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An Exploration of Dual Systems via Time Pressure Manipulation in Decision-making Problems

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Mathematical Behavioral Sciences

by

Lisa Guo

Dissertation Committee:
Assistant Professor Jennifer S. Trueblood
Professor Louis Narens, Chair
Professor Michael D. Lee

2017

DEDICATION

To

my parents, Hongzhi Guo & Hua Lin

my friends and loved ones

in recognition of their (persistent) encouragement

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I would like to express my deepest appreciation to Jennifer S. Trueblood, who has patiently and continually guided me through this journey of research and scholarship. Her work ethic, advice, and support have made my dissertation possible. Her encouraging words have been with me across state lines, from California to Tennessee, and I will always be grateful to have been her student.

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Guo, L., Trueblood, J. S., & Diederich, A. (2017). Thinking Fast Increases Framing Effects in Risky Decision Making. *Psychological Science*, 0956797616689092**.**

Fisher, C., **Guo, L.**, Blaha, L. (In progress). Modeling Continuous Human Information Processing with Trace Conditioning. *Proceedings of the 39th Annual Conference of the Cognitive Science Society*.

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Guo, L. (2014). An Investigation of Time Pressure on Framing Effects in Risky Choice. Talk given at Graduate Student Conference at the University of California, Irvine.

Guo, L. & Trueblood, J.S. (2013). Modeling Riskless Choice in Dual Process Decision-making. The 34th Annual Conference of the Society for Judgment and Decision Making, Toronto, ON.

Guo, L. (2012). Affective Decision-making. Talk given at the Institute for Mathematical and Behavioral Sciences, Graduate Student Conference at the University of California, Irvine.

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ABSTRACT OF THE DISSERTATION

An Exploration of Dual Systems via Time Pressure Manipulation in
Decision-making Problems

By

Lisa Guo

Doctor of Philosophy in Mathematical Behavioral Sciences

University of California, Irvine, 2017

Assistant Professor Dr. Jennifer S. Trueblood (Vanderbilt University)

Every day, decisions need to be made where time is a limiting factor. Regardless of situation, time constraints often place a premium on rapid decision-making. Researchers have been interested in studying this human behavior and understanding its underlying cognitive processes. In previous studies, scientists have believed that the cognitive processes underlying decision-making behavior were consistent with dual-process modes of thinking. Critics of dual-process theory question the vagueness of its definition, and claim that single-process accounts can explain the data just as well.

My aim is to elucidate the cognitive processes that underlie decisions which involve some level of risk through the experimental manipulation of time pressure. Using this method, I hope to distinguish between competing hypotheses related to the origin of the effect. I will explore three types of decisions that illustrate these concepts: risky decision-making involving gambles, intertemporal choice, and one-shot public goods games involving social cooperation. In our experiments, participants made decisions about gambles framed as either gains or losses; decided upon intertemporal choices for smaller but sooner rewards or larger but later rewards; and played a one-shot public goods game involving social cooperation and contributing an amount of money to a group. In each case, we experimentally manipulated time pressure, either within subjects or among individuals.

Results showed under time pressure, increased framing effects under in both hypothetical and incentivized choices; and greater contributions and cooperation among individuals, lending support to the dual process hypothesis that these effects arise from a fast, intuitive system. However, our intertemporal choice experiment showed that time constraints led to increased selection of the larger but later options, which suggests that the magnitude of the reward may play larger role in choice selection under cognitive load than previously studied. This diverges from the current dual-process interpretation that myopic choices under time pressure favor smaller but sooner rewards, and suggests that more studies are needed in this realm to disentangle the intuitive from the deliberative system through the manipulation of cognitive load.

INTRODUCTION

In everyday life we often find ourselves in settings where we need to make choices with limited time to fully deliberate upon the situation. The stakes vary, from encountering a yellow light while driving and needing to risk getting caught in the red or safely slowing down; to navigating fast-paced Wall Street where high-velocity strategic decisions separate the bankrupt from the successful. Regardless of situation, time constraints often place a premium on rapid decision-making.

Researchers are interested in exploring the effects of time pressure on decision-making behavior. Consider the effects of someone encountering a traffic light while driving. If the light turns from green to yellow, the decision-maker is suddenly faced with a decision that has to be made quickly. He or she can either slow down safely to a stop to avoid running a red light, or maintain or increase speed to cross the intersection. Either way, the decision requires quick thinking and involves two options, one which is guaranteed but perhaps as a lower payoff (slowing down to a stop adds time to the commute), and the other which involves some risk but has a higher payoff (running through the yellow light to risk getting caught in the red, but reducing overall travel time). My aim is to elucidate the cognitive processes that underlie these types of decisions through the manipulation of time pressure.

In previous studies, researchers have believed that the cognitive processes underlying decision-making behavior were consistent with dual-process modes of thinking. The intuitive mode encompasses fast processes that are affective, automatic, and emotional, while the deliberative mode is comprised of slower processes that are analytical, calculating, and rational. Critics of dual-process theory question the vagueness of its definition, and claim that single-process accounts can explain the data just as well (Osman, 2004; Kruglanski and Gigerenzer, 2011). There are many dual-process theories and labels which currently exist, which can lead to confusion and make the many distinctions between them difficult to pin down. To remedy some of this uncertainty, I refer to the intuitive system as that which is likely to be engaged under time pressure, as opposed to categorizing the system as intuitive through a post-hoc evaluation of naturally occurring reaction times.

As mentioned earlier, Kruglanski and Gigerenzer's (2011) single-process unified theory of decision making based on rule processing is a contender against dual-process theory. The premise of this single process theory addresses the fact that any automatic cognitive system can be modeled computationally and described as following "rules" of cognitive processes, whether concrete or abstract. Thus, evidence that intuition and deliberation are both rule-based cannot prove one way or another if they arise from distinct cognitive mechanisms.

However, in favor of dual-process theory, calling both cases "rules" may be a semantic device to collapse intuitive and deliberative systems into one entity. Evans and Stanovich (2013) presented three separate sources for evidence to dissociate intuitive and deliberative processing. The first is a psychometric approach: individual differences in working memory capacity and intelligence can lead to biases and influence responses. Dual-process theory has offered an explanation for many tasks in the heuristics and biases literature that have paradoxical patterns in the data in that modal responses display negative correlations with rationality or cognitive sophistication (Stein, 1996). That is, past research literature has discovered that individual responses sometimes deviate from normative or rational behavior on reasoning tasks (Kahneman and Tversky, 2000; Stanovich, 2009).

The second piece of evidence in favor of dissociating intuitive and deliberative processing into a dual-process theory of cognitive processing is through neural imaging (Evans and Stanovich, 2013). Neural imaging has shown that different brain areas are active when intuitive or deliberative processing is being observed. For instance, different areas of the brain light up when reason-based responses are observed, versus when responses are belief-based (Neys, Vartanian, and Goel, 2008; Goel and Dolan, 2003). For instance, in monetary decisions based immediate or delayed rewards, prefrontal and frontal cortical regions were activated in mental simulations of future possibilities, whereas immediate decisions were associated with the limbic system (McClure, Laibson, Loewenstein, and Cohen, 2004).

Lastly, Evans and Stanovice (2013) suggest experimental manipulation as a method of dissociating the intuitive and deliberative processing systems. Experimental manipulations range from decreasing deliberation through time pressure; increasing cognitive load; or priming calculation by instruction or motivation. Several experiments have demonstrated the successful use of experimental manipulations in separating the intuition and deliberation. For example, in the Wason four-card selection task, speeded tasks increased matching behavior (Roberts and Newton, 2001), and in making analytical inferences from conjunction fallacy problems, a sharp decrease in correct responding occurred when cognitive load was applied to working memory (Neys, 2006). While these examples are used for a different task than I am focusing on, their foundational principles remain the same.

My aim is to elucidate the cognitive processes that underlie decisions which involve some level of risk through the experimental manipulation of time pressure. Using this method, I hope to distinguish between competing hypotheses related to the origin of the effect. I will explore three types of decisions that illustrate these concepts: risky decision-making involving gambles, intertemporal choice, and one-shot public goods games involving social cooperation. In risky decision-making, individuals choose between a sure option and a gamble, with an emphasis on the framing effect. Intertemporal choices involve deciding between a smaller but immediate reward, which can be seen as riskless and sure; and a larger but later reward, which takes into account the delay of several days to weeks, requiring a delay of gratification until a later time. One-shot public goods games involving social cooperation and donating a portion of one's endowment also illustrate the safe but sure option to donate nothing (and get a certain reward), or risk donating to the for a chance to win more, at the cost of potentially ending up with less than one started with.

CHAPTER 1

Risky Decision-Making

Every day, people find themselves in situations in which speeded, or "snap," decisions need to be made. The stakes vary: For example, one person might encounter a yellow light while driving and have to decide whether to risk getting caught running a red light or safely slowing down, whereas another person might work at a fast- paced Wall Street brokerage, where high-velocity strategic decisions separate the bankrupt from the successful. Regardless of the situation, time constraints often place a premium on rapid decision making.

Researchers have also been intrigued by the finding that decision makers respond in different ways to objectively equivalent variations of the same problem. For example, imagine you win $300, and you have a choice between receiving an additional $100 for sure and taking a gamble offering a 50% chance to gain $200 and a 50% chance to gain nothing. Suppose you prefer the sure option of receiving the additional $100. Now, consider a different situation in which you win $500 and have a choice between losing $100 from your winnings for sure and taking a gamble offering a 50% chance to lose nothing and a 50% chance to lose $200. In this situation, you find yourself selecting the gamble. This pattern of choices demonstrates a *framing effect* because your preferences between the sure option and the gamble change depending on the description of the problem, even though the expected value of the outcomes is the same.

According to theories of rational decision making (including expected-utility theory), people's decisions should be *description invariant*. That is, the manner in which the options are presented should not influence choices. A classic finding in risky decision making is that people tend to be risk averse when a problem is presented as a gain and risk seeking when the same problem is presented as a loss (Kahneman and Tversky, 1979; Tversky and Kahneman, 1981). These types of framing effects have been documented in a variety of situations, including medical and clinical decisions (O'Connor, Boyd, Warde, Stolbach, and Till, 1987; O'Connor, Pennie, and Dales, 1996), consumer choices (Levin and Gaeth, 1988; Loke and Lau, 1992), and social dilemmas (Brewer and Kramer, 1986; Fleishman, 1988). The goal of the present research was to explore how time pressure interacts with framing effects in risky decision making. In particular, does time pressure exacerbate or mitigate framing effects? Previous research provides support for both of these possibilities.

Svenson and Benson (1993) examined the influence of time pressure in choices among lotteries as well as the famous Asian disease problem (Kahneman and Tversky, 1979). Their results showed that time pressure (a 40-s response deadline) reduced framing effects, which suggests that the effects evolve over time. These results are consistent with findings in multialternative, multiattribute choice situations that have shown context effects, such as the attraction (Huber, Payne, and Puto, 1982), compromise (Simonson, 1989), and similarity (Tversky, 1972) increase with longer deliberation time.

These effects illustrate how choices between a fixed set of options can be altered by the inclusion of other options. Recent work by Pettibone (2012) and Trueblood, Brown, and Heathcote (2014) has shown that context effects emerge with increased deliberation, in line with predictions from sequential-sampling models of decision making (Roe, Busemeyer, and Townsend, 2001; Trueblood et al., 2014).

Some researchers have suggested that framing effects may be the result of two different systems of reasoning— the intuitive and deliberative systems. The intuitive system is responsible for fast processes that are affective, emotional, and automatic, while the deliberative system is responsible for slower processes that are more analytical, rational, and calculating in nature (Chaiken and Trope, 1999; Kahneman and Frederick, 2002; Mukherjee, 2010; Sloman, 1996; Stanovich and West, 2000). In a recent neuroimaging study, De Martino, Kumaran, Seymour, and Dolan (2006) found that in risky decision making, framing effects were associated with increased activation in the amygdala, whereas activity in the orbital and medial prefrontal cortex was related to a reduction of these effects. In particular, increased activation in the amygdala was associated with participants' tendency to choose sure options when the problem was framed as a gain and risky options when the problem was framed as a loss. Participants who behaved more rationally showed greater activation in the orbital and medial prefrontal cortex. These results support dual- process theory, which proposes that there is conflict between deliberative processes and an intuitive, "emotional" amygdala-based system. If framing effects are mainly driven by the fast, intuitive system, then they should increase under time pressure. With restricted deliberation time, the deliberative system is less likely to be engaged.

Our aim was to distinguish between these two competing hypotheses related to the origin of framing effects. On one hand, framing effects could evolve through the deliberation process as described by Svenson and Benson (1993) and in a similar manner as context effects in preferential choice (Pettibone, 2012; Trueblood et al., 2014). On the other hand, framing effects could result from an intuitive system that produces quick automatic responses to stimuli. We tested these hypotheses in three experiments.

Experiment

The stimuli were adapted from those used by De Martino et al. (2006). At the start of each trial, participants were given an initial amount of money. They then chose between a sure option to keep a portion of the initial amount and a gamble to possibly keep the entire initial amount, with the sure option presented in either a gain or loss frame. In both frames, the gamble was identical and presented in a pie chart color-coded to represent the probability of winning and losing. Participants completed two blocks of trials, one of which they performed under time pressure. Four variations of this task were run, manipulating several "tuning variables" (e.g., color of the pie chart) that were expected to have no influence on the results. These variations were included to make sure that our findings were attributable to the actual framing effect rather than to some arbitrary experimental variables. This procedure would provide evidence of the robustness of the phenomenon and its replicability.

Method

Participants. A total of 195 individuals (159 female, 36 male; mean age = 20.24 years) from the University of California, Irvine, received course credit for participating in the experiment (regardless of performance). All participants were undergraduate students and English speakers. We set a target sample size of about 50 participants for each of the four experimental variants. This sample size was selected on the basis of previous experiments using a within-subjects time-pressure manipulation in decision making (Trueblood et al., 2014). The lab could accommodate up to 6 participants during a single session. We stopped data collection with the session that would meet (and potentially exceed) the target sample size. For this final session, we allowed up to 6 participants to sign up in anticipation of no-shows. Thus, some experimental variants had slightly fewer than 50 participants, and others had slightly more than 50 participants.

Stimuli and design. The experiment was run in two blocks, each block consisting of 144 test trials: 72 with gain frames and 72 with loss frames. We also included 16 catch trials in each block to assess accuracy and engagement in the task, for a total of 160 trials per block (320 trials total). The catch trials had nonequivalent "sure" and "gamble" options, one of which had a significantly larger expected value.

For the test trials, 72 dollar amounts were selected randomly from a uniform distribution ranging from \$20 to \$90 to serve as the initial starting values. In addition, 72 probabilities were drawn randomly from a pool of three normal distributions (Ms = .28, .42, and .56; SDs = .20) to serve as the probability of winning the gamble. The initial amounts and probabilities of winning the gamble were randomly paired to form 72 unique test trials. From these pairs, we created the sure option for each trial to match the expected value of the gamble, depending on whether the gamble was framed in terms of a gain or a loss. For instance, for an initial amount of $78 and a winning- gamble probability of .26, the sure option would either be “keep $20” (gain frame) or “lose $58” (loss frame). There were also 32 total catch trials, 16 with a gain frame and 16 with a loss frame. The initial starting values for these trials ranged from $20 to $90, as in the test trials. In half of the catch trials, the sure option had a higher expected value than the gamble option. In the other half, the gamble option had a higher expected value than the sure option. Note that all gambles were hypothetical because there were no real consequences for participants’ decisions. Previous research has shown that there are no differences in the framing effect in hypothetical and real choices (Kühberger, Schulte-Mecklenbeck, and Perner, 2002).

We were interested in the framing effect that occurs with risky decision making between sure and gamble options. For this experiment, a framing effect would occur when (a) in the gain frame, the decision maker chose the sure option and (b) in the loss frame for the same problem, the decision maker chose the gamble option. Thus, we categorized risk-averse behavior in gain trials and risk-seeking behavior in equivalent loss trials as a framing effect.

The two blocks were differentiated by the presence or absence of time pressure. In the time pressure (TP) block, participants were told that their goal was to respond quickly, and in each trial, they were given 1,000 ms to make a choice. A latent but unstated goal of the TP block was to earn money. To ensure that participants felt time pressure, we gave them only one direction: to respond quickly. If they failed to make a choice within 1,000 ms, they received a feedback message stating that they did not earn any money on that particular trial because they did not respond in time. If the participant made a choice within the allotted time frame, they did not receive any feedback.

In the no time pressure (NTP) block, participants were told that they should "maximize [their] money" (in all but the losses variation; see Variations in Design) and were not penalized for the amount of time they took to respond. In this block, we reinforced the goal of maximizing earnings by providing feedback after every trial explaining the amount of money earned on that trial.

Our experimental design was based on ones used in perceptual decision making to study the speed/accuracy trade-off (Wickelgren, 1977). In accuracy conditions, participants are typically instructed to maximize accuracy and often receive feedback related only to accuracy. In speed conditions, participants are typically told to maximize speed and often receive feedback related only to speed.

Procedure. During the main task, the order of the two blocks and the 160 trials in each block was randomized. At the start of each trial (in both the gain and loss frame, shown in Figs. 1c and 1d, respectively), participants were given an initial starting amount (e.g., "You are given $78") and the goal for that block (e.g., "Respond Quickly"). Participants were told that they would not be able to retain the entirety of the initial amount but would have to choose between a sure option and a gamble option. Two seconds after the initial amount was displayed, the screen automatically progressed to this choice screen. The choice screen contained two pie charts, one of which presented the sure option and one of which presented the gamble. In the gain frame, participants selected between keeping a portion of the initial amount for sure and taking a gamble that could result either in their keeping or losing all of the initial starting amount (equivalent to getting \$0 for the trial). The probability of winning the gamble varied on each trial. For example, in Figure 1c, the sure amount was \$20, whereas the gamble involved a .26 probability of keeping the starting amount (\$78) and a .74 probability of losing it. Note that the expected value of the gamble was $.26 \times \$78 = \$20$, which was the same outcome as the sure option. In the loss frame, the procedure was identical to that in the gain frame. For example, in Figure 1d, the gamble outcomes involved either a .26 probability of keeping the initial starting amount of \$78 and a probability of .74 of losing the entire amount.

The only difference between the gain and loss frames was the framing of the sure option. In the loss frame, the sure option was framed in terms of losing a portion of the initial amount. For example, a sure loss of \$58 was equivalent to a sure gain of \$20. Thus, the payoffs in the gain and loss frames were identical. In the gain frame, the sure option was presented in a fully light-gray pie chart (e.g., \$20). In the loss frame, the sure option was presented as an amount lost in a fully dark-gray pie chart (e.g., –\$58). For both the gain and loss frames, the gamble option was presented in a pie chart representing the probability of keeping the entirety of the initial amount or losing the initial amount (e.g., .74 dark gray: –\$78 and .26 light gray: \$78).

Before starting the experiment, participants completed three guided practice trials in which they were told to select specific options (i.e., the gamble or sure thing). After the guided practice, participants completed an additional 10 practice trials in which they could respond freely. Practice trials were the same as test trials, except that (a) no instruction was given before the task appeared and (b) a legend appeared below the pie charts for each option explaining the amounts that could be won or lost (see Figs. 1a and 1b).

Variations in design. In this experiment, we aimed to test participants across a range of different tuning variables, and thus ran four variations of the experiment. In Variation 1 (49 participants), the wedges of the pie chart were color-coded to indicate keeping an amount (represented by green) and losing an amount (represented by red). Additionally, the sure option was always placed on the left-hand side of the screen, while the gamble option was always placed on the right-hand side of the screen. Variation 2 (49 participants) was identical to Variation 1 except that the wedges of the pie chart were rendered in gray-scale to indicate keeping an amount (represented by light gray) and losing an amount (represented by dark gray), as shown in Figure 1. Variation 3 (53 participants) was identical to Variation 1 except for the placement of the sure and gamble options. In this variation, the sure option was randomly placed on either the left-hand or right-hand side of the screen. Finally, Variation 4 (44 participants) involved changing the framing of the instructions from “maximize your money,” a more positive goal, to “minimize your losses,” a more negative goal. This variation was otherwise identical to Variation 1.

Results

We analyzed the data from all 195 participants, removing the catch trials. The average proportion of catch trials answered correctly was .85. We found that there was no significant difference in the between-subjects variations, $F(3, 191) = 0.24$, $p > .250$, $\eta2 <$

.01, and therefore collapsed the results for the remaining analyses. Next, we ran a 2 (block: TP, NTP) × 2 (frame: gain, loss) analysis of variance on the probability of selecting the gamble. As Table 1 shows, there was a significant effect of frame, $F(1, 194) = 339.394$, $p < .001$, $\eta 2 = .635$. This suggests that behavior was consistent with the framing effect (i.e., the tendency to be risk seeking when presented with a loss frame and risk averse when presented with a gain frame). There was also an interaction between block and frame, $F(1, 194) = 76.175$, $p < .001$, $\eta 2 = .285$, which showed that there was an increase in the framing effect for the TP block compared with the NTP block. The mean response time for the NTP block was 2,096 ms (SD = 3,010 ms), while the mean response time for the TP block was 558 ms (SD = 408 ms). The data used in this analysis are available on the Open Science Framework at https://osf .io/9gyvd/.

Figure 2 shows the proportion of individual choices for the gamble in the TP and NTP blocks for the gain frame and loss frame. In the gain frame, the majority of participants (138 out of 195, or .71) selected the gamble more often in the NTP block than in the TP block, showing increased risk aversion under time pressure. In the loss frame, the majority of participants (113 out of 195, or .58) selected the gamble more often in the TP block than in the NTP block, showing increased risk seeking under time pressure. In the gain frame, the mean proportion of gambles selected in the NTP block was .40, compared with .31 in the TP block. In the loss frame, the mean proportion of gambles selected in the NTP block was .59, compared with .65 in the TP block. Table 2 shows the proportions of participants who selected the gamble in each of the variations. As mentioned earlier, these variations manipulate tuning variables that should have been irrelevant to the task. Our results confirmed this prediction. Frame and time pressure had similar influences on behavior in all four between-subjects variations.

We also analyzed the framing effect on the problem level. For each participant and each pair of corresponding gain-loss choice problems, we calculated a framing-effect score for the TP and NTP conditions. This score was calculated by subtracting the proportion of times the gamble was chosen in the gain frame from the proportion of times the gamble was chosen in the loss frame. A positive score indicates evidence for the standard framing effect, in which gambles are preferred more in a loss frame than in a gain frame. A higher score in the TP condition than in the NTP condition shows evidence for an increased framing effect under time pressure.

Figure 3 shows the framing-effect scores for the TP and NTP conditions for each problem, averaged across participants for the four experimental variations. All of the problems in each variation had a positive framing-effect score in the TP condition, and the large majority had a positive framing-effect score in the NTP condition as well (72 out of 72 in Variation 1, 68 out of 72 in the Variation 2, 71 out of 72 in Variation 3, and 70 out of 72 in Variation 4). This shows evidence for the standard framing effect, in which gambles are preferred more often in the loss frame than in the equivalent gain frame. Further, more problems had a larger framing-effect score in the TP condition than in the NTP condition (68 out of 72 in Variation 1, 64 out of 72 in Variation 2, 71 out of 72 in Variation 3, and 68 out of 72 in Variation 4), which shows an increase in the framing effect under time pressure.

Our main finding that framing effects increase with time pressure was further corroborated by a Bayesian repeated measures analysis of variance performed using the open-source software package JASP (JASP Team, 2016). In Tables 3 and 4, we report Bayes factors (BFs) comparing each model with all other possible models (BF_{model}) as well as with the null model (BF_{10}) along with the BFs for the inclusion of specific variables ($BF_{inclusion}$). A BF greater than 10 is typically considered strong support for the model or variable in question (Kass and Raftery, 1995). The Bayesian analysis supported our earlier claim that the tuning variations had no influence on the experimental results, that is, our results were attributable to the actual framing effect rather than to some arbitrary experimental manipulations ($BF_{inclusion} = 0.02$). A model that included block, frame, and the interaction of block and frame was preferred to all other models ($BF_{model} = 304.86$) as well as to the null model ($BF_{10} > 1{,}000$). Also, the BF for inclusion of both variables was large, $BF_{inclusion} \approx \infty$ for the inclusion of frame and $BF_{inclusion} > 1{,}000$ for the inclusion of block. Thus, the data support the conclusion that a model with both frame (gain vs. loss) and time pressure (present vs. absent) gives the best account for the probability of choosing the gamble in the task.

Modeling

During our data analyses, we also modeled the behavior associated with the framing effect, based upon what we found in our experiment. We developed a sequential sampling model that assumes a separate sampling process for the intuitive and deliberative systems. Our model is an extension of the multiattribute attention switching (MAAS) model (Diederich, 1997; Diederich and Oswald, 2014), which predicts rich patterns of choice probabilities including preference reversals. In our extension of the MAAS model, drift rates are defined as

$$d = V_G - V_S \tag{1}$$

where V_G is the subjective value of the gamble and V_S is the subjective value of the sure thing as calculated by prospect theory (Tversky and Kahneman, 1992). For an option j, the subjective value is the sum over the weighted values of each outcome:

$$V_j = \sum_i w(p_i)v(x_i) \tag{2}$$

where $w(p_i)$ is the decision weight for outcome i with probability p; and $v(x_i)$ is the value function applied to outcome i and amount x. The decision weights are defined as:

$$w(p) = \frac{p^c}{(p^c+(1-p)^c)^{1/c}} \tag{3}$$

where the c parameter represents positive payoffs. Values of the parameters that are nearer to 1 indicate more linear perceptions of probability.

The prospect theory value function is defined as:

$$v(x) = \begin{cases} x^\alpha \; if \; x \geq 0 \\ -\lambda|x|^\beta \; if \; x < 0 \end{cases} \tag{4}$$

We assume there are two drifts; one associated with the intuitive system and one associated with the deliberative system. We use the equations above to calculate the drift rates for both systems, but allow for different parameter values (i.e., α, β, λ, and c) for the two systems. Further, we assume that the intuitive system precedes the deliberative system so that there is a switch in drift rates during the course of a trial (i.e., the two systems are acting sequentially, with the intuitive system acting first). We assume the intuitive system operates first because it is characterized as being quick and automatic.

Figure 4 shows three different simulations of a loss-frame trial: choosing the gamble (upper, positive boundary) or choosing the sure thing (lower, negative boundary).

In this process, evidence accumulates over time until it crosses one of the two boundaries. The speed with which the evidence accumulation process approaches one of the boundaries is the drift rate, with a positive drift rate approaching the gamble boundary and a negative drift rate approaching the sure thing boundary. The separation between the two boundaries determines the amount of evidence that must be accumulated before a decision is made. We assume that the difference between the thresholds is smaller for the time pressure condition (TP in Figure 4) and larger for the no time pressure condition (NTP in Figure 4). For sequential sampling models, previous research has shown that the difference between the TP and NTP conditions is typically explained by a change in the boundaries (Ratcliff and Rouder, 1998). At some point $t > 0$, there is a switch from the intuitive to the deliberative system, after which the evidence accumulation continues until a boundary is reached.

We illustrate that our model can capture the main experimental result of increased framing effects under time pressure by applying it to one set of choices from the experiment as shown in Table 5. We set the parameter values for the sample trial as shown in Table 6. Parameter values for the intuitive system were based upon Tversky and Kahneman's prospect theory values (1992). These parameter values were used by Tversky and Kahneman to account for a wide range of choice behavior including the fourfold pattern of risk attributes, which includes framing effects similar to the ones discussed here. Because the deliberative system is characterized as being rational, we set the parameter values to 1 so that subjective values were the same as expected values.

To incorporate the reference point, denoted by r, we assume the subjective value of the gamble is:

$$V_G = w(p_+)v(r) \tag{5}$$

where p_+ is the probability of keeping this amount. For gambles, participants either receive r or 0 and $v(0) = 0$. Because the gamble is described the same way in both the gain and the loss frames (that is, participants see the same pie chart), we assume that V_G is the same in both frames.

However, the sure option is described differently in the two frames. In the gain frame, participants are told they can keep s and in the loss frame, they are told that they will lose $l = r - s$. To capture these differences in framing, we assume that the subjective value of the sure thing in the gain frame is:

$$V_s(s) = v(s) \tag{6}$$

and in the loss frame is:

$$V_S(r - l) = V_S(r) + V_S(-l) = v(r) + v(-l) \tag{7}$$

Note that the decision weights are equal to 1 since there is no risk or uncertainty involved in the sure option.

For the example gamble described in Table 5, we searched over different switch times (i.e., amount of time spent in the intuitive system before switching to the deliberative system) between 3 and 1000 ms and over different values for the difference between the thresholds between 2 and 10. Figure 5 shows a heatmap plot of the probabilities of choosing the gamble for the gain frame. We see the expected trends that illustrate the framing effect: as the difference between bounds decrease (i.e., corresponding to increased time pressure), the probability of choosing the gamble decreases (i.e., the sure option is selected more often). Also, as the switch time increases (i.e., spending more time in the intuitive system), the probability of choosing the gamble decreases. Similarly, Figure 6 shows the probabilities of choosing the gamble for the loss frame. Again we see the expected framing effect: as the difference between bounds decreases, the probability of choosing the gamble increases for losses. As the switch time increases, the probability of choosing the gamble increases.

Using a risky decision-making task and the element of time pressure, the present experiment investigated the framing effect and its relationship to dual process theory. The results from our study show that there was a greater occurrence of the framing effect when decision-makers were put under time pressure. These results add to a growing body of literature suggesting that framing effects are driven by the intuitive system. The present results extend the findings from De Martino et al. (2006), but using a different presentation of options (a pie chart for the sure option in addition to the gamble option), a feedback system, and most importantly an element of time pressure that allowed for distinguishing between a fast, emotional response and a deliberative, calculated response.

Most past dual process models have been verbal models, which do not provide exact predictions. Our model is one of the first formalized accounts of dual systems of reasoning. Further, our model is dynamic, taking into account the timing of the two systems. In our approach, we use a sequential sampling model where the intuitive and deliberative systems are associated with different evidence accumulation processes. Such a model is able to take into account the two different cognitive processes of the intuitive and the deliberative system, as well as incorporate a switch in the sequential processing of the intuitive to the deliberative system. Our model explains the framing effects found in both our studies and previous findings. Future modeling could explore additional reaction time models, such as the trace conditioning model (see Appendix A).

Conclusions

Participants in the experiment showed risk-averse behavior when presented with a gain frame and risk-seeking behavior when presented with a loss frame, in accordance with the standard framing effect. Further, our results showed an increase in the framing effect under time pressure. These results were supported by both traditional and Bayesian statistical tests. The results held when we accounted for several experimental variations. These results diverge from those of Svenson and Benson (1993). Their time-pressure condition was quite long (40 s) compared with ours (1 s). Thus, participants in the Svenson and Benson (1993) study might have employed different decision strategies than our participants.

The results from our experiment showed that participants more frequently chose the sure option for gains and the gamble option for losses when there was greater pressure to make quick decisions. These results are consistent with a dual-process explanation of framing effects, in which the effect is driven by the quick, intuitive system. Our findings are complementary to neuroimaging results of De Martino et al. (2006), which showed increased activation in the amygdala when participants exhibited framing effects.

Our results are also consistent with the predictions of a dual-process model recently proposed by Loewenstein, O’Donoghue, and Bhatia (2015), which assumes that choices arise from the interaction of the deliberative system (a utility function) and the intuitive system (an affective motivation function). Their model also incorporates a willpower function, in which the depletion of willpower results in increased weight on the intuitive system. They show that the model can account for a wide range of phenomena in the domains of intertemporal choice, risky decision making, and social preferences. Notably, the model predicts that when willpower is depleted, framing effects will increase in risky decision making. Time pressure provides one avenue to restrict willpower. Thus, our experiments provide empirical support for their model predictions. Note that some of our results (such as risk aversion in gains and risk seeking in losses) are also consistent with prospect theory (Kahneman and Tversky, 1979). However, prospect theory cannot explain why framing effects increase with time pressure.

While our results are consistent with a dual-process explanation, we cannot rule out single-process accounts. Our results could have arisen from a single process that involves an attention-switching mechanism as proposed in models derived from decision-field theory (Busemeyer and Townsend, 1993; Roe et al., 2001) and the multistage attention-switching model (Diederich, 2016). In these models, preference evolves over time and is modulated by changes in attention. Preference for a given option might depend on the order of attended attributes or the time spent attending to an attribute. Time pressure might alter the attention process (e.g., by altering the time spent attending to different features), which would result in changes of behavior. In particular, time pressure could change attention to the lowest ranked payoff, as suggested by the transfer-of-attention-exchange (TAX) model (Birnbaum and Chavez, 1997).

Future work could examine other manipulations aimed at distinguishing intuitive and deliberative processes, such as decreasing deliberation with cognitive load (e.g., see Whitney, Rinehart, and Hinson, 2008) or manipulating affect (Pachur, Hertwig, and Wolkewitz, 2014; Suter, Pachur, and Hertwig, 2016). In general, we encourage researchers to use direct manipulations (such as time pressure) in testing ideas from dual-process theory. As discussed by Krajbich, Bartling, Hare, and Fehr (2015), using response time data alone to infer that choices are “intuitive” is inherently flawed because of the multiple sources of variability in data. Direct manipulations avoid the problems with reverse inference and lend more direct support for dual-process accounts.

CHAPTER 2

Intertemporal Choice

Intertemporal choice – which involves decisions that play out over time – is ever-present in daily life. Decisions concerning investments, spending, diet, education, and relationships all contain intertemporal tradeoffs. Previous research has been done in the fields of economics, psychology, and neuroscience in an effort to study the various perspectives on intertemporal choice. Historically, it has been assumed that delayed rewards were discounted at a constant rate over time. However, recent theoretical and empirical advances from the economic, psychological, and neuroscience perspectives have revealed more complex accounts of how individuals make intertemporal decisions (Berns, Laibson and Loewenstein, 2007; Loewenstein, 2015).

We are interested in furthering the exploration of current dual process models of ITC, taking into account the documented effects of affective myopia in decision-making. Loewenstein et. al (2015) explored an application of a dual process model of behavior to decisions which involve tradeoffs between current and future outcomes, assuming that the affective system is primarily driven by short-term payoffs whereas the deliberative system takes into account both short-term and long-term payoffs, reflecting existing dual process theories of intertemporal choice in economics (Benhabib and Bisin, 2005; Bernheim and Rangel, 2004; Fudenberg and Levine, 2006; Shefrin and Thaler, 1988; Thaler and Shefrin, 1981). Additionally, willpower, cognitive load, or affective intensity have been found to reflect increased myopia in amount of ice cream people will eat (Vohs and Heatherton, 2000), impulse buying (Vohs and Faber, 2007), and increased procrastination (Vohs et al., (2014). In more of a lab setting, individuals who partook in depletion tasks before making intertemporal choices were also more likely to choose the smaller, short-term reward over the larger, delayed reward (Vohs et. al, 2012). This previously established framework indicates that decision makers are more likely to give into the shorter, more tempting choices when they are repeatedly confronted with such temptation, leading to decreases in willpower. In my experiment I expect time pressure, which is also considered a form of cognitive stress, to have a similar effect.

Experiment

The stimuli in my experiment were created in the typical intertemporal choice format. At the start of each trial, participants were presented with two options involving payoffs that occur at different times. They then chose between the sooner but smaller option (SS), or larger but later option (LL). Participants completed two blocks of trials, one under time pressure, and one without time pressure.

Method

Participants. A total of 54 individuals (35 female; mean age = 22.04 years) from Vanderbilt University received payment for participating in the experiment in the form of an exact payout of a randomly selected test trial. All participants were undergraduate students and English speakers. We set a target sample size of about 50 participants for this experiment, and the lab could accommodate up to 6 participants during a single session. We stopped data collection with the session that would meet (and potentially exceed) the target sample size. Thus, this experiment concluded with slightly more than 50 participants.

Stimuli and design. The experiment was run in two blocks, each block consisting of 270 test trials. We also included 10 catch trials in each block to assess accuracy and engagement in the task, for a total of 280 trials per block (560 trials total). The catch trials had SS choices with a larger reward and sooner payout than its corresponding LL option, making the SS choice the dominating choice.

Test trials were created with three conditions: SS amount (\$3.00, \$5.50, \$9.75), LL multiplier (1.2, 1.7, 2.5), and LL delay (7 days, 15 days, 30 days). From these 3x3x3 conditions, we created 27 unique test trials, with the SS option for each trial as an SS amount with no delay (i.e., "now"), and the corresponding LL option for that trial as combinations of the LL multiplier and LL delay. For instance, a test trial could read "\$5.50 now or \$6.60 in 15 days" since (\$5.00*1.2 = \$6.60), as shown in Figure 7 (c, d). There were also 10 catch trials per block, each catch trial having an SS option that dominates the LL option in both reward and duration. For example, "\$9.75 now or \$5.50 in 7 days." Participants are notified at the beginning of the experiment that they will be paid according to a randomly selected trial within the experiment. Before beginning the test trials, participants were given a set of practice trials: two guided practice trials directed participants to choose either the SS option (option 'z') or the LL option (option 'm'); succeeded by 10 free response practice trials in which participants could freely choose their own responses. The practice trials were not recorded, nor were they factored into the final payout.

The two test blocks were differentiated by the presence or absence of time pressure. One block is a time pressure block (TP) where participants are told that their goal is to "Respond quickly" and for each trial, are given 1600 ms to make a choice. Since the task involves earning money, a latent but unwritten goal of the TP block is to earn money. To ensure time pressure, the directions given to participants in the TP block were as follows: "Please respond as quickly as possible. You must act fast, and failing to do so will result in earning nothing on that trial. Assume that the payout dates and amounts are guaranteed." If they failed to make a choice within the time pressure limit of 1600 ms, they receive a feedback message that states that they did not respond in time and did not earn any money on that particular trial. If the participant makes a choice within the allotted time frame, they do not receive any feedback on that trial.

The other block is a no time pressure block (NTP). For this block, participants are given the following instructions: "Your goal is to pick the option you prefer. Please think carefully about your choices and take your time to make your decisions. Do not rush. There is no penalty for going slowly. As before, assume that the rewards and payout dates are guaranteed." At the beginning of each trial, the words "Take your time" are displayed across the top of the screen to reminds participants that there is no time pressure in these trials.

Regardless of whether a trial was a TP or NTP trial, there was an automatic skip mechanism built into the experiment to move onto the next trial after 5000 ms. The instructions describing this read: "In each trial, there is an automatic skip mechanism. If you do not make your decision within 5 seconds, the program will proceed to the next trial. In such a case, the screen will read 'Timeout'."

The experiment also included a questionnaire which included the Cognitive Reflection Test (CRT), and questions assessing self-control, impulsivity, and trust in the Commodore System. The trust questionnaire applied to the Commodore Card system, which is the method of delivery that was used for the delayed reward option at Vanderbilt. Money that could be used as cash on campus ("Commodore Cash") would be directly deposited into students' ID cards on the nearest business day to the delayed reward time. The questions can be found in Appendix B.

Procedure. The two blocks and the 280 trials in each block were randomized. As shown in Figure 7, each trial presented the two options, SS and LL, and the goal for that block (e.g. “Respond Quickly”). Participants were instructed that they should make choices quickly (if in the TP block) or take their time to make a choice (if in the NTP block). 5 s after the choice screen was presented on each trial, the screen automatically progressed to the next trial if no response was given. After completing both blocks of trials, participants answered the questionnaire and then received their payment.

Results

We analyzed the results from all 54 participants. The average proportion of catch trials answered correctly was 0.70. The mean reaction time for the no time pressure block was 1885 ms (std=816 ms) while the mean reaction time for the time pressure block was 1154 ms (std=255 ms). The average probability of choosing the LL option in the NTP condition was 0.464 ($t(53) = -0.956$, $p = 0.344$, SD = 0.277), while the average probability of choosing the LL option for the TP condition was 0.553 ($t(53) = 1.190$, $p =$

0.240, SD = 0.327). This is not statistically different from 50% in either condition, which indicates that participants were as likely to behave impulsively as they were to behave deliberately. Subsequently, I found a significant effect of block on the probability of choosing the LL option ($F(1,53) = 19.22$, $p < 0.001$). That is, there was a greater proportion of LL choices in the TP block, 0.553, versus the NTP block of 0.464. The differences in the probability of choosing LL for the TP and NTP blocks is shown grouped by different conditions in Figure 8.

The results from repeated measures ANOVA testing reveal additional details about possible relationships between condition, block, and overall LL choice proportion. There was a significant effect of SS amount on overall LL choice proportion ($F = 5.027$, $df = 2$, $p = 0.015$), but broken down by block, there was a slightly significant effect on SS amount and choosing the LL option without time pressure ($F = 1.992$, $df = 2$, $p = 0.069$). This indicates that the greater the starting SS amount, and consequently, the greater the reward for the LL amount (since each of the multipliers is greater than 1), the more likely that the LL option would be chosen for that trial, particularly if given ample time to deliberate.

Also of interest was whether or not each condition (SS amount, LL multiplier, and LL delay) had an effect on overall LL choice proportion. Because conditions were discrete, I used Spearman's rank coefficient ρ_s and found near-significance for the LL delay condition and overall LL choice ($\rho_s = -0.379$, $p = 0.058$). Evaluating LL choice by block, I found that the condition of delay without time pressure was significant at $\rho_s = -0.382$, $p = 0.050$, while delay with time pressure was not significant ($\rho_s = -0.160$, $p = 0.426$). This indicates that while the length of delay (7 days, 15 days, 30 days) may have an inverse effect on the proportion of LL choices (that is, the longer the delay, the less often the LL option is selected), the effect is only significant if individuals are given ample time to deliberate.

Due to an error in coding the self-control and impulsivity measures questionnaire, only the CRT and trust questionnaires could be analyzed. I found neither a significant relationship nor correlation between CRT scores and LL choice behavior. That is, those with smaller CRT scores were not more or less likely to choose the sooner option than those with larger CRT scores; consequently, time pressure did not have a significant influence in conjunction with CRT scores on choice behavior.

Trust in the Commodore delivery system was an important measure to consider; if participants did not believe that the money would be delivered to them in the future, their choice behavior would be affected. Figure 9 shows how trust scores impacted the probability of choosing the LL option. There were two questions in the trust questionnaire, each one measuring the trust in the delivery system on a scale of 1 (no trust in the system) to 5 (full trust in the system), making the total possible score out of 10. Those with low trust scores tended to choose the LL option less than those with higher trust scores ($F = 2.316$, $df = 7$, $p = 0.041$).

While it is reasonable that these results should occur, as participants who did not believe they would get a payment later would not reasonably choose the later option, these particular results deviate from the original intention and instruction of the experiment, which is meant to examine choice behavior under the belief that payments will be rewarded in both the present and future. Thus, I re-evaluate the analyses, analyzing results with low trust scores (between 2 and 4) removed. The following analyses reflect the removal of eight participants due to their low trust scores (see Appendix B for participant numbers and detailed information).

Again, there is a significant effect of block on the probability of choosing the LL option ($F(1,45) = 16.05$, $p < 0.001$). There are more LL choices in the TP block (0.595 proportion of choices as LL) versus the NTP block (0.504 proportion of choices as LL). As well, there is near-significance for the LL delay condition and overall LL choice ($\rho_s = -0.361$, $p = 0.064$). Examining LL choice by block, I found that LL delay and LL choice with no time pressure was significant at $\rho_s = -0.425$, $p = 0.027$, while LL delay and LL choice under time pressure was not significant ($\rho_s = -0.181$, $p = 0.366$). This verifies what we found earlier, that the length of delay (7 days, 15 days, 30 days) may have an inverse effect on the proportion of LL choices, but the effect is only significant without time pressure.

To corroborate these results, I looked at a Bayesian repeated measures ANOVA with model comparison for the various combinations of block and condition (SS amount, LL multiplier, and LL delay). The results of the Bayesian repeated measures ANOVA suggest Block alone, and Block + LL delay, could be reasonable models to explain LL choice behavior (Table 7).

Conclusions

Participants in the experiment showed a tendency to select the LL option when put under time pressure (TP condition). Conversely, when given ample time to deliberate, behavior tends to be more myopic, that is, participants tend to select the sooner but smaller option. Further, the results showed an increase in overall LL choice proportion as the magnitude of the reward increased, as well as a decrease in LL choice proportion without time constraint when rewards became further delayed. These results were supported by both traditional and Bayesian statistical tests.

However, our results diverge from dual process theory and from studies past, since participants in our study displayed a tendency to select the smaller but sooner option more frequently when given ample time to deliberate, instead of when pressed with a time constraint. Even after removing those who did not trust the money would be delivered in the future, this pattern of behavior remains. To explain this, it is conceivable that the magnitude of the reward became an integral feature of the problem for decision-makers under time pressure. That is, when pressed for time, participants focused on, and favored, the larger reward in the LL option as opposed to the smaller but immediate reward in the SS option. This diverges from the myopic tendencies noted in previous studies, where the reward delivery time seemed to drive behavior (participants favoring the smaller but sooner option under cognitive load).

The results from my experiment bring to light diverging results from the established framework. We found that decision makers are more likely to choose the longer, later rewards when put under cognitive load (in this case, time pressure). Existing theories explain myopic behavior as that which gives into the temptation of the shorter, immediate rewards; however, our study brings to light evidence that “tempting” choices may not be limited to the time that a reward is paid out, but may also be derived from the magnitude of the rewards themselves. The behavior we found warrants further exploration to disentangle the intuitive system, one that has in the past has been thought of as myopic, emotional, and more easily susceptible to temptation, from the deliberative system which is thought of as more rational and calculated.

CHAPTER 3

Social Cooperation

Cooperation is one of the core behavioral principles of human social life. In choosing to cooperate, individuals sometimes experience a personal cost in order to benefit others. Despite this, in many cases individuals are still willing to sacrifice for the common good (Ledyard, 1997; Fehr and Schmidt, 1999; Rilling et al., 2002; Zelmer, 2003; Bowles and Gintis, 2011; Chaudhuri, 2011). Rand, Greene, and Nowak (2012) explored how our social intuitions are shaped by daily experiences, and how those intuitions influence our default responses as being more selfish or more cooperative. Bear and Rand (2016) formalized this hypothesis mathematically, but despite this foundation, the conclusions of how each system in the dual-process framework relates to cooperative behavior are muddled. Several economic experiments have investigated contribution decisions in the dual-process framework using a public goods paradigm, with inconclusive results.

Rand et al. (2012) found that intuitive decision-making was linked to higher contribution decisions in standard public goods games, by experimentally manipulating decision times. A meta-analysis of 51 studies (Total N = 15,850, having checked for publication bias as well) found a positive relationship between intuition and cooperation in one-shot economic games with time pressure, cognitive load, ego depletion, or intuition/deliberation inductions (Rand, 2016). However, Tinghög et al. (2013), Verkoeijen and Bouwmeester (2014), and Duffy and Smith (2014) were unable to replicate the result. Piovesan and Wengström (2009) found that deliberation was associated with more generous contributions in dictator games; that is, faster reaction times were associated with more egoistic, self-serving choices. The framework presented by Loewenstein and O'Donoghue (2004) suggests that such selfish decisions may be faster since there is less conflict between intuitive and deliberative reactions. However, Schulz, Fischbacher, Thöni, and Utikal (2012) concluded the opposite in their study of dictator games under cognitive load. This goes to show that many studies examining the effects of intuition and deliberation on cooperation have conflicting conclusions. I took place in Rand's Registered Replication Report to further examine the relationship between intuition and cooperation. The protocol for a replication of Study 7 from Rand et al. (2012) was developed by Samantha Bouwmeester and Peter Verkoeijen. The original study's first author, David Rand, provided extensive input and guidance throughout the process, including providing the original materials and scripts. The study aims to measure the size and variability contributions as a result of time pressure in a one-shot public goods game as reported by Rand et al. (2012).

Experiment

The study replicates the between-subjects comparison (time pressure and forced delay) reported by Rand et al. (2012) from their Study 7, using a laboratory setting with college-student participants. The experiment assesses whether or not responding under time pressure leads to greater cooperation than responding after a forced delay, and also whether increased contributions under time pressure is associated with experience, comprehension, and compliance with task requirements. All data and analyses can be found at https://osf.io/scu2f/.

Method

Participants. A total of 156 students (Time pressure n = 78; 56 Female; Forced delay n = 78; 43 Female, Mean age = 21.4) were recruited from the Department of Psychology human subject pool at Vanderbilt. Participants were paid a show-up fee of $5 and were tested in groups (group size ranged from 8 to 24 in multiples of 4). The minimum group size ensured that participants believed that the payoff depended on other people and that they could not determine which of the other people in the room were in their group, as specified in the protocol. If the total number of participants attending a session did not end up as a multiple of 4, the extra participants were paid the “show up” fee and were not tested. These participants had the option of returning for a later session. We used the provided Qualtrics scripts without changes. The lab we used (Wilson Hall 120) was an open computer lab without dividers between computers (see photo on OSF). However, the computers were spaced far apart, and we do not think participants felt observed by other participants or the experimenter. The lab could accommodate up to 30 participants in one sitting. Although our preregistered plan specified that we would recruit at least 160 participants, we were unable to recruit enough people to meet our target sample size before the end of the academic semester, ending with a total of 156 participants.

Stimuli and design. The study materials, instructions, scripts, and post-study questionnaires were converted into a Qualtrics script (http://www.qualtrics.com). The experiment was a one-shot public goods game, in which participants were given an initial amount of $4 and had to decide how much of the initial amount to contribute to the group. The total group contribution would then be doubled and split evenly among the group members. There were two between-subjects conditions, Time pressure, in which participants had to decide on their contribution amount within 10 seconds; and Forced Delay, in which participants had to think for at least 10 seconds on how much to contribute. Following the contribution screen, participants had to answer a set of questionnaires measuring to measure: (a) comprehension of the task, (b) their justification for their contribution, (c) individualism/collectivism (Singelis, Triandis, Bhawuk, and Gelfand, 1995), (d) experience with tasks of this sort, (e) experience with research participation more generally, (f) self-reported perceptions of trust in others, (g) awareness of the research hypothesis, (h) sex, age, and country, and (i) how many of the participants in the room they knew.

Procedure. Participants were randomly assigned to either the Time Pressure condition or the Forced Delay condition. The experimenter and other participants were blind to condition assignment. Additionally, participants were unaware that any other conditions to the experiment existed. The instructions given to participants were as follows:

> You have been randomly assigned to interact with 3 of the other people in the room. All of you receive this same set of instructions. You cannot participate in this study more than once. Each person in your group is given $4 for this interaction. You each decide how much of your $4 to keep for yourself, and how much (if any) to contribute to the group's common project (from 0 to 400 cents). All money contributed to the common project is doubled, and then split evenly among the 4 group members. Thus, for every 2 cents contributed to the common project,

> each group member receives 1 cent. If everyone contributes all of their $4, everyone's money will double: each of you will earn $8. But if everyone else contributes their $4, while you keep your $4, you will earn $10, while the others will earn only $6. That is because for every 2 cents you contribute, you get only 1 cent back. Thus you personally lose money on contributing. The other people really will make this decision too – there is no deception in this study. Once you and the other people have chosen how much to contribute, the interaction is over. None of you can affect each other's payoffs other than through the single decision in this interaction.

On the next screen, participants were asked to decide how much to contribute by using a slider. Participants were able to choose an exact amount by moving the slider to the left or right of the center starting value. Participants in the Time Pressure condition were told: "Please make your decision as quickly as possible. You must make your decision in less than 10 seconds!" The screen showed a timer that counted down from 10. Participants in the Forced Delay condition were told: "Please carefully consider your decision. You must wait and think for at least 10 seconds before making your decision!" The screen showed a timer that counted up from 0. The script recorded each participant's contribution and their decision time.

After their decision, participants answered questions and surveys to measure task comprehension, experience, and demographic information. Participants were paid by randomly grouping them with 3 other participants (without replacement) to determine the group contribution and payout. At the end of the experiment, participants were paid the equally-divided group payout plus the show-up fee. Experiment design, specifications, and collected data can be found on the OSF page: https://osf.io/3km2q/

Results

The following data were excluded from further analyses: participants who did not complete all tasks, who did not move the slider to select a specific contribution amount, or when the experimenter/computer incorrectly administered the task or instructions. The following analyses were done with these exclusions in place (Time pressure n = 75, Forced delay n = 68). All data can be found on the laboratory's Open Science Framework page (https://osf.io/3km2q/) and on the main page for the RRR.

The overall mean contribution, without any exclusions, under the time pressure condition was $2.67 (out of $4.00), SD = $1.33, while the overall mean contribution under the forced delay condition was $2.66, SD = $1.59. The difference in means between conditions (time pressure minus forced delay) was $0.01, with a 95% confidence interval of (-$0.47, $0.49). There is no significant difference between the time pressure and forced delay conditions, when taking into account all participants without exclusion. The same holds true when performing a Bayesian ANOVA on the data as well (see Table 9).

It is important to take into account the different exclusion criteria (experienced, non-compliant, non-comprehending, or a combination of all three). Figure 10 shows the results of the analyses with the following exclusions: experienced (individuals who have participated in studies similar to this one), non-compliant (individuals who did not adhere to the time constraints), non-comprehending (individuals who did not correctly answer the comprehension check), and any combination of the three. When excluding participants based on their experience, non-compliance, or comprehension alone, results were similar to those which did not exclude any participants. That is, there was no significant difference between mean contribution amounts under time pressure and under forced delay. For exact mean contribution values, standard deviations, and participants counts in each exclusion condition, please see Table 8; and for the concurring Bayesian analyses, see Table 9.

When excluding participation based on all three of the exclusion criteria, mean contributions under time pressure (\$3.60, SD = \$1.06, n = 21) were significantly higher (t = 2.347, p = 0.022) than mean contributions under forced delay (\$2.69, SD = 1.60, n = 37). The difference in means between conditions with all exclusion criteria applied (time pressure minus forced delay) was \$0.92, with a 95% confidence interval of (\$1.70, \$0.13). Our Bayesian analyses agree with this result: once we exclude any of the criteria, the probability of the model which includes block (time pressure and forced delay), given the data, is 0.718 (over the null model). In Table 8, we report Bayes factors (BFs) comparing each model with all other possible models (BF_{model}) as well as with the null model (BF_{10}), and in Table 9 we report with the BFs for the inclusion of specific variables ($BF_{inclusion}$). With these exclusions applied, we see a significant difference: participants under time pressure tend to contribute higher amounts of money than those who are forced to reflect upon their choices. These analyses are consistent with the results from Rand's (2016) meta-analysis.

Conclusions

The primary analysis of the data, without any exclusions, yielded results similar to Rand's previous (2012, 2016) studies and meta-analyses. However, the differences between mean contributions under time pressure and forced delay were not significant. Using the different exclusion criteria to pare down the data is somewhat controversial. Recent studies have shown that excluding non-compliant individuals could bias results: if slower responders tended to contribute less, then excluding the non-compliant responders (those that were too slow in the time pressure condition or too fast in the forced delay condition) could bias results in favor of greater mean contributions under time pressure (Tinghög et al, 2013). However, while excluding non-compliant individuals alone, the mean contributions under time pressure were still not significantly different from the forced delay condition (see Table 8). Additionally, excluding non-compliant individuals may be confounding the effect of individuals experiencing conflict in their decisions, as internal conflict is often associated with longer decision times (Evans, Dillon, and Rand, 2015; Krajbich, Bartling, Hare, and Fehr, 2015; Rand, 2016). Thus, identifying cooperativeness is difficult because as cooperation becomes less attractive, internal conflict and decision times increase, leading to a potentially inflated time pressure effect when cooperation is more attractive (Rand, 2016).

Overall, the results from this study indicate that time pressure tends to result in increased contributions in a social one-shot public goods game, but only if many exclusion criteria are applied, which results in excluding many of the participants from the experiment. Our results are corroborated by both frequentist and Bayesian analyses. At best, these results suggest that the effect that we have been searching for may not exist: leaving all participants in the study showed no significant difference between the two conditions. Overall, this replication study used time pressure to manipulate intuition and deliberation in the context of social cooperation, whose results support previous findings only when many controversial criteria are applied. While it fails to provide unequivocal support that a dual-process model of cognitive processing may be involved in decisions concerning social cooperation, it contributes to the overall progression of our understanding of this type of cognitive processing.

Replication Project Conclusions

In total, 21 laboratories including ours participated in the registered replication study, for a grand total of 3,603 participants. Since this replication project spanned international borders, the currencies varied from study to study, so the meta-analyses for the labs were calculated using mean percentage contribution amounts for each condition, and the difference in means between conditions (time pressure minus forced delay). Across all participants, the meta-analytic effect size was -0.10 percentage points (equivalent to less than \$0.01 out of \$4.00), which was smaller and in the opposite direction of the original study (8.6 percentage point difference (\$0.34 out of \$4.00) between time pressure, M = 49.4% (\$1.98), and forced delay conditions, M = 40.8% (\$1.63)). Excluding participants based on experience or comprehension yielded similar results, with a meta-analytical effect size of -2.12 (equivalent to -\$0.10 out of \$4.00) for excluding experience and 0.57 (equivalent to \$0.02 out of \$4.00) for excluding non-understanding. When excluding participants who did not meet time constraints, the meta-analytical effect size grew to 10.49 percentage points (equivalent to \$0.42 out of \$4.00). When applying all three exclusion criteria, the meta-analytic effect size was greater still, at 12.36 percentage points ($0.49 out of $4.00). In all analyses, variability across labs was consistent with what would be expected by chance.

Thus, the results from the replication study revealed that the effect of time pressure on contributions was smaller when all participants were included. The effect is more pronounced when excluding non-compliant individuals, but past research has suggested that excluding these participants may result in a bias in favor of greater contributions in the time pressure condition (Tinghög et al, 2013). While the replication report manipulated intuition using time pressure, the authors suggest that investigating other manipulations such as cognitive load, may lead to more robust effects (Rand, 2016).

GENERAL DISCUSSION

Past studies have shown that human behavior can be susceptible to the way that options are presented. In risky decision-making, De Martino et al. (2006) demonstrated through neuroimaging that the framing effect was specifically associated with amygdala activity, suggesting a key role for an emotional system in mediating decision biases. We approached this idea from a different angle, using exogenous manipulation of time pressure to explore the foundations of the cognitive processing underlying the increasing impact of the framing effect under such conditions. Our results showed that participants choose the sure option for gains and the gamble option for losses more frequently when forced to make a quick decision than when given ample time to deliberate. These results are consistent with the hypothesis that framing effects can be explained under dual process theory, in which the effect is driven by the quick, intuitive system. The results are further corroborated by the predictions of Loewenstein, O'Donoghue, and Bhatia's (2015) dual-process model of behavior. However, we still cannot rule out the possibility of a single process such as one involving a switching mechanism (Busemeyer and Townsend, 1993; Roe et al., 2001) or the multistage attention-switching model (Diederich, 2015).

Our second study further explored the possibility of a dual-systems approach to cognitive processing through intertemporal choice. Under time pressure, behavior diverged from the traditional myopic pattern, that is, participants tended to select the larger but later option. Further, the results showed an increase in overall LL choice proportion as the magnitude of the reward increased, as well as an increase in LL choice proportion under time pressure as rewards became further delayed. These results suggest that the magnitude of the reward may play a larger role in decision under time pressure than studies have previously found. These results call for more exact methods of disentangling the intuitive system, from the deliberative system in the realm of intertemporal choice. For instance, choices that were categorized as "tempting" and "myopic" may not be solely based upon the time that a reward is paid out, but may also take into consideration the magnitude of the reward.

Finally, our registered replication study of Rand's social cooperation one-shot public goods game showed that decisions made under time pressure resulted in significantly larger contributions as decisions made after a forced delay only when taking into account the controversy surrounding the exclusion of non-compliant individuals. As a whole, this replication study used time pressure to manipulate intuition and deliberation in the context of social cooperation, whose result suggest that there may not be any significant effect of time pressure on social cooperation decision-making. Only when many participants are removed, do the results support the previous findings, lending only weak support that a dual-process model of cognitive processing may underlie decisions involving social cooperation.

Future work could also examine other experimental manipulations aimed at distinguishing intuitive and deliberative processes, such as decreasing deliberation with cognitive load. Having people maintain a cognitive load of random letters or numbers while making their decisions might produce a similar separation of the intuitive and deliberative processes as putting people under time pressure. As recently discussed by Krajbich, Bartling, Hare, and Fehr (2015), simply using response time data alone to infer that choices are "intuitive" is inherently flawed due to the multiple sources of variability in data. Direct manipulations such as time pressure avoid the problems with "reverse inference" and lend more direct support for dual-process accounts. Future experiments could continue to build upon these results.

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APPENDIX A

Risky Decision-Making Experiment Supplementary Material


PRACTICE : You are given $70.
PRACTICE : Given $70
Z
M
$39
-$70
$70
Keep $39
(Lose $31)
Keep (All)
Lose (All)
A
PRACTICE : You are given $97.
PRACTICE : Given $97
Z
M
-$57
-$97
$97
Lose $57
(Keep $40)
Keep (All)
Lose (All)
B
Respond Quickly
You are given $78.
Given $78
Z
M
$20
-$78
$78
C
Maximize Your Money
You are given $78.
Given $78
Z
M
-$58
-$78
$78
D

Fig. 1. Screenshots from example practice trials (a, b) and test trials (c, d). On each trial, participants were first told how much money they would start with (top row); participants were also given an instruction on test trials. After 2 s, the initial screen was replaced with a decision screen (bottom row). On trials with a gain frame (a, c), participants were given two choices: a sure option (left pie chart), in which there was a 100% chance that they would gain the money indicated, and a gamble (right pie chart), in which there was a probability (which varied from trial to trial and which was indicated by the size of the wedges in the pie chart) of keeping the full starting amount or losing all of it. Trials with a loss frame (b, d) worked the same way, except that the sure option was framed in terms of how much money would be lost rather than gained. Decision screens in practice and test trials differed primarily in that on practice trials, on-screen text reminded participants of the values of each option. There were four variations of the experiment. In Variations 1, 3, and 4, potential gains were presented in green, and potential losses were presented in red; in Variation 2 (shown here), potential gains were presented in light gray, and potential losses were presented in dark gray. The locations of the pie charts showing the sure and gamble options (left vs. right) were always the same in Variations 1, 2, and 4, but they changed randomly from trial to trial in Variation 3. Finally, the framing of the on-screen instructions differed: In Variations 1 through 3, participants were told to "Maximize Your Money," a more positive goal, whereas in Variation 4, they were told to "Minimize Your Losses," a more negative goal.

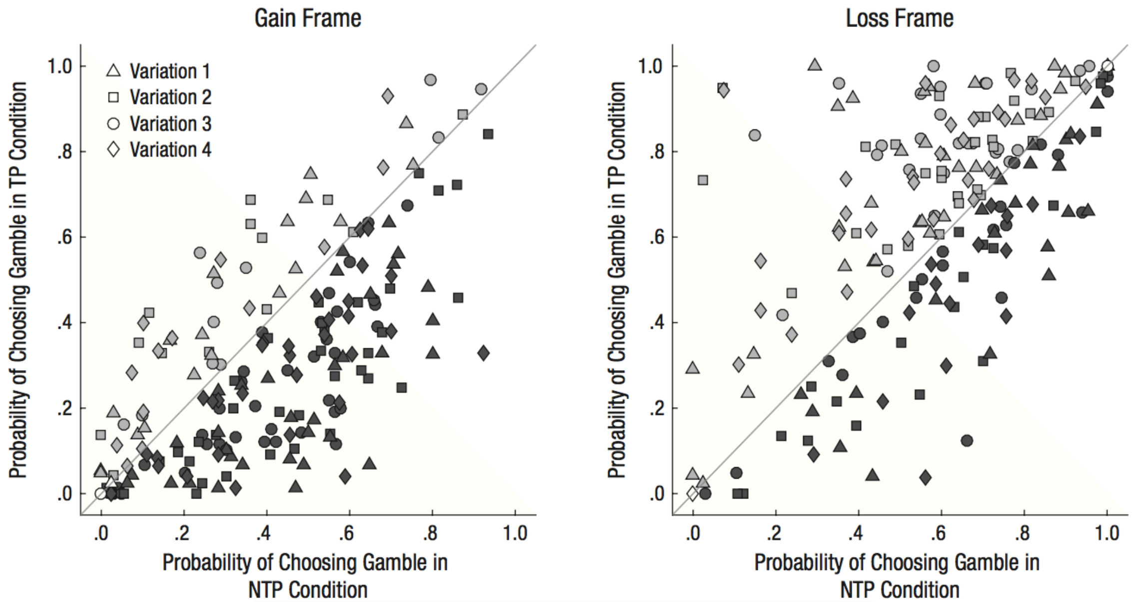


Fig. 2. Scatterplots showing the probability of choosing the gamble in the time-pressure (TP) block as a function of the probability of choosing the gamble in the no-time-pressure (NTP) block. Results are shown for each of the four experimental variations, separately for trials with a gain frame and a loss frame. Light-gray shading (on data points above the diagonal line) indicates that the probability of choosing the gamble was greater in the TP than in the NTP block, dark-gray shading (on data points below the diagonal line) indicates that the probability of choosing the gamble was greater in the NTP than in the TP block, and no shading indicates that the probability was equal.

Table 1. Repeated Measures ANOVA with block (TP, NTP), frame (gain, loss), and variation, examining the probability of selecting the gamble.

	Sum of Squares	*df*	Mean Square	*F*	*p*	η^2
Block	0.067	1	0.067	2.317	0.13	0.012
Block * Variation	0.02	3	0.007	0.234	0.872	0.004
Residual	5.496	191	0.029			
Frame	13.298	1	13.298	339.394	<.001	0.635
Frame * Variation	0.147	3	0.049	1.25	0.293	0.007
Residual	7.484	191	0.039			
Block * Frame	1.186	1	1.186	76.175	<.001	0.285
Block * Frame * Variation	0.008	3	0.003	0.168	0.918	0.002

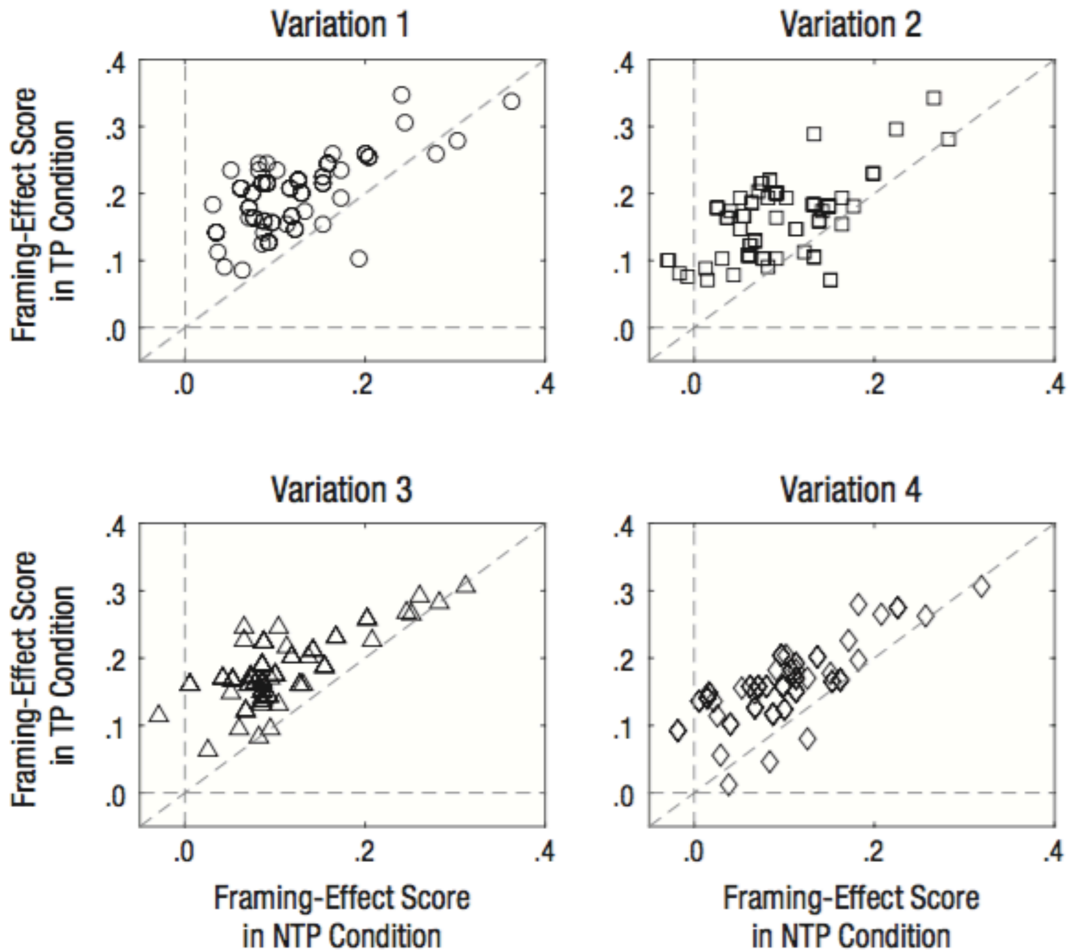
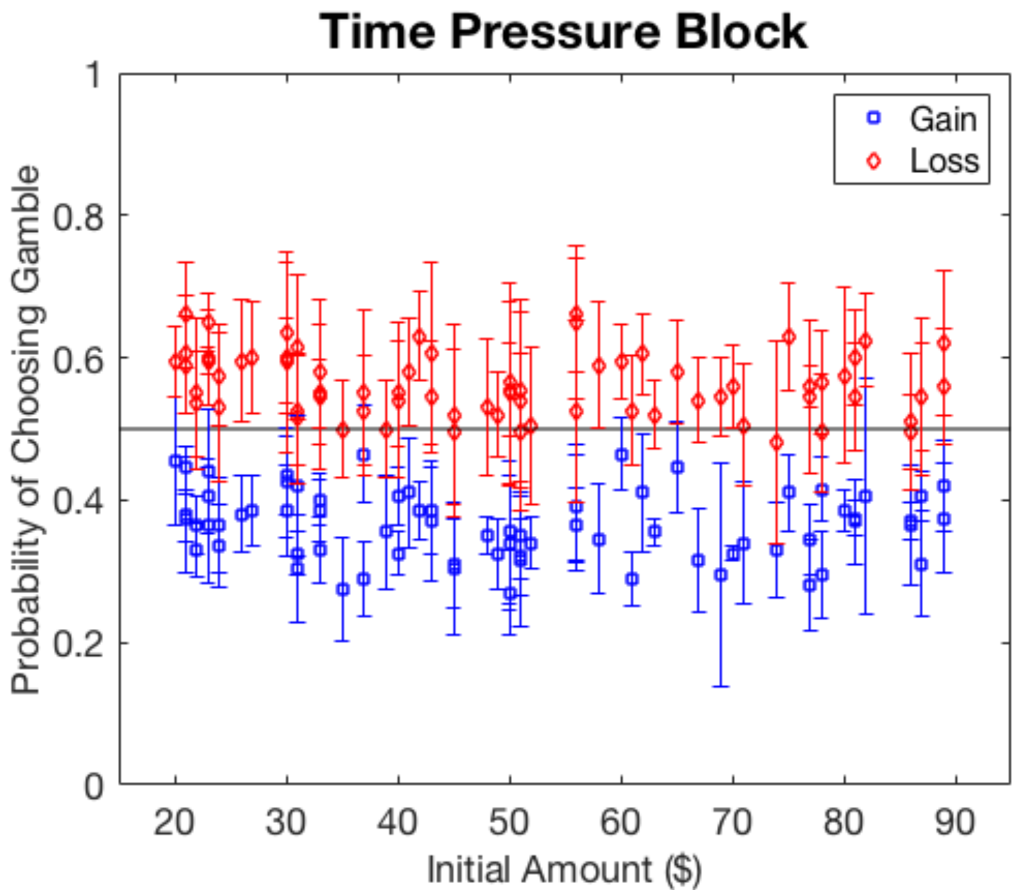
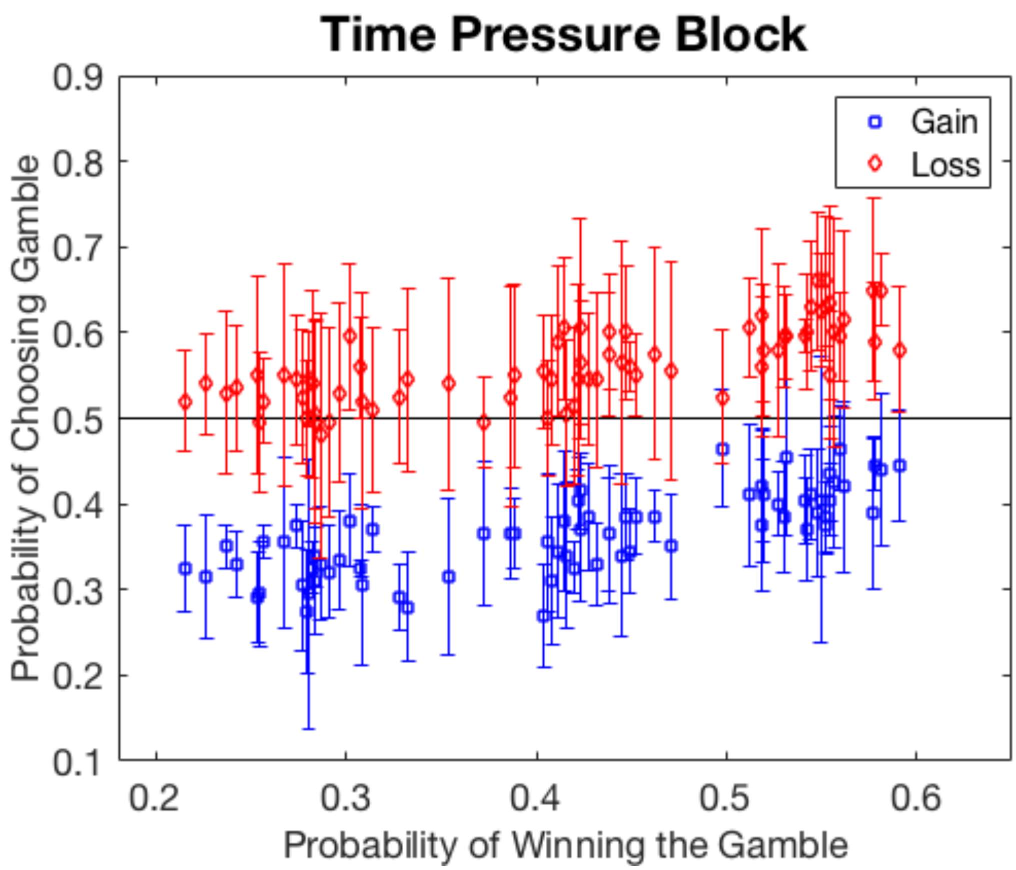


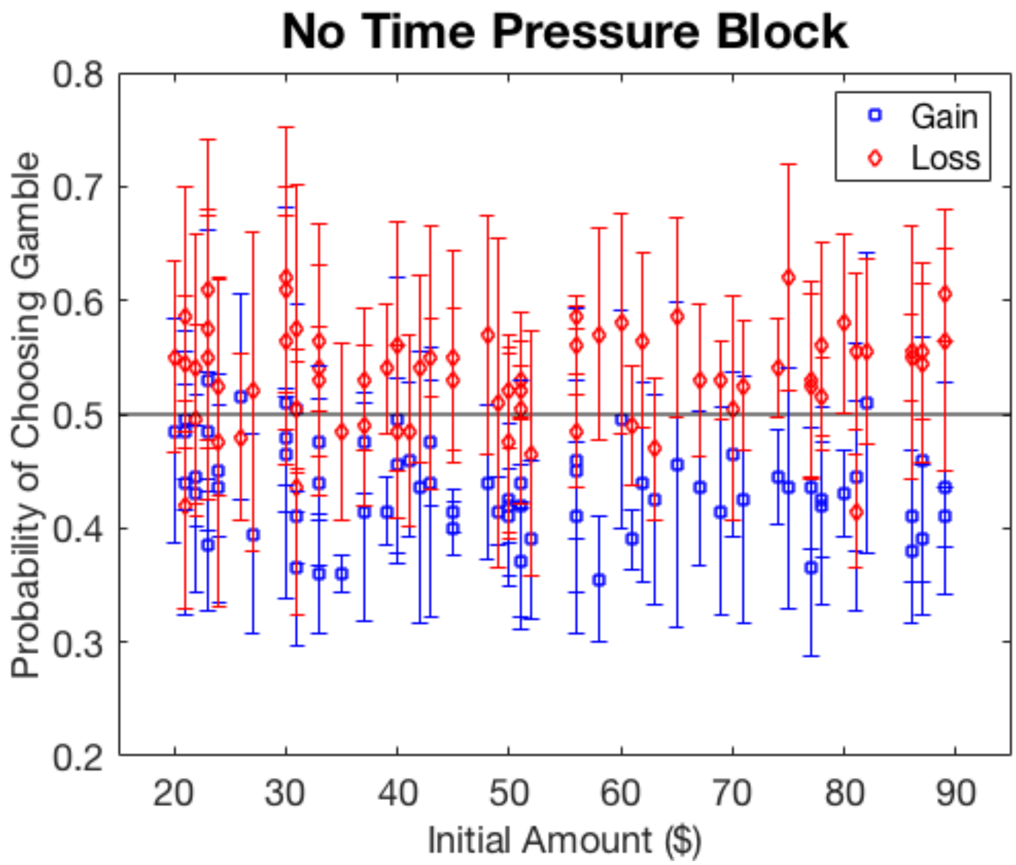
Fig. 3. Scatterplots showing the relationship between mean framing-effect scores in the time- pressure (TP) and no-time-pressure (NTP) conditions at the problem level, separately for each of the four variations. Framing-effect scores were calculated by subtracting the proportion of times the gamble was chosen in the gain frame from the proportion of times the gamble was chosen in the loss frame. Points above the horizontal dashed line indicate that there was a framing effect in the TP condition, points to the right of the vertical dashed line indicate that there was a framing effect in the NTP condition, and points above the dashed diagonal line indicate that the framing effect was larger in the TP than in the NTP condition.



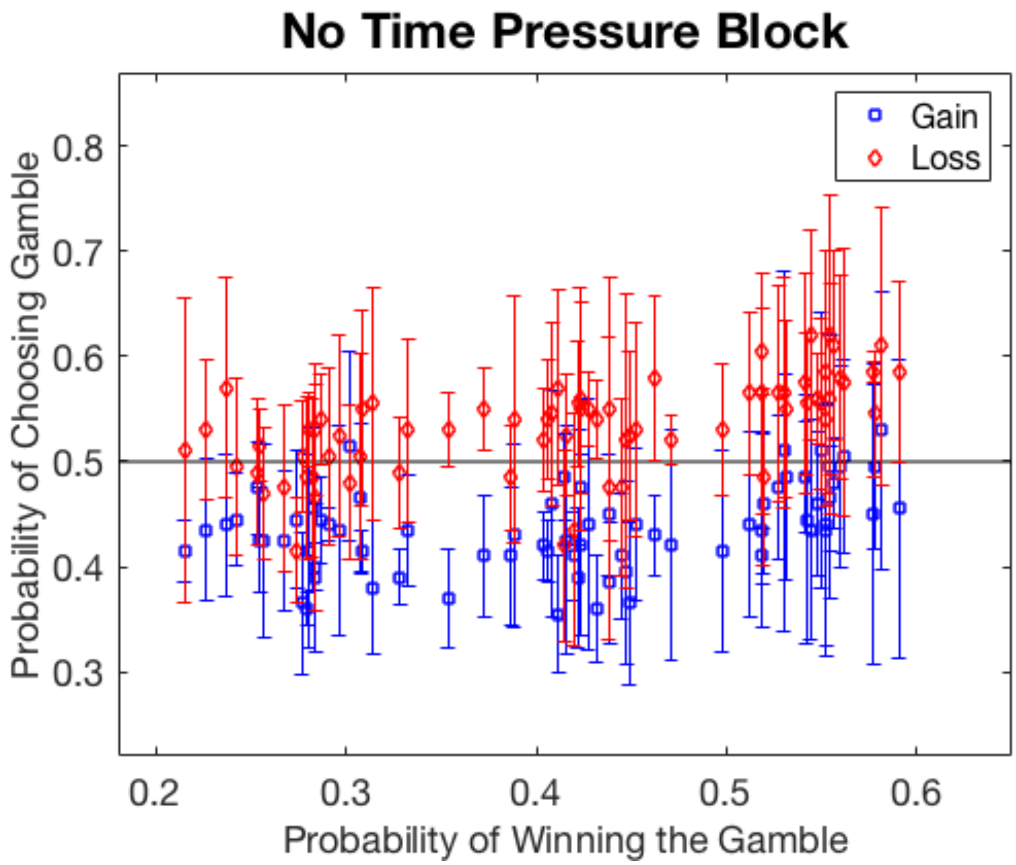
Plot of all collapsed data from all 4 variations under the time pressure condition, ascending by initial amount (in dollars). Note that the probability of choosing the gamble for the gain frame (blue squares) is well below 0.5, while the probability of choosing the gamble for the loss frame (red diamonds) is above 0.5. This behavior is consistent with the framing effect.



Plot of all collapsed data from all 4 variations under the time pressure condition, ascending by the probability of winning the Gamble. The probability of choosing the gamble for the gain frame (blue squares) is well below 0.5, while the probability of choosing the gamble for the loss frame (red diamonds) is above 0.5. This behavior is consistent with the framing effect.



Plot of all collapsed data from all 4 variations under the no time pressure condition, ascending by initial amount (in dollars). The probability of choosing the gamble for both the gain and loss frames is around 0.5 (i.e., framing effect is reduced for the NTP condition).



Plot of all collapsed data from all 4 variations under the no time pressure condition, ascending by the probability of winning the gamble. The probability of choosing the gamble for both the gain and loss frames is around 0.5 (i.e., framing effect is reduced for the NTP condition).

Table 2. Descriptive statistics for block (TP, NTP) and frame (gain, loss) for the probability of selecting the gamble in the four variations.

Variation	Block	Frame	Mean	SD	N
RG	NTP	Gain	0.401	0.227	49
		Loss	0.617	0.231	
	TP	Gain	0.301	0.237	
		Loss	0.692	0.262	
BW	NTP	Gain	0.430	0.255	49
		Loss	0.590	0.246	
	TP	Gain	0.327	0.244	
		Loss	0.637	0.280	
Random	NTP	Gain	0.402	0.238	53
		Loss	0.591	0.267	
	TP	Gain	0.292	0.237	
		Loss	0.642	0.277	
Losses	NTP	Gain	0.389	0.231	44
		Loss	0.558	0.231	
	TP	Gain	0.314	0.208	
		Loss	0.623	0.254	

Table 3. Bayesian Repeated Measures ANOVA with block (TP, NTP), frame (gain, loss), and variation, examining the probability of selecting the gamble.

Models	P(M)	P(M|Data)	BF_M	BF_{10}	% error
Null model (incl. subject)	0.053	7.90E-79	1.42E-77	1	
Block	0.053	1.22E-79	2.20E-78	0.155	1.398
Frame	0.053	5.29E-08	9.52E-07	6.69E+70	1.284
Block + Frame	0.053	1.30E-08	2.35E-07	1.65E+70	1.743
Block + Frame + Block*Frame	0.053	0.944	304.861	1.20E+78	2.774
Variation	0.053	1.95E-80	3.51E-79	0.025	0.395
Block + Variation	0.053	2.98E-81	5.36E-80	0.004	1.259
Frame + Variation	0.053	2.48E-09	4.46E-08	3.14E+69	6.401
Block + Frame + Variation	0.053	6.30E-10	1.13E-08	7.98E+68	6.738
Block + Frame + Block*Frame + Variation	0.053	0.051	0.959	6.41E+76	8.043

Table 4. Effects From the Bayesian Repeated Measures Analysis of Variance on the Probability of Selecting the Gamble.

Effects	P(incl)	P(incl|data)	$BF_{Inclusion}$
Block	0.737	1.000	6.423E+06
Frame	0.737	1.000	∞
Variation	0.737	0.056	0.021
Block * Frame	0.316	1.000	3.126E+07
Block * Variation	0.316	7.537E-04	0.002
Frame * Variation	0.316	0.005	0.010
Block * Frame * Variation	0.053	1.569E-06	2.824E-05

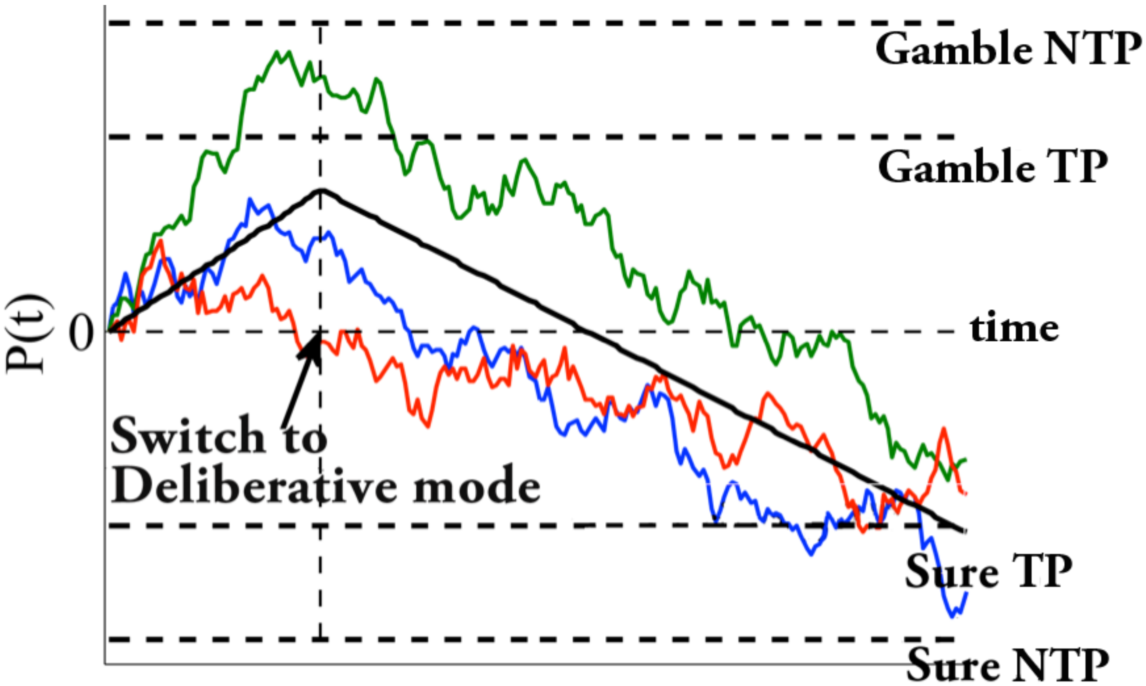


Fig. 4. An example of three trials in the Loss frame. The trajectories symbolize the accumulation process for three different loss trials. In one trial (green) the process reaches the boundary for choosing gamble under the time pressure condition before the switch occurs. In the other trials (red and blue) the process reaches the boundary for choosing the sure option under the time pressure condition after the switch.

Table 5. Sample trial used for modeling.

Type of Amount	Amount
Reference point ("You are given $")	64
Sure Gain ("Keep $")	36
Sure Loss ("Lose $")	28
Gamble Amount ("Keep All $")	64
Probability of Gain (probability of "Keep All $")	0.56

Table 6. Parameter values used for modeling.

Intuitive*	Deliberative
$\alpha_I = 0.88$	$\alpha_D = 1.00$
$\beta_I = 0.88$	$\beta_D = 1.00$
$\lambda_I = 2.25$	$\lambda_D = 1.00$
$c_I = 0.61$	$c_D = 1.00$

* From Tversky and Kahneman, 1992

Values nearer to 1 indicate more linear perceptions of probability.

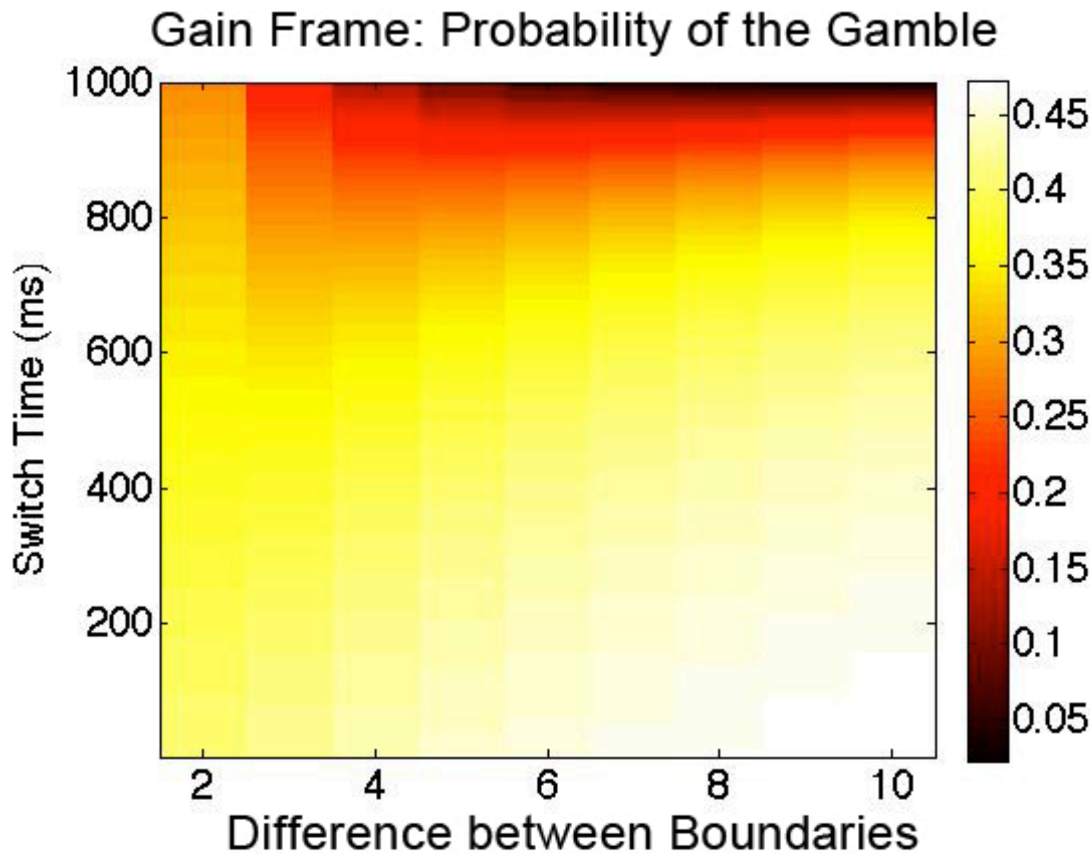


Fig. 5. Heatmap of the probability of choosing the gamble in the gain frame simulation trial, with the difference between the TP and NTP boundaries on the x-axis; the switch times on the y-axis, and the heat scale legend on the far right.

We see the expected trends that illustrate the framing effect: as the difference between bounds decrease (i.e., corresponding to increased time pressure), the probability of choosing the gamble decreases (i.e., the sure option is selected more often).

Also, as the switch time increases (i.e., spending more time in the intuitive system), the probability of choosing the gamble decreases.

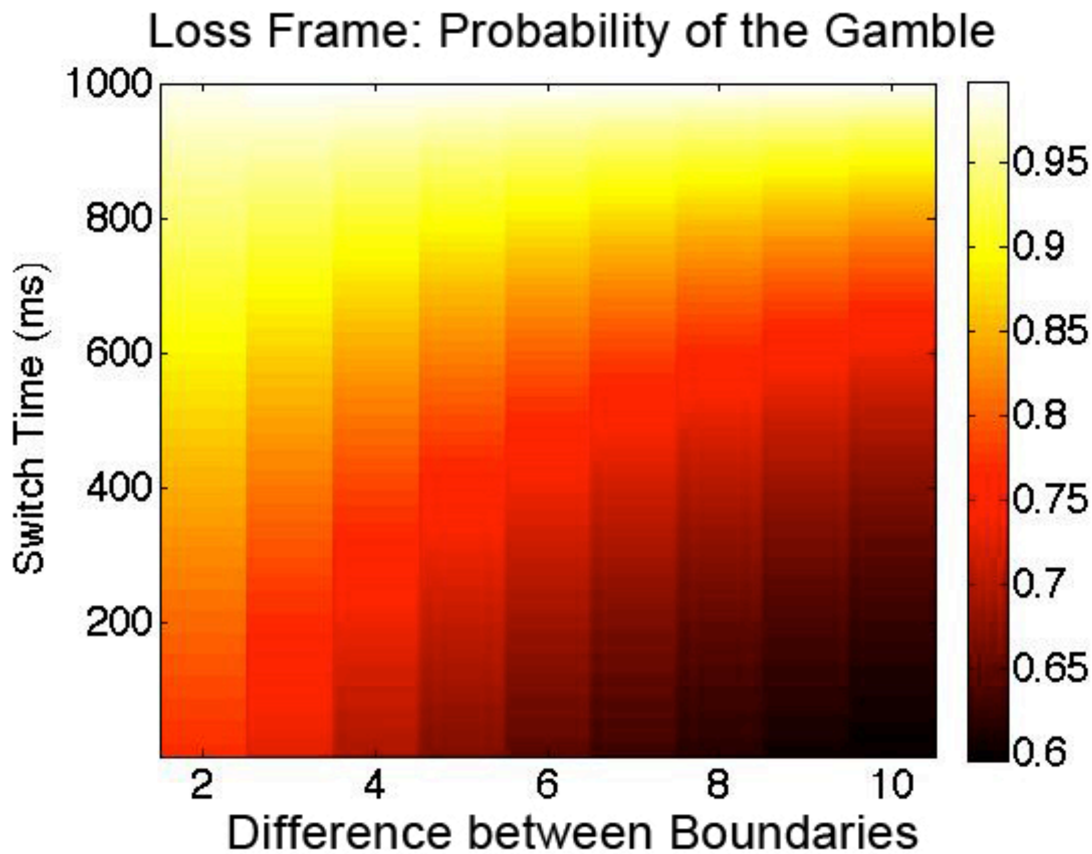


Fig. 6. Heatmap of the probability of choosing the gamble in the loss frame simulation trial, with the difference between the TP and NTP boundaries on the x-axis; the switch times on the y-axis, and the heat scale legend on the far right.

Again for the loss frame we see the expected framing effect: as the difference between bounds decreases, the probability of choosing the gamble increases for losses. As the switch time increases, the probability of choosing the gamble increases.

Additional Model Considerations

During my summer at Pacific Northwest National Laboratory as a PhD intern, I worked with Dr. Leslie Blaha and Dr. Christopher Fisher on a project involving modeling human information processing using trace conditioning. The trace conditioning model is a human reaction time model which could potentially have many applications, including describing cognitive decision-making. Attached is the technical report summarizing my findings.

Modeling Continuous Human Information Processing Using Trace Conditioning With a Cyber Defense Literature Review

Lisa Guo

ABSTRACT

We developed and explored a model for continuous processing. Continuous information processing pertains to the fine-grain dynamics of a decision, located on one end of a gradient of stages that describes how humans process information. Discrete, coarse-grain representation resides on the other end. The goal of Project 1 is to capture the complex underlying dynamics of continuous information processing via a trace conditioning model. Our first task was to implement a version of the trace conditioning model. We derived it from mathematically supported foundations and technical details in the literature (Machado, 1997; Los, 2001). Next, we simulated the model using our code and reproduced the results from Los (2001), validating that our model replicates the literature. Our next step involves fitting the model to human data to test the model's abilities to capture empirically documented effects. With this foundation established, future development of our model could include tasks with feedback and multiple simultaneous tasks.

INTRODUCTION

We live in a complex world which demands the use of cognitive models that can accommodate real-time updates, adjustments, and feedback. Take, for instance, the ubiquitous act of driving a car. One must continually assess the environment (scanning for road hazards such as potholes, wild animals, or changing weather conditions); the traffic (how congested the roads are with other vehicles, the direction of traffic flow); and react to signals (from other drivers, traffic lights, and traffic signs). Much of this feedback may be occurring simultaneously, and one must continually update one's actions toward the goal of getting to some destination. My project is motivated by the need for models that can capture these kinds of complex dynamics, including making multiple simultaneous decisions, stimuli that appear without warning, and decisions with varying levels of feedback. This project adds to a growing body of literature describing the dynamics of human decision-making in more realistic contexts, outside of a structured lab setting.

The demands for such a model go beyond decisions that we might encounter in day to day life. From the use of real-time electron microscopy imaging of cancer cells, to continuous monitoring of cyber defenders against insider attacks, real-time monitoring of events plays an integral part in tasks which can put human lives, organizational safety, and financial resources at stake (Sokolov et al., 2003; Claycomb et al., 2014; Blaha et al., 2016). Current and past research has begun to address these needs, introducing models such as the ACT-R model (Fisher et al., 2016; Fisher et al., 2015; Blaha et al., 2016); linear ballistic accumulator (LBA; Brown & Heathcote, 2008); diffusion model (Ratcliff, 1978; Ratcliff & Rouder, 1998); trace conditioning (Los et al., 2001; Los, 2013); with additional research looking into the complex patterns that exist with responses and response times (Jones et al., 2013). This paper explores and expands upon the trace conditioning model in an effort to further our understanding of the dynamic underlying processes of human decision-making behavior and expand the models' capabilities as a step towards a continuous and eventually real-time model of processing.

Methods and models

Our work aims to expand and build upon the trace conditioning model to generate predictions about reaction times based on the underlying cognitive processes involved in the decisions. This section will delve deeper into the background behind the diffusion and trace conditioning models.

The trace conditioning model takes into account the tendency for humans to exhibit strong influences of preparation, both when provided with information on the requirements of an impending task, but also in reaction time tasks where prior information consists of just a single warning that a target stimulus is going to appear. Specifically, it examines the role of nonspecific preparation and how it develops as a real-time process, suggesting that the duration of the foreperiod (FP; the interval between the warning stimulus, WS, and the imperative stimulus, IS) as well as the FP-variability across trials, have significant effects on reaction time (Niemi & Näätänen, 1981). This nonspecific preparation can be attributed to the learning rules associated with classical and operant conditioning.

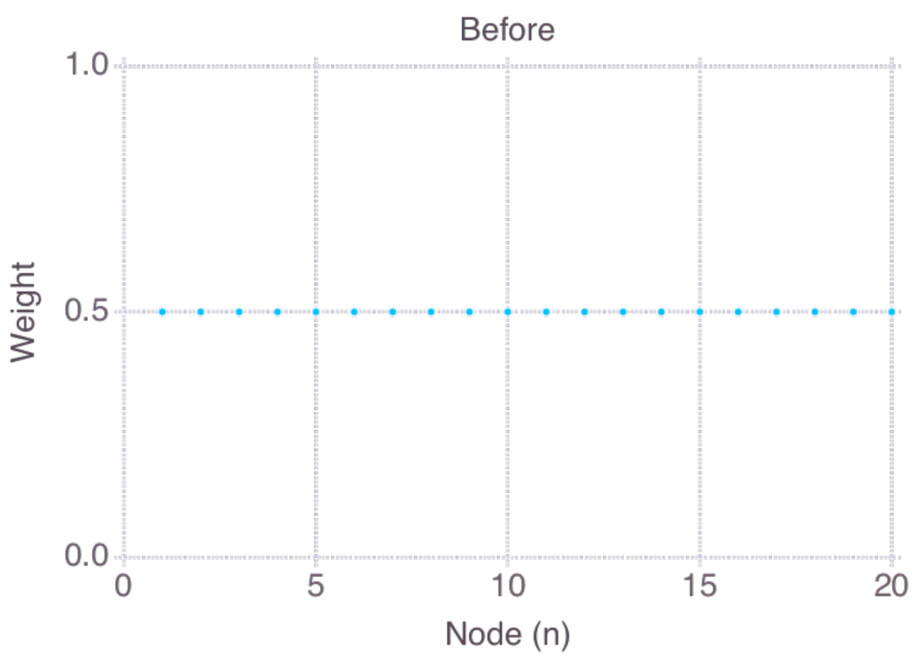
In classical conditioning, the foundation of an experiment revolves about the initial association between an unconditioned stimulus (UCS) and an unconditioned response (UCR). In Pavlov's classical study (1972), meat powder was the UCS, which elicited the UCR of saliva production from his dog. Then in the acquisition phase, a conditioned stimulus (CS) is introduced before the UCS (in Pavlov's study, a tone). Subsequently, the CS becomes associated with the UCS in this paired presentation, even though at first the two were unrelated. As a result of this association, the CR (production of saliva) occurs when CS is presented by itself. Reaction time experiments involving nonspecific preparation are analogous to classical conditioning. The IS can be seen as the UCS, and the tendency to respond is the UCR. The WS is related to the CS, which ends up causing a CR (response) to develop, resulting in the overall behavior of the participant preparing for the upcoming IS.

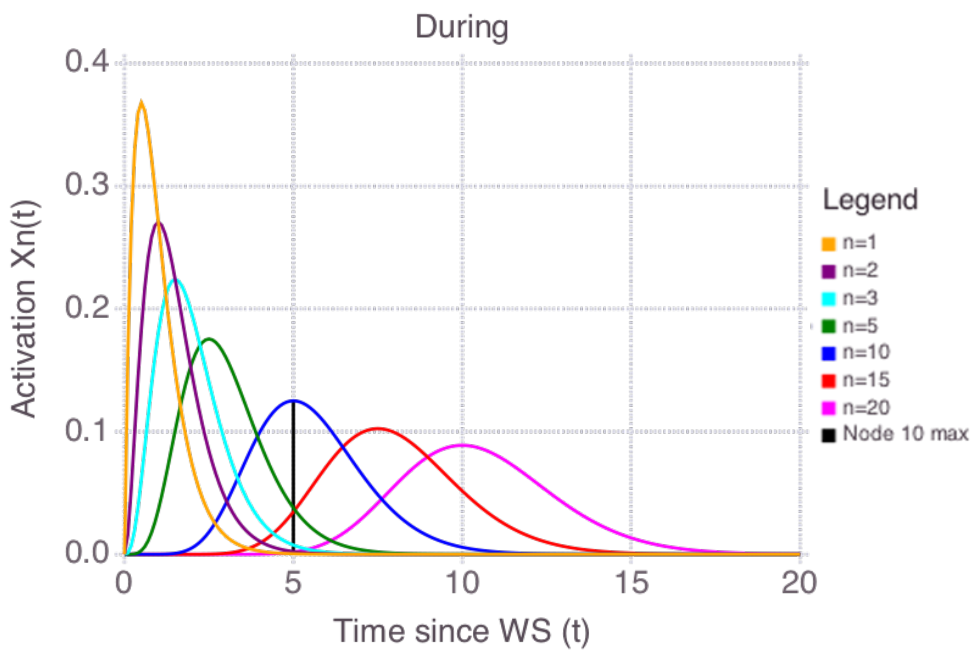
The formal trace conditioning model is a structure that layers timing nodes, a preparation node, and connection weights between the nodes (Los, 2001). Each timing node is connected to the next sequential timing node and also to the preparation node. The connections between timing nodes and the preparation node have adjustable weights. When the WS is presented, activation propagates through the timing nodes, with each timing node contributing to the eventual activation of the preparation node based on its own activation and its own weight. The preparation node reflects the participants' preparatory state and from past literature, is inversely related to RT (Niemi & Näätänen, 1981). The weights of the timing nodes are determined by learning rules: extinction (occurs during foreperiod), reinforcement (after the IS is presented) and are described by a system of linear differential equations. These equations serve as the mathematical foundation for the trace conditioning model. Together, they describe the cascade of activation which flows through the timing nodes at the presentation of the WS.

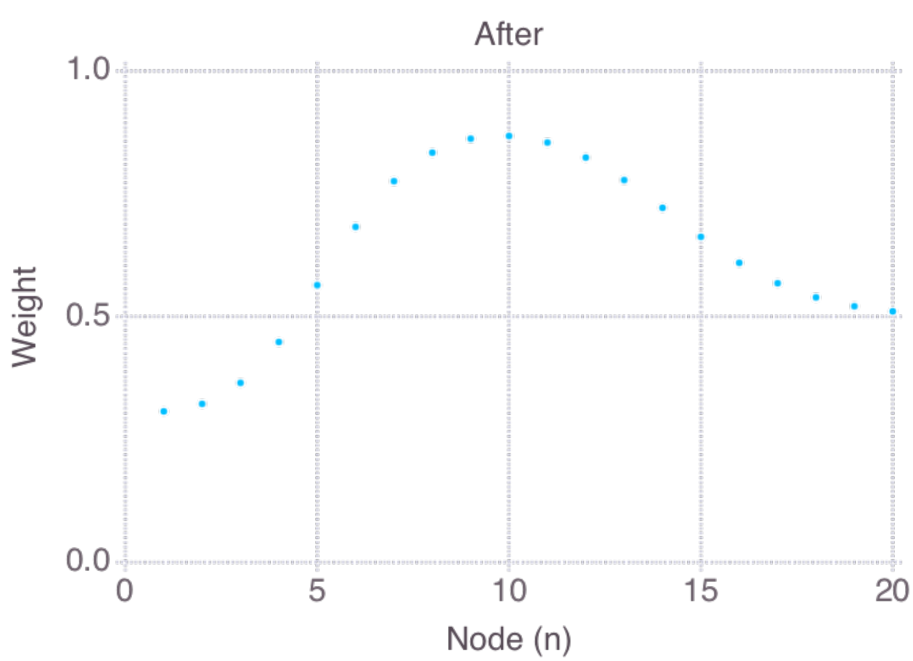
Functionality and results

One of our tasks this summer was to implement a version of the trace conditioning model from its mathematically supported foundations and the reported technical details in the literature (Machado, 1997; Los et al., 2001). We coded the model using Julia, a dynamic programming language for technical computing (Bezanson et al., 2012). We captured the activation, extinction, and reinforcement of the timing nodes as functions reflecting Equations 5, 7, and 9, and used Equation 10 for predicting response times (see Appendix for code).

Next, we simulated the model using our code with the goal of reproducing the results and plots from Los et al. (2001). We began by reproducing Plot 4a, b, and c from the text. This plot describes the weights before a single trial, set at an arbitrary value of 0.5 (a); the activation functions during the trial, with $\lambda = 2$, $\alpha = 1$, and $\beta = 12$, with the IS presented at $t = 5$ (b); and lastly, the weights after the trial (c). A key feature of Plot 4b is that the curve of each node intersects its adjacent node at the latter node's maximum. Plot 1 in this report shows the successful replication of these results.





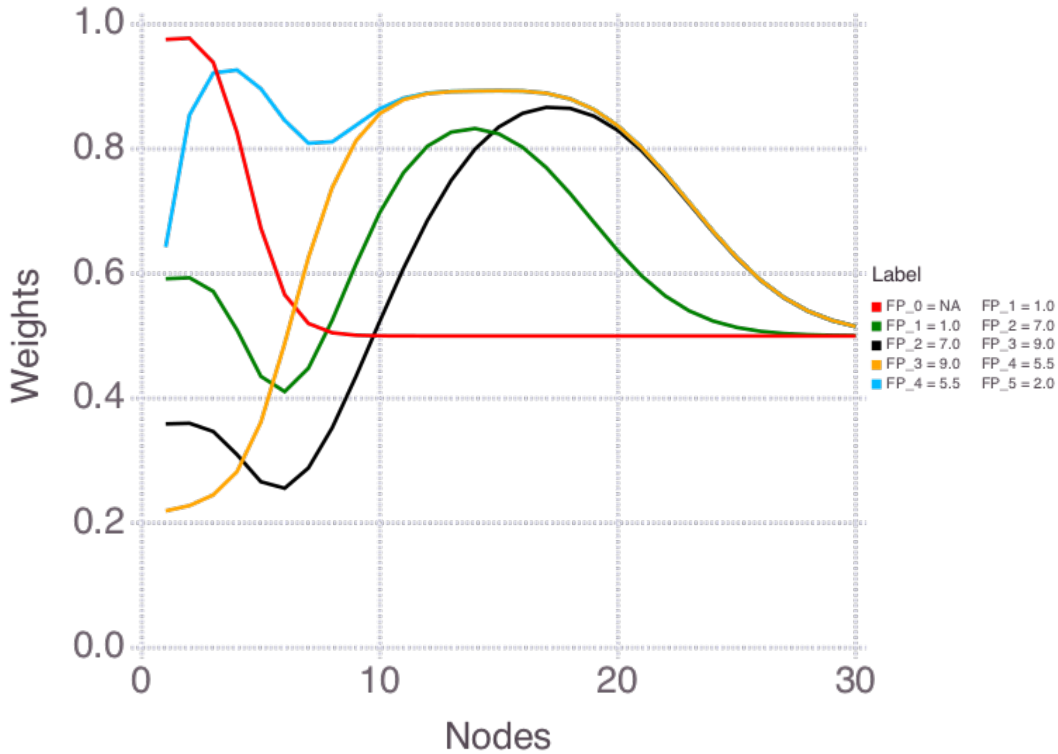


Plot 1: Replication of Plot 4 from Los et al. (2001). The first panel shows the weights before a single trial. The weights are set to 0.5 for illustrative

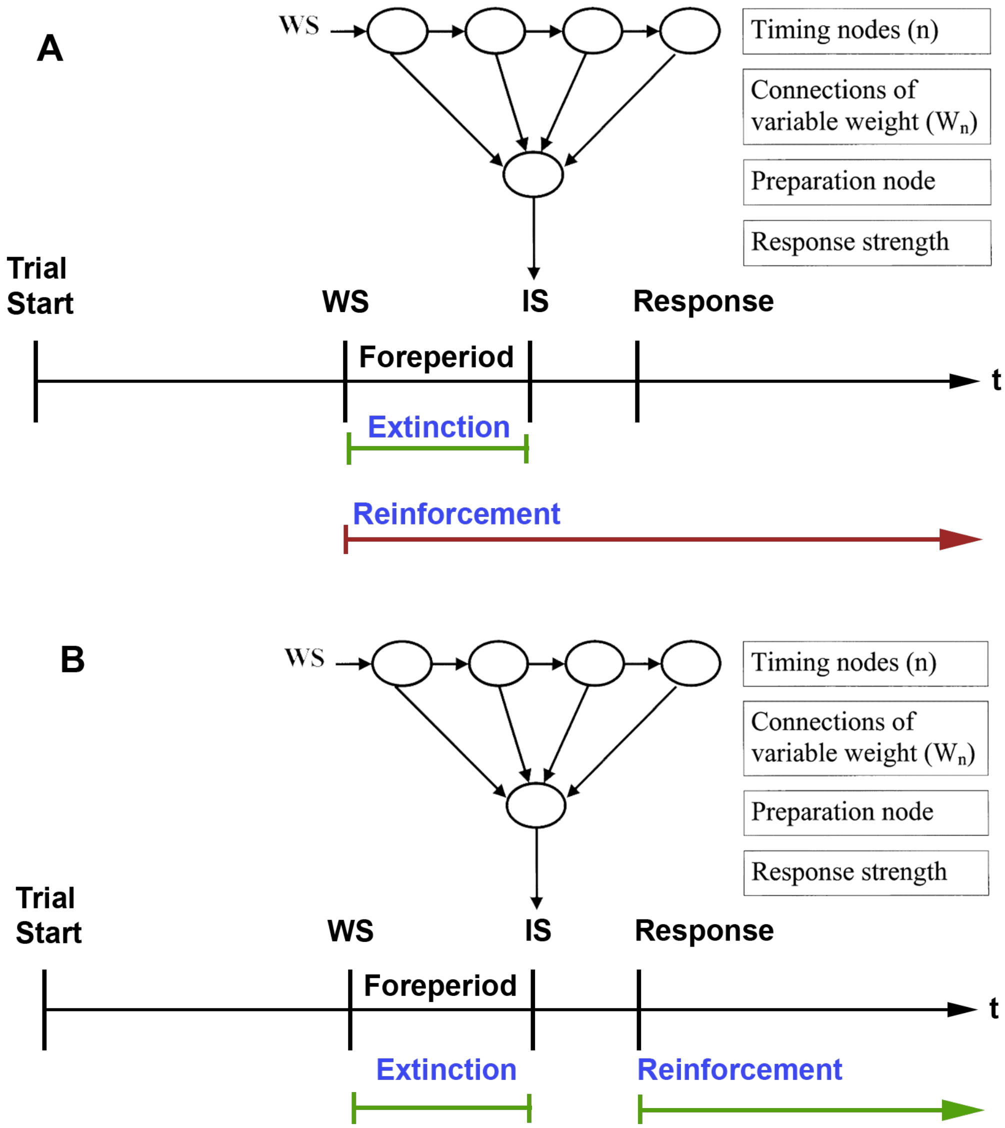
clarity. The authors note in the text that these initial weights are arbitrary; indeed, we tested this in our code and found that even with arbitrary individual initial weights, the results remained unchanged. The middle panel shows the activation function during the trial for nodes 1, 2, 3, 5, 10, 15, and 20, with parameter values $\lambda = 2$, $\alpha = 1$, and $\beta = 12$, with the IS presented at $t = 5$. A black horizontal line is drawn on node 10, illustrating the imperative moment of the depicted trial at $t = 5$, when node 10 is maximally active. The final panel of the plot shows the weights after the trial. Note that node 1 in the first panel begins with a weight of 0.5. The node is highly active during the FP (after WS but before IS), but since the IS is presented after node 1, its corresponding weight decays, as reflected in the last panel. Since node 10 was maximally active during the IS, its corresponding weight is reinforced, as reflected in the last panel. The farthest nodes, such as node 20, were neither active during the FP nor IS, so their corresponding weights remain nearly unchanged at 0.5.

Next, we simulated the model predictions of reaction times as a function of block type (pure or mixed), foreperiod of the current trial, and foreperiod of the previous trial. In pure blocks, the same FP occurred on each trial (either 0.5, 1.0, or 1.5 s). Mixed blocks, on the other hand, had an equal probability of FP being 0.5, 1.0, or 1.5 s on each trial. During this step, we discovered an error in our code. The plot that our code produced was qualitatively similar to the ones in the literature, however, our mean reaction times were slightly too fast.

To remedy this issue, first we carefully examined each of the functions involved in the trace conditioning model. We compared the activation, extinction, and reinforcement functions individually back to each of the equations that they corresponded to. Finding no errors there, we coded an additional function that plotted a trial-by-trial change in weights. This code is an extension of Plot 4c in Los et al. (2001), which only showed a single trial's change in weights. We did this because we wanted to make sure that sequences of trials, not just individual trials, were behaving accordingly. In other words, that the timing node weights were changing not only according events occurring on one particular trial, but according to previous trials as well. As noted in the literature, the weights of the current timing nodes (which lead to the current response) are affected by all of the preceding trials' timing node weights. Plot 2 below shows an example of the trial-by-trial change in weights for five sequential trials (FP = 1.0, 7.0, 9.0, 5.5, and 2.0 s). Overall, the node weights appear to be qualitatively behaving as we would expect.



Plot 2: Multiple trial-by-trial change in weights. Plot shows sequential trial weights, with initial weights set at arbitrary value of 0.5. Thirty nodes are represented on the x-axis, with their corresponding weights after each trial on the y-axis. The first trial has a foreperiod of 1.0 s (in red); second trial FP = 7.0 s (green); third trial FP = 9.0 s (black); fourth trial FP = 5.5 s (orange); and fifth trial FP = 2.0 s (blue). After the first trial (red), the node weights reflect the IS being presented at 1.0 s, with earlier nodes being highly activated and later nodes remaining unaffected (remaining at the initial weight of 0.5). The node weights after the second trial (green) are affected by both the FP and by the weights on trial 1. We see the effect of the FP on trial 2 as node 14 is maximally active at the presentation of IS at 7.0 s. Additionally, the weights after trial 1 influence trial 2, as seen in the earlier nodes of trial 2, as the weights are greater than the initial weight of 0.5. These same trends continue for trials 3, 4, and 5. See Appendix for parameter values used in this simulation.

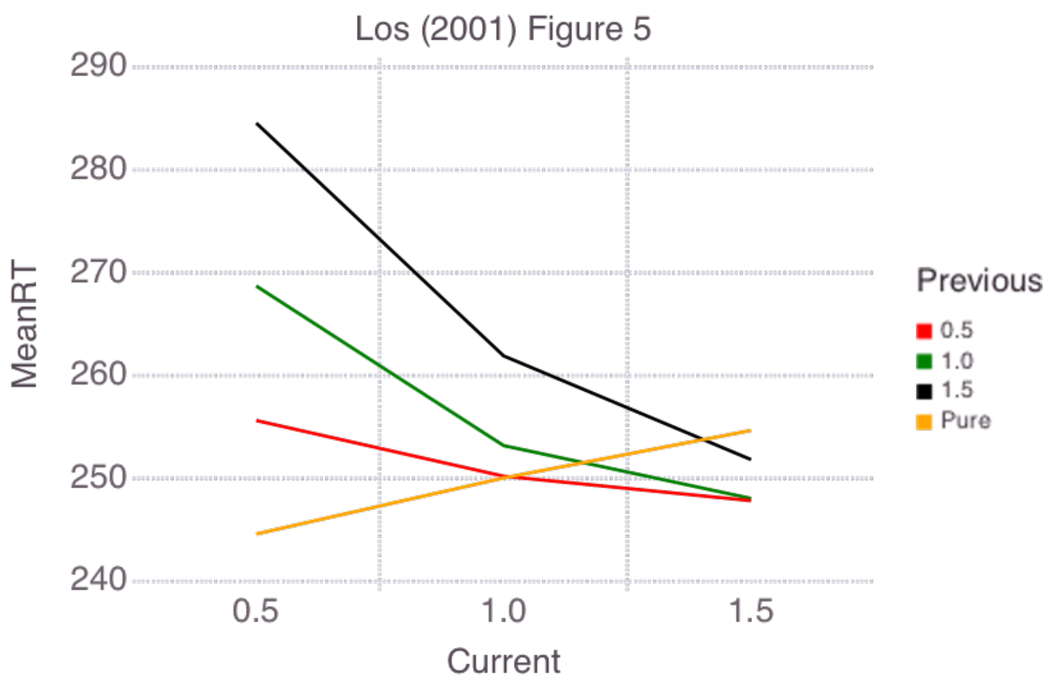


Plot 3: Illustration of sequence of functions in original code (with error in reinforcement equation placement) and amended code. Plot 3A illustrates the sequence events captured by our original code (with error). The node

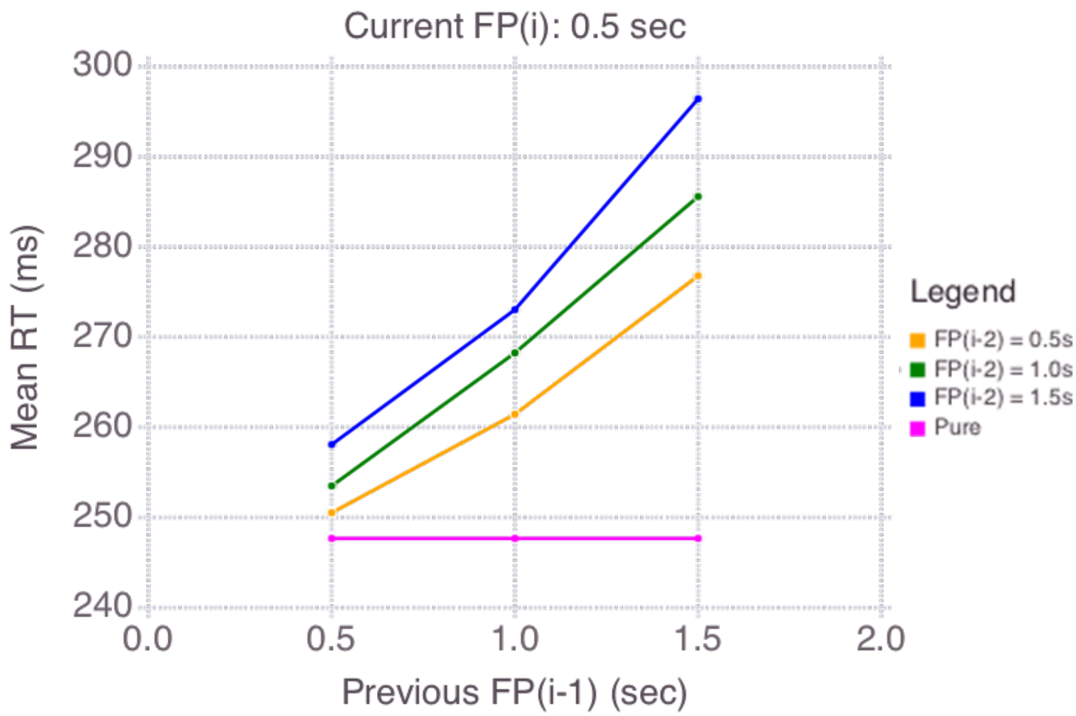
diagram is borrowed from Los et al. (2001) and illustrates the path of timing node weights and activation once the WS is presented. The line diagram below demonstrates a timeline if events across a single trial, beginning from the trial start on the far left, after which some point the WS is presented. The time between the presentation of the WS and IS is the foreperiod (FP), after which the response occurs. In our original code, both the extinction and reinforcement functions lay within the FP. The extinction function occurs in its correct place (denoted by the green bracket below its label), but the reinforcement equation has been misplaced (denoted by the red arrow), as it had been coded to occur at any point after the presentation of WS. Plot 3B shows how we amended the misplacement. The extinction function remains in the same place, but the reinforcement function has been moved to its correct location, occurring after the response (denoted by the green arrow).

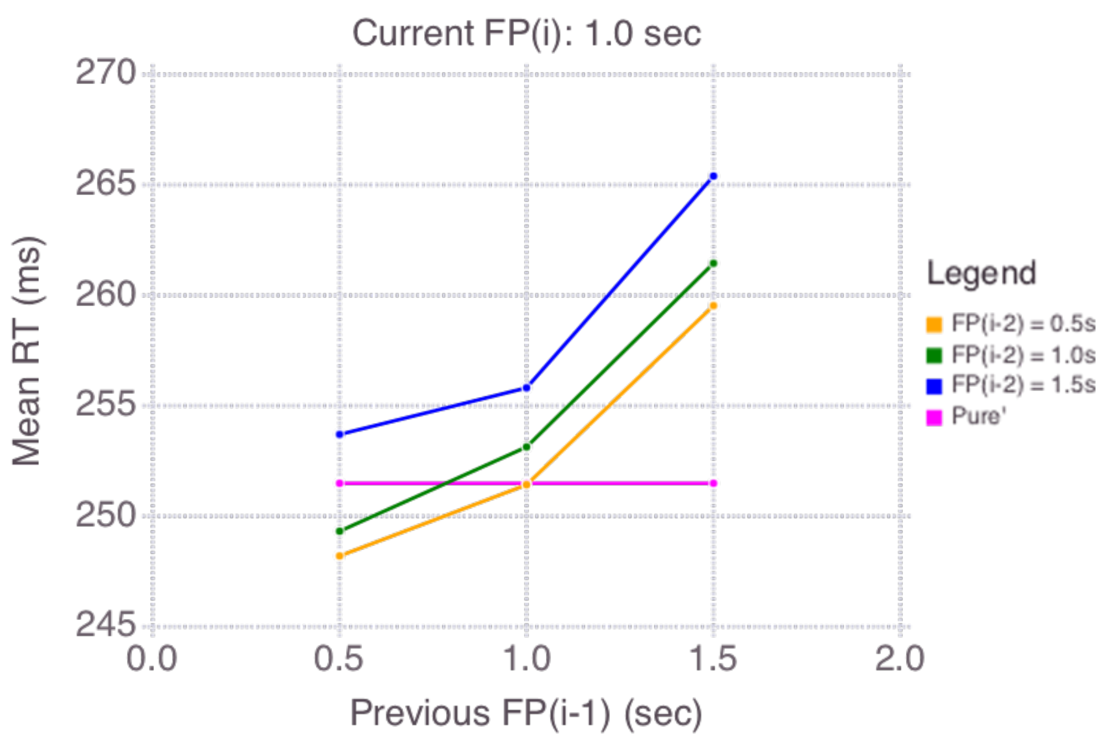
The issue of our simulated mean reaction times being slightly off from the results in the literature persisted. At this point, we had examined each piece of the model individually, tried various sets of parameter values, and tested for both individual and sequential trial behavior. We had exhausted our toolkit in an effort to identify the error. We held a "Huddle Room" meeting and invited two interdisciplinary guests, Dr. Joseph W. Houpt and graduate student Tim Balint for their advice. Together, we discovered where the error lie in our code. In our trace conditioning model code, where we compute the response function value at FP (the duration of the foreperiod), the reinforcement function was placed in a chronologically incorrect order. Reinforcement should occur post-response, whereas in our original code, reinforcement was grouped with activation and extinction, falling into the set of processes that occur during the FP. The top panel of Plot 3 shows our original sequence of events (the incorrect ordering), compared to the modified sequence of events, shown in the bottom panel.

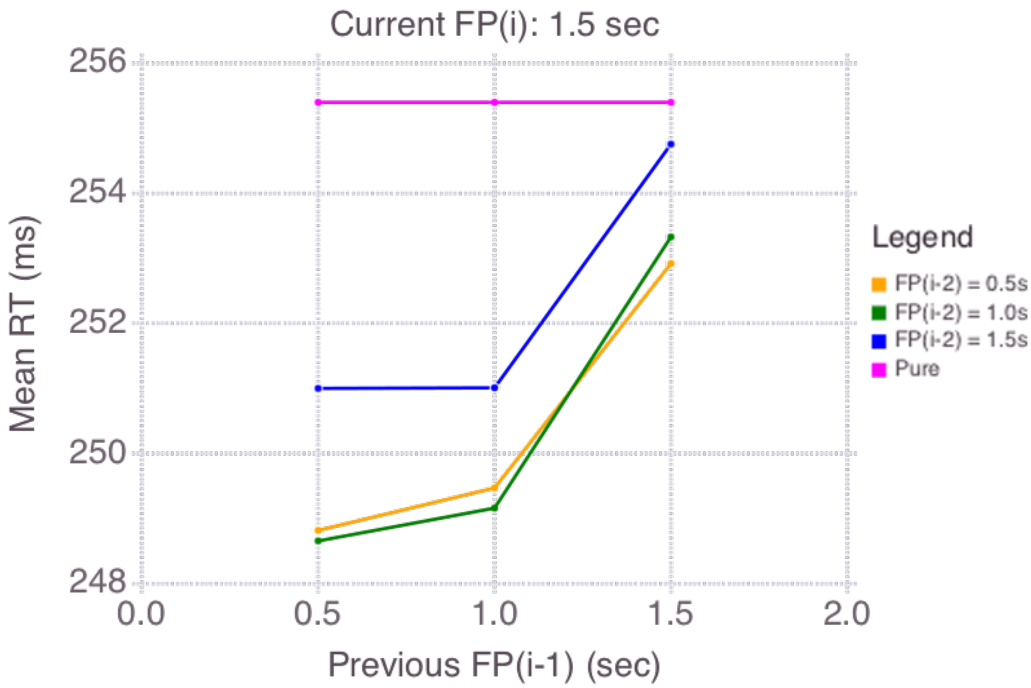
After revising our code, we were able to successfully replicate Plot 5 from Los et al. (2001). Our results were now matched the results from the literature both qualitatively and quantitatively. Plot 4 shows the plot from our code. We then replicated Plot 6 from Los et al. (2001) without any further issue. These plots captured the empirically supported behavioral results. That is, the tendency for reaction times to long FPs to be insensitive to the duration of the preceding FP. Furthermore, the reaction times to long FPs tend to decrease compared to reaction times to short FPs (the foreperiod effect). The simulations also captured the nature of sequential effects in mixed blocks. That is, for an FP of 0.5 s, the model yielded increasingly longer reaction times for preceding trials with a longer FP.



Plot 4: Replication of Los et al. (2001), Plot 5. Predicted mean reaction times (y-axis) as a function of block type, current foreperiod (0.5, 1.0, or 1.5 s; x-axis) and previous foreperiod (0.5, 1.0, or 1.5 s; lines). Our simulated plot replicates Plot 5 from the literature, capturing the same empirical effects found in their data. That is, the tendency for mean reaction times to be longer when a shorter FP is preceded by a longer FP. Additionally, mean reaction times tend to be faster for long FPs, regardless of previous FP. We also capture the crossover effect from pure blocks and mixed blocks.

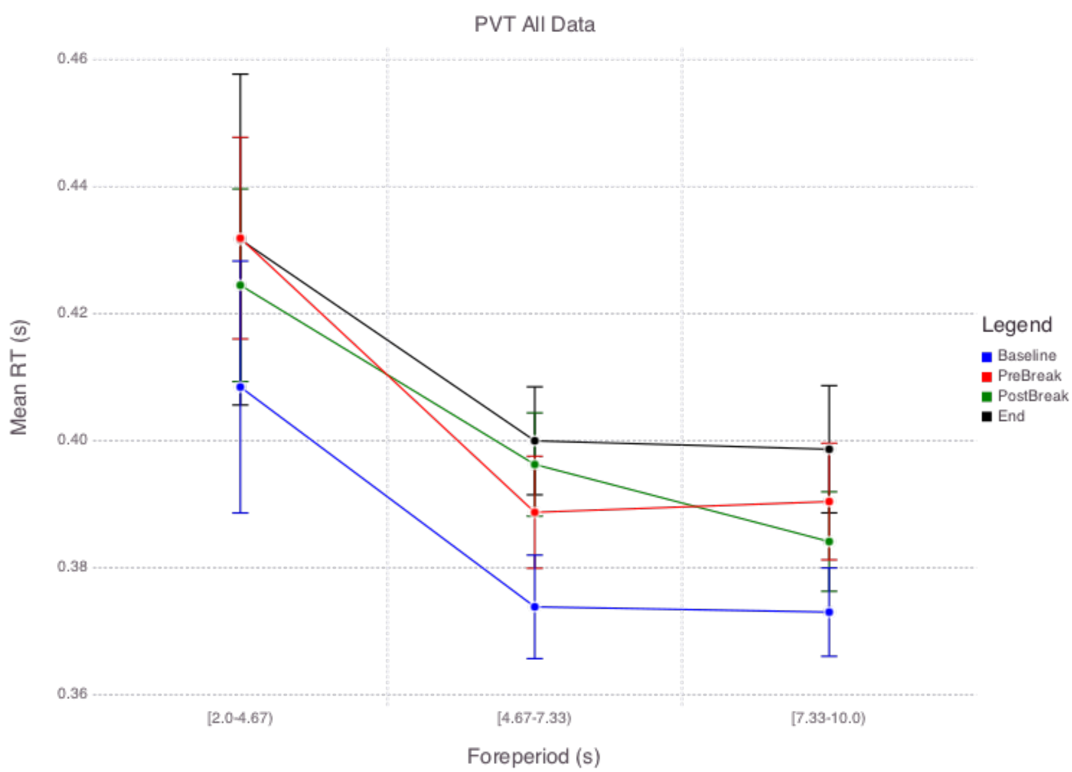

Current FP(i): 0.5 sec
300
290
280
270
260
250
240
0.0
0.5
1.0
1.5
2.0
Mean RT (ms)
Previous FP(i-1) (sec)
Legend
FP(i-2) = 0.5s
FP(i-2) = 1.0s
FP(i-2) = 1.5s
Pure

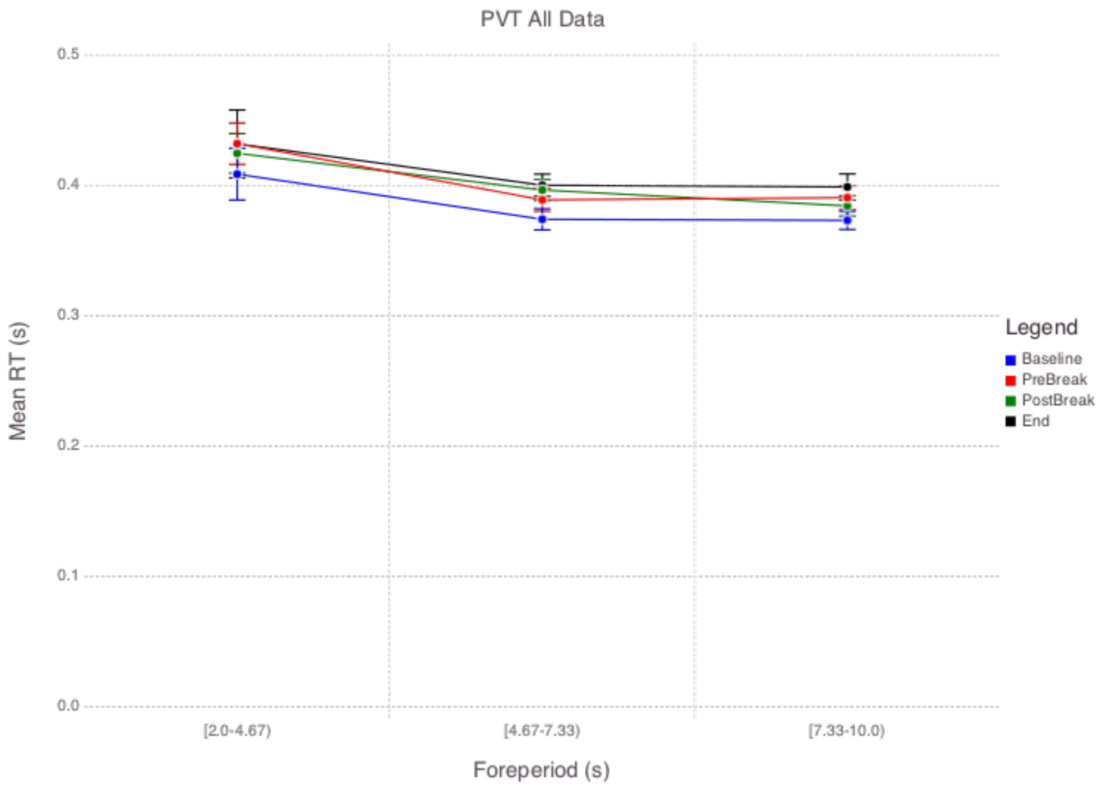

Current FP(i): 1.0 sec
270
265
260
255
250
245
0.0
0.5
1.0
1.5
2.0
Mean RT (ms)
Previous FP(i-1) (sec)
Legend
FP(i-2) = 0.5s
FP(i-2) = 1.0s
FP(i-2) = 1.5s
Pure'



Plot 5: Replication from Los et al. (2001), Plot 6. Simulated mean reaction times (y-axis) in pure blocks (horizontal lines) and in mixed blocks as a function of current foreperiod (0.5, top panel; 1.0, middle panel; or 1.5 s, bottom panel), previous foreperiod (0.5, 1.0, or 1.5 s; x-axis), and the foreperiod of the trial before the previous (0.5, 1.0, or 1.5 s; lines).

In order to test our model's abilities to capture empirically documented effects outside of the dataset collected by Los and colleagues, we fit the TCM to data from a psychomotor vigilance test (PVT). The data was kindly shared with us from our colleagues at PNNL, Matt Nowatzke and Lyndsey Franklin, collected earlier this summer. The PVT is a simple 10-minute detection task that requires subjects to respond as quickly as possible to a visual stimulus. The stimulus appears after a random 2-10 sec foreperiod (FP). Each participant took the PVT at four different time intervals in their 3-hour experimental session: (1) At the start of the experiment (Baseline); (2) After doing a cognitive depletion task for approximately 1.5 hours (PreBreak); (3) After a break halfway through the experiment (PostBreak); and finally at the end of another cognitive depletion task, approximately 1.5 hours after returning from the break (End). We analyzed the data from 10 participants, and the results are as follows.

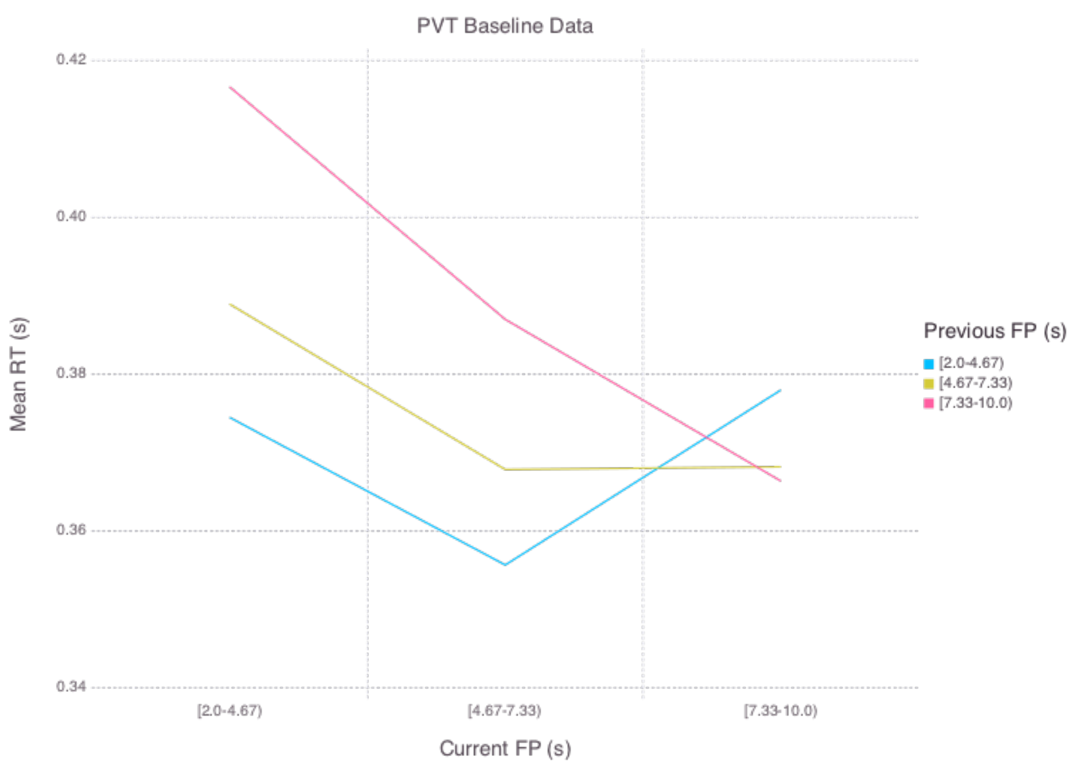


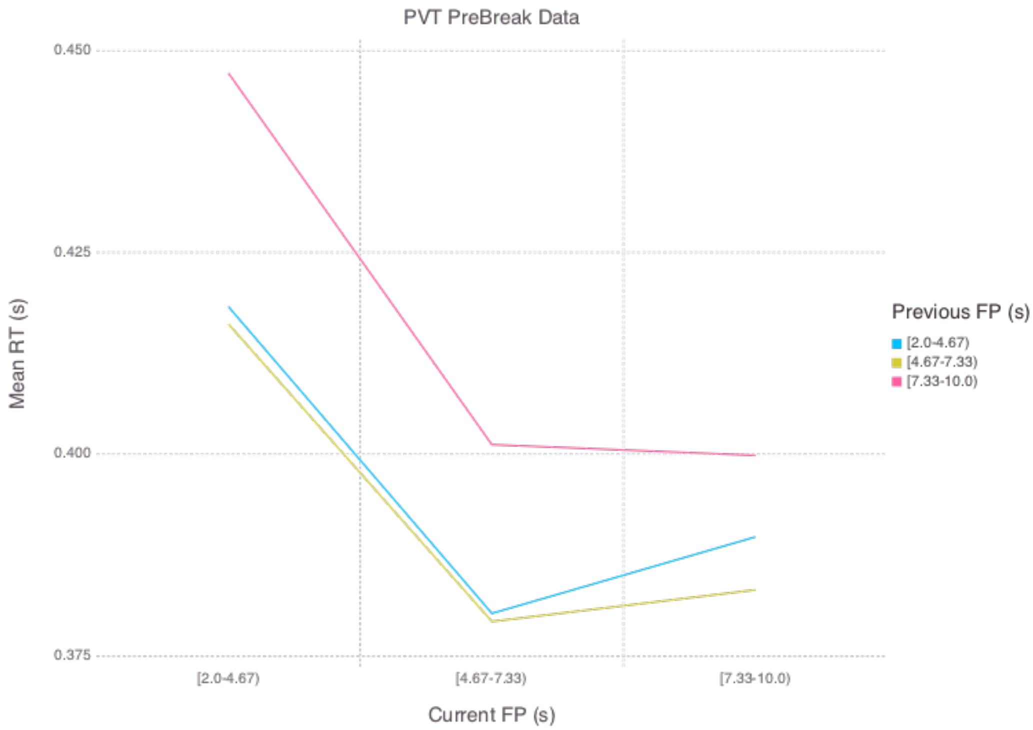


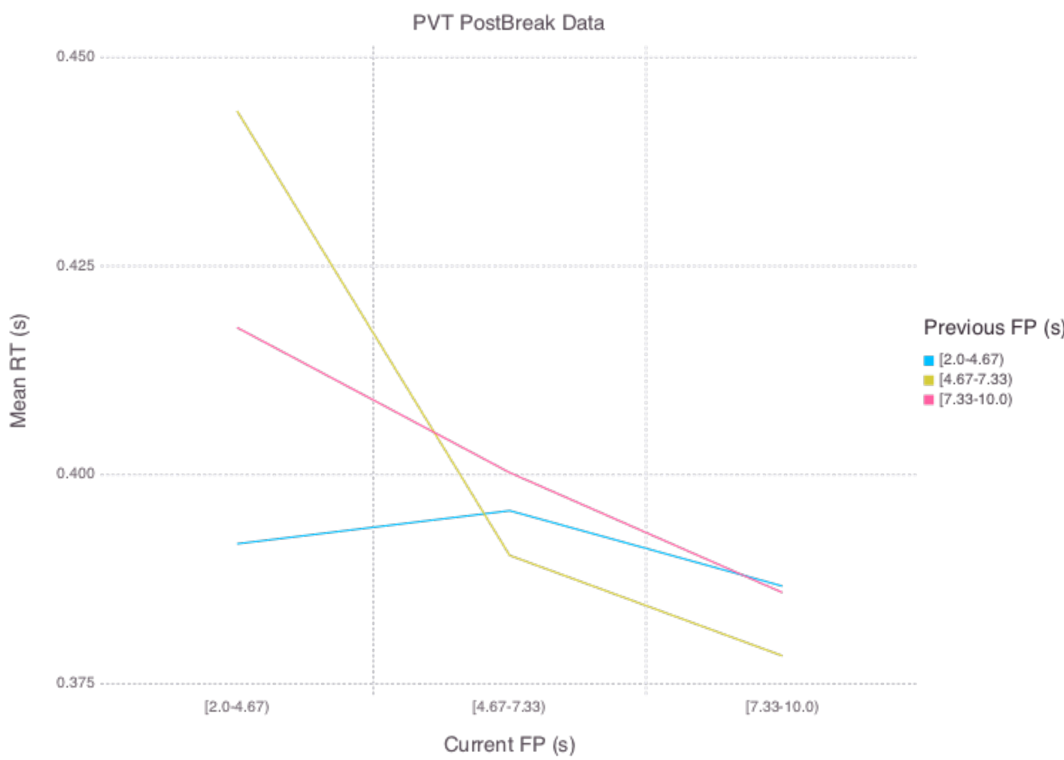
Plot 6: Observed data from the PVT dataset collected at PNNL. The top panel shows the four sessions as separate lines (Baseline, PreBreak, PostBreak, End). Mean reaction times (s) are shown as a function of foreperiod length (short = 2.0-4.67 s; medium = 4.67-7.33 s; long = 7.33-10.0 s). The bottom panel fixes the y-axis (reaction time) from 0.0-0.5 s to provide a more comprehensive view of the differences in reaction times across the sessions.

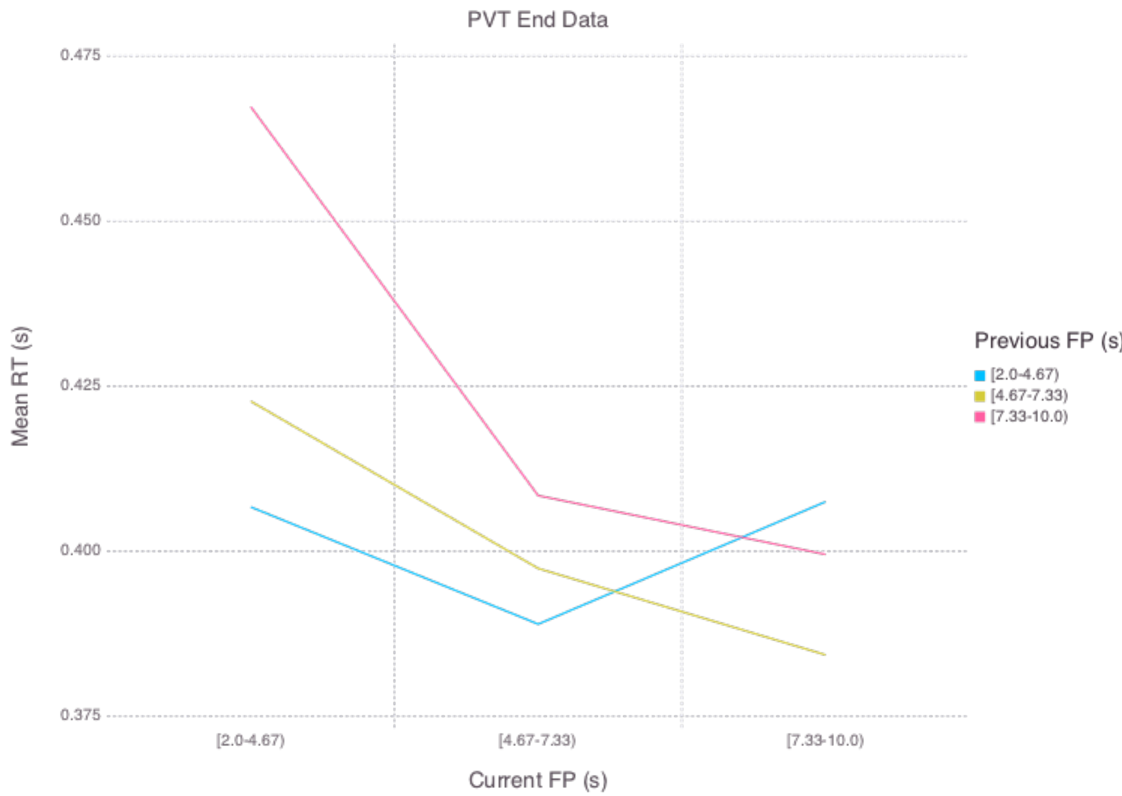
From Plot 6 above, we see the effects of fatigue throughout the three-hour experimental sessions. As the sessions progress, mean reaction times generally increase. There is evidence of the foreperiod effect in the observed data as well (for all sessions). Specifically, we generally see lower mean reaction times for longer foreperiods. This effect is somewhat muddled for medium- and long-foreperiods, as there is not a large difference between the mean reaction times.

In Plot 7 below, we see that there is evidence for the sequential effect in some sessions as well. In the Baseline and End sessions, we see the effect: short foreperiods preceded by medium and long foreperiods are associated with longer mean reaction times. The PreBreak session provides some evidence of the sequential effect; however, the mean reaction times in trials with short and medium foreperiods seem to be nearly identical. PostBreak behavior is a bit irregular in general. This could be due to the fact that the break was not regulated across participants. Breaks would last from between 5 to 15 minutes, and participants were free to do as they wished during the break time (use the restroom, walk around, stay in the experiment room). Participant break activity was not recorded. Plot 8 provides insight into the magnitude of the sequential effect. In general, early sessions

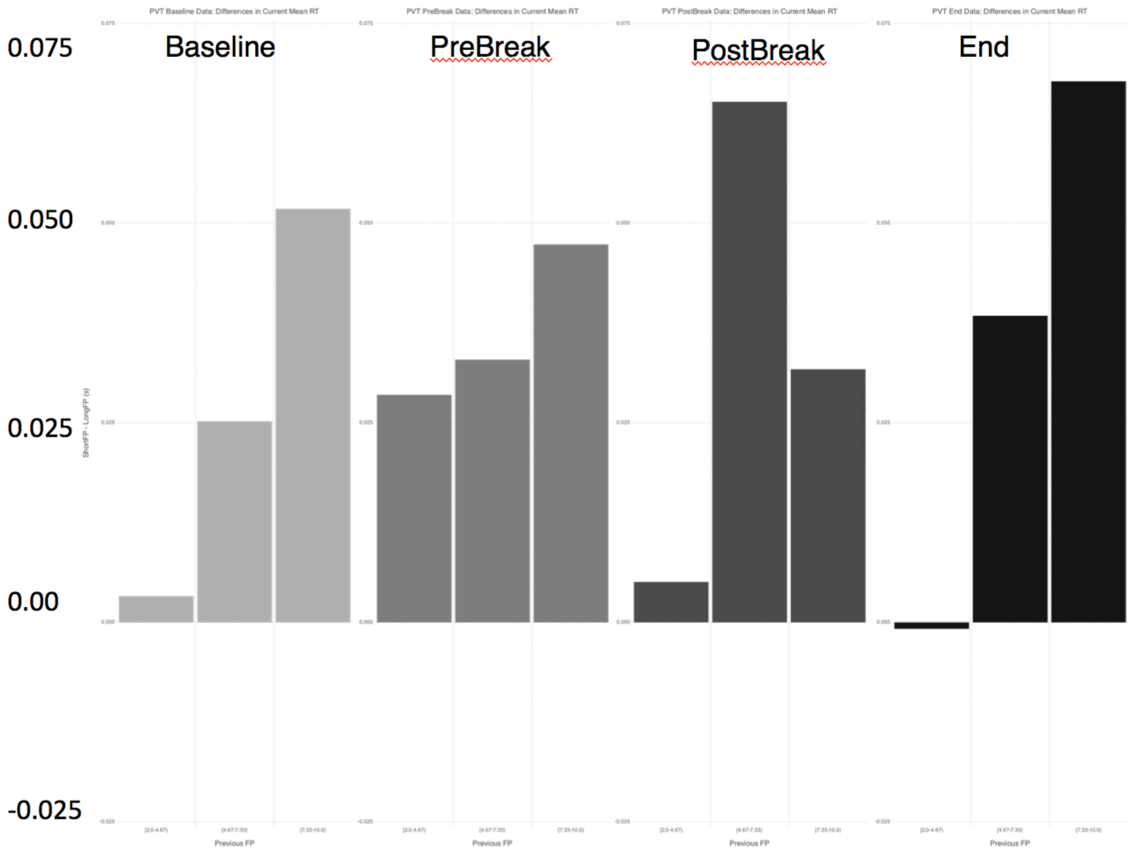



PVT PreBreak Data
0.450
0.425
0.400
0.375
Mean RT (s)
[2.0-4.67)
[4.67-7.33)
[7.33-10.0)
Current FP (s)
Previous FP (s)
[2.0-4.67)
[4.67-7.33)
[7.33-10.0)


PVT PostBreak Data
0.450
0.425
0.400
0.375
Mean RT (s)
[2.0-4.67)
[4.67-7.33)
[7.33-10.0)
Current FP (s)
Previous FP (s)
[2.0-4.67)
[4.67-7.33)
[7.33-10.0)



Plot 7: Mean reaction times (y-axis) as a function of current foreperiod (x-axis), and previous foreperiod (lines). The first panel corresponds to the Baseline session, the second panel corresponds to the PreBreak session, the third panel is the PostBreak session, and the final panel is the End session.

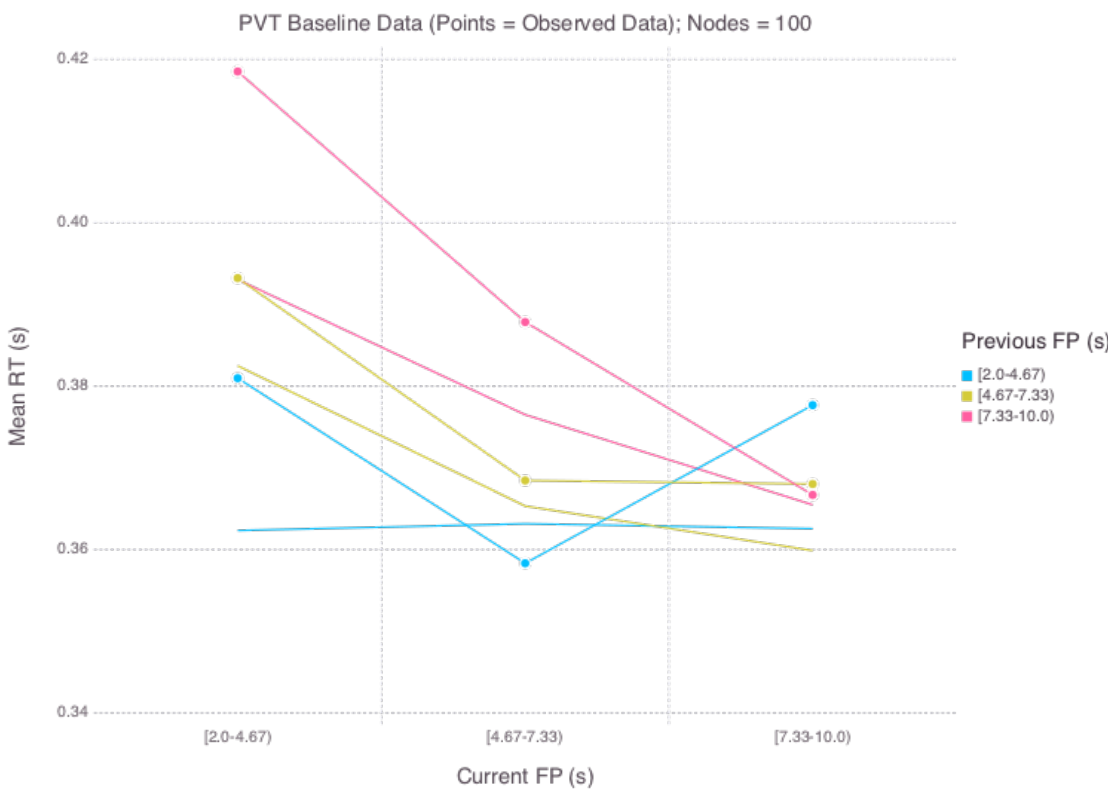


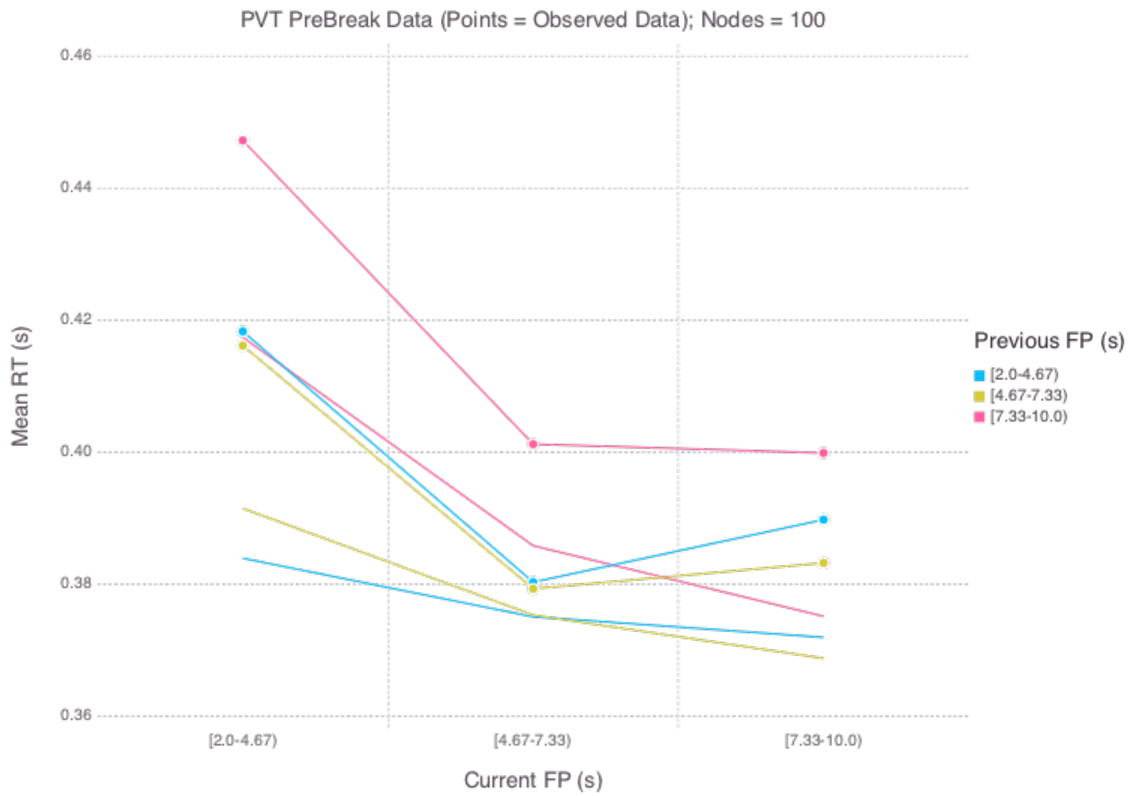
Plot 8: Difference in current mean reaction time for each session, as a function of previous foreperiod. The far left panel corresponds to the Baseline session, followed by PreBreak, PostBreak, and End, respectively.

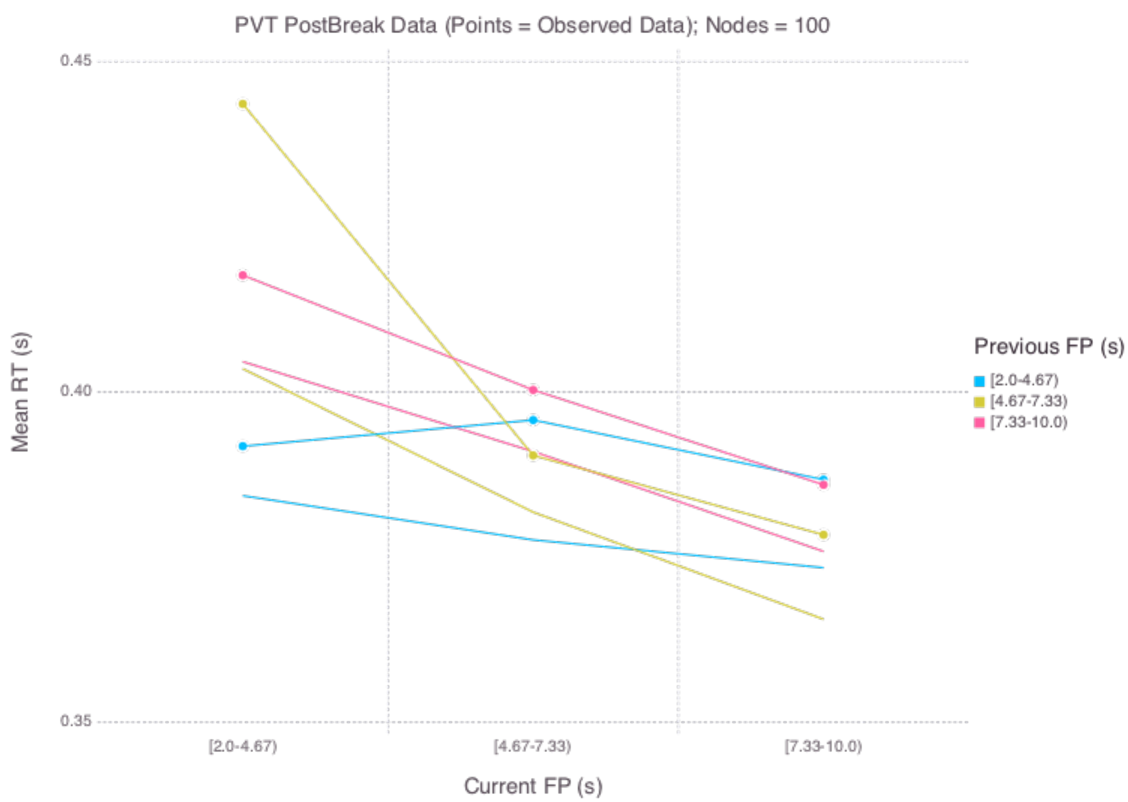
Next, we fit the trace conditioning model to the PVT data. We fit the model with maximum likelihood estimation, which takes the raw data files (in .json format), converts them into an array of arrays, with each sub-array containing subject data (foreperiods and reaction times). The best-fitting algorithm works as follows:

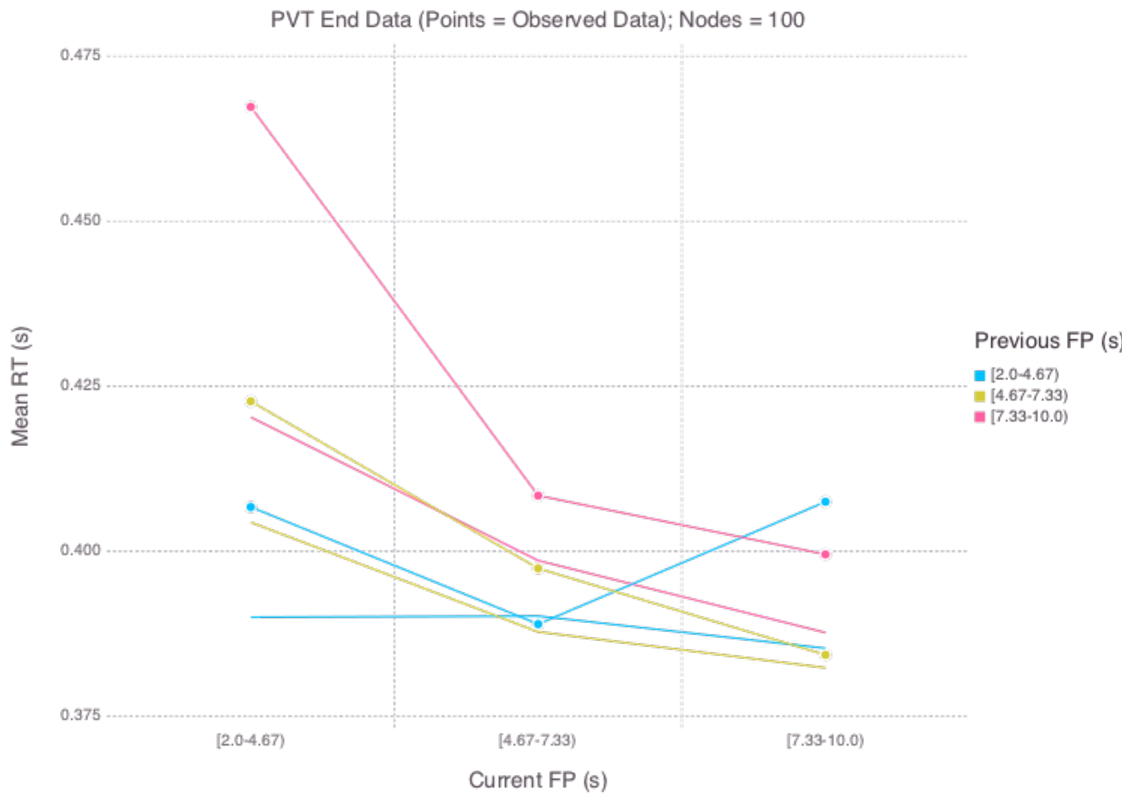
1) sample candidate starting points in the plausible parameter space (defined by the constraints variables)
2) compute the likelihood of the candidates
3) optimize a subset with the highest likelihood (in this case a subset of 1 out of 200 works well.)

The TCMfit() function (see Appendix for function code) uses maximum likelihood to fit the model to a single subject, working much like linear regression. The model predicts a mean RT, given the current sequence of trials and parameters. This prediction is a parameter in a normal distribution and the standard deviation (shape parameter) is the "error" term. Thus we avoid averaging but instead computing the likelihood of each data point given the model predictions. The TCMfitwrap() has a subject loop that calls TCMfit() and produces a matrix of best fitting parameters and log likelihood (maximum values). We fit the model with four different node values across the four sessions, leading to a total of 16 combinations. Below, in Plot 9, we show the results of the model fit for 100 nodes, which seemed to generally correspond with the lowest RMSE values across sessions. To see the remaining model plots and parameter values for all combinations, please see the Appendix. One thing we noticed was that the model fits seem to be producing reaction times that were slightly too low. We believe that the RT0 constraint may be the cause of this. Indeed, looking at the tables for the individual parameter fits in the Appendix, we see that many of the best-fitting RT0 values were hitting the upper bound of the constraint (0.2 s, or 200 ms). In subsequent model fits, we will consider raising the RT0 upper limit in order to see if we can achieve a better fit.




PVT PreBreak Data (Points = Observed Data); Nodes = 100
0.46
0.44
0.42
0.40
0.38
0.36
Mean RT (s)
[2.0-4.67)
[4.67-7.33)
[7.33-10.0)
Current FP (s)
Previous FP (s)
[2.0-4.67)
[4.67-7.33)
[7.33-10.0)


PVT PostBreak Data (Points = Observed Data); Nodes = 100
0.45
0.40
0.35
Mean RT (s)
[2.0-4.67)
[4.67-7.33)
[7.33-10.0)
Current FP (s)
Previous FP (s)
[2.0-4.67)
[4.67-7.33)
[7.33-10.0)



Plot 9: Simulated mean reaction times (y-axis) as a function of current foreperiod (x-axis) and previous foreperiod (lines), for four sessions (top panel Baseline, second panel PreBreak, third panel PostBreak, and final panel End). 100 nodes were used in the model fits for all four sessions. Observed data is represented by points on lines, and predicted data is represented by lines only.

Over the course of these ten weeks, we became intimately familiar with the trace conditioning model. We coded and implemented a version of the model based on its mathematical foundations and accompanying literature. We then simulated the model to validate that it behaved as reflected in past studies. Along the way, we encountered issues with model behavior stemming from a mismatch in the sequential ordering of the reinforcement learning rule. The road to discovering where this error lay was not straightforward and required us to explore several avenues of interest before we located the source of the inaccuracy. Eventually, we successfully validated the model by reproducing the documented results and effects. Afterward, we fit the model to human data to test the model's abilities to capture empirically documented effects such as the foreperiod effect and the sequential effect. This is an important step from simply reproducing the results from human data collected by Los and colleagues because we used data that has not been fit with the trace conditioning model before.

Future Directions

With the current foundation for the trace conditioning model in place, future development beyond the scope of this summer could involve tasks without fixed foreperiods, tasks with feedback, and multiple simultaneous tasks. We might also consider incorporating fatigue into the model in a collaborative effort with authors Matt Walsh and Glenn Gunzelmann at the Air Force Research Laboratory. The goal we have in mind for future development is centered about making small steps toward a real-time processing model that is dynamic and more suited to the type of decision making humans take part in outside of a laboratory setting

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Coding the Model

This section provides additional details pertaining to the implementation of the trace conditioning model, along with the parameter settings of the simulations that led to the outcomes reported in Codes 3, 4, and 5 from the continuous modeling text. The source model, along with more complete coverage, can be found in Machado (1997) and Los et al. (2001).

Three key functions involved in the trace conditioning model are the activation, extinction, and reinforcement functions. See Codes 1, 2, and 3 below for our code for each, respectively, based upon the equations described in the text.

```
function Activation(λ,n,FP)
    #Activation of the nth node at time FP
    act = (exp(-λ.*FP)*(λ.*FP)^n)./prod(2.0:n)
    return act
  end
```

Code 1: Activation function for the trace conditioning model.

```
function Extinction(λ,α,n,FP,w0)
    #w is the associative weight
    #w0 is the initial value of the associative weight
    #on current trial
    f(t)= Activation(λ,n,t)
    #Integrate from 0 through FP
    val,err = hquadrature(f, 0.0,FP;
            reltol=1e-8, abstol=0, maxevals=0)
    w = w0.*exp(-α.*val)
    return w
  end
```

Code 2: Extinction function for the trace conditioning model.

```
function Reinforcement(w,β,act)
    #Adjusts weights following a response
    #d is the reinforcement interval. Absorbed into β
    #as in Los 2001
    #w and act are the activations of node n at time FP
    w = 1 - (1 - w).*exp(-β.*act)
    return w
  end
```

Code 3: Reinforcement function for the trace conditioning model.

Integral to our simulation procedures were the equations for the predicted response time (Code 4), as well as the trace conditioning model code itself (Code 5), which ties together the previous Codes and equations.

```
function RT(A,B,RT0,ACT,W)
    NDT = A./(B + sum(ACT.*W)) + RT0
    return NDT
```

```
  end
```

Code 4: Reaction time function for the trace conditioning model.

```
function TC_Model(parms,FP,W0)
   #Computes response function value at FP, the duration
   #of the Foreperiod
   ###################################
   #Parameters
   ###################################
   λ = parms[1]
   A = parms[2]
   B = parms[3]
   α = parms[4]
   β = parms[5]
   RT0 = parms[6]
   ###################################
   #Update Weights and Activation
   ###################################
   #Number of Nodes
   N = size(W0,1)
   #Vector of node activation
   ACT = fill(0.0,N)
   #Loop over nodes
   for n = 1:N
     ACT[n] = Activation(λ,n,FP)
     #Adjust weights according to Extinction
     #W0 is the initial weights on current trial
     W0[n] = Extinction(λ,α,n,FP,W0[n])
     #Adjust weights according to reinforcement
   end
   #Transforms Activation and weights into
   #Instantenous value for Non-Decision Time
   #Predicted at FP, the stimulus onset
   #Post-Response Reinforcement(w,β,act)
   NDT = RT(A,B,RT0,ACT,W0)
   #W is output as the new W0 for the next trial.
     for n = 1:N
     W0[n] = Reinforcement(W0[n],β,ACT[n])
     end
   return NDT,W0
 end
```

Code 5: Trace conditioning model code. Note that this code reflects the correct ordering and placement of the reinforcement function, an error that we had to overcome in earlier versions of this model.

Over the course of implementing and simulating our model, we worked with many sets of parameters. With regard to Codes 4 and 5 in the text (which replicated Codes 5 and 6 of Los et al. (2001)), we used the parameter values in Chart 1.

	Parameters					
	λ	α	βd	A	B	RT_0
Plot 3	2	1	12	70	0.5	190.95
Plot 4	4.39	3.2	1.89	38.1	0.19	190.95
Plot 5	4.46	3.35	3.66	52.9	0.22	183.91

Chart 1: Estimated parameter values used to fit the data from Los et al. (2001).

In the process of replicating the codes from Los et al. (2001), we encountered difficulties with the correct implementation of our model. In order to pinpoint the error, we created code that illustrated the qualitative trial-by-trial behavior of node weights for any given FP. The code for this code is an extension of the code used for the last panel in Code 3 of the main text (Code 4c in Los et al. (2001)). The code is reproduced below, in Code 6. The corresponding parameters we used for Code 3 in the main text are reproduced in Chart 1.

```
function CodeWeights(parms,FPlist,W0)
       Nw = size(W0,1)
       Ntrials = size(FPlist,1)
       Label = fill("",Ntrials)
       Weights = []
       Nodes = rep(1:Nw,Ntrials)
       Label[1] = string("FP_0 = NA","FP_1 = ",FPlist[1])
       for i = 2:Ntrials
         Label[i] = string("FP_",i-1," = ",FPlist[i-
1],"FP_",i," = ",FPlist[i])
       end
       Label = rep(Label,1,Nw)
       for trial = 1:Ntrials
         FP = FPlist[trial]
         PredRT,W0 = TC_Model(parms,FP,W0)
         push!(Weights, W0[:])
       end
       Weights = vcat(Weights...)
       DF = DataFrame(Nodes = Nodes,Weights = Weights,Label
= Label)
       p = code(DF, x="Nodes", y="Weights", color="Label",
Geom.line(),

     Scale.color_discrete_manual("red","green","black","ora
nge"))
       return p
     end
```

Code 6: Code for codeting trial-by-trial change in weights. Takes the following inputs: parameters (parms = [λ;A;B;α;β;RT0]); FPlist (sequential list of foreperiods for each trial; FPlist = [1, 7, 9, 5.5, 2]); and W0, initial weights (W0=fill(0.5,N)). The number of nodes we used was N=30.

We also wrote several functions detailing how to simulate the model for different types of blocks. We generated predictions for response time (nondecision time) as a function of FP using the code in Code 7. Mixed-block simulation is shown in Code 8, and pure-block simulation is described in Code 9.

```
function Simulation(parms,FPvec,W0)
    #Generate predictions for Non-Decision time as a
    #function of FP
    Ntrials = size(FPvec,1)
    Time = [0.0:.1:10;]
    Nt = size(Time,1)
    NDTvec = DataFrame(Time = zeros(Nt*Ntrials),
      FPprev = zeros(Nt*Ntrials), NDT = zeros(Nt*Ntrials))
    cnt = 0
    #First trial
    FP = FPvec[1]
    NDT,W0 = TC_Model(parms,FP,W0)
    for trial = 1:Ntrials
      FP = FPvec[trial]
      for t in Time
        cnt += 1
        NDT,W = TC_Model(parms,t,W0)
        NDTvec[:Time][cnt] = t
        NDTvec[:FPprev][cnt] = FP
        NDTvec[:NDT][cnt] = NDT
      end
      #Update Trial
      NDT,W0 = TC_Model(parms,FP,W0)
    end
    return NDTvec
  end
```

Code 7: Code for generating predictions for response time (nondecision time) using the trace conditioning model.

```
function MixedBlocksSim(parms,FPlist,W0,Ntrials)
     #Preallocate your outputs if you know the size
     RTvec = fill(0.0,Ntrials)
     FPvec = fill(0.0,Ntrials)
     for trial = 1:Ntrials
       #Randomly sample Foreperiod
       FP = sample(FPlist)
```

```
        #Outputs predicted RT and adjusted weights
        #which feed back into the model on the next trial
        PredRT,W0 = TC_Model(parms,FP,W0)
        RTvec[trial] = PredRT
        FPvec[trial] = FP
      end
      return FPvec,RTvec
    end
```

Code 8: Code for generating predictions for response time (nondecision time) in mixed blocks, using the trace conditioning model.

```
function PureBlocksSim(parms,FPlist,W0,Ntrials)
      #Preallocate your outputs if you know the size
      Ncond = size(FPlist,1)
      RTmat = fill(0.0,Ntrials,Ncond)
      for cond = 1:Ncond
        for trial = 1:Ntrials
          FP = FPlist[cond]
          PredRT,W0 = TC_Model(parms,FP,W0)
          RTmat[trial,cond] = PredRT
        end
      end
      RTmeans = mean(RTmat,1)[:]
      return RTmat,RTmeans
    end
```

Code 9: Code for generating predictions for response time (nondecision time) in pure blocks, using the trace conditioning model.

```
function PredData(Data,OutParms)
    numParms = 11
    Nsubj = size(OutParms,2)
    GetParms = fill("",Nsubj, numParms)
    for i = 1:Nsubj
     GetParms[i,:] = split(OutParms[i],",")
    end
    SubjParms = float(GetParms)

    DataPred = Any[Array{Float64,2} for subj = 1:Nsubj] #
ISI, RT (s)

    for subj = 1:Nsubj
     parms = SubjParms[subj,2:6]
     FP = Data[subj][:,1]
     N = length(FP)
     W0 = fill(0.5,N)
     RTvec = fill(0.0,N)
     for i = 1:N
```

```
          tempRT,W = TC_Model(parms,FP[i],W0)
          RTvec[i] = tempRT + SubjParms[subj,7] # Add
individual RT0 terms
     end

     DataPred[subj] = Data[subj][:,1]
     DataPred[subj] = hcat(DataPred[subj], RTvec)
    end
    return DataPred
  end

function SampleParameters(Nsweep,Constraints)
  Np = size(Constraints,1)
  parms = zeros(Nsweep,Np)
  for p = 1:Np
    parms[:,p] =
rand(Uniform(Constraints[p,1],Constraints[p,2]),Nsweep)
  end
  return parms
end

function ParmBound(parms,Constraints,x)
    LB = Constraints[:,1]
    UB = Constraints[:,2]
    OutParms = zeros(size(parms));
    if x == 0
        for i = 1:size(parms,2)
            OutParms[:,i] = (UB[i]-LB[i])./(1+exp(-
parms[:,i]))+LB[i];
        end
    else
        for i = 1:size(parms,2)
        OutParms[:,i] = -log((UB[i]-LB[i])./(parms[:,i]-
LB[i])-1);
        end
    end
    return OutParms
end

function
TCMfitwrapper(Data,Nnodes,Constraints,Npoints,Nbest,Dist)
    NSubj = size(Data,1)
    Np = size(Constraints,1) + 1
    f(x) = TCMfit(x,SubData,Nnodes,Constraints,Dist)
    #Best Fitting parameters
    BFparms = fill(0.0,NSubj,Np)
```

```
    #Initialize SubData index so that scope is outside of
subject Loop
    #and accessible by f(x)
    #Number of parms + 1 for LL
    Np = size(Constraints,1) + 1
    SubData = 0.0
    for subj = 1:NSubj
      #Find a good starting point by sampling the parameter
space. Optimize the
      #Starting point with the highest likelihood
      SubData = Data[subj]
      StartParms =
Sweep(Npoints,Nbest,Nnodes,SubData,Constraints,Dist)
      TempParms = fill(0.0,Nbest,Np)
      for b = 1:Nbest
        parms0 = StartParms[:,b]
        #Convert to 1d array
        #parms0 = parms0[1:end]
        optimum = optimize(f,parms0,method=NelderMead(),
          show_trace = false,iterations = 500, x_tol = 1e-
3)
        #Extract Best Fitting Parameters
        parms = ParmBound(optimum.minimum',Constraints,0)
        #Log Likelihood
        LL = -optimum.f_minimum
        TempParms[b,:] = hcat(parms,LL)
      end
      #Index best fitting run
      MaxIdx = findmax(TempParms[:,end])[2]
      BFparms[subj,:] = TempParms[MaxIdx,:]
      println("Subject")
      println(subj)
      println(BFparms[subj,:])
    end
    return BFparms
 end

function
Sweep(Nsweep,Nbest,Nnodes,SubjData,Constraints,Dist)
   parms = SampleParameters(Nsweep,Constraints)
   parms0 = ParmBound(parms,Constraints,1)'
   Pparms = [parms0[:,i] for i = 1:Nsweep]
   LL = pmap(x-
>TCMfit(x,SubjData,Nnodes,Constraints,Dist),Pparms)
   LL = vcat(LL...)
   idx = tiedrank(LL) .<= Nbest
   return  parms0[:,idx]
```

```
 end

function GetData(dir,session,Seconds)
  #Parse subject ID from file name (assumes consistent
naming convention)
  GetSubjID(x) = split(split(x,"Subject")[2],session)[1]
  #This should make the file subseting a little more robust
to changes to the folder
  #contents
  wkdir = pwd()
  cd(dir)
  FileIdx = map(x->contains(x,".Json"),readdir()) & map(x-
>contains(x,session),readdir())
  FileList = readdir()[FileIdx]
  Nsubj = size(FileList,1)
  SubList = map(x->GetSubjID(x),FileList)
  #Initialize Array of Arrays
  #Each subarray will contain subject data
  Data = Any[Array{Float64,2} for subj = 1:Nsubj]
  #Loop over files
  if Seconds
     for subj = 1:Nsubj
          file = FileList[subj]
          f = open(file)
          jFile = JSON.parse(f)
          close(f)
          #Exclude False Starts
          idx = jFile["Data"] .> .150
           Data[subj] = Float64[jFile["ISI"][idx]
jFile["Data"][idx]]
          end
     else
          for subj = 1:Nsubj
               file = FileList[subj]
               f = open(file)
               jFile = JSON.parse(f)
               close(f)
               #Exclude False Starts
               idx = jFile["Data"] .> .150
                Data[subj] = Float64[jFile["ISI"][idx]
jFile["Data"][idx]*1000.0]
               end
     end
     cd(wkdir)
  return Data,SubList
end
```

```
function CompareBaselineModel(Data,results)
  #Compare model to Gaussian Model
  BIC(LL,Np,Nd) = -2.0*LL + Np*log(Nd)
  #Bayes Factor approximation
  BICweight(BICs) = exp(-.5*(BICs-minimum(BICs)))/sum(exp(-
.5*(BICs-minimum(BICs))))
  Nsubj = size(Data,1)
  #Log likelihood for TCM
  LLtcm = results[:,end]
  BFW = fill(0.0,Nsubj)
  LLg = fill(0.0,Nsubj)
  #Number of parms for TCM
  Np = size(results,2) - 1
  for subj = 1:Nsubj
    SubData = Data[subj][:,2]
    Nd = size(SubData,1)
    mu = mean(SubData)
    sigma = std(SubData)
    LLg[subj] = sum(logpdf(Normal(mu,sigma),SubData))
    BICg = BIC(LLg[subj],2,Nd)
    BICtcm = BIC(LLtcm[subj],Np,Nd)
    BFW[subj] = BICweight([BICtcm BICg])[1]
  end
  return BFW,LLg
 end

function Code_SE(SubData)
  #This function divides the RTs into short medium and long
foreperiods
  #then generates a code for the sequential effect.
  ISI = SubData[:,1]
  rt = SubData[:,2]
  Nbins = 3
  bins = linspace(2,10,Nbins+1)
  #Mean RTs conditional on ISI intervals
  DF = DataFrame(Previous = fill("",Nbins^2),Current=
fill("",Nbins^2),
    MeanRT = zeros(Nbins^2))
  Label = map(x->string(round(bins[x],2),"-",
round(bins[x+1],2)),1:Nbins)
  cnt = 0
  for t1 = 1:Nbins
    for t = 1:Nbins
      cnt += 1
      #t1 indexes bins on trial t + 1 (Current Trial)
      #t indexes bins on trial t (Previous Trial)
```

```
      #Create an index identifying trials that occur within
bin boundaries for current and previous ISI/foreperiod
      #ISI[2:end] and ISI[1:end-1] are current and previous
ISIs respectively
      idx = (ISI[2:end] .> bins[t1]) & (ISI[2:end] .<=
bins[t1+1]) & (ISI[1:end-1] .> bins[t]) & (ISI[1:end-1] .<=
bins[t+1])
      DF[cnt,1] = Label[t]
      DF[cnt,2] = Label[t1]
      DF[cnt,3] = mean(rt[[false;idx]])
    end
  end
  p1 = code(DF, x="Current", y="MeanRT", color="Previous",
Geom.line(),Scale.color_discrete_manual("red","green","blac
k"))
  return p1
end
```

APPENDIX B

Intertemporal Choice Experiment Supplementary Material

Intertemporal Choice Experiment Questionnaire

CRT

A bat and a ball cost $1.10 in total. The bat costs a dollar more than the ball. How much does the ball cost? _________ cents.

If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? _________ minutes.

In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it take s 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? _________ days.

Intertemporal Choice Experiment Questionnaire

Self-Control

Using the scale provided, please indicate how much each of the following statements reflects how you typically are.

1. I am good at resisting temptation.
2. I have a hard time breaking bad habits. (R)
3. I am lazy. (R)
4. I say inappropriate things. (R)
5. I do certain things that are bad for me, if they are fun. (R)
6. I refuse things that are bad for me.
7. I wish I had more self-discipline. (R)
8. People would say that I have iron self- discipline.
9. Pleasure and fun sometimes keep me from getting work done. (R)
10. I have trouble concentrating. (R)
11. I am able to work effectively toward long-term goals.
12. Sometimes I can not stop myself from doing something, even if I know it is wrong. (R)
13. I often act without thinking through all the alternatives. (R)

["1: Not at all", "2", "3", "4", "5: Very much"]

Intertemporal Choice Experiment Questionnaire

Impulsiveness

People differ in the ways they act and think in different situations. This is a test to measure some of the ways in which you act and think. Do not spend too much time on any statement. Answer quickly and honestly.

1. I plan tasks carefully. (R)
2. I do things without thinking.
3. I make-up my mind quickly.
4. I am happy-go-lucky.
5. I do not pay attention.
6. I have \'racing\' thoughts.
7. I plan trips well ahead of time. (R)
8. I am self controlled. (R)
9. I concentrate easily. (R)
10. I save regularly. (R)
11. I \'squirm\' at plays or lectures.
12. I am a careful thinker. (R)
13. I plan for job security. (R)
14. I say things without thinking.
15. I like to think about complex problems. (R)
16. I change jobs.
17. I act on impulse.
18. I get easily bored when solving thought problems.
19. I act on the spur of the moment.
20. I am a steady thinker. (R)
21. I change residences.
22. I buy things on impulse.
23. I can only think about one thing at a time.
24. I change hobbies.
25. I spend or charge more than I earn.
26. I often have extraneous thoughts when thinking.
27. I am more interested in the present than the future.
28. I am restless at the theater or lectures.
29. I like puzzles. (R)
30. I am future oriented. (R)

["Rarely/Never", "Occasionally", “Sometimes”, "Often", "Almost Always/Always"]

Intertemporal Choice Experiment Questionnaire

Incentive Check (Trust)

How much do you trust the service in delivering the bonus payment to your Commodore Card safely?

How much do you trust the service in delivering the bonus payment to your Commodore Card on time

["Strongly doubt", "Doubt", 'Neutral', "Believe", "Strongly believe"]

Intertemporal Choice Experiment Low Trust Scores

The table below describes participants who had low trust scores on the incentive check questionnaire. 8 subjects were removed from additional analyses for having trust scores less than or equal to 4.

Trust Score	1-2	3-4	5-6	7-8	9-10
Subj #	106	103	107	108	101
	135	113	112	110	102
	143	119	131	111	104
	145	121	134	118	105
			139	120	109
			140	127	114
				128	115
				133	116
				137	117
				141	122
				144	123
				149	124
				152	125
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					154

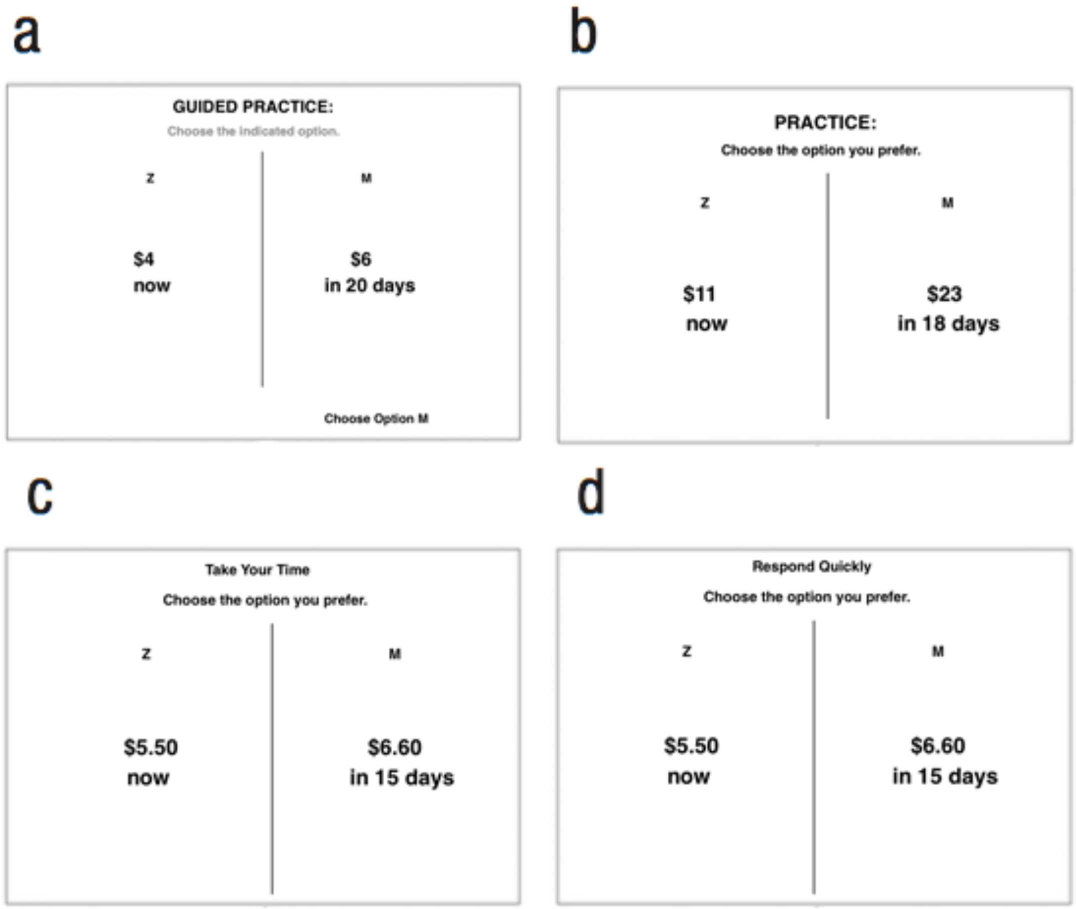


Fig. 7. Screenshots from example practice trials (a, b) and test trials (c, d). On each trial, participants were given two choices, a smaller but sooner payout (SS) on the left side of the screen, or a larger but later payout (LL) on the right side of the screen; participants were also given an instruction on test trials. On guided practice trials (a), participants were instructed to choose either option 'z' (SS option) or option 'm' (LL option). Free response practice trials (b) instructed participants to choose whichever option they preferred. After 5 s, the screen would automatically progress to the next trial if no response was given, after displaying a message reading "Timeout". Decision screens in practice and test trials differed primarily in that on practice trials, on-screen text reminded participants to either "Take Your Time" (no time pressure block, (c)), or to "Respond Quickly (time pressure block, (d)).

Intertemporal Choice Experiment Unusual Participants

NTP Condition:
Participants 106 & 142 have 0.000 choice probability for LL
Participant 152 has 1.000 choice probability for LL

TP Condition:
Participant 106 has 0.007 choice probability for LL
Participant 146 has 0.993 choice probability for LL

Table showing the repeated measures ANOVA to test block (TP or NTP).

Within Subjects ANOVA

	Sum of Squares	*df*	Mean Square	*F*	*p*
Block	0.213	1	0.213	19.22	<0.001
Residual	0.588	53	0.011		

There is a **significant effect of block** on the probability of choosing the LL option (greater proportion of LL choices in the NTP block**, 0.553 vs 0.464**).

Correlation between Overall LL choice and conditions

Spearman's rank coefficient

LL delay and Overall LL choice probability:
$\rho_s = -0.3792$; $p = 0.0576$

LL multiplier and Overall LL choice probability:
$\rho_s = -0.1195$; $p = 0.5539$

SS amount and Overall LL choice probability:
$\rho_s = 0.3352$; $p = 0.0872$

ANOVA details for conditions (SS amount, LL multiplier, and LL delay)

LL delay and Overall LL choice probability: $F = 1.906$; $df = 2$; $p = 0.171$

LL multiplier and Overall LL choice probability: $F = 1.797$; $df = 2$; $p = 0.192$

SS amount and Overall LL choice probability: $F = 5.027$; $df = 2$; $p = 0.015$

SS amount and LL choice probability in NTP block: $F = 2.799$; $df = 2$; $p = 0.81$

SS amount and LL choice probability in NTP block: $F = 1.992$; $df = 2$; $p = 0.069$

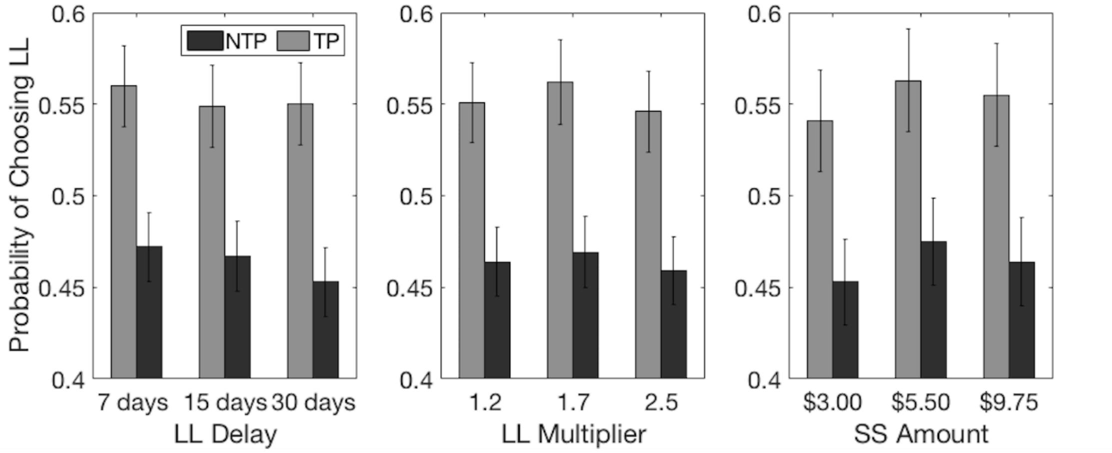
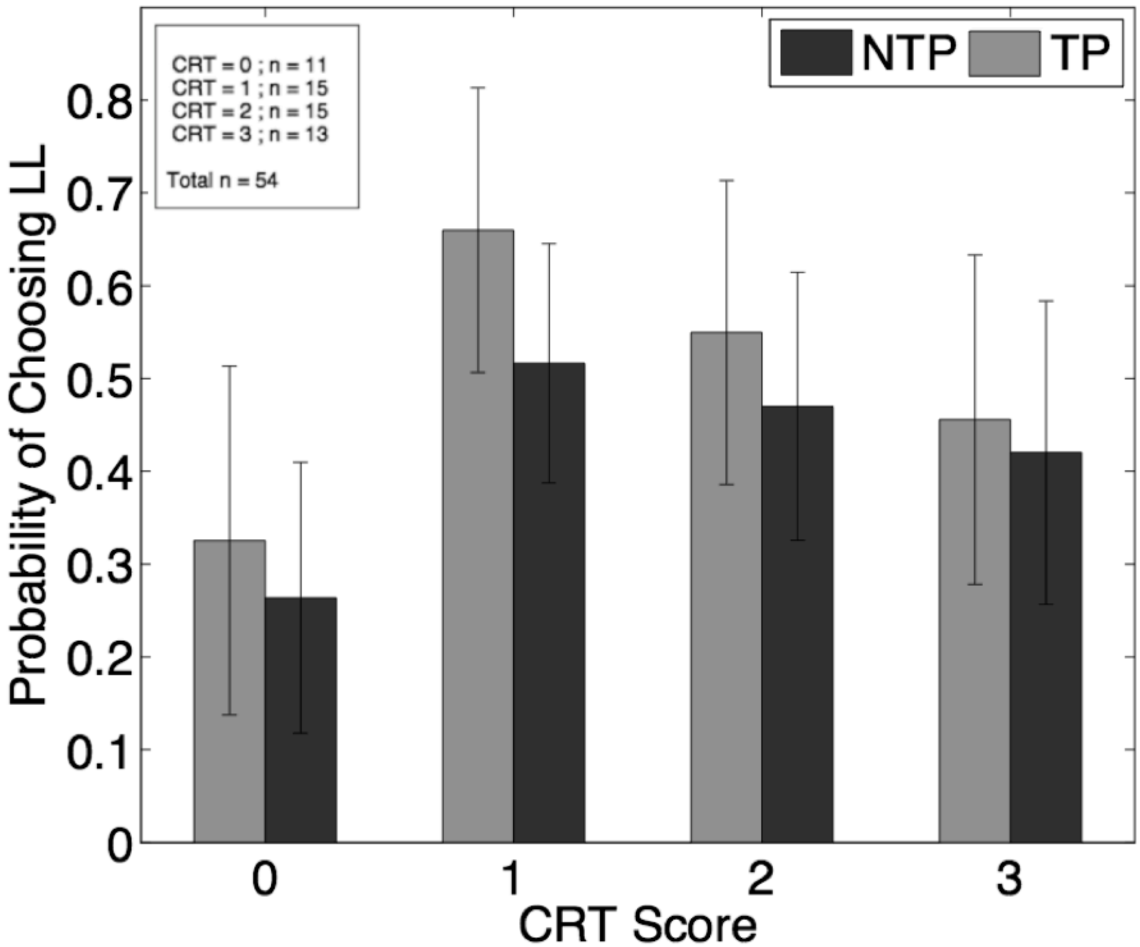


Fig. 8. Difference in LL choice proportion between TP and NTP blocks, grouped by LL delay (far left), LL multiplier (center), and SS amount (far right). The probability of choosing the LL option is significantly greater for all conditions in the TP condition (light gray) versus the NTP condition (dark gray).



Histogram of the CRT scores from the ITC experiment (x-axis) and the probability of choosing LL (y-axis). Problems are either scored 1 (correct) or 0 (incorrect), for a maximum score of 3. Bars are grouped by block, with dark gray representing the NTP block and light gray as TP.

CRT = 0 seems to prefer the SS option, while those who scored 1 or above tended to prefer the LL option in general.

Existing theory on CRT suggests that those with lower CRT scores will go for the SS option (e.g., displaying impulsive behavior).

However, if we look at only the data on CRT=0: $t(10) = 1.02$; $p = 0.3317$.

We do not get significant preference for SS for the CRT = 0 group.

Spearman's rank correlation between CRT and Overall LL Choice:
$\rho_s = 0.1953$; $p = 0.3269$

Repeated measures ANOVA table examining the effects of Block and CRT.

Within Subjects ANOVA

	Sum of Squares	*df*	Mean Square	*F*	*p*
Block	0.201	1	0.201	18.254	<0.001
Block * CRT	0.038	3	0.013	1.151	0.338
Residual	0.55	50	0.011		

We do not get a significant effect of CRT score on the probability of choosing the LL option.

Between subjects ANOVA for CRT, no significance found.

Between Subjects ANOVA

	Sum of Squares	*df*	Mean Square	*F*	*p*
CRT	0.442	3	0.147	0.848	0.474
Residual	8.684	50	0.174		

Table showing the results from a Bayesian repeated measures ANOVA on block and CRT.

Models	**P(M)**	**P(M|data)**	**BF_M**	**BF_{10}**	**% error**
Null model	0.200	0.002	0.007	1	
Block	0.200	0.583	5.593	334.372	0.754
CRT	0.200	8.939E-04	0.004	0.513	2.856
Block + CRT	0.200	0.205	1.755	174.875	2.013
Block + CRT + Block*CRT	0.200	0.109	0.492	62.768	11.636

No significant evidence pointing toward the model that includes CRT.

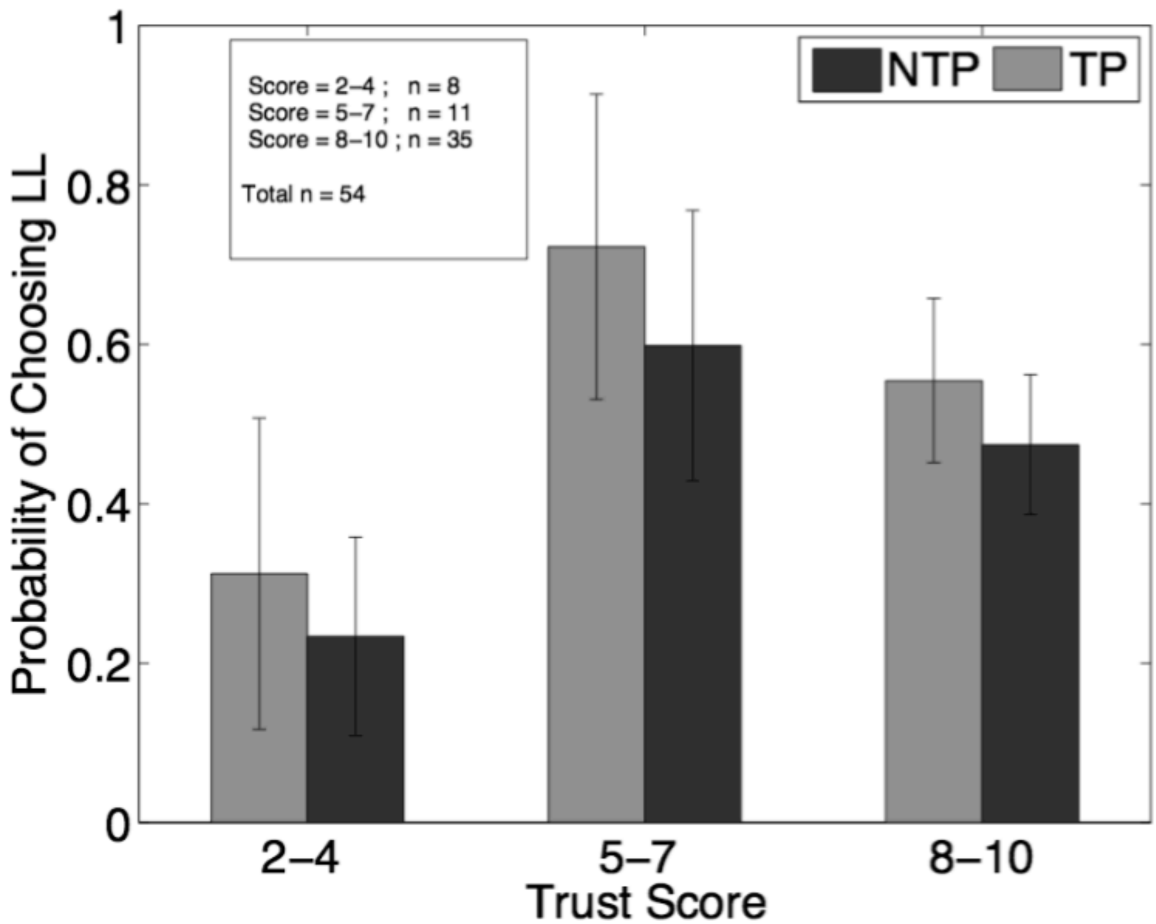


Fig. 9. Difference in LL choice proportion grouped by trust score (2=lowest, no trust; 10=highest, full trust). No time pressure in dark gray; time pressure in light gray. The probability of choosing the LL option is significantly greater for higher trust scores than for lower trust scores.

Table 7. Bayesian repeated measures ANOVA examining proportion of LL choices, model combinations including block and condition (SS amount, LL multiplier, and LL delay). Conditions listed in the table are abbreviated for: SS Amount (ssAmt), LL multiplier (LLmult), and LL delay (LLdelay).

Models	P(M)	P(M|data)	BF_M	BF_{10}	% error
Null model	0.063	4.656E-22	6.848E-21	1.000	
Block	0.063	0.152	2.683	3.323E+20	0.762
ssAmt	0.063	1.528E-22	2.292E-21	0.335	1.036
Block + Ssamt	0.063	0.081	1.324	1.777E+20	1.073
Llmult	0.063	1.589E-22	2.383E-21	0.348	0.418
Block + LLmult	0.063	0.104	1.738	2.274E+20	1.917
ssAmt + LLmult	0.063	7.461E-23	1.119E-21	0.163	0.572
Block + ssAmt + LLmult	0.063	0.072	1.167	1.581E+20	3.959
LLdelay	0.063	1.736E-22	2.605E-21	0.380	0.668
Block + LLdelay	0.063	0.195	3.638	4.276E+20	3.891
ssAmt + LLdelay	0.063	8.769E-23	1.315E-21	0.192	5.577
Block + ssAmt + LLdelay	0.063	0.126	2.171	2.770E+20	2.785
LLmult + LLdelay	0.063	8.551E-23	1.283E-21	0.187	0.579
Block + LLmult + LLdelay	0.063	0.155	2.747	3.390E+20	3.931
ssAmt + LLmult + LLdelay	0.063	4.573E-23	6.859E-22	0.1	0.849
Block + ssAmt + LLmult + LLdelay	0.063	0.115	1.944	2.513E+20	4.526

Bayesian repeated measures ANOVA for model comparison including block and Trust.

Models	P(M)	P(M|data)	BF_M	BF_{10}	% error
Null model	0.200	0.001	0.005	1.000	
Block	0.200	0.435	3.078	338.682	1.502
Trust	0.200	2.000E-03	0.007	1.292	2.419
Block + Trust	0.200	0.518	4.929	403.124	23.258
Block + Trust + Block*Trust	0.200	0.045	0.186	34.687	6.316

There is evidence for the model that includes block and Trust, so we run another set of analyses in the ITC experiment with low trust scores removed.

Correlation between Overall LL choice and conditions
Low Trust Scores Removed

Spearman's rank coefficient

LL delay and Overall LL choice probability (no low trust):
$\rho_s = -0.3612$; $p = 0.06374$

LL multiplier and Overall LL choice probability (no low trust):
$\rho_s = -0.1748$; $p = 0.3820$

SS amount and Overall LL choice probability (no low trust):
$\rho_s = 0.2593$; $p = 0.1923$

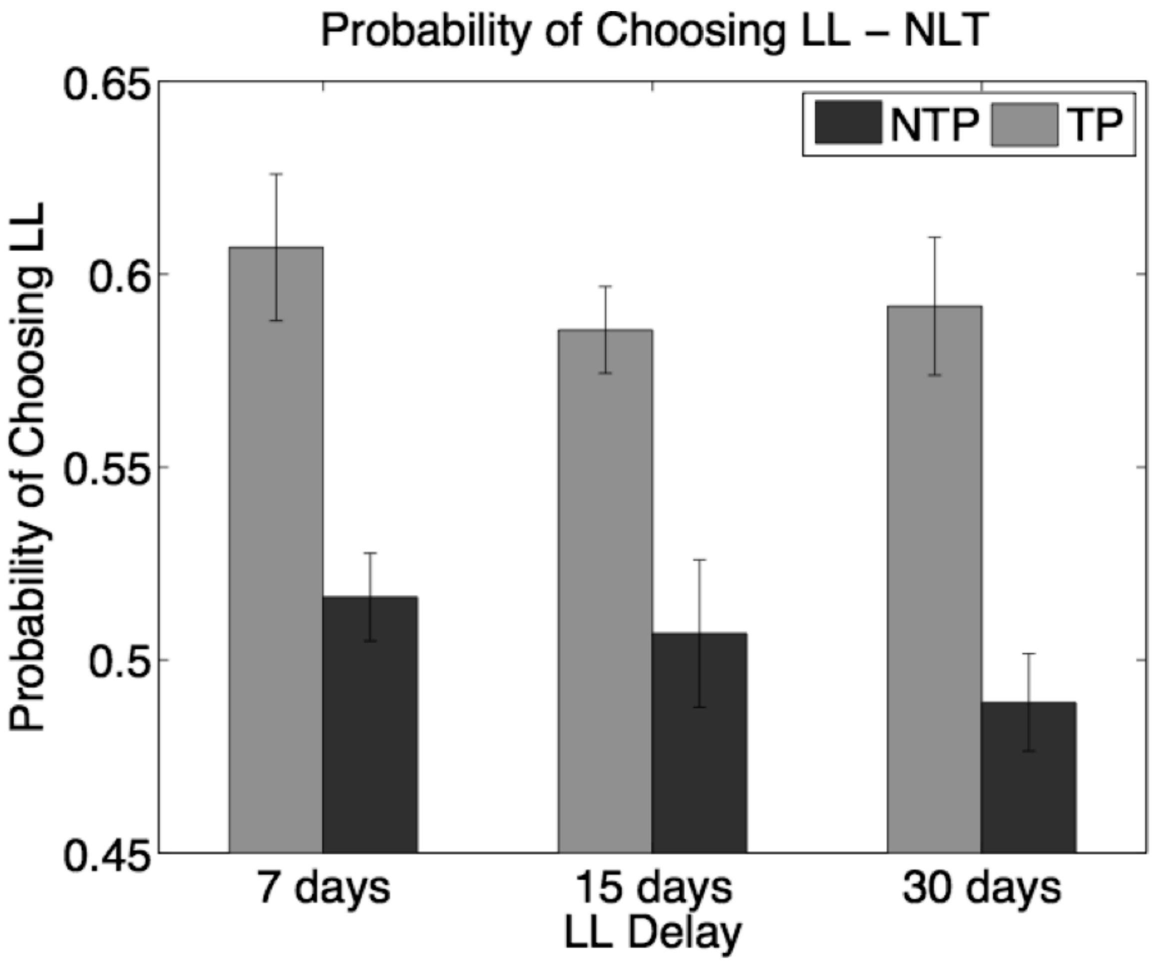


Figure showing the probability of choosing the LL option with LL delay (low trust scores removed). No time pressure block illustrated in dark gray, time pressure block in light gray.

Spearman's rank correlation suggested a possible relationship between LL delay and LL choice under time pressure (with low scores removed).

Results from ANOVA (low trust scores removed):

LL delay and probability of choosing LL overall: $F = 1.878$; $df = 2$; $p = 0.175$

LL delay and probability of choosing LL with NTP: $F = 0.905$; $df = 2$; $p = 0.418$

LL delay and probability of choosing LL with TP: $F = 2.744$; $df = 2$; $p = 0.084$

No significant relationship between LL delay and LL choice.

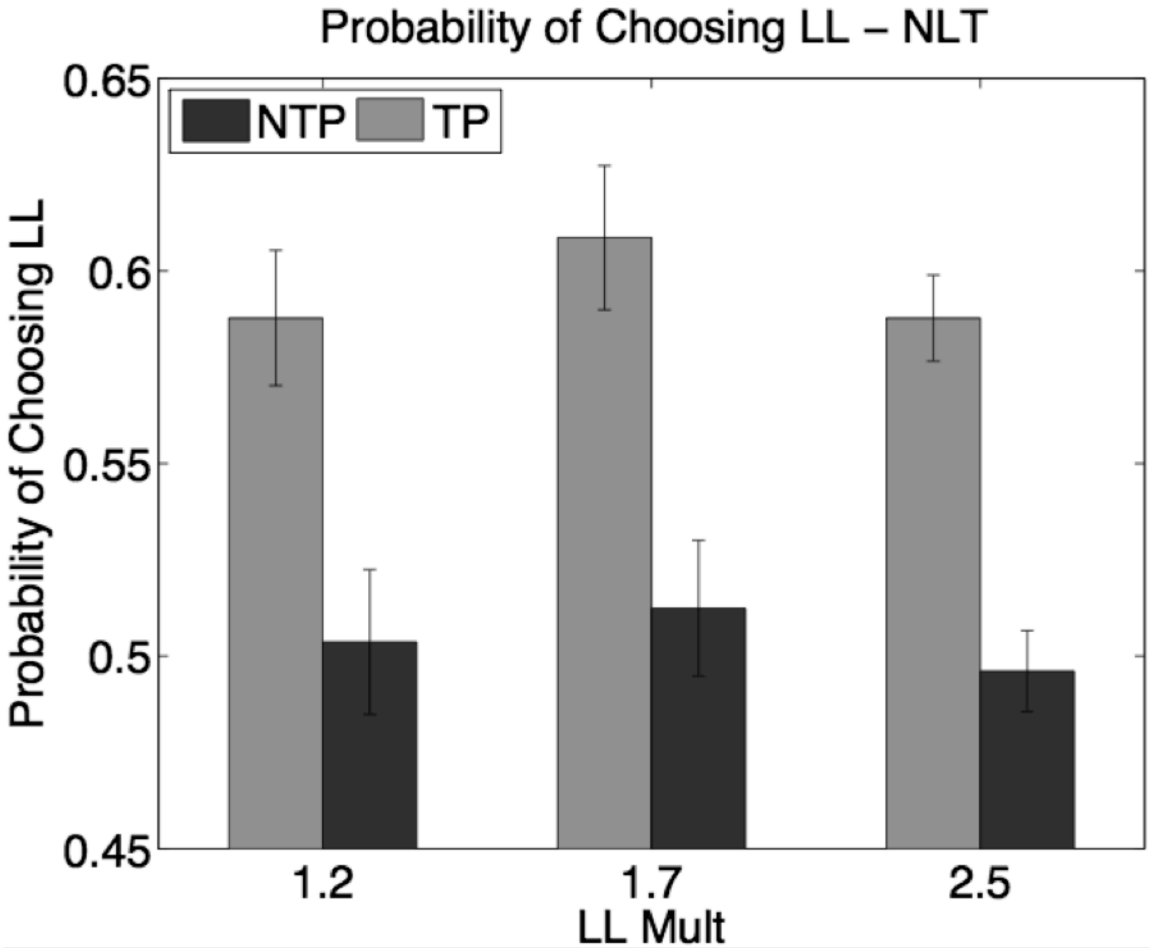


Figure showing the probability of choosing the LL option with LL multiplier (low trust scores removed). No time pressure block illustrated in dark gray, time pressure block in light gray.

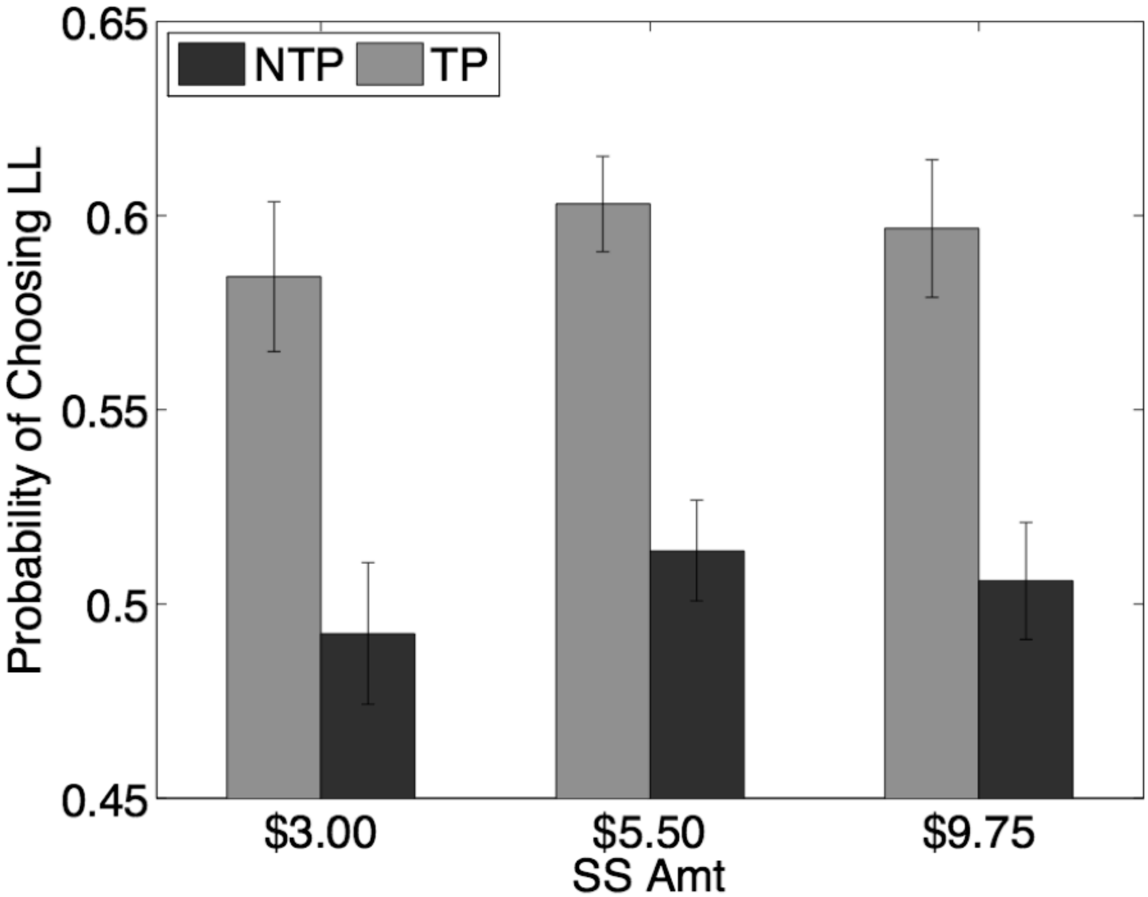


Figure showing the probability of choosing the LL option with SS amount (low trust scores removed). No time pressure block illustrated in dark gray, time pressure block in light gray.

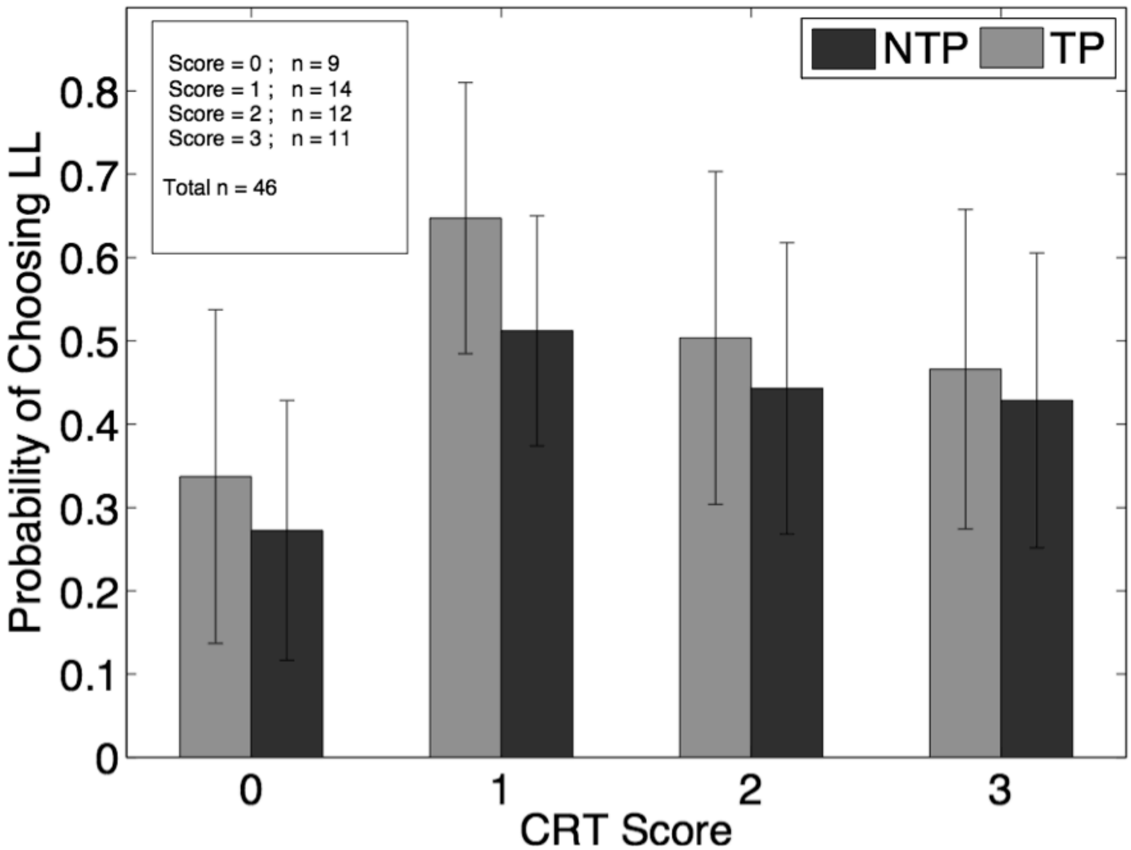


Figure showing CRT score and the probability of choosing the LL option, with low trust scores removed. Scores are grouped from a minimum of 0 to maximum of 3. No time pressure block in dark gray; time pressure block in light gray.

APPENDIX C

Social Cooperation Replication Project Supplementary Materials

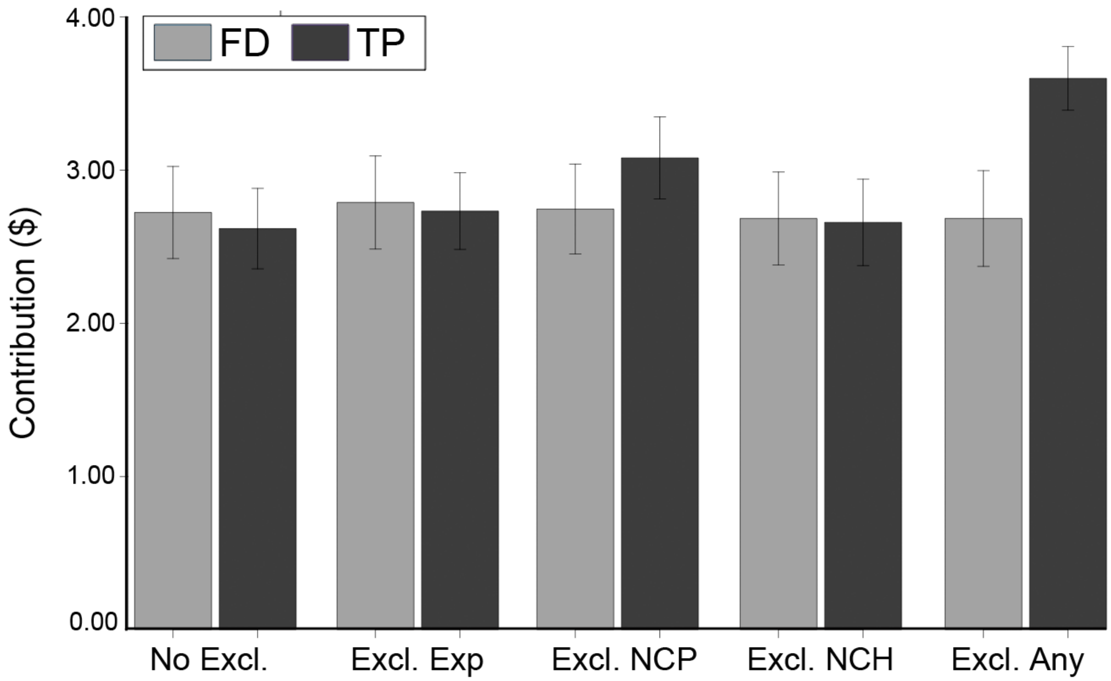


Fig. 10. Plot of the mean contribution amounts (out of $4.00) for various exclusions under time pressure (TP) and forced delay (FD) conditions. From the far left, no exclusions (No Excl.), excluding experienced individuals (Excl. Exp), excluding non-compliant individuals (Excl. NCP), excluding non-comprehending individuals (Excl. NCH), and excluding any combination of the three exclusion criteria (Excl. Any). Contributions made under time pressure are shaded in dark gray; contributions made under the forced delay condition are shaded in light gray. For numbers of participants in each category and exact values of mean contributions and standard deviations, see Table 8.

Table 8. Mean contributions (out of $4.00), standard deviations, and individual counts for all data and exclusions (experienced, non-compliant, non-comprehending, and any combination of the three). The last two columns correspond to *t*-values and *p*-values illustrating if the means between conditions are significantly different.

	Time Pressure			**Forced Delay**				
	N	Mean Contribution ($)	Standard Deviation	N	Mean Contribution ($)	Standard Deviation	*t*	*p*
All (No Exclusions)	78	$2.62	$1.34	77	$2.72	$1.54	0.454	0.650
Excluding Experienced	60	$2.73	$1.29	53	$2.78	$1.55	0.218	0.828
Excluding Non-Compliant	34	$3.28	$1.27	72	$2.74	$1.50	1.816	0.072
Excluding Non-Comprehending	59	$2.66	$1.44	56	$2.55	$1.64	0.371	0.711
Excluding Any	21	$3.60	$1.06	37	$2.69	$1.60	2.347	0.022

Table 9. Bayesian ANOVA for all data and exclusions (experienced, non-compliant, non-comprehending, and any combination of the three).

	Models	P(M)	P(M|Data)	BF_M	BF_{10}	% error
All (No Exclusions)	Null Model	0.500	0.840	5.253	1.000	
	Block (TP/NTP)	0.500	0.160	0.190	0.190	6.901E-06
Excluding Experienced	Null model	0.500	0.830	4.894	1.000	
	Block (TP/NTP)	0.500	0.170	0.204	0.204	3.000E-03
Excluding Non-Compliant	Null Model	0.500	0.519	1.080	1.000	
	Block (TP/NTP)	0.500	0.481	0.926	0.926	8.896E-05
Excluding Non-Comprehending	Null Model	0.500	0.826	4.742	1.000	
	Block (TP/NTP)	0.500	0.174	0.211	0.211	4.497E-04
Excluding Any	Null Model	0.500	0.282	0.392	1.000	
	Block (TP/NTP)	0.500	0.718	2.552	2.552	2.366E-04

Bayesian ANOVA analysis of effects for all data and exclusions (experienced, non-compliant, non-comprehending, and any combination of the three).

	Effects	P(incl)	P(incl | data)	$BF_{inclusion}$
All (No Exclusions)	Block (TP/NTP)	0.5	0.16	0.19
Excluding Experienced	Block (TP/NTP)	0.5	0.17	0.204
Excluding Non-Compliant	Block (TP/NTP)	0.5	0.481	0.926
Excluding Non-Comprehending	Block (TP/NTP)	0.5	0.174	0.211
Excluding Any	Block (TP/NTP)	0.5	0.718	2.552