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Examining the Influence of Executive Resources and Mathematical Abilities on Framing Biases

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EXAMINING THE INFLUENCE OF EXECUTIVE RESOURCES AND
MATHEMATICAL ABILITIES ON FRAMING BIASES

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Abstract

The finding that the presentation of a choice (i.e., either as a loss or a gain) can affect and bias our willingness to engage in risk is one of the paramount findings of behavioral economics. First discussed by Tversky and Kahneman (1981), the framing effect demonstrates that when given two choices framed as a loss, we tend to become risk seeking. However, when the exact same outcome is presented as a gain, we become risk averse, choosing the more conservative option, regardless of the actual expected value. The effect is not limited to general research samples but has been demonstrated using domain specific frames in samples of educators (Fagley, Miller, & Jones, 1999), financial professionals (Roszkowski & Snelbecker, 1990), and physicians (Christensen, Heckerung, Mackesy-Amiti, Bernstein, & Elstein, 1995). Despite extensive research on framing biases, the exact underlying mechanisms accounting for the effect have not yet fully been explained. Extant studies have found relationships between various aspects of executive function (e.g., working memory and attention) and risky decision making, as well as links between mathematical ability and decision-making strategies, yet no work to date has fully explored the joint contribution of these factors, nor how they may contribute to or shield us from potential framing biases. The present study utilized a battery of nine tasks measuring the constructs working memory, selective attention, inhibitory control, cognitive impulsivity, math achievement, general numeracy, math anxiety, and framing resistance to explore the joint contribution of executive ability and mathematical traits upon framing resistance. While small correlations were found between the predictive measures and framing resistance, structural equation modelling explained little more than the Pearson coefficients. The current data raises questions about the influence of age and life experience on framing bias within conventional methods of decision-making research.

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Chapter 1

Introduction

Kahneman and Tversky's (1979) prospect theory is a classic and widely taught paradigm within both behavioral economics and cognitive psychology. Prospect theory outlines the manner in which humans make decisions between risky options, and subsequent research has demonstrated we do so using fast, and often inaccurate, heuristics. The novelty of Kahneman and Tversky's theory was not that it demonstrated optimal decision making based on careful measurement of risk versus reward, but rather how we use simple mental shortcuts to arrive at suboptimal decisions due to the limited capacity of our cognitive systems. The framing effect (Kahneman & Tversky, 1984), the finding that we can be biased to a decision based on its presentation as a loss or gain, is an extension of prospect theory which arguably has even deeper implications for theories of how our decision making is flawed and imprecise. These early findings of Kahneman and Tversky opened the door to a deeper discussion about human decision making and even fostered the development of the field of behavioral economics, eventually garnering Kahneman a 2002 Nobel Prize in economics sciences. *The Economist* (2015) magazine recently named Kahneman the seventh most influential economist in the world, and yet he is a cognitive psychologist whose research has primarily focused on decision making. Clearly this research has utility not only within the field of cognition, but also to those examining the more applied aspects of human behavior in financial domains. The framing effect is of great interest to those within marketing, as contemporary marketing research is exploring framing biases in marketplaces including (but not limited to) hospitality (Mattila & Gao, 2017), fuels and energy (Moon, Bergey, Bove, & Robinson, 2016), tourism (Hall, 2016), and public opinion (Lee, Change, Kim, & Lee, 2016).

And yet, with all the adulation of Kahneman and Tversky's work, there still remain many unanswered questions within the study of decision making. The following will outline the basic findings of Kahneman and Tversky's early work, culminating with the formulation of prospect theory and subsequent discovery of the framing effect. Further, subsequent recent research will be discussed outlining the underlying mechanisms potentially accounting for decisions made under risk and our framing biases, including shortcomings within these current lines of inquiry. Particularly, while prospect theory and the related framing effects neatly demonstrate that people consistently make suboptimal, fast and frugal decisions, the underlying mechanisms which often result in poor decisions are not yet fully understood. While several studies discussed below have attempted to examine how individual differences contribute to these behavioral outcomes, how these behaviors are influenced by the joint contribution of executive function, as well as differences in mathematical ability and math anxiety have yet to be examined.

Prospect Theory and Framing Effects

Prior to the formulation of prospect theory, traditional approaches to human decision making looked something akin to expected utility theory (EUT). Initially formulated by Swiss mathematician and physicist Daniel Bernoulli (1738), EUT proposes that decision in the face of risk is not reliant on carefully calculated, expected values of an outcome, but rather one's personal accounting of the "utility" of the outcome. For example, the expected utility of one dollar is far greater to a beggar than for someone with vast riches. While this theory holds across some scenarios, subsequent research has demonstrated that a great deal of contextual variables can influence the outcome of these types of decisions. Framing effects, which will be discussed in detail later, can have a large influence and bias decision making beyond utility. While EUT

posited some basic guidelines, which may apply in decision making scenarios, the theory and subsequently proposed mathematical models are an oversimplification of behavior in the real world. Curiously, EUT was the predominant view of how people made rational choices until the late 1970s when prospect theory emerged.

Prospect theory (Kahneman & Tversky, 1979) differs from expected utility theory, positing that fair gambles are more attractive when we are anticipating a loss, than when we are expecting a gain. That is, we are more likely to take the sure money bet even when a gamble with a larger payout is available. Conversely, we are less likely to take a smaller but certain loss and would rather gamble for a chance to lose nothing or take a greater hit. We are risk seeking in anticipation of loss, but risk averse in anticipation of a gain. In their seminal paper, Kahneman and Tversky demonstrated behavioral evidence of this phenomenon, illustrating the shortcomings of EUT.

In their early studies, Kahneman and Tversky define risky decision making as any scenario that gives a choice of options between prospects or gambles. These prospects are essentially contracts yielding some outcome; sometimes these outcomes are certain (x), other times they are probabilistic (x, p). In the classic EUT view of prospects, a prospect is an acceptable one if the resulting utility from integrating the prospect's gains with one's own wealth exceed the utility of those existing assets alone. Individuals who prefer certain prospects (x) over gambles are characterized as "risk averse," and this aversion was generally seen as the predominate form of behavior within EUT. Kahneman and Tversky illustrate numerous decision-making phenomena violating these assumptions.

Kahneman and Tversky named the first of these violations the “certainty effect.” Take for example the following problem (the values denote Israeli currency, of which the median net monthly income was roughly 3,000 in 1979):

Choose between

A: 2,500 with probability .33 2,400 with probability .66 0 with probability .01	B: 2,400 with certainty.
18% chose	82% chose

Here, 82 percent of participants chose B, the certain choice of 2,400, even though A has an expected value of 2,409. Now consider an additional problem.

Choose between

C: 2,500 with probability .33 0 with probability .67	D: 2,400 with probability .34 0 with probability .66
83% chose	17% chose

In this second problem, participants overwhelmingly chose C, the option with a higher expected value. The disparate types of responding seen between these two problems violates equations of expected utility characterized by French economist Allais (1953) and illustrates the certainty effect. This finding however is not bound to problems containing sure bets, nor to simply monetary decisions.

Choose between

A: 50% chance to win a three-week tour of England, France and Italy	B: A one-week tour of England, with certainty.
22% chose	78% chose

Choose between

A: 5% chance to win a three-week tour of England, France and Italy	B: 10% chance to win a one-week tour of England.
67% chose	33% chose

Here we see a similar pattern of responding when faced with scenarios involving a potential vacation outcome. In the first example, participants tend to choose the outcome with certainty, but when forced to gamble take the prospect with a larger expected value. These examples demonstrate that this violation is not bound simply to monetary choices, but rather generalize across domains.

A second finding in Kahneman and Tversky's early prospect theory work is the "reflection effect." While the certainty effect demonstrated behaviors in scenarios involving gains, the reflection effect illustrates behaviors in the face of losing outcomes. Specifically, if we change the monetary problems demonstrating the certainty effect from gains into potential losses we see responding switch, such that participants who are typically risk averse in the face of potential gains suddenly become risk seeking.

Choose between

A: 80% chance of losing 4,000 20% chance of losing nothing	B: Losing 3,000 with certainty.
92% chose	8% chose

This finding too violates the assumptions of EUT, as consistent with the above example, participants will consistently choose the option with a lower expected value.

In addition to finding the seemingly disparate risk aversion profiles in the face of loss versus gain, Kahneman and Tversky found that individuals tend to disregard shared components between multiple options, and instead focus on the characteristics which distinguish them. This finding is known as the “isolation effect.” Take for example the following problem:

Consider the following two-stage game. In the first stage, there is a probability of .75 to end the game without winning anything, and a probability of .25 to move into the second stage. If you reach the second stage, you have a choice between

A: 4,000 with a probability of .8	B: 3,000 with certainty
--------------------------------------	----------------------------

Your choice must be made before the game starts, i.e., before the outcome of the first stage is known.

Probabilistically, this scenario is no different than choosing between 4,000, .20 and 3,000, .25, and when testing this exact scenario 65% of respondents prefer the 4,000 choice. However, in the above two-part scenario, participants overwhelmingly chose option B at a rate of 78%, wherein

most appear to be completely ignoring or isolating the first part of the scenario, opting to simply make a choice between 4,000, .8 or 3,000. This is an interesting finding, as it demonstrates that people do not construct complete mental models of a problem, but rather focus on individual components, making decisions on limited amounts of data. This is similar to the type of biases within the framing effect, wherein individuals tend to fixate on or “isolate” the framing language, subsequently biasing their decisions.

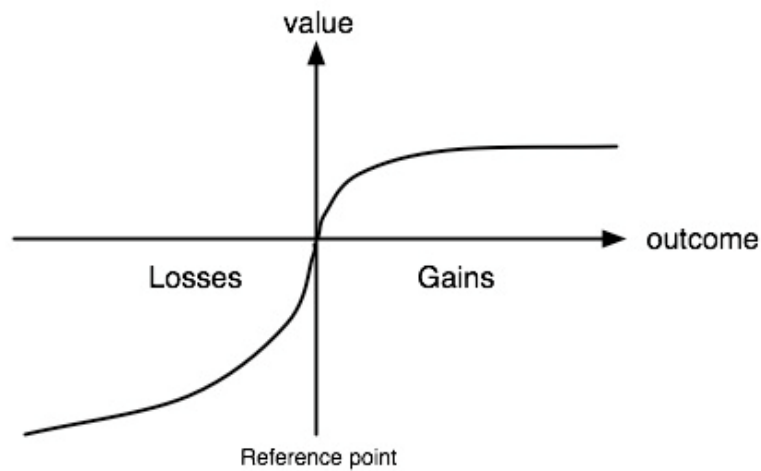


Figure 1. Tversky and Kahneman’s S-shaped function

Following the development of prospect theory, Tversky and Kahneman (1981) examined how the wording or “framing” of choices in a task affects our decisions about those choices. Expanding on their previous research into prospect theory, the two explored whether the typically found S-shaped function (see Appendix A for a graph of the function), exhibited by participants in the face of probabilistic decisions, would shift on account of the questions’ framing. Within their framing experiments, participants would be asked questions like the following:

Imagine that the U.S. is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimate of the consequences of the programs is as follows:

If Program A is adopted, 200 people will be saved.

If Program B is adopted, there is 1/3 probability that 600 people will be saved, and 2/3 probability that no people will be saved.

Which of the two programs would you favor?

Respondents to this question tend to be typically risk averse, with 72 percent choosing Program A, a finding which has been replicated by subsequent researchers even when examining the bias within samples of medical professionals (McGettigan, Sly, O'connell, Hill, & Henry, 1999). However, when two negatively framed programs ("people will die") with the same expected values were proposed to a different group of respondents, a significant shift in responding occurs:

If Program C is adopted, 400 people will die.

If Program D is adopted, there is 1/3 probability that nobody will die, and 2/3 probability that 600 people will die.

Which of the two programs would you favor?

In this instance, most participants chose Program D over C to a frequency of 78 percent, a far more risk seeking pattern of responding. Both pairs of scenarios have the same expected values ($A = C$; $B = D$), and yet we find a strong disparity in responding based on the verbiage of the choice. This illustrates the typical finding of the framing effect; choices presented in a positive frame tend to be chosen more favorably (i.e., we are more risk averse), whereas choices

presented as a potential loss tend to be viewed less favorably (i.e., we become more risk seeking). This behavior has been found even with domain-specific frames presented to educators (Fagley, Miller, & Jones, 1999), financial professionals (Roszkowski & Snelbecker, 1990), and physicians (Christensen, Heckerung, Mackesy-Amiti, Bernstein, & Elstein, 1995). Kahneman and Tversky (1984) extend the mathematical function applied to prospect theory to describe the framing effect, essentially demonstrating that the framing of questions as either gains or losses exhibits the type of responding demonstrated in the function originally derived to explain risk seeking or risk averse behavior in the face of gains and losses.

Tversky and Kahneman (1992) describe the decision-making process within all of the above examples as having two stages: 1) a beginning stage of editing, and 2) a stage of evaluation. The editing portion is a beginning assessment of the offered choices, in an effort to simplify them representationally (not mathematically). The second phase is an evaluation of the edited prospects to choose the one with more value. Next, the editing phase will be discussed in greater detail, as the process itself relies heavily on executive resources, despite Kahneman and Tversky not addressing any constructs under the umbrella of executive function in their early works.

The first portion of the editing phase is the “coding” portion, wherein the prospects offered in a gamble or decision are encoded relative to a reference point. This reference point in monetary scenarios is typically relative to one’s current wealth, but it applies across health and other domains as well. This current state acts as the reference point, upon which the potential gains or losses of a prospect are weighed. Following the “coding” portion is the “combination” phase, wherein an individual will combine outcomes with identical values (e.g., 100, .25; 100, .25 becomes 100, .50), allowing for a simpler evaluation. Next is the “segregation” phase, where

prospects with a greater amount of risk are separated from those prospects which are more certain (e.g., 100, .80; 50, 1.0 is reconstructed as a sure gain of 50 and a risky prospect of 100, .80). All of these processes should require the engagement of working memory for the corresponding operation or representational manipulation. Despite this, Kahneman and Tversky never explicitly discuss the cognitive underpinnings of the editing phases. One can infer some of the underlying processes from the resulting behavioral responses seen in risky choice problems, as later we will discuss several studies attempting to pin down the underlying characteristics accounting for prospect decisions and framing biases. However, the full breadth of the underlying cognitions contributing to these processes, as well as the influence of individual differences is yet to be fully elucidated.

“Cancellation” is an additional portion of the editing phase, and one not so dependent on executive function, but rather the absence of it. As in the example problem given to describe the isolation effect earlier, cancellation is the process of essentially ignoring attributes of a problem that are shared across multiple prospects. For example, if one prospect has a 20 percent chance of winning \$500 and a 10 percent chance of losing \$100, and a second prospect has a 40 percent chance of winning \$200 and a 10 percent chance of losing \$100, the possibility of losing then gets ignored across both prospects. Much like our usage of heuristics as mental shortcuts, this cancellation reduces computational load, and yet can alter responding such that we miss the overall probability of an outcome. The anomalies found within the problems described above may be the result of editing prospects, as our edits are quick, potentially error prone, and not computationally exacting. As such, it begs the question, do differences in one’s math ability and executive resources play a large part in the types of responding participants make in the face of

prospects? Are individuals with a greater degree of mathematical fluency and sophistication less apt to “isolate,” opting to calculate expected outcomes instead?

Following this editing phase, individuals evaluate the now-edited prospects and choose the one of highest value. Of note here is the resulting outcomes are changes in wealth or welfare, rather than isolated states. This type of evaluation is more like a decision based on a change in states, rather than some isolated finite position. In this sense, evaluation is similar to basic principles in perception, wherein individuals are responding to differences in sensory stimuli, whether it is brightness, physical size, loudness, or temperature; contextual components and previous experience shape perception of the current sensory inputs. Kahneman and Tversky (1979) argue that the same contextual and experiential attributes are important to judgments of risk outcomes, as one person’s level of wealth may very well be poverty for another wealthier person.

These phases outlined by Kahneman and Tversky serve rather as descriptives for the basic underlying procedure of decision making; however, it must be considered that this form of decision making itself is a byproduct of a limited cognitive system, one that uses quick and inaccurate heuristics to make decisions. This begs the question: to what degree do differences in cognitive ability affect decision making; or alternatively, with sufficient cognitive resources, might people not rely on these shortcuts at all? A wide array of research has demonstrated the impact of variations in executive functions on problem solving ability, including topics such as arithmetic (Mazzocco & Kover, 2007), spatial reasoning (Greenberg, Bellana, & Bialystok, 2013; Handley, Capon, Copp, & Harper, 2002), and syllogistic reasoning (Gilhooly & Fioratou, 2009). It stands to reason that these same underlying constructs (i.e., working memory,

attention, inhibitory control) must have some influence on our reliance or lack thereof on shortcuts in risky decision making.

Decision Making and Executive Function

The term executive function is used to describe several aspects of higher order cognitive processes including attention, working memory, inhibitory control, abstract reasoning, problem solving, emotional regulation, mental simulation and planning (Diamond, 2013; Miyake, Friedman, Emerson, Witzki, & Howerter, 2000). For the purposes of this study however, we focus on topics relating particularly to those aspects of executive function that appear to be most critical for decision making, namely; attentional components including inhibition and selective attention, and working memory. Recent work exploring the relationships between these constructs and decision-making processes will be discussed in greater detail below.

Before discussing more experimentally-driven approaches to modelling decision making and the contributions of executive function, it is important to mention a model proposed by Gigerenzer and Goldstein (1996). Using algorithmic computer models, the pair eloquently illustrated how our limited cognitive systems result in “bounded” forms of rationality, arguably an extension of Simon’s (1956) notion of satisficing. That is, with limited time and a finite amount of processing power, we come to conclusions about given scenarios using rational systems bounded by these constraints, often simply choosing a solution which may not be optimal, but exceeds some threshold compared to alternatives. With their approach, Gigerenzer and Goldstein demonstrate multiple methods that can be used to arrive at solutions with this limited system. The models include such approaches as “take the best” or “take the last” in a series of items presented, methods that seem not terribly dissimilar from the heuristic approaches

discussed by Tversky and Kahneman (1975). The models proposed by Gigerenzer and Goldstein however are contingent on a particular allowance of computational abilities and parameters. That is, with fixed states and availability of resources, their estimates were something akin to the mean of a population. While this might serve as a proxy for how we most often make decisions, this type of modeling fails to account for the myriad of human variability. A model of reasoning might demonstrate entirely different patterns of responding given a better algorithm (i.e., a proxy for more mathematical ability) and more computational resources (i.e., better executive ability). Further, their model does not account for potential dual-process approaches to reasoning, a topic we will discuss in greater detail later.

More recently, efforts have been made to examine the relationship between executive abilities and decision-making performance using large task batteries and big samples. One such study used a collection of tasks to examine the relationships between several executive constructs (Del Missier, Mäntylä, & de Bruin, 2012). This included working memory (tested using a letter span and n-back tasks), inhibitory aspects of attention (stop-signal and Stroop tasks), Raven's progressive matrices (fluid intelligence), and probability judgment ability (measured via an 11-item measure). Additionally, participants completed several decision-making tasks including the Iowa gambling task, consistency in perception of risk, the ability to apply decision rules, and a resistance to framing measure. Of particular interest was that the letter-memory task (a working memory measure) had a statistically significant moderate correlation with performance on the applying rules task. This measure also had a moderate correlation with fluid intelligence measures and probability judgment scores. Curiously, the letter-memory task did not demonstrate a statistically significant relationship to any of the other risk and decision-making tasks. N-back performance, the additional working memory measure,

had a statistically significant moderate positive correlation with confidence measures on the decision-making task, yet no statistically significant relationship with any of the other decision-making measures. It is important to note here that past research has demonstrated n-back tasks to be a poor proxy for working memory performance (Kane, Conway, Miura, & Colflesh, 2007), and the letter span task (a single task procedure) is arguably a less valid measure of working memory ability compared to better standards such as rotation span or symmetry span (Draheim, Harrison, Embretson, & Engle, 2016). Ultimately Del Missier et al.'s study, while ambitious in scope, missed the mark with measures that falter as appropriate indices of executive function, resulting in underpowered results and lackluster coefficients between the measures. More accurate and robust assessments coupled with better statistical approaches, proposed later in this paper, offer a more optimal approach to exploring the relationship between executive functions and decision making under risk.

Developmental research has attempted to identify the underlying factors contributing to our “cognitive sophistication” in decision making (Toplak, West, & Stanovich, 2014). Here researchers examined performance on a battery of tasks of students across second through ninth grade. Measuring such factors as fluid intelligence, Stroop performance, working memory via sentence span, as well as thinking dispositions via the need for cognition scale, performance on these tasks was compared to rational thinking ability measured via belief bias syllogisms, base rate sensitivity, and framing resistance. The correlational analysis using composite z-scores reported here demonstrate a strong relationship between a composite score comprised of executive function measures ($r = .65$) and moderate relationship with thinking disposition ($r = .28$) to performance on reasoning tasks. While this is marginally compelling, the nature of the analysis gives this study limited utility, as more complex methods, such as structural equation

modelling, would have been a more appropriate fit for the type and amount of data collected ($N=204$). Utilizing latent variables (reducing explanatory power) in lieu of composite z-scores typically yields a more compelling picture of the relationships between factors within a task battery (Kline, 2015).

Another study using a large task battery examined the contributions of multiple executive functions to decision making in the “Applying Decision Rules” or ADR and the “Consistency in Risk Perception” CRP tasks (Del Missier, Mäntylä, & de Bruin, 2010). The ADR task requires participants to use a given procedure in the selection of choice (e.g., buying a DVD player). The DVD players in one such scenario would vary on features such as picture quality, and participants would be instructed to use approaches including satisficing or lexicographic (i.e., choose based on a most important attribute, then select on secondary attributes). The CRP task asks participants questions such as “what is the probability that you will get into a car accident while driving during the next year?” The same question will then be asked a second time, but evaluating a longer time line (e.g., 5 years); performance is then graded based on individuals’ consistency in their projection of risk across the given durations. The researchers additionally collected data testing participants’ ability to update working memory representations, shift between tasks and information sets, and inhibit responses to stimuli. The results indicated the ADR task had a moderate relationship with shifting ability, while the CRP had moderate relationships with performance on the updating tasks. Specifically, as shifting and updating ability increased, so too did performance on the ADR and CRP tasks respectively. Of note here is the theory that both shifting and updating are considered to be functions of working memory (Miyake, et al., 2000). Surprisingly, no measures of mathematical ability were collected, as it

could be posited that consistency in risk projections would vary as a function of an individual's ability to scale probabilities over time.

A compelling experiment examined the relationship between working-memory load and impulsivity (Hinson, Jameson, & Whitney, 2003). Particularly, this study further examined the phenomenon of delay discounting, the finding that immediately available reward (as opposed to time delayed) has a greater effect on performance (Myerson & Green, 1995). Here, Hinson et al. loaded participants' working memory (particularly, their phonological loop) by having them remember a string of five numbers and report on the numbers after making a monetary judgment. The monetary judgment required participants to make a decision between two hypothetical options; the first, a smaller amount of money ranging from \$100 – \$900 available immediately, and the second option ranging from \$1,100 - \$2,000 available after some delay ranging from as short as 1 week to as long as 2 years. In a control block of the task, participants completed this monetary judgment under no working memory load. The results indicated participants demonstrated greater amounts of impulsivity while under working memory load. That is, they had a lower propensity to take the delayed but higher value reward while their executive resources were taxed. This finding is of particular interest, as while impulsivity might be a characteristic or trait which can have some degree of stability individual to individual, simple manipulations of cognitive load can have a state dependent effect on decision making, demonstrating some influence of executive function on delay discounting. Surprisingly, this study collected no measure of inhibitory control, a construct also related to risk taking (White, McDermott, Degnan, Henderson, & Fox, 2011).

Elsley et al. (2016) examined the relationship between selective attention and risk, administering a battery of tasks to assessing attention, impulsivity, anxiety, and risk-taking

behaviors. Particularly, anxiety was measured using the Multidimensional Anxiety Scale for Children (MASC; March, 1997), the Balloon Analogue Risk Task (BART) was administered as a proxy for a child's willingness to engage in risk (Lejuez et al., 2002), and impulsivity was assessed using the Barratt Impulsiveness Scale (Patton, Stanford, & Barratt, 1995). Additionally, participants' attention was measured during an fMRI scan in which tasks assessing both selective and divided attention were administered. Critical for the aims of the present study, brain activation during selective attention and divided attention tasks was positively correlated with BART performance (i.e., as propensity for risk reduced, participants were more likely to exhibit fMRI patterns associated with higher attentional control). This relationship may underlie an early life trajectory that extends into adult behaviors such as diminished risk assessment ability if an individual possesses lower amounts of selective or inhibitory attentional control.

Another compelling finding from Elsey et al.'s (2016) study was that participants scoring higher on the anxiety measure showed reduced recruitment of frontoparietal networks during the attentional tasks, an area of the cortex associated with multiple aspects of executive function. The authors hesitate to take a strong stance on the underlying cause for this but argue it may be due to individual inability to cope with the task. This resulted in behavioral disengagement from the task, and subsequently lower levels of frontoparietal activation. Relatedly, within the domain of mathematical cognition we repeatedly find that individuals high in math anxiety exhibit a global pattern of math avoidance, whether via taking fewer math courses in college or by simply disengaging from math problems that are mentally demanding (Hembree, 1990). These same math avoidant behaviors may influence risky decision making, with those exhibiting high math anxiety more readily succumbing to framing biases rather than calculating expected value of an outcome. Research on inhibitory control and decision making when gambling has found similar

effects to the aforementioned study (Stevens et al., 2015), finding that inducing behaviors which mimic inhibitory response (i.e., inducing a delayed response via stop signal) results in more conservative bets. This may be a generalized phenomenon wherein inhibitory control, whether facilitated by an internal locus of control or external signal, has a positive influence on decision making in the face of risk.

Similar effects have been found regarding the central tendency bias, the finding that we tend to underestimate values above a groups average, and overestimate values below a groups average, tethering evaluations to the center of a distribution and failing to notice deviations below or beyond the mean (Goldstone, 1994). In a recent study, researchers tested whether high amounts of cognitive load would cause participants to exhibit a greater central tendency bias (Allred, Crawford, Duffy, & Smith, 2016). In their experiment, researchers manipulated working memory load, requiring participants to either retain two or six digits in working memory while performing a primary task. The primary task was to adjust a target line to match a presented line displayed for 1.5 seconds prior to the target. This essentially served to measure their central tendency bias in a visual task using line lengths as stimuli. The results indicated that cognitive load increases central tendency effects, as participants exhibited a greater propensity to produce closer to average line lengths under the high load condition. This finding is compelling, as it demonstrates a pronounced central tendency bias in basic perceptual judgments. From this we can infer that in other domains where a central tendency bias has been found (e.g., Likert scale judgments; James, Demaree, & Wolf, 1984), presumably requiring more engagement of executive resources to produce subject judgments, we will find a similar increase in central tendency when under cognitive load (or with lower executive resources available).

Several researchers have proposed theories of dual reasoning systems for decision making (Evans, 2003; Sloman, 1996). While there are slight differences proposed between these models, the underlying assumptions posit two basic systems. The first system is reliant on prior knowledge, beliefs, and experience, resulting in heuristic usage and/or habituated, non-critical lines of decision making. The second system is analytical, and facilitates reasoning in a more logical manner, weighing pros and cons, calculating expected outcomes. The system reliant on existing knowledge operates rapidly with little computational demand, whereas the logical system is slower and demanding of executive resources. These systems can however sometimes function concurrently, wherein an individual may engage more executive resources to reason through a problem, only to ultimately be influenced or biased by an existing heuristic shortcut. Conversely, the analytic system may sometimes override the belief-generated response of the heuristic system (Stanovich & West, 2000). However, the criteria around who, when, and why or how one of these two systems dominate any given scenario is yet to be fully explained by the literature.

Neys (2006) attempted to explore the relationship between the dual-process model of reasoning and an individual's level of working memory. Specifically, this study examined the relationship between working memory scores on the Operation Span task (La Pointe & Engle, 1990) and reasoning performance under load. The reasoning task consisted of basic syllogistic reasoning problems, where participants had to judge whether or not a conclusion logically followed two premises (e.g., Premises: All fruits can be eaten. Hamburgers can be eaten. Conclusion: Hamburgers are fruits.). Some of the conclusions to the syllogisms were in conflict with believability (e.g., Premises: All flowers are animals. All animals can jump. Conclusion: Flowers can jump.) but followed logically from the premises. An additional dual task

manipulation was added to the reasoning portion in the form of a dot memory task where participants were presented with a matrix of dots prior to the reasoning problem. After responding to the reasoning problem, answering whether the conclusion correctly followed the premises, they had to recall the arrangement of the dot matrix. In the low working-memory load condition, the matrix consisted of three dots in a horizontal line, whereas in the high load condition participants needed to remember a more complex four dot array. There was no difference in performance between the low, medium, and high working memory groups across low and high load conditions in the reasoning task for non-conflict syllogisms. However, when the syllogism was in conflict with believability, the high working memory group outperformed both the medium and low working memory groups in both low and high load conditions. The low working-memory group performed particularly poorly under high load for the conflict syllogisms.

Neys (2006) interprets these results across groups as being a result of reliance on one of the two dual-process systems for reasoning. When under high load, those with lower working-memory ability do not inhibit the non-plausibility of a conflict syllogism to arrive at a correct conclusion, instead simply producing a response based on experience regardless of syllogistic logic. Conversely, the high working-memory group, with resources to spare under load can still correctly represent and assess the given conclusion. This has implications for the present study, as this dual-process system might very well underlie different types of responding when presented with a frame. Those with higher executive resources may opt to calculate an expected value of two given framing scenarios, modeling both and holding those representations in working memory. Those with lower amounts of executive resources may err by simply succumbing to the valence (e.g., lives saved vs. lives lost) of the frame. However, this dual-

processing approach has not yet been fully examined within framing task performance, or with a large battery of tasks measuring aspects of working memory, attentional control, or math ability to propose a more robust model of the contributing cognitive factors. A novel study (Slothuus, 2008) has proposed a dual-process model for framing effects, but the scope of the design focused on measures of values and political affiliation, and their relationship to the judgments of political legislation.

The aforementioned dual systems may account for the findings of many of these studies. When free of load, with sufficient executive resources, many individuals may default to the analytical approach to problem solving. However, once under load, it could be that the logical system falters, and we regress to reliance on shortcuts and available pieces of prior knowledge. The same phenomenon may occur when a prospect or frame requires too many resources within the editing phase. Some studies have demonstrated that in scenarios where this cognitive burden is lessened, whether by varying the features of prospect (e.g., from a word problem to discrete figures, or from a written presentation to a visual one) or prompting an individual to derive a solution from experience, individuals alter which of the dual systems become utilized to make a decision, even when faced with a biasing frame.

A study examining the presentation format of frames and its effect on decisions made by police officers found effects akin to this notion, demonstrating the presentation format of numerical information influenced framing biases (Garcia-Retamero & Dhimi, 2013). Experienced police officers were administered a framing task in which they were given scenarios about terrorist identification techniques. A positive frame in this task is as follows: “When using this technique, 91 in 100 known terror suspects who organized and committed an attack were correctly identified as posing an imminent danger.” A negative frame would word this scenario

as “9 in 100... were not correctly identified.” The participants then had to indicate whether or not they would implement the screening program or technique. As expected, the sample of police officers exhibited the anticipated framing effect found across most samples and professions, with the positive frame viewed more favorably than the negative. In an additional condition, researchers added visual aids in the form of icons demonstrating the proportion of individuals identified or not identified in a sample of terrorist suspects. When the visual aid was added, regardless of the accompanying framing vignette, participants exhibited no framing effect, and exhibited greater confidence in their decision to choose one program over another. The researchers interpreted this effect as being a byproduct of more elaborate, “quantitative processing” of the numerical information. That is, in not having to manipulate the numerical information into a representational format, per Kahneman and Tversky’s editing phase, executive resources are not taxed, and hence the framing effect is reduced.

Further, recent work has demonstrated that one’s ability to construct representations of frames from experience reduces framing bias (Gonzalez & Mehlhorn, 2016). That is, having more memory to draw upon lessens the effect. Here, researchers examined the body of framing research to further explore how presentation format and experience affects performance. As expected, their meta-analysis supports a conclusion that visual presentation results in reduced framing biases, as do framed scenarios which relate to an individual’s past experience. Collectively, these recent explorations of the framing effect demonstrate that any manipulation that allows for shortcutting of the editing phase results in less bias. Simply put, taking a risky proposition out of numerical format and into a more visual representation results in less bias. One could further extrapolate upon this conclusion, hypothesizing that those with math deficits

or affective aversions to math should have a harder time editing propositions out of numerical space thus resulting in a propensity for greater reliance on frames.

Some questions about these phenomena are still unanswered. First, do those with better executive abilities rely less on the experience and context-based aspect of the dual system? That is, are their decision-making processes when facing risk more analytic than the average predicted performance of research samples? Second, to what end does mathematical achievement affect reasoning ability, particularly in times when a decision requires weighing the pros and cons of numerical information? Further, some research has suggested, mathematical achievement may be influenced early on by individual differences in executive abilities and may be the result of a trajectory established as early as age 3 (Anobile, Stievano, & Burr, 2013; Steele, Karmiloff-Smith, Cornish, & Scerif, 2012). Do differences in decision-making performance vary as a function of math achievement, or is this ability all moderated by overall executive ability? With this in mind, the following section will discuss the extant (but sparse) literature examining the relationship between mathematical ability and decision making.

Arithmetic, Numerical Judgments, and Executive Function

While a modest amount of research has explored the independent relationships between executive functions and decision making, very little work has examined the relationships between arithmetic abilities and decision making. There does however exist a body of evidence examining the contributions of executive function to the development and mathematical fluency of arithmetic abilities (i.e., better executive ability = better math skills). There is a strong possibility that an underexplored mediating factor in decision making under risk is arithmetic ability. If given infinite time and procedural knowledge to weigh the values of two prospective

options, it is likely we would arrive at decisions more akin to calculation of expected values with less bias resulting from framed language. The following section will discuss the extant literature covering the relationship between arithmetic abilities and executive function, giving attention (when available) to relationships between arithmetic abilities and decision-making research.

As discussed previously, one critical aspect of executive function is working memory. While some debate exists about the underlying components of working memory, the construct itself is generally agreed to be a system of mechanisms responsible for the integration, manipulation, and temporary storage of information in a person's current locus of attention (Miyake & Shah, 1999). Simply put, it is the "mental workbench" of our cognition, and a core component of the higher-order construct referred to as executive function (Baddeley, Della Sala, & Robbins, 1996; Miyake, et al., 2000). Critical for the focus of the present study is the finding that working memory is imperative for basic mathematical abilities including mental arithmetic (DeStefano & Lefevre, 2004). Typically, studies within the domain of mathematical cognition utilize a dual-task approach to examine the particular contributions of working memory to arithmetic ability. One such example of this is Seyler, Kirk, and Ashcraft's (2003) study, which demonstrated that subtraction problems requiring the participant to borrow (i.e., taking a 1 from the tens column to the singles) utilizes working memory resources, and causes diminished letter recall performance when administered as a dual-task.

Further, the contribution of working memory in the development of arithmetic abilities has been examined across numerous elementary-school-aged samples. Even after controlling for such factors as overall intelligence and a child's in-class attentiveness, performance on working memory tasks is predictive of the development of more sophisticated counting and calculation strategies in basic addition (Geary, Hoard, & Nugent, 2012). Typically developing later than

counting based strategies in addition, children eventually memorize the basic arithmetic facts, allowing older children and adults to simply recall the facts from memory when presented with basic problems. Even this shift from strategy use to memorization has been found to be hindered by lower working memory capacity (Barrouillet & Lépine, 2005). For a full review of comparable developmental studies see Raghobar, Barnes, and Hecht (2010).

Similar studies have examined the relationship between other components of our executive function and math performance, particularly sustained selective attention and inhibitory attentional control. In one such study examining this relationship, children around the age of 10 completed an object tracking task measuring visual sustained attention, and a battery of math tasks including Arabic numeral reading, writing, multiplication, addition, subtraction, and counting, along with an additional measure of reading ability (Anobile, Stievano, & Burr, 2013). Overall, the findings suggested a relationship between attention and math ability, however a similar relationship was not found between attention and reading performance. Similar results were found in an even younger sample of children ages 3 to 6 tested longitudinally (Steele, Karmiloff-Smith, Cornish, & Scerif, 2012). This study measured both sustained attention and selective attention in conjunction with basic counting and arithmetic tasks. The study demonstrated that the attentional measures were not only predictive of a child's current mathematical ability, but also predicted performance on math tasks one year later, a finding that has been corroborated by subsequent research (Hassinger-Das, Jordan, Glutting, Irwin, & Dyson, 2014).

Recently, efforts have been made to bridge and examine the collective contributions of these constructs (i.e., attention and working memory), which underlie executive function to determine their joint contribution to mathematical development and performance (Fuhs,

Hornburg, & McNeil, 2016; Samuels, Tournaki, Blackman, & Zilinski, 2016). Critically, these studies demonstrate that multiple underlying components including selective attention and inhibitory control, along with multiple measures of working memory independently contribute to developmental trajectories of math performance. Important for the present study is the finding that aspects of attention as well as working memory contribute jointly to basic arithmetic abilities. If one accepts the assumption that some individuals when presented with a risky prospect will compute some basic evaluation of expected values using mental arithmetic, then their performance should demonstrate a joint contribution of these individuals' overall executive abilities and mathematical ability. Further, while inhibitory or selective aspects of attention have clear contributions to the development of mathematical abilities, our ability to inhibit or select from an array of relevant and irrelevant information within a risk prospect may also vary as a function of this aspect of executive control (i.e., the ability to ignore a frame and attend to the relevant pieces of information).

If one examines the canon of tasks within mathematical cognition looking for a near proxy to Kahneman and Tversky's prospect theory experiments, the classic number comparison task has some similar rudiments. Here, participants judge between two displayed numbers as to which is larger in value, responding typically via button press (Dehaene, Dupoux, & Mehler, 1990). Within this task, we find a standard artifact known as the "numerical distance effect," in which participants' response times are inversely related to numerical distance. That is, participants are faster and more accurate at indicating which of two numbers is larger (or smaller) when the numerical distance separating the two numbers is relatively large (e.g., 2 and 7) than when it is comparatively small (e.g., 3 and 2). It is theorized that the presentation of a single number not only activates the mental representation of that number, but also its

surrounding neighbors (e.g., viewing the number 2 also activates the numbers 1 and 3). This basic effect is not all that compelling or relevant to the present topic of this paper; however, this basic phenomenon has been found to become even more pronounced in those with high levels of math anxiety (Maloney, Ansari, & Fugelsang, 2011). If basic number comparison tasks cause such interactions with math anxiety, it should be expected that more complex numerical tasks in the judgment of risk (i.e., prospect or framing decisions) will produce similar interactions with math anxiety. Further, one of the prevailing theories of mathematics anxiety is that the ruminations associated with high levels of math anxiety compromise available working memory, resulting in impaired performance in numerical and mathematics tasks (Ashcraft & Kirk, 2001). Hence, when tasked to choose between two risk scenarios requiring manipulations within working memory, interactions with math anxiety should be expected.

Recently a model was proposed demonstrating the processes in which symbolic magnitudes are weighed and evaluated in working memory (Chen, Lu, & Holyoak, 2014). Here, Chen et al. evaluated the extant literature covering the comparison of symbolic magnitudes across an array of features; from basic assessments like smaller or larger, to more abstract scenarios such as judging between two animals as to which is *fiercer* or *smarter*. The proposed mathematical model based on their findings, known as the Bayesian Analogy with Relational Transformations (BARTlet), outlines how people produce judgments by applying “dimension-specific weights,” similar to Kahneman and Tversky’s (1979) notion of contextual reference points. The responses generated to two symbolic options are formed and manipulated in working memory, and are sensitive to contextual influences (e.g., a question’s polarity, “smaller” or “larger”). While this model does not address the specifics of how frame affects magnitude judgments, polarity may very well serve as a proxy for frame and result in a similar predictive

model if applied here. Further, adding an affective profile, which interacts with working memory in the form of math anxiety, along with varied math ability, make modeling behaviors in the face of framing a bit muddier. It is likely there are contributions from all of these underlying factors affecting our behavioral outcomes in the face of risk.

A recent study examined the relationship between numerical abilities, affective components like fear or hope, and our propensity to overweigh or under weigh risks (Petrova, Pligt, & Garcia-Retamero, 2014). In the task assessing risk, participants were told to imagine they owned a camera worth 500 Euros, and that they were acquiring insurance to protect the camera from loss or theft. In a *neutral* condition, the camera was said to be purchased from a website. In an *affective* condition, the camera was a birthday present from their favorite grandfather. In a *reappraisal* condition, the participants were instructed to additionally note two or three strategies they could use to mitigate the emotional pain or positive affect resulting from either the loss or gain of the camera. Participants were presented with probabilities of the likelihood of the camera being lost and told that they had 500 Euros to spend on insurance to avoid the loss with a certain probability. In addition to deciding an amount they would spend on an insurance premium, participants then indicated on a scale from 0 to 100 their degree of fear of losing their camera. Each participant also completed the Berlin Numeracy Test (Cokely, Galesic, & Schulz, 2012). The results indicated participants showed an overweighting of the likelihood of loss in the affective conditions and were thus more likely to pay a higher premium. Those with higher numeracy exhibited more linear responding in their insurance premium choice relative to potential risk, an effect that was more pronounced when given the reappraisal instructions (i.e., more critical thinking about the loss resulted in more rational strategies for risk mitigation). These findings have compelling implications for this current study, particularly, that

affective components play a role in risk mitigation, as we might expect with math anxiety. Further, this seems to suggest that individuals with greater numerical ability are better at mitigating affective components of risk, particularly when given more time to engage in elaborative thinking (i.e., constructing more precise representations of two options via the use of executive resources).

Chapter 2

Current Study

In order to examine the joint contributions of executive function (i.e., working memory, inhibitory control, selective attention), fluency with basic probabilities, math achievement, and math anxiety upon framing biases, the experiment utilized a battery of tasks to accurately assess all of these underlying constructs. This resulted in a large data set, permitting a more robust form of statistical analysis; structural equation modelling (SEM). SEM has not been commonly employed in the examination of framing effects but is regarded as having a great deal of efficacy in examining individual differences and their contribution to behavioral outcomes within a dependent measure of interest (MacCallum & Austin, 2000).

It was expected that individuals with better performance on measures of executive control will show a less pronounced framing bias than their peers, as some preliminary evidence exists for this assertion (Del Missier, Mäntylä, & de Bruin, 2010). Further, as demonstrated in the introduction, there exists a strong relationship between executive functions and the development of mathematical fluency. As such, it was also expected that there may be a high amount of covariance between measures of executive function and math achievement. However, the statistical methods employed for our analysis allow for examination of the interaction between math achievement and executive functions, such that detection of the influence of math achievement on framing bias over and above executive function is possible. Simply put, it was expected that those individuals with better performance on executive measures coupled with high measures of math achievement would be the most resistant to framing biases.

Further, given the relationship between working memory and math anxiety, it was expected that when confronted with probability judgments within a framing prospect, those with

high measures of math anxiety would exhibit a greater framing bias, succumbing more readily to prospect's framing language, and exhibiting math avoidant behavior we find in other performance scenarios. Given however that the mechanism underlying performance deficits in those with math anxiety is the taxation of working memory resources, it is possible that individuals with higher amounts of executive function coupled with math anxiety may see a less pronounced framing bias than their peers with a lower degree of executive ability and high levels of math anxiety.

Chapter 3

Method

Participants

Two-hundred undergraduates (137 female, mean age = 20.6 yrs.) from the University of Nevada Las Vegas participated in this study and received course credit upon completion. Ten participants were not included in subsequent analyses due to data loss, experimenter error, or the subject not adhering to protocol, resulting in a combined dataset of one-hundred and ninety participants. Given accepted sample standards (minimum $N = 180$) for the implementation of structural equation modeling (SEM; Kline, 2015) and the standards within individual differences research, two-hundred was adequate. Further, the rule of $N:q$ puts this study at an estimate of 180 required participants, wherein q is the number of observed variables (9 in this battery), and N represents the number of required participants per variable, generally to the ratio of 20:1 (Kline, 2015). Additional samples were collected to account for attrition or experimenter error and serve to potentially give more explanatory power to the models.

Materials and Procedure

Executive Function - Working Memory Tasks

Rotation span – The rotation span task is a complex span measure requiring participants to remember a sequence of long and short arrows presented one at a time in sequence (Harrison et al., 2013). The randomly presented set sizes can vary from 2 to 5 items, and participants must select the arrows from a random array in the order that they appeared. Each set size is presented three times for a total of twelve trials. The secondary task of this dual-task measure requires

participants to assess whether a rotated letter is forward-facing or mirror-reversed. These letters need to be mentally rotated, as they are offset from their typical orientation in addition to being potentially mirror-reversed. Participants enter a yes or no response judgment via key press as to the mirrored orientation of these letters prior to reporting the arrow span sequence they viewed at the start of a trial. Performance results in a dependent measure in the form of a partial span score, the number of arrows recalled in the correct order. Recent evidence has demonstrated that rotation and symmetry span tasks have higher psychometric validity than conventionally used operation span tasks (Draheim, Harrison, Embretson, & Engle, 2016) and as such should be considered the two paramount measurements in assessing working memory.

Symmetry span – The symmetry span task requires participants to recall a series of squares presented serially within a 4 x 4 grid (Unsworth, Redick, Heitz, Broadway, & Engle, 2009). Again, set sizes range from 2 to 5 items in the 4 x 4 grid, presented in a random order. The secondary task has participants assess whether a figure presented within an 8 x 8 grid is symmetrical. The dependent measure is again partial-span score, the number of squares recalled in the correct serial order. Again, each set size is presented three times for a total of twelve trials. This task, in conjunction with the rotation span, serves as a measurement of working memory within our overall assessment of executive function.

Executive Function - Inhibitory Control / Selective Attention Tasks

Stop Signal – A stop signal task is used as one measure of inhibitory control (Logan, 1994; Salthouse, Atkinson, & Berish, 2003). Particularly, the stop signal is characterized as a measure of one's ability to inhibit an ongoing signal or habituated response. This is in contrast to the ability to inhibit an irrelevant distractor, which is measured using a Stroop task discussed below. In each trial of the stop signal task, an arrow (either < or >) is presented in the middle of

the screen, and participants are required to identify the direction of the arrow by a specific key press. They are also instructed to not respond when they are cued with a corresponding “beep” sound immediately after the letter (i.e., the stop signal). A pause occurs at the beginning of each trial 1000 ms before the arrow target. The stop signal, when present, follows between 200 and 600 ms after the letter. Participants are instructed to act as quickly and as accurately as possible before completing 3 blocks of 50 trials. The dependent measure of this task is correct responses, (i.e., no response on a stop trial or an arrow press on a go trial). The version of the task administered for this study used an adaptive mechanism and slowed the stop signal if participants waited until the end of a trial to respond, making it more difficult if participants chose to wait before making their response. This implementation increases task difficulty and reduces the ability of participants to game the task by simply waiting until the end of the average latency window for the beep.

Stroop – The classic Stroop task is a measure assessing participants’ ability to inhibit or ignore irrelevant but salient distractors (Lamers, Roelofs, & Rabeling-Keus, 2010; Stroop, 1935). Within the framing effect, the frames of a risk vignette (e.g., “deaths” vs. “lives saved”) exert an influence on responding in most participants; however, those who ignore the frame and choose based solely on expected utility of the choices might be accounted for by individual differences in inhibitory control, particularly toward distracting stimuli. As such, the Stroop task is an appropriate addition to the present study’s test battery. In our modified version of the Stroop, participants are randomly presented with a series of 96 word-triples. The center triple is displayed in color (e.g., blue, green, yellow, red), with half the trials presenting a congruent stimulus word (e.g., the word “green” displayed in green), and the other half presented incongruent stimuli words (e.g., the word “green” displayed in yellow). Participants are asked to

identify the color the word is printed in by pressing a key corresponding to one of the two surrounding words flanking the center word in the triple (e.g., “yellow” or “green”) surrounding the central target. Participants are again instructed to respond as quickly and as accurately as possible. The dependent measure in this task is reaction time.

Cognitive Reflection Test – The Cognitive Reflection Test (CRT) is a measure designed to assess the ability to override intuitively available, yet incorrect answers to three basic story arithmetic problems (Frederick, 2005). For example: *A bat and a ball cost \$1.10 in total. The bat costs \$1.00 more than the ball. How much does the ball cost?* The obvious impulse answer is “10 cents.” However, with a moment more reflection, we quickly realize that a ball costing 10 cents only leaves \$1.00 remaining for the bat, resulting in a cost difference of 90 cents between the two items. The correct answer is of course, 5 cents (See Appendix A for all three questions of the CRT). A recent study demonstrated that the three questions of the CRT are a useful predictor of heuristic usage, demonstrating that individuals with a tendency to rely on mentally available information are more prone to making the obvious impulse responses to the CRT (Toplak, West, & Stanovich, 2011). The same relationship has not been examined within the domain of prospect framing. However, given related evidence, we should infer that participants who perform poorly on the CRT will exhibit a greater framing effect in the decision-making task discussed below. Participants are allowed ten minutes to complete this measure.

Math Achievement, Numeracy, & Math Anxiety

Wide Range Achievement Test 3 – The arithmetic portion of the Wide Range Achievement Test 3 (WRAT) was administered to measure each participant’s math achievement. This mathematics assessment is a fifteen-minute test containing 40 items. Problems range in difficulty from simple arithmetic and fractions, to solving for unknowns in linear equations.

Participants are given a point for each correct answer, and scores range from 0 to 40. As opposed to the numeracy task discussed below, the WRAT assesses mathematical fluency across a larger selection of math abilities (see Appendix B for full WRAT questionnaire).

Numeracy Scale – The 11-item numeracy scale assesses aspects of mathematical ability that may differentiate from overall mathematical achievement (Lipkus, Samsa, & Rimer, 2001).

Specifically, the seven-item scale assesses how well participants can 1) perform simple mathematical operations on risk magnitudes, 2) convert from proportions to percentages and vice-versa, and 3) convert probabilities into proportions. For example: *If Person A's risk of getting a disease is 1% in ten years, and person B's risk is double that of A's, what is B's risk?*

While this scale will measure some of the abilities required for the WRAT, it assesses specifically the ability to implement the most basic of arithmetic procedures to calculate risk. An individual may score poorly on the WRAT (e.g., < 20), but still possess the necessary abilities to answer all eleven items of numeracy scale correctly (See Appendix C for the numeracy scale).

Participants are allowed ten minutes to complete this measure.

Short Math Anxiety Rating Scale – The twenty-five item Short Math Anxiety Rating Scale (SMARS) measures participants' level of math anxiety (Alexander & Martray, 1989). The SMARS has participants rate math-related scenarios (e.g., "Having to use the tables in the back of a mathematics book") on how much anxiety each scenario would elicit. This is reported using a five-point scale ranging from "not at all anxious" to "highly anxious." An individual's responses are totaled resulting in a math-anxiety score ranging from 25 to 125 (See Appendix D for full SMARS questionnaire).

Decision Making

Framed Risky Decision Problems – The framing task consists of a total of fourteen framed risky choice problems. Half of the problems are gain-framed (e.g., “lives saved” or “will live”) and half of the problems are loss-framed (e.g., “lives lost” or “will be killed”). In each of these problems (see Appendix E), participants indicate which of the two choices they prefer when making the decision using a six-point scale ranging from “definitely would choose option 1” to “definitely would choose option 2.” This differs from the conventional framing paradigm proposed in Tversky and Kahneman’s (1981) original study in which the decision was merely binary. Recent evidence found in the development of a shorter 7-item “resistance to framing” measure (a subscale of the Adult Decision-Making Competence measure) demonstrated that using this Likert-style scale results in greater variability across participants scores, allowing for better overall measurement of framing bias (Bruine de Bruin, Parker, & Fischhoff, 2007).

The problems cover subjects ranging from disease and health risks, financial decisions, employment, education, and environmental topics. The probabilities outlined in each problem are varied (ranging from one-third to three-fifths) and based on questions from past studies of framed risk choices (Bruine et al., 2007; Kühberger, 1998; Levin & Chapman, 1990; Tversky & Kahneman, 1981). The dependent measure here is a “framing resistance” score aggregated from all of the participant’s choices denoting their propensity to deviate from the typical framing bias (i.e., to seek risk in the face of loss or avoid risk when facing a gain). Participants are required to press the space bar after reading each trials vignette, which displays the two actions from which they can choose, allowing the calculation of participants response time per trial along with framing bias.

All tasks, with the exception of the WRAT, Numeracy, and CRT measures were completed on a PC running E-Prime 2.0 software (Schneider, Eschman, & Zuccolotto, 2012). Participants completed the battery of tasks in one session lasting no longer than two hours, with an average estimate of one hour and thirty minutes per participant. The task order of the nine measures was randomized across the participants, with the exception of the framing measure, which was always administered first.

Chapter 4

Results

Table 1
Means, Standard Deviations, and Ranges for Task Battery items

Variables	<i>M</i>	<i>SD</i>	Minimum	Maximum
Framing Resistance	-4.32	5.66	-19.00	8
WRAT	28.87	4.82	18	38
Numeracy	7.2	2.6	0	11
CRT	0.68	0.98	0	3
SMARS	64.92	19.2	28	109
Rotation Span	26.28	8.41	0	42
Symmetry Span	27.77	7.94	7	42
Stroop	169.92	99.47	-94.35	515.46
Stop Signal	53.66	6.42	20.67	68.33

Notes. Stroop values here were calculated participants' mean congruent trial reaction time subtracted from mean incongruent trial reaction time. Stop Signal values are percent correct.

Table 1 presents means, standard deviations, and ranges for all measures. Most measures had straightforward scoring mechanisms. For the WRAT, numeracy scale, and cognitive reflection test, the dependent measure was total correct answers. The SMARS score is the sum across all twenty-five questions in the measure, with higher scores indicating higher levels of math anxiety. The dependent measure for the rotation and symmetry span tasks is “partial span score.” Partial span score is the total number of items recalled in the correct order and the method preferred for use in individual differences approaches like this current study (Conway et al., 2005). The dependent measure for the Stroop task is the difference in participants' reaction times between incongruent (e.g., the word *yellow* presented in green) and congruent trials (e.g., the word *yellow* presented in yellow). A within-subjects t-test was conducted, demonstrating

that participants were significantly faster on congruent trials ($M = 1011$ ms) than incongruent trials ($M = 1181$ ms), $t(186) = 23.36, p < .001$. The difference between the two reaction times on the Stroop is more appropriate as a dependent measure for the models discussed later, as it controls for general differences in participants' response latencies unrelated to the underlying construct of the Stroop (i.e., selective attention). Higher Stroop difference scores indicate less attentional control on the trials. The dependent measure for the stop-signal task was error rates across the three blocks of stop signal trials, indicating the participant's propensity to inhibit their response to the "stop" sound on an individual trial.

Lastly, the main dependent measure of interest, framing resistance, was calculated using a method similar to that in the resistance to framing measure, by calculating how consistently the participant answered in accordance with typical samples when facing a framed scenario (Bruine de Bruin, Parker, & Fischhoff, 2007). Remember, when the scenario is framed as a gain, most samples are risk averse, versus when a scenario is framed as a loss, where most samples are risk seeking. To calculate this, the six-point Likert scale (1, 2, 3, 4, 5, 6) was converted to a range of -3 to 3, wherein negative values on a trial represent responses in line with a framing bias, and positive values indicate a resistance to the framing bias. For example, suppose a participant is given the following options and response scale:

If Program A is adopted, 200 people will be saved.

If Program B is adopted there is a 1/3 probability that 600 people will be saved, and a 2/3 probability that no people will be saved.

Which program would you use?

1	2	3	4	5	6
<i>Definitely would choose A</i>					<i>Definitely would choose B</i>

Given that this is a positive frame (e.g., “will be saved”) we should expect risk averse responding on this trial: options 1, 2, or 3. These three options represent a susceptibility to framing, and are recoded as -3, -2, -1, whereas a choice of 4, 5, or 6 is recoded to 1, 2, or 3 indicating a resistance to framing. Conversely, in the negatively framed version of the same options below (e.g., “will die”), we would expect our sample to respond in a risk seeking manner.

If Program A is adopted, 400 people will die.

If Program B is adopted there is a 1/3 probability that no one will die, and a 2/3 probability that 600 people will die.

Which program would you use?

1	2	3	4	5	6
<i>Definitely would choose A</i>				<i>Definitely would choose B</i>	

Responses indicating a risk seeking preference in the face of loss; 4, 5, or 6 above, are recoded as -1, -2, or -3 indicating framing susceptibility. Responses indicating risk aversion; 1, 2, or 3 are recoded as 3, 2, 1, indicating a framing resistance. The framing-resistance score for each participant is the sum of these values across the fourteen framing trials, with positive total scores indicating a general resistance to framing bias, and negative total scores indicating that their responses were biased overall and in line with expected framing responses.

Table 2 demonstrates the correlations across all of the task battery (see Appendix F for scatter plots of all predictive measures and framing resistance). As expected, there was a moderate degree of covariance across most measures, especially across the math and arithmetic-centric tasks. WRAT performance correlated moderately with the numeracy measure, $r = .528$, $p < .001$, which should be expected, as much of the first half of the WRAT assesses general arithmetic ability, skills required for the general probability calculations of the numeracy

measure. As expected, WRAT score had an inverse correlation with math anxiety scores collected via the SMARS, $r = -.38, p < .001$, consistent with literature demonstrating a relationship between math achievement and math anxiety (Beilock & Maloney, 2015). Numeracy exhibited a similar inverse correlation to SMARS $r = -.344, p < .001$. Additionally, both the WRAT and numeracy measures had low to medium correlations with working memory performance, with the WRAT correlating moderately with both the rotation span, and symmetry span tasks, $r = .391, p < .001; r = .403, p < .001$, and the numeracy measure having a small to moderate correlation with rotation and symmetry span tasks, $r = .310, p < .001; r = .304, p < .001$. This is consistent with previous work demonstrating a relationship between working memory function and mathematical abilities, and the obvious utilization of working memory for both basic arithmetic and more procedurally driven forms of mathematics (for review see Moore, McAuley, Allred, & Ashcraft, 2014).

Table 2
Correlations Among Task Battery Measures

	Framing Resistance	WRAT	Numeracy	CRT	SMARS	Rotation Span	Symmetry Span	Stroop
Framing Resistance		.176*	.096	.252**	-.166*	.175*	.186*	-.148*
WRAT			.528**	.446**	-.380**	.391**	.403**	-.107
Numeracy				.430**	-.344**	.310**	.304**	-.072
CRT					-.319**	.304**	.220**	-.209**
SMARS						-.211**	-.186*	.037
Rotation Span							.577**	-.050
Symmetry Span								-.001
Stroop								

* $p < .05$, ** $p < .01$. Stop Signal excluded due to participants performing at chance.

Regarding the working memory tasks, rotation span had an expected high-moderate correlation with symmetry span, $r = .577, p < .001$. While these two measures are the preferred

tasks for obtaining a psychometrically valid measure of working memory (Draheim et al., 2016), there is still some question as to whether they tap into different underlying modal constructs. That is, the symmetry span task may be more dependent on visuospatial working memory for both the processing and memory portions of the task, while rotation span utilizes visuospatial resources for the rotation portion but relies on phonological rehearsal for the sequential order of the arrows in the memory portion, despite Draheim et al.'s (2016) argument of the contrary. As such, it stands to reason that there are some performance differences within participants across the two tasks.

The three-item Cognitive Reflection Test (CRT) yielded a significant correlation with all other predictive measures in the test battery. Specifically, CRT performance had moderate positive correlations with WRAT, $r = .446, p < .001$, and numeracy scale scores, $r = .430, p < .001$. CRT performance had a small positive correlation with rotation span, $r = .304, p < .001$, and symmetry span scores, $r = .220, p < .01$. CRT was inversely related to Stroop difference score latencies, $r = -.209, p < .01$, indicating as participants performance on the Stroop improved, performance improved on the CRT. Lastly, CRT performance was inversely related to math anxiety ratings of the SMARS, $r = -.319, p < .001$. While these results are not particularly compelling within the purview of this current study, the finding that a simple three-item measure yields a moderate degree of correlation with tasks across multiple constructs begs further discussion.

Stroop performance, as demonstrated above, yielded nearly no significant relationships with other predictive measures, except the CRT. This appears to be indicative of the notion that Stroop taps into a separate component of executive function (i.e., selective attention), and that

this attentive ability has some relationship to an individual's degree of cognitive impulsivity demonstrated on their CRT performance.

Stop signal performance yielded the least interesting results of the test battery, with no significant relationships of value to any of the other predictive measures. Reaction time on the task was positively related to Stroop reaction time, $r = .206, p < .01$, as should be expected when comparing the latencies of two reaction time tasks. The lack of meaningful data here may be due to the general difficulty of the stop signal task employed for this experiment. The mean error rate for the task was 53.66% ($SD = 6.42$), indicating participants were performing at chance in their ability to inhibit their response on trials where the stop signal beep was present. This resulted in a leptokurtic distribution, and as such, the data failed to yield enough variability to be utilized in the models discussed below.

Recall that the dependent measure from the framing task was participants' resistance to framing. Scores on this ranged from -19 to 8 ($M = -4.32, SD = 5.66$) with negative scores indicating an overall susceptibility to framing across the 14 framed vignettes, and a positive score indicating a resistance to framing. Overall the framed vignettes used in the task yielded a biased sample, but not to the typical degree found in the studies from where the vignettes were aggregated (see Table 3 for bias results by item). Of the fourteen framed scenarios used in the task, nine managed to produce responses in our sample indicative of a group bias; that is, over half of the sample responded in line with the predicted framing bias. Of the five scenarios that did not produce overall biased responding, four had negative framing language (i.e., a risk seeking bias was expected in the sample, but the data indicates a risk averse sample for that item). Within those nine scenarios that produced a bias, negative frames tended to only produce a marginally biased sample (55 – 65% choosing the risky option). Generally speaking, it seems

the positive frames induced more biased responding (risk averse responses) than did negative frames (risk seeking responses). This may be due to a number of reasons addressed in the discussion section.

Table 3
Framing Bias Results by Item

Item Number	Frame Valence	Vignette Category	Percentage of Biased Responses in sample	Replicated expected sample bias?
1	positive	public health	41.17 %	no
2	positive	finance	73.89 %	yes
3	positive	public health	71.63 %	yes
4	negative	public health	55.23 %	yes
5	negative	public health	41.37 %	no
6	negative	finance	25 %	no
7	positive	personal health	69.61 %	yes
8	positive	finance	80.4 %	yes
9	negative	public health	52.45 %	yes
10	negative	environmental	65.68%	yes
11	positive	finance	73.04 %	yes
12	positive	public health	56.87 %	yes
13	negative	education	47.05 %	no
14	negative	public health	47.05 %	no

Possibly due to the underwhelming bias yielded overall, the framing resistance scores have less compelling correlations with independent predictors within our test battery. Framing resistance had a small but significant correlation with scores on the WRAT, $r = .176, p < .05$, indicating that as math achievement increased so did framing resistance, consistent with the hypothesis proposed. Scores on the numeracy measure did not yield a significant relationship to framing resistance, $r = .096, p = .225$. The CRT yielded the strongest overall relationship to framing resistance, $r = .252, p < .001$. SMARS scores yielded a small but expected inverse

relationship with framing resistance, $r = -.166, p < .05$. Both of the span tasks yielded small but significant positive relationships with framing resistance: rotation span; $r = .175, p < .05$, symmetry span, $r = .186, p < .05$. Lastly, Stroop yielded a significant inverse relationship with framing resistance, $r = -.148, p < .05$, indicating that participants with a lower framing resistance tended to suffer more interference on the Stroop task. Unfortunately, analyzing correlations using only the nine items within the framing task that yielded the expected sample bias did not lead to any increase in the strength of relationships between the predictive measures on framing resistance.

Further, recall that reaction times were recorded for both the duration spent reading the framing vignette, and for time spent reading and deciding between the two potential options. Partialling from the correlations the average reading time for the vignette, average reading/decision time for the options, or total time spent across both portions of the trial gives no additional insight into the factors mitigating the relationship between the task battery and framing resistance. There is no clear relationship between time spent reading the vignette, $r = -.009, p = .89$, time spent on the choices, $r = -.016, p = .82$, or the sum of both averages across trials, $r = -.029, p = .69$, to framing resistance. It might be expected that if a dual-process approach (heuristic v. calculation) was employed differentially by participants within the sample, that the latency time spent reading might disentangle those participants who calculated an expected value on a frame from those who simply succumbed to the framing language. However this is not clearly evident in the latency data, nor did these latencies have any clear relationship to any of the other predictive measures of the battery.

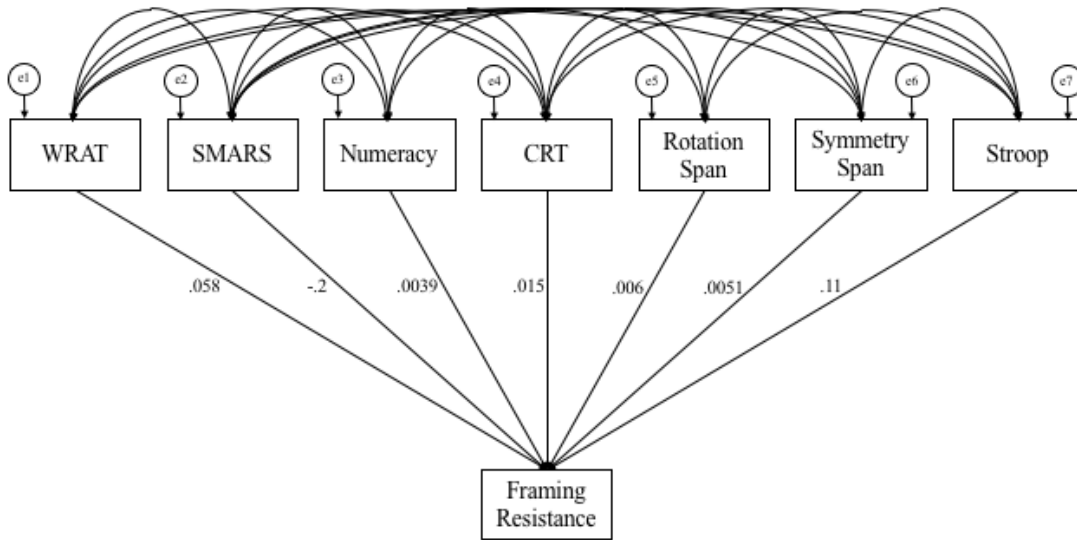


Figure 2. Full Path Model. Values on solid lines represent unstandardized regression coefficients.

While the correlations between predictors and framing resistance were not particularly strong, the large sample size of this study allows the data to be examined in a number of more robust multivariate approaches. As such, a path model was constructed using all variables, accounting for covariance across all predictive measures, to examine the influence of our predictors on overall framing bias (see Figure 2). This full path model accounts for shared covariance across the predictors, and in doing so reduces the coefficients compared to a standard regression approach. The fit indices for this model however are poor, $\chi^2(21) = 270.36, p < .001$, $CFI = .000$, $RMSEA = .261$, and the paths in the model do not reach statistical significance, likely as a result of the weak relationships between the predictors and framing resistance.

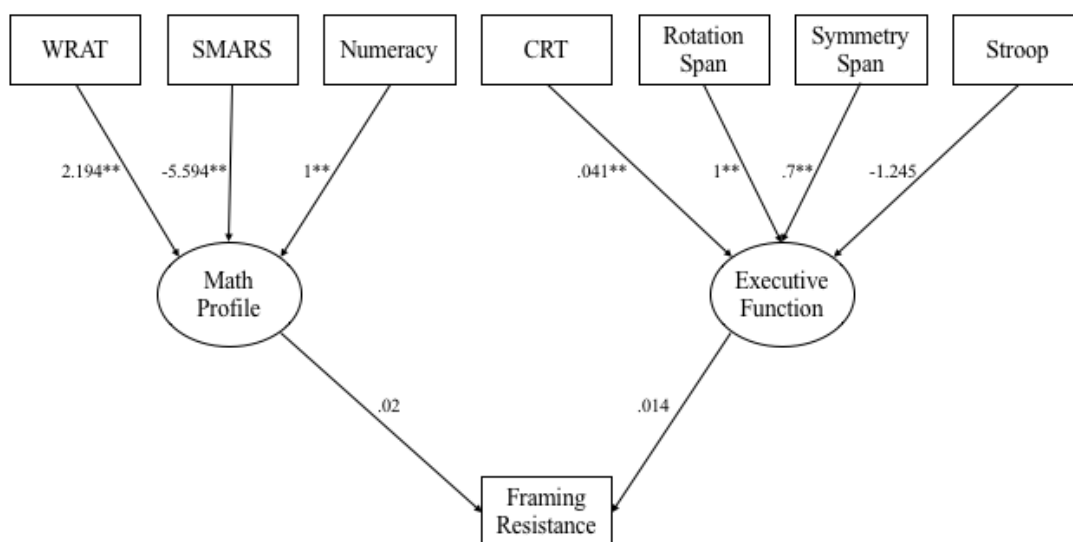


Figure 3. Full SEM Model. Values on solid lines represent unstandardized regression coefficients. ** $p < .01$.

A structural equation model (SEM) with two latent variables, *executive function* - comprised of Stroop, rotation span, symmetry span, and CRT scores - and *math profile* - comprised of numeracy, SMARS, and WRAT (see Figure 3) - converges but yields little insight or explanatory power over and above the basic correlation matrix or path model. Rather, the two latent variables are not statistically significant predictors of framing resistance. However, three of the four variables comprising the executive measures (rotation span, symmetry span, and CRT) each contribute a significant amount of variance to the latent construct *executive function*, indicating Stroop is a poor fit for this construct with the given data. A more appropriate way to bifurcate these may be *executive control* for the span measures and CRT, and a construct akin to *selective attention* for Stroop. All three of the math predictors contribute significantly to the construct, *math profile*. Overall fitness measures for the entire model however are poor $\chi^2(19) = 93.914, p < .001, CFI = .699, RMSEA = .151$, although they are considerably better than the path

model. Again, this is likely due to the poor correlations found between the predictive measures and framing resistance.

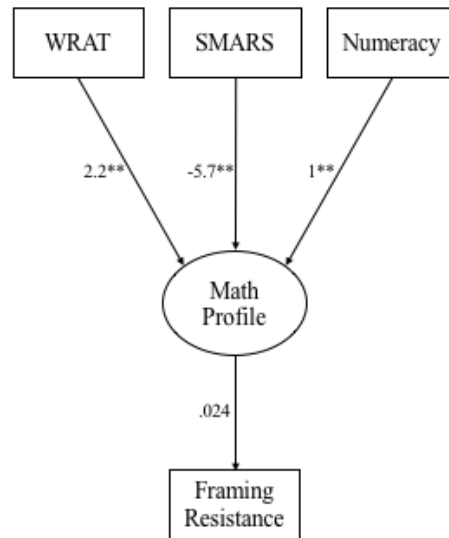


Figure 4. Math Measures SEM model. Values on solid lines represent unstandardized regression coefficients. ** $p < .01$.

Isolating the *math profile* construct and observed math measures (see Figure 4) yields acceptable fit indices, $\chi^2(2) = 1.456, p = .48, CFI = 1.0, RMSEA < .001$, but it does not quite reach statistical significance ($p = .16$). A comparable model comprised of only the *executive function* construct and observed measures again yields improved fit indices, $\chi^2(5) = 11.52, p < .042, CFI = .93, RMSEA = .086$, but again fails to reach significance.

Additional models using framing resistance as a dependent measure can be found in Appendix G but were excluded from the results section due to some redundancy. To explore additional relationships between executive function and math outcomes, additional models were constructed excluding framing resistance from the analysis, instead using math variables as dependent measures. As individual differences methods are typically not employed to examine

factors like math anxiety or math achievement, this dataset provided a unique opportunity to do just that. These models and the additional discussion around them can also be found in Appendix G.

Framing Bias and Demographically Related Caveats to Present Theory

In general, the results of this study fell short of supporting a strong relationship between general executive functioning, mathematical proficiencies, and mathematical anxiety to individual outcomes in framing bias susceptibility. The data however is not in support of an overall null hypothesis due to the fact that the relationships between our predictive measures were small but generally in line with the predictions of the study. Assuming our sample participants were typical and equivalent to the general samples of participants utilized in studies of framing bias, the data would lend itself to the conclusion that an individual's math profile coupled with general executive resources contributes a small but significant portion of variance to framing bias outcomes, but that there still exists a large degree of unaccounted variance in the data to be potentially explained by other individual factors. If this is the case, what are these other factors? The usual suspects come to mind; general problem solving, motivation, personality factors, grit, need for cognition, vigilance, etc. Undoubtedly, these constructs when statistically modelled would contribute some degree of variability to decision making in general, but to argue that general measures of cognitive faculty (e.g., span measures and Stroop) or cognitive impulsivity (e.g., CRT – which tends to predict heuristic usage well; Toplak, et al., 2014) coupled with mathematical aptitudes should not account for the majority of variance in framing bias is dubious.

Conversely, it is likely that the present study suffers from a sampling problem. While the relationships between the battery measures and framing bias was not as robust as originally predicted, the current sample did not replicate the degree of bias typically found in published

studies utilizing the same framing scenarios. With that in mind, there is a case to be made that the biases found within the current sample were largely driven by a subset of the participants who possessed the requisite life experience necessary to elicit the expected biases. And subsequently, the reduced framing bias in the sample resulted in less interpretable relationships between our predictive measures and framing bias overall. Of note within the data is the finding that within participants twenty-two years of age or older ($n = 29$, $M = 28.56$), the basic linear correlations between framing resistance and six of our measures is stronger than the relationship in the full sample (Pearson's r : WRAT = .332, numeracy = .285, CRT = .396, rotation span = .311, symmetry span = .413, Stroop = -.241). However, this small subset comprising 15.2% of the total participants precludes more robust modelling techniques such as SEM. The extant literature on framing biases, while not typically addressing this explicitly in general studies of framing, seems to support this idea that life experience and/or age enhances framing biases. Further, age had a significant positive relationship with total framing trial latency, $r = .211$, $p < .001$, indicating the older the participant, the greater likelihood they spent extra time on the framing trials. Several studies supporting this age-dependent hypothesis are discussed below.

A recent study examined a single factor from our research battery, numeracy, and its relationship to the presentation format, graphical or numerical, of framed scenarios (Kreiner & Gamliel, 2017). Two-hundred and eighty-seven Israeli undergraduates participated in this study and gave responses to four framed scenarios (two positive, two negative) presented in an entirely visual format (i.e., an infographic) or in a format comparable to the present study; textual vignettes with numerical information. Participants additionally completed a thirteen-item numeracy measure similar to the one utilized in the present study. Curiously, a moderate relationship was found between framing bias and general numeracy in the text-based

presentation format ($r = -.42$), indicating as numeracy went up, overall bias as predicted by the scenario's frame decreased. Recall that framing resistance was not significantly related to scores on the numeracy measure and that WRAT performance only yielded a correlation of .176 with framing resistance (Note: framing resistance scores can be inverted to indicate a bias score, and the relationships are trending in the same direction). The disparity in the strength of the relationship in Kreiner and Gamliel's study compared to the present data begs the question, why did participants in our sample not demonstrate the same relationship between framing bias and our mathematical (or executive) measures?

When reviewing Kreiner and Gamliel (2017), three key factors stand out. First, the average age of the sample was 24.2 years of age, four years older than the mean age of our sample. Second, the sample was pulled from a small Israeli college comprised of students whose focus is on research primarily in robotics, cognition, and marine sciences. Similarly, Tversky and Kahneman's (1981) initial framing study was likely comprised of more mature students having been conducted at Stanford. And lastly, the four questions participants completed in the framing task covered topics only on human papilloma virus prevention via condom use along with driving safety. Collectively, these three factors point to the conclusion that the present sample did not demonstrate a comparable framing bias or the relationship between framing and numeracy (and perhaps all other factors) based on demographic and life experience factors within in the sample. Given the average age and research focus of the Israeli college students, it is likely there are some key differences in the life history and present motivations of Kreiner and Gamliel's sample. Particularly, these students likely had more experience with factors involved in risk mitigation and likely had some demographic differences that resulted in their choice to attend a research focused institute – not to mention two years of required military service under

their belts. It is possible that these key differences resulted in an adult sample that possessed a more experienced and hardened behavioral approach resulting in a better distribution of bias responses when presented with framed scenarios.

The results of Ghazal, Cokely, and Garcia-Retamero's (2014) study would further corroborate the hypotheses of the present study, while demonstrating that older, more educated samples tend to exhibit a greater framing bias. After administering the Berlin Numeracy Test and a set of framed financial decision problems to a highly educated sample in Holland ($n = 5408$; 30% of the sample possessing a master's degree or above), the data revealed a relationship between numeracy-measure performance and framed financial-decision performance ($r = .264, p < .001$). The strength of this relationship is comparable to the coefficients found across the predictive measures of the current studies' data; however, it is considerably higher than our non-significant coefficient of .096 for numeracy. An additional point of interest is the finding that Ghazal et al.'s participants exhibited a relationship between time spent on the framing problems and framing bias ($r = .26, p < .001$). Within the present sample, the older participants spent longer amounts of time deliberating on the framing problems, a factor that may have been of interest relating to our predictive measures had the older subset of our data not been too small. The relationships found between latency and decision making along with numeracy and decision making might be indicative that the more numerate participants in Ghazal et al.'s study were more likely to calculate an expected outcome value when presented with a pair of framed prospects.

Also related to our current findings is a study examining age related differences in the framing effect (Kim, Goldstein, Hasher, & Zacks, 2005). Published in the *Journal of Gerontology*, the research aimed to compare differences in framing biases between a college age

sample (aged 17 to 28 years, no mean reported) and older adults (aged 58 to 78). The study used two problems, the classic Asian disease problem (item 3 in our framing measure) and a cancer treatment problem (similar to item 7 in our measure but with different numerical values). Kim et al.'s young respondents did not demonstrate a reliable framing bias on the Asian disease problem, although that question in our measure did elicit a biased response in roughly 71% of our sample, while participants responded with a moderate bias on the cancer problem, comparable to our data. Older adults in the study's sample showed a considerable framing effect for both the Asian disease problem and cancer treatment scenario. Earlier decision-making research offers an explanation for such findings. Previous work demonstrates that past experience with a subject matter (Johnson & Drungle, 2000) and older adults' apparent propensity to deliberate longer and more thoughtfully on information evoking emotional responses through valences in framing (Peters, Hess, & Västfjäll, 2007) may account for increased framing biases. Collectively, studies demonstrating age-related differences in decision making and particularly framing bias show that the general effect as reported in early work by Kahneman and Tversky may not be a standard universal for adults, and that when exploring framing biases, factors such as age and life experience must be taken into account. Others however have argued these findings are a byproduct of limited cognitive resources in adults, resulting in their reliance on a heuristic-based approach to decision making (Hess, Rosenberg, & Waters, 2001). However, this account is a bit simplistic and fails to account for the work demonstrating a reduction in framing biases across educated samples.

Multiple studies exploring framing messaging in health care have demonstrated that the positive or negative valence of frames differentially affects older versus younger populations (Löckenhoff & Carstensen, 2007; Lockwood, Chasteen, & Wong, 2005; Shamaskin, Mikels, &

Reed, 2010). Generally, studies to this end find that older adults typically respond better to health care messaging that is framed positively. For example, an older individual might be more likely to engage in self-directed cancer screenings if a pamphlet advocating for such behavior used language discussing the positive aspects of prevention versus the negative symptoms and outcomes of the pathology. Further, memory of information within a frame tended to be more salient when presented in a positive light within older samples (Shamaskin et al., 2010). While this does not directly address why the negative frames in our sample tended to elicit less bias, it may point to a potential age-related effect of negative frames. It is possible that the younger demographic of our sample simply ignores the negative framing language in most instances due to inexperience, with this negative framing language grounding the possible outcome in reality no greater than a positive frame. That is, older adults tend to actively inhibit the negative language in favor of positive language, while the younger set is merely indifferent. This assertion does need more data; however, the finding that most negative frames in our sample did not elicit bias may be spurious and a byproduct of an underwhelming framing effect in undergraduates in general.

While the goal of the present study was to examine how individual differences across multiple cognitive factors account for general biases in framed decision making, others have offered theoretical accounts in lieu of behavioral evidence. In a review, Levin, Schneider, and Gaeth (1998) discuss the possible mechanisms underlying the framing effect and argue that in general, the framing of a choice in either positive or negative language facilitates the recall of corresponding favorable or negative associations in memory. From these associations and corresponding affective state changes, we succumb to the expected bias in outcome. While this explanation is parsimonious, there is frankly a lack of compelling behavioral evidence for this

claim, particularly considering the underwhelming framing bias encountered in the present study's sample, and the myriad of data from aging research demonstrating the inconsistencies of the framing effect across demographics. Collectively, the research demonstrates framing effects are most robust in older, more experienced populations, despite the more general literature treating framing biases as a general adult cognitive universal.

Kahneman proposed a similar theoretical explanation, the *What You See Is All There Is* (WYSIATI), in his popular 2011 work *Thinking, Fast and Slow*, to account for many biases including framing. This WYSIATI principle is akin to other heuristic theories explaining quick knee-jerk decisions reliant on available or representative pieces of episodic memory, but explicitly refers to the availability of information within the individual's attentional scope. This is not too dissimilar from system 1 (heuristic) v. system 2 (thoughtful and procedural) approaches to decision making (Kahneman, 2003), but again is ultimately an incomplete account of the puzzle of human decision making. Without explicitly asking participants about their decision-making process (a procedure not always employed in decision-making research) or finding that magic neuroimaging technique to explicitly monitor the underlying processes in real-time, the WYSIATI account (and system 1 v. 2 approaches for that matter) is insufficient to explain why we make biased judgments, and also does not explain the subsets of research samples that do not exhibit the framing bias at all. However, these explanations may be a sufficient theoretical account of the behavior which biased decision makers engage in without attempting to explain the underlying cognitive or affective causes. Given the extant literature on the matter (and the present study's data), these theoretical conclusions are generally poor or should be conveyed with an asterisk (e.g., *given sufficient life experience with the framed information, participants will mostly demonstrate a bias in line with the framing language).

Again, however, it is important to reiterate here that neither of the above accounts explain why there is a consistent subset of any framing study sample that does not exhibit a consistent bias.

Framing Bias, Math, and Executive Abilities

Despite the underwhelming results within our sample, the data is consistent with general trends of the extant literature exploring framing biases. While not particularly robust, the results paint a slightly larger, albeit incomplete, portrait of how executive aspects of human cognition, coupled with general mathematical abilities and traits influence individuals' susceptibility or resistance to framing. Particularly, facets of executive ability - selective attention, working memory, and cognitive impulsivity - all demonstrate a relationship with framing resistance. As resources within these domains increase, participants tend to demonstrate a reduction in framing bias. Individuals' math profiles also have a relationship to framing resistance, particularly as math achievement increases and as math anxiety decreases, participants tend to demonstrate a reduction in framing bias. Still there exists a question mark over the causal chain in these findings. Possibly due to the age-related sampling problems of the current data, the modeling approaches failed to disentangle independent amounts of covariance across our measures, and how these independently contribute to framing susceptibility. There is a notable dearth of individual differences research within the current literature employing batteries of predictive measures across executive function and math ability; however, many previously discussed studies have tackled independent contributions of executive attributes or numeracy in isolation.

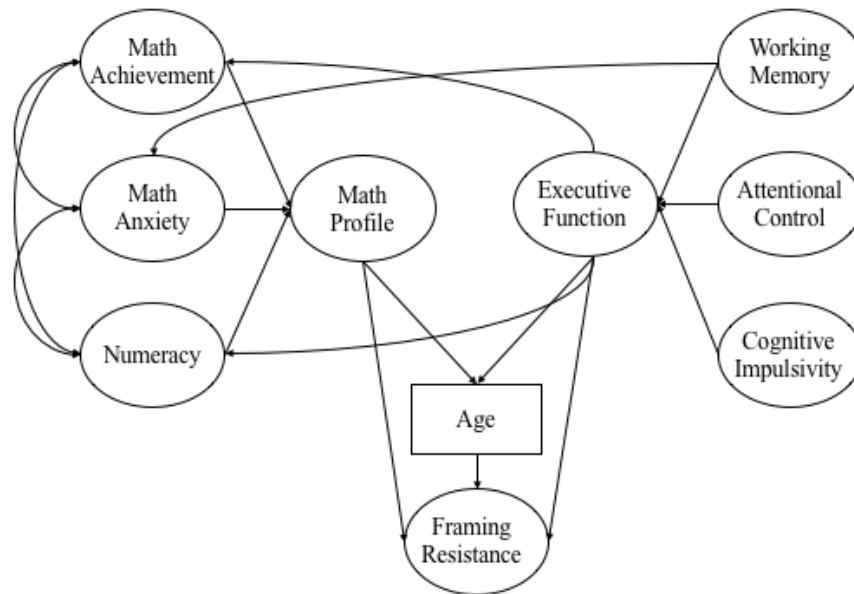


Figure 5. Theoretical model demonstrating the influence of executive constructs on mathematical fluencies and anxiety, and the subsequent influence of this math profile coupled with executive function influencing framing bias mediated through age.

Given the developmental relationships between executive abilities and mathematical achievement, disentangling how these factors relate to framing biases becomes even murkier. As discussed in the introduction, there is a clear influence of general executive abilities on a child's level of math achievement, a relationship that likely persists into adulthood and makes determining the influence of one factor over another on problems requiring numerical processing rather dicey. With this in mind, a proposed theoretical model demonstrating the joint influence of executive ability and math aptitudes upon framing bias can be seen in Figure 5, wherein mathematical proficiencies, particularly procedural understanding of mathematics demonstrated via *math achievement* along with *numeracy* are both influenced by general *executive function*, comprised of *working memory*, *attentional control*, and *cognitive impulsivity*. These mathematical proficiencies in turn are influenced by and conversely affect the individual

development of *math anxiety*, which is also directly influenced by *working memory*.

Collectively, these independent math constructs constitute one's *math profile*, which will govern the general procedural approach to how an individual utilizes mathematical information in the real world. This *math profile*, coupled with the internal calculation engine that is *executive function*, then directly influence the individual's *framing resistance*, mediated through *age*.

Analysis using age as a mediator within the current sample failed to yield any compelling results likely due to the small subset of the sample over the age of twenty-one.

In relation to the above model, the current data adds evidence to the notion that executive function and mathematical performance have a relationship that persists into adulthood, extending the current developmental literature supporting this early relationship. A relationship between WRAT performance and executive measures should be expected in adulthood, as much of the WRAT requires procedural knowledge, and those with a hindered developmental trajectory will likely never learn the appropriate procedures. However, a relationship between executive components and numeracy is novel, as basic probability judgments on the numeracy measure are essentially reapplication of the same procedures across questions and require only strategies typically acquired in elementary school. Regardless, this may just be a byproduct of the pressure of an experimental environment or time constraints of the measure (10 minutes) limiting processing fluency. Further, the working memory measures had a moderate relationship to math anxiety. While evidence demonstrates a relationship between math anxiety and working memory in performance outcomes (for review see Chang & Beilock, 2016), the current data may support the notion that working memory, presumably a fixed trait, has some direct influence on math anxiety outcomes that persist into adulthood.

The Curious Case of “Cognitive Impulsivity”

One of the curious findings in the data, and arguably cognition as a whole, is the strong relationship between the three-item cognitive reflection test (CRT) and the other predictive measures in the task battery. Generally, the CRT elicited moderate relationships with all of the other predictive measures in this study, spanning the gamut across cognitive tasks and math measures, including math anxiety. In the behavioral sciences, the CRT has been linked to heuristic usage and biases (Toplak, West, & Stanovich, 2011), intuition (Pennycook, Cheyne, Koehler, & Fugelsang, 2016), moral judgment (Baron, Scott, Fincher, & Metz, 2015), and even demonstrates performance differences as a function of hormones in both men and women (Bosch-Domènech, Brañas-Garza, & Espín, 2014; Nave, Nadler, Zava, & Camerer, 2017). Particularly relevant to this study, the CRT has been linked to math anxiety, with one study concluding that increased math anxiety reduces reflection and performance on the CRT (Morsanyi, Busdraghi, & Primi, 2014). From a researcher’s perspective, the extant literature on the CRT raises questions about construct validity. Is the CRT tapping into multiple domains, such that it can be used as a general catch-all correlating with performances across a myriad of disciplines?

A recent analysis of the CRT’s construct validity utilized a modelling approach to exploring factors outside of impulsivity or reflection (Campitelli, & Gerrans, 2014). To this end, the researchers administered the CRT in conjunction with a numeracy measure, syllogistic reasoning task, and an actively open-minded thinking (AOT) measure. Rather than relying on the typical assumption that the questions of the CRT relied specifically on impulsivity control and the propensity for cognitive reflection, the researchers added a mathematical parameter to their factor analysis; “probability of using an adequate mathematical procedure.” Ultimately the

findings demonstrated a better model fit when a mathematical procedure component was added to the model design, leading to the conclusion that general numerical fluencies affect performance on the CRT. Pertinent to the data of the present study, this may explain why we find such robust relationships between the CRT and other math related measures, as CRT performance in some part may be a byproduct of mathematical proficiencies, or at the very least indicative of a trait that covaries considerably with mathematical outcomes. Given the relationship between CRT performance and both math performance and anxiety outcomes, there is a compelling case to be made for researchers within the domain of mathematical cognition to include this short measure when examining factors of math achievement or anxiety.

General Discussion and Methodological Considerations

The general findings of this study point in particular directions regarding the methodological approaches that should be employed to explore framing biases across samples. While the current data shed a small amount of light on individual outcomes in framing biases, the inconsistency of bias scores and small relationships between the predictive measures and framing bias failed to paint a large picture of the individual causal contributors to framing bias. From here, specific methodological approaches should be employed to provide a more complete picture of the relationship between executive function, math proficiencies, and framing biases.

Researchers examining bias must consider the demographic makeup of their samples and, at the very least, choose appropriate questions that their sample will have some familiarity with. Particularly, undergraduate samples primarily comprised of freshman are a poor place to start if in need of a sample likely to elicit biases on questions of health or financial matters; the two topics most often included in framing bias studies. Experts or industry specific samples may be

an opportune place to start if in need of sufficient experience to match the task demands. In the present study, the data may have yielded more compelling results had participation been restricted by age group, as evidenced by the small older subset of our data eliciting stronger predictive relationships to framing bias. This would of course drastically increase the data collection time window. Further, to exhaustively model individual differences data with more than two latent variables, increasingly larger sample sizes are required, which also becomes an impediment to data collection timelines.

Additionally, implementing a post-task check that requires participants to report the strategy used to make their decision between framed options should be implemented. Several studies, including this paper, have proposed dual-process theories on decision making and the effect of framing (Evans, 2003; Kahneman, 2003; Sloman, 1996), and yet almost never do we see a post-task check in these studies simply asking participants how they came to a decision. While response latencies and covariance structures of data can give a great deal of inferential ability to the researcher drawing conclusions, in the matter of framing biases, and decision making in general, we are yet to have any conclusive model differentiating who within a sample will rely on one process over another or why particular individuals rely on their chosen process based on observational data.

Simon's (1956) early proposal of satisficing, Tversky and Kahneman's (1992) "editing" and "evaluation" phases of decision making, and Gigerenzer and Goldstein's (1996) modelling efforts all offer elegant explanations of the decision-making process, and yet with half a century of research into the matter we still have not found a unified model based on observation. What has been established however is a body of constructs (e.g., working memory, numeracy, expertise, age) that clearly relate to online decision-making processes. Is the lack of

conclusiveness a byproduct of the methods? A review through the individual differences literature on decision making will yield many studies combining a handful of quick measures generally from a single domain (e.g., numerical skills, reasoning ability, or working memory, but rarely in tandem). At this point it is safe to conclude what measurement choices will yield to effects or publishable relationships, but not unified conclusions. To borrow from Rouder, Morey, Verhagen, Province, and Wagenmakers (2016), in the case of framing biases, there might be “free lunch” in inference.

The goal of the present study was to provide a more thorough framework of how mathematical aptitudes and executive components affect framing biases or decision making as a whole, but due to limitations in our sample demographic the data came up short. With this in mind, an improved version of the current study should look as follows. First, a wider age range, comprised of a thorough adult sample (ages eighteen to seventy) would allow for appropriate analysis of mediation effects of age upon the relationship between executive functions, math aptitudes, and framing biases. Post-task checks should be implemented to examine any direct links between self-reported strategy use and directly observed measures of executive ability and math performance. This would add further empirical support to the notion that with higher executive ability coupled with math aptitudes we are more likely to rely on an effortful, calculated approach and less heuristic based behavior in decision making.

Future Applications

Framing is still a widely studied topic within journals of marketing and advertising research. Advertisers, guided by past efforts of cognitive psychologists, have realized the efficacy in framing their messages to potential consumers, preying on their willingness to engage

in risky behavior in the face of loss. However, not all who apply this research have vulture-like intent. Recent studies have examined how frames can be beneficial to patients in choosing between health care options and mitigating their risks (see Gallagher & Updegraff, 2012 for a meta-analysis). Further studies into the individual causal attributes of framing susceptibility may help identify how we can mitigate these factors, lending to message framing in more socially conscious efforts, resulting in better behavioral outcomes for both health factors, and responsible consumer behaviors alike.

Beyond the obvious academic importance of work exploring the causal factors in framing biases and the typical applied use of framing research for marketers, modern computing and internet auditing tools offer potentially novel approaches for employing user data to predict framing susceptibility. For example, companies like Amazon already aggregate massive amounts of user data to better offer products consumers are likely to purchase based on those they have already bought. This machine learning approach is a standard practice for those working with “big data;” however, modern web technology also allows for the aggregation of usage habits (e.g., time spent on the portion of a website relative to others, and subsequent “impression” data based on user engagement). The inference we can draw from such data is not a far cry from basic processing theories like the *eye mind hypothesis*, which assumes information that people are visually fixated upon is what they are thinking about (Just & Carpenter, 1984). That is, if we spend more time on a portion of a website, measured via latency or perhaps mouse movements, we are likely giving more attention to that information. From this, we might also infer that longer time spent dwelling on pages or paragraphs in general can tell us something specific about processing fluencies of the individual, a crude but possibly effective proxy for general executive abilities. Couple this usage data with the readily available demographic data

collected and shared across services like LinkedIn, Facebook, or Google, and the machine learning approaches employed to algorithmically select products can also be used to strategically frame marketing language to individuals based on the combination of usage habits and demographic information. For example, a cognition professor with an expertise in statistics (as gleaned from their LinkedIn data) combined with an above average click-through speed on their google results might lend itself to a lower predicted framing susceptibility and, consequently; different forms of targeted ads. It is likely such efforts are already underway combining usage data with purchase history and demographic data to more selectively target advertising efforts. The framing language of these adverts is a possible next step in the fine tuning of these ad deployments, as draconian as it sounds.

Conclusions

As one of the few studies to jointly examine the individual contributions of mathematical ability and executive function upon framing biases, the results support a general conclusion that the two subsets of constructs measured - math profile and executive functions - jointly contribute to an individual's resistance to framing. However, the weak strength of the relationships and demographic makeup of our sample points to several methodological considerations in studies of framing bias. Particularly, the age of participants and general life experience with topics including finance and health may exert a large influence on the degree of framing bias exhibited in a study's sample. Due to limitations likely caused by these demographic factors in the present sample, it was impossible to disentangle the individual contributions of mathematical traits and executive function upon individuals' framing resistance. Further studies exploring these relationships should consider sampling from populations outside of university subject pools to

obtain age distributions spanning from early to late adulthood. This approach may elucidate whether ample executive resources coupled with mathematical proficiencies and sufficient life experience lead to a reduction in framing susceptibility. Specifically, collecting a large sample and administering a battery comparable to this study's measures, comprised of a normal distribution of ages ranging from 18 to 70 years of age, and subsequently modeled with appropriate multivariate techniques may be sufficient to demonstrate a two-system approach to decision making (heuristic v. expected value calculation). This is a difficult task within the purview of current behavioral science methods but potentially exhaustive enough to derive more universal conclusions and settle the vast discrepancies among decision making research.

Appendix A

Cognitive Reflection Test

1. A bat and a ball cost \$1.10 in total. The bat costs \$1.00 more than the ball. How much does the ball cost?
2. If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?
3. In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?

Appendix B

Arithmetic portion of the Wide Range Achievement Test 3 (WRAT)

WRAT 3 ARITHMETIC/A MEASURE OF NUMBER COMPUTATIONS

S. Code # _____

REDUCE ALL ANSWERS TO LOWEST TERMS				
1	2	3	4	5
$1 + 1 = \underline{\quad}$	$\begin{array}{r} 5 \\ - 1 \\ \hline \end{array}$	$2 + 7 = \underline{\quad}$	$8 - 4 = \underline{\quad}$	$\begin{array}{r} 32 \\ 24 \\ +40 \\ \hline \end{array}$
6	7	8	9	10
$\begin{array}{r} 9 \\ + 3 \\ \hline \end{array}$	$\begin{array}{r} 36 \\ - 15 \\ \hline \end{array}$	$3 \times 4 = \underline{\quad}$	$\begin{array}{r} 68 \\ +23 \\ \hline \end{array}$	$\begin{array}{r} 7 \\ \times 6 \\ \hline \end{array}$
11	12	13	14	15
$\begin{array}{r} 23 \\ \times 3 \\ \hline \end{array}$	$\begin{array}{r} 33 \\ - 17 \\ \hline \end{array}$	$6 \div 2 = \underline{\quad}$	$4 \overline{)16}$	$\begin{array}{r} 17 \\ \times 4 \\ \hline \end{array}$
16	17	18	19	20
$\begin{array}{r} 724 \\ -597 \\ \hline \end{array}$	$\begin{array}{r} 229 \\ 5048 \\ 63 \\ +1381 \\ \hline \end{array}$	$\frac{15}{5} = \underline{\quad}$	$9 \overline{)4527}$	$\frac{1}{3} + \frac{1}{3} = \underline{\quad}$
21	22	23	24	25
$2\frac{1}{2} + 1\frac{1}{2} = \underline{\quad}$	$\begin{array}{r} 823 \\ \times 96 \\ \hline \end{array}$	$.42 = \underline{\quad} \%$	$\frac{1}{4} \times \frac{1}{2} = \underline{\quad}$	$\begin{array}{r} 38 \\ \times 2.4 \\ \hline \end{array}$

WRAT 3 ARITHMETIC/A MEASURE OF NUMBER COMPUTATIONS

$$\frac{3}{10} + \frac{3}{4} =$$

Ans: _____

$$6\frac{1}{4}$$

$$1\frac{5}{8}$$

$$+ 4\frac{1}{2}$$

$$\frac{2}{5} \text{ of } 35 = \underline{\hspace{2cm}}$$

$$27 \overline{)384}$$

$$\begin{array}{r} 6.23 \\ \times 12.7 \\ \hline \end{array}$$

26

27

28

29

30

$$2 - \underline{\hspace{2cm}} = \frac{1}{4}$$

$$10\frac{1}{4}$$

$$-7\frac{2}{3}$$

Add:

$$\begin{array}{r} -X - Y - 23 \\ X - Y + 22 \\ \hline \end{array}$$

$$15\% \text{ of } 175 =$$

Ans: _____

Write as common fraction in lowest terms:

$$.075 = \underline{\hspace{2cm}}$$

31

32

33

34

35

$$\frac{r^2 - 5r - 6}{r + 1}$$

Ans: _____

$$3p - q = 10$$

$$2p - q = 7$$

$$p = \underline{\hspace{2cm}} \quad q = \underline{\hspace{2cm}}$$

Reduce:

$$\frac{K^2 + K}{K^2} \cdot \frac{3K - 3}{K^2 - 1}$$

Ans: _____

$$f(x) = 3x^2 + x - 7$$

Find $f(-2)$

Ans: _____

36

37

38

39

40

S. Code # _____

Appendix C

Numeracy Scale

1. Imagine that we roll a fair, six-sided die 1,000 times. Out of 1,000 rolls, how many times do you think the die would come up even (2, 4, or 6)?
2. In the BIG BUCKS LOTTERY, the chances of winning a \$10.00 prize are 1%. What is your best guess about how many people would win a \$10.00 prize if 1,000 people each buy a single ticket from BIG BUCKS?
3. In the ACME PUBLISHING SWEEPSTAKES, the chance of winning a car is 1 in 1,000. What percent of tickets of ACME PUBLISHING SWEEPSTAKES win a car?
4. Which of the following numbers represents the biggest risk of getting a disease? 1 in 100, 1 in 1000, 1 in 10
5. Which of the following represents the biggest risk of getting a disease? 1%, 10%, 5%
6. If Person A's risk of getting a disease is 1% in ten years, and Person B's risk is double that of A's, what is B's risk?
7. If Person A's chance of getting a disease is 1 in 100 in ten years, and Person B's risk is double that of A, what is B's risk?
- 8A. If the chance of getting a disease is 10%, how many people would be expected to get the disease out of 100?
- 8B. If the chance of getting a disease is 10%, how many people would be expected to get the disease out of 1000?
9. If the chance of getting a disease is 20 out of 100, this would be the same as having a ____% chance of getting the disease.
10. The chance of getting a viral infection is .0005. Out of 10,000 people, about how many of them are expected to get infected?

Appendix D

Short Math Anxiety Rating Scale (SMARS)

Please rate each item in terms of how anxious you would feel during the event specified. Use the following scale and record your answer in the space to the left of the item:

Scale:

1 = Low Anxiety

2 = Some Anxiety

3 = Moderate Anxiety

4 = Quite a bit of Anxiety

5 = High Anxiety

- 1. Receiving a math textbook.
- 2. Watching a teacher work an algebra problem on the blackboard.
- 3. Signing up for a math course.
- 4. Listening to another student explain a math formula.
- 5. Walking to math class.
- 6. Studying for a math test.
- 7. Taking the math section of a standardized test, like an achievement test.
- 8. Reading a cash register receipt after you buy something.
- 9. Taking an examination (quiz) in a math course.
- 10. Being given an additional set of problems to solve on paper
- 11. Being given a set of addition problems to solve on paper.
- 12. Being given a set of subtraction problems to solve on paper.
- 13. Being given a set of multiplication problems to solve on paper.
- 14. Being given a set of division problems to solve on paper.
- 15. Picking up your math textbook to begin working on a homework assignment.
- 16. Being given a homework assignment of many difficult math problems, which is due the next time the class meets.
- 17. Thinking about an upcoming math test one week before.
- 18. Thinking about an upcoming math test one day before.
- 19. Thinking about an upcoming math test one hour before.

- __20. Realizing that you have to take a certain number of math classes to meet the requirements for graduation.
- __21. Picking up a math textbook to begin a difficult reading assignment.
- __22. Receiving your final math grade on your report card.
- __23. Opening a math or statistics book and seeing a page full of problems.
- __24. Getting ready to study for a math test.
- __25. Being given a "pop" quiz in a math class.

Appendix E

Framed Risky Decision Problems

Problem 1 (positive frame)

Imagine a hospital is treating 32 injured soldiers, who are all expected to lose one leg. There are two doctors that can help the soldiers, but only one can be hired:

If Doctor A is hired, 20 soldiers will keep both legs.

If Doctor B is hired, there is a 63% chance that all soldiers keep both legs and a 37% chance that nobody will save both legs.

Which doctor do you recommend?

1	2	3	4	5	6	
Definitely would choose A				Definitely would choose B		

Problem 2 (positive frame)

Because of changes in tax laws, you may get back as much as \$1200 in income tax. Your accountant has been exploring alternative ways to take advantage of this situation. He has developed two plans:

If Plan A is adopted, you will get back \$400 of the possible \$1200.

If Plan B is adopted, you have a 33% chance of getting back all \$1200, and a 67% chance of getting back no money.

Which plan would you use?

1	2	3	4	5	6	
Definitely would choose A				Definitely would choose B		

Problem 3 (positive frame)

Imagine that the US is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimate of the consequences of the programs are as follows:

If Program A is adopted, 200 people will be saved.

If Program B is adopted there is a 1/3 probability that 600 people will be saved, and a 2/3 probability that no people will be saved.

Which program would you use?

improve; you must sell now. You contacted a real estate broker who has suggested two possible options:

Plan A: Sell your house not for the current best offer and lose \$24,000 of the appreciation

Plan B: Sell your house at an auction. There is a 1/3 chance you will lose none of the \$36,000 appreciation. However, there is a 2/3 chance that you will lose all of the appreciation.

Which plan would you select?

1	2	3	4	5	6
Definitely would choose A				Definitely would choose B	

Problem 7 (positive frame)

Imagine that your doctor tells you that you have a cancer that must be treated. Your choices are as follows:

A: Surgery: Of 100 people having surgery, 90 live through the operation, and 34 are alive at the end of five years.

B: Radiation therapy: Of 100 people having radiation therapy, all live through the treatment, and 22 are alive at the end of five years.

Which treatment would you choose?

1	2	3	4	5	6
Definitely would choose A				Definitely would choose B	

Problem 8 (positive frame)

Imagine that your client has \$6,000 invested in the stock market. A downturn in the economy is occurring. You have two investment strategies that you can recommend under the existing circumstances to preserve your client's capital.

If strategy A is followed, \$2,000 of your client's investment will be saved.

If strategy B is followed, there is a 33% chance that the entire \$6,000 will be saved, and a 67% chance that none of the principal will be saved.

Which of these two strategies would you favor?

1	2	3	4	5	6
Definitely would choose A				Definitely would choose B	

Problem 9 (negative frame)

The United States is expecting the outbreak of a new strain of AIDS which is expected to kill 2000 persons. Two alternative programs were developed to combat the disease. Assume that the exact scientific estimates of the consequences of the programs are as follows:

Program A: 1200 people will die.

Program B: 2/5 probability that nobody will die, and 3/5 probability that 2000 people will die.

Which of the two programs do you choose?

1	2	3	4	5	6
Definitely would choose A				Definitely would choose B	

Problem 10 (negative frame)

Imagine that recent evidence has shown that a pesticide is threatening the lives of 1,200 endangered animals. Two response options have been suggested. Review them and decide which option you would use.

If Option A is used, 600 animals will be lost for sure.

If Option B is used, there is a 75% chance that 400 animals will be lost and a 25% chance that 1,200 animals will be lost.

Which of the two options do you favor?

1	2	3	4	5	6
Definitely would choose A				Definitely would choose B	

Problem 11 (positive frame)

A large manufacturer has recently been hit with a number of economic difficulties and it appears as if 6000 employees (some salaried and some hourly) will be laid off. The company would prefer not to make these layoffs but also must maintain a solid financial position. The vice president of production has been exploring alternative ways to avoid this crisis and has developed two plans.

Plan A: This plan will save 2000 jobs

Plan B: This plan has a 1/3 probability of saving all 6000 jobs, but has a 2/3 probability of saving no jobs.

Which plan would you select?

1	2	3	4	5	6
Definitely would choose A				Definitely would choose B	

Problem 12 (positive frame)

Imagine that your community is preparing for an unusual food shortage, which is expected to kill 60 people through starvation. Two alternative programs to combat the food shortage have been proposed. Assume that the exact scientific estimates of the consequences of the programs are as follows:

Program A: 20 people will be saved from starvation

Program B: 1/3 probability that everyone will be saved from starvation. 2/3 probability that nobody will be saved from starvation.

Which program would you select?

1	2	3	4	5	6
Definitely would choose A				Definitely would choose B	

Problem 13 (negative frame)

Imagine that in one particular state it is projected that 1000 students will drop out of school during the next year. Two programs have been proposed to address this problem but only one can be implemented. Based on other states' experiences with the programs, estimates of the outcomes that can be expected from each program can be made. Assume for purposes of this decision that these estimates of the outcomes are accurate and are as follows...

If Program A is adopted, 600 of the 1000 students will drop out of school.

If Program B is adopted there is a 2/5 chance that none of the 1000 students will drop out of school and 3/5 chance that all 1000 will drop out of school.

Which program would you favor for implementation?

1	2	3	4	5	6
Definitely would choose A				Definitely would choose B	

Problem 14 (negative frame)

The National Cancer Institute has two possible treatments for leukemia which could become standard treatments across the country. There are adequate resources to implement only one treatment program.

Treatment A: Of every 10,000 people who get leukemia, 5,000 will die.

Treatment B: 1/2 chance that no people of every 10,000 who get leukemia will be die, and 1/2 chance that 10,000 of every 10,000 who get leukemia will die.

Which of the two treatments would you favor?

1
Definitely would
choose A

2

3

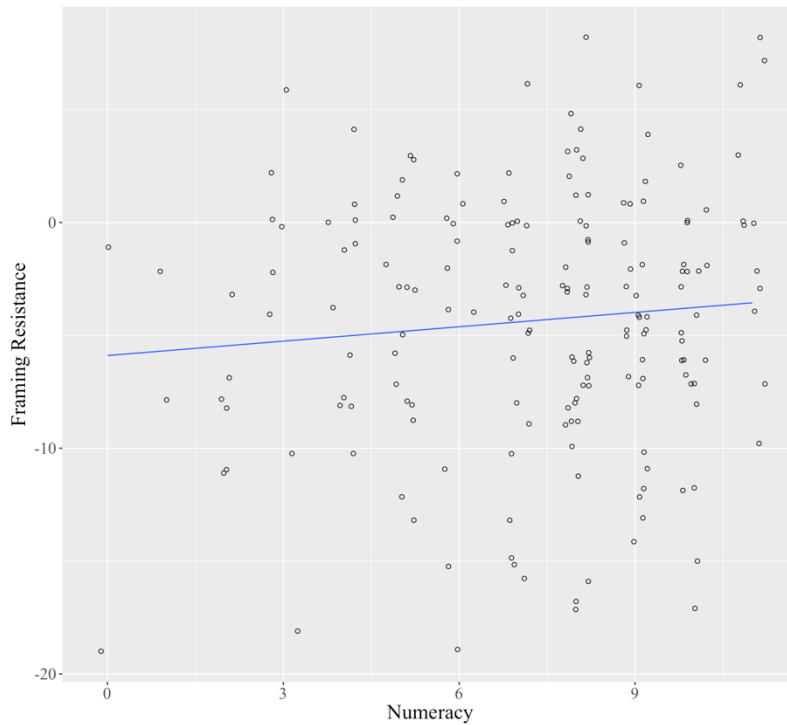
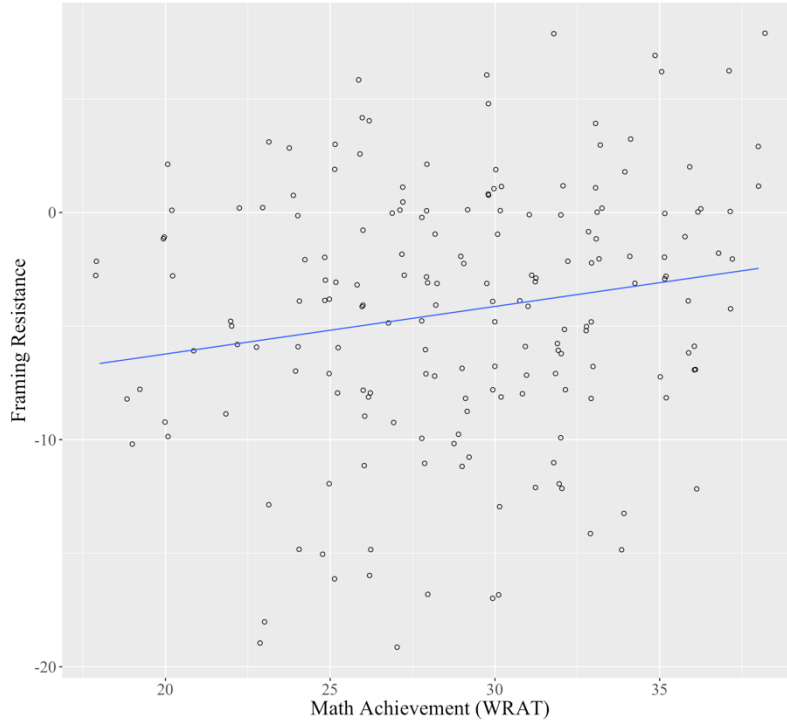
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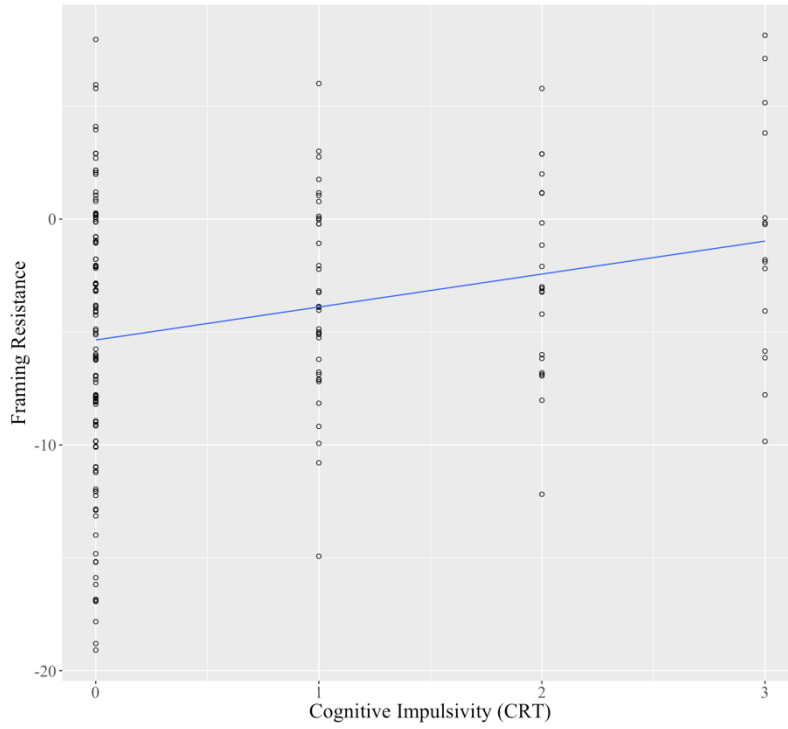
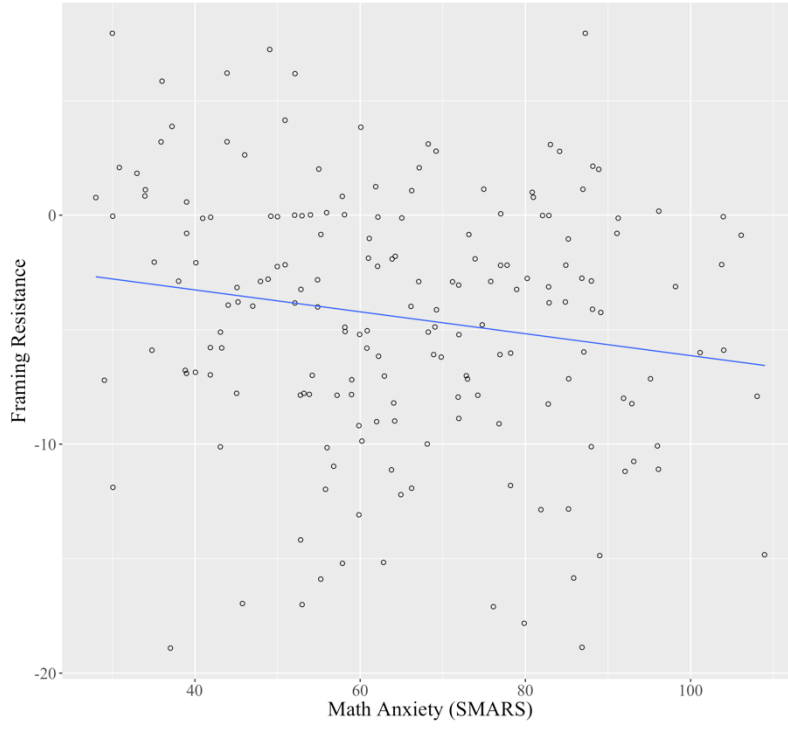
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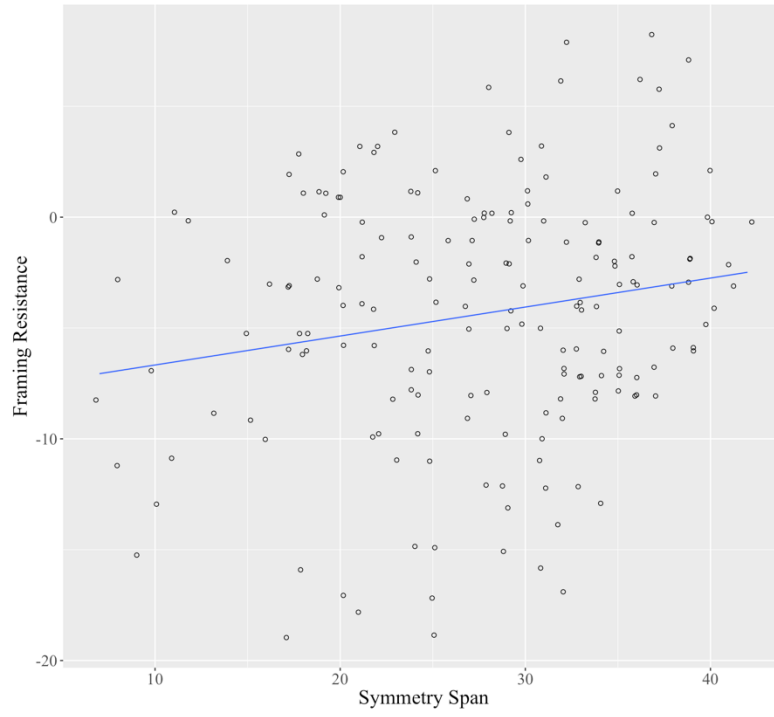
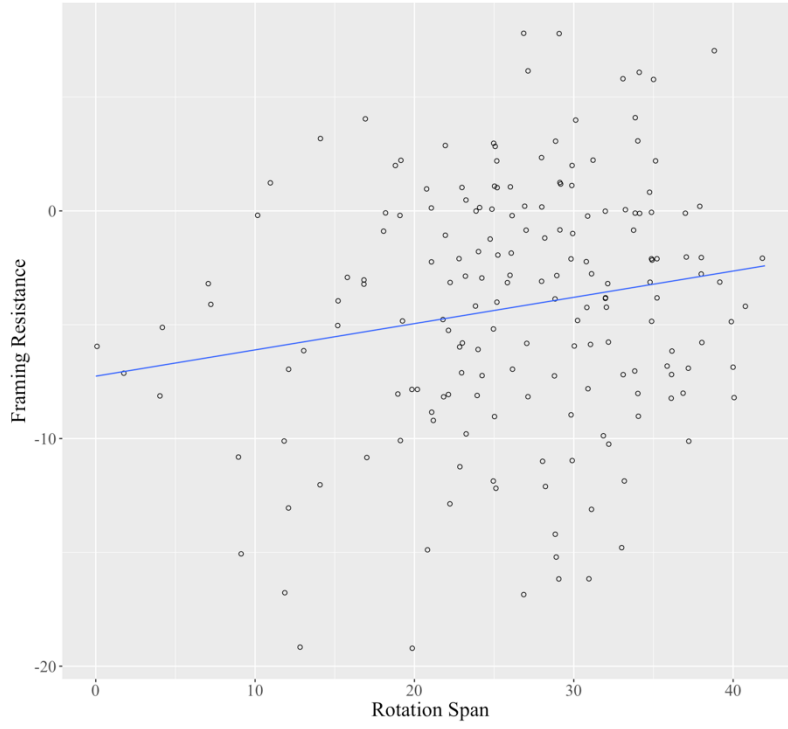
6
Definitely would
choose B

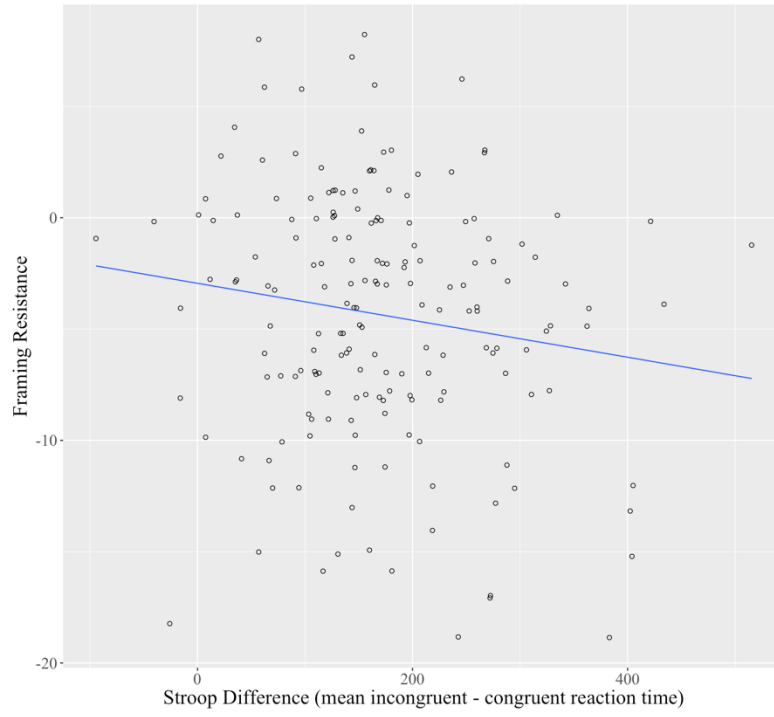
Appendix F

Scatter Plots of Predictive Measures and Framing Resistance
(jitter applied to visually offset equivalent scores across participants using ggplot2 in R; Wickham, 2009)









Note: smaller Stroop values indicate slower Stroop performance

Appendix G

Additional Models and Discussion

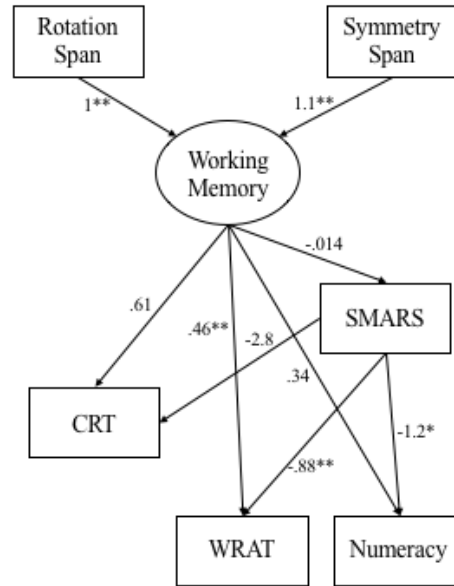


Figure 6. Additional Model 1. Values on solid lines represent unstandardized regression coefficients. * $p < .05$, ** $p < .01$.

The model seen in Figure 6 demonstrates a significant relationship between our observed span tasks and the latent variable *working memory*. Working memory in turn significantly predicts math achievement (*WRAT*). However, working memory does not significantly predict a participant's math anxiety (*SMARS*), nor does it have any direct influence on *numeracy* measure performance. That is, within the model, working memory is showing no relationship to *SMARS* scores. This does not discount the possible developmental relationships between math anxiety and working memory, nor the real time contributions of both to online math performance measured with the *WRAT*. *SMARS* scores did significantly predict both math achievement and *Numeracy* scores. *SMARS* did not significantly predict *CRT* performance as we might infer from Morsanyi, Busdraghi, and Primi (2014), however the relationship was in the predicted direction

(i.e., math anxiety reduces CRT performance) and almost breached significance ($p = .064$). Fit indices for this model however are poor, $\chi^2(14) = 81.734, p < .001, CFI = .563, RMSEA = .167$. A more appropriate model for the data is below.

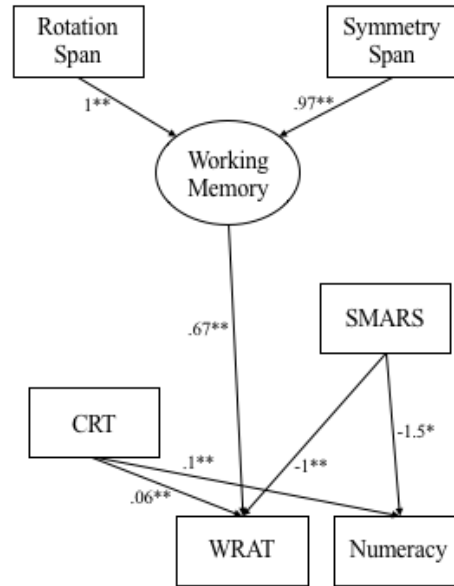


Figure 7. Additional Model 2. Values on solid lines represent unstandardized regression coefficients. ** $p < .01$.

Figure 7 demonstrates a model with good fit to the data, $\chi^2(7) = 11.495, p = .118, CFI = .977, RMSEA = .06$. Here, *working memory*, math anxiety (*SMARS*), and *CRT* all significantly influence *WRAT* performance, and math anxiety and *CRT* both significantly influence *numeracy* performance. While this fits the data well, it raises some theoretical questions about why the *CRT* predicts *WRAT* and *numeracy* measure outcomes. If we take this at face value, it would indicate that cognitive reflection or impulsivity influences math abilities. However, it might be that the relationship between these measures is more explained by a construct like “need for cognition,” which at least one study has linked to *CRT* performance (Frederick, 2005).

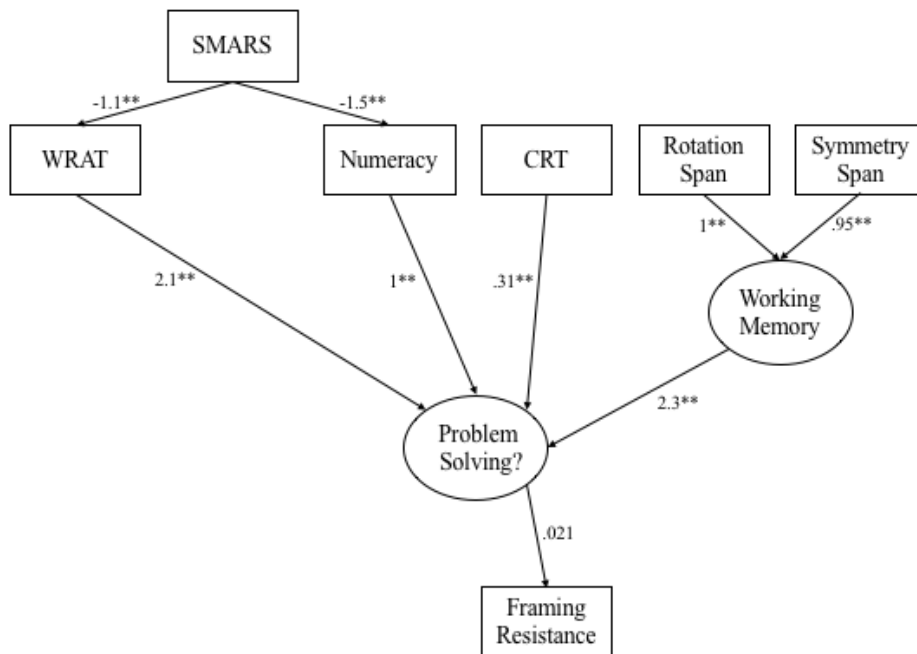


Figure 8. Additional Model 3. Values on solid lines represent unstandardized regression coefficients. * $p < .05$, ** $p < .01$.

Of the models constructed to explain framing resistance, Figure 8 results in the best fit indices, $\chi^2(18) = 12.647, p = .812, CFI = 1.0, RMSEA < .001$, however the model still fails to yield a significant relationship with *framing resistance* ($p = .233$). Here, a latent variable *problem solving?* (potentially, general problem solving ability) influenced by *WRAT*, *numeracy*, *CRT*, and *working memory*. While this model produces the best fit, there is some uncertainty of what this *problem solving?* construct is, but it serves here as a simple way to pool the variance across our measures to produce better model fit. Fit aside, because there is no clear theoretical reason to pool *WRAT*, *numeracy*, and *CRT* performance into a single latent variable, this was excluded from the discussion portion of this report.

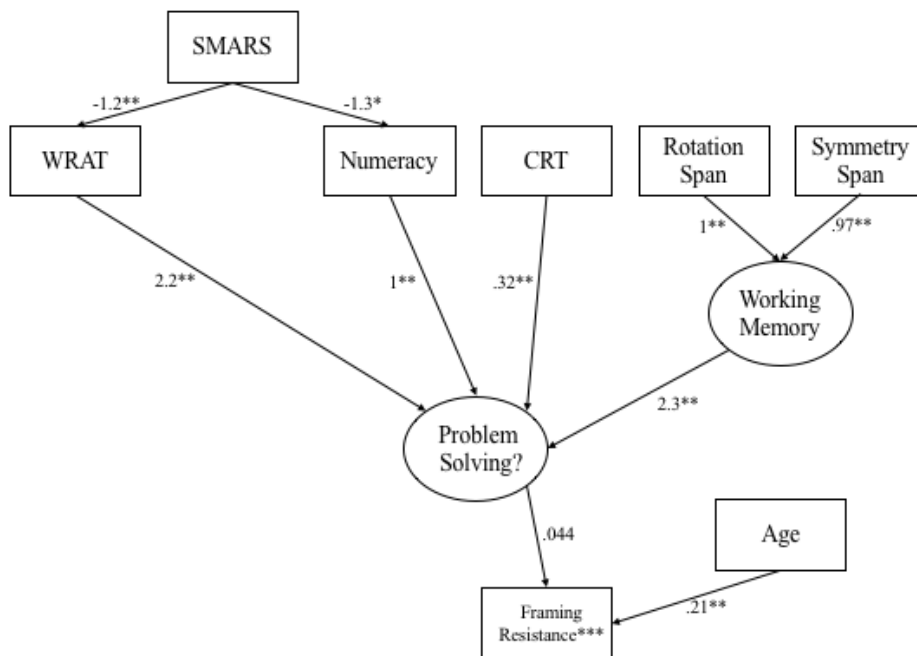


Figure 9. Additional Model 4. Values on solid lines represent unstandardized regression coefficients. * $p < .05$, ** $p < .01$.

Lastly, Figure 9 demonstrates a model including *age* as a significant predictor of *framing resistance*, but only when excluding items 1, 5, 6, 13, and 14 from the framing bias score.

Recall, these were the five items on the measure which did not yield overall biased responding in the sample. *Age* was not a significant predictor in any models constructed utilizing all scenarios within the framing measure. Here, the construct *problem solving?* again does not significantly relate to *framing resistance*. Fit indices for this model are acceptable but not as good as the model in Figure 8, $\chi^2(18) = 27.4, p = .072, CFI = 0.964, RMSEA = .055$.

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White, L. K., McDermott, J. M., Degnan, K. A., Henderson, H. A., & Fox, N. A. (2011).

Behavioral inhibition and anxiety: The moderating roles of inhibitory control and attention shifting. *Journal of Abnormal Child Psychology*, 39(5), 735-747.

Wickham, H. (2009). *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York.

Curriculum Vitae

Gabriel Allred
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Education

Graduate: University of Nevada, Las Vegas

Doctoral

Major: Experimental Psychology (cognitive emphasis)

Advisor: Mark Ashcraft, Ph.D.

Dissertation: *Examining the Influence of Executive Resources and Mathematical Abilities on Framing Biases*

Master's

Major: Experimental Psychology (cognitive emphasis)

Advisor: Mark Ashcraft, Ph.D.

Master's Thesis: *Hands, and Numbers, and Dots, Oh My! Examining the Effect of Nearby-hands on Counting and Subitizing.*

Undergraduate: University of Nevada, Las Vegas

Fall 2011

Degree: Bachelor of Arts

Major: Psychology

Spring 2007

Degree: Bachelor of Arts

Major: Anthropology

Publications

Moore, A., **Allred, G. A.**, An, W., Ashcraft, M. H. (2017). The cognitive-affective profile of local task avoidance in mathematical problem solving: a study in task-evoked pupillary response. (in revision)

Moore, A. M., McAuley, A. J., **Allred, G. A.**, & Ashcraft, M. H. (2014). Mathematics anxiety, working memory, and mathematical performance. In *The Routledge International Handbook of Dyscalculia and Mathematical Learning Difficulties* (pp. 326-336). London: Routledge.

Presentations

Allred, G.A., Larson, K.G., Arestides, A.A., & Warren, R. (2016, August) *Relationship Between Implicit Learning and Cognitive Disposition*. Poster presented at the Air Force Research Labs Summer Research Summit, Wright Patterson Air Force Base, Dayton, OH.

Allred, G.A. (2016, August) *Assessing Cognitive Dispositions of Intelligence Analysts: Proposed model and introductory studies*. Talk presented at the Air Force Research Labs Summer Research Summit, Wright Patterson Air Force Base, Dayton, OH.

Moore, A. M., Allred, G. A., An W., & Ashcraft M. H. (2015, November) *Pupillary Response and Mental Multiplication*. Poster presented at the annual meeting of the Psychonomic Society, Chicago, IL.

Allred, G. A., An W., & Ashcraft M. H. (2015, May) *Math avoidance in the eyes? Pupillary Response Differences in Multiplication*. Poster presented at the meeting of the Western Psychological Association, Las Vegas, NV.

Allred, G. A. (2014, March). *N-Back, Numerical Distance, and Nearby Hands*. Talk presented at the University of Nevada Las Vegas Professional Seminar

Allred, G. A. (2013, May). *Numerical Distance Effects in N-Back and the Influence of Math Anxiety*. Talk presented at the University of Nevada Las Vegas Professional Seminar

Moore, A. M., Allred G. A., Ashcraft M. H. (2011, November). *Calibrating Adults' Estimates in Dot Enumeration*. Poster presented at the meetings of Psi Chi, National Honor Society in Psychology (UNLV chapter) conference, Las Vegas, NV. 3rd place award.

Moore, A. M. & Ashcraft, M. H., Allred, G. A. (2011, May). *Influence of Endpoint Knowledge in Dot Enumeration*. Poster presented at the annual meeting of the Association of Psychological Science, Washington, D.C.

Allred, G. A. (2006, April). *Community and Spirituality in Rave Culture: A Look into the Psychology of a Youth Movement*. Talk presented at the meetings of the Society for the Anthropology of Consciousness, Pacific Grove, CA.

Awards & Grants

Graduate Summer Stipend	Summer 2017
Repperger Fellowship (Air Force Research Labs 711 th Human Performance Wing)	Summer 2016
Association for Psychological Science Student Caucus (APSSC) Grant Project Title: <i>Holding onto Memories: Using Tablet Computers to Improve Age-Related Memory Deficits</i>	Fall 2016
University of Nevada Las Vegas Access Grant	Spring 2012

Psi Chi, National Honor Society in Psychology, Poster Competition,
University of Nevada Las Vegas(3rd place)

Spring 2011

Additional Research Experience

Repperger Fellowship

Summer 2016

Air Force Research Lab 711th Human Performance Wing

Duties: Conducted applied research for the Human Performance Wing of the Air Force Research Labs at Wright Patterson Air Force Base in Dayton, OH. Included multiple studies applied to intelligence analyst performance and workflows

Research Assistant

Summer 2015

The Nevada Institute for Children's Research and Policy (NICRP)

Duties: Writing and preparation of statewide reports on childhood health factors that influenced public policy and legislation protecting children. Analysis and screening of large sets of survey data ($N > 10,000$), also survey design.

Program Director

Summer 2014

Sport Social, Las Vegas, NV

Duties: Managing the daily operations and activities of a social skills development program designed for children with autism. Tracked behavioral metrics and milestones for reporting to state funding agencies.

Research Assistant and Lab Manager

Fall 2010 – Spring 2011

Mathematical Cognition Lab

University of Nevada, Las Vegas, Psychology Department

Principle Investigator: Mark Ashcraft Ph. D.

Duties: Learned the use of experimental protocol to examine the nature of cognitive enumeration and math anxiety. Was involved in all aspects of experimental design, IRB application, data collecting, entry, and interpretation. Gained extensive knowledge in the use of *E-Prime* for experimental design, and *SPSS* and *Excel* programs for data analysis.

Teaching Experience

University of Nevada, Las Vegas

Fall 2017

Instructor, Research Methods in Psychology (PSY 240)

Introduction to research methods, including experimental design, data collection, ethics, and evaluation scientific research.

University of Nevada, Las Vegas

Spring 2016 - Fall 2016

Instructor, Cognitive Psychology (PSY 316)

Covers the major areas of cognitive psychology including attention, pattern recognition, memory, language, and problem solving.

University of Nevada, Las Vegas

Fall 2014 – Spring 2017

Instructor, Introduction to Psychology (PSY 101)

Introduction to psychology, including sensation-perception, cognition, physiological psychology, learning, personality, development, social psychology, assessment, and history.

University of Nevada, Las Vegas

Fall 2014 – Spring 2014

Teaching Assistant, Introduction to the Psychology Major (PSY 200)

Service

University of Nevada, Las Vegas

Fall 2015-Spring 2016

4th year cohort representative of The Experimental Psychology Student Committee

University of Nevada, Las Vegas

Fall 2014-Spring 2015

Vice President of The Experimental Psychology Student Committee

University of Nevada, Las Vegas

Fall 2012 – Spring 2013

1st year cohort representative of The Experimental Psychology Student Committee

Professional Affiliations, Certifications and Honor Societies

Responsible Conduct of Research Certified via CITI

Society for the Teaching of Psychology

Association for Psychological Science

Psi Chi, National Honor Society in Psychology