Research Article

Fixed Attributes and Discounting Behavior

Effects of Holding One Attribute Constant During an Intertemporal Choice Task

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Abstract: Delay discounting tasks present alternatives that differ in two attributes: *amount* and *delay*. Typically, choice is modeled by application of a *discount function* to each option, allowing alternative-wise comparison. However, if participants make decisions by comparing attributes, manipulations that affect the salience of either attribute may affect patience. In Experiment 1, participants completed one block of trials in which amount was a *fixed attribute* (constant across trials), and another in which delay was fixed. Consistent with the hypothesis that the varying attribute would be more salient, participants exhibited less patience in the amount-fixed condition. Moreover, this effect was larger for participants who responded more quickly when making choices that favored the varying attribute. In Experiment 2, these findings were extended by adding trial blocks with a working memory dual task. We replicated the fixed-attribute effect, along with the aforementioned association with reaction time. Contrary to expectation, the fixed-attribute effect was not larger when participants were under working memory load. Instead, working memory load was associated with more patient responses, which may be related to idiosyncrasies of the task including the absence of immediate rewards. Overall, results suggest a fixed-attribute effect on patience, which is consistent with a multi-attribute decision framework.

Keywords: delay discounting, attribute salience, multiattribute decision making, dual-task

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The general tendency to value expectancies less the further they are in time is commonly referred to as "delay discounting." Partly because of its plausible connection to socially and clinically important outcomes, a great deal of work has been directed at measuring individual delay discounting (for reviews, see Amlung et al., 2017; Mishra & Lalumière, 2017; Tang et al., 2019). In a typical psychology or behavioral economic research study, participants choose from a series of reward pairs in which the larger reward is more delayed in time (e.g., "Do you want $10 in 1 week, or $20 in 2 months?"). An individual's degree of delay discounting is then characterized by modeling her choices with a function that includes one or more free parameters. Although no functional form matches all intertemporal choice behavior, as we discuss below, reasonably good fits are sometimes obtained with the single-parameter hyperbolic function most commonly used in psychology:

$$V = \frac{A}{1 + Dk} \tag{1}$$

where V is the present value (PV) of a delayed reward, A is the future amount, D is the delay, and k is a parameter that determines the extent to which future rewards are discounted (Mazur, 1987). Accordingly, a larger k represents more discounting of a delayed reward. Particularly within the applied psychology literature, hyperbolic discounting is sometimes presumed to be established good practice for modeling discounting data (Odum, 2011; Rung & Madden, 2018). However, the idea that human discounting is well-described by a hyperbolic function, or any other discounting function, is not a universal empirical conclusion among researchers in the area (Andersen et al., 2014; Hofmeyr et al., 2017; Luhmann, 2013; Marzilli Ericson et al., 2015). In

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addition, given that no parameter in Equation 1 modifies amount, the equation implies that value scales linearly with amount. As Andersen et al. (2008) demonstrated theoretically and empirically, assuming linearity, when the relationship between value and amount is actually concave, biases estimates of discounting parameters upward and can lead to incorrect inferences if the extent of concavity varies across study participants (see also Harrison et al., 2010; Lopez-Guzman et al., 2018; Pine et al., 2009).

Approaches Emphasizing the Active Construction of Preference

Intertemporal decisions are multi-attribute since alternatives vary in both (1) *amount* and (2) *delay*. Preference in multi-attribute decisions can be understood as dependent on a constructive process (Payne et al., 1993). For instance, Tversky and Simonson (1993) found that the order of preference between two alternatives in a multi-attribute decision is affected by the addition of a third alternative, particularly one that is far inferior to the other alternatives on one attribute. This context-specificity of preference suggests that rather than directly assessing the value of alternatives and comparing them, the decision maker, at least in part, separately evaluates and compares attributes among alternatives. Accordingly, the impact of particular attributes on a multi-attribute decision depends on the processes engaged during evaluation and the limitations of attention and memory (Busemeyer & Johnson, 2004; Weber & Johnson, 2009). Consistent with this perspective, attribute salience manipulations affect both visual fixation times and preferences (Milosavljevic et al., 2012; Shimojo et al., 2003; Towal et al., 2013), and there is evidence that the duration of attention to an attribute affects its weighting during decision making (Orquin & Mueller Loose, 2013).

Although work on delay discounting is often agnostic regarding mechanism, perhaps because of its roots in economics and operant learning, there is evidence that otherwise anomalous behavior can be understood as the result of a constructive process in which attributes are evaluated in context. Accordingly, the influence of the *amount* and *delay* attributes is moderated by factors that alter the way in which they are attended to and compared during decision making. For example, using either the smaller, sooner (SS) or larger, later (LL) alternative as the default in a discounting task can affect delay discounting. Specifically, Loewenstein (1988) found that an SS default yields steeper discounting relative to an LL default. One way of explaining this effect is that the default option functions as the status quo, thereby causing the attribute of the alternative that is superior (i.e., the size of the reward) to be viewed as a potential gain, and the attribute of the alternative that is inferior (i.e., the delay to the reward) to be viewed as a potential loss. Kahneman and Tversky (1979) argue that there is a general tendency for losses to be asymmetrically impactful relative to gains, implying the attribute that is framed as a loss will tend to have greater influence on choice. This explanation treats intertemporal preference as the result of context-dependent evaluation of each attribute separately; see also Weber et al. (2007) for a distinct constructionist explanation of this effect.

The idea that delay and amount attributes are compared directly against one another has also been used to explain nonadditive discounting. According to the standard model, discounting of a reward over a given delay should be the same whether that delay is presented in one quantity or broken down into intervals. The finding of systematic deviations from additivity (Read, 2001; Scholten & Read, 2006), especially subadditive discounting, can be explained by attribute comparison in which money is weighed *against* time (Scholten et al., 2014). That is, rather than integrating the two attributes to derive an overall value for each alternative prior to comparison (*alternative-wise* comparison), the decision maker makes *attribute-wise* comparisons, sequentially comparing the two amounts and the two delays (Scholten & Read, 2010). Indeed in direct comparisons based on drift-diffusion modeling, Dai and Busemeyer (2014) found attribute-wise comparison models outperformed alternative-wise models built upon exponential *or* hyperbolic discounting functions.

Given attribute-wise comparison, delay discounting may be influenced by the amount of attention devoted to each attribute. Consistent with this idea, Reeck et al. (2017) conducted an eye-tracking study and found that participants with longer fixation time on the amount attribute, as opposed to the delay attribute, during an intertemporal choice task exhibited less delay discounting. Using both eye-tracking and drift-diffusion modeling, Amasino et al. (2019) similarly reported that participants who discounted at low rates attended primarily to the amount attribute.

In addition to providing an explanation of observed framing effects on intertemporal choice, recognition of the role that attribute-wise comparison plays in intertemporal decision making can suggest new framing effects (Amasino et al., 2019). In sensory domains, attention orients to change, whereas aspects of stimuli that are constant over time receive less attention (Rensink et al., 1997; Simons & Rensink, 2005). An analogous relationship between constancy and attention may be present in multiattribute decision making. That is, holding one attribute constant across a series of intertemporal choices may affect discounting by decreasing the attention that the unchanging attribute receives relative to the varying attribute. For this to be the case, it must be true that responses during intertemporal choice tasks are influenced by the questions that were recently encountered. Lempert et al. (2015) demonstrated that recent questions do indeed affect responses to new items. In particular, when only one alternative (either the SS or LL) was highly variable in both amount and delay, markers of physiological arousal were linked to the value of that alternative relative to recent questions, while preferences were biased in the direction of the lower variance alternative (with variance here referring to the range of *both* the amount and delay of the alternative).

Here we investigate the effect of fixing one attribute during an intertemporal choice task. In the first experiment, participants completed an adaptive discounting procedure in two blocks (order counterbalanced). In one block, amounts were held constant across all trials (the "amount-fixed" condition) and delays varied based on an adaptive procedure designed to provide relatively precise intervals for a participant's indifference point. In the other block (the "delay-fixed" condition), delays were held constant and amounts were adjusted to derive indifference point intervals. *We hypothesized that discounting would be lower in the delay-fixed condition since the absence of variation on this dimension would lead to relatively greater attention to the amount attribute (and thereby tend to favor choice of the LL reward).*

Experiment 1: Fixed Attributes

Method

Participants

Participants were 200 adults (inclusion age range 19–55) recruited from Prolific (http://www.prolific.co). They were required to participate by computer (rather than smartphone), and eligibility was restricted to participants with at least a 95% approval rating based on their past participation in experiments. Participants were paid US $1.50 for completing the study. Eight participants (4%) chose the same alternative on all trials of at least one condition (regardless of amounts and delays presented) and were excluded from the analysis (five all SS and three all LL). Response time medians in these cases were less than half that of retained participants (881 ms compared with 2,031 ms). The remaining participants' age ranged from 19 to 49 (M = 26.86, SD = 7.17), 83 were female, 108 were male, and 1 participant did not provide information on sex (see Table 1). Thirty-nine participants were from Portugal and 36 were from Poland. The rest of the participants were from the United Kingdom (n = 28), Italy (n = 20), Greece (n = 9), and 29 other countries, mainly in Europe, but also in Asia, Africa, and South America. Twenty-nine participants reported English as their first language, followed by Portuguese (n = 20), Polish (n = 18), and Spanish (n = 9).

Table 1. Demographic characteristics of participants in Experiment 1

Characteristic	N	%
Age		
18–25	106	55.21
26–35	59	30.73
36–45	23	11.98
46–55	4	2.08
Sex		
Female	83	43.22
Male	108	56.25
Other/unknown	1	0.52
Nationality		
Portugal	39	20.31
Poland	36	18.75
The United Kingdom	28	14.58
Italy	20	10.42
Other/unknown	69	35.59
First language		
English	29	15.10
Not English	80	41.67
Unknown	83	43.23

Procedure

Before the task, participants were informed that they would make two series of 24 choices (one series with delay-fixed and one with amount-fixed), and 1 out of 25 participants would be selected to receive one choice made as a bonus payment (after the indicated delay for that trial). They then received instructions to press key [1] to choose the alternative presented on the left and key [2] to choose the alternative presented on the right. For each trial, participants had 6 seconds to respond. If they had not responded within 6 seconds, the task proceeded automatically. As they made a choice, the selected alternative turned red, after which both alternatives disappeared. Then, the next question was presented. After instructions, participants completed nine practice trials to familiarize themselves with the trial format prior to the start of the experiment. These nine questions were static intertemporal choice questions taken from the medium magnitude subset of the Monetary Choice Questionnaire (MCQ) of Kirby et al. (1999). The number of LL choices each participant made on the (abridged) MCQ was used to give an estimated starting k value for the first fixed attribute discounting task (FADT) block. Then, participants completed two blocks of the FADT, the order of which was counterbalanced. On each trial, two alternatives were presented on either side of the display, with the varying attribute in bold font, and side of the SS and LL reward randomized. The running estimate of k was increased after each SS choice (by multiplying the current estimate of k by $10^{1/8}$) and decreased after each LL choice (by multiplying the current estimate of k by $1/10^{1/8}$). The running estimate from the last choice of the first block was carried over to the second block as the starting k value.

In the delay-fixed condition, the delay to the SS reward was always 5 days, and the delay to the LL reward was always 90 days. During these trials, only the amounts changed from one trial to the next. The LL reward was randomly generated as a number between \$20 and \$40 using a discrete, uniform distribution, and the corresponding smaller amount was generated based on the following formula:

$$\frac{A_{LL}}{1 + kD_{LL}} = \frac{A_{SS}}{1 + kD_{SS}} \tag{2}$$

where A_{LL} is the amount of the LL reward, A_{SS} is the amount of the SS reward, D_{LL} is the delay to the LL reward, D_{SS} is the delay to the SS reward, and k represents a running estimate of the participant's degree of discounting. In the amount-fixed condition, the SS reward was always \$25, and the LL reward was always \$30. The delay to the SS reward varied as a random number, following a discrete, uniform distribution, between 1 and 9 days, and the delay to the LL reward was generated according to Equation 2. The mean delay for the SS reward in the amount-fixed condition matched the SS delay in the delay-fixed condition (both 5 days), and the LL reward in the amount-fixed condition matched the mean LL reward in the delay-fixed condition (both \$30). Throughout, function-generated values were rounded to the nearest dollar (no amounts with cents) and number of days (no decimals). Experiment 1 was completed remotely. See Figure 1 for an illustration of the task. Data and code for the experiment and analyses are available at https://osf.io/86ztd/ (Monterosso et al., 2021).

Analyses of Delay Discounting

In the first analysis of preference, a *Simple Fitting Procedure* outlined in Kirby et al. (1999) was used to estimate condition-specific k values on the basis of Equation 1. In the fitting procedure, a fixed set of possible k values is tested for consistency with each participant's set of choices. The set of possible k values that were tested included 46 natural logarithm (ln) spaced values, where the range was based on values that could arise in the adaptive procedure. For each of these 46 $\ln(k)$ values, the algorithm compared the 24 choices the participant made to the choice that would be expected if the participant discounted hyperbolically with that particular value of k. The scoring algorithm identified the test value for k that was consistent with the largest number of choices, averaging multiple values in the case of ties.

In complementary analyses, data were modeled using *Maximum Likelihood (ML) estimation*; see the Electronic Supplementary Material, ESM 1, for further details on the estimation approach. Specifically, to estimate k in Equation 1 we formed a latent index of the difference in the present values of the SS and LL rewards presented to subjects in the experiment (Andersen et al., 2008; Hofmeyr et al., 2017). The value of this index is determined by the magnitudes of the rewards, their associated delays, and a candidate estimate of k. We used a cumulative logistic distribution function to link this latent index to participants' binary choices: specifically, choice of SS = 0 and

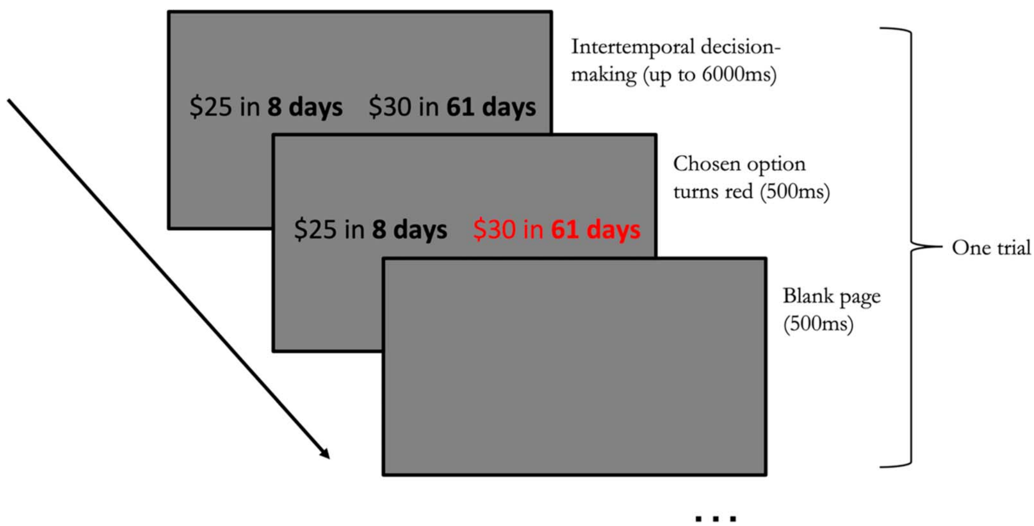

Figure 1. Task illustration of Experiment 1 (one trial in the amount-fixed condition).

choice of LL = 1. This "logit" link function determines the likelihoods of selecting the SS and LL rewards given the value of the latent index, which depends on the attributes of the rewards and the candidate estimate of k. ML estimation is then used to find the value of k that maximizes the likelihood of observing the data, viz., choices, from the experiment.

To investigate whether fixed attributes affect discounting behavior, we made the parameter k a linear function of age, gender, nationality, whether the participant speaks English as a first language, and, critically, whether amount or delay was the fixed attribute for a set of choices. We also incorporated the possibility that participants made behavioral errors in the experiment, e.g., choosing the SS reward when they actually preferred the LL reward, by estimating the parameter k jointly with a Fechner (1860/1966) error term μ. To account for the fact that participants made multiple choices in the experiment, we clustered the standard errors of the estimates by participant identifier.

Finally, we carried out a *"Model-Independent" Analysis* based on observed inconsistency across different questions. For some pairs of questions, there is a combination of answers that is not consistent with any deterministic discounting function (assuming only that *amount* is positively related to value, and *delay* is negatively related to value). If in one question choosing an option (SS or LL) is as good or better in every way than is choosing that option in another question, it is inconsistent to only prefer that option in the latter. Pairs of questions for which such an inconsistency was possible were common *within* a fixed attribute condition (occurring for approximately 50% of all question pairs since one attribute is fixed). Observed inconsistencies (relative to possible inconsistencies) within an experimental condition provide a measure of noise that is not distorted by any mismatch between a discounting function presumed by the researcher and that which best accounts for a particular participant's data, for example, if the researcher presumes hyperbolic discounting, but a participant is better characterized by exponential discounting (Andersen et al., 2008).

Model-independent inconsistency was also considered as an approach to assess the effect of condition. Although somewhat rare, participants sometimes encountered pairs of questions *between* conditions in which an inconsistent set of responses was possible. For example, if one question in the amount-fixed condition was $25 in 6 days vs. $30 in 88 days, and one question from the delay-fixed condition was $26 in 5 days vs. $29 in 90 days, then it would be inconsistent if a participant chose SS in the first question and LL in the second, because SS is a more attractive option in the second question in all ways (it is larger and sooner, and pitted against an alternative that is smaller and more delayed). If inconsistencies that imply steeper discounting in the amount-fixed condition (as in the example above) occur more than inconsistencies that imply steeper discounting in the delay-fixed condition, it would imply a fixed-attribute effect on discounting consistent with the study hypothesis.

Results

Demographics and Delay Discounting

The discounting parameter $\ln(k)$ (averaged across conditions of the FADT) was used to examine overall associations with demographic variables. For the variable age, correlational analyses (Spearman's rho) were used, and for categorical demographic variables (sex, nationality, and first language), analyses of variance (ANOVAs) were conducted. In order to avoid inflating degrees of freedom, categories with fewer than 10 participants were not included in analyses of demographics. No significant correlation was found between age and delay discounting, nor did we observe associations between discounting and sex, nationality, or first language (English vs. other; see Table 2).

Based on the Simple Fitting Procedure, the median best-fitting discounting parameter was $k = 0.025$ for the amount-fixed condition, and $k = 0.014$ for the delay-fixed condition. Paired t-tests of $\ln(k)$ values between conditions indicated steeper discounting in the amount-fixed condition compared to the delay-fixed condition ($t(191) = 4.63$, $p < 0.001$). The distribution of differences in participant $\ln(k)$ values across the two conditions is presented in Figure 2. A total of 122 participants (63.5% of the sample) were more patient during the delay-fixed condition, whereas only 55 participants (28.6% of the sample) were more patient during the amount-fixed condition; the remaining 15 participants (7.8%) did not differ across conditions. Of the 24 items per condition, the mean number of responses inconsistent with participant best-fit k was 6.8 ± 2.3 in the amount-fixed condition and 6.9 ± 1.9 in the delay-fixed condition, which did not differ by paired t-test ($t(191) = 0.85$, $p = 0.39$).

ML Estimation Results

Nine participants who chose the same alternative (all SS or all LL) on the MCQ items were dropped from ML analyses because models with these participants failed to converge. Table 3 presents ML estimates of the hyperbolic discounting function. The estimates only include a dummy variable that captures whether amount or delay was the fixed attribute for a set of trials. Table 3 shows that participants discount at a significantly higher rate ($p < .001$) in the amount-fixed condition in comparison to the delay-fixed condition (the omitted, base category). By contrast, there is no statistically significant evidence of greater subject stochasticity by fixed attribute condition. Nevertheless, a joint test of the Constant and Amount Fixed covariate for the Fechner error term equation is statistically significant ($p < .001$), and it is important, therefore, to take this into account in subsequent analyses.

Table E1 in ESM 1 provides additional, heterogeneous preference results that include age, gender, nationality, whether the participant speaks English as a first language, and the Amount Fixed covariate in the equation for the discounting parameter *k*. These results are summarized in Figure 3, which plots the estimated discounting parameter across the amount-fixed and delay-fixed conditions.

Model-Independent Inconsistency

Participants were inconsistent (in the model-independent sense described above) on 6.5% ± 4.1% (M ± *SD*) of trial pairs in the amount-fixed condition for which inconsistency was possible, and on 5.5% ± 4.5% of trial pairs in the delay-fixed condition for which inconsistency was possible. Because the distributions were skewed, inconsistency within conditions was compared nonparametrically using the Wilcoxon signed-rank test for related samples. A significant difference was observed ($Z = 2.82$, $p = .005$) with greater inconsistency in the amount-fixed condition.

Trial pairs *across* conditions in which an inconsistency was possible were rare (see discussion above). Most participants ($n = 151$, 78.6%) had no such trial pairs. However, across all participants, there were a total of 529 trial pairs in which model-independent inconsistency was possible and would imply greater patience, viz., less discounting, in the *amount-fixed* condition. Inconsistency was observed in 20 of these trials (3.8%). There were 536 trial pairs in which model-independent inconsistency was possible and would imply greater patience in the *delay-fixed* condition. Inconsistency was observed in 76 of these instances (14.2%). Thus, the pattern of inconsistency is directionally consistent with greater patience in the delay-fixed condition. This pattern was confirmed statistically by estimating a logit model of inconsistent choice across conditions on a dummy variable that tracks whether an inconsistent choice implies more or less discounting in the amount-fixed or delay-fixed condition. Given that multiple observations from the same participant are not independently distributed, we clustered the standard errors of the estimates to account for this. We find that discounting is significantly higher, viz., patience is significantly lower, in the amount-fixed condition relative to the delay-fixed condition ($p = .036$).

Reaction Time

Median reaction time (RT) across all participants ranged from 653 to 3,978 ms. The average of median RTs during the delay-fixed condition was 2,173 ± 730 (M ± *SD*) and 2,097 ± 810 for the SS and LL choices, respectively. During the amount-fixed condition, the average of median RTs was 2,178 ± 732 and 2,163 ± 694 for the SS and LL choices, respectively. These data were modeled using repeated measures ANOVA with attribute condition and choice of SS or LL as independent within-participant variables. Consistent with Luo et al. (2014), responses were slower for SS choices (F (1, 191) = 4.15, $p = .04$). RT did not differ by FADT condition (F (1, 191) = 0.98, $p = .32$), and no interaction was observed between condition and RT (F (1,191) = 1.93, $p = .17$).

Participants who responded more quickly across conditions exhibited greater tendency to discount more steeply during the amount-fixed relative to delay-fixed conditions ($r(192) = .21$, $p = .004$). We computed a *varying-attribute speed advantage* score based on RTs as follows: (RT of $\mathrm{LL}_{\text{Delay-fixed}}$ − RT of $\mathrm{SS}_{\text{Delay-fixed}}$) + (RT of $\mathrm{SS}_{\text{Amount-fixed}}$ − RT of $\mathrm{LL}_{\text{Amount-fixed}}$). This score quantified each participant's tendency to be faster when selecting the alternative that was superior on the varying (possibly more salient) attribute. We reasoned that participants who pay more attention to the varying attribute may respond more quickly when selecting the alternative superior on that attribute. Consistent with expectation, Figure 4 shows that

Table 2. Fixed-effects ANOVA results using ln(*k*) (averaged across conditions) as the criterion

Predictor	Sum of squares	*df*	Mean square	*F*	*p*	Partial η²	Partial η² 90% CI
Intercept	1,067.57	1	1,067.57	140.13	.000		
Sex	0.02	1	0.02	0.00	.963	.00	[.00, 1.00]
Error	1,439.86	189	7.62				
Intercept	348.74	1	348.74	55.79	.000		
Nationality	39.80	3	13.27	2.12	.104	.05	[.00, .11]
Error	743.84	119	6.25				
Intercept	394.00	1	394.00	59.89	.000		
First language	0.13	1	0.13	0.02	.888	.00	[.00, .01]
Error	703.93	107	6.58				

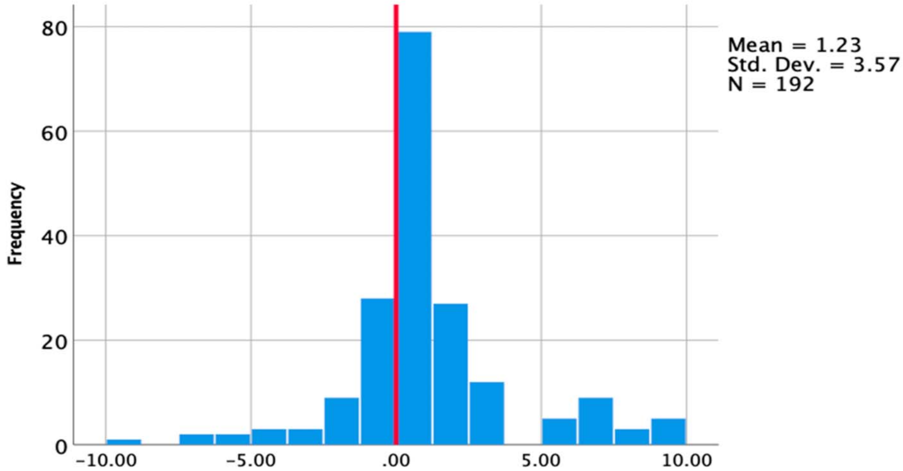

Figure 2. Difference in discounting parameter ln(k) estimates (amount-fixed − delay-fixed).

individuals with greater varying-attribute speed advantage scores evidenced greater tendency to discount more steeply in the amount-fixed condition (r(192) = .26, p < .001). To further explore this association, we separately examined the associations between the fixed attribute effect on discounting and the two difference scores that were combined to form the *varying-attribute speed advantage* composite (RT of $LL_{Delay\text{-}fixed} - SS_{Delay\text{-}fixed}$, and RT of $SS_{Amount\text{-}fixed} - LL_{Amount\text{-}fixed}$ separately). A greater fixed attribute effect was correlated with both (1) faster responses when choosing the LL than SS during the delay-fixed condition (r(192) = .15, p = .04) and (2) faster responses when choosing the SS than LL during the amount-fixed condition (r(192) = .21, p = .003).

Discussion

In Experiment 1, we observed that holding an attribute fixed had a significant impact on discounting behavior. Using the Simple Fitting Procedure, the best-fitting k parameter for the majority of participants was lower (greater patience) during the delay-fixed condition, with only 28.6% exhibiting the opposite pattern. The complementary ML estimation results also showed that participants discounted significantly more in the amount-fixed condition relative to the delay-fixed condition, and this result remained significant when adjusting for observable demographic characteristics (see Table E1 in ESM 1). Although opportunities for model-independent inconsistency across conditions were rare (and not uniform across participants), there was also a statistically significant pattern of greater inconsistency when it implied more patience in the delay-fixed condition than when it implied more patience in the amount-fixed condition.

Measures of the noise in participant response yielded mixed results. In the model-independent analyses, inconsistency was significantly more prevalent in the amount-fixed (6.5%) than delay-fixed (5.5%) condition. This is in keeping with prior evidence (Ebert & Prelec, 2007) that the effect of delay on value is in general more stochastic than the effect of amount (or probability). We did not, however, observe evidence of greater numbers of inconsistencies in responses relative to the Simple Fitting Procedure (hyperbola-based) measure of discounting. It is notable that the median numbers of responses inconsistent with best-fit k-values were high. Given the adaptive procedure, participants received many questions in which a small divergence from the hyperbola-based best-fit causes an inconsistency. Moreover, whereas the model-independent measure identifies internal inconsistency in responses (a reasonable measure of noise), scores tied to best-fit k estimation partly reflect the degree to which the participant happens to respond to the trade-off in a way that conforms to Equation 1, which has been shown to vary considerably between individuals (Andersen et al.,

Table 3. Discounting function maximum likelihood estimates: Fixed attributes

	Hyperbolic discounting	
	Estimate	*SE*
Discounting parameter (k)		
Amount fixed	0.1208***	0.0366
Constant	0.0002	0.004
Fechner error (μ)		
Amount fixed	−80.8255	85.2557
Constant	114.8954	84.9559
N	8,739	
Log-likelihood	−6,009	

Note. Results account for clustering at the individual level. *p < .05, ** p < .01, *** p < .001.

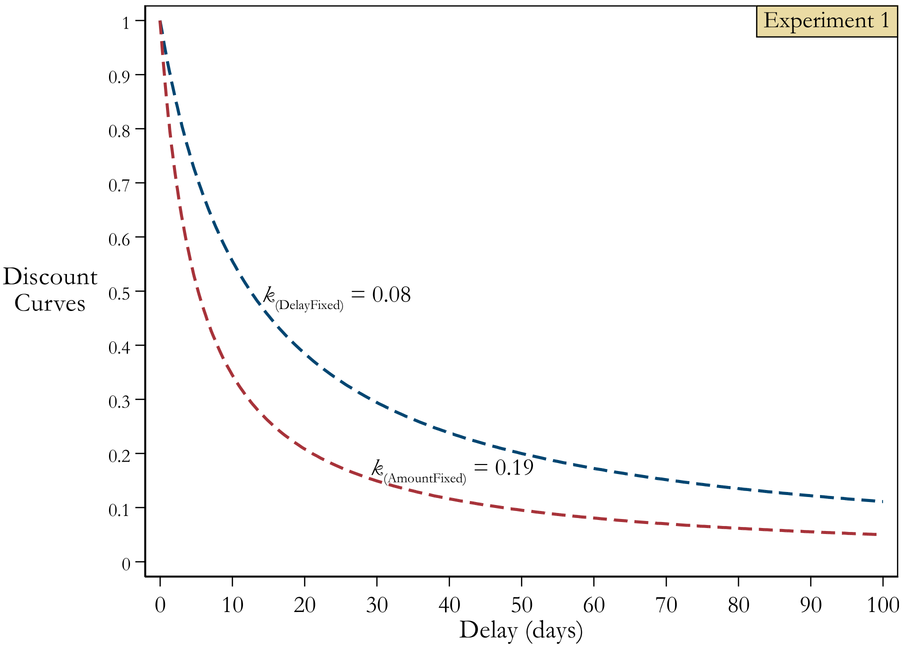

Figure 3. Estimated discounting parameter (k) according to fixed attribute condition.

2008). For this reason, we believe model-independent inconsistency is a better measure of noise.

Taken together, the results of Experiment 1 indicate that participants were more patient when delay was fixed than when amount was fixed. One plausible mechanism for this is that the study manipulation affects the relative salience of attributes. If only one attribute varies across trials, it may capture a greater share of attention during decision making and so exert greater influence on choice. Thus, when delay is fixed, participants may attend more to amounts, thereby making the LL reward the more attractive alternative. Although this *attribute salience* explanation is speculative, there is some suggestive support for it in the RT data. First, participants who responded more quickly exhibited larger fixed-attribute effects. Milosavljevic et al. (2012) argue that when participants are placed under greater exogenous time pressure, the influence of the most salient attribute on multi-attribute decisions is enhanced. It is plausible that a similar effect is present when participants choose to respond more quickly during self-paced decisions. Second, the tendency of participants to respond more quickly when making choices in which the condition's varying attribute was superior (choosing the SS reward when delay was the varying attribute, and choosing the LL reward when amount was the varying attribute) was

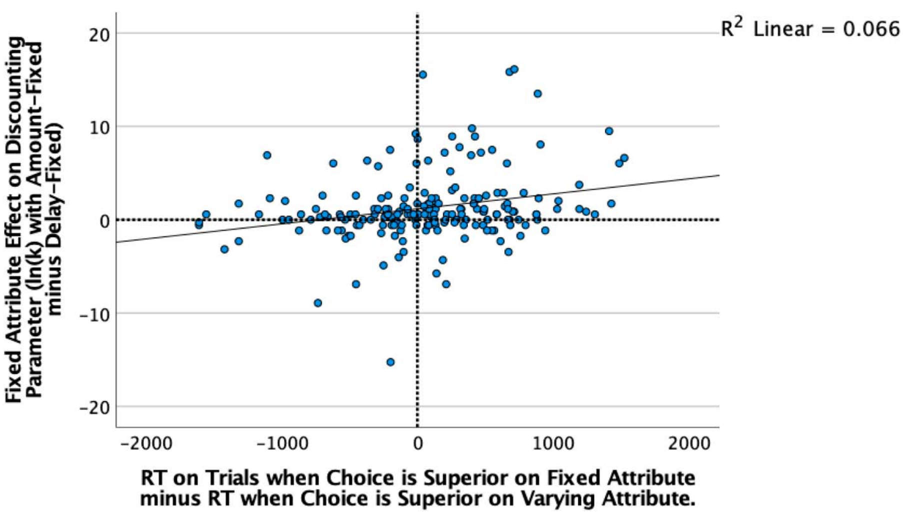

Figure 4. Association between the fixed attribute effect on discounting parameter ln(k) and the varying-attribute speed advantage scores.

also correlated with a greater tendency to discount more steeply in the amount-fixed relative to delay-fixed conditions. This is consistent with the possibility that the observed effect on preference was related to the degree to which the varying attribute was attended to disproportionately.

Experiment 2: Replication and Test for Interaction With Memory Load

Experiment 2 was carried out to replicate and extend the findings of Experiment 1. The primary extension of Experiment 2 was directed at assessing the possible interaction between fixed attributes and working memory demands during intertemporal choice. It has been suggested that forgoing SS rewards in favor of LL rewards is an act of cognitive control (Shamosh et al., 2008) and is dependent on the limited resource of working memory (McCabe et al., 2010). However, studies examining the relationship between working memory and discounting have yielded mixed results. On the one hand, lower working memory capacity has been associated with steeper delay discounting (Szuhany et al., 2018), and there is experimental evidence suggesting an association between working memory and discounting behavior. For example, Hinson et al. (2003) required participants to make intertemporal choices either with or without concurrent working memory demands and reported that memory load was associated with greater discounting of monetary rewards (see also Getz, 2013). They interpret this finding as evidence that, "… limits on [working memory] WM function, either intrinsic or extrinsic, are predictive of a more impulsive decision-making style" (Hinson et al., 2003, p. 298). Also lending support for this view, Aranovich et al. (2016) reported that when intertemporal questions were presented immediately after a task designed to overwhelm working memory, participants generally low in working memory capacity tended to exhibit greater discounting.

However, not all data have been consistent with the hypothesized link between working memory and discounting. A re-analysis of the Hinson et al. (2003) data, conducted by Franco-Watkins et al. (2006), suggested that working memory load induced more random responding rather than greater discounting. Adapting a different paradigm to evaluate discounting, Ebert (2001) asked participants to indicate how much they valued a series of events (e.g., "Tomorrow you win a 20-inch TV") and found that taxing cognitive functions by both imposing time pressure and a concurrent auditory task led to an *increase* in overall valuation for future events (suggestive of *less* discounting when under working memory load). Thus, the effect of taxing working memory on delay discounting is not robust and consistent across implementations.

Working Memory Load and Attribute Salience

Mann and Ward (2007) proposed a model called *attentional myopia*, which states that when an individual's attentional capacity is limited, their behavior will be more affected by highly salient internal or external cues and less affected by secondary (more distal) stimuli. Consistent with the attentional myopia hypothesis, after a high-load compared to a low-load cognitive task, participants' attention was attenuated and more influenced by salient external cues (e.g., eating more under cognitive load when food-cues were salient, but eating less under cognitive load when diet cues were salient). Similar results were observed with smoking-promoting versus smoking-inhibiting cues and help-promoting versus help-inhibiting cues (Mann & Ward, 2007; Wallaert et al., 2014). Relatedly, Milosavljevic et al. (2012) found that at forced, rapid decision speeds, cognitive load increased the bias that visual saliency has on decisions. Following the logic of Mann and Ward (2007), we hypothesized that a working memory load during the FADT would lead to a stronger impact of the varying (more salient) attribute on preference. Thus, working memory load would lead to increased discounting when amount was fixed, and decreased discounting when delay was fixed.

Method

Participants

Participants were 167 adults (inclusion age range 19–55) recruited from Prolific (http://www.prolific.co). They were required to participate by computer (rather than smartphone), and eligibility was restricted to participants with at least a 95% approval rating based on their past participation in experiments. Participants were paid $4.00 for completing the study (which took approximately 15 min to complete). Twenty participants (11.9%) chose the same alternative on all trials of at least one condition (regardless of amounts and delays presented) and were excluded from analysis. Response time medians for these participants were less than half that of retained participants (1,247 ms compared with 2,618 ms). These participants primarily chose SS on all responses (17 of 20), despite the titration procedure. Additionally four participants (2.4%) were dropped due to median response times below 500 ms. Thus, a total of 143 participants were included in data analyses.

Participants' age ranged from 18 to 54 (M = 30.38, SD = 9.21), 71 were female, 69 were male, and three participants did not provide information on sex (see Table 4). Thirty-seven participants were from the United Kingdom and 29 were from the United States. The rest of the participants were from Poland (n = 17), Portugal (n = 8), Canada (n = 6), and 25 other countries, mainly in Europe, but also in Asia, Africa, and South America. Seventy-nine participants reported English as their first language.

Procedure

The task used in Experiment 2 was similar to Experiment 1 with a few modifications (in addition to the inclusion of working-memory blocks). These changes included: a different range of the SS_{delay} in the amount-fixed condition (5–50 days, generated using a discrete, uniform distribution) and a different range of the LL_{amount} in the delay-fixed condition ($10–$80, again generated using a discrete, uniform distribution). For the discounting parameter k, within each block, it started at 0.01, increased ¼ log step after choice of the SS reward, and decreased ¼ log step after choice of the LL reward (rather than 1/8 log step adjustments used in Experiment 1). Participants completed four blocks of the FADT, the sequence of which was randomized. We employed a 2 × 2 design: amount-fixed versus delay-fixed, crossed with presence versus absence of concurrent working memory load. During the working memory load condition, the participants were asked to memorize a five-character random letter string before the first, ninth, and seventeenth trials, and recall and type the most recently presented letter string after the eighth, sixteenth, and 24th trials. See Figure 5 for an illustration of the task.

After finishing the four experimental conditions, participants completed the MCQ (Kirby et al., 1999), which consists of 27 items requiring choice between SS and LL rewards. Notably, all questions in the MCQ include an immediate alternative, whereas no questions in the FADT include immediate alternatives. The Simple Fitting Procedure described in Kirby et al. (1999) was used to fit each participant's responses using the hyperbolic discounting function. Data and code for the experiment and analyses are available at https://osf.io/86ztd/.

Results

Demographics and Delay Discounting

The discounting parameter ln(k) obtained from the MCQ was used to examine overall associations with demographic variables. For the variable age, correlational analyses (Spearman's rho) were used, and for categorical demographic variables (sex, nationality, and first language), ANOVAs were carried out. In order to avoid inflating degrees of freedom, categories with fewer than 10 participants were not included in analyses of demographics. In addition, since more than 50% of participants' first language was English and the rest varied across 20 different languages, we collapsed the first language into two groups: English and not English. No significant correlation was found between age and delay discounting on the MCQ, nor did we observe statistically significant associations between discounting and sex, first language (English vs. other), or nationality (see Table 5).

Table 4. Demographic characteristics of participants in Experiment 2

Characteristic	N	%
Age		
18–25	54	37.76
26–35	50	34.97
36–45	27	18.88
46–55	12	8.39
Sex		
Female	71	49.65
Male	69	48.25
Other/unknown	3	2.09
Nationality		
The United Kingdom	37	25.87
The United States	29	20.28
Poland	17	11.89
Other/unknown	60	41.96
First language		
English	79	55.24
Not English	62	43.36
Unknown	2	1.40

Condition Effects on Discounting

Based on the Simple Fitting Procedure (described above), the median best-fitting discounting parameter for trials *without* memory load was k = 0.10 for the amount-fixed condition and k = 0.033 for the delay-fixed condition. The median best-fitting k for trials *with* memory load was k = 0.078 for the amount-fixed condition and k = 0.025 for the delay-fixed condition. Individual participant ln(k) parameter fits were modeled using repeated measures ANOVA with (1) fixed-attribute condition and (2) presence versus absence of working memory load as within participant factors. Consistent with Experiment 1, a main effect of fixed attribute was observed (F (1, 142) = 8.06, p = .005) with participants exhibiting less discounting in the delay-fixed than amount-fixed condition. Combining across memory and nonmemory conditions, the distribution of this fixed attribute effect (ln(k) of amount-fixed minus delay-fixed) is presented in Figure 6.

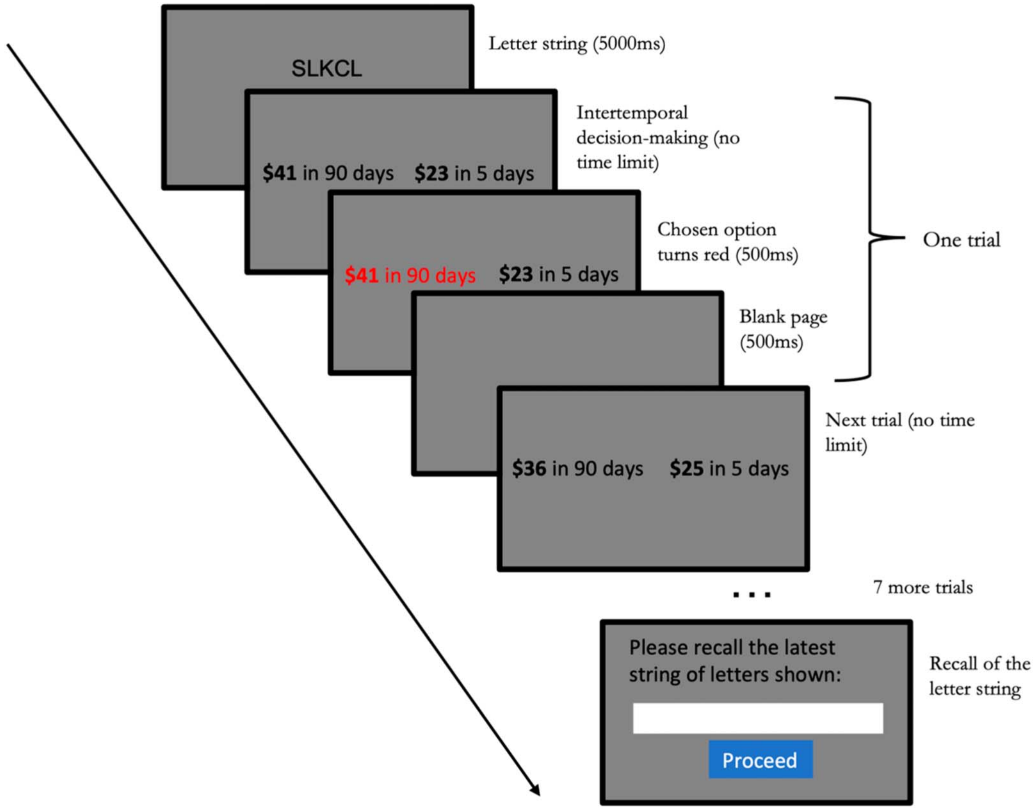

Figure 5. Task illustration of Experiment 2.

We also observed a main effect of working memory load (F (1, 142) = 11.4, p < .001) with lower discounting when participants were exposed to working memory load. Contrary to our hypothesis, we observed no interaction between fixed attributes and the presence of the working memory manipulation (F (1, 142) = 0.02, p = .90, see Figure 7).

Of the 24 items per condition, the mean number of responses inconsistent with hyperbola-based parameter best-fit k was 5.8 ± 2.0 in the amount-fixed condition without working memory, 6.3 ± 1.9 in the delay-fixed condition without working memory, 5.9 ± 1.8 in the amount-fixed condition with working memory, and 6.4 ± 2.0 in the delay-fixed condition with working memory. Based on repeated measures ANOVA, the number of inconsistent responses did not differ based on working memory (F (1, 142) = 0.93, p = .34) but were more common in the delay-fixed condition (F (1, 142) = 10.8, p < .001). No interaction between working memory and fixed attribute condition was observed (F (1, 142) = 0.29, p = .59).

ML Estimation Results

Table 6 presents ML estimates of the hyperbolic discounting function. In contrast to Experiment 1, we pooled data across the amount-fixed, delay-fixed, *and* MCQ tasks to incorporate all participant choices in the experiment and enhance statistical power. Indeed, without the inclusion of MCQ data, ML estimation failed to converge. Thus, the fixed-attribute results in Table 6 are relative to the MCQ estimates (the omitted, base category). In addition, we included an interaction of fixed-attribute condition and working memory load, so it is essential post estimation to adjust for this interaction when analyzing the effects of the fixed-attribute conditions (and working memory load). Adopting this approach, the estimate of k = 0.024 for the MCQ, k = 0.022 for the delay-fixed condition, and k = 0.047 for the amount-fixed condition. The estimate of k for the amount-fixed condition is significantly higher than the delay-fixed condition (p = .035) and the MCQ (p < .001), but there is no statistically significant difference in estimates between the delay-fixed condition and MCQ.

Table E2 in ESM 1 provides additional, heterogeneous preference results that include age, sex, nationality, whether the participant speaks English as a first language, and the fixed attribute and working memory covariates in the equation for the discounting parameter k. We find that estimates of k are significantly higher in the amount-fixed condition relative to the MCQ (p = .011) and the delay-fixed condition (p = .003), and that estimates of k for the

Table 5. Fixed-effects ANOVA results using *k* from the MCQ as the criterion

Predictor	Sum of squares	*df*	Mean square	*F*	*p*	Partial η^2	Partial η^2 90% CI
Intercept	1,220.46	1	1,220.46	397.26	.000		
Sex	0.06	1	0.06	0.02	.886	.00	[.00, .01]
Error	423.97	138	3.07				
Intercept	223.48	1	223.48	68.32	.000		
Nationality	9.90	2	4.95	1.51	.227	.04	[.00, .11]
Error	261.69	80	3.27				
Intercept	1,460.06	1	1,460.06	482.53	.000		
First language	8.16	1	8.16	2.70	.103	.02	[.00, .07]
Error	420.59	139	3.03				

MCQ are higher than estimates of *k* for the delay-fixed condition, although this latter result only approaches statistical significance (p = .083). These results are summarized in Figure 8, which plots the estimated discounting parameter across the amount-fixed and delay-fixed conditions.

In contrast to the results in Figure 7, ML estimates of the effect of working memory, after adjusting for the interaction of fixed-attribute condition, is not significantly related to discounting behavior (p = .654). We discuss this inconsistency in results below.

Model-Independent Inconsistency

During trial blocks *without* working memory load, for trial pairs in which inconsistency was possible (in the model-independent sense described above), participants were inconsistent in 3.18% ± 3.2% of pairs in the amount-fixed condition, and 2.52% ± 3.44% of trials in the delay-fixed condition. During trial blocks *with* working memory load, participants were inconsistent in 2.85% ± 3.44% of pairs in the amount-fixed condition and 3.06% ± 3.27% of pairs in the delay-fixed condition. The distribution of participants' inconsistency was generally right-tailed, so inconsistency data were converted to ranks prior to analyses. Based on repeated measures ANOVA, no main effect of fixed-attribute condition (F (142, 1) = 1.00, p = .32) or the presence of working memory load was observed for the model of inconsistency (F (142, 1) = 0.01, p = .97). However, there was a marginally significant interaction between fixed-attribute condition and the presence of working memory load (F (142, 1) = 3.70, p = .057). To explore the basis of this marginally significant interaction, the effect of attribute on inconsistency was assessed separately for the blocks without working memory

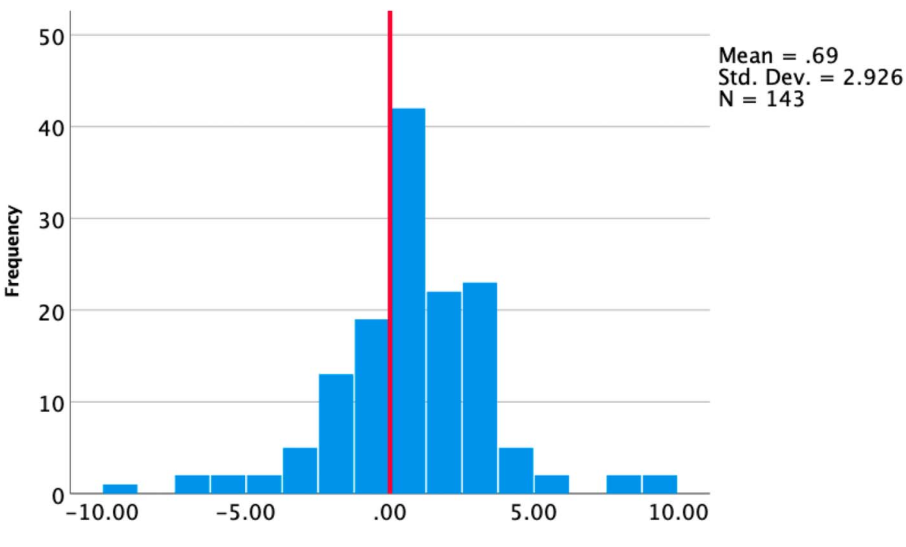

Figure 6. Difference in discounting parameter ln(*k*) estimates (amount-fixed – delay-fixed).

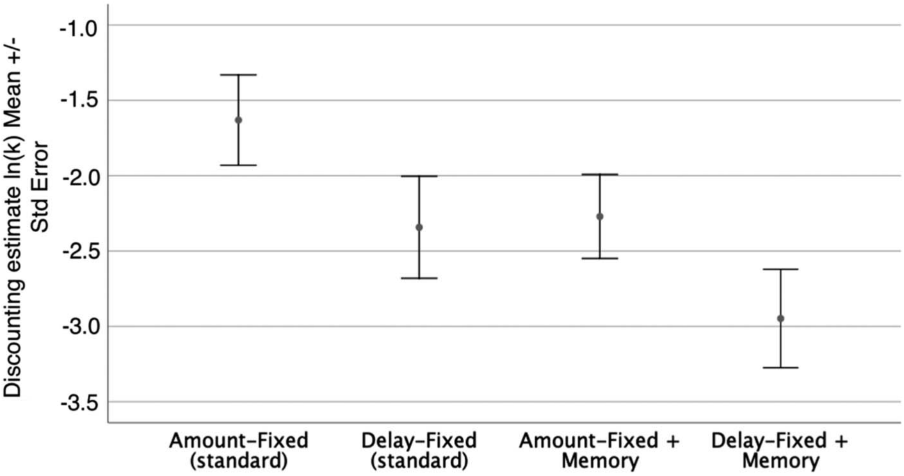

Figure 7. *M* and *SE* of ln(*k*) across study conditions (higher values indicate steeper discounting).

demand and for the blocks with working memory demand. In blocks without working memory demand, greater inconsistency was present during the amount-fixed relative to delay-fixed condition ($Z = 2.25$, $p = .025$), as was the case in Experiment 1. However, in blocks with working memory demand, there was no evidence of a difference in inconsistency between fixed-attribute conditions ($Z = 0.33$, $p = .74$). Because these data were ranks and thus not normally distributed, we reanalyzed amount-fixed versus delay-fixed inconsistencies, this time using Friedman's two-way ANOVA by ranks. Similar results were obtained, with significantly higher inconsistency ranks in the amount-fixed than delay-fixed condition when considering blocks without working memory demands ($\chi^2(1) = 5.12$, $p = .02$), but not in blocks with working memory demands ($\chi^2(1) = 0.48$, $p = .49$).

Table 6. Discounting function maximum likelihood estimates: Fixed attributes and working memory

	Hyperbolic discounting	
	Estimate	*SE*
Discounting parameter (*k*)		
Delay fixed	0.0033	0.0209
Amount fixed	0.0280**	0.0096
Memory load	−0.0096	0.0085
Delay fixed × memory load	−0.0015	0.0214
Constant	0.0238***	0.0031
Fechner error (μ)		
Constant	32.5029***	2.7565
N	16,974	
Log-likelihood	−11,286	

Note. Results account for clustering at the individual level. $*p < .05$, $**p < .01$, $***p < .001$.

There were no trial pairs in which a pattern of responses was possible that would be inconsistent in the direction of implying greater discounting in the delay-fixed than amount-fixed condition, so it was not possible to consider if inconsistency (see above) suggested a systematic difference in discounting between attribute conditions. This difference from Experiment 1 is related to the change in range of days associated with the SS in the amount-fixed condition of Experiment 2 (5–50 days as opposed to 1–9 days). This meant that in Experiment 2, the SS could not be sooner than it was in the delay-fixed condition (always 5 days).

Reaction Time

RTs are presented in Table 7 separated by fixed-attribute condition, the presence or absence of working memory load, and whether an SS or LL choice was made. These condition-specific RTs were analyzed by repeated measures ANOVA with fixed attribute (amount-fixed vs. delay-fixed), working memory load (present vs. absent), and choice (SS vs. LL) as within subjects factors. RTs were significantly longer for amount-fixed than delay-fixed blocks (F (1, 142) = 22.86, $p < .001$), and significantly longer on trials without working memory load than trials with working memory load (F (1, 142) = 7.85, $p = .006$). Faster responses during trials with working memory load is consistent with strategic speeding-up. Because responses were self-paced, participants would reduce the time the character strings needed to be retained by rushing through decisions. RTs did not differ significantly between SS and LL choices (F (1, 142) = 0.44, $p = .51$). No significant two-way or three-way interactions were observed (all p values > .2).

As in Experiment 1, we examined the association between RT and the main effect of attribute condition.

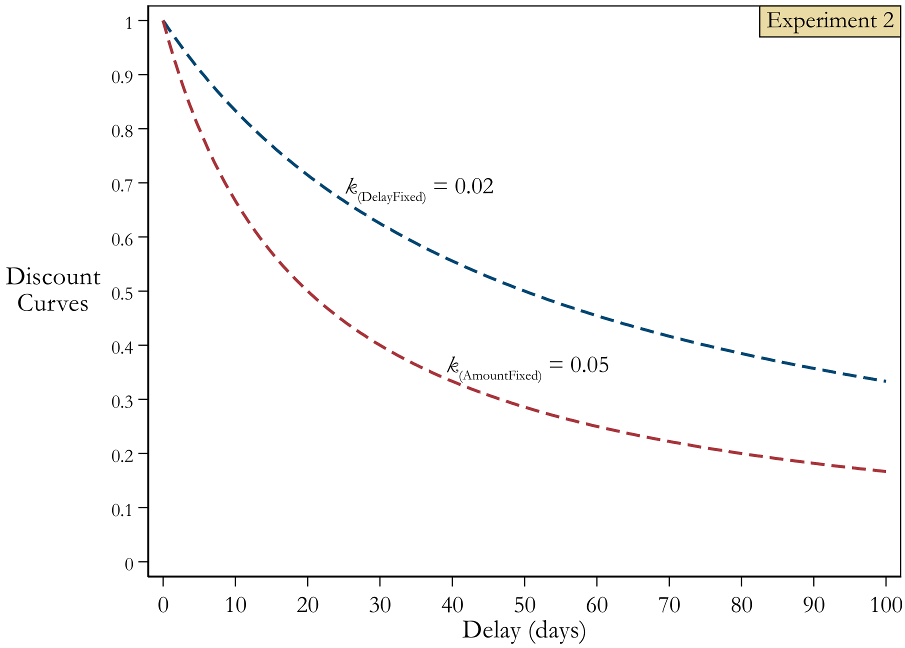

Figure 8. Estimated discounting parameter (k) according to fixed attribute condition.

Across all trials, we observed a marginally significant trend toward a greater overall attribute effect (operationalized as k-parameter fits for blocks with amount-fixed minus k-parameter fits for blocks with delay-fixed) for participants with lower mean RT across all conditions ($r(143) = -.142$, $p = .09$). This effect was qualitatively similar when considering just the blocks without working memory demand ($r(143) = -.14$, $p = .095$) and just the blocks with working memory demand ($r(143) = -.11$, $p = .19$).

Following a similar approach to that used in Experiment 1, we computed RT difference scores directed at quantifying how much faster participants responded when their preferred option was superior on the varying attribute (choice of the SS when delay was the varying attribute and choice of the LL when the amount was the varying attribute). Collapsing across memory conditions, greater *varying-attribute speed advantage* was associated with a larger fixed-attribute effect on discounting ($r(143) = .20$, $p = .02$). One participant's composite was an extreme outlier (more than three times below the first quartile of the interquartile range). With this participant's composite censored, the same association remained significant ($r(142) = .22$, $p = .008$). Focusing on blocks without working memory load, a significant association was observed between varying-attribute speed advantage and the fixed-attribute effect on discounting ($r(143) = .21$, $p = .01$). A similar, though only marginally significant, pattern was observed for blocks with working memory demand ($r(143) = .14$, $p = .086$).

Finally, we examined whether the effect of concurrent working memory demand on discounting was associated with participants' accuracy on the working memory task. Because a high percentage of participants had no errors ($n = 68$, 46.2%), we compared the overall effect of working memory load on delay discounting (the difference between discounting overall in conditions with concurrent working memory load and overall discounting in conditions without working memory load) among those without memory errors versus those with memory errors. Based on an unpaired t-test, we observed no significant difference between those without memory errors and those with memory errors ($t(142) = -0.10$, $p = .92$).

Discussion

The results of Experiment 2 provide a replication of the primary finding of Experiment 1. Participants were significantly more patient in the delay-fixed conditions relative to the amount-fixed conditions. Results from the ML estimation procedure were consistent with this, indicating steeper discounting in the amount-fixed than delay-fixed conditions of the FADT. The MCQ (Kirby et al., 1999) discounting estimate fell between the estimates from the FADT conditions, but the MCQ estimate was closer to the delay-fixed condition and differed significantly only from the amount-fixed condition. However, the comparability of estimates between the MCQ and FADT is complicated by the fact that the MCQ has no delay to the SS reward in every trial, whereas the FADT included a nonzero delay to the SS reward in every trial.

Table 7. Condition-specific reaction time in Experiment 2

	Working memory load							
	Present				Absent			
	Choice				Choice			
	SS		LL		SS		LL	
Fixed attribute	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Amount	3,188	1,478	3,141	1,682	3,550	2,380	3,573	2,533
Delay	2,961	1,192	2,944	4,151	2,900	1,311	3,045	2,371

Note. LL = larger, later alternative; SS = smaller, sooner alternative.

As in Experiment 1, consideration of RT data provided some support for the interpretation of the finding as related to attribute salience. First, the effect of fixed-attribute condition tended to be larger in participants that responded more quickly, although this association was only a trend in Experiment 2. This is consistent with the previously reported finding that the influence of the most salient attribute in a multi-attribute context is enhanced when responses are made under time pressure (Milosavljevic et al., 2012). In addition, we found that participants who tended to respond more quickly when they were making choices that favored the varying attribute (i.e., choosing the SS during the amount-fixed condition and choosing the LL during the delay-fixed condition) evidenced a significantly greater effect of fixed attributes on delay discounting. One possible interpretation of this replicated result is that the shared variance reflects a connection of both findings to the degree of attentional advantage participants give to the varying attribute. For participants who attend least to the fixed attribute, decisions would be expected to be more influenced by the varying attribute, and participants would plausibly respond more quickly when the attribute receiving prioritized attention was superior.

We were also interested in testing the hypothesis that the fixed-attribute effect would be enhanced when participants were under concurrent working memory load, which we hypothesized would disproportionately reduce attention to the fixed (less salient) attribute. However, we observed no support for this hypothesis. Instead, we observed a main effect of the working memory task, with lower discounting when participants were in the working memory load condition. Surprisingly, evidence of this effect of working memory load was absent in the ML estimation. One contributing factor could be the inclusion of the MCQ data in the ML analysis, which was necessary for model convergence. Unlike the fixed-attribute conditions of the FADT that were crossed with working memory, all MCQ trials had no working memory load. A second contributing factor could be the inclusion of the Fechner error term for participant stochasticity in the ML analysis only.

Model-independent inconsistency was lower in Experiment 2 than Experiment 1. This is unsurprising given the adaptive procedure utilized ¼ log steps rather than ⅛ log steps. Unlike Study 1, in the hyperbola-based analysis of Study 2 participants made significantly more choices that were inconsistent with their best-fit k-values during the delay-fixed condition. This was directionally opposite to the findings from the model-independent measure of inconsistency observed in both Study 1 and Study 2, which indicated more inconsistency in responses during the amount-fixed condition of the task. It is important to keep in mind that inconsistency score in the analyses based on k estimates presume hyperbolic functional form. If performance during the delay-fixed condition was more orderly but less hyperbolic than in the amount-fixed condition, the observed pattern of results would be obtained. As noted above, we consider the model-independent measure a better indication of response noise since it is not confounded by assumption of hyperbolic functional form.

General Discussion

In two experiments, we showed that discounting can be affected by fixing the amount or delay attribute of SS and LL rewards across a series of trials. Specifically, we observed that discounting was steeper when amount was fixed relative to when delay was fixed. These results are consistent with the possibility (though do not prove) that holding one attribute constant reduced attention allocated to it, causing that attribute to have a reduced impact on valuations. Supporting this assertion, there is extensive evidence that information seeking (often operationalized by eye fixation) "... obeys the imperative to reduce uncertainty" (Gottlieb et al., 2013, p. 2; see also Sharot & Sunstein, 2020) and thereby favors variable over fixed aspects of stimuli. The fact that the fixed attribute effect was larger in participants who responded (1) more quickly in general and (2) especially quickly when selecting the alternative that was superior on the varying attribute, both lend circumstantial support for the attentional salience interpretation.

However, we observed no support for our hypothesis that concurrent working memory load would interact with fixed attributes. We instead observed some evidence of a general *decrease* in discounting (greater patience) when working memory was taxed. As noted above, participants were slower and more inconsistent when delay, rather than amount, was the attribute that varied from one trial to the next. This is in keeping with evidence that people find it more difficult to evaluate *delay* than amount (Ebert & Prelec, 2007). It is possible that when under working memory load, the processing of this more difficult attribute was disproportionately reduced, leading to greater relative focus on amounts and thus reduced discounting. It may be relevant that the FADT did not include immediate alternatives, unlike previous work showing the opposite effect of working memory (Hinson et al., 2003). It is possible that a working memory demand would increase preference for an alternative with no delay at all, thereby leading to an opposite inference regarding the effect of working memory load on discounting behavior.

Although speculative, the challenge of comparing delays when under working memory load could also be relevant with regard to the absence of the hypothesized increase in the fixed-attribute effect when memory was taxed. An enhanced attentional advantage for the varying attribute under working memory load could have been offset by a general increase in difficulty comparing delays, which might lead at least some participants to prioritize the amount attribute, even when amount was fixed. Alternatively, the working memory load could have increased some participant's utilization of simple heuristics (Marzilli Ericson et al., 2015) that reduced the relevance of the relative attention paid to each attribute. A simple rule in each condition (e.g., choose the later amount if it is at least $5 larger in the delay-fixed condition) makes any salience difference between attributes irrelevant. Even if those participants that did not rely on decision rules did, in fact, tend to respond with a larger fixed-attribute effect when under working memory load, it might have been offset by other participants' use of decision rules. Of course, additional data are necessary to assess whether either of these explanations is correct.

Limitations

Several limitations of the study should be noted. First, an adaptive discounting procedure was used in both experiments. While this has the advantage of allowing overall discounting to be measured quickly, the approach results in most trials including alternative pairs that are near a participant's indifference point, which is not well suited to estimating discounting *functions* using ML methods. This is particularly true for participants with a higher degree of response stochasticity, since a wider range of questions is needed to reasonably estimate functions for these individuals. Indeed, even without inclusion of a second parameter to model utility function curvature, the ML model was only able to converge for Experiment 2 analyses when MCQ participant data were incorporated. In addition, Hofmeyr (2021) discusses the difficulties in disentangling the effects of risk and time on choice, particularly when some options, for example, those with very long delays, may be perceived as more risky than others. Subsequent research should examine the effect of fixed attributes in a context without an adaptive procedure.

Second, the working memory task used in Experiment 2 was open to strategies that complicate interpretation. Because responses were self-paced, participants could reduce the time that character strings needed to be retained by rushing through decisions. Participants could also have disregarded the study instructions and written down the letters they were supposed to memorize. Although participant compensation was not connected to working memory performance, some participants may have written down memory targets, which would impact several analyses presented above. Future in-lab research should address this possibility.

Third, participants in the study had only a 1 in 25 chance of getting one randomly selected trial paid out. It is likely that this lowered engagement relative to what it would have been if all participants received payout from at least one trial. It is plausible that the observed fixed-attribute effect is moderated by the level of participant engagement, perhaps with lower engagement leading to larger effects. Future research should provide salient incentives to all participants to promote payoff dominance (Smith, 1982; Harrison, 1989, 1992, 1994).

Finally, it should be noted that the participant pools in the two studies presented were from a highly diverse set of countries, and the rewards were all in US dollars. Although we did not observe statistical evidence of differences by nation, the number of participants from most nations was low, so the potential to investigate this is limited.

Conclusion

Limitations notwithstanding, these data show that participants exhibit more patience when delays are fixed than when amounts are fixed. While this pattern is not easily explained from a *discounting function* perspective, the effect is unsurprising when task behavior is approached from a multi-attribute decision framework.

Electronic Supplementary Material

The electronic supplementary material is available with the online version of the article at https://doi.org/10.1027/1618-3169/a000535

ESM 1. Explanation of the ML estimation approach and additional results for Experiment 1 and Experiment 2.

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Open Data
All data, scoring scripts, and task scripts are available at: https://osf.io/86ztd/ (Monterosso et al., 2021).

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