

Framing the Future First: Medial Temporal Lobe Activation Discriminates Delay and Acceleration Framing in Intertemporal Choice

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People often discount future rewards, embracing smaller rewards that are delivered sooner rather than waiting for larger rewards delivered later. Previous behavioral research has demonstrated that people are more patient when options are presented as decisions to accelerate rather than delay consumption. This behavioral effect is well-established in the literature, but the underlying neural mechanisms have not been identified. We examined the neural correlates of delay and acceleration framing in intertemporal choice. We find greater activation in the hippocampus, amygdala, and anterior insula when options were framed as decisions to delay rather than accelerate consumption. These findings are consistent with theoretical accounts that posit that preferences are constructed. Specifically, the heightened activation observed in medial temporal regions may reflect more vivid representations of sooner outcomes in delay versus acceleration framing. These results provide insight into contextual effects in intertemporal choice specifically and preference construction more broadly.

Keywords: intertemporal choice, decision neuroscience, hippocampus, framing effects, preference construction

Supplemental materials: <https://doi.org/10.1037/npe0000122.supp>

Intertemporal choice underpins important decisions humans face daily, from deciding whether to eat indulgent foods to saving for retirement. The tradeoff between lower valued sooner options and more valuable future options

determines many life outcomes (Golstein et al., 2014), and much research has focused on how to increase willingness to postpone immediate rewards. Most prior neuroscience research on intertemporal choice has focused on identifying neural

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Bernd Figner, Elke U. Weber, and Eric J. Johnson designed the experiment. Bernd Figner and Amy R. Krosch collected the data. Crystal Reeck, Jason Steffener, and Bernd Figner analyzed the data. Crystal Reeck, Bernd Figner, Elke U. Weber, and Eric J. Johnson prepared the manuscript. All authors were involved in editing the

manuscript. Data are available at https://osf.io/mpe74/?view_only=b43409bb8c0e419a9570596179ffd851 and <https://neurovault.org/collections/NAABLORD/>.

NSF-SES-0922743 (Elke U. Weber/Bernd Figner) and SNF-PA001-15327 (Bernd Figner) supported this work.

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correlates of parameters from computational discounting models (Kable & Glimcher, 2007; McClure et al., 2004).

Such discounting models, however, cannot account for a critical contextual effect in intertemporal choice—the well-documented asymmetry observed in discounting when options are framed as decisions to delay or accelerate consumption (Loewenstein, 1988; Malkoc & Zauberman, 2006; Reeck et al., 2017; Weber et al., 2007). When options are framed as decisions to delay consumption (with the sooner option as the default), people often make more impatient choices than when options are framed as decisions to accelerate consumption (with the later option as the default).

This difference likely emerges due to the constructed nature of preferences (Lichtenstein & Slovic, 2006). One account, Query Theory, suggests that people first retrieve reasons favoring the default option and then consider reasons for pursuing the alternative (Weber et al., 2007). Because of output interference (which makes contradictory or competing information harder to recall once initial information is brought to mind), information favoring the first option considered comes to mind more easily and diminishes activation of arguments favoring alternative choices (Anderson et al., 1994). This creates an asymmetry such that greater pro-default information is recalled. In delay, the default is the smaller, sooner (SS) option; in acceleration, it is the larger, later (LL) option. Because sooner events are represented more concretely (Malkoc & Zauberman, 2006; Trope & Liberman, 2000) and involve retrieval of more vivid detail than more distant future events (Schacter et al., 2007; Tamir & Mitchell, 2011), delay framing (i.e., smaller sooner default) should result in greater activation in regions involved in intertemporal preference construction than acceleration framing (i.e., larger later default). This differential activation occurs because the default option is typically considered first and, in the delay frame, this default is the SS option which will be represented with more associative detail than the LL option is represented with in the acceleration frame. This asymmetry suggests that acceleration decisions may promote patience by diminishing representation of the SS option by framing the future first.

While prior work has identified the neural regions that are involved in representing value

during intertemporal choice (Kable & Glimcher, 2007; McClure et al., 2004), the neural correlates of delay and acceleration framing remain uncharacterized. Elucidating the neural correlates of this critical contextual effect on intertemporal choice would clarify the neurocognitive architecture that is involved in the construction of preferences. The present research sought to delineate neural activation in delay and acceleration framing in order to inform understanding of preference construction in intertemporal choice.

Method

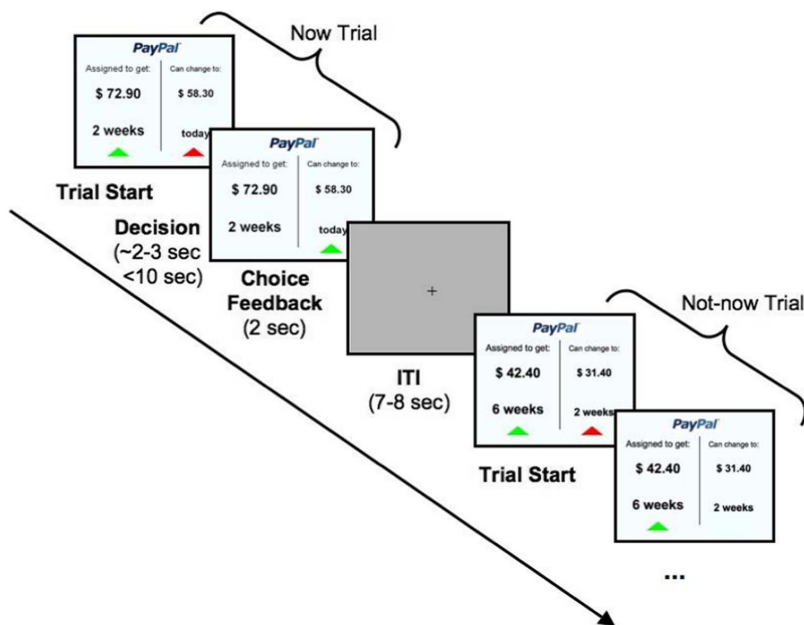
Participants

Twenty participants (12 women, mean age = 26.0 years old) participated in the experiment in exchange for payment. The sample size is commensurate with other neuroimaging studies of intertemporal choice (Kable & Glimcher, 2007; McClure et al., 2004). Participants were screened for contraindications for participating in MR scanning (e.g., implanted metal, claustrophobia) and were all right-handed. Imaging data from one participant were excluded from all analyses due to excessive motion. All participants provided informed consent and all procedures were approved by the Columbia University Institutional Review Board.

Materials and Procedure

After providing informed consent, participants completed an intertemporal choice task. On each trial of this task (Figure 1), participants chose between a smaller amount of money that would be delivered sooner (SS, e.g., \$58.90 today) and a larger amount of money that would be delivered later (LL, e.g., \$72.90 in 2 weeks). A set of 72 different option pairs was constructed using a process similar to previous research involving intertemporal choice (McClure et al., 2004; Reeck et al., 2017). SS reward amounts were drawn from a distribution with a mean of \$45 and a standard deviation of \$20, constrained so that all amounts fell between \$15 and \$85. The set of choice pairs was then constructed by varying (a) the SS delivery time (today or in 2 weeks), (b) the delay between the SS and LL delivery times (2 or 4 weeks delay), and (c) the relative difference in the dollar amounts between the two

Figure 1
Two Example Trials From the Intertemporal Choice Task



Note. Each trial began with the presentation of two options, one of which was a smaller amount of money that was delivered sooner and the other of which was a larger amount of money delivered later. A triangle appeared beneath each option. Participants made their selection in a self-paced fashion, with a maximum of 10 s to deliberate on each trial. Once they made their selection, a green triangle was presented underneath their chosen option, and this display remained on the screen for 2 s. After a 7–8 s jittered intertrial interval, the next trial began. Acceleration and Delay framed trials were presented in separate runs, and the gift certificate participants decided about also varied between runs.

options (1, 3, 5, 10, 15, 20, 25, 35, or 50%). Two option pairs were generated for each of the 36 combinations of these features, for a total of 72 unique choice trials.

The key manipulation in the present experiment was whether the choice was framed as a decision to delay or accelerate consumption by making either the SS or the LL option the default (Loewenstein, 1988; Malkoc & Zauberman, 2006; Reeck et al., 2017; Weber et al., 2007). When the SS reward was presented as the default option, switching to the LL reward would delay consumption. Conversely, when the LL reward was presented as the default option, switching to the SS reward would accelerate consumption. The default option was always presented on the left side of the display, printed in larger font, with a green triangle beneath it, and with text indicating that the participant was assigned to get this option. The alternate option was always

presented on the right side of the display in smaller font with a red triangle beneath it and text indicating that the participant could change to this option (see Figure 1). The default was always presented on the left so that natural reading order would reinforce the left option (which would likely be read first) as the default. Note that there was no actual switching cost from the default to the alternative option since participants had to indicate either choice via button press. Participants' decisions were self-paced, with a maximum deliberation time of 10 s. Once participants made a selection, a green triangle appeared beneath the selected option for 2 s, followed by a 7–8 s jittered intertrial interval. Thus, the initial presentation of the green triangle beneath the left option also reinforced that this option was the default.

Delay versus acceleration framing was manipulated between functional scanning runs.

Two runs featured delay framing and two featured acceleration framing, with the order counterbalanced across participants (delay-accelerate-accelerate-delay or accelerate-delay-delay-accelerate). To help participants differentiate between the two frames, the rewards for the two choice options were provided as gift certificates from different providers (Amazon and PayPal) counterbalanced across the two framing conditions. The same set of 72 option pairs was presented in both the delay and accelerate conditions, and the trials presented in each run consisted of the same number of each of the 36 trial types. Participants initially practiced this task briefly outside the scanner, completing a few delay and acceleration trials. The duration of each functional run was fixed, such that participants completed on average 128 choice trials (range: 117 to 137 trials) while undergoing functional magnetic resonance imaging. To ensure that the task was incentive-compatible, participants were informed that one of these choices would be randomly selected and they will receive the gift-certificate reward they chose on that trial, delivered after the experiment via email (but redeemable only after the trial-specified delay).

Behavioral Analyses

The main model analyzed choice—SS versus LL—as a function of framing (acceleration or delay), the immediacy of the SS option (available Now vs. Not Now), the interaction between framing and SS immediacy, the time difference between the SS and LL (2 or 4 weeks), the relative difference in reward magnitudes between the SS and LL, and the reward magnitude of the SS. In addition to these fixed effects, we included a random intercept varying over participants, random slopes varying over participants for each of the fixed effects, as well as all possible pairwise covariances between the random effects. Thus, this model constitutes a “maximal model” with respect to the random effects, as recommended by Barr et al. (2013) to safeguard against inflated Type 1 errors. All categorical predictors (framing and SS immediacy) were sum-to-zero coded. All the other, continuous predictors were standardized. The models were implemented using the package brms (Bürkner, 2017) in (R Core Team, 2019), which provides an interface to Stan (Carpenter et al., 2016). All models were run with six chains with each 2,000 iterations (1,000

of which were warm-up). We used brms’s default priors. All models were checked for convergence via the Rhat values and visual inspection of the trace plots. We deemed a regression coefficient statistically significant if its 95% posterior credible interval (CI) did not include 0 (for marginally significant effects, we inspected the 90% CI).

To better characterize the interaction between frame and immediacy we report in the main text, we ran four follow-up models, analyzing choice separately for (a) now trials, (b) not-now trials, (c) delay-framed trials, and (d) acceleration-framed trials. These models were identical to our main choice model, except that they were run always on the respective subset of the data and always excluded the relevant respective predictor (i.e., the separate models for the now trials and the not-now trials did not include the immediacy predictor; similarly, the separate models for the delay-framed and the acceleration-framed trials did not include the frame predictor).

Response times were analyzed using a similar model as that employed for choice data, using the same fixed and random effects as our main choice model. The dependent variable was the trial-level response times (RT). Since they showed a non-normal distribution, we used a generalized linear mixed-effects model with a shifted lognormal distribution, which provided a good fit to our data. Behavioral data are available via the Open Science Framework: https://osf.io/mpe74/?view_only=b43409bb8c0e419a9570596179ffd851.

Image Acquisition and Analysis

Functional and anatomical images were acquired with a 1.5 T twin-speed GE MRI scanner using an echo-planar pulse sequence and an eight-channel head coil (TR = 2.0 s, TE = 34 ms, flip angle = 90°). Twenty-nine contiguous axial slices covering the full brain were acquired along the AC-PC plane, with a 64 × 64 matrix and 22.4 cm field of view; FOV (slice thickness = 3.5 mm, slice separation = 0 mm). High-resolution structural images were acquired using a 3D SPGR sequence (124 slices, matrix size = 256 × 256, FOV = 22.0 cm).

Functional MRI data were analyzed using Statistical Parametric Mapping software (SPM8, Friston et al., 1995). The first five acquisitions were discarded to allow for signal stabilization. Functional images for each participant were corrected for slice acquisition timing, realigned to

correct for motion, and coregistered with the participant's high-resolution structural scan. Each participant's bias-corrected high-resolution structural image was normalized to the Montreal Neurological Institute (MNI) ICBM 152 template using unified segmentation (Ashburner & Friston, 2005). The resulting transformation parameters were then applied to the functional images, which were spatially smoothed using a Gaussian kernel of full-width half-maximum 8.0 mm³. Functional images had a final spatial resolution of 3.5 mm × 3.5 mm × 3.5 mm.

A general linear model was constructed for each participant with a total of eight regressors modeling task effects. Separate regressors were constructed for the trial onsets of each condition as a function of the framing (delay or acceleration), the delivery timing of the SS reward (today or 2 weeks), and the participant's decision (selecting the SS option or the LL option). For each task effect regressor, two additional regressors were included to model parametric effects of the trial options' subjective value and the participant's response time. To generate estimates of subjective value for each trial, we estimated each participant's individual discount rate. As the overwhelming majority of the literature reports better fits for hyperbolic than exponential discounting models (Green & Myerson, 2004), we used Mazur (1987) standard one-parameter model of hyperbolic discounting: Subjective Value = Objective Amount/(1 + $k \times$ Delay), where *Delay* indicates the time of delivery (in years) and k is a constant that is specific to each participant and indicates the steepness of the participant's discounting (with larger values indicating steeper discounting and zero indicating no discounting at all). For each participant, the hyperbolic discount rate k best explaining their choice pattern was estimated by fitting a logistic curve to their choices (plotting choice of SS vs. LL as a function of the indifference-implied discount rate of each choice pair). The participant's estimated discount rate was thus the discount rate at which the participant would be predicted to choose the SS and LL with equal probability. The discount rate was used in the fMRI analysis to compute a regressor reflecting the subjective discounted value of the choice options presented in a trial. The results presented here are used for this regressor the sum of the subjective discounted values of the SS and the LL. In supplemental analyses not presented in this

article, we used instead (a) the difference in subjective discounted values between the SS and LL and (b) two separate values for k (one for Delay and one for Acceleration) to compute the sum and the difference regressors. For each of these variations, the results remained qualitatively the same. Time points were convolved with the canonical hemodynamic response, and linear contrasts between conditions of interest were estimated for each participant and subsequently employed in second-level random effects analyses to obtain mean t -images. SnPM (Winkler et al., 2014) was employed to compute a combined cluster-extent and voxel-height threshold to correct for multiple comparisons. A voxel-height threshold of $p < .01$ was employed to generate corrected thresholds with a family-wise error rate of $p < .05$ for the whole-brain analyses reported below. We also sought to examine the interaction between framing and choice¹ examining two key anatomical regions of interest: Medial prefrontal cortex and medial temporal lobe. For the medial prefrontal region of interest (ROI), Brodmann's areas 8, 9, 10, 11, 12, 24, 25, and 32 were combined in the AAL atlas to create a mask that would encompass the medial prefrontal cortex. For the medial temporal lobe, the AAL hippocampus and parahippocampal gyrus were combined to create a mask. SnPM was employed to identify activation in these regions with a family-wise error rate of $p < .05$. Parameter estimates were extracted from significant clusters using Marsbar (Brett et al., 2002). Data are available at <https://neurovault.org/collections/NAABLORD/>

Results

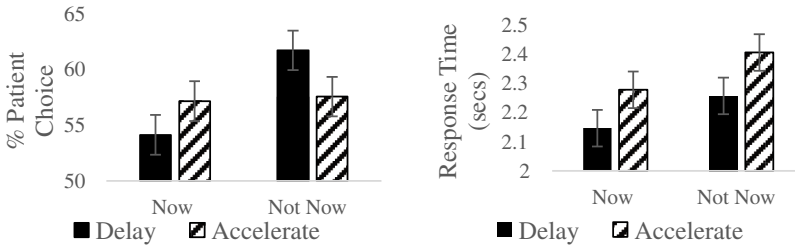
Behavioral Results

We used a Bayesian mixed-effects model to analyze choice as a function of framing (acceleration or delay), the immediacy of the SS option (available Now vs. Not-now), the interaction between framing and SS immediacy, the time difference between the SS and the larger later

¹ A supplemental analysis was conducted following a reviewer's suggestion to interrogate this interaction without the inclusion of parametric modulation by the subjective value of the presented options. The results were qualitatively similar, although the findings from the hippocampus were less widespread and did not survive cluster thresholding.

Figure 2

Left Panel: Proportion of Larger, Later Choices and Right Panel: Mean Response Times as a Function of Frame (Accelerate or Delay) and Immediacy (Now or Not-Now Trials)



Note. Error bars represent ± 1 SEM.

(LL) option (2 or 4 weeks), the relative difference in reward magnitudes between the SS and LL, and the reward magnitude of the SS. The main effects of frame and immediacy on choice were nonsignificant ($B = 0.05$, $SE = 0.14$, 95% CI $[-0.21, 0.33]$; $B = 0.25$, $SE = 0.22$, 95% CI $[-0.19, 0.70]$, respectively). There was, however, a significant interaction between framing and immediacy, $B = -0.35$, $SE = 0.12$, 95% CI $[-0.60, -0.12]$, see Figure 2. To better characterize the interaction between frame and immediacy, we ran separate follow-up models for (a) Now and Not-now trials and (b) for delay-framed and acceleration-framed decisions. In Now trials, we found participants made significantly more patient choices in acceleration compared to delay framing, $B = 0.35$, $SE = 0.15$, 95% CI $[0.06, 0.67]$, consistent with prior literature (Loewenstein, 1988; Malkoc & Zauberman, 2006; Reeck et al., 2017; Weber et al., 2007). There was no significant difference in Not-now trials, $B = -0.33$, $SE = 0.25$, 95% CI $[-0.84, 0.13]$. Similarly, in delay-framed decisions, we observed a significant immediacy effect, $B = 0.59$, $SE = 0.28$, 95% CI $[0.05, 1.16]$, with more impatient choice when an immediate reward was available compared to when all rewards were in the future. In acceleration-framed decisions, the immediacy effect was not significant, $B = -0.10$, $SE = 0.25$, 95% CI $[-0.58, 0.40]$. In addition, we found significant effects in the expected directions for relative reward differences, $B = -0.35$, $SE = 0.12$, 95% CI $[-0.60, -0.12]$, SS amount, $B = -0.35$, $SE = 0.12$, 95% CI $[-0.60, -0.12]$, and time difference, although this latter effect was only marginally significant, $B = -0.35$, $SE = 0.12$, 90% CI $[-0.51, -0.04]$.

To investigate whether framing and/or immediacy affected response time (RT), we ran a model

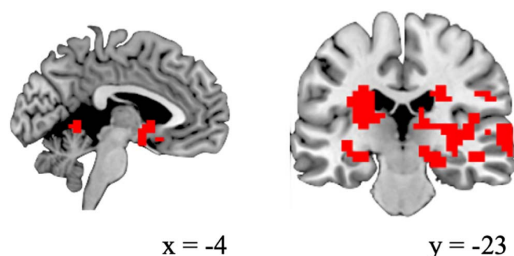
similar to the choice model reported above, but with RT as the dependent variable. The only significant effect was that participants were slightly faster in Now than Not-now trials, $B = 0.03$, $SE = 0.01$, 95% CI $[0.003, 0.06]$, Figure 2, possibly due to somewhat higher processing demands when both time points were in the future. All other effects were nonsignificant (see Supplement for details).

Neural Correlates of Framing

Our central goal was to characterize the neural correlates of framing options in intertemporal choice, identifying neural regions exhibiting differential activation for delay versus acceleration. As the key manipulation was the frame in the present experiment, we first examined which regions exhibited differential activation in delay versus acceleration framing. Whole-brain analyses revealed a network of regions that exhibited greater activation under delay compared to acceleration framing (Figure 3), including hippocampus, amygdala, and insula (Supplemental Table 1). No regions were identified that exhibited greater activation for acceleration compared to delay.² Additionally, no regions exhibited significant activation that tracked the interaction between accelerate versus delay framing and the immediacy of the SS option. The greater observed activation in the medial temporal lobe in delay is consistent with constructed preferences accounts of asymmetric discounting.

² A supplemental analysis compared subjective value of the options presented between acceleration and delay frames. No significant differences in activation were identified.

Figure 3
Neural Correlates of Option Framing



Note. Selected regions exhibiting greater activation for delay compared to acceleration framing are displayed. Whole-brain corrected, $p < .05$. MNI coordinates for activation peaks are listed in [Supplemental Table 1](#). Activation map is available on NeuroVault.

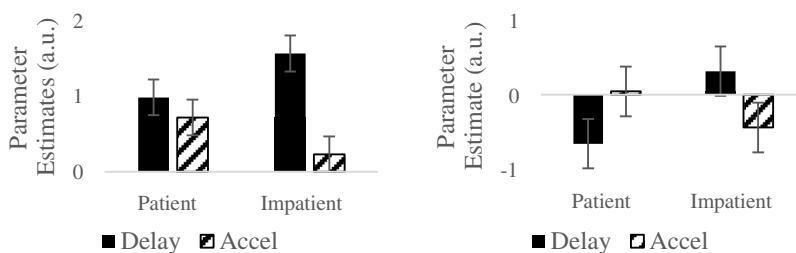
To clarify the role of these regions in constructing preferences, we next examined interactions between option framing and choice. For this analysis, we focused specifically on activation in the medial temporal lobe or medial prefrontal cortex. Significant interactions between option framing and choice were identified in medial temporal lobe (peak MNI $x, y, z = 26, -24, -16$) and medial prefrontal cortex (peak MNI $x, y, z = -2, 7, 54$). Parameter estimates were extracted from these significant clusters ([Figure 4](#)) to interrogate this interaction, revealing different patterns in the two regions. In the medial temporal lobe, greater activation was observed for impatient choices when they were made with delayed compared to accelerate framed options, $t(18) = 3.76, p = .001, d = 0.86$, while no such difference was observed between patient choices in the two frames, $t(18) = 0.86, p = .399$. This pattern is consistent with the notion that the SS option is represented more vividly with more details constructed during imagination in the delay than the

accelerate frame. In the medial prefrontal cortex, a different pattern emerged. For patient choices, greater activation was observed for accelerate compared to delay framed options, $t(18) = 2.67, p = .016, d = 0.61$, while for impatient choices marginally greater activation was observed for delay compared to accelerate framed options, $t(18) = 2.05, p = .056, d = 0.47$. This crossover pattern may be due to the fact that this region overlaps with the default mode network, with greater deactivation consistently found when choosing the option that is not promoted by the framing. This pattern may indicate that participants need to engage more with the task in order to choose the nondefault option in each case, thus leading to the observed deactivation of these regions.

Discussion

Our goal was to delineate differences in neural activation between delay and acceleration frames in intertemporal choice. When options were framed as delays, we observe greater neural activation in the hippocampus, amygdala, and anterior insula—regions previously implicated in intertemporal choice. Anterior insula may play a role in projecting the self across time ([Craig, 2009](#)), an important process in delay discounting ([Clewett et al., 2014](#)), and insula damage alters intertemporal discounting ([Sellitto et al., 2015](#)). Animal models reveal that lesions to both the hippocampus ([Cheung & Cardinal, 2005](#)) and the amygdala ([Winstanley et al., 2004](#)) result in more impatient decisions. Both regions have been implicated in episodic processing supporting intertemporal choice ([Peters & Buchel, 2011](#)). Medial temporal lobe structures are argued to play an essential role in supporting

Figure 4
Parameter Estimates Extracted From Medial Temporal Lobe (Left Panel) and Medial Prefrontal Cortex (Right Panel)



Note. Error bars represent ± 1 SEM.

intertemporal choice by representing different available outcomes (Peters & Buchel, 2011), consistent with our results.

While we observed that people were more patient in the acceleration than the delay frame on trials featuring an immediate outcome, we did not observe a main effect of delay versus acceleration framing on choice. This observed null effect could be due to the sample size, as we have identified this framing effect in larger samples (Reeck et al., 2017). This effect, however, is well-established behaviorally in the literature (Loewenstein, 1988; Malkoc & Zauberman, 2006; Reeck et al., 2017; Weber et al., 2007), but mostly in designs that manipulated the framing between participants and with many fewer trials. Recent work has revealed that individual differences in search processes during intertemporal choice moderate the effect of option framing on intertemporal choice (Reeck et al., 2017). It could be the case that these individual differences in the present sample resulted in an overall null effect of framing on behavior, but with a different composition of participants the traditional effect would emerge. We did not observe any neural regions whose activation tracked the interaction of framing and immediacy of the SS option.

Although asymmetric discounting is well-established in the behavioral literature, the present research is the first examination of the neural basis for this observed difference in intertemporal decisions. By characterizing the neural correlates of option framing in intertemporal choice, the present work advances general understanding of the neurocognitive processes that support this behavioral effect and promote patience. While neural data alone are insufficient to isolate the mechanisms underlying these phenomena, they provide valuable insight into potential processes contributing to such effects. Indeed, the present findings are consistent with a Query Theory account that emphasizes differences in retrieval in response to delay versus acceleration frames (Weber et al., 2007). Specifically, people recall more details favoring the default option, which is the SS option in delay framing and the LL option in acceleration framing. Because sooner events are represented with richer associative detail (Malkoc & Zauberman, 2006; Schacter et al., 2007; Tamir & Mitchell, 2011), this asymmetry should result in greater activation in the delay frame than the acceleration frame, consistent with our findings. The observed interaction between

option framing and choice in the medial temporal lobe is consistent with this account, as the greatest activation was observed when participants selected the SS option in delay framing. This greater activation likely reflected more associative detail recalled when imagining obtaining the default, sooner reward (Schacter et al., 2007; Tamir & Mitchell, 2011). Conversely, it may instead be the case that the greater observed activation reflects increased effort required to imagine the delayed option when the choice is framed as a decision to delay consumption. This interpretation is more consistent with the pattern observed in medial prefrontal cortex, which exhibited greater deactivation when the nondefault option was selected. This pattern may reflect the need to exert greater effort to consider and select the nondefault choice. Future research should characterize these mechanisms and clarify circumstances in which each may be more dominant in shaping behavior.

Our findings also dovetail with a growing literature implicating the hippocampus in preference construction more broadly during decision-making. Rodent experiments have demonstrated that the hippocampal activity during decisions predicts the selected environment (Johnson & Redish, 2007), consistent with the notion that hippocampus represents predictions of outcomes to support decision-making (Johnson et al., 2007). Hippocampal activation has also been linked to preference construction when people imagine new experiences that are based on combining familiar components (Barron et al., 2013). Patients with hippocampal lesions have also been found to exhibit more inconsistencies in their choices from among a set of options (Enkavi et al., 2017), consistent with the theory that hippocampus helps represent the value of options during preference construction (Gluth et al., 2015). These findings implicate hippocampus in representing options' value during decision-making broadly, but medial temporal lobe has also been implicated in representing outcomes during intertemporal choice. The hippocampus is involved in imaging future episodic events during decision-making (Benoit et al., 2011; Lebreton et al., 2013; Peters & Buchel, 2010), and hippocampal lesion patients fail to show benefits from episodic imagining of future outcomes during intertemporal choice (Palombo et al., 2015). The present results extend this prior work by showing that activation in medial temporal lobe

structures also discriminates between delay and acceleration framing. Indeed, the previously observed behavioral increases when future options are presented with specific associative detail to make them easier to imagine or when options are framed as decisions to accelerate consumption may rely on a similar mechanism mediated by the medial temporal lobe. In the former, episodic thinking allows for richer associative detail in imagining the LL option thus promoting patience; in the latter, acceleration framing reduces the vividness of imagination for the SS option thus promoting patience. Taken together, these findings suggest that the medial temporal lobe supports intertemporal choice through the representation of outcomes while people are deliberating between options and constructing their preferences.

Overall, the present findings implicate the medial temporal lobe and the anterior insula in constructing preferences during intertemporal choice. Differences observed between delay and acceleration framing of options indicate these neural regions may be especially important for representing different outcomes during decision-making, consistent with previous theoretical accounts (Peters & Buchel, 2011; Weber et al., 2007). This has potential implications for possible interventions. Framing the future first appears to encourage a different imagining of options while preferences are constructed. This and other interventions based on value construction may thus provide a flexible means to encourage patience.

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Received April 21, 2020

Revision received February 2, 2021

Accepted February 5, 2021 ■