Features of Imagination that Contribute to Value-based Decision Making

by

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Dissertation submitted in partial fulfillment of
the requirements for the degree of Doctor
of Philosophy in the Department of
Psychology and Neuroscience in the Graduate School
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ABSTRACT

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Abstract

Humans make a variety of choices every day. Some of these choices are pretty mundane like whether to eat pancakes or oatmeal for breakfast. Others cost a little more, have a little bit of a longer impact, like which vacuum cleaner to buy on Amazon. And finally, there are choices that we don't make very often—maybe even just once, that have enormous consequences in our lives like whether to choose Duke for graduate school. Deciding to choose one option over a set of alternatives involves imagining the future value that could be obtained by making those choices. Research on value-based decision making has recently begun to assess the impact of memory-related processes in making prospective decisions. Given that remembering the past and imagining the future rely on the same cognitive and neural mechanisms, researchers have investigated how imagining the future and remembering the past shift choice behavior. However, much of this research has focused on relatively abstract choices made in a laboratory setting rather than potentially more impactful long-term decisions that we make in everyday life. Overall, it is unclear to what extent memory-related systems impact a range of choices that humans make in everyday life from minor financial transactions to consequential life choices. Across three studies, I examine the role of the constructive memory process of imagination in decisions between shorter-term monetary rewards available at different temporal delays as well as longer-term consequential life choices

like career decisions. Chapter 1 provides a general overview of past research on the role of constructive memory processes in making decisions. In chapter 2 (Study 1), after rehearsal of hypothetical imagined future events, younger adults and older adults made choices between larger-later and smaller-sooner monetary rewards. Some of the trials included a cue that invoked the imagined future event whereas other trials did not include a cue. Younger adults were more likely to choose larger, delayed monetary rewards on trials where the imagined future event was cued compared to trials without a cue. However, older adults did not show an effect of cued imagination. Across age groups, functional neuroimaging data revealed that trials with an imagination cue elicited greater engagement of regions that are part of the default mode network including the posterior cingulate cortex, angular gyrus, and medial prefrontal cortex. This network is commonly engaged during thinking about past memories as well as imagining the future in many studies that did not focus on decision making. Interestingly, this difference in neural activity did not vary across age groups even though the behavioral effect of the cue was limited to younger adults. In Chapter 3, I explore the effects of imagining previous successes and failures on choices between larger-later and smaller-sooner monetary rewards (Studies 2a & 2b). I find no conclusive evidence of differences in decisions based on whether people imagined successes or failures, even when comparing to a non-imagined, emotionally neutral control condition. Finally, in chapter 4, I extend this work into more complex career decision

making. In a pilot study (Study 3), greater enjoyment of an imagined future career was associated with increased preference for that career option. Given the small and variable effects of imagining the future on decision making in Studies 1-3, two additional studies (Study 4a & 4b) evaluated the effects on decision making of an individual's ability to vividly visualize, a different cognitive measure potentially relevant to thinking about and imagining the future. Using multivariate analyses, we found that vividness of visual imagery along with a set of individual difference measures related to future time perspective, self-efficacy, and well-being were associated with a set of variables crucial to career decision making. Together, these studies qualify our understanding of the role of imagination and visual imagery in decision making from choices between small rewards in the laboratory and consequential life choices. Overall various forms of imagination had relatively small and inconsistent effects on both laboratory-based and real-world decisions, whereas visual imagery had a moderate and consistent shared effect on real world decisions. The findings have broad implications for guiding prospective decisions in humans across the life span. For example, educational institutions currently have little to no focus on imagination and imagery in guiding developing students toward their future lives. There are critical opportunities in higher education to integrate imagination and imagery into living and learning communities to support students in their transitions to independent and rewarding careers.

Dedication

To my family who have inspired me to pursue a life of creativity and service.

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1. Introduction

In everyday life, people are frequently confronted with binary choices, or choices between two options. Should I eat a banana or a doughnut for breakfast? Should I buy something right now or invest in a 401k? Should I go to a state school or a private university? None of these choices has an objective "right" answer, but nonetheless, we must make choices to proceed through life. In these circumstances, individuals make choices based on subjective value which represents an individual's perceived value of each option. According to a value maximization economic model, individuals prefer the item with the greatest subjective value (Samuelson, 1937).

But how is subjective value calculated? In the context of binary choice, there has been a great deal of focus on drift diffusion models of evidence accumulation (Krajbich et al., 2010; Ratcliff, 1978). That is, during the decision making process, people attend to different features of the choice—accumulating evidence—until they reach a decision threshold at which time they will make their choice.

What are these different features? The features differ based on the context, but in the breakfast example, individuals may balance taste and health features as well as food texture, social desirability, or cleanliness. For the two more existential questions, the features themselves become even more complex, abstract, and temporally extensive. For example, an individual may need to consider current stipend levels, future earnings, mentor fit, prestige, future placements, location, personal life, etc. when choosing between a state or private graduate program. Critically, these features are not restricted to the present, but draw upon past experience as well as projecting into hypothetical future scenarios. Indeed, the drift diffusion model itself was based on a model of memory (Ratcliff, 1978)!

In particular, these choices likely rely on specific and richly detailed memory for individual events such as imagining what my life might be like at each of the schools I am debating between or imagining myself golfing at Pebble Beach during retirement. This memory construct for specific and vividly experienced events is known as episodic memory (Tulving, 1985). More recent proposals have suggested that episodic memory systems do not merely recapitulate the past but allow for the flexible recombination of past events into hypothetical events from the past, present, or future (Schacter & Addis, 2007).

Another important feature of human cognition is flexible attention. Humans can attend to cues in the environment as well as direct thought inwardly, a process known as mind-wandering (Smallwood & Schooler, 2015). Importantly, mind-wandering also relies on the same default mode network as episodic memory and imagination. Moreover, for the purposes of this dissertation, mind-wandering is significantly more likely to involve future-oriented content compared to past-oriented content (Baird et al., 2011; Seli et al., 2017). Intentional mind-wandering, deliberately attending thoughts inwardly, is also significantly more likely to be future-oriented than unintentional mind-wandering, though mind-wandering in either situation is more likely to be future-oriented than past-oriented (Seli et al., 2017).

However, the role of episodic memory in decision making and the reward learning literature more broadly has received scant attention (Gershman & Daw, 2017). From a computational perspective, episodic memory actually solves some paradoxes of reinforcement learning which limit the applicability of current models to complex real-world decision making (Gershman & Daw, 2017). Given this theoretical functional overlap between episodic memory wherein the capacity for constructive episodic processes enables planning and decision making, the lack of attention on episodic memory and the related neural systems until the past decade is surprising. In this introductory chapter, I will review the overlapping anatomical regions that contribute to subjective value and episodic memory and introduce a particular application of episodic memory and its effects on decision making which will form the basis of the first two empirical chapters.

1.1 Functional Neural Networks of Memory and Decision Making

Episodic memory and decision making not only relate to each other in the theoretical sense, but anatomically, subjective value and episodic memory depend on a common network of regions known as the default mode network (Benoit & Schacter, 2015; Clithero & Rangel, 2014). The default mode network is a network of regions including the hippocampus, PCC, mPFC, and inferior parietal lobule which are canonically associated with task deactivation, or resting state, and internally-directed cognition (Buckner et al., 2008). Previous meta-analyses of the default mode network have identified that the network is engaged in a variety of tasks (Laird et al., 2009; Spreng et al., 2009). For example, Spreng et al. (2009) found that the default mode overlapped with tasks including memory, prospection, navigation, and theory of mind. In a follow-up experimental study, Spreng & Grady (2010) found that compared to a perceptual-motor control condition, participants who imagined the future, the past, or the perspective of another reliably activated regions that corresponded to the default mode network, particularly with regard to functional connectivity in the mPFC. Although there was substantial overlap between the three imagine conditions, theory of mind was preferentially associated with lateral temporal regions and memory and prospection corresponded to medial temporal regions, anterior and posterior cingulate cortices, and mPFC (Spreng & Grady, 2010).

Furthermore, there is a considerable literature suggesting certain regions (generally overlapping with the default mode network) including the medial temporal lobes, the mPFC, the PCC, retrosplenial cortex, lateral temporal, and parietal regions play a role in episodic future thinking (for review see Schacter et al., 2017). Given the experimental insight that imagining the future and remembering the past correspond to regions of the default mode network, more recent work has shifted to meta-analyzing these experimental results to identify reliable clusters of activity across studies involving memory and imagination. Each of the following meta-analyses implement the activation likelihood estimation approach to coordinate-based meta-analysis (Eickhoff et al., 2012). In this method, coordinate-based activation voxels are converted to probability distributions and compared across studies to see regions which are jointly activated across studies compared to an independent, null distribution. As a result, I will describe these significant joint activations across studies as clusters. One early meta-analysis of episodic future thinking investigated the conjunction between personal goals and motivation and episodic future thinking (Stawarczyk & D'Argembeau, 2015). Stawarczyk and D'Argembeau (2015) found that the future thinking domain clustered significantly in mPFC, PCC, retrosplenial cortex, parahippocampal cortices, hippocampus, and middle/superior frontal gyrus (see Figure 1a). Meanwhile, personal goal processing additionally included clusters in caudate and inferior frontal gyrus. The conjunction revealed clusters in mPFC, PCC, posterior inferior parietal lobule, right parahippocampal cortex, left middle temporal gyrus (Stawarczyk & D'Argembeau, 2015). In a meta-analysis by Benoit and Schacter (2015), episodic future thinking generally clustered more densely in retrosplenial cortex, parahippocampal cortex, hippocampus, PCC, posterior inferior parietal lobule, temporal gyrus, and middle/superior frontal gyrus. When comparing studies between memory for the past and future, fiction, and counterfactual thoughts, clusters representing the overlap of memory and simulation were mostly in the default mode network and including several prefrontal regions, anterior cingulate cortex (ACC), lateral temporal cortex, parahippocampal cortex and hippocampus, PCC, and more (Benoit & Schacter, 2015). Clusters that were correlated more with simulation compared to memory for the past were in the dorsolateral PFC (dlPFC) and posterior inferior parietal lobule, dorsomedial PFC, PCC, precuneus, right medial temporal lobe (MTL), lateral temporal cortex, postcentral gyrus, cerebellum, and PFC (Benoit & Schacter, 2015). Except for the cerebellum, all overlapped with the default mode network, although several are also part of the frontoparietal control network (Benoit & Schacter, 2015).

There has been a reasonable amount of literature investigating the representation of subjective value in the brain; that is, during tasks involving subjective value, in which regions of the brain does blood oxygenation level dependent (BOLD) activation track with subjective value? According to two major meta-analyses, positive correlations with subjective value significantly clustered in the medial prefrontal cortex (mPFC) and surrounding cortical and subcortical structures, particularly the striatum, and the posterior cingulate cortex (PCC) (Bartra et al., 2013; Clithero & Rangel, 2014; see Figure 1b and c). Some regions show non-linear, potentially salience effects, including the striatum and anterior insula (Bartra et al., 2013). That is, the striatum and anterior insula were activated regardless of the valence of the outcome—reward or punishment. When comparing decision to outcome stages, positive subjective value correlations clustered in ventromedial prefrontal cortex (vmPFC) and surrounding frontal cortical regions (Bartra et al., 2013; Clithero & Rangel, 2014). Clithero and Rangel (2014) also noted clusters in dorsal PCC. In general, the striatum and vmPFC seem to index subjective value according to a utility model (Bartra et al., 2013). Using slightly different meta-analytic methodologies, these groups of researchers concluded slightly different things about the distribution of reward modality distribution. Using an image-based meta-analysis, Clithero and Rangel (2014) identified that correlations with monetary reward clustered in the vmPFC, ventral striatum, dorsal PCC, and superior frontal gyrus while correlations with the primary reward of food clustered in posterior regions of the vmPFC. This led Clithero and Rangel (2014) to propose a posterior to anterior gradient of value representation with concrete rewards represented in posterior regions and abstract rewards in more anterior regions. Using coordinate-based meta-analysis, Bartra and colleagues (2013) only quantitatively identified denser clustering in the striatum between monetary and primary rewards, although qualitatively both anterior PFC and PCC seem to only be engaged during monetary reward valuation. Intriguingly, PCC seems to be preferentially engaged during tasks involving monetary reward. Again, these regions comprise a posteromedial cluster and a frontal cluster which broadly overlap between simulation and decision making. However, beyond casual observation, serious investigation of the overlapping network topologies is limited.

Acikalin et al. (2017) subsequently examined the correspondence between default mode network and the subjective value network. The conjunction between the subjective value network and default mode network revealed clusters in the vmPFC, striatum, ventral and dorsal PCC, and bilateral amygdala, with the maximal ALE statistic in the vmPFC (see Figure 1 for more detail). There was little evidence of specialization of the default mode or subjective value networks in the vmPFC whereas ventral PCC seems to be specific to default mode network. These studies linking memory to the default mode network and subjective value to the default mode network are a critical first step, but the explicit link between memory, particularly episodic memory, and subjective value-based decision making has yet to be studied quantitatively in this way.

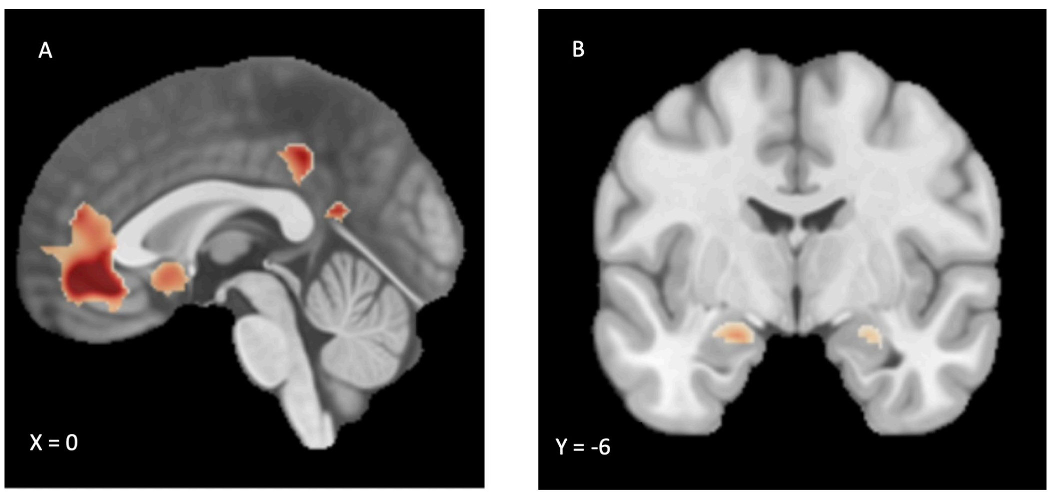

Figure 1: ALE maps from Acikalin et al., 2017 show clustering across studies involving DMN and subjective value. Specifically, mPFC, striatum, PCC (panel A), and MTL clusters (panel B) can be observed in these maps. Source images can be seen at *neurovault <dot> org/collections/1653/*

Some headway has been made by researchers investigating the role of the hippocampus and the medial temporal lobes in decision making (Wimmer & Shohamy, 2012). The hippocampus and the medial temporal lobes are essential to episodic memory function. Connecting decision making to the hippocampus, therefore, is of paramount interest to researchers at the intersection of memory and decision making. Since midbrain dopamine projections to the striatum are widely understood to calculate reward prediction errors and subsequently represent subjective value, these regions and the dopamine neurons within them are crucial for reinforcement learning (Schultz et al., 1997). Though that literature largely focuses on the striatal system underlying reinforcement learning, midbrain dopamine neurons also project to the hippocampus (Gasbarri et al., 1994). Correspondingly, the hippocampus exhibits novelty-related prediction errors (Wittmann et al., 2007). Additionally, the hippocampus can modulate striatal dopamine and subsequent activity (Legault & Wise, 1999). Importantly, a critical aspect of the neuroanatomy of the reward circuitry is that the shell of the nucleus accumbens (in the ventral striatum) receives dense projections from the hippocampus as well as another medial temporal lobe region, the amygdala (Haber & Knutson, 2010). The shell of the nucleus accumbens also receives dense projections from the vmPFC and OFC (Haber & Knutson, 2010). This anatomical convergence of prefrontal and medial temporal lobe regions in the striatum supports the correlational evidence from the meta-analyses of the default mode network literature that these regions seem to interact during subjective valuation. Given these direct connections, engaging memory systems ought to influence reward and choice behavior.

1.2 Is Episodic Memory Necessary for Time Discounting?

How can we engage memory systems while making choices? One way of addressing this is by investigating the role of episodic memory systems in one of the most frequently studied phenomena in decision science: time discounting. Time discounting refers to the decrease in an individual's subjective value of a reward (e.g. an amount of money) as the time to delivery of that reward increases. In the laboratory, time discounting is often studied using intertemporal choices where participants must make choices between a smaller-sooner reward and a larger-later reward (e.g. 10 dollars today or 20 dollars in 2 weeks). There are a couple categories of ways that people quantify time discounting. One method is to calculate a percentage, or ratio, of delayed choices made (Benoit et al., 2011; Palombo et al., 2015). Another method is to model discounting using a function—typically a hyperbolic function (Green & Myerson, 2004). Both methods lead to an estimate of an individual's discount rate. Percentage-based methods do not make assumptions about the shape of the discounting curve, but are less sensitive measures of discount rate. Meanwhile, model-based methods of estimating discount rates are more sensitive measures, but do make assumptions about the shape of the discounting curve. There are considerable individual differences in discount rates (Peters & Büchel, 2011). Since intertemporal choice requires comparing present and future rewards, the capacity to vividly imagine future events, or mental time travel, has been suggested to be critical to decision making (Boyer, 2008). Therefore, might individual differences in episodic memory explain these substantial individual differences in discount rates?

One way to answer this question is to study time discounting in amnesic patients who have damage to the medial temporal lobe regions and exhibit severe deficits in episodic memory. Does a basic time discounting paradigm require episodic future thinking? In a case study with famous amnesic patient KC, the answer is no (Kwan et al., 2012). KC demonstrated time discounting within the normal range of control participants. He seemed to use his intact semantic strategies when explaining his process (Kwan et al., 2012). With additional patients and the addition of a probability discounting task, Kwan and colleagues (2013) replicated the Kwan et al. (2012) finding that discount rates do not differ between amnesic patients and controls. Subjective reports were varied among patients with some using event-like knowledge, semantic knowledge about economics, and "gut feelings" (Kwan et al., 2013). Likewise, based on a time perspective scale, amnesic patients were not limited to a present-orientation (Kwan et al., 2013). These findings in the neuropsychological literature suggest that multiple strategies aside from episodic memory might be deployed to make intertemporal choices. Similarly, compensatory mechanisms related to the preservation of crystallized intelligence explain preserved decision making capacity in older adults (Li et al., 2013).

Overall, recent research has begun to identify the role of memory-related processes in decision making across adulthood. However, the prior studies of the effects of episodic future thinking on time discounting have been limited to investigation of neural mechanisms in separate studies of younger and older adults. More generally, studies of the role of memory and imagination on choice have been limited to lab-based tasks and have not yet been extended to more consequential decisions made in everyday life.

2. Effect of Episodic Future Thinking on Time Discounting in Younger and Older Adults

Researchers have posited that a potential functional account for constructive memory systems is the ability to plan for future events (Atance & O'Neill, 2001; Boyer, 2008). Given these theoretical accounts, scientists have studied the role of imagination on time discounting, a decision making phenomenon where subjective value of rewards declines with increasing time (Peters & Büchel, 2010). In a recent meta-analysis of several different manipulations of time discounting, there was a small but consistent effect of reductions in discounting after imagining future events (Rung & Madden, 2018). This finding is supported by a recent study which reanalyzed six datasets investigating the reductions in discounting following episodic future manipulations using the same analytical procedure for each study (Peters et al., 2020). Henceforth, I will refer to these reductions in discounting following manipulations of episodic future thinking as the *tag effect.*

The relative contributions of episodic and semantic memory to the tag effect are currently unclear. Internal event details which are a standard measure of episodic detail do not generally correlate with the strength of the tag effect (Peters & Büchel, 2010). There are theoretical concerns which may lead to this lack of association. For example, semantic memory is proposed to play a critical role in episodic memory, in particular for prospection, to provide scaffolding for future events (Irish & Piguet, 2013). Perhaps internal event details only capture a portion of the qualitative vividness of an imagined episode. Even within studies, though, semantic manipulations have led to opposite patterns of results. For example, Benoit et al. (2011) specifically hypothesized and found that episodic tagging led to reduced discounting when compared to a semantic condition involving listing items that money could buy. However, Palombo et al. (2016) found that discount rates were lower in amnesic patients when the patients were provided semantic support through the explicit reminder of items of a specific value.

While Sasse et al. (2017) did not find significant evidence for the effect of paired episodic future events on discounting behavior in older adults, a new, larger, behavioral study has found evidence for the effect of paired episodic future events on discounting behavior in older and younger adults (Mok et al., 2020). Nevertheless, older adults showed less of an effect of the paired events than young adults, although this is driven by different baseline discount rates in the sample (Mok et al., 2020). One explanation of this age interaction for the tag effect is that gradual declines in cognitive control and functional engagement of the anterior cingulate cortex and medial temporal lobes diminish the tag effect (Sasse et al., 2017). However, this hypothesis has only been tested in one sample consisting of only older adults (Sasse et al., 2017).

Another explanation offered for this age difference arises from the theoretical model of mental time travel discussed previously. The suggestion is that declines in episodic memory across older adulthood contribute to the impairment of the mental time travel proposed to underlie the tag effect. In a traditional time discounting task, older adults have more available compensatory strategies to adopt (Li et al., 2013). However, episodic tagging is designed as a manipulation based in episodic memory capabilities. Harnessing semantic scaffolding may boost the tag effect in older adults. Ironically, one way to accomplish this is by using an episodic specificity induction (Madore et al., 2014). Using an adapted version of the autobiographical interview (Levine et al., 2002) to prompt an episodic mindset during narrative reporting of a video led to a greater amount of episodic details reported about autobiographical memories prompted by pictures (Madore et al., 2014). For the purposes of boosting the tag effect, whether this boost occurs through episodic details or via semantic support is not essential. What matters is that the extra rehearsal for each event prior to the task should make the events easier to recall for all age groups when cued by the tag. In the present study, we added a structured rehearsal period for each possible future event prior to making intertemporal choices that were either paired with possible future events or unpaired while undergoing fMRI in individuals across the lifespan.

2.1 Method

2.1.1 Participants

Healthy participants were recruited from the Research Triangle region around Durham, North Carolina for behavioral sessions and fMRI scanning at Duke University. 63 adults (ages 25-80, M=52.40, SD=19.12, 27 males) participated in the study.

Participants were medically and cognitively healthy with scores above 24 on the Montreal Cognitive Assessment (MOCA; Nasreddine et al., 2005) and normative scores on the NIH Toolbox (Gershon et al., 2013). 28 subjects were removed from the analysis for excessive motion or other fMRI artifacts (12 subjects), systematic behavior on the discounting task (1 subject (2 including 1 with fMRI artifacts), poor model fit (8 subjects) and not yet preprocessed (7 subjects). As a result, 35 subjects were included in the fMRI analysis below. Approval for the study protocol was obtained from the Duke Health Institutional Review Board and all participants completed informed consent.

2.1.2 Procedure

On the first day, participants completed the neurological measures (NIH Toolbox and MOCA) and a cognitive and personality battery. They also practiced the experimental tasks. On the day of the scan, participants first saw a set of eight events and associated time periods presented as words on a computer screen using Psychopy. Participants were instructed to imagine what they would be doing, who they would be with, and any sights sounds, or other details specifically associated with the event. After viewing the events for the first time, participants described aloud the imagined events. They were then probed to specifically describe a person they imagined at the event, the location that they imagined, how they imagined it fit into their life at the moment, and how they would spend the money at the event. After the first block of events with descriptions, participants saw each event again two more times. Before scanning, participants rated each event on scales of vividness and emotional valence and arousal. In the scanner, participants completed four runs of intertemporal choice trials where they made decisions between a smaller amount of money ($11-$34) today and a larger amount of money ($25-$35) in the future (1-180 days) (Senecal et al., 2012). For the first run, participants only saw the intertemporal choice on the screen (see Figure 2A). For the second through the fourth runs, participants saw trials with or without paired events on the screen (see Figure 2A and B).

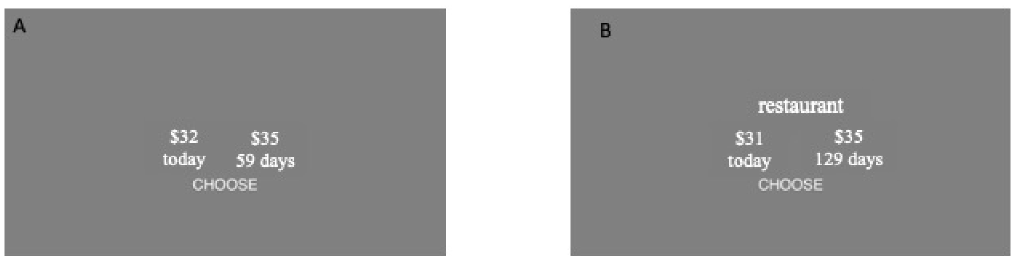

Figure 2: Panel A shows the layout of a control trial. Panel B shows the layout of an event paired trial.

Participants were given up to 6 seconds to make their choice, which was subsequently highlighted for one second. The intertrial interval was drawn from an exponential distribution with a mean of 3 seconds. The additional time leftover during each choice trial was added to the intertrial interval time.

2.1.3 Behavioral Analysis

Subjective values were modeled using a hyperbolic discounting function $SV = R/(1 + kD)$ where R represents the monetary reward, k represents the discount rate, and D represents the number of days in the delay. We fit the data using a softmax decision function with a custom python script which generally provided a good fit with the data. We removed seven participants with a Bayes Information Criterion above 100 removes several identifiable outliers (whose difference scores are 10 times larger than the average). We generated discount rates (*k)* for control trials and event-paired trials separately. These discount rates were transformed using a square root function in order to linearize the variable. These square root-transformed discount rates were also used to compute the subjective value for the chosen item which was used in the fMRI analysis described below.

2.1.4 fMRI Acquisition

Brain images were collected using a 3 T GE MR750 scanner with a 32-channel head coil. We acquired high resolution anatomical scans using T1-weighted imaging (repetition time= 2.161 ms, echo time = 3.04 ms, 272 acquisitions, voxel dimensions = 1 X 1 X 1.). We acquired functional images using a T2* weighted multiband scan with 63 2 mm slices with a repetition time of 2 seconds, an echo time of 30 ms, and a flip angle of 77 degrees.

2.1.5 fMRI Preprocessing

Preprocessing was done using fMRIPrep version 1.4.1 (Esteban, Markiewicz, et al. (2018); Esteban, Blair, et al., (2018); RRID:SCR_016216). This section of the methods section describing the preprocessing steps is the boilerplate which is automatically generated by fMRIPrep. "Results included in this manuscript come from preprocessing performed using *fMRIPrep* 1.4.1 (Esteban, Markiewicz, et al. (2018); Esteban, Blair, et al. (2018); RRID:SCR_016216), which is based on *Nipype* 1.2.0 (Gorgolewski et al., (2011); Gorgolewski et al. (2018); RRID:SCR_002502).

2.1.5.1 Anatomical Data Preprocessing

The T1-weighted (T1w) image was corrected for intensity non-uniformity (INU) with N4BiasFieldCorrection (Tustison et al., 2010), distributed with ANTs 2.2.0 (Avants et al., 2008, RRID:SCR_004757), and used as T1w-reference throughout the workflow. The T1w-reference was then skull-stripped with a *Nipype* implementation of the antsBrainExtraction.sh workflow (from ANTs), using OASIS30ANTs as target template. Brain tissue segmentation of cerebrospinal fluid (CSF), white-matter (WM) and gray-matter (GM) was performed on the brain-extracted T1w using fast (FSL 5.0.9, RRID:SCR_002823, Zhang, Brady, and Smith, 2001). Volume-based spatial normalization to one standard space (MNI152NLin2009cAsym) was performed through nonlinear registration with antsRegistration (ANTs 2.2.0), using brain-extracted versions of both T1w reference and the T1w template. The following template was selected for spatial normalization: *ICBM 152 Nonlinear Asymmetrical template version 2009c* [Fonov et al. (2009), RRID:SCR_008796; TemplateFlow ID: MNI152NLin2009cAsym].

2.1.5.2 Functional Data Preprocessing

For each of the 14 BOLD runs found per subject (across all tasks and sessions), the following preprocessing was performed. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep*. A deformation field to correct for susceptibility distortions was estimated based on *fMRIPrep*'s *fieldmap-less* approach. The deformation field is that resulting from co-registering the BOLD reference to the same-subject T1w-reference with its intensity inverted (Wang et al., 2017; Huntenburg, 2014). Registration is performed with antsRegistration (ANTs 2.2.0), and the process regularized by constraining deformation to be nonzero only along the phase-encoding direction, and modulated with an average fieldmap template (Treiber et al. 2016). Based on the estimated susceptibility distortion, an unwarped BOLD reference was calculated for a more accurate co-registration with the anatomical reference. The BOLD reference was then co-registered to the T1w reference using flirt (FSL 5.0.9, Jenkinson and Smith, 2001) with the boundary-based registration (Greve and Fischl, 2009) cost-function. Co-registration was configured with nine degrees of freedom to account for distortions remaining in the BOLD reference. Head-motion parameters with respect to the BOLD reference (transformation matrices, and six corresponding rotation and translation parameters) are estimated before any spatiotemporal filtering using mcflirt (FSL 5.0.9, Jenkinson et al., 2002). BOLD runs were slice-time corrected using 3dTshift from AFNI 20160207 (Cox & Hyde, 1997, RRID:SCR_005927). The BOLD time-series (including slice-timing correction when applied) were resampled onto their original, native space by applying a single, composite transform to correct for head-motion and susceptibility distortions. These resampled BOLD time-series will be referred to as *preprocessed BOLD in original space*, or just *preprocessed BOLD*. The BOLD time-series were resampled into standard space, generating a *preprocessed BOLD run in ['MNI152NLin2009cAsym'] space*. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep*. Several confounding time-series were calculated based on the *preprocessed BOLD*: framewise displacement (FD), DVARS and three region-wise global signals. FD and DVARS are calculated for each functional run, both using their implementations in *Nipype* (following the definitions by Power et al., 2014). The three global signals are extracted within the CSF, the WM, and the whole-brain masks. Additionally, a set of physiological regressors were extracted to allow for component-based noise correction (*CompCor*, Behzadi et al., 2007). Principal components are estimated after high-pass filtering the *preprocessed BOLD* time-series (using a discrete cosine filter with 128s cut-off) for the two *CompCor* variants: temporal (tCompCor) and anatomical (aCompCor). tCompCor components are then calculated from the top 5% variable voxels within a mask covering the subcortical regions. This subcortical mask is obtained by heavily eroding the brain mask, which ensures it does not include cortical GM regions. For aCompCor, components are calculated within the intersection of the aforementioned mask and the union of CSF and WM masks calculated in T1w space, after their projection to the native space of each functional run (using the inverse BOLD-to-T1w transformation). Components are also calculated separately within the WM and CSF masks. For each CompCor decomposition,

the *k* components with the largest singular values are retained, such that the retained components' time series are sufficient to explain 50 percent of variance across the nuisance mask (CSF, WM, combined, or temporal). The remaining components are dropped from consideration. The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. The confound time series derived from head motion estimates and global signals were expanded with the inclusion of temporal derivatives and quadratic terms for each (Satterthwaite et al. 2013). Frames that exceeded a threshold of 0.5 mm FD or 1.5 standardised DVARS were annotated as motion outliers. All resamplings can be performed with *a single interpolation step* by composing all the pertinent transformations (i.e. head-motion transform matrices, susceptibility distortion correction when available, and co-registrations to anatomical and output spaces). Gridded (volumetric) resamplings were performed using antsApplyTransforms (ANTs), configured with Lanczos interpolation to minimize the smoothing effects of other kernels (Lanczos, 1964). Non-gridded (surface) resamplings were performed using mri_vol2surf (FreeSurfer).
Many internal operations of *fMRIPrep* use *Nilearn* 0.5.2 (Abraham et al. 2014, RRID:SCR_001362), mostly within the functional processing workflow. For more details of the pipeline, see the section corresponding to workflows in *fMRIPrep*'s documentation."

fMRIPrep generated a json file with motion and other nuisance regressors. We used the denoiser package from Arielle Tambini and colleagues (github <dot> com/arielletambini/denoiser) to remove the following ten nuisance regressors: CSF, white matter, standardized DVARS, framewise displacement, and 6 motion regressors.

2.1.6 Univariate Analysis

The preprocessed images were entered into a general linear model (GLM) using FSL. The model included regressors for event-paired trials, control (no event) trials, and event-paired trials and control trials parametrically modulated by the subjective value of the chosen item, independently calculated for event trials and control trials. For the first analysis, the regressors of interest were event-paired trials and control (no events) trials with the primary contrast of interest being event-paired greater than control. In the second analysis of interest, we parametrically modulated the event-paired and control trials by the subjective value of the chosen item independently calculated for each trial type as described above. The contrast of interest for this analysis was event-paired subjective value greater than control subjective value.

2.2 Results

2.2.1 Paired-episodic Events and Discounting Behavior

Using a linear mixed effects model using the lmer function in R, we find a significant main effect of trial type (*b* (unstandardized coefficients reported here and hereafter)=-0.048, 95% CI [-0.071, -0.023]), a small but significant main effect of age (*b*=-

0.002, 95% CI [-0.003, -0.001]), and a small but significant interaction (*b*=0.0008, 95% CI [0.0004, 0.001]), see Figure 2a.

Using percent sooner choice revealed a main effect of trial type (event-paired vs. control; *b* = -0.10, 95% CI [-0.15, -0.05]), a small age effect (*b* = -0.0045, 95% CI [-0.008,-0.001]), and a small age by trial type interaction (*b* = 0.002, 95% CI [0.0009,-0.0027]), see Figure 2b. We tested robustness in a larger sample (n=43) which included subjects with a poor model fit for square root k. With these additional subjects, the same linear mixed effects model using percent sooner choice as a measure of discounting revealed a main effect of trial type (event-paired vs. control; *b* = -0.08, 95% CI [-0.13, -0.03]), non-significant main effect of age, (*b* = -0.003, 95% CI [-0.007, 0.0003], as well as a very small age interaction (*b* = 0.0013, 95% CI [0.0004, 0.002], see Figure 2d. Using a linear mixed effects model for the sample including poorly fit k using k as a measure of discounting, we found a non-significant main effect of condition (*b*= -0.01, 95% CI [-0.03, 0.001], a significant, though very small, main effect of age (*b* = -0.00046, 95% CI [-0.00082,-0.0001]) and a small but significant interaction between trial type and age (*b*=0.0003, 95% CI [0.00001, 0.0005]). Upon inspection, the effect is driven by older adults who are more impatient during event-paired trials compared to control trials (see Figure 2c).

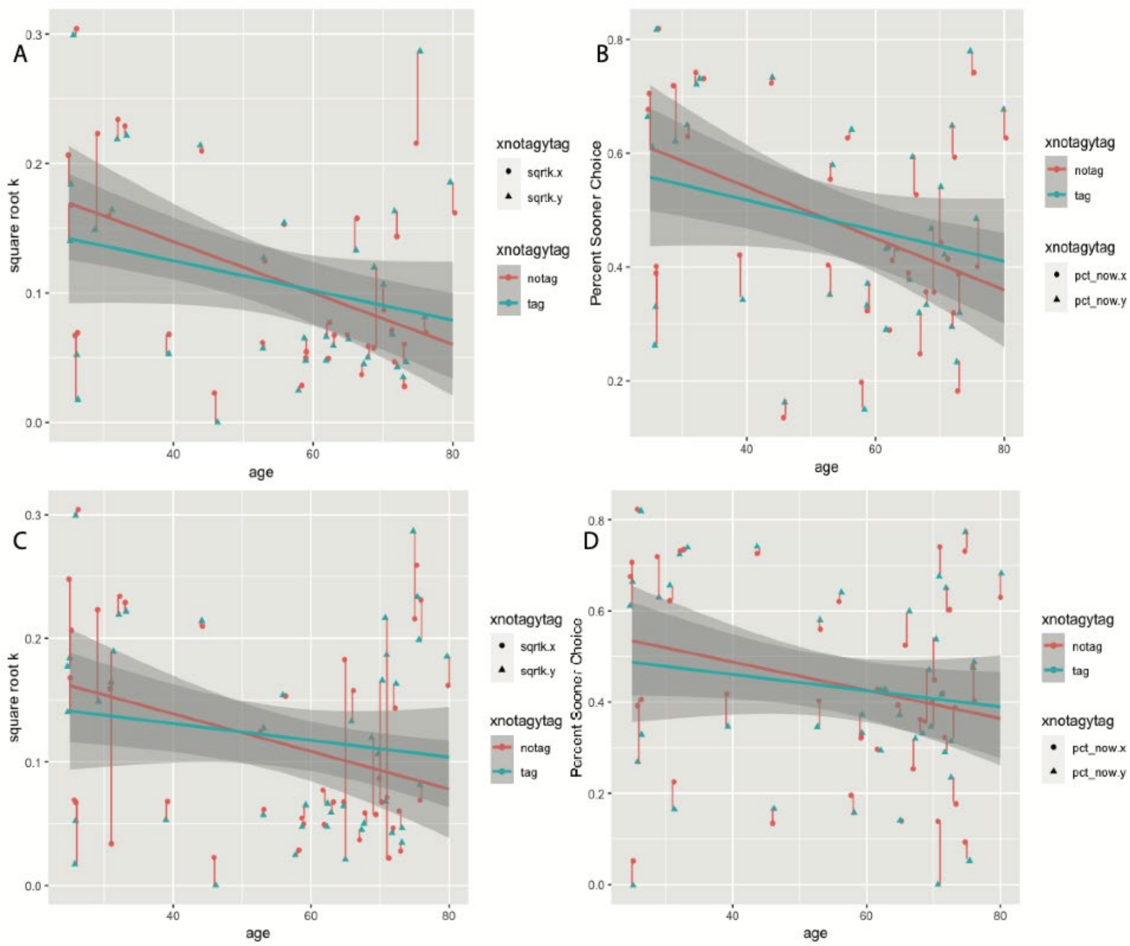

Figure 3: The association between the tag effect on discount rate across adulthood. A. In the sample with well-fit k data, there is a main effect of age, a main effect of trial type, and an interaction between age and trial type, in which the tag effect in younger adults is not present in older adults. B. These same effects are consistent when using a simpler measurement of discounting, percent choice. C. The k results are not robust to inclusion of poorly fitting subjects, as the trial type main effect is not significant in this model. D. However, both main effects and the interaction, though weaker, are significant when percent choice is the dependent variable with the larger sample.

2.2.2 Paired-episodic Events and the Brain

The contrast event-paired greater than non-event-paired using a z-statistic threshold of 3.1, cluster-corrected at $p < .05$, identified several regions of the default mode network including the posterior cingulate cortex, retrosplenial cortex, ventromedial prefrontal cortex, orbitofrontal cortex, and lateral parietal cortex (specifically angular gyrus). There were additional clusters in middle temporal gyrus and visual cortex which may be due to task demands of viewing and reading cues as opposed to engaged imagination. Specifically, there was greater activation in all of these regions for event-tagged trials compared to control trials.

Using the contrast event-paired SV greater than non-event-paired SV and a z-statistic threshold of 3.1 cluster-corrected at $p <.05$, there were no significant effects. That is, subjective-value-related activity did not vary across the event-tagged and control trials.

Table 1: Significant clusters for the contrast of episodic event-tagged trials greater than control trials. Z-statistics (Max Z) and MNI coordinates (X, Y, Z) for peak voxels within clusters.

Brain Region	Cluster size (voxels)	P	Max Z-statistic	X	Y	Z
Precuneus/PCC	2351	<0.001	6.6	-4.5	-54.5	15.5
Angular Gyrus (L)	904	<0.001	5.49	-42.5	-66.5	27.5
Lingual Gyrus	470	<0.001	5.45	3.5	-84.5	-6.5
Middle Temporal Gyrus (L)	71	0.003	4	-62.5	-0.5	-18.5

Middle Temporal Gyrus (L)	71	0.003	4.44	-60.5	-44.5	-8.5
Orbitofrontal Gyrus (L)	67	0.004	5.68	-38.5	35.5	-14.5
vmPFC	46	0.03	3.84	-6.5	59.5	-10.5

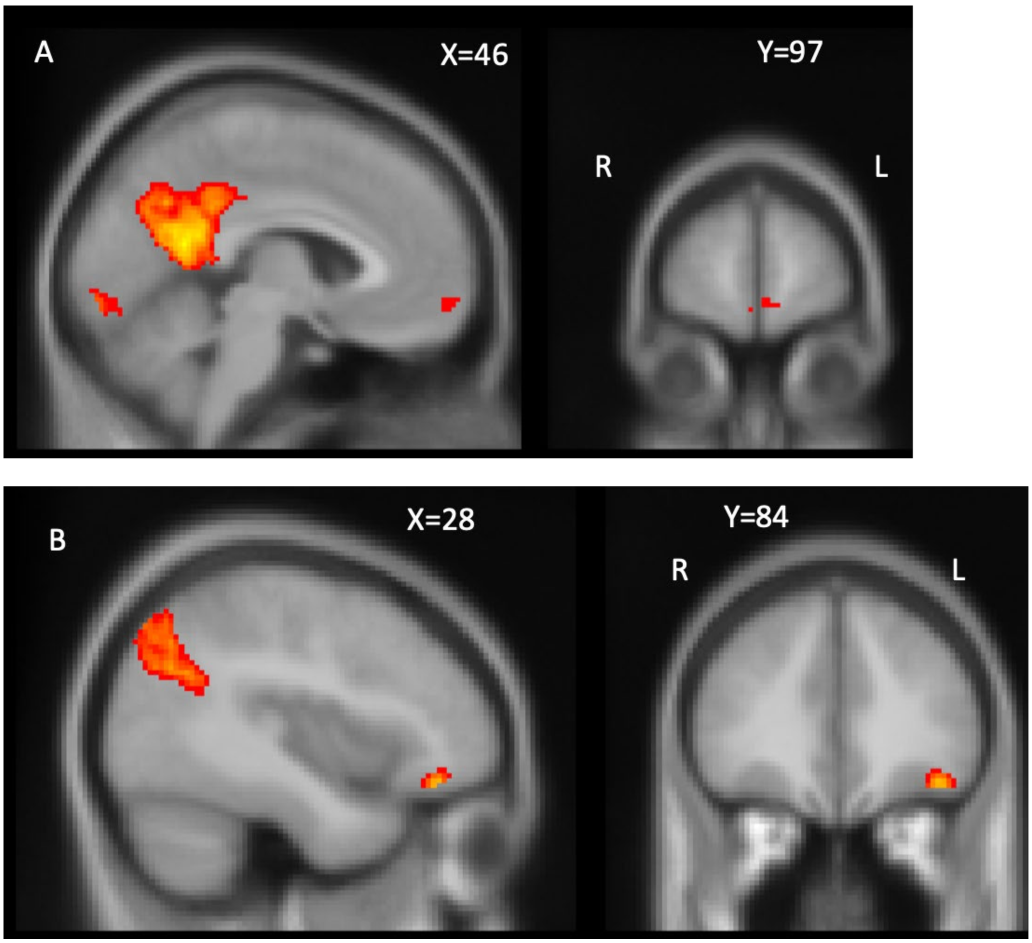

Figure 4: Main clusters from tag trials greater than no-tag trials contrast. These clusters are canonically part of the default mode network. Panel A includes the PCC/Retrosplenial cortex cluster and the mPFC cluster. Panel B includes the OFC cluster and the angular gyrus cluster

2.3 Discussion

Here we replicate the finding that pairing events with intertemporal choices promotes future oriented choice compared to trials that are unpaired. We find a smaller overall effect than previous studies, but our lifespan sample conforms to trends seen in the literature (Sasse et al., 2017). The lack of a tag effect in older adults in our sample is perhaps not surprising given that older adults showed lower levels of time discounting in the control condition. Across trials types, we found a significant reduction in discounting across adulthood in our sample. This is mostly consistent with a large meta-analysis of discounting in aging which finds very small to no age-related reductions in time discounting across hundreds of thousands of participants (Seaman et al., 2020). The lack of a tag effect in older adults is disappointing because the rehearsal strategies prior to scanning were intended to provide semantic scaffolding for older adults to rely upon during tag trials in the hope of enhancing the tag effect in older adults. Sasse et al. (2017) found that older adults with a larger tag effect also had more flexible attentional control measured by being better at responding to a target which was the same color as distractors on some trials. Our study did not include these measures, so we cannot evaluate the consistency of this potential moderator.

There are several possible reasons why we did not find the behavioral effect. First, neuroimaging studies of the tag effect with events from the future typically use titrated choice sets (e.g. Benoit et al., 2011; Peters & Büchel, 2010). With titrated choice sets, most choices are at an individual's indifference point, so additional information from the imagined event may provide the necessary evidence boost to induce a future oriented choice. However, in our study with a fixed set of choices across the decision space, imagined events may have less of an impact on choice behavior when there are fewer choices near the indifference point. Given the small but consistent effect of tags in previous studies, this explanation seems plausible. One potential implication of this work is that imagining future events may promote future-oriented thinking only for difficult intertemporal choices.

The neuroimaging analyses replicated past finding that regions of the default mode network increase in activity during trials that involve imagining future events. This neural finding of greater activation in posterior cingulate cortex, retrosplenial cortex, angular gyrus, ventromedial PFC, and the orbitofrontal cortex suggests that participants were indeed doing the task as instructed and provide suggestive evidence for enhanced engagement of episodic memory during the event-tagged trials. Phenomenologically, participants also reported imagining the events during the scan session based on post-task qualitative data.

Even though the neuroimaging analyses suggested that the tags effectively increased default mode network activity across age groups, the older adults showed a smaller effect of the event tags. Exploratory individual difference analyses evaluated whether individuals who showed the largest enhancement of default mode activity on tagged trials also showed the largest behavioral effects of tags. Unfortunately, this analysis did not identify any significant individual difference effects.

A final consideration is whether our manipulation of rehearsing events three times each prior to the scan in order to semanticize these events led to a decrease in the tag effect during scanning. Since some previous studies using semantic control conditions find that semantic tasks do not convey the advantages of episodic future thinking, this may be a possible explanation for our smaller effect here and continued lack of an effect in older adults (Benoit et al., 2011; Zhang et al., 2018). Given the neural finding of the default mode network during event trials, this seems unlikely. However, we cannot conclude either for or against this hypothesis given the null finding and the lack of a control group.

Overall, the current study generally supports the existing literature in the existence of the tag effect, but does not provide evidence that rehearsing events multiple times before making choices has any influence on the choices that individuals make. This corresponds to findings that episodic detail does not explain the relationship between imagination and choice and potentially extends this explanation into semantic memory. In a previous study on the tag effect, the affective experience of imagined events explained some of the relationship between imagination and choice (Benoit et al., 2011). In the next chapter, I explore how the content of an imagined event, either positive successes or negative failures, influences time discounting.

3. Effects of an Emotional Induction on Time Discounting

In the previous chapter, we replicated the finding that imagining the future can shift discount rates for younger adults. Participants engaged in the imagination process, as evidenced by greater engagement of regions of the default mode network during event-paired trials in contrast to control trials. As detailed in the introduction, much of the literature on the function of imagination and its potential role in decision making has focused on future-oriented thought (Benoit et al., 2011; Peters & Büchel, 2010). However, work in mind-wandering has found that merely engaging in self-reflection, which involves autobiographical memory, can promote later future-oriented thinking during a task where participants were interrupted and probed about the content of their mind-wandering (Smallwood et al., 2011). This suggests that an intervention to promote greater future-orientation during a subsequent task of interest need not be future oriented itself. Indeed, Lempert and colleagues (2017) found that cueing positive autobiographical memory decreased discount rates relative to control trials without cues. Importantly, this intervention included several choices after the cue (or after the non-cue) as opposed to the studies like the one in chapter 2 with explicitly paired trials (Lempert et al., 2017). A potential confound arises, however, due to the possibility that the autobiographical engagement might lead to a mood induction which may mediate or moderate the relationship between imagination and discounting.

Incidental emotional valence can influence decision making behavior (Lerner et al., 2015). However, incidental emotional valence by itself can have differing effects. For example, positive valence may increase impatience in extraverted individuals (Hirsh et al., 2010) or when using picture cues instead of memory cues (Lempert et al., 2017). Meanwhile positive valence leads to greater patience in other samples (Ifcher & Zarghamee, 2011; Pyone & Isen, 2011). Further research has demonstrated that positive valence on its own may be insufficient to cause reliable differences, but that different categories of emotion may specifically lead to different choice behaviors (DeSteno et al., 2014). Specifically, when using autobiographical memory cues, gratitude, but not happiness, led to more patient choices in an intertemporal choice paradigm (DeSteno et al., 2014). However, general positive autobiographical memories and future events, presumably spanning different types of positive emotions, have also been found to lead to more patient choices in an intertemporal choice paradigm (Ballance et al., 2020; Bulley et al., 2019; Lempert et al., 2017; Liu et al., 2013; Zhang et al., 2018). Overall, the findings are relatively mixed.

The relationship between negative emotion and discounting is even less clear. Some studies find that negative emotion leads to more impatient behavior (S. Guan et al., 2015; Lerner et al., 2012; Liu et al., 2013; Zhang et al., 2018). Lempert et al. (2017) found that negative emotional memories had no influence on time discounting. Still other studies have found that imagining negative future events leads to more patient choice (Ballance et al., 2020, Bulley et al., 2019). Like with positive emotions, the variability may be explained in a variety of ways. For example, different categories of negative emotion may have opposite effects on choice preferences (Lerner et al., 2012; Luo et al., 2014).

With little consistency in the field with regard to how mood and emotional memory influence decision making, we sought to explore whether imagining successes or failures from an individual's past, which should reflect an individual's general self-efficacy and also carry a specified valence, would lead to different discount rates. Two studies evaluated effects of emotional memory on choice. The second study added a neutral picture description condition and used a validated adaptive choice set (Toubia et al., 2013) to evaluate emotional memory effects.

3.1 Study 2A

3.1.1 Method

3.1.1.1 Participants and Procedures

253 participants of various ages (age: M=50.6, sd=18, range= 20-85) were recruited using Qualtrics Panels. Participants first responded to questionnaires assessing visualization ability (VVIQ: Marks, 1973) and general self-efficacy (Schwarzer & Jerusalem, 1994). The measure of visualization ability was included as an exploratory additional variable related to imagination that may be related to decision making. The measure of self-efficacy was included as another measure that might be associated with

an individual’s ability to make prospective, long-term decisions. Using a two group between subjects design, participants either were instructed to imagine two successes from their life or two failures from their life. Specifically, for failures they were asked to “visualize a past event in your life where you were disappointed and/or ashamed of yourself. Perhaps you fell short of your objectives, or failed to complete a task.” For successes, they were asked to “visualize a past event in your life that conjures up feelings of pride and/or personal success. Perhaps you achieved something great or contributed in a meaningful way.” In both groups, participants were then instructed to “describe the event in as much detail as possible. For example, describe the colors, people objects, emotions, and so forth.” After imagining both events from their lives, they rated each of these events on the “feeling” and “intensity” scales (Lempert et al., 2017). Feeling measured how the event made them feel from “very bad” to “very good” on a seven point scale, while intensity measured how intense they found the event on a four point scale from not intense to very intense (Lempert et al., 2017). Participants then responded to 51 trials of intertemporal choices where they made decisions between smaller amounts of money now and larger amounts of money later (Senecal et al., 2012). This is the same choice set and task (without tags) used in Study 1 (Chapter 2) above. For this study, discounting was measured by calculating the percentage of larger-later choices were selected by each participant.

3.1.2 Results

For the primary analysis of interest, there was no significant difference in time discounting rate between the group that imagined successes and the group that imagined failures (t_{249}=-1.51, *d*=0.190, *p*=0.13), see figure 5. Specifically, the group that imagined successes showed the same preference for smaller, sooner rewards as the group that imagined failures. This effect was robust to removing 16 participants with questionable responses in their event descriptions ($t_{231.4}$=-1.12, *d*=0.146, *p*=0.26). There were no age differences in intertemporal choice in this study (*b*=0.001, p=0.4) and age did not interact with condition (*b*=-0.0005, p=0.8).

An exploratory analysis evaluated whether individuals who showed the strongest emotional responses during the imagination exercise, as assessed with feelings ratings, showed more of an effect on decision making that individuals who showed weaker emotional responses during imagination. There was no significant interaction between feeling ratings and condition on choice, (*b*= –0.014, *p*=0.5).

Additional exploratory analyses evaluated how visual imagery and self-efficacy were related to discounting as well as other measures in the study. The trait individual difference measure of visual imagery (VVIQ) was significantly correlated with average emotional intensity ratings (*r*=-.15, p=0.02), income (*r*=-.15, p=0.02), and self-efficacy (GSES) (*r*=-.44, p<0.001). Self-efficacy was correlated with average emotional intensity ratings (r=.14, p=0.025) and income (r=0.21, p<0.001). Visual imagery and self-efficacy were uncorrelated with time discounting, (r=0.045, p=0.5; r=0.029, p=0.7, respectively).

Given some limitations in the design of Study 2A, we completed another study that included a control condition and an adaptive choice set in the time discounting task.

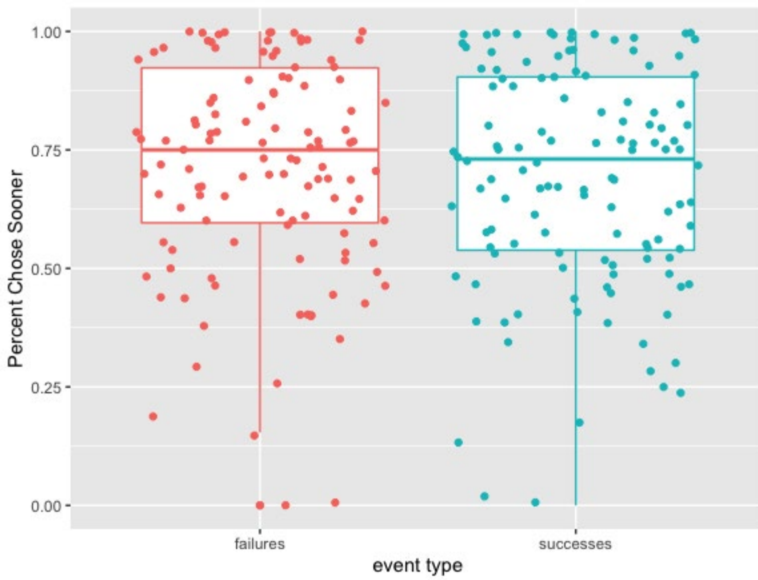

Figure 5: In study 2A, there was no significant difference in percent sooner options chosen between the imagine failures and imagined successes groups

3.2 Study 2B

3.2.1 Method

3.2.1.1 Participants and Procedure

380 young to middle-aged participants (age *M*= 33.67, *sd*=8.35, range=18-50) were recruited through Qualtrics Panels. 349 participants (age *M*=34.10, *sd*=8.18, range=18-50) were included in the time discounting analysis after participants were removed

automatically by the parameters set by the DEEPTime analysis package—exclusion reasons included excessive speed and systematic choices (e.g. all left or all right).

Table 2: Descriptive statistics for Study 2B

	Imagine Failures N=114	Neutral Pictures N=114	Imagine Successes N=121
Age (years) Mean (sd)	34.29 (8.64)	34.51 (7.70)	33.55 (8.21)
Gender Percent female	51.8%	49.1%	47.9%
Feeling (1-7) Mean (sd)	2.05 (1.14)	4.61 (0.90)	5.99 (1.06)
Intensity (1-4) Mean (sd)	3.11 (0.79)	2.29 (0.83)	3.20 (0.69)
Time discounting (square root k) Mean (sd)	0.13 (0.10)	0.14 (0.10)	0.13 (0.10)

The present study was packaged with another study for recruitment through Qualtrics. Participants first responded to questionnaires assessing visualization ability (VVIQ: Marks, 1973) and general self-efficacy (Schwarzer & Jerusalem, 1994) along with several questionnaires for the other study. The study was conducted as a three-group between subjects design, with three conditions: imagine successes, imagine failures, and describe neutral pictures. The neutral picture condition was adapted from Gaesser et al., 2011. The participant instructions for the two imagination conditions were identical to those in the equivalent conditions in Study 2A. For the neutral picture condition, participants were told, "In this part you will see a picture of an event or activity. In the text box, describe the picture in as much detail as possible. For example, describe the colors, people, objects, emotions, and so forth." Successes, failures, and neutral pictures corresponded to positive, negative, and neutral emotional valence, which can be seen in table 2. Participants then completed measures of time and risk preference using the DEEP risk and DEEP time questionnaires, which were presented in counterbalanced order (Toubia et al., 2013). Unlike the time discounting tasks used in the prior studies, DEEP uses an adaptive choice set to efficiently estimate an individual's discount rate.

3.2.1.2 Behavioral Analysis

DEEP uses a Markov Chain Monte Carlo process to estimate discount rates in a Bayesian framework (Toubia et al., 2013). However, with only twelve questions, there was no mixing of the Markov chains, which means that the model did not stabilize on the discounting estimates. Re-running the model, produced new estimates with different relationships among them each time. Furthermore, DEEP uses a beta-delta model to estimate discount rates instead of the simpler hyperbolic model that the rest of this dissertation relies on making comparisons across studies challenging. As a result, we used the same k estimation script from Study 2 to analyze the DEEP data. While the k estimation script we developed is more reliable than the DEEP model, we cannot guarantee its validity for the same reasons of a limited sample of only 12 questions.

3.2.2 Results

For the primary analysis of interest, there were no significant differences in time discounting between the group that imagined successes, the group that imagined failures, and the group that did not imagine, ($F_{2,346}$=0.47, p=0.6 η_p^2=0.003). Once again, there was no differential effect of condition such that participants in all conditions showed similar preferences for smaller, sooner rewards. There were no age effects, controlling for event type, (b=0.0019, p=0.07), and no interaction between either dummy-coded regressors for neutral vs. failures or successes vs. failures (b=-0.0022, p=0.2; b=-0.0016, p=0.3, respectively).

Additional exploratory analyses were conducted to understand the relationship between the content of what was being imagined and the effect on discounting. There were no main effects of group or feeling ratings and no interaction between group and feeling rating on time discounting (all ps>0.3, see Table 3).

Table 3: Regression table with time discounting as the independent variable

Predictor	Estimate (standard error)	*p*
intercept	0.13 (0.02)	<0.0001
neutral (relative to failures)	-0.04 (0.05)	0.4
successes (relative to failures)	0.01 (0.05)	0.8
feeling	-0.001 (0.008)	0.9
neutral*feeling	0.01 (0.01)	0.4
Successes*feeling	-0.002 (0.01)	0.9

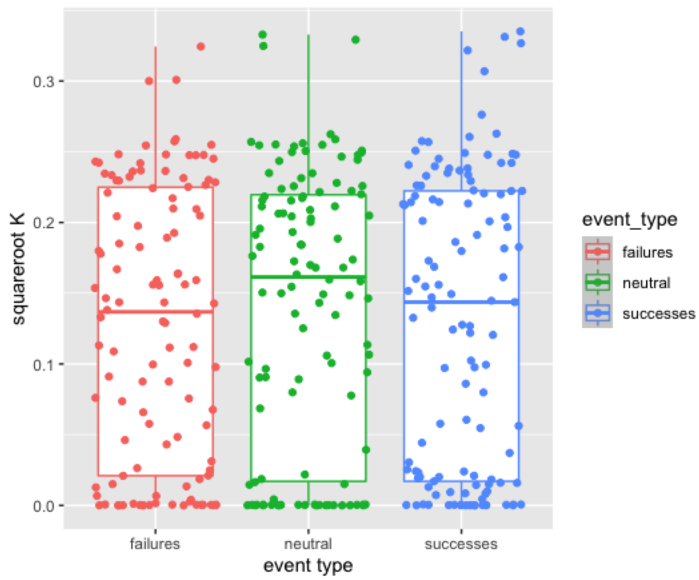

Figure 6: There was no significant difference in discounting across event types in Study 2B

3.3 Discussion

The findings across two studies suggest that emotional memories do not have a powerful influence on prospective decisions between monetary rewards available at different temporal delays. The lack of effects may be viewed as consistent with the broader literature which shows mixed to no effects of emotional memory and mood on choice. Our study found no evidence of a change in discount rates based on imagining successes or failures (Studies 2a & 2b), even when compared to a neutral non-imagining condition (Study 2b). While the largest studies of this topic have found small effects such that positive and negative events lead to decreased discounting (Ballance et al., 2021; Bulley et al., 2019), several studies have found evidence that remembering negative events contributes to greater discounting. For example, viewing a sad video and then writing a reflection on a sad event from your past led individuals to have greater discount rates when compared with individuals who did these tasks in a neutral and a disgust condition (Lerner et al., 2012). Likewise, transient negative emotion from IAPS pictures led to greater discounting compared to neutral or positive pictures (S. Guan et al., 2015). In two separate studies from the same research group, imagining negative future events led to greater discounting (Liu et al., 2013; Zhang et al., 2018). Why might we see an effect of negative memory, but not see the prospection boost predicted from both the imagination and mind-wandering literature? Memory and future thinking have been compared within the same study before. In a study involving food choices and discounting behavior, remembering the past was not as effective at reducing time discounting compared to imagining the future (Dassen et al., 2016). Given that the effects we are comparing our findings against tend to explicitly pair choices with imagination, it makes sense that block effects from a preceding imagination induction may show different effects. This is compounded by the lack of an overall effect of rehearsal training prior to scanning in chapter two.

There are also potential study design considerations that may explain differences in effects across studies. Previous studies of this phenomenon have used either between subjects or within subjects paradigms. Between subjects studies tend to use neutral imagery conditions (e.g. Ballance et al., 2021; Bulley et al., 2019). Within subjects studies often use unconstrained control conditions such as in the previous chapter (e.g. Chapter

2, Lempert et al., 2017, Peters & Büchel, 2010). However, our control condition was a neutral picture description condition. While this is similar to mood induction studies which may use pictures to induce emotional states, it is not necessarily the best comparison for two imagery conditions. There are two possibilities for why this may be the case. First, the hypothesis set out initially in this dissertation is that the engaging imagery and emotional valence are independent contributors to decision making. In our control condition we have manipulated both. The initial hypothesis was that this would lead to a double hit. Since previous between subjects studies have shown that neutral imagination leads to greater discounting than either emotional imagination condition, then we presumed to replicate that effect (Ballance, et al., 2021; Bulley et al., 2019). We also thought that imagination independently would lead to greater changes in discounting because of imagination performs better than non-imagination-based manipulations (Benoit et al., 2011). Future studies in this field ought to use two control conditions, a neutral imagine condition and a neutral description condition in order to determine whether the contributions of imagination and affect are independent determinants of choice.

The second study in this chapter attempted to use a different measure of time discounting that could more precisely estimate discount rates. Unfortunately, using this alternate task did not reveal any new effects of emotional memory on choice. More generally, this open source time discounting task used in Study 2B was challenging to analyze and produced unstable estimates of discount rates. This was especially disappointing given that the goal of this shared tool is to provide an accessible resource for the field. While we have concerns about the reliability of the discounting estimates in the second study, our own struggles with this instrument may lead to improvements in the DEEP algorithm or clarifications available for scientists interested in using this tool in the future.

Overall, our findings contribute to the general mixed findings of emotional memory on time discounting. While the question of the relative contributions to intertemporal choice differences of memory system engagement versus emotional impact of imagination remains an outstanding question, the small and often mixed results of these studies suggest that either the domain of choice or the type of manipulation may not be as promising a pathway for future human behavior change interventions. Given the small to inconsistent effects of various forms of imagination on classic laboratory-based intertemporal choice tasks, it could be more interesting for future research to expand the scope of studies both with respect to the measures of imagination and the measures of decision making. For example, career decision making is an important choice that individual’s make in everyday life which often requires balancing memory for one’s own skills and experiences with planning for a potential future where one might find value and reward.

4. Extending the Study of Imagination and Visual Imagery into the Domain of Career Decision Making

Much of the cognitive psychology and neuroscience work on imagination and its influence on human decision making has been in the domain of financial saving and investment or in self-control and food choice. These are discrete, and often regular, decisions which can have an impact on a long-term outcome. Some choices that we make are actually quite rare, but the impact on long-term outcomes can be similar or even greater than our financial or eating choices. For example, choosing whether to get married (and to whom) or which car to buy or what kind of career one might have. Imagination may play an even larger role in these choices since they are not simple binaries—they actually require an integration of options across time and place and into an unknown future. In fact, in the domain of counseling psychology, imagination, specifically guided imagery, has been studied for almost a century (Stoltz et al., 2018). According to Career Construction Theory (Savickas, 2005), career choices ought to coalesce around your individual values and goals. This framework mirrors a similar construct that has been studied in the financial domain with much success—future self-continuity, the degree to which one feels connected to their future self (Ersner-Hershfield et al., 2009a; Ersner-Hershfield et al., 2009b). In those studies, greater future self-continuity predicts future-oriented choices including saving more for retirement (Ersner-Hershfield et al., 2009a; Ersner-Hershfield et al., 2009b). In Career Construction

Theory, when choosing careers, individuals ought to be able to generate a narrative about themselves which connects their current and long-term values to their career choices and outcomes (Savickas, 2005). This contrasts to a traditional career approach which follows a static ladder, where an individual enters on the bottom rung and ascends in that role—an approach that centers the job as opposed to the individual—and which does not correspond with the flexible transitions necessary for the information age (Savickas et al., 2009).

Beyond imagination, there are a number of additional factors that contribute to successful career outcomes. For example, Meijers & Lengelle (2012) review cases where career-seeking individuals use different narrative techniques. Likewise, in their work exploring career anchors and career orientations which refer to a more static and a more flexible, respectively, perspective on their career identity, Rodrigues et al. (2013) identify that individuals may hold multiple orientations towards careers and that these orientations can change over time. According to one of the most prominent models of career decision making, the social cognitive career theory, there are two primary drivers of successful career decision making: self-efficacy and outcome expectations (Lent et al., 1994; Lent & Brown, 2013). In a separate line of work, self-efficacy has been found to be correlated with visual imagery using an adapted version of the VVIQ (McMichael et al., 2021). Given this finding and the long history of using guided imagery as a career counseling technique, the relationship between visualizing ability and career choice may provide a potential avenue for identifying individuals who may benefit more from guided imagery as a counseling technique.

Three studies evaluated the potential roles of guided imagery, visual imagery abilities, self-efficacy, and other psychological factors for making career decisions. In the first study (Study 3), participants either imagined a career that they preferred or a known career, a college professor, that was selected for them. Change in preference for imagined careers and non-imagined careers were computed. I hypothesized that prompting imagination of a novel career option would facilitate students' openness to that as a possible career. In a second set of studies (Studies 4a & 4b), we explored how visualizing ability (Marks, 1973), general self-efficacy (Schwarzer & Jerusalem, 1994), and other covariates might show a multivariate association with a set of career variables including career self-efficacy (Lent et al., 2016), career exploration behaviors (Stumpf et al., 1983), and future work self salience (Strauss et al., 2011). The overall goal of this set of studies was to better link cognitive and social psychological measures and approaches with theories in the counseling psychology literature.

4.1 Study 3

4.1.1 Method

In this pilot study, 48 students responded to a short survey during a lecture for an undergraduate course at Duke University. Students were asked to generate an ideal career that they would like to pursue. This career was contrasted with the default option of a career as a college professor. Students first rated how much they knew from experience about their preferred career and a college professor. They then rated their own preferences for these careers and how easily they could imagine themselves in those careers. Next, students were assigned to either the imagine ideal career condition or the imagine professor condition in which they did a short, guided imagery exercise based on the future work-self salience scale (Strauss et al., 2011). After responding the VVIQ (Marks, 1973) and the CSES (Lent et al., 2016), students then re-rated their career preferences and how easily they could imagine those careers.

4.1.2 Results

There were no significant group differences between those who imagined being in their ideal career or imagined being a professor in visual imagery ability ($t_{38.53}$=-0.949, d=0.28, p=0.3), career self-efficacy ($t_{33.83}$=-0.190, d=0.06, p=0.9), or future work-self salience ($t_{37.97}$=1.66, d=0.50, p=0.1). Measuring the difference between individuals' preference for the imagined option and for the non-imagined (control) option, we found no significant difference from pre-imagination to post-imagination (t_{46}=1.07, d=0.16, p=0.3), see figure 7.

We then investigated the differences in preferences for the different career options regardless of whether they imagined being in their ideal career or being a professor. Here we found no significant differences in the change in preference for their ideal career from pre-imagination to post-imagination collapsing across the groups that imagined being in their ideal career or being a professor ($t_{44.67}$=-0.78, d=0.22, p=0.4) nor for the change in preference for college professor from pre-imagination to post-imagination collapsing across the groups that imagined their chosen career or a professor ($t_{40.77}$=0.49, d=0.14, p=0.6). There was also no difference between participants' change in how easily they could imagine career options regardless of whether they imagined the career option or not, (t_{47} = -0.26, d=0.037, p=0.8).

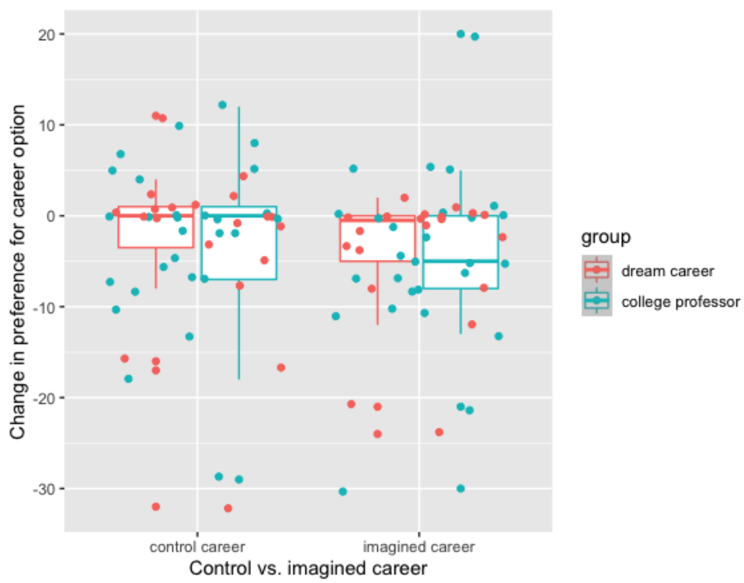

Figure 7: There was no significant difference between the change in preference for control career and imagined career.

We then investigated the relationship between change in career preferences and groups (imagine professor vs. imagine ideal career) in a linear model. The change in the preference for college professor was predicted by the change in preference for the ideal career (b=0.79, p=0.004), but there was no group effect (i.e. imagine professor vs. imagine ideal career) (b=-3.38, p=0.2) nor interaction between ideal career preference and group (b = -0.36, p=0.3). The overall model was significant and predicted 20% of the variance in the change in preference of the professor (Adjusted R-squared=0.20, p=0.005). However, this model was not significantly better than the simple model with only change in preference for the ideal career as a predictor (model 2: b=0.54, p<0.001, Adjusted R-squared=0.20; comparison: p=0.4).

Given the hypothesized role of emotion during imagination in decision making tasks as described in Chapter 3, we conducted exploratory analyses to evaluate whether the degree of enjoyment of the imagined career event predicted a change in the preference for the professor option when controlling for the known predictor of change in preference for their chosen career. Even when controlling for chosen career, there was a significant effect of degree of enjoyment on the change in preference for the career option (b=3.88, p=0.009). Furthermore, the overall model which included a group by enjoyment interaction term, was also a better model than the simple model with only change in preference for the chosen career (Adjusted R-squared: 0.32; comparison: $F_{42,3}$=3.69, p=0.02). Using a mixed effects model to examine whether controlling for within group variance altered this finding, enjoyment of imagined careers was still a significant predictor of change in career preference across imagination vs. control and group (b=2.1, 95% CI [0.42, 3.70]).

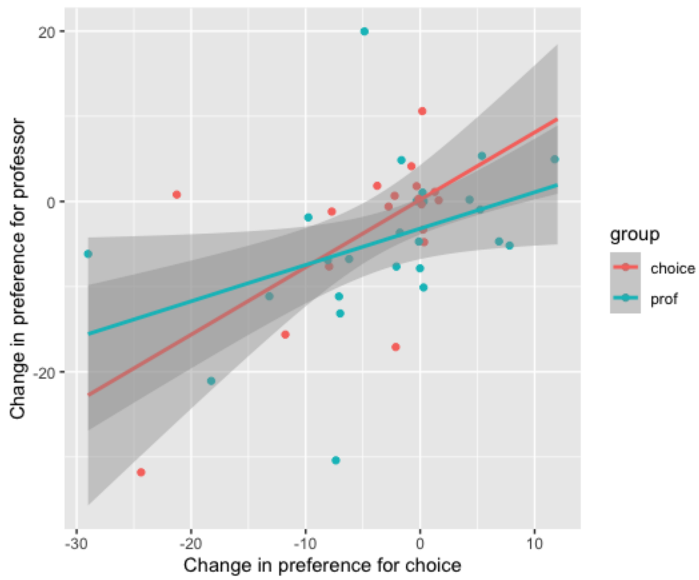

Figure 8: The greatest predictor of a change in preference for college professor as a career is the change in preference for their chosen career. There was no significant interaction with the content of career imagined.

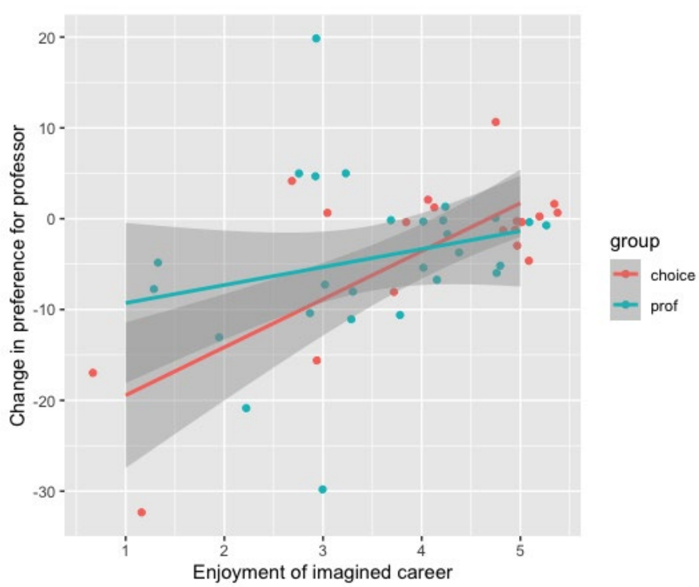

Figure 9: Enjoyment of imagined career also predicted change in preference for professor when controlling for change in preference for their chosen careers. Note, however, that most of the change is values are negative, suggesting that less enjoyment of imagined events led to a decrease in preference after imagination. There was not a significant interaction with group.

4.2 Study 4A and 4B

4.2.1 Method

4.2.1.1 Participants

104 participants (age: *M*=33.1, *sd*=9.1, range=18-50; 52 female) recruited through Qualtrics panels responded to a series of questionnaires. 21 participants were dropped from analysis due to failing to properly respond to reverse coded items. Therefore, data from 83 participants were used in the analysis.

4.2.1.2 Measures

4.2.1.2.1 Vividness of Visual Imagery Questionnaire (Marks, 1973)

VVIQ (Marks, 1973) is a measure of visual imagery ability with 16 items where participants are asked to imagine four scenarios (e.g. visualize a rising sun) and focus on 4 different elements for each scenario (e.g. the sky clears and surrounds to sun with blueness). Participants rate the the vividness of each image on a five-point scale ranging from no imagery at all (1) to "perfectly clear and lively as real seeing" (5).

4.2.1.2.2 General Self-Efficacy Scale (Schwarzer & Jerusalem, 1994)

General self-efficacy scale (Schwarzer & Jerusalem, 1994) is a ten-item questionnaire that assesses levels of optimistic self-belief for general goals (e.g. "I can always manage to solve difficult problems if I try hard enough"). Participants respond on a four-point scale of agreement from not at all true (1) to exactly true (4).

4.2.1.2.3 Future time perspective (Carstensen & Lang, 1996)

Future time perspective (Carstensen & Lang, 1996) is a measure of how people feel about their futures (e.g. "There is plenty of time in my life to make new plans" or "I have the sense time is running out"). Participants respond on a seven-point scale ranging from very untrue (1) to very true (7). The satisfaction with life scale (Diener et al., 1985) is a five-item scale that measures individual's perception of their well-being (e.g. "If I could live my life over, I would change almost nothing"). Participants respond on a seven-point scale from strongly disagree (1) to strongly agree (7).

4.2.1.2.4 Future self-continuity (Ersner-Hershfield et al., 2009b)

Future self-continuity (Ersner-Hershfield et al., 2009b) is a measure of the degree to which individuals feel connected to their future selves. This was assessed with a single item where participants selected one of seven pairs of concentric circles which represented their current self and future self and the degree of overlap that they felt between these two selves.

4.2.1.2.5 Career self-efficacy (Lent et al., 2016)

The Career Exploration and Decision Self-Efficacy scale (Lent et al., 2016) is an eight-item scale that measures an individuals confidence in their ability to explore and make decisions about potential careers (e.g. "How much confidence do you have in your ability to make a well-informed choice about which career path to pursue?"). Participants rated on a 10 point scale ranging from no confidence at all (0) to complete confidence (9).

4.2.1.2.6 Career exploration behaviors (Stumpf et al., 1983)

The career exploration survey (Stumpf et al., 1983) is a 59-item scale which assesses a variety of sub-constructs related to individual's exploration of potential careers. For the purposes of our studies, we focused on two subsections: environment exploration and self-exploration. The environment explorations questionnaire includes six items, and asks "to what extent have you behaved in the following ways over the last 3 months?" Participants responded on a five-point scale from little (1) to a great deal (5) on items such as "sought information on specific areas of career interest." The self-exploration questionnaire includes five items, and asks "to what extent have you done the following ways over the last 3 months?" Participants responded on a five-point scale from little (1) to a great deal (5) on items such as "understood a new relevance of a past behavior for my future career."

4.2.1.2.7 Future work- self salience (Strauss et al., 2011)

Future work-self salience (Strauss et al., 2011) assesses the ease with which participants' can imagine their future careers. It is a three-item questionnaire of statements such as "the mental picture of this future is very clear." Participants rate their agreement with the statements on a five-point scale from strongly disagree (1) to strongly agree (5).

4.2.1.3 Analysis

Using the yacca package in R, we performed a canonical correlational analysis exploring the multivariate relationships between a set of non-career variables self-efficacy and VVIQ (as well as future time perspective, satisfaction with life, and future self-continuity) and a set of career outcomes (career self-efficacy, future work salience, and career exploration behaviors).

In Study 4B, 380 participants responded to the same set of questionnaires as study 4A in a pre-registered replication. The data was analyzed using the same CCA framework and package.

4.2.2 Results

In study 4A, using a canonical correlational analysis, we found that there was a significant overall model effect, driven entirely by the first canonical function (Bartlett's Chi Square test: X^2=100, p<0.0001). The canonical correlation between the two sets for the significant canonical variable was 0.84, see figure 10. Inspection of the structural coefficients suggests that self-efficacy, VVIQ, SWLS, and future time perspective are the contributors from the predictor variable set and career self-efficacy and future work salience are the contributors from the criterion variable set, see Table 4.

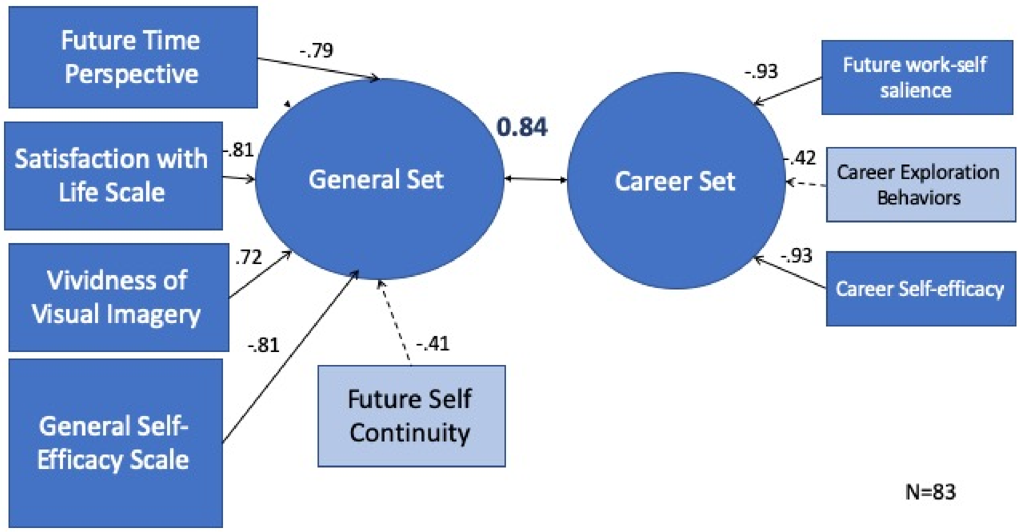

Figure 10: The canonical correlation between the sets and the structural coefficients (loadings) of the measures onto the canonical variables

Table 4: Canonical variate coefficients and structural coefficients (loadings) for Study 4A

Variable	Coefficient	Structural coefficient (r_s)
General Set		
Visualizing Ability	0.021	0.72
General Self-efficacy	-0.055	-0.81
Future Time Perspective	-0.032	-0.79
Future Self-Continuity	-0.053	-0.41
Satisfaction with Life	-0.046	-0.81
Career Set		

Future work-self salience	-0.178	-0.93
Career Exploration	-0.004	-0.42
Career Self-efficacy	-0.041	-0.93

We were surprised to find that career exploration did not load onto the criterion variable set. Therefore, we ran two exploratory CCAs using subsamples of individuals who either expect to change jobs (n=46, career exploration r_s =-0.50) or those who do not (n=31, career exploration r_s =-0.32).

In study 4B, a preregistered replication, we again found a significant canonical correlation driven entirely by the first canonical variable (Bartlett's Chi Square test: X^2=362, p<0.0001). The canonical correlation between the two sets for the significant canonical variable was 0.79, see figure 11. We confirmed the general structure of the canonical function, with career exploration behaviors loading onto our criterion variable set, in contrast to the previous study, see figure 11 and table 5. This supports the relationship between general cognitive and motivational factors and career beliefs.

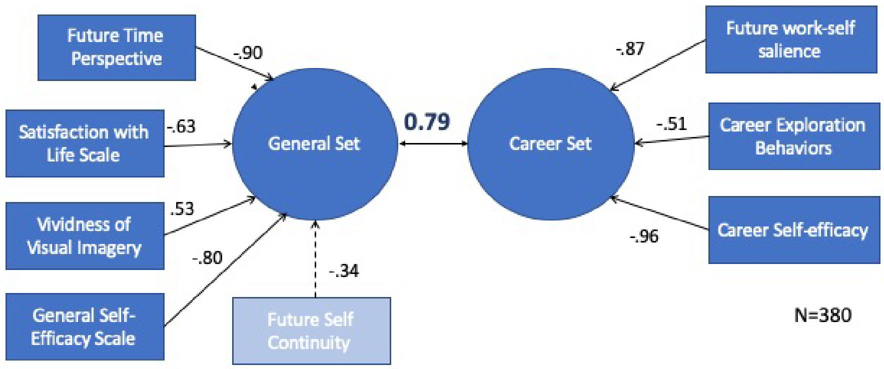

Figure 11: The correlation between the canonical variables and the structural coefficients (loadings). In this larger sample, career exploration behaviors also loaded onto the career set

Table 5: Canonical variate coefficients and structural coefficients (loadings) for Study 4B

Variable	Coefficient	Structural coefficient (r_s)
General Set		
Visualizing Ability	0.013	0.53
General Self-efficacy	-0.056	-0.80
Future Time Perspective	-0.054	-0.90
Future Self-Continuity	-0.070	-0.34
Satisfaction with Life	-0.019	-0.64
Career Set		
Future work-self salience	-0.124	-0.87
Career Exploration	-0.008	-0.51
Career Self-efficacy	-0.039	-0.96

4.1.3 Discussion

We found that the best predictor of a change in the preference for the college professor, novel career option, was a change in the preference for student's ideal career. This was true independent of whether they did a brief guided imagery exercise. This may indicate that the imagination procedure had little impact on their preferences. Indeed, the tight coupling of preferences for their preferred career and the given option of professor suggests that participants anchored on one or the other in determining their ratings. Likewise, when collapsing groups into an imagined career and a control career, there was no difference in the change in preference between the imagined career option and the control career option. However, we did find a significant effect of enjoyment of what they imagined which contributed to the change in preference for the given option of professor even when controlling for the change in preference for their chosen career. The model including both of these terms (and a non-significant interaction term with which career was imagined) explained over 30% of the variance of the change in preference for career. This is actually quite impressive and suggests an affective component may be at play in this preference shift. Emotion has historically been understudied in field of vocational decision making (Emmerling & Cherniss, 2003; Hartung, 2011). In one study, job search behaviors were increased in individuals who expressed more positive emotion, but this did not translate to more submissions of resumes to jobs (Kim & Lee, 2021). Similarly, positive emotions were not related to resumes submitted or early job success, but was related to actually securing employment (Turban et al., 2009). Interestingly, previous research has found that though positive affect influences job clarity, a predictor of later success, negative affect has no influence on career behaviors (Côté et al., 2006). However, in our study, the effect of imaginative enjoyment predicting change in preference was driven by a relationship between lower enjoyment and decreased preference. Our measure of change in preference for career, however, is different from previous behavioral measures.

As a result, we sought to explore the relationship between a set of measures of self-efficacy, well-being, future time perspective, and visualizing ability to determine how they related to a set of common attributes of career decision making. We found that in a small exploratory sample, visualizing ability, well being, general self-efficacy, and future time perspective were related to the more cognitive attributes of career decision making, but not with the action of career exploration behaviors. In a larger sample, we found the same set of general variables were related to the entire set of career variables including the active exploration of potential careers. Surprisingly, in both the exploratory and confirmatory samples, future self-continuity, a construct that seems particularly relevant to career decision making and which has been studied as a co-variate in the career literature previously, did not load onto the canonical variable. Given the way that CCA computes linear combinations across the sets of variables, it may simply be that future self-continuity does not load well onto the general variable set that we included it in. Importantly, our analysis confirms that well-being and general self-efficacy are related to attributes that lead to successful career decision making. Even more excitingly, visualizing ability which is a feature of imagination, also contributed to the shared variance of the general set on the career set. While previous studies have used structural equation modeling to determine relationships between career-relevant latent and measured variables (e.g Cabras & Mondo, 2018), this pair of studies used a canonical correlational analysis to explore the relations between sets of variables. In particular, this pair of studies adds visualizing ability, a basic feature that can contribute to imagination. This might explain a mechanism for how guided imagery supports career decision making. Overall, though study 3 suggests that imagination may not lead to changes in preference on its own, studies 4A and 4B suggest that one's visual imagery ability has a role in the career decision making process.

5. Conclusion

The principal aim of this dissertation was to identify how imagination supports future-oriented, value-based decision making. In the first two empirical chapters, I examined the limitations of how different features (temporal focus and emotional valence) contribute to changes in discounting behavior during intertemporal choices. In the fourth chapter, I explored whether imagination leads to preference changes in different career options and explored a framework of career decision making that integrates imagery ability and general self-efficacy and well-being into more traditional measures that contribute to career decision making. Overall, this dissertation suggests caution for imagination as an intervention on its own in simple lab-based financial decisions and career decision making, but that the capacity for imagining might be particularly relevant for younger adults as a part of a suite of decision making tools to aid in difficult choices.

In Chapter 2, we replicated the effect of imagining future events on time discounting in younger adults, but also found an interaction such that the effect did not persist into older adulthood. This was despite the addition of extra pre-scan rehearsal of the paired events which was intended to lead to greater semanticization of these imagined events. Semantic support was predicted to be particularly beneficial to older adults since it would provide scaffolding from preserved semantic memory systems (Craik & Rose, 2012). Effects of semantic interventions on time discounting have occasional opposing effects. In amnesia patients who cannot rely on episodic memory, semantic support for paired event trials leads to lessened discount rates across those trials (Palombo et al., 2016). However, for a small sample of younger adults, imagining episodically was more effective at promoting future oriented choice compared to a semantic condition (Benoit et al., 2011). Our events were fairly generic, everyday events which might not promote the necessary motivation for savings behavior (e.g. gas station, grocery store). Although our choice set was optimized for estimating discount rates, the choices sampled the entire choice space, whereas previous studies often use titrated choice sets to maximize effects. Finally, the lack of a paired-events effect in our older adult sample is confounded by their overall lower discount rates compared to younger adults. Therefore, we cannot definitively claim that our semanticization process was ineffective since we may find that in samples of older adults with higher discount rates, we actually find an effect of the semanticized events. For example, although Sasse and colleagues (2017) did not find an effect of paired events in older adults, a finding that we replicate in these results, Mok and colleagues (2020) did find an effect, albeit smaller compared to younger adults, in their sample of older adults. Another important detail is that the overall effect persists even when including older adults, despite the interaction. While the behavioral effects of tagging is beginning to mature as a research area, there are still topics left to explore, some of which we aim to explore as we continue collecting data from the presented dataset.

For example, in the financial domain, there is still remaining work to be done with exploring how network changes might underlie the effect or lack of effect of imagination on time discounting. Even in traditional time discounting studies there has been limited work on networks and using graph theoretic measures. Applying graph theoretic measures to understand how changes in task-based networks between different conditions in an intertemporal choice task can clarify how these networks contribute to different choices. For example, while the graph theoretic measures in the literature (Chen et al., 2019) might correlate with overall discounting behavior, graph theoretic measures of specific task conditions can help understand how transient network configurations contribute to different choices. Likewise, such graph theoretic approaches during task can also differentiate the network properties underlying manipulations of intertemporal choice such as the tag effect.

In Chapter 3, we expanded our focus from imagining the future into reflecting on the past. Previous studies have studied how autobiographical reflection may promote later future-oriented thought (Smallwood et al., 2011) and decreased time discounting (Lempert et al., 2017). We found in a first sample where participants either imagined a pair of successes or a pair of failures, that there was no significant difference between groups for discount rates. In a replication sample, our discounting measure may not have been stable enough to correctly estimate discounting. However, the null result corresponded to the results seen in the earlier study. The crowning achievement of large sample size and reasonable methods has recently been completed (Ballance et al., 2021). Given their small findings and our null findings, efforts to manipulate discount rates using emotion are considerably weaker than imagination on its own. While our current studies did not successfully disentangle the different contributions of mood inductions and episodic memory engagement to shifts in lab-based intertemporal financial choice, these may be questions better answered using field studies or more applied domains of decision making. Indeed, there have been successful interventions using imagination, particularly for health-related behaviors (Daniel et al., 2013; Dassen et al., 2016; Lipkus et al., 2022). However, the relationships do not suggest a simple one-size-fits-all intervention strategy. Why might there be complex interactions predicting behavior in health-related scenarios compared to monetary scenarios? For financial choices, money is a secondary reward—it is highly valued, but is only valuable in terms of what it can purchase. Indeed, one of the reasons interventions are encouraged and funded in the financial domain is because investment historically has not been incentive enough for the average person to save or invest. Given that the low stakes incentive-compatible choices done in the scanner in Study 1 or the hypothetical choices in Study 2A and 2B do not quite capture the market forces of real financial choices, in Study 3, 4A, and 4B we explored higher stakes choices that are relevant to young and middle-aged adults: career choice.

We found that the degree of enjoyment of an imagined career predicted change in preference for a non-preferred career when controlling for change in preference for a preferred career. There was no effect of which career was imagined which suggests this independent prediction of enjoyment might be due to greater willingness to explore after a positive imagined career (for similar theory, see Seo et al., 2004). An important part of the career literature is that an important component of career success is determined by one's appraisal of your career as a success for yourself, what is known as subjective career success (Gattiker & Larwood, 1986). That is, someone may consider themselves successful as a Goldman Sachs trader, while another may find themselves successful as an FDA inspector. These careers have different appraisals across the community, but as long as the career aligns with one's view of themselves, they can view themselves as successful (Bretz & Judge, 1994). Finding this kind of intrinsic satisfaction with one's career is driven by career self-efficacy and increased willingness to explore and gather new information (Abele & Spurk, 2009). Imagining alternative careers is one method to explore a setting in which one may be successful and find joy.

Recently, in my own work, I have been studying practicum and capstone coursework for graduate students in which graduate students engage in client-based projects. This mutually beneficial arrangement allows students to gain networking and project experience in a domain that is different from the classroom and laboratory experience, while clients gain the advantage of new voices in the room and develop a potential hiring pathway. These semester or yearlong experiences allow students to develop experiences upon which they can scaffold imagined careers. For many students in graduate school, their work experience may be primarily academic-based or service-based and may have little understanding or exposure to corporate roles. Expanding the infrastructure of these programs may allow students to more easily imagine themselves in careers outside the academy. As our work demonstrates, merely imagining oneself enjoying a career is able to shift preferences for an alternative career. The direction of our effect, however, suggests some caution. In our work (but for other perspectives see Côté et al., 2006), we found that lower enjoyment was associated with a decrease in preference. This suggests that imagining a bad experience at a job may not motivate people to explore alternative careers.

Institutional structures in academia contribute to this disconnect between curriculum and career imagination. Career centers have historically been situated in divisions of student affairs as opposed to academic affairs, where they are generally an optional service among many which may only be encountered by students actively recruiting or actively seeking out help. Recently, there has been a trend in repositioning career centers into academic affairs or more diverse offices across campus (Helbig & Matkin, 2021). This repositioning allows the better integration of career theory and resources into the academic training and development of students.

Overall, the growing trend to integrate career preparedness and foresight into the curriculum across academic stages will greatly benefit students. The hallmark of a liberal arts education is to instill a love of learning and exploration across disciplines. However, this has often been at the expense of learning about career opportunities. Indeed, at the graduate level, PhD programs have historically treated themselves as professional degrees for researchers, a career path that has always been a minority. The work in this dissertation suggests that while there may not be benefits to imagining specific future careers, imagination and visual imagery may lead general increases to openness to pursue any career. Career adaptability is a vital attribute for the "boundaryless" careers of the 21st century (Y. Guan et al., 2019; Lent & Brown, 2013). As a result, encouraging students to visualize and imagine themselves applying the skills they have learned in the classroom and in internship opportunities to a variety of career and life situations, then they may be more confident in their career competencies.

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Biography

Eric Juarez earned his A.B. degree magna cum laude with highest honors in psychology with a secondary in visual and environmental studies from Harvard College in 2017. At Harvard, he was a John Harvard Scholar in 2016 and wrote a thesis in the lab of Professor Daniel Schacter. In 2017, he wrote, directed, edited, and starred in the short film, "First Film: 2562" which was presented at the 2017 VES student film showcase and the 2018 International Association for the Study of Dreams Annual Conference. He began his doctoral program with a Dean's Graduate Fellowship in 2017. In 2019, he was awarded an Honorable Mention from the National Science Foundation GRFP. At Duke, he has been involved in a number of service and leadership roles. He has published research and commentary in *Psychology and Aging, Trends in Cognitive Science, Human Brain Mapping, and Aging, Neuropsychology, and Cognition*. He was honored as a 2022 Presidential Management Fellowship Finalist and a 2022 Consortium for Faculty Diversity Fellow. In Fall 2022, he will begin an appointment as a Visiting Lecturer in the department of Psychology and Education at Mount Holyoke College in Western Massachusetts.