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SYNTAX FOR CALCULATION OF DISCOUNTING INDICES FROM THE MONETARY CHOICE QUESTIONNAIRE AND PROBABILITY DISCOUNTING QUESTIONNAIRE

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Abstract

The 27-item Monetary Choice Questionnaire (MCQ; Kirby, Petry, & Bickel, 1999) and 30-item Probability Discounting Questionnaire (PDQ; Madden, Petry, & Johnson, 2009) are widely used, validated measures of preferences for immediate versus delayed rewards and guaranteed versus risky rewards, respectively. The MCQ measures delayed discounting by asking individuals to choose between rewards available immediately and larger rewards available after a delay. The PDQ measures probability discounting by asking individuals to choose between guaranteed rewards and a chance at winning larger rewards. Numerous studies have implicated these measures in addiction and other health behaviors. Unlike typical self-report measures, the MCQ and PDQ generate inferred hyperbolic temporal and probability discounting functions by comparing choice preferences to arrays of functions to which the individual items are preconfigured. This article provides R and SPSS syntax for processing the MCQ and PDQ. Specifically, for the MCQ, the syntax generates k values, consistency of the inferred k, and immediate choice ratios; for the PDQ, the syntax generates h indices, consistency of the inferred h, and risky choice ratios. The syntax is intended to increase the accessibility of these measures, expedite the data processing, and reduce risk for error.

Keywords

delay discounting; probability discounting; syntax; MCQ; PDQ

Delay discounting is a behavioral economic measurement of the reduction in the present value of a future reward as the delay to that reward increases. Relatedly, probability discounting is a behavioral economic measurement of the reduction in the value of a reward as the chance of receiving the reward decreases. In delay discounting tasks, individuals

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choose between small rewards available immediately and larger rewards available after a delay (Madden & Bickel, 2009). In probability discounting tasks, individuals choose between small guaranteed rewards and a chance at winning larger rewards (Green & Myerson, 2004). By systematically varying reward amounts and either delay to or likelihood of receipt, overall indices of choice preferences can be calculated (Odum, 2011; Rachlin, 2006). Considerable research has connected performance on these measures (particularly delay discounting) with addiction, attention deficit hyperactivity disorder, and obesity (Amlung, Gray, & MacKillop, 2016; Amlung, Petker, Jackson, Balodis, & MacKillop, 2016; Jackson & MacKillop, 2016; MacKillop et al., 2011; Poltavski & Weatherly, 2013; Wiehler & Peters, 2015). Furthermore, elevated preferences for immediate and risky rewards (as measured by delay and probability discounting tasks) have been connected to a broad range of health behaviors (e.g., medication adherence, sexual risk-taking; Bruce et al., 2015; MacKillop et al., 2015).

Two widely used and extensively validated questionnaire-based measures of these constructs are the Monetary Choice Questionnaire (MCQ) (Kirby et al., 1999) and the Probability Discounting Questionnaire (PDQ) (Madden et al., 2009). The MCQ consists of 27 dichotomous choices between smaller-immediate and larger-delayed monetary rewards that are preconfigured to provide estimates of an individual's delay discounting rate. Three magnitudes are assessed, providing separate discounting rates for small ($11–$35), medium ($20–$60), and large ($31–$85) rewards, as well as an overall discounting rate. The PDQ is similar insofar as it is composed of 30 preconfigured items across three 10-question blocks (block 1: $20 guaranteed or a [10–83%] chance of $80; block 2: $40 guaranteed or a [18–91%] chance of $100, block 3: $40 guaranteed or a [40–97%] chance of $60). The PDQ was developed 10 years after the MCQ and has been applied less extensively, but nonetheless is increasingly in use.

Although both measures have the advantage of being relatively short and easy to administer, they can be difficult to score and interpret efficiently and accurately. Unlike typical self-report measures, the MCQ and PDQ generate inferred hyperbolic temporal and probability discounting functions by comparing empirical choice preferences to arrays of functions to which the individual items are preconfigured. The relative complexity of these measures can discourage use for individuals who are not familiar with the protocol. Therefore the goal of this article is to increase the accessibility of these constructs by providing R and SPSS syntax (IBM Corp., 2011; R Core Team, 2016) for automating calculation of indices of delay discounting and probability discounting from the MCQ and PDQ. Specifically, the article will: 1) briefly review the procedures for generating discounting indices (e.g., k and h values); 2) describe the syntax provided; and 3) discuss handling of missing values.

Generating Indices of Preferences for Immediate and Risky Rewards

Monetary Choice Questionnaire

An individual's rate of delay discounting is commonly quantified using a hyperbolic discounting function. The following equation was provided by Mazur (1987):

$$V = A / (1 + kD),$$

where V is the present value of the delayed reward A at delay D, and k is a free parameter that determines the discount rate. The higher one's discount rate (k) is, the more they discount larger future rewards. The original table from Kirby et al. (1999) is provided in Table 1. An example of applying this formula can be seen by examining the final item on Table 1 ("$31 today" or "$85 in 7 days"), where $V = \$31$, $A = \$85$, and $D = 7$. Solving for k generates the listed k value of .25.

According to Kirby et al.'s (1999) method, the k value chosen reflects the hyperbolic discounting function that exhibits the highest consistency among the participants' choices. For example, a participant with a discount rate of $k = 0.10$ would show equal preference for "$33 today" and "$80 in 14 days," so if they chose the smaller immediate reward, then they would have a discounting rate greater than 0.10. In a question where the immediate reward is less and the delayed reward is larger and sooner (e.g., "$31 today" or "$85 in 7 days"), a discounting rate of 0.25 would correspond to indifference between those two rewards. If the participant chose the $85 delayed reward, then they would have a discounting rate less than 0.25. From these two trials, it can be inferred that the participant has a discount rate between 0.10 and 0.25. The geometric mean is used to calculate the overall k values to avoid underweighting the smaller value (e.g., in this example, $k = 0.16$).

The calculation of k becomes more complicated when individuals respond inconsistently on the task (i.e., switching between immediate and delayed responding multiple times) and more details are provided elsewhere on the calculation of the most consistent k value (Kirby et al., 1999). Briefly, because participants' choices are not always perfectly consistent with any single value of k, many possible combinations of responses can yield the same k value. For example, a k value of 0.16 would also be assigned if an individual selected the delayed option for the first item (i.e., "$78 today" or "$80 in 162 days"), reverted back to all immediate choices for the next seven items (i.e., k rank 2–8), and then selected delayed for the final option (i.e., "$31 today" or "$85 in 7 days"). Because the majority of the responses are immediate until the point of indifference when they switch from immediate to delayed on the last two items (as in the above example), $k = 0.16$ would still be assigned. In this instance the individual would be assigned a consistency value of 89% because eight of his or her nine responses were consistent with this inferred k value (i.e., 8/9 = 89%; meaning $k = .16$ accurately captures responding on all items except the first one: "$78 today" or "$80 in 162 days"). The discount rate that yields the highest consistency across trials is used as the participant's k value, and in the instance where two or more k values are equally consistent, their geometric mean is computed. Inconsistent responding may indicate poor task effort (e.g., inattention, random responding) and reduces the accuracy of k estimation. Therefore, for each given magnitude, we recommend that investigators consider excluding data when consistency is below 80% and strongly recommend excluding data with lower than 70% consistency. Ultimately, of course, quality control parameters are up to the investigator.

We have generated R and SPSS syntax that automatically generates k values, consistency of the inferred k value, and immediate choice ratios (ICR: i.e., an alternative model-free discounting index reflecting the number of immediate reward choices divided by the total number of choices; Ainslie & Monterosso, 2003; Mitchell, Fields, D'Esposito, & Boettiger, 2005). The basic premise of the syntax is that there is a finite set of possible response patterns based on the nine binary choices per magnitude (i.e., $2^9 = 512$ possible combinations). Building on this premise, the syntax generates a unique sequence number for each magnitude using a binary coding system where the first question is multiplied by 1, the second by 2, third by 4, fourth by 8, fifth by 16, sixth by 32, seventh by 64, eighth by 128, and ninth by 256. After generation of these unique sequence numbers, three lookup operations are conducted using premade tables (see online Supplementary Materials), whereby each individual sequence is assigned the k value, consistency, and ICR associated with that response pattern (see Supplementary Materials for full syntaxes with step by step annotations). It is common for the distribution of k values to be positively skewed and a correction for the non-normal distribution is recommended, such as a natural log or base-10 transformation. Furthermore, to reduce the number of variables, it may be prudent to generate an average k, average consistency, and average ICR by calculating the mean of the values for each of the three magnitudes of the task or using principal components analysis for data reduction (e.g., Amlung & MacKillop, 2014).

Probability Discounting Questionnaire

The procedure for calculating the h index for the PDQ is generally analogous to the k index of the MCQ, and uses the following equation (Rachlin, Raineri, & Cross, 1991):

$$V = A/(1 + h\Theta),$$

where V is the present value of the uncertain reward A at odds against winning Θ (i.e., $(1 - p)/p$; p = probability of winning), and h is a free parameter that determines the discount rate. Therefore, h and k are inversely related in terms of pathological choice patterns, higher hs = more risk averse and higher ks = more future discounting. Madden et al. (2009) provided a table of these values for the PDQ which is provided in Table 2. An example of applying this formula can be seen by examining the final item on Table 2, (i.e., "$40 for sure" or "a 30-in-31 chance of winning $60 [97% chance]"), where V = $40, A = $60, and Θ = .03. Solving the equation for h generates the listed h value of 16.17.

The h value reflects the hyperbolic discounting function that exhibits the highest consistency among the participants' choices. For example, a participant with a discount rate of 9.5 would be indifferent between "$40 for sure" and "an 18-in-19 chance of winning $60 [95% chance]," so the selection of the guaranteed reward would reflect a discount rate greater than 9.5. In a question where the chance of winning is higher (e.g., "$40 for sure" or "a 30-in-31 chance of winning $60 [97% chance]"), a discount rate of 16.17 would demonstrate indifference between those two options. If the participant chose the risky $60 reward ("risky" meaning any reward with < 100% chance of receipt), then he or she would have a discount rate less than 16.17. From these two trials, it could be inferred that the participant has a discount rate between 9.5 and 16.17. Again, the geometric mean is used to calculate the overall h values to avoid underweighting the smaller value (e.g., in this example h = 12.835).

The calculation of h becomes more complicated when individuals respond inconsistently on the task (i.e., switching between guaranteed and risky choices multiple times) and more details are provided elsewhere on the calculation of the most consistent h value (Madden et al., 2009). Briefly, because participants' choices are not always perfectly consistent with any single value of h, many possible combinations of responses can yield the same h value. For example, an h value of 12.83 would also be assigned if an individual selected the risky choice for the first item (i.e., "$40 for sure" and "a 2-in-5 chance of winning $60 [40% chance],"), reverted back to all guaranteed choices for the next eight items, and then selected the risky option for the final item (i.e., "$40 for sure" or "a 30-in-31 chance of winning $60 [97% chance]"). Because the majority of the responses are guaranteed until the point of indifference when they switch from guaranteed to risky on the last two items (as in the above example), $h = 12.83$ would still be assigned. In this instance the individual would be assigned a consistency value of 90% because nine of his or her ten responses were consistent with this inferred h value (i.e., 9/10 = 90% meaning $h = 12.385$ accurately captures responding on all items except the first one: "$40 for sure" and "a 2-in-5 chance of winning $60 [40% chance]"). The discount rate that yields the highest consistency across trials is used as the participant's h value, and in the instance where two or more h values are equally consistent, their geometric mean is computed. Again, inconsistent responding may indicate low task effort and reduce the accuracy of h estimation. Therefore, we recommend that investigators consider excluding any participants who exhibit < 80% consistency on any of the three blocks of 10 questions. This is especially the case because the level of risk is not randomized by item, clearly diminishing in terms of risk.

The syntax provided automatically generates h values, consistency of the inferred h, and risky choice ratios (RCR; i.e., the number of risky choices divided by the total number of choices; this was generated as a parallel to the frequently used ICR from the MCQ). Like the MCQ, the syntax generates a unique sequence number for each of the three blocks of 10 questions using a similar binary coding system (first item multiplied by 1, second by 2, third by 4, fourth by 8, fifth by 16, sixth by 32, seventh by 64, eighth by 128, and ninth by 256, and tenth by 512, yielding $2^{10} = 1024$ unique sequences). After generation of these unique sequence numbers, three lookup operations are conducted using premade lookup tables included in the Supplementary Materials, whereby each individual sequence is assigned the h value, consistency associated with that response pattern, and RCR (see Supplementary Materials for full syntax). It is common for the distribution of h values to be positively skewed and a correction for the non-normal distribution is highly recommended (e.g., natural log transformation; Madden et al., 2009). Furthermore, to reduce the number of variables, it is often prudent to generate an average h, average consistency, and average RCR by calculating the mean of the values for each of the three blocks of the task.

Use of the Syntax

SPSS

The SPSS syntax requires that the item headers be named MCQ1-MCQ27 for the MCQ and PDQ1-PDQ30 for the PDQ. The items are presented in the order designated by the table presented by Kirby et al. (1999) and Madden et al. (2009), so the first question (MCQ1) would be “$54 today” and “$55 in 117 days”. The item responses must be coded as 1 for the immediate (or guaranteed) option and 2 for the delayed (or risky) option. Once the data are formatted properly and the missing values are handled (see Missing Values), the syntax can simply be run and the corresponding MCQ or PDQ indices will be generated and added to the open SPSS dataset. Sample data and an accompanying readme file are included as Supplementary Materials.

R

The R syntax requires four files to run. First, as the syntax is written, the data should be in a text file, entitled “MCQdata.txt” or “PDQdata.txt”. The first column should be entitled “SubjID” and the subsequent columns MCQ1–MCQ27 or PDQ1–PDQ30. Again the responses should be coded as 1 for the immediate (or guaranteed) option and 2 for the delayed (or risky) option. Additionally, the following three lookup table files should be included: “lookup1.txt”, “lookup2.txt”, and “lookup3.txt”. Once the data is formatted properly, the missing values are handled (see Missing Values), and the working directories are updated, simply run the syntax and the corresponding MCQ or PDQ indices will be generated as a text file entitled “MCQindices.txt” or “PDQindices.txt”. Sample data and an accompanying readme file are included in Supplementary Materials.

Missing Values

The number of possible iterations of values for items that have one or more missing values would increase the number of possible response sequences to 3^9 (19,683) and 3^{10} (59,049) for MCQ and PDQ, respectively. Therefore, the current syntax is not designed to manage missing values, and these values must be handled prior to running the syntax. There are three methods for handling missing values: 1) simply exclude that particular individual from the analyses; 2) impute the missing value (e.g., Buuren & Groothuis-Oudshoorn, 2011); or 3) manually code the missing value(s) as the previous response (e.g., a missing value for item #22 on the MCQ could be coded as the response entered for #26, because that is the next closest response option). The appropriateness of these options will likely differ across studies and is beyond the scope of this manuscript. However, regarding options 2 and 3, it is important to note that only 9 or 10 responses are recorded per reward magnitude. Therefore, we recommend exclusion if more than one response is missing.

Conclusion

This manuscript presents syntax for quickly calculating indices of delay and probability discounting on the MCQ and PDQ. It is worth noting that the syntax provided here is only applicable to the MCQ and PDQ. While these measures have been used extensively in prior research (Kirby et al., 1999, cited > 1100 times and Madden et al., 2009, cited > 100 times), there are many other methods for assessing discounting. These include task-based measures involving systematically adjusting reward amounts and delays to estimate indifference points (whereas the MCQ and PDQ do not systematically assess indifference points: Du, Green, & Myerson, 2002), experiential discounting tasks (Reynolds & Schiffbauer, 2004; Smits, Stein, Johnson, Odum, & Madden, 2013), and abbreviated measures for rapid estimation of discounting rates (eight and five trials, respectively: Gray, Amlung, Acker, Sweet, &

MacKillop, 2014; Koffarnus & Bickel, 2014). One primary advantage of the MCQ and PDQ measures is that they are brief measures and can be administered in a variety of formats (e.g., paper and pencil format, survey software). However, prior to the syntax provided by this manuscript (and see the recently developed excel spreadsheets for MCQ processing; Kaplan et al., 2016), the generation of hyperbolic indices and consistencies was analytically burdensome. A future priority is developing standardized analysis tools for efficient and accurate estimation of discounting rates using other measures.

Another important caveat is that the syntax generates two discounting indices, hyperbolic discounting rate (k and h) and the immediate/risky choice ratio. These are among the most commonly used metrics (for a review see Green & Myerson, 2004) and provide investigators with model-based indices (i.e., k and h) and model-free indices (i.e., ICR and RCR); however, other approaches are also used. These include alternative discounting models, such as a nonlinear curve fitted with logistic transformation, exponential models, hyperboloid models, and heuristic models, (Green, Fry, & Myerson, 1994; Killeen, 2015; Marzilli Ericson, White, Laibson, & Cohen, 2015; Prelec & Loewenstein, 1991; Rachlin et al., 1991), as well as other model-free methods, such as area under the curve (Myerson, Green, & Warusawitharana, 2001). Although the MCQ and PDQ were originally designed to be analyzed using Mazur's (1987) hyperbolic discounting model, these other models of discounting are viable alternatives and researchers should consider exploring the pros and cons of each method of generating overall discounting.

More broadly, it is important to note that this syntax is intended to facilitate research using the MCQ and PDQ, but is not to stifle or discourage research on variations of assessing discounting, or modeling the resulting data. The premise is that the traditional scoring has given rise to many interesting findings and would benefit from automation, but not that it is necessarily optimal. Future investigations of alternative scoring strategies may ultimately supersede this approach, although that is an empirical question.

In sum, the syntax provided is intended to be a highly efficient tool for calculating indices from the MCQ and PDQ. The MCQ and PDQ are widely used and validated measures of preferences for immediate and risky rewards, and have been used to implicate these constructs in relation to addiction, attention deficit hyperactivity disorder, and other health behaviors (e.g., Amlung et al., 2016; Bruce et al., 2015; Jackson & MacKillop, 2016; MacKillop et al., 2011, 2015; Poltavski & Weatherly, 2013; Wiehler & Peters, 2015). Ideally, the syntax will accelerate calculation of indices, reduce the risk for scoring error, and make these measures accessible to a wider audience.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1

Monetary Choice Questionnaire

Order	SIR	LDR	Delay in days	*k* at indiff.	*k* rank
13	\$34	\$35	186	.00016	1
1	\$54	\$55	117	.00016	1
9	\$78	\$80	162	.00016	1
20	\$28	\$30	179	.00040	2
6	\$47	\$50	160	.00040	2
17	\$80	\$85	157	.00040	2
26	\$22	\$25	136	.0010	3
24	\$54	\$60	111	.0010	3
12	\$67	\$75	119	.0010	3
22	\$25	\$30	80	.0025	4
16	\$49	\$60	89	.0025	4
15	\$69	\$85	91	.0025	4
3	\$19	\$25	53	.0060	5
10	\$40	\$55	62	.0060	5
2	\$55	\$75	61	.0060	5
18	\$24	\$35	29	.016	6
21	\$34	\$50	30	.016	6
25	\$54	\$80	30	.016	6
5	\$14	\$25	19	.041	7
14	\$27	\$50	21	.041	7
23	\$41	\$75	20	.041	7
7	\$15	\$35	13	.10	8
8	\$25	\$60	14	.10	8
19	\$33	\$80	14	.10	8
11	\$11	\$30	7	.25	9
27	\$20	\$55	7	.25	9
4	\$31	\$85	7	.25	9

Note. SIR = small immediate reward, LDR = large delayed reward. The syntax generates *k* values to the ninth decimal place to increase precision. In the event that a participant selects all delayed (or all immediate) options, they are automatically assigned the minimum (or maximum) *k* value. Table from Kirby et al. (1999).

Table 2

Probability Discounting Questionnaire

	Certain Amount ($)	**Probability of Winning**	**Probabilistic Amount ($)**	***h* at indiff.**
Part 1	$20	0.1	$80	0.33
	$20	0.13	$80	0.45
	$20	0.17	$80	0.61
	$20	0.2	$80	0.75
	$20	0.25	$80	1
	$20	0.33	$80	1.48
	$20	0.5	$80	3
	$20	0.67	$80	6.09
	$20	0.75	$80	9
	$20	0.83	$80	14.65
Part 2	$40	0.18	$100	0.33
	$40	0.22	$100	0.42
	$40	0.29	$100	0.62
	$40	0.33	$100	0.74
	$40	0.4	$100	1
	$40	0.5	$100	1.5
	$40	0.67	$100	3.04
	$40	0.8	$100	6
	$40	0.86	$100	9.21
	$40	0.91	$100	15.17
Part 3	$40	0.4	$60	0.33
	$40	0.46	$60	0.43
	$40	0.55	$60	0.61
	$40	0.6	$60	0.75
	$40	0.67	$60	1.01
	$40	0.75	$60	1.5
	$40	0.86	$60	3.07
	$40	0.92	$60	5.75
	$40	0.95	$60	9.5
	$40	0.97	$60	16.17

Note. The syntax generates *h* values to the ninth decimal place to increase precision. In the event that a participant selects all risky (or all guaranteed) options, they are automatically assigned the minimum (or maximum) *h* value. Table from Madden et al. (2009).