Amount and time exert independent influences on intertemporal choice

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ABSTRACT

Choices often involve trade-offs between smaller, sooner and larger, later outcomes. Canonical intertemporal choice models assume that reward amount and time until delivery are integrated within each option prior to comparison. We use a novel multi-attribute drift diffusion modeling (DDM) approach to show that attribute-wise comparison, in which amounts and times are compared separately rather than integrated, better represents the choice process. We find that accumulation rates for amount and time information are uncorrelated, but the difference between those rates strongly predicts individual differences in patience. Moreover, patient individuals incorporate amount earlier than time information into the decision process. Using eye tracking measures, we link these modeling results to attention, showing that patience results from a rapid, attribute-wise process that prioritizes amount over time information. Thus, we find evidence that intertemporal choice reflects the interaction of two distinct processes – one for amount, the other for time – whose combination determines choice.

Intertemporal choices involve tradeoffs between the value of rewards (e.g., monetary amounts) and the delay before those rewards are experienced (e.g., time before receipt). Such tradeoffs are found in many domains of decision making, from deciding to invest for retirement rather than purchase a luxury good to choosing an indulgent dessert that will potentiate subsequent weight gain. Laboratory experiments have connected intertemporal decisions (e.g., between smaller, sooner (SS) and larger, later (LL) monetary rewards) to a variety of life outcomes. As examples, individuals who consistently make impatient choices are more likely to have reduced financial saving, higher rates of gambling and substance addiction, fewer preventative health behaviors, and lower academic success[1–5]. However, there is also an interaction with experience such that childhood socioeconomic status can impact intertemporal choices[6]. On the other end of the spectrum, extreme patience is associated with obsessive compulsive disorder and anorexia[2]. Therefore, understanding the process of intertemporal choice across individuals could facilitate interventions for common failures of patience such as insufficient saving as well as pathological dysfunctions like addiction.

Substantial research shows that intertemporal choices – at least within economic contexts – can be characterized by a discounting function with parameter(s) determined by choice behavior [7,8]. Many current models use hyperbolic discounting, which assumes that rewards lose value very rapidly over short delays and then more slowly over longer periods of time. A single hyperbolic discount rate (k) describes choices, such that a higher k indicates steeper discounting of future rewards and thus more impatient choices, whereas a lower k indicates more patient choices. Such hyperbolic option-wise models have been generally accepted, not only because the discount rate provides a useful single measure that relates to individual differences[1–3,5] but also because it accounts for preference reversals as rewards become more proximal in time[9–12]. Yet, it is also known that directing attention toward one attribute (e.g., time) can alter decisions[13–16] – consistent with an alternative hypothesis that amount and time contribute to intertemporal choice through attribute-wise processes in which amount and time attributes are compared separately in the decision process, rather than integrated within an option[17–21].

Here, we show that amount and time make dissociable contributions to individual differences in intertemporal choice. This claim requires that three conditions be met. First, intertemporal choices should be better modeled by the combination of independent (and, ideally, uncorrelated) parameters for amount and time than by either of those parameters in isolation. If this condition holds, two individuals could exhibit the same intertemporal patience (i.e., the same apparent k value) through different combinations of decision weights on amount and time. Second, a model that combines amount and time parameters in an attribute-wise manner (i.e., comparing amounts to amounts and times to times) should be better matched to choice behavior than a similar option-wise model that integrates amount and time information to determine the value of each option. Third, amount and time should have distinct influences on the attentional process during choice, measured independently of choice behavior; if such attentional effects are observed, they would provide an important lever for shifting the process of choice.

Our experiments provide evidence that meets all three of these conditions. We investigated the dynamic process of intertemporal choice using multi-attribute drift diffusion modeling (DDM) [22–25]. This approach builds on prior work indicating that intertemporal choice – like other forms of value-guided decision making – involves a dynamic accumulation of evidence before reaching a decision threshold[19,26]. However, unlike prior studies, our multi-attribute model allows a novel separation of the contributions of amount and time in multiple parts of the decision process.

Drift diffusion models split up the decision process into fundamental components that underlie choice and response time, allowing us to test each component as a possible (non-mutually exclusive) mechanisms for individual differences in intertemporal choice while controlling for other parts of the decision process[27]. First, variation in the drift slope for amount compared to time could account for differences in patience. A higher drift slope for one attribute increases the weight it carries in evidence accumulation, similarly to a decision weight in a regression model. Thus, a steeper drift slope for amount would promote more patient choices. Another possible mechanism is attribute latency, or the temporal advantage that results if one attribute is processed earlier than another. Faster attribute latency for one attribute will initially bias the choice toward the better value on that attribute before the other attribute starts influencing value accumulation[28]. Finally, decision bounds represent response caution, which can manifest as a tradeoff in speed vs. accuracy[29]. Differences in boundaries could contribute to individual differences in choice with lower bounds relating to faster, less cautious, and noisier responses, although bounds do not directly bias choice in one direction.

We integrated DDM modeling with measures of gaze location obtained through eye tracking, which provides real-time assessments of information processing in advance of the execution of a decision[24,30–34]. We examine not only the relative bias in gaze, which has been linked to overall patience in intertemporal choice[35], but also the pattern of eye movements across information in the display, which can reveal variation in decision heuristics across individuals[36,37]. We fit our models individually for each participant within a large sample and then confirmed all results using a second, similarly large replication sample. Thus, our approach combines evidence from choice behavior, response time, gaze duration, and saccade patterns – all of which converge on a common conclusion that amount and time information contribute independently to intertemporal choice.

RESULTS

Strategy for Analysis

We adopted a multi-stage procedure for data collection, analysis, and replication (see Supplementary Information). Successful analyses in the primary sample determined which analyses were conducted in the replication sample. All analyses are reported in this paper, regardless of replication success.

Choices depend upon subjective value

We first examined how trial-to-trial variation in subjective value (SV) – specifically, the difference in SV between the two options – influenced choices, RTs, and gaze fixations. As expected, choices followed a logistic function, such that the proportion of choices to the higher-SV option increased with increasing relative SV (Figure 1a). Additionally, trials that had relatively greater differences in SV were associated with faster response times and fewer fixations, while trials where SV was more matched between the options had longer response times and a higher number of fixations (Figure 1b,c). All effects observed in the first sample were well-replicated in the second sample. We conclude from these manipulation checks that our task has appropriate psychometric properties; specifically, participants' choices and response times were well-explained by our modeling approach (i.e., estimating SV based on fitted *k*-values).

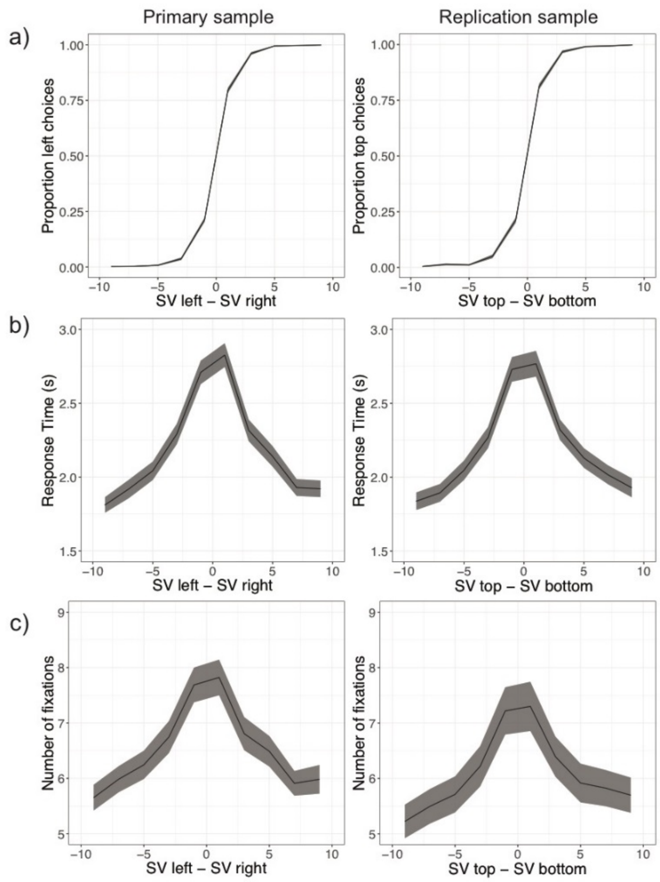

Figure 1. Subjective value (SV) predicts (a) choices, (b) response time, and (c) gaze fixations measured using eye tracking. Panels (a) and (b) exclude participants who made only patient choices, leaving a primary sample size of N = 105 and a replication sample size of N = 79. Panel (c) excludes participants who made only patient choices or who had insufficient eye-tracking data for analysis, leaving a primary sample size of N = 93 and a replication sample size of N = 68. Darker lines represent mean values; shading represents SEM.

Eye tracking predicts both individual choices and overall patience

Next, we examined whether eye-tracking data predicted variation across trials in choices and variation across participants in patience. We partitioned every trial into five time bins, and then measured total looking time to each choice option within each bin (Figure 2a). Participants showed a strong initial fixation bias toward the left option (in our primary sample) or the top option (in our replication sample), which likely reflects cultural biases in attention to information positioned at the top left of a display[30]. However, beginning with the middle time bin, there was a divergence such that participants increasingly directed their gaze toward the chosen option. The location of the final fixation was a strong predictor of choice; participants chose the last-fixated option on approximately 75% of trials. Again, all effects were fully replicated in both samples.

While these results link eye gaze to specific choices, there could also be trait effects such that looking time predicts overall patience across trials. We found a strong positive correlation between participants' *option index* and their fitted *k* values (Supplementary Figure 1), such that those participants whose gaze was most biased toward the LL option exhibited the greatest patience in their choices (primary sample: $r(91) = 0.68$, $p = 1.0 \times 10^{-13}$); the same effect was observed in our replication sample ($r(66) = 0.47$, $p = 5.7 \times 10^{-5}$). These results suggest that individual differences in intertemporal choice reflect the relative weighting that participants place upon different choice options – a conjecture we explore in more depth in the following sections.

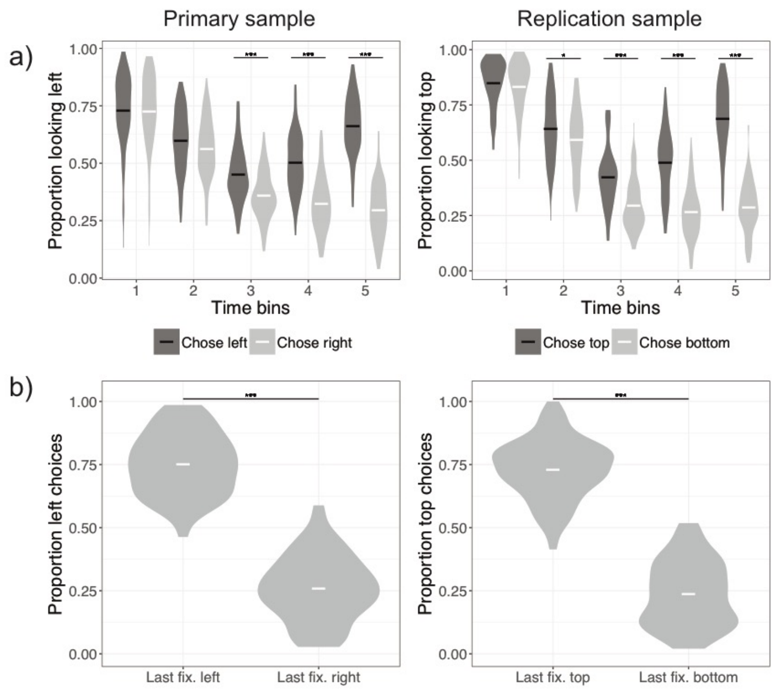

Figure 2. Validation of eye-tracking data as a predictor of choice. We examined the relationship between gaze location and eventual choices in all participants with sufficient eye-tracking data (primary sample, N = 105; replication sample, N = 85 participants). a) We first split trials into five equal time bins according to whether participants chose the left or right option (top or bottom, in replication sample). Participants' eye gaze began to predict their eventual choice by the third time bin, in both samples. b) Next, we split trials according to whether the final fixation was to the left or right option (top or bottom, in replication sample). Final fixation location was a strong predictor of eventual choice. Violin plots show data density, and horizontal lines illustrate means. Significance calculated by unpaired t-tests. *p<.05, **p<.01, ***p<.0001.

Comparison: Attribute-wise vs. option-wise models

We tested two drift diffusion models that fit the same number of parameters and that separate the contributions of amount and time in the decision process, but that differ in how and when these two attributes contribute to the decision process. The attribute-wise model, equation (3), assumes that people make direct comparisons between amounts and direct comparisons between times, whereas the option-wise model, equation (2), assumes that people integrate time and amount for a given option before comparing options. Nearly all participants were better fit by an attribute-wise model (Binomial tests, primary sample: 113/117, $p < 2.2\text{x}10^{-16}$; replication sample 99/100, $p < 2.2\text{x}10^{-16}$), and analyses reported in the following sections use parameters from that model (see Supplementary Figure 2 for option-wise results). Moreover, the difference in fit was correlated with discount rate (Figure 3; primary sample: $r(103) = 0.71$, $p < 2.2\text{x}10^{-16}$; replication sample: $r(77) = 0.41$, $p=1.9\text{x}10^{-4}$) such that more patient individuals' choices were much better fit by an attribute-wise model, while very impatient individuals' choices tended to be more similarly fit by both models.

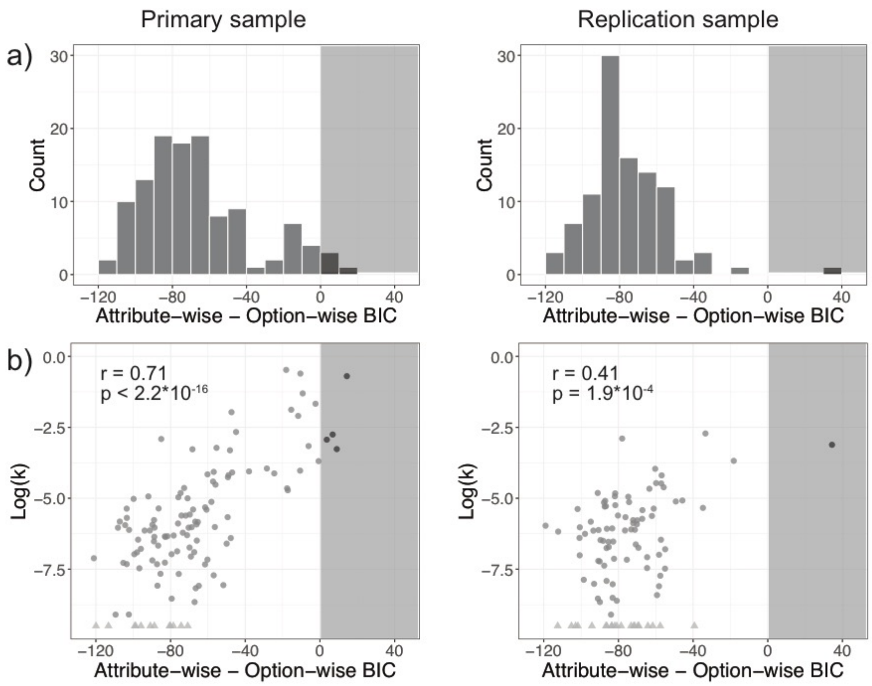

Figure 3. DDM model comparison using a Bayesian Information Criterion (BIC). Shown are data from all participants; note that participants with only patient choices (primary sample, N = 12; replication sample, N = 21) were excluded from subsequent statistical testing. a) A histogram of the difference in BIC for each participant across models. b) The difference in BIC is compared with individual discount rate, log(k). Participants with all patient choices are displayed in light gray triangles at -9.5 on the y-axis for illustrative purposes. Gray shading indicates values better fit by the option-wise model, whereas no shading indicates values better fit by the attribute-wise model (lower BIC values indicate better fit).

Drift slopes: Amount and time independently contribute to intertemporal patience

Because intertemporal choices involve trade-offs between two attributes – amount and time – those attributes influence choice in opposite directions; that is, an increased decision weight on time would potentiate SS choices, while an increased decision weight on amount would lead to LL choices. Within the DDM, an increased weight on one attribute would be evident in a steeper drift slope compared to the other attribute. For every participant, we used a multi-attribute DDM (see Methods) to estimate the unique drift slopes associated with amount information and with time information. We found that these two drift slopes were uncorrelated across participants, with minimal shared variance (Figure 5a; primary sample: $r(115) = -0.02$, $p = 0.85$; replication: $r(98) = -0.03$, $p = 0.74$) supporting the conclusion that amount and time represent separate contributors to intertemporal choice.

We next examined whether the difference between drift slopes for amount and time related to patience in intertemporal choice. We found a striking relationship therein (Figure 4b), such that more patient individuals accumulate amount information at a faster rate than time information, whereas more impatient individuals accumulate time information at a faster rate than amount information (primary sample, $r(103) = -0.89$, $p < 2.2\times10^{-16}$); this effect was again present in our replication sample ($r(77) = -0.85$, $p < 2.2\times10^{-16}$). Together, these results demonstrate that intertemporal patience results from the combination of two independent factors—time and amount—rather than a single factor or a slower overall drift slope (i.e., the sum of the axes on Figure 4a). Instead, preferences in intertemporal choice are proportional to the difference between these drift slopes.

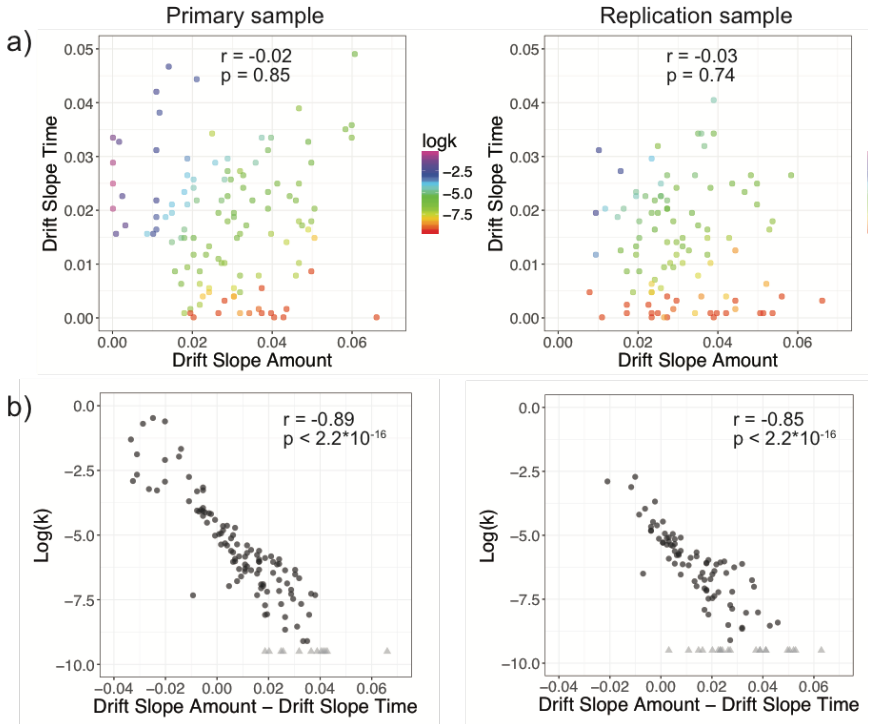

Figure 4. Intertemporal patience reflects the difference in drift slopes for amount and time. a) We found that the drift slopes for amount (x-axes) and for time (y-axes) were uncorrelated across participants. The colormap indicates the log(k) value for each participant; note that participants with similar levels of intertemporal patience had different combinations of drift slopes for the two attributes. b) However, the difference in drift slopes was a very strong predictor of intertemporal patience, in both samples. Participants with all patient choices are displayed in light gray at -9.5 on the y-axis for illustration and excluded from statistics.

Attribute latency: Temporal advantage of amount information contributes to patience

While the previous section shows that attribute-specific differences in drift slope are closely connected to intertemporal choice, differences in attribute latency could amplify (or moderate) those effects. We found that the latency for amount information was shorter than that for time information overall (paired t-test, primary sample, mean difference of 190ms, $t(116) = -5.52$, $p = 2.1x10^{-7}$; replication sample, mean difference of 269ms, $t(99) = -7.75$, $p = 8.1x10^{-12}$), and that the difference between attribute latencies for amount and time was positively correlated with *k* values (Figure 5, primary sample: $r(103) = 0.54$, $p = 3.1x10^{-9}$; replication: $r(77) = 0.37$, $p = 7.7x10^{-4}$). That is, people who are more patient begin accumulating amount information more quickly, while those who are less patient begin accumulating time information more quickly. Unlike for drift rate, attribute latencies for amount and for time were positively correlated ($r(115) = 0.46$, $p = 1.1x10^{-7}$; replication: $r(98) = 0.56$, $p = 1.6x10^{-9}$), indicating that there are both attribute-specific components that relate to intertemporal patience and a common component to attribute latency that reflects overall speed of processing.

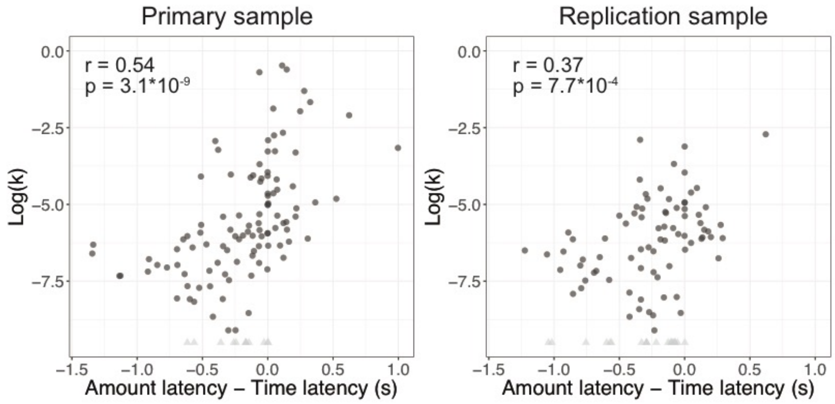

Figure 5. Intertemporal patience is predicted by the relative attribute latency for amount and time. Participants with all patient choices are displayed in light gray triangles at -9.5 on the y-axis for illustration and excluded from statistics.

Decision Bounds: Intertemporal patience does not result from expanded bounds

Within the DDM, the decision boundary provides a measure of how much evidence is required before making a choice – and thus expanded bounds could be plausibly linked to patient intertemporal choices. However, there were no correlations between decision bounds and discount rate in either sample (primary sample: r(103) = -0.10, p = 0.29; replication sample: r(77) = 0.09, p = 0.45). Moreover, we find a positive correlation between discount rate and response time such that intertemporally impatient participants actually take longer to make choices than more patient participants (primary sample: r(103) = 0.33, p = 7.1×10^{-4}; replication sample: r(77) = 0.43, p = 8.5×10^{-5}, Supplementary Figure 3). Together, these data suggest that there is no systematic relationship between intertemporal patience and the amount of evidence required to make a decision; instead, attribute-specific latency and drift slopes account for the variance in intertemporal choices.

Attribute index: Gaze biases correspond to higher attribute-specific drift slopes

If amount and time represent independent attributes of intertemporal choice, there should be observable attentional biases toward one attribute or the other that relate to variation in drift slope. We tested this hypothesis by examining whether differences in drift slope showed a relationship with our *attribute index,* which quantifies relative looking time at amount versus time information (Figure 6a). There was a significant positive correlation between difference in drift slope and relative gaze in both the primary sample (r(103) = 0.52, p = 1.4×10^{-8}) and the replication sample (r(83) = 0.58, p = 5.7×10^{-9}). That is, individuals direct more attention toward the attribute for which they show a higher drift slope.

Payne Index: Gaze transitions indicate attribute-wise processing

While the results from the previous sections show attribute-specific biases in decision making, they do not show that participants directly compare attribute values when making decisions. To obtain direct evidence for attribute-based comparisons, we identified all gaze transitions in our eye-tracking data and then measured the relative proportions of attribute-based transitions (e.g., SS time to LL time) and option-based transitions (e.g., SS time to SS amount). The difference in transition probabilities is quantified by the *Payne index*[38], for which positive values reflect more option-based gaze transitions. We observed a strong negative correlation between the Payne Index and the difference in attribute drift slopes: individuals with a higher drift slope for amount were indeed more likely to engage in attribute-wise comparisons, while those with a higher drift slope for time used more option-wise comparison (Figure 6b primary sample: r(103) = -0.61, p = 7.2×10^{-12}; replication: r(83) = -0.59, p = 4.0×10^{-9}). Moreover, those with higher Payne index values tended to look more at amounts than times (r(103) = -0.60, p = 2.0x10^{-11}, replication r(83) = -0.76, p < 2.2x10^{-16}, Supplementary Figure 4). Together, these results indicate that people who make more patient choices tend to directly compare the amounts offered (and largely ignore temporal information), whereas those who are less patient tend to integrate amount and time within an option before comparing the two options.

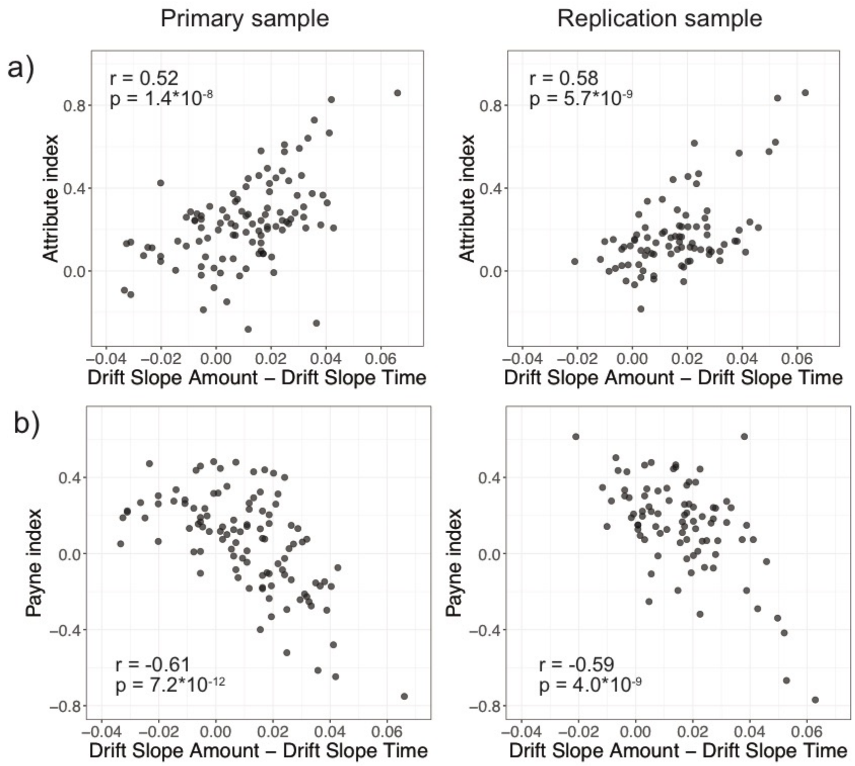

Figure 6. Differences in drift slope between amount and time attributes are reflected in measures of attention. a) The attribute index measures relative looking at amounts (index>0) versus times (index<0). Across participants, a bias toward looking at amounts was associated with a greater drift slope for amount information. b) The Payne index measures the relative likelihood of gaze transitions within options (index>0) or between attributes (index<0). Participants who tended to make more attribute-wise transitions also showed a greater drift slope for amount information. Both analyses include all participants with sufficient eye-tracking data (primary sample, N=105; replication sample, N=85).

Summary of key results

Our hypothesis that amount information and time information are processed in an independent, attribute-wise manner was supported by converging evidence from choice behavior, modeling, and eye tracking. All key results were observed in each of the Primary and Replication samples, independently (Table 1) and would also remain significant following Bonferroni correction for the number of analyses run in this study.

We also ran three additional analyses not reported in the main paper. First, we examined the relationship between discount rate and our eye tracking indices (Supplementary Figure 5). Attribute Index (i.e., relative bias in gaze toward amount information) and intertemporal patience as measured by log(k) were significantly correlated in both our primary and replication sample (primary sample: r(91) = -0.47, p = 1.6x10^{-6}; replication sample: r(66) = -0.35, p = .0034). Payne Index and intertemporal patience, again measured by log(k) showed a significant relationship in our primary sample (r(91) = 0.52, p = 7.0x10^{-8}) but not in our replication sample (r(66) = 0.20, p =0.11); thus, we do not discuss this result further. Next, we examined whether the location of first fixation was correlated with relative attribute latency; this was again significant in our primary sample ($r(103) = -0.33$, $p = 7.2 \times 10^{-4}$) but not in our replication sample ($r(83) = -0.12$, $p = 0.27$), and not considered further. Finally, we examined differences across response time and eye tracking indices for correct compared to error trials (Supplementary Figure 6). We found significantly longer response times for SS errors compared to correct LL choices (paired t-test, primary: $t(77) = 7.1$, $p = 6.0 \times 10^{-10}$; replication: $t(58) = 5.3$, $p = 2.0 \times 10^{-6}$). We also found a higher option index for SS errors compared to correct LL choices (paired t-test, primary: $t(77) = 7.4$, $p = 1.6 \times 10^{-10}$; replication: $t(58) = 5.1$, $p = 4.2 \times 10^{-6}$) and a lower option index for LL errors compared to correct SS choices (paired t-test, primary: $t(57) = -6.8$, $p = 7.4 \times 10^{-9}$; replication: $t(38) = -4.2$, $p = 1.6 \times 10^{-4}$), but no differences in Payne index or attribute index values. No other analyses were conducted on these data.

Measure	Primary sample	Replication sample
Correlation with log(*k*)		
Attribute-wise minus Option-wise BIC	0.71***	0.41**
Response Time	0.33**	0.43***
Standardized β in regression on log(*k*)		
Fit measures	*Adj. R^2=0.87* *F(3,101)=237.4* *$p < 2.2 \times 10^{-16}$*	*Adj. R^2=0.86* *F(3,75)=159.4* *$p < 2.2 \times 10^{-16}$*
Drift slope	-0.81***	-0.85***
Attribute latency	0.28***	0.37***
Decision bounds	0.04	-0.01
Correlation with difference in drift slopes		
Attribute Index	0.52***	0.58***
Payne Index	-0.61***	-0.59***
Correlation with attribute index		
Payne Index	-0.60***	-0.76***

Table 1: Results Summary. Correlations and standardized betas are reported with significance indicated by asterisks. $^{+}$p<.1, *p<.05, **p<.01, ***p<.0001.

See Supplementary Tables 1-2 for option-wise results and more detailed analyses separating amount and time contributions.

DISCUSSION:

High rates of temporal discounting are associated with negative real-world outcomes such as obesity, less financial investing, and shorter life expectancy[1–5]. Thus, understanding the mechanisms of intertemporal choice can provide crucial information that informs policy and interventions. Our experiments investigated the processes of intertemporal choice using a combination of behavioral analyses, computational modeling, and measurements of eye gaze during choice. We consistently observed evidence in support of a simple conclusion: Amount information and time information contribute independently to the process of choice, with the nature of their contributions related to an individual's intertemporal patience. Using multi-attribute drift diffusion modeling, we showed that attribute-wise differences in the rate and latency of information accumulation predict subject-to-subject variability in choices. Moreover, measurements of eye-gaze transitions during the choice process revealed inter-individual variability in attribute-wise versus option-wise comparison patterns. Collectively, these results provide new insight into the mechanisms of intertemporal choice.

Three features of our results are particularly novel. First, we show that the processing of amount information and time information are not only separable within models, but unlike previous models[19] have dissociable contributions to the process of choice. Importantly, because drift slopes for amount and time were uncorrelated, the difference between them is not an artifact of combining two factors explaining the same variance in discount rate. Second, because the pattern of gaze transitions provides an index of overt attention[31,39–43], we connect parameters extracted from diffusion models to observable online behavior during the period of choice. This connects biases observed in the models (e.g., a steeper drift slope for amount information) to potential heuristics observed in eye movements (e.g., attribute-wise transitions between amounts). Third, our large sample size and replication strategy allowed us to make strong claims about inter-individual variability in intertemporal patience. We showed, for example, that the overall biases toward amount information in drift slope and latency are modulated by participants' preferences, with more patient individuals showing more bias toward amount information. Understanding inter-individual variability in the mechanisms of intertemporal choice will be particularly important for studies of groups characterized by excessively impatient choices (e.g. people with addiction[3]).

High-patience individuals showed striking – and potentially counterintuitive – pattern of behavior. Rather than exhibiting a slow and analytic comparison process that integrated all available information, they tended to employ a heuristic strategy of directly comparing amounts and choosing the larger. In contrast, low-patience individuals showed a more balanced process of examining both amounts and times, as evident in gaze tracking and model parameters. This combination of results – with "good" decisions arising from heuristics, and "bad" decisions arising from a more analytic comparison process – seems counter to rational choice models. However, it echoes previous findings in other choice domains that point to the use of heuristics as a characteristic feature of effective decision making[44–47]. Interventions to promote intertemporal patience by encouraging analytic integration of outcome attributes might not be effective, accordingly. Instead, patient decisions might be nudged through interventions that encourage comparison of amounts, rather than times to delivery, which could be considered a "cost" or "penalty"[15,48,49]. Attentional manipulations may be particularly effective for decisions involving relatively short periods of time until reward delivery; in such cases, attention toward the time component increases the number of smaller, sooner choices[14–16]. While our study cannot disentangle whether attentional bias itself drives choice or whether some underlying preference drives both attentional biases and choices, future interventions could provide strong tests of the directionality of our effects by attempting to force the "patient" attentional patterns we observed.

Because both this study and others[28] have found that attributes processed more rapidly have an overall advantage in choice, interventions intended to encourage patient choices could draw attention to amount information before time information (e.g., via sequential presentation or a manipulation of stimulus salience)[50–54]. Similarly, to facilitate attribute-wise transitions during the process of choice, amounts could be placed closer to each other and further from time information to encourage attribute-wise processing, or information could be revealed in step-wise manner that promotes attribute comparison[37,55–61].

Notably, intertemporal patience (i.e., a preference toward waiting for larger, later rewards) is does not result from reduced from choice impulsivity (i.e., responding quickly when making choices). We hypothesize that this response-time finding, which may appear counterintuitive at first glance, is driven by differences in how impatient and patient individuals approach these choices. Specifically, patient individuals use a heuristic-like attribute-wise comparison of amounts, whereas impatient individuals use a more analytic approach that integrates time and amount information – a more time-intensive process that involves comparison of attributes with very different qualities.

In this study, we have very few people at the extreme end of impatience. Because of this, we lack a complete picture of how the decision process influences intertemporal patience – particularly in the mechanisms of pathologically impatient choices (e.g., in addiction). Specifically, we hypothesize that a heuristic (that is, attribute-wise) approach may also be utilized in extremely impatient people, who may compare between each option's time-to-delivery attribute instead of their amounts. If this is true, it would create a quadratic relationship between response time and patience. Some evidence in our data supports this relationship; in our larger primary sample, which has many more extremely impatient individuals simply due to its large size, this relationship is best fit by a quadratic curve (Supplementary Figure 3). However, we cannot make broad conclusions from this as our replication sample does not have a sufficient number of extremely impatient individuals to confirm this finding. Future experiments could test the shape of this relationship across a larger sample with people at the more extreme end of impatience, and with varying stimuli sets that manipulate the frequency of attractive LL or SS options for a given individual's discount rate. It is worth noting that individuals in the middle of the patience spectrum may be easiest to shift from option-wise to amount-biased, attribute-wise, fixation patterns.

Although temporal discounting has a profound influence on overall well-being and life outcomes, relatively few effective interventions have been developed to improve choice. By using a multi-attribute drift diffusion model paired with eye tracking analyses, we find that patient and impatient individuals have distinctly different approaches to information gathering, with profound differences in resulting choice. These results highlight several candidate mechanisms through which interventions could improve intertemporal patience. If successful, these interventions could help individuals focus more on the benefits of future rewards rather than the cost of waiting for these rewards. These interventions could also be extended to domains beyond financial decision-making to improve choice across many contexts.

METHODS

Participants: *Primary Sample*. We recruited 117 subjects (mean age=21.3 years, SD=2.3 years; 75 female). Before data collection, we established a target sample size of 100 participants. Because of a data collection error with a second unrelated task completed by the same participants, we collected additional participants who completed both tasks – leading to a final sample of 117 for this experiment. Of these participants, 12 were excluded from eye tracking analyses because of poor-quality or insufficient data (subjects were excluded if in 50% or more of the eye tracking data one or both eyes could not be identified or if their calibration was poor.) All participants were recruited from the Durham, NC and Duke University communities and provided informed consent under a protocol approved by the Institutional Review Board of Duke University.

Participants: *Replication Sample*. We recruited 100 subjects (mean age=21.5 years, SD=2.0 years; 68 female); 15 of whom were excluded from eye tracking analyses because of poor-quality or insufficient data. All recruitment, consent, and instructional procedures were identical to those of our Primary Sample.

Procedure. Following informed consent, participants read a brochure about financial decision making; that brochure described either a traditional information-based strategy or a social cognition strategy. Note that because initial analyses revealed that the strategies did not evoke differences in ITC behavior that replicated across experiments, we hereafter combine across them in all reported analyses. Participants then completed two independent economic decision making tasks – an intertemporal choice task (reported here) and a shopping task (reported elsewhere) – in randomized order. After both tasks, subjects provided open-ended feedback about the strategies they used during decision making and completed the Abbreviated Barratt Impulsivity Scale (ABIS) as a general measure of individual differences in impulsivity [62]. Because the ABIS did not correlate with intertemporal choice across samples, we do not further report on its relationship to other variables. See Supplementary Figure 7 for a detailed description of our analysis and replication workflow.

Tasks. Participants completed 141 intertemporal choices. The SS choice was always available that day and varied between $0.50-$10, while the LL choice was always $10 but delivered between 1-365 days later. In the Primary experiment (Figure 7, top row), the choice options were displayed on the left and right sides of the screen, with amount on top and time on bottom. In the Replication experiment (Figure 1, bottom row), the choice options were displayed at the top and bottom of the screen; with left-right position of time and amount information counterbalanced across the first and second halves of the experiment. The left-right (Primary) or top-bottom (Replication) order of the SS and LL options was randomized across trials.

Participants indicated their chosen option via keyboard button press. The task was self-paced with a 10s maximum response time; most choices were much faster (primary sample: mean RT=2.21s, SD=.70; replication sample: mean RT= 2.14s, SD=.64). At the end of the experiment, each participant received a base payment of $6 (cash) for their participation, and 1 trial was resolved for additional payment in an Amazon gift certificate that was delivered via email at the date on that trial. We used this payment method to minimize transaction costs and risk of delivery for future rewards[13,63,64]; that is, subjects could be confident that they would receive the chosen reward on the promised date, with no additional time or effort commitment on their part.

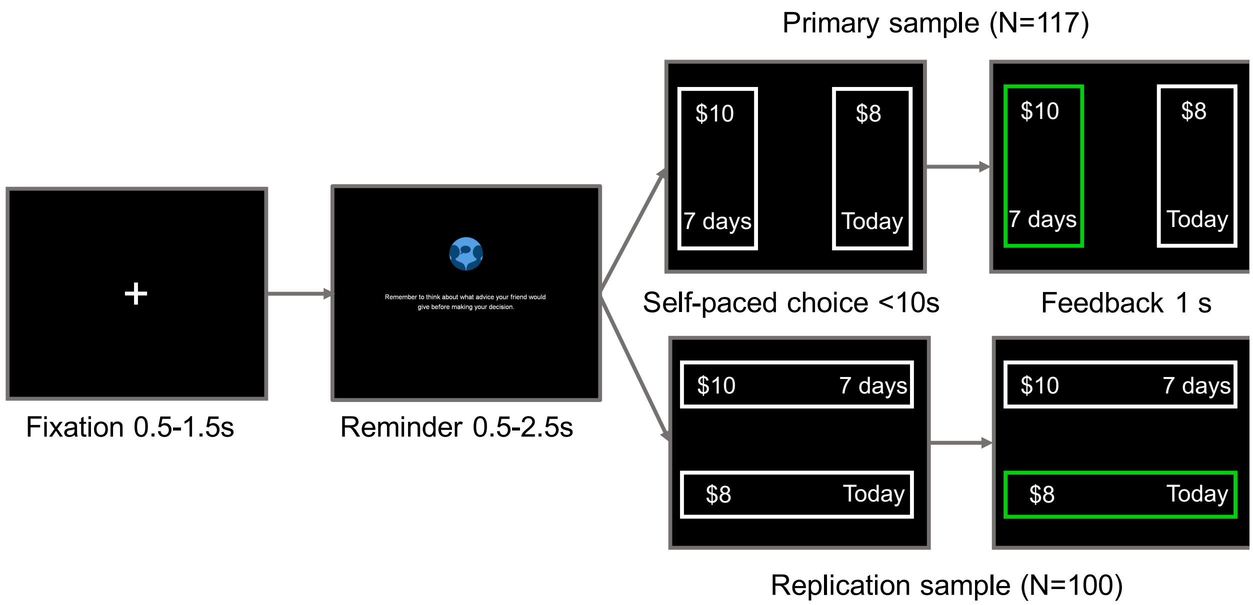

Figure 7. Intertemporal choice task. On every trial, participants saw a fixation cross followed by a reminder to follow the task instructions. Next, they viewed and made a choice between a LL and SS option and received 1s of feedback highlighting the choice made.

Eye tracking. Tasks were presented on a Tobii T60 eye tracker, which uses an unobtrusive camera system to sample gaze position at 60hz while allowing free head motion by the participant. We established areas of interest (AOIs) around the four pieces of information present on each display; each AOI was 350 by 350 pixels within the 1280 by 1024 total resolution of the screen. Before ROI analyses (gaze indices), we preprocessed the gaze position data using a clustering algorithm that identified drifts in calibration and then shifted the centers of mass of fixation clusters into the appropriate AOIs.

Analysis:
Modeling intertemporal value. For each subject, we used maximum likelihood estimation to identify their temporal discounting coefficient (*k*) within a hyperbolic function (Equation 1).

Equation 1: $$SV = \frac{A}{1+kT}$$

In this equation, SV is the subjective value of an option for an individual, A is its amount (in dollars), T is the time until its delivery (in days), and *k* is the discount rate. In addition, because *k*-values are non-normally distributed, we use a natural log transformation of *k* for analysis[16,65,66]. Participants with uniformly patient choices or almost all patient choices with a few highly inconsistent choices (Primary Sample, N = 12; Replication Sample, N = 21) could not be fit by this function and were excluded from statistical analysis; on figures, their data is shown in lighter gray triangles to facilitate comparison with the other participants. Once *k* was identified for a given subject, we used its value to estimate the subjective value of the LL options on each trial, assuming a linear utility function for money over the range of values used; note that the subjective value for each SS option is equivalent to its nominal value, under this approach.

Multi-attribute DDM models: To examine individual differences in the processing of amount and time information, we fit two multi-attribute DDM models for each participant, one based on attribute-wise comparison and the other on option-wise comparison.

DDMs assume that people stochastically accumulate evidence toward one choice option or the other until a relative value signal (RVS) reaches a decision boundary, triggering the execution of the choice[67,68]. Our computational implementation of the DDM involved the following steps. First, we model the decision as a choice between two options (i.e., left or right in the primary sample, top or bottom in the replication sample) that differ in two attributes: amount and time. We assume that the relative value signal (RVS) is unbiased and starts at 0, equidistant from the decision boundaries for the two options; this assumption is appropriate because of our randomization of options to left/right or top/down locations (see Supplement for additional analyses). Second, we estimate separate attribute latency values for amount (t_A^*) and for time (t_T^*). These values reflect the interval after the onset of the stimulus when no information is accumulating related to that attribute; both attribute latency values include perceptual and motor processing[22,69], while differences between latency values reflect a *temporal advantage* of one attribute over the other. The RVS accumulates in 10 ms time steps according to the amounts and times of each option weighted by separate drift slopes for time and amount attributes (δ_{A} or δ_{T}). All terms in the model are proportional to a stochastic error signal (ϵ_t) that is defined by a Gaussian distribution centered at 0 with variance σ^2 = 0.1.

In our option-wise model, equation (2), amount and time for each option are integrated in an option-wise manner similar to typical hyperbolic models. Prior to the attribute latency for a given attribute, the average over the experiment is used in place of the actual amounts or times on that trial as a scaling factor.

Equation 2: $RVS_t = RVS_{t-1} + \frac{\delta_A \cdot A_{left}}{1+\delta_T \cdot T_{left}} - \frac{\delta_A \cdot A_{right}}{1+\delta_T \cdot T_{right}} + \epsilon_t$

Where: $A_{left}, A_{right} = \bar{A}$ if $t < t_A^*$;
$T_{left}, T_{right} = \bar{T}$ if $t < t_T^*$.

In comparison, in our attribute-wise model, equation (3), following a period of time, the latency for each attribute, that attribute begins contributing to the RVS according to the difference in values.

Equation 3: $RVS_t = RVS_{t-1} + \delta'_A(A_{left} - A_{right}) + \delta'_T(T_{left} - T_{right}) + \epsilon_t$

Where: $A_{left} - A_{right} = 0$ if $t < t_A^{*\prime}$;
$T_{left} - T_{right} = 0$ if $t < t_T^{*\prime}$.

We estimate the parameters of this model for each participant, independently, from their response time and choice data. To improve the stability of our estimation process, we excluded the 2.5% slowest and 2.5% fastest response times for each subject. We simulated each participant's data 1000 times to identify the combination of parameters that best generated their choices and response time distribution (using 8 RT bins for each subject) – and averaged the top 10 fits to determine our final parameter estimates. The two models take different forms, but both fit the same five parameters – amount latency, time latency, amount drift slope, time drift slope, and decision boundary – while holding noise and bias constant (Supplementary Methods, Supplementary Figure 8 for additional information). This similarity means that model fits can be directly compared on a subject-by-subject basis.

We used the Bayes Information Criterion (BIC) to compare model fits. The equation for the criterion is BIC = -2 x log likelihood + d x log(N) where N is the sample size and d is the number of parameters fit. Lower scores indicate better fit. See Supplementary Figures 9 and 10 for average model-predicted and actual choice and response time for each individual.

Indices of looking behavior. We derived three measures of gaze behavior from our eye tracking data. All measures were scaled to a -1 to 1 range. The *attribute index,* equation (4) describes the proportion of time a participant looked at the amount AOIs (compared to the total time looking at AOIs); positive values indicate more time spent looking at amounts, negative indicate more time spent looking at time AOIs.

Equation 4: $\frac{Gaze\ points\ in\ Amount\ ROIs - Gaze\ points\ in\ Time\ ROIs}{Gaze\ points\ in\ Amount\ ROIs\ +\ Gaze\ points\ in\ Time\ ROIs}$

The *option index,* equation (5) measures the proportion of time a participant looked at SS AOIs (again compared to the total looking time); positive values indicate looking at SS options, negative at LL[35].

Equation 5: $\frac{Gaze\ points\ in\ Immediate\ option\ ROIs - Gaze\ points\ in\ Delayed\ option\ ROIs}{Gaze\ points\ in\ Immediate\ option\ ROIs\ +\ Gaze\ points\ in\ Delayed\ option\ ROIs}$

Finally, the *Payne index*[38], equation (6), quantifies whether transitions in gaze tend to be within options (e.g., from the SS amount to the SS time; positive Payne index) or within attributes (e.g., from the SS amount to the LL amount; negative Payne index).

Equation 6: $\frac{Option{-}wise\ transitions\ -\ Attribute{-}wise\ transitions}{Option{-}wise\ transitions\ +\ Attribute{-}wise\ transitions}$

Statistics: All correlations are two-sided Pearson's product-moment correlations. All t-tests are two-sided Welch's t-tests, indicated in the text whether or not they are paired t-tests. Binomial tests reported are two-sided and compared to a hypothesized probability of 0.5. Note: R does not report p-values lower than 2.2×10^{-16}, so we report this value for any tests with a p-value smaller than this value.

Data Availability: Data that support the findings of this study will be made available on the Open Science Framework upon publication.

Code Availability: Code will be made available on the Open Science Framework and GitHub upon publication.

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AUTHOR CONTRIBUTIONS:

DRA, REK, and SAH designed the experiment. DRA analyzed the data, with input from NJS and SAH. NJS provided code for analyses. DRA, NJS, REK, and SAH wrote the paper.

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