (CADI)	$D(t) = e^{(e^{-ct}-1)}$ for $c>0$ $D(t) = e^{-t}$ for $c=0$. $D(t) = e^{(1-e^{-ct})}$ for $c<0$,	Bleichrodt et al. (2009)	*N=1*
Constant relative decreasing impatience (CRDI)	$D(t) = e^{t^{1-d}}$ for $d>1$ $D(t) = t^{-1}$ for $d=1$ $D(t) = e^{-t^{1-d}}$ for $d<1$	Bleichrodt et al. (2009)	*N=1*
Q-exponential	$D(t)= [e^{q[ka \ln(1+bt)]}]^{-1}$	Han and Takahashi (2012)	*N=1*
Magnitude-dependent expected discounted utility	$D(t)=e^{-d(r_x t)}$, where $r_x t$ is speed-adjusted time.	Baucells and Heukamp (2012)	*N=1*
Double exponential	$D(t)=\omega \sum_{\tau=0}^{T} D_{\beta}(\tau) +$ $(1-\omega) \sum_{\tau=0}^{T} D_{\delta}(\tau)$	McClure et al. (2007)	*N=1*
Fixed costs	$D(t)=1$ for $t=0$ and $D(t)=(1+r)^{-t}$ - b/y for $t>0$.	Benahbib et al. (2010)	*N=1*
Logistic	$D(t)=(1 + e^{a(\ln(t)-b)})^{-1}$	Patt et al. (2021)	*N=1*
Sub-additive	$f_{T\cdot n} = \prod_{t=1}^{T} f_{T\cdot n\cdot t}$	Read (2001)	*N=1*
Tau-discounting	$D(t)=1$ for $t=0$ and $D(t)=(1+r)^{-(t+\tau)}$ for $t>0$.	Bleichrodt et al. (2022)	*N=1*

4.2. Theoretical characteristics

Table 2 shows the frequency with which each discounting model was applied in the included methods. Other theoretical characteristics of the methods included are summarized in Figure 3, which shows the proportion of methods that: i) did not include any parametric assumptions for measuring discount rates (non-parametric), ii) were used to measure discount rates using more than one type of discount function (multiparametric), iii) assumed linear utility of outcomes (linear utility), iv) made a distinction between gains and losses when measuring the discount rate or utility function (reference-dependence), v) included tasks able to measure negative discounting and vi) used elicitation procedures that also included risky outcomes. The figure (inspired by Cohen et al., 2020) shows that the majority of methods was applied with only a single discount function (65.9%), with methods that used no parametric assumptions for discounting being rare (7.1%). Furthermore, the majority of methods developed assumed linear utility (64.7%), no reference-dependence (in discounting or utility, 91.7%) and strictly positive discounting (76.4%). Only few methods used risk as part of their methods for measuring discount rates (22.3%).

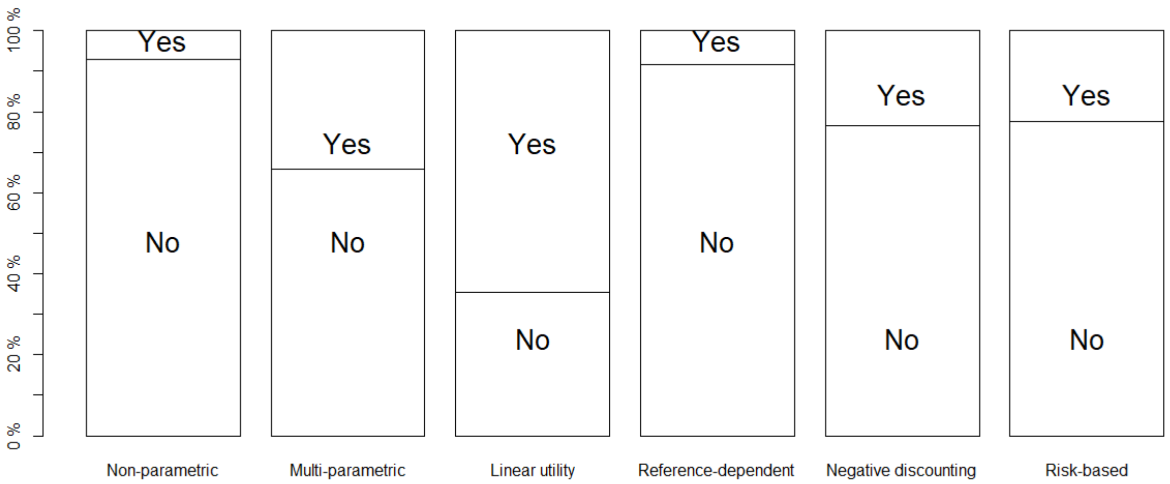

Figure 3. Theoretical characteristics of included methods

4.3. Operationalization of methods

We present extracted data on methods across three different subcategories.

4.3.1. <u>Study characteristics</u>

Most methods were developed in and tested with participants recruited from the United States (n=47) or Europe (predominantly in the Netherlands: n=8, and the United Kingdom: n=7). Outside of the US and Europe, development of methods for measuring discount rates seems concentrated in high-/middle-income countries (e.g. Japan and Israel, and China); in fact, no methods were developed in (and, thus, specifically for) low-income countries. Over 50% of the sample relied on student populations (n = 47) and a minority of the methods was developed with general public (n = 19) or substance (ab)using (n = 7) populations.

Studies on average lasted for 50.8 (SD = 68.1) minutes and used 54.6 (SD=72.6) questions. This seems rather long, but several very short and efficient methods were also included

(Koffarnus and Bickel, 2014, Montiel Olea and Strzalecki, 2014, Toubia et al., 2013, Ahn et al., 2020), e.g. with completion times between 1-10 minutes (for up to 50 questions). It is worth noting, however, that this data could not always be extracted, as study duration (54 out 85 studies) and the number of tasks (8 out of 85) contains missing data. This was caused by many studies not explicitly mentioning completion time and/or the number of tasks being variable. Most studies used some form of computer-assisted approach (54 out of 85), with non-computerized tasks often relying on paper-based approaches (26 out of 85). Unsurprisingly, computerized studies were far less prevalent in studies published before 2000 (only a single study: Richards et al. (1999)) than after 2000 (52 out of 67).

4.3.2. Outcome and delay characteristics

We extracted data on the size of the outcomes and delays included in each study. Across all 85 included methods, a minority was what we refer to as 'unbounded', which means that the minimum and/or maximum outcome (n = 11) or delay (n = 4) included in the study would be unclear to us a priori, e.g. as it depended on respondents' preferences (see for examples: Olivola and Wang, 2016, Lipman et al., 2019). For methods that included bounds, we can summarize the minimum and maximum of the outcomes for which discounting was elicited. For health measures, many different types of health outcomes can be observed, e.g. life duration in good (e.g. Khwaja et al., 2007), impaired (e.g. Cairns, 1992) or varying health states (e.g. Jonker et al., 2018) or lives saved (e.g. Olsen, 1993). Summarizing these to a single scale is not straightforward. Hence, for ease of interpretation, we focus our analysis of amounts only on monetary discounting, as this enables us to convert amounts used in any study regardless of local currencies to 2023 dollars[2]. Table 3 shows quantiles for the minimum, maximum and range of the amounts used, suggesting that large heterogeneity exists in the amounts considered. In 2023 USD, the highest outcomes were considered in Rachlin et al. (2000), whilst the lowest (negative) outcome was considered in Ostaszewski (2007).

Table 3. Quantiles for minimum, maximum amounts (in 2023 dollars) and the longest delays used in unique methods for measuring discount rates.

Quantiles	**Minimum**	**Maximum**	**Highest delay**
Min.	$-4368.35	$0.48	0.00013 days
Q1	$0	$48.15	90 days
Median	$5.36	$390	730 days
Q3	$120.73	$3823,89	7300 days
Max.	$35480.50	$1,760,000	36500 days

Finally, we summarize the included delays across all studies (excluding studies with unbounded duration), by reporting maximum delays included (expressed in days) in Table 3. Maximum delays range from 0.00013 to 36500 days, with a mean of 4180 days (SD=6436). The maximum delay is right-skewed, with many methods having maximum delays between 30 and 366 days (25 out of 85). The shortest delays were being considered in Greenhow et al. (2015), i.e. 1.5 seconds, and the longest in Cropper et al. (1994), i.e. 100 years. Note that studies varied in the descriptors used for describing delays, with frequencies differing

[2] For simplicity we take, when needed, the conversion rate from local currencies to dollars on January 1st of the year in which the paper was published, which we transform to 2023 USD.

between descriptors. That is, studies reported time in seconds (9 out of 85), minutes (2 out of 85), hours (4 out 85), days (26 out of 85), weeks (17 out of 85), months (31 out of 85), and years (48 out of 85).

4.3.3. Elicitation characteristics

Most methods elicited preferences with choice-based methodologies (65 out of 85) and relied on indifferences (59 out of 85). Methods that relied on indifferences typically elicited these indifferences in outcomes (43 out of 59) rather than for delays, with the most often used search procedures being matching (n = 14), titration (n = 11), (multiple) price lists (n = 10) and bisection (n = 9). Only half of methods were operationalized with real incentives (41 out of 85). Methods that were not incentive compatible were often those with health frames (17 out of 44) or non-health methods developed outside of economics (16 out of 44). Finally, most studies, in line with the field's focus on relating discount rates to individual behaviour, elicited discount rates at the individual level (69 out of 85).

5. Discussion

In this study we reported a systematic review of *unique methodologies* for measuring discount rates, conducted using an exhaustive, multi-database search strategy. By using a search strategy that yielded relevant papers from a wide array of journals and disciplines, we were able to identify a total of 85 unique methodologies for measuring discount rates, and describe and distinguish between them along their main theoretical and operational characteristics. Rather than presenting an exhaustive overview of all 85 methods, we have focused our results section on describing trends, and refer readers interested in the full overview to the online interactive table containing all extracted data. In the Discussion, our focus will be on interpreting the trends and clusters identified in our review, as well as discussing some of the difficulties with identifying unique methods (and the corresponding limitations to our approach).

5.1. Trends identified across included methods for measuring discount rates

Our review identified a couple of bibliographic trends within the set of unique methods for discount rates we identified. Measurement of discount rates is a growing field, with the number of unique methods being published increasing at a nearly fourfold rate in 20 years. Perhaps as a consequence, our network analyses suggest that a degree of disconnection exists between the different disciplines in which these methods are developed. Similar to conclusions by Barlow et al. (2017) in their review of discount rates and smoking, limited overlap in citations between economics/marketing and (neuro)psychology journals can be identified. Our study, furthermore, suggests that methods for measuring discount rates in health economics/health policy are particularly disjointed from other work in this field. We find that a large number of unique methods that have been developed for measuring discount rates in the health domain. That is, our review finds that health is the most common non-monetary outcome domain used in unique methods, with discount rates elicited for e.g. years of life (Höjgård et al., 2002), lives saved (Olsen, 1993), and quality of life improvements (Chapman, 1996, Khwaja et al., 2007). This somewhat isolated methodological innovation may be caused by potential applications of health discount rates that fall predominantly in the scope of the health economics and health policy fields. That is, measured discount rates for health outcomes are a source of input in economic evaluation of health technology (Drummond et al., 2015, Attema et al., 2018b), and may also be used to improve health valuation (Attema and Brouwer, 2009, Lipman et al., 2019, Lipman et al., 2022b, Jonker et al., 2018).

Our review, furthermore, identified limited heterogeneity in the theoretical characteristics of the methods used. Although methods have been applied to estimate discount rates in over 15 different discount functions, a small set of discounting functions makes up the majority of them. Even though empirical evidence provides little support for its validity (Frederick et al., 2002), constant discounting was the most used discounting function, followed by the two discount functions that psychologists and economists often rely on to model decreasing impatience, i.e. Mazur discounting and quasi-hyperbolic discounting, respectively. These discounting functions are attractive due to their tractable and straightforward modelling of decreasing impatience, but both are typically applied assuming a linear utility function. Seeing as utility is typically concave instead, discount rates elicited for these functions would be biased upwards (i.e. for the majority of methods included in our review), as methods that account for this bias are rarely used (Andersen et al., 2008, Abdellaoui et al. 2010, Attema et al., 2012). Furthermore, most methods are not capable of estimating negative discount rates, which would also yield upward bias (as individuals with truly negative discount rates would trend towards zero time preferences). Such bias is most likely in contexts where negative time preference is often present, e.g. the health domain, (Lipman et al., 2022c, Lipman et al., 2022a). Indeed, most methods identified may be considered somewhat inflexible, restricting the outcome domain (to gains only), admissible discount rates and/or applying only one discount function. Methods using multiple discount functions are a minority, and non-parametric methods are especially rare.

On the other hand, our review identified large heterogeneity in how unique methods were operationalised. Several key insights can be identified from these characteristics. Methods for measuring discount rates have, similar to much of contemporary social science (Henrich et al., 2010), been mostly developed in Western countries with highly educated student samples. This may severely limit the scope of application as well as external validity of these methods. More work on measuring discount rates at a global scale or in non-Western contexts is needed (Falk et al., 2018), particularly on the development of methods uniquely adapted to these contexts. Study durations and questionnaire lengths varied significantly, with some methods being notably efficient, taking only 1-10 minutes to complete and others instead requiring significant time and effort to complete. However, it is important to acknowledge that we were often unable to extract data on study duration and the number of tasks. We find similarly large heterogeneity in the outcomes and delays included in each method. In particular, researchers selecting methods may worry about magnitude effects (Frederick et al., 2002), i.e. the observation that discount rates decrease for higher outcomes. It is unlikely that, e.g., discount rates elicited for outcomes higher than million 2023 USD (Rachlin et al., 2000) are comparable to amounts ranging between 5-85 dollars (Kirby and Maraković, 1995). Methods that have no limits to the amounts or delays (e.g. Attema et al., 2010) suffer from similar risks of incomparability, as the amounts could become exceedingly large. Delays were also highly heterogeneous, and perhaps more importantly, described with heterogeneous descriptors (e.g. days, weeks, months). This may harm comparability, as Craig et al. (2018) show that the choice of delay descriptor is non-trivial and will affect the estimated discount rate. Finally, many different elicitation procedures were identified, which differed in their reliance on direct choice, on the need for respondents reaching indifference and in terms of incentive-compatibility. Note that in many cases the elicitation procedure is not a defining characteristic of the method, i.e. a method that relied on matching (Thaler, 1981) may also be operationalized as a (multiple) price list (Coller and Williams, 1999) and vice versa. Our review offers little insight into which elicitation procedure is ultimately preferable, which is a question open for future research.

5.2. *Clusters of unique methods for measuring discount rates*

Although our review identified too many unique methods to allow discussing each in detail, the majority of unique methods identified are what Cohen et al. (2020) consider *money received earlier or later (MEL),* which make up 60% of the studies they identified in their review. These methods offer respondents time-dated monetary amounts, typically a smaller amount *now* for a larger amount *later* (Rachlin et al., 1991, Rachlin et al., 2000, Du et al., 2002). The main differences between methods manifest in how these time-dated monetary amounts are offered and how respondents' preferences for those amounts are elicited. For example, some unique contributions were expanding the outcome domain under consideration for MEL methods, e.g. from gains to losses (Estle et al., 2006) and introducing new elicitation procedures, e.g. convex time budgets (Andreoni and Sprenger, 2012) or (multiple) price lists (Coller and Williams, 1999). In our continued contemplation of the extracted data, we identified few clusters of methods with similar characteristics that expand on or deviate from MEL methodology, that may warrant further discussion.

First, a set of neuro-imaging discount rate measures was identified, e.g. for use with (functional) magnetic resonance imaging (Koffarnus et al., 2017, Mitchell et al., 2005, Peters and Büchel, 2009, Ballard and Knutson, 2009). Such scanning techniques imply some restrictions on the method for measuring discounting: i) individuals should be able to complete it during scanning, ii) scanning time ideally is short to minimize discomfort, iii) the method should allow identifying neurological processes that influence intertemporal choice (Frost and McNaughton, 2017). As a consequence, these methods are often choice-based, using e.g. (random) binary choice, relatively few tasks are used, and tasks involve simple procedures (i.e. only gains, no indifferences elicited). Their main advantage, hence, is their ability to capture discount rates during neuro-imaging, whilst their main disadvantage relies in the limited freedom in designing the intertemporal trade-offs that such neuro-imaging implies.

Second, a set of highly flexible methods can be identified, which avoid restrictions related to a single functional form for the discount or utility function. Robustness is often a key consideration in these non-parametric methods (e.g. Attema et al., 2018a). Robustness can be taken to mean being able to measure discount rates without restrictions on the shape of the utility function (Attema et al., 2016, Takeuchi, 2011), the sign of outcomes (Abdellaoui et al., 2013), or assumptions about the sign of discount rate (Rohde, 2019, Lipman and Attema, 2020). However, flexibility may come at a cost. In particular, these tasks may involve relatively long completion times (e.g. 60 minutes, Blavatskyy and Maafi, 2018), and often rely on potentially error-prone and difficult to implement process of chaining indifferences (Attema et al., 2010, Lipman et al., 2019). Hence, although these flexible methods have attractive theoretical qualities, a set of feasibility considerations may limit their applicability outside economic experiments. In particular, flexibility may come at the cost of increased length and (potentially) difficulty of the method for measuring discount rates.

Third, a set of highly efficient choice-based methods can be identified, which sacrifice flexibility to be able to identify discount rates with as few questions as possible. They typically restrict themselves to estimating discount rates assuming one discount function applies, e.g. Mazur discounting (Pooseh et al., 2018). Some form of an adaptive or chained elicitation procedure is used, in which each subsequent choice is assumed to reveal information about and further elucidate the 'true' discount rate. These methods typically restrict the possible discount rates to a predefined parameter space, often strictly positive (Toubia et al., 2013, Koffarnus and Bickel, 2014). Examples are bisection or Bayesian adaptive elicitation procedures, where the former 'zooms in' on the true discount rate by chaining questions such that half of the possible (remaining) parameter space is excluded (Koffarnus and Bickel, 2014), and the latter identifies the most informative question based by chaining questions to update the posterior distribution of potential discount rates that fit an individual's preferences (Cavagnaro et al., 2016, Ahn et al., 2020). These restrictions enable the use of a small number of questions and have short completion times, with a single elicited indifference. In that sense, such efficient choice-based methods resemble matching studies in which respondents are asked to fill-out-the-blank in a single indifference to estimate discount rates. One may even consider the widely used monetary choice questionnaire (Kirby and Maraković, 1995) to fall within this cluster, although with 27 non-chained questions it remains quite long. The main advantage of these methods is their efficiency, whereas their main disadvantage is the potential lack of robustness that results from restricting the method to a single discounting function and/or a pre-defined parameter space.

Fourth, a cluster of methods exist that measures experiential discount rates, i.e. they quantify discount rates for intertemporal choices where individuals are exposed to real delays during measurement (Reynolds and Schiffbauer, 2004), akin to discounting measures used in animal research (Jimura et al., 2009). Such methods are unique, as for most other methods, if delayed outcomes are delivered at all, delays are experienced after measurement of discount rates is completed. Such experiential discounting measures take different forms, e.g. deciding between squirts of juice now or later (McClure et al., 2007), waiting for small monetary amounts (Johnson, 2012) or intertemporal trade-offs within videogame settings (Greenhow et al., 2015). Imposing delays *during measurement* on individuals restricts the delays that can be studied – they are typically between a few second and a few minutes. The main advantage of these methods is their ability to measure discount rates for experienced delays, whilst the main disadvantage is that such delays are only feasible on short timeframes.

5.3. How to determine if methods are 'unique'?

A key result of this study is the identification of 85 unique methods for measuring discount rates. Yet, this result also hinges on a challenge and potential limitation of this study: even with our inclusion/exclusion criteria in place, a team of experts advising, and frequent coordination between the authors during screening, it remained difficult to define *exactly* what makes a method unique. Ultimately, deciding which methods were unique and which were not relied on a value judgment by the authors based on a subjective assessment of the methodological progress made compared to earlier work. As a unique methodological contribution is hard to quantify, it is worth to explicitly mention at least three debatable judgments, that may explain why some studies are (not) included. First, we decided that unique methods would encompass first applications of (now well-known) elicitation procedures, e.g. (multiple) price lists (Coller and Williams, 1999) or convex time budgets (Andreoni and Sprenger, 2012). Yet, we excluded extensions of methods to other domains, even though such extensions may yield new methodological insights. For example, the monetary choice questionnaire (Kirby and Maraković, 1995) has been extended to measure discount rates for many different commodities, e.g. food (Dassen et al., 2015), weight loss (Lim and Bruce, 2015) and pain-free days (Tompkins et al., 2016). Yet, the main methodological change in these studies involves replacing all monetary outcomes with a different commodity, which we considered a (relatively) insignificant extension of existing methods. Using that same exclusion criterion, we also exclude important methodological contributions such as Augenblick et al. (2015) who extend convex time budget methodology to measure discount rates for effort. Second, some studies introduced applications of existing methods, designed specifically to enable measurement of discount rates in conjunction with other economic preferences on a large scale (Falk et al., 2023, Falk et al., 2018). In our view such work is crucial in advancing the measurement of discount rates, but given its reuse of existing elicitation procedures we considered it an application of existing methods. Third, a range of studies was excluded that relied on estimating discount rates based on matching questions in panel data sets (e.g. Borghans and Golsteyn, 2006, Kang and Ikeda, 2014). Such studies provide important methodological insights into the *methods for estimating* of discount rates, but, in our view, rely on existing *measurement* methods.

5.4. Strengths and (other) limitations of this study

Our review of unique methods for measuring discount rates has several strengths that underline our contribution to the literature. Primarily, the multi-database exhaustive search strategy aimed at including methods *measuring* discount rates from various disciplines sets the study apart from other bibliographic work or reviews conducted (Cohen et al., 2020, Frederick et al., 2002, Matousek et al., 2022). Through the network analysis conducted we also illustrated why a multidisciplinary focus is needed when exploring the measurement of discount rates. Furthermore, the interactive table provided as Online Supplement should support future practitioners and researchers aiming to measure discount rates in selecting a method that fits their purpose. Still, several limitations apply to our work.

First, we were unable to locate 5 records identified through title and abstract screening as potentially relevant methods for inclusion. After asking for library support in locating these full texts, no further attempts were made to gain access (e.g. purchasing access, or contacting first authors). Second, given the large number of full-text identified during title and abstract screening, as well as during full-text review, it was not feasible for both authors to extract data from all records – which is typically recommended (Moher et al., 2009). As such, the reliability of final inclusion/exclusion decisions and/or extracted data could be limited. Both authors did coordinate at regular intervals, and inconsistencies were resolved where they were apparent from the extracted data by the first authors. Third, we focused our review on measuring discount rates in humans, which restricts the methods identified. Some potentially unique methods were developed in animal research and were, as a consequence, not included in our study (e.g. Foscue et al., 2012, Mazur, 1987), even though they are or could be extended to human subjects. Furthermore, our review of relevant methods excluded records in which no discount rates were estimated, i.e. exclusively theoretical contributions. This implies that several highly relevant contributions to the field of measuring discount rates are not included. Finally, by only including unique methods, this study merely describes the many different methods, rather than quantitatively comparing the elicited discount rates that the methods yield. Hence, our work offers little insight into concerns about the measured discount rates, such as internal or external validity. Following up on our work with head-to-head comparisons of a selected number of methods and/or using meta-analysis to summarize each method's performance are important avenues for future research.

5.5. Concluding remarks

Our review has shown that many theoretical and methodological degrees of freedom exist for researchers designing or choosing a method for measuring discount rates. Through systematic review methodology, we identified 85 unique methods for measuring discount rates and extracted data on the most important degrees of freedom in the design of these methods. Our review, we hope, will provide researchers aiming to measure discount rate, to select a method that aligns with the importance they assign to different characteristics of the methods. Our paper is published alongside an interactive online table that may help readers to find a method that suits their needs, as it enables filtering and sorting on important characteristics on outcome domains. Ultimately, a gold standard method for measuring discount rates may not be a feasible aspiration, given the widespread application and relevance of discount rates. Some applications may ask for a flexible method that can capture discount rates of any sign and form with little bias, whereas for other applications an efficient method providing reasonably precise insights into heterogeneity in discount rates may suffice.

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Appendix A: Network analyses of included keywords and search strings used per database.

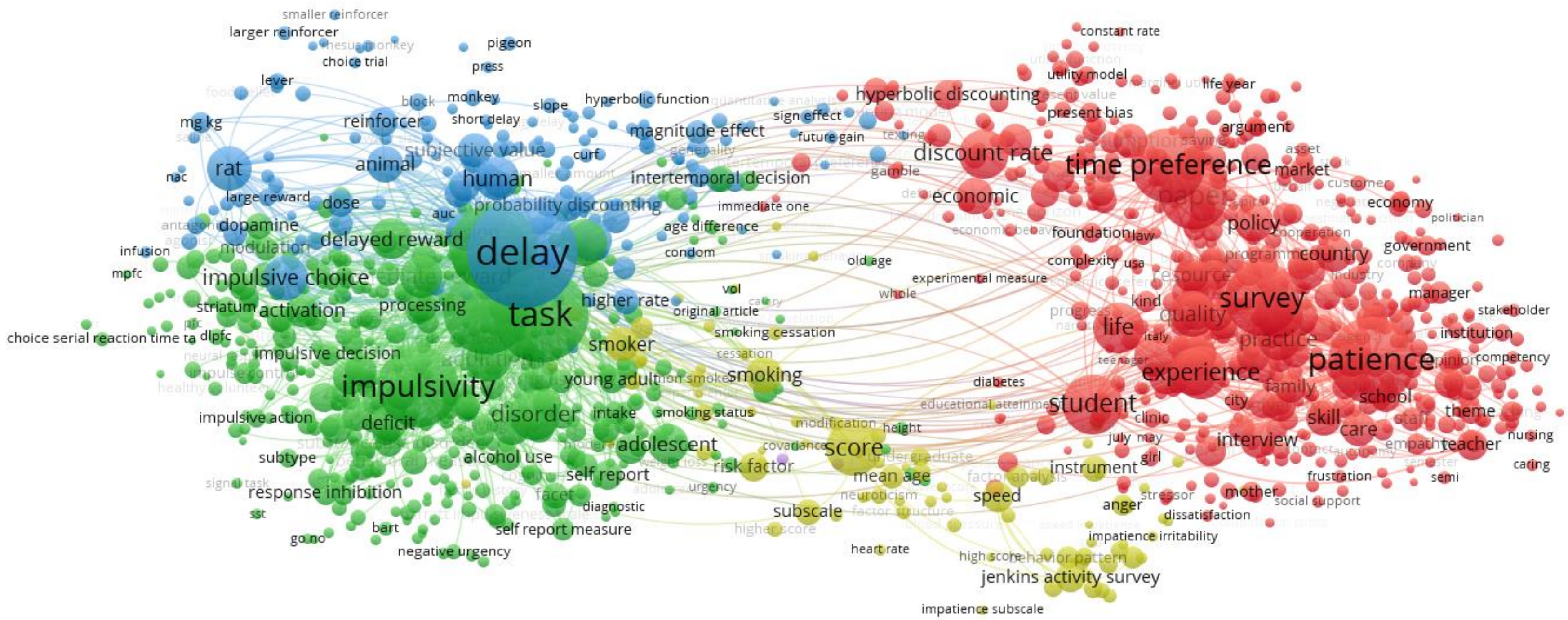

Figure A1. VOSviewer visualization of keywords for reports selected for screening.

Web of Science

TS=("decision-making" OR "choice behavior*" 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 behavior*" 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. Data extraction form

This Appendix contains the data extraction form prepared before full-text review, which was also shared and discussed with the team of experts advising on the review process. All details are found in Table B1.

Table B1. Extracted data and explanation fields used to coordinate between authors and maintain consistency in extracted data.

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 number 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

Appendix C. Full list of included papers

Table C1. Citations for all included methods for measuring discount rates

Thaler (1981)	Ostaszewski (2007)	Bosworth et al. (2015)
Fuchs (1982)	Onay and Öncüler (2007)	Greenhow et al. (2015)
Benzion et al. (1989)	Andersen et al. (2008)	Shavit and Rosenboim (2015)
Rachlin et al. (1991)	Ballard and Knutson (2009)	Towe et al. (2015)
Cairns (1992)	Bond et al. (2009)	Cavagnaro et al. (2016)
Olsen (1993)	Jimura et al. (2009)	Civai et al. (2016)
Cropper et al. (1994)	Peters and Büchel (2009)	Ferecatu and Önçüler (2016)
Dolan and Gudex (1995)	Zauberman et al. (2009)	Ida and Goto (2016)
Chapman (1996)	Abdellaoui et al. (2010)	Kowal and Faulkner (2016)
Cairns and van Der Pol (1997)	Attema et al. (2010)	Olivola and Wang (2016)
Kirby (1997)	Coble and Lusk (2010)	Koffarnus et al. (2017)
Coller and Williams (1999)	Forstmeier et al. (2011)	McDonald et al. (2017)
De Pol and Cairns (1999)	Takeuchi (2011)	Abdellaoui et al. (2018)
Richards et al. (1999)	Andreoni and Sprenger (2012)	Blavatskyy and Maafi (2018)
Kirby et al. (1999)	Attema et al. (2012)	Cox and Dallery (2018)
Chesson and Viscusi (2000)	Carlsson et al. (2012)	Hayashi and Blessington (2018)
Ganiats et al. (2000)	Han and Takahashi (2012)	Jonker et al. (2018)
Rachlin et al. (2000)	Ida and Ogawa (2012)	Pooseh et al. (2018)
Van der Pol and Cairns (2001)	Johnson (2012)	Scherbaum et al. (2018)
Du et al. (2002)	Johnson and Bruner (2012)	Bradford et al. (2019)
Höjgård et al. (2002)	Laury et al. (2012)	Lipman et al. (2019)
Cameron and Gerdes (2003)	Abdellaoui et al. (2013)	Lukinova et al. (2019)
Lane et al. (2003)	Attema and Versteegh (2013)	Rohde (2019)
Reynolds and Schiffbauer (2004)	Toubia et al. (2013)	Ahn et al. (2020)
Mitchell et al. (2005)	Dubé et al. (2014)	Burgaard and Steffensen (2020)
Estle et al. (2006)	Gray et al. (2014)	Cheung (2020)
Khwaja et al. (2007)	Montiel Olea and Strzalecki (2014)	Grammatikopoulou et al. (2020)
McClure et al. (2007)	Koffarnus and Bickel (2014)	Xu et al. (2020)
		Patt et al. (2021)

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