# EVIDENCE FOR A FREQUENCY HEURISTIC IN EXPERIENCE-BASED DECISION-MAKING

A Dissertation

by

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ABSTRACT

Most decision models focus on the role of expected value. However, gain-loss frequency, that is how often gains versus losses are experienced, is another important aspect of choice behavior. In decision from experience paradigms, people make choices and receive a series of gains and/or losses as feedback, and hence gain-loss frequency is salient in this decision context. Also, much research indicates that people are highly sensitive to frequency information. Thus, people might rely on gain-loss frequency to make decisions. This work examined whether and how people use frequency information in experience-based decision-making and further investigated some important psychological and developmental aspects of using frequency information. In Study 1, a *frequency heuristic* where people track the frequency of gains and losses and choose the option with frequent gains and rare losses was formalized, and an Expectancy-Frequency-Perseveration (EFP) model which accounts for this frequency heuristic was developed. In different decision-making paradigms and on various model performance criteria, EFP models consistently performed well and often outperformed other models without the frequency value component in terms of fitting human choice behavior, suggesting a crucial role of frequency information and the pervasiveness of the frequency heuristic in experience-based decision-making. Study 2 investigated the role of working memory (WM) in the use of the frequency heuristic. This study manipulated WM load and employed a decision-making task where the frequency heuristic is counterproductive. Behavioral results showed that participants with intact WM resources were biased towards options with frequent gains and rare losses (but with lower expected

values), compared to those under WM load, indicating that WM load reduces reliance on gain-loss frequency. Consistent with the behavioral results, computational modeling results suggest that WM load diminishes attention to the frequency information. Thus, Study 2 provides evidence that WM contributes to the use of the frequency heuristic. Study 3 replicated these main results from Study 2. Furthermore, Study 3 reveals that at least one role of WM is to contribute towards making accurate gain-loss frequency judgments, which in turn could form a basis for applying this heuristic. Study 4 revealed a life-span trajectory of the use of the frequency heuristic, that is, people tend to utilize the frequency heuristic more with advancing age. Hence, it appears that the WM demand for using the frequency heuristic is not so strong that normal (healthy) age-related cognitive decline would constrain the use of it. These seemingly contradictory findings suggest a moderate WM demand for applying this heuristic. The “irregular” position of the frequency heuristic on the map of the dual-process models and its implications are discussed.

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# NOMENCLATURE

| | |
|---|---|
| EFP | Expectancy-Frequency-Perseveration |
| VPP | Value-Plus-Perseveration |
| PVL | Prospect Valence Learning |
| RL | Reinforcement Learning |

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# 1. INTRODUCTION

Decision-making is a critical part of everyday life, from minor decisions such as whether to pick a new restaurant for dinner or eat at one you frequently visit to major ones such as choosing the right college. Most decision theories hold that decisions are made based on each option's expected value, the payoff value that an option is expected to yield. Besides expected value, another important aspect of an option is the frequency of gains and losses that it yields or the frequency of positive versus negative experiences that it brings. Frequency information might also be important in decision-making. The present work was intended to investigate the role of frequency information in decision-making.

## 1.1 Dominating Role of Expected Value in Decision-Making Theories

In decision-making research, researchers ask participants to work on various decision-making tasks to investigate how people make decisions. These decision-making tasks are based on two major paradigms. One is *decisions from description* where participants are explicitly given possible outcomes of each alternative and corresponding probabilities. For example, consider the choice between a gamble with a 75% chance to win $1000 (with a 25% chance to win nothing) and the option of obtaining $700 for sure. Choice behavior in decisions from description is often modeled by prospect theory (Kahneman & Tversky, 1979) which assumes that decision makers form and compare expected utilities for alternatives and choose the one with the highest expected utility. In

the example described above, prospect theory assumes that a decision maker compares expected subjective utilities, $\pi(1000)\times\omega(0.75)\ vs.\ \pi(700)$[1].

Recently, another paradigm, *decisions from experience*, has attracted continuously growing attention (e.g., Hertwig, 2012; Hertwig, Barron, Weber, & Erev, 2004; Hills & Hertwig, 2010). By contrast to description-based decision-making, in this context, participants have no access to outcome distribution information (i.e., potential outcomes and probabilities to obtain them) at the beginning of the task, but have to learn it by making repeated choices and gaining feedback or experience. Despite some marked differences in choice behavior between description-based and experience-based decision-making (see Hertwig & Erev, 2009, for a review), many theories on decisions from experience assume that people track expected values through certain learning mechanisms such as reinforcement learning (Sutton & Barto, 1998) across trials, and choose the option that produces the highest expected value. Therefore, existing decision theories emphasize the role of expected value in both description-based and experience-based decision-making.

### 1.2 Sensitivity to Frequency Information

Frequency of occurrence is a fundamental aspect of experience that people regularly encode and is critical in a variety of behavior (Zacks & Hasher, 2002). Frequency processing is studied in a wide range of psychology areas such as learning (Sedlmeier, 2002), memory (Burgess, 1998), judgment (Gigerenzer & Hoffrage, 1995), social cognition (Zajonc, 1968), and language (Aslin, Saffran & Newport, 1998). For

[1] π and ω are psychophysical functions for outcome and probability, respectively.

instance, Aslin and colleagues (1998) indicates that babies' sensitivity to the frequency of co-occurrence of different sounds is crucial in language acquisition. Also, people are more likely to make right judgments when information is presented in a frequency format compared to in a probability format (Gigerenzer & Hoffrage, 1995). A large body of frequency processing literature centers on examining whether people can make valid frequency judgments. Most research suggests that people can make accurate frequency judgments for events in either everyday life (e.g., Lichtenstein, Slovic, Fischhoff, Layman, & Combs, 1978; Shapiro, 1969) or laboratory events (e.g., Hintzman & Block, 1971; Mutter & Goedert, 1997). For example, participants could accurately judge the frequency of presentation of words from a list (Hintzman & Block, 1971) and how often a sentence was repeated in a gist versus a verbatim form (Gude & Zechmeister, 1975). These findings indicate the importance of frequency information in human behavior and people's deep sensitivity to it.

### 1.3 Frequency Information in Decision-Making

Although it is limited, some prior work provides evidence to support an important role of frequency information in decision-making. In a classical work, Zajonc (1968) found attitude enhancement of repeated exposure. For instance, increased frequency of presenting nonsense words was associated with enhanced affective connotation of the words, and increased presentation frequency of photographs led to enhanced favorability. Enhancement in attitude to an object might form the basis of a choice.

Another paper on consumer decision-making revealed that the number of positive and negative attributes that a brand possesses shapes consumers' choices (Alba & Marmorstein, 1987). In a legal decision-making study, researchers examined real trial records of sentencing and examined how legal decision makers make sentencing decisions in theft, fraud, and forgery (von Helversen & Rieskamp, 2008). They found that actual sentences were best predicted by a cognitive mapping model which is based on counting the number of presence of factors from a penal code list for a criminal. These studies indicate a critical role of frequency information in consumer and legal decision-making.

The two studies above are about description-based decision-making since all the attributes are presented to decision makers prior to their choices. A candidate task for examining how gain/loss frequency shapes behavior in decisions from experience is the Soochow Gambling Task (SGT). Chiu and colleagues (2008) designed the SGT as an experience-based decision-making task, in which the effect of gain-loss frequency on performance directly contrasts with that of expected value. The decks with the best long-term value give less frequent gains and more frequent losses than the decks with lower long-term values. Chiu and colleagues found that most participants selected the options with higher gain frequency and lower loss frequency (but with lower expected values) rather than the options with higher expected values (but with rare gains and frequent losses). Hence, decision makers in some situations indeed use frequency information to make decisions, sometimes to their detriment.

## 1.4 Overview of Present Research

Making a choice purely based on expected value appears to be rational since our goal is to maximize gains or pleasure and minimize losses or pain. Nevertheless, people might also use frequency information to make decisions. On the one hand, prior work demonstrates a critical role of frequency information in a wide range of human behavior (e.g., Burgess,1998; Sedlmeier, 2002; Aslin et al., 1998) and people's great sensitivity to frequency information (e.g., Gigerenzer & Hoffrage, 1995; Lichtenstein et al., 1978; Mutter & Goedert, 1997). On the other hand, in various decision contexts especially experience-based decision-making, frequency information such as gain-loss frequency is salient due to the decision context. For instance, in an experience-based decision-making task, people make choices and receive a series of gains and/or losses as feedback, and hence each option is associated with certain gain-loss frequency. Given these reasons, it is likely that frequency information could be a prominent factor in decision-making.

The goal of the present research was to systematically investigate the use of frequency information in experience-based decision-making where frequency information is salient. Specifically, this work examined whether and how people use frequency information in experience-based decision-making and further investigated some important psychological and developmental aspects of using frequency information. Study 1 adopted a computational modeling approach to examine whether frequency information is used and how it is integrated into one's decision. Having established the fundamental role of frequency information in decision-making, Study 2 assessed the role of working memory (WM) in the use of a frequency heuristic in

decision-making. Study 3 sought to replicate the results from Study 2 and further examined whether WM would contribute to making accurate judgments on the gain-loss frequency information. Study 3 also evaluated the role of WM in frequency processing in a typical frequency processing task. Study 4 investigated life span change of the use of frequency information in decision-making. In the following sections, I overview each study and review relevant literature.

### 1.4.1 Overview of Study 1

A wide range of computational models have been proposed and established for experience-based decision-making (e.g., Ahn, Busemeyer, Wagenmakers, & Stout, 2008; Busemeyer & Stout, 2002; Erev & Roth, 1998; Worthy, Pang, & Byrne, 2013). Most models share some important characteristics such as using a prediction error, the difference between expected and actual outcomes, to update expected values for each option and make a choice based on a Softmax rule. For the purpose of the current work, the models of interest are roughly grouped into three categories. Models in the first category consider only expected value, that is, the tendency to choose an option with the highest expected value. Some examples are reinforcement learning (Sutton & Barto, 1998) and prospect valence learning models (Ahn et al., 2008; Steingroever, Wetzels, & Wagenmakers, 2014). The second type of models account for both expected value and perseveration which is the tendency to consecutively choose the same option over trials. The value-plus-perseveration (VPP) model (Worthy et al., 2013) is a typical example. Worthy et al. (2013) found that the VPP model outperformed the models considering merely expected value such as the PVL models, hence indicating an important role of

perseveration in accounting for choice behavior. The third type are models that also incorporate gain/loss frequency information. These are the type of models that Study 1 aimed to develop. These models consider three important factors that might contribute to decision-making: expected value, preservation, and frequency, and thus they are called Expectancy-Frequency-Perseveration (EFP) models.

To assess the role of frequency information, a *frequency heuristic* was formalized. The basic idea is that one maintains a frequency value of each option while performing a decision-making task and the frequency value for an option increases by 1 when a gain is received upon selecting an option and decreases by 1 when a loss is received. The frequency value decays over time to account for memory decay. It is referred to as a heuristic because it fits the key feature of heuristics: simplified rule-based strategies which ignore part of the information (Gigerenzer & Gaissmaier, 2011; Shah & Oppenheimer, 2008). Using this frequency heuristic or relying on the gain-loss frequency value to make decisions ignores the magnitude of gains and losses. A computational model (the EFP model) with this frequency value component was built. I then applied the frequency heuristic-based model to three representative decision-making paradigms which are widely used in recent experience-based decision-making research, and compared it to other established models without the frequency value component. If decision makers use frequency information, the EFP model would fit and/or predict their choice behavior better than other models.

### 1.4.2 Overview of Study 2

Study 2 was intended to assess the role of working memory (WM) in the use of the frequency heuristic in experience-based decision-making. WM is a control system used for temporary storage and information manipulation with limits on both its storage and processing capabilities (Baddeley & Hitch, 1974). It is crucial to a variety of higher-order cognitive tasks (see Engle, 2002, for a review). WM might contribute to the decision-making processes in experience-based decision-making. Recently, a number of studies have examined the role of WM on choice behavior in a widely used decision-making task, the Iowa Gambling Task (IGT; Bechara, Damasio, Damasio, & Anderson, 1994). Turnbull and colleagues (2005) investigated the effect of WM on choice behavior in the original IGT by manipulating WM load with a dual-task paradigm but did not observe significant effects of WM load. Moreover, a recent review summarized correlational studies that examined the association between working memory capacity (WMC) and the IGT and found little evidence to support an association between them (Toplak, Sorge, Benoit, West, & Stanovich, 2010). In contrast, other work does suggest that WM contributes to decision-making in IGT-like tasks. First, some evidence emerging from brain lesion and neuroimaging studies has indicated that normal functioning of the dorsolateral prefrontal cortex (DLPFC), widely thought to be a neural substrate of WM (Cohen et al., 1997; Jonides et al., 1993), is necessary for doing well in the IGT (Fellows & Farah, 2005; Li, Lu, D'Argembeau, Ng, & Bechara, 2010; Manes, Sahakian, Clark, & Rogers, 2002). Second, behavioral studies that employed variants of the IGT and manipulated WM load found that WM load impairs performance on these

tasks, implying that WM might contribute to IGT choices (Dretsch & Tipples, 2008; Hinson, Jameson, & Whitney, 2002; Jameson, Hinson, & Whitney, 2004). Together, this line of research presents a mixed picture of the relation between WM and choice behavior in the IGT, but it seems that more evidence from studies manipulating WM load leans towards supporting the notion that WM contributes to choice behavior in IGT-like tasks.

However, the reward structure of the IGT limits its contribution to our understanding of the relation between WM and utilization of the frequency heuristic, because the effects of expected value and gain-loss frequency are confounded in the IGT. Hence, it would be unclear whether WM contributes to the use of expected value or frequency information in decision-making if an effect of WM load on the IGT performance is observed. In contrast, another experience-based decision-making task discussed earlier, the SGT, has a distinct reward structure which contrasts the effect of expected value directly against that of gain-loss frequency. In the SGT, choosing the advantageous decks yield frequent (but small) losses and infrequent (but large) gains, while the disadvantageous decks give rare (but large) losses and frequent (but small) gains. Thus, if focusing on the frequency of gains and losses, one would choose the bad decks more often and perform poorly. If WM load enhances SGT performance, it indicates that cognitive load reduces the utilization of the frequency heuristic; if WM load diminishes performance, it implies that cognitive load improves the use of the frequency heuristic. Hence, Study 2 used the SGT to examine the role of WM in the use of the frequency heuristic.

This heuristic appears simple but might be WM-sensitive. In prior studies (Otto, Taylor, & Markman, 2011; Worthy, Otto, & Maddox, 2012), it was found that a win-stay-lose-shift strategy, which entails remembering the outcome (win or loss) of past trials and shares some similarity with the frequency heuristic, was predominant among participants without a concurrent WM-demanding task. In contrast, individuals who performed both a decision-making task and a concurrent task tended to prefer a strategy that implicitly integrated past outcomes. These results imply that tracking the gain-loss frequency and utilizing the frequency heuristic could be WM-intensive.

In Study 2, WM load was manipulated by a dual-task paradigm such that one group of participants performed the SGT only, whereas another group of participants performed the SGT and a WM-demanding task concurrently. The effect of WM load on SGT performance would provide much insight into whether the utilization of a frequency heuristic is WM-dependent. Furthermore, Study 2 employed the EFP model developed in Study 1 to decompose the contribution of gain-loss frequency and expected value to choice behavior in the SGT, further delineating the underlying psychological mechanism.

### 1.4.3 Overview of Study 3

With respect to frequency processing, a large body of work has focused on a basic issue, frequency judgment (for a review, see Sedlmeier & Betsch, 2002). In typical studies, participants are asked to view a series of items, such as words, sentences, or pictures, which appear in different frequencies, and then to make a frequency judgment for each target item. Researchers are often interested in how accurate a judgment is and

what factors influence the accuracy. Some early work found that frequency judgment accuracy is invariant with respect to several factors, suggesting that people are highly sensitive to frequency information. Hasher and Zacks (1984) accordingly proposed that the processing of frequency information is effortless and automatic.

Age is the first factor that is suggested to have no impact on frequency judgment accuracy. One child development study (Hasher & Zacks, 1979) compared children from kindergarten and grades 1, 2, and 3. Children were shown a list of pictures of familiar objects, occurring 1, 2, 3 or 4 times. Participants were then asked to judge the frequency of each object. The estimated frequency increased as a function of the actual frequency, but no clear difference in the judgment accuracy was observed across the four age groups. In a similar study, Attig & Hasher (1980) compared three groups of adults (mean ages are 22, 43, and 68 years) on the frequency judgment accuracy of a list of words with different frequencies of occurrence, and all age groups were found to be equally sensitive to frequency information. These studies suggest that cognitive functioning change with age does not impact frequency judgment, in contrast to typical findings of changes on most explicit memory tasks over age (e.g., Naito, 1990; Rovee-Collier, 1997). Second, Zacks and colleagues (1982) compared college students from two universities with a 140-point difference in the verbal Scholastic Aptitude Test scores, and did not find a significant difference in frequency judgment accuracy between the two groups of students. Third, intention to code frequency information does not increase accuracy (Zacks, Hasher, & Sanft, 1982; Zechmeister, King, Gude, & Opera-nadi, 1975). Instructing participants that they would be tested on frequency did not enhance

their accuracy compared to informing them that they would have a memory test, while giving test-appropriate instructions improved participants' performance on a free recall memory test. Taken together, the evidence on the three factors supports the notion that frequency processing is automatic.

However, the most important criterion supporting automaticity of an operation is the test under cognitive load manipulation (Jonides, 1981; Shiffrin & Schneider, 1977; Baddeley, 2012). Zacks and colleagues (1982) indeed reported a study which appeared to provide evidence to support that competing task demands did not reduce frequency judgment accuracy. They compared frequency judgment of three groups of participants who received different instructions. Participants were informed either a forthcoming recall test, a forthcoming frequency test, or both. Zacks and colleagues argued that participants who were told both upcoming tests were under a condition of higher cognitive load since they needed to prepare for both the frequency and the recall tests. In this study, they found that participants received different instructions, presumably with different levels of cognitive load while coding the frequency information, exhibited similar frequency judgment performance. Naveh-Benjamin and Jonides (1986), however, argued that the results of this experiment were problematic since preparation for a recall test would not be expected to impede frequency judgment if memory trace mediating recall also facilitates frequency judgment, which is likely to be the case. Thus, Naveh-Benjamin and Jonides (1986) manipulated cognitive load by asking participants to count either forward by 1's (easy condition), backward by 3's (medium condition) or backward by 11's (hard condition). With this manipulation, they observed a clear effect

of cognitive load such that participants made more accurate judgments under the easier condition than those under the more difficult condition. In a similar study, Sanders and colleagues (1987) also found the interference effect of cognitive load on frequency judgment (Sanders, Gonzalez, Murphy, Liddle, & Vitina, 1987). Put together, it appears that frequency processing is not influenced by age, verbal ability, or intention. However, the evidence of automaticity with respect to the central criterion, test under cognitive load manipulation, is somewhat mixed.

Study 2 was intended to examine whether WM contributes to the utilization of frequency information in experience-based decision-making. If evidence supporting it is revealed, what remains unclear is whether WM load reduces the accuracy of gain-loss frequency estimation or if it interferes with other components of the process of using frequency information. Given that some work suggests that frequency judgment is automatic, it is possible that WM load does not impair frequency estimation but other components in the process such as integrating frequency information and expected value. One purpose of Study 3 was to investigate whether WM load would reduce frequency judgment accuracy in a decision-making task, thus causing a problem to utilizing the frequency information. A similar experimental procedure as Study 2 was adopted in Study 3. That is, one group of participants performed the SGT under a single task condition, while the other group did it under a dual-task condition. The key difference was that at the end of experiment, all participants were required to estimate the frequency of gains and losses for each deck, which allowed for investigating the effect of WM load on frequency judgment accuracy. The current findings on

automaticity of frequency judgment are mixed, but studies that manipulated cognitive load generally suggest that accurate frequency judgment requires cognitive resources. I thus hypothesized that WM load would impair the accuracy of gain-loss frequency judgment in the decision-making task. Additionally, Study 3 sought to replicate the results from Study 2.

Study 3 also examined the effect of WM load on the frequency judgment accuracy in a word frequency judgment task, with an intention to add evidence to previous work suggesting that cognitive load impairs frequency judgment in classical frequency processing tasks. WM load was manipulated by the same dual-task paradigm as for the decision-making task. The last purpose of Study 3 was to compare the effects of WM load on frequency judgment in the typical frequency processing task, the word frequency judgment task, and the decision-making task. Decision-making is presumably a more complicated process than word frequency judgment. Thus, even if WM load does not reduce the judgment accuracy in the word frequency judgment task, it might diminish the accuracy in the decision-making task. Also, it is possible that frequency judgment is generally WM-demanding, and thus WM load would exhibit similar effects on judgment accuracy in the word frequency judgment task and decision-making task.

### 1.4.4 Overview of Study 4

Decision-making is a core competence in all ages. Understanding how decision-making changes across the life-span is critical as older adults comprise an increasing proportion of the global population. For example, by 2030, it is estimated that there will be 72.1 million older persons who represent 19% of the US population, about one in

every 5 Americans. Given the potential importance of frequency heuristic in decision-making, Study 4 was intended to evaluate the aging effects on the use of the frequency heuristic.

Heuristics are often considered as simplified strategies or shortcuts that are used for effort reduction (Shah & Oppenheimer, 2008; Gigerenzer & Gaissmaier, 2011). Age-related cognitive decline (Park et al., 2002) can bias older adults towards heuristics in decision-making (Carpenter & Yoon, 2011; Mata, Schooler, & Rieskamp, 2007; Worthy & Maddox, 2012). For instance, older adults are more susceptible to the way how options are framed (i.e., framing effect) than younger adults (Kim, Goldstein, Hasher, & Zacks, 2005). The authors argued that diminished cognitive ability limits older adults' information processing to superficial features of the problem (e.g., framing or the way the choices are described), resulting in susceptibility to choice framing. Also, older adults have a stronger satisficing tendency (Chen & Sun, 2003). This tendency is often associated with using heuristics since it only requires one to reach a satisfactory goal, whereas a maximizing tendency requires one to rely on systematic and deliberative processing to obtain the best outcome. Chen and Sun (2003) argued that older adults' satisficing tendency is shaped by age-related cognitive decline. Furthermore, life experience can allow older adults to have access to more heuristics and thus use them more often, even when applying them is not adaptive (Castel, Rossi, & McGillivray, 2012). In summary, age-related cognitive decline and life experience lead to enhanced use of heuristics with advancing age.

Study 4 also used the SGT which has a salient frequency component to examine the life-span change in the use of the frequency heuristic. Three group of adults, younger, middle-aged, and older adults, performed the SGT. Studies 2 and 3 examined the role of WM in the use of the frequency heuristic and I hypothesized that WM load would diminish its utilization. If the two studies find that the use of the frequency heuristic is not WM-demanding, it is very likely that older adults would use the frequency heuristic more than younger adults, as implied by older adults' general preference to heuristics, and thus perform worse in the SGT. Nevertheless, if Studies 2 and 3 reveal evidence supporting a WM-dependent nature of using the frequency heuristic, whether people use it more with advancing age might be reduced to the question of whether declined cognitive ability in older adults would constrain the use of the frequency heuristic. If it would, older adults might not be able to use it; if it would not, older adults might use it more often.

# 2. STUDY 1

## 2.1 Overview of Study 1

Prior work indicates that frequency information is critical in human behavior and people are highly sensitive to frequency information (see Sedlmeier, 2002, for a review). And the frequency of gains and losses (or of other task features) are salient in experience-based decision-making tasks. I thus propose that frequency information might be a fundamental component in experience-based decision-making. To test this possibility, Study 1 adopted a computational modeling approach, which could answer not only whether frequency information is used in experience-based decision-making but also how it is integrated into one's decision. The Expectancy-Frequency-Perseveration (EFP) models were developed for three representative paradigms which are widely used in recent experience-based decision-making research. These EFP models are similar and all account for the three important factors in decision-making. Each model was only slightly adapted to accommodate each paradigm's task features. The EFP models were compared to other established models for each task which do not include the frequency component.

To rigorously compare these models, I adopted three methods for model comparison. First, models were fit to each participant's choices trial-by-trial by a maximum likelihood method, and model fits were then compared to determine the model that provided the best post hoc fits. Second, best-fitting parameters from the first method were used to simulate choices, which were then compared to participants' behavior to see which model generated choices that best mirrored participants' behavior. The

simulation method is another common approach to assess the ability of a model to account for behavior (Steingroever, Wetzels, & Horstmann, 2013; Worthy et al., 2013). The third method is a generalization criterion method which compares models' ability to make a priori predictions of new conditions (Busemeyer & Wang, 2000). A model can perform greatly on fitting a training dataset when the model is excessively complex, whereas it might meanwhile perform poorly on making a priori predictions. The generalization method was used to detect this overfitting issue of a model. Given people's sensitivity to frequency information and the salience of gain-loss frequency in experience-based decision-making, the prediction was that the EFP models would consistently perform better than other models without the frequency component.

In each of the following sections, decision-making tasks of a paradigm and related research are briefly introduced, corresponding computational models are then specified, and finally model comparison results based on each method are presented.

## 2.2 Paradigm 1: The Iowa and Soochow Gambling Tasks

### 2.2.1 Task Description

The Iowa Gambling Task[2] (IGT) is perhaps the most popular decision-making task in the literature (Beitz, Salthouse, & Davis, 2014). It is often used as a psychological measurement of decision-making capacity. The IGT has been heavily utilized to examine choice behavior in various clinical populations (e.g., brain damage, substance abuse, neurodegenerative disease; for a recent review, see Buelow & Suhr, 2009), developmental samples (e.g., Beitz, Salthouse, & Davis, 2014; Wood,

[2] The findings on the role of WM in choice behavior in the IGT was discussed in Section 1.4.2.

Busemeyer, Koling, Cox, & Davis, 2005), and healthy adults (e.g., Fein, McGillivray, & Finn, 2007). In this task, players choose between four decks of cards, which yield both gains and losses. The reward schedule is shown in the top half of Table 1. Unbeknownst to players, Decks A and B are disadvantageous because they have a negative net expected value, while Decks C and D are advantageous because they have a positive net expected value. The task is initially challenging because the disadvantageous decks consistently yield larger gains (100 versus 50 points), yet they also provide larger losses, resulting in a negative net value.

Although it is assumed that players make choices according to expected values for options in the IGT, critiques have been raised regarding the impact of gain-loss frequency (Chiu et al., 2008; Dunn, Dalgleish, & Lawrence, 2006; Steingroever et al., 2013). In the IGT, Decks A and C give frequent losses (on 50% of trials), while Decks B and D give less frequent losses (on 10% of trials). A tendency to avoid decks with frequent losses will not influence the net amount of points gained since the high-frequency loss decks are evenly split across the advantageous and disadvantageous decks. The SGT was recently developed to further distinguish the influence of expected value and gain-loss frequency (Chiu et al., 2008). Its reward schedule is shown at the bottom of Table 1. In this task the two advantageous decks (C and D) also give the most frequent losses – on 80% of trials compared to only 20% of trials for the disadvantageous decks. Thus, a tendency to avoid decks that give frequent losses will lead to poor performance, but a tendency to focus on the net long-term expected values of each deck will lead to good performance.

### 2.2.2 Model Description

A range of computational models have been applied to the IGT and SGT data. Prospect valence learning (PVL) models and value-plus-perseveration (VPP) models are currently the most promising ones (Ahn et al., 2008; Steingroever, Wetzels, & Wagenmakers, 2015; Worthy et al., 2013). As with reinforcement learning (RL) models used broadly (Sutton & Barto, 1998), the basic assumptions behind the PVL models are that outcomes of past decisions are integrated to determine expected values for each option, and that decision makers tend to choose options with larger expected values than options with smaller expected values (Ahn et al., 2008). Specifically, the PVL-Delta model utilizes a Delta learning rule that assumes that the expected values for each option are recency-weighted averages of the payoffs received on each trial (Rescorla & Wagner, 1972; Sutton & Barto, 1998); the PVL-Decay model uses a Decay learning rule which assumes that the expected values of all options decay over time (Erev & Roth, 1998). The VPP model further accounts for both the tendencies to choose the option with the highest expected value and to perseverate or stay with the same option over consecutive trials (Worthy et al., 2013). Nevertheless, as discussed above, attention to gain-loss frequency is another important component of decision-making behavior. As such, this work developed the EFP model which accounts for attention to expected value, frequency of net losses versus gains, and perseveration, which I believe are three critical mechanisms underpinning behavior in decision-making tasks.

**Table 1 Reward schedules for the Iowa Gambling Task (IGT) and Soochow Gambling Task (SGT)**

*IGT Reward Schedule*

| | **Deck A** | **Deck B** | **Deck C** | **Deck D** |
|---|---|---|---|---|
| 1 | 100 | 100 | 50 | 50 |
| 2 | 100 | 100 | 50 | 50 |
| 3 | 100, **−150** | 100 | 50, **−50** | 50 |
| 4 | 100 | 100 | 50 | 50 |
| 5 | 100, **−300** | 100 | 50, **−50** | 50 |
| 6 | 100 | 100 | 50 | 50 |
| 7 | 100, **−200** | 100 | 50, **−50** | 50 |
| 8 | 100 | 100 | 50 | 50 |
| 9 | 100, **−250** | 100, **−1250** | 50, **−50** | 50, **−250** |
| 10 | 100, **−350** | 100 | 50, **−50** | 50 |
| Net expected value | -250 | -250 | 250 | 250 |

*SGT Reward Schedule*

| | **Deck A** | **Deck B** | **Deck C** | **Deck D** |
|---|---|---|---|---|
| 1 | 200 | 100 | **−200** | **−100** |
| 2 | 200 | 100 | **−200** | **−100** |
| 3 | 200 | 100 | **−200** | **−100** |
| 4 | 200 | 100 | **−200** | **−100** |
| 5 | **−1050** | **−650** | 1050 | 650 |
| 6 | 200 | 100 | **−200** | **−100** |
| 7 | 200 | 100 | **−200** | **−100** |
| 8 | 200 | 100 | **−200** | **−100** |
| 9 | 200 | **−650** | **−200** | **−100** |
| 10 | **−1050** | 100 | 1050 | 650 |
| Net expected value | −500 | −500 | 500 | 500 |

*Bold values indicate amount lost on each trial. Decks A and B are disadvantageous in both tasks. In the IGT decks A and C give high-frequency losses, while in the SGT the advantageous decks (C and D) give high-frequency losses. See* (Bechara et al., 1994) *for the full table for the IGT which lists payoffs for the first 40 cards drawn from each deck. In the present task the sequence was repeated for cards 41–80 and 81–100 so that a participant could potentially select the same deck on all 100 draws. See* (Chiu et al., 2008) *for the full table which lists payoffs for the first 40 cards drawn from each deck. In the present task the sequence was repeated for cards 41–80 and 81–100 so that a participant could potentially select the same deck on all 100 draws.*

*PVL Models*

The PVL-Delta and PLV-Decay models are often applied to choice data of the IGT and SGT (Ahn et al., 2008). The PVL models both have three components: a utility function, a value-updating rule, and an action-selection rule. However, the PVL-Delta model utilizes a delta rule (see below for details) for value-updating which updates only the expected value of the chosen option on each trial and leaves the values of the unchosen option unchanged. In contrast, the PVL-Decay model uses a decay rule (see below for details) which assumes that the expected values of all options decay over time. The PVL-Decay model also indirectly accounts for tendencies to perseverate because values for each deck tend to decay as they are selected less frequently (Worthy et al., 2013). The two models utilize the same utility function and action-selection rule.

The prospect theory utility function assumes that the evaluation of each outcome follows the utility function derived from prospect theory (Ahn et al., 2008; Kahneman & Tversky, 1979). The utility function has diminishing sensitivity to increases in magnitude, and different sensitivity to losses versus gains. The utility, *u(t)*, on trial *t*, of each net outcome, *x(t)*, is:

$$u(t) = \begin{cases} x(t)^{\propto} & if\, x(t) \geq 0 \\ -\lambda |x(t)|^{\propto} & if\, x(t) < 0 \end{cases} \quad (1)$$

Here α is a shape parameter ($0 < \alpha < 1$) that determines the shape of the utility function. As α approaches 1, utility increases in direct proportion to the outcome value. As it approaches 0, the utility function reduces to a stepwise function. λ represents a loss aversion parameter ($0 < \lambda < 5$) that governs the sensitivity of losses compared to gains. A

value of λ greater than 1 indicates that an individual is more sensitive to losses than gains, and a value less than 1 indicates greater sensitivity to gains than to losses.

The value-updating rule determines how the utility $u(t)$ is used to update expected values or expectancies $E_j(t)$ for the chosen option, *i*, on trial *t*. The PVL-Delta rule utilizes the delta rule (Rescorla & Wagner, 1972) which assumes that expectancies are recency-weighted averages of the rewards received for each option:

$$E_i(t) = E_i(t-1) + \phi \cdot [u(t) - E_i(t-1)] \quad (2)$$

$\phi$ represents the recency parameter ($0 \leq \phi \leq 1$) that describes the weight given to recent outcomes in updating expectancies. As $\phi$ approaches 1, greater weight is given to the most recent outcomes in updating expectancies, indicating more active updating of expectancies on each trial. As $\phi$ approaches 0, outcomes are given less weight in updating expectancies. When $\phi = 0$ no learning takes place, and expectancies are not updated throughout the task from their initial values.

In contrast, the PVL-Decay model utilizes the decay rule (Erev & Roth, 1998) in which expectancies of all decks decay, or are discounted, over time. The expectancy of the chosen deck is then added to the current outcome utility:

$$E_i(t) = A \cdot E_i(t-1) + \delta_i(t) \cdot u(t) \quad (3)$$

The decay parameter $A$ ($0 \leq A \leq 1$) determines the extent to which the past expectancy is discounted. $\delta_j(t)$ is a dummy variable that is 1 if deck *j* is chosen and 0 otherwise.

The action-selection rule uses a Softmax rule (Sutton & Barto, 1998) to determine the predicted probability that deck *j* will be chosen on trial *t*, Pr[$G_j(t)$]:

$$Pr\big(G_j(t)\big) = \frac{e^{\theta(t)\cdot E_j(t)]}}{\sum_{j=1}^{4} e^{[\theta(t)\cdot E_j(t)]}} \tag{4}$$

In the present work I utilize a trial-independent action-selection rule for all the RL models fit to the data:

$$\theta(t) = 3^c - 1 \tag{5}$$

Here $c$ ($-5 \leq c \leq 5$) represents the response consistency or exploitation parameter. A high value indicates that one's choices are deterministic. A low value signifies more random responding over the course of the task.

*VPP Model*

The VPP model assumes that an individual keeps track of both expectancies and perseveration strengths for each deck (see Worthy et al., 2013). The expectancies ($E_j(t)$) for each *j* choice were computed according to Equations 1 and 2 above, the same as the PVL-Delta rule. The perseveration ($P_j(t)$) strengths for each *j* option were determined by a more general form of the decay rule that has previously been utilized to model perseveration or autocorrelation among choices (Kovach et al., 2012; Schönberg, Daw, Joel, & O'Doherty, 2007). The perseveration term for chosen option *i*, on trial *t*, differs depending on whether the net outcome, *x(t)*, was positive or negative:

$$P_i(t) = \begin{cases} k\cdot P_i(t-1) + \varepsilon_{pos} & \text{if } x(t) \geq 0 \\ k\cdot P_i(t-1) + \varepsilon_{neg} & \text{if } x(t) < 0 \end{cases} \tag{6}$$

Here $k$ ($0 \leq k \leq 1$) represents a decay parameter similar to *A* in Equation 3 above for the PVL-Decay model. The tendency to perseverate or switch is incremented, each time an option is selected, by $\varepsilon_{pos}$ and $\varepsilon_{neg}$ which vary between -1 and 1. Positive values indicate a tendency to persevere by choosing the same option on succeeding trials,

whereas negative values denote a tendency to switch. The overall value of each option was determined by taking a weighted average of the two terms in the model, the expected value and the perseveration strength of each *j* option:

$$V_j(t) = w_{E_j} \cdot E_j(t) + (1 - w_{E_j}) \cdot P_j(t) \quad (7)$$

where $w_{E_j}(0 \leq w_{E_j} \leq 1)$ quantifies the weight given to the expected value for each option. Values greater than .5 indicate greater weight given to the expected value of each option, and values less than .5 indicate greater weight based on the perseverative strength of each option. These values $V_j(t)$ were entered into a Softmax rule to determine the probability of selecting each option, *j*, on each trial, *t*, which is the same as Equations (4) and (5) above for the PVL models except that the VPP model utilizes $V_j(t)$ instead of $E_j(t)$. The direct inclusion of perseverative values is the major difference between the VPP model and the PVL models. The PVL-Delta model does not account for tendencies to perseverate or switch, while the PVL-Decay model account for these tendencies indirectly via the decay rule.

*EFP Model*

In contrast to the PVL models with a single expected value term and the VPP model with expected value and perseveration terms, the EFP model includes three terms to account for three critical components of choice behavior: expected value, gain-loss frequency, and perseveration. Increasing the number of terms may ostensibly improve the fit of the model or lead to overfitting simply because the model has too many parameters. Considering this, the EFP model was designed such that it captures these three important psychological components while being as parsimonious as possible.

The first model assumption is that after a choice is made and feedback ($gain(t)$ and $loss(t)$) is presented, the utility $u(t)$ for the choice made on trial *t* is given by:

$$u(t) = gain(t) - \rho \cdot |loss(t)| \tag{8}$$

Here $\rho$[3] represents a *loss aversion* parameter ($0 \leq \rho \leq 5$) that governs the sensitivity of losses compared to gains. A value of $\rho$ greater than 1 indicates that an individual is more sensitive to losses than gains, and a value less than 1 indicates greater sensitivity to gains than to losses. Note that the EFP model assumes that the subjective utility is linearly proportional to the actual payoff amount, in contrast to the PVL models that use a nonlinear function. One major reason for the nonlinear function in the PVL models is to indirectly account for the gain-loss frequency (Ahn et al., 2008). The EFP model directly captures sensitivity to gain-loss frequency (see below) and thus a shape parameter is unnecessary. Additionally, using a linear function improves the parsimony.

The EFP model then assumes that the utility $u(t)$ is used to update expected values or expectancies $E_j(t)$ for the chosen option, *i*, on trial *t*, using a delta rule:

$$E_i(t) = E_i(t-1) + \phi \cdot [u(t) - E_i(t-1)] \tag{9}$$

Here $\phi$ represents the *recency (or learning)* parameter ($0 \leq \phi \leq 1$) that describes the weight given to recent outcomes in updating expectancies. The utility function in the EFP model is the same as that in the PVL-Delta and VPP models.

[3] Here $\rho$ has a similar meaning as $\lambda$ in the PVL models. Since the EFP and PVL models have different utility functions, different letters for loss aversion are used to distinguish them.

The perseveration term in the VPP model was designed to model the tendency to perseverate following gains and to switch following losses. Thus, it also implicitly captures the frequency of gains and losses. The EFP model decomposes the tendency to select the option with infrequent losses and frequent gains and the tendency to perseverate. The frequency term for chosen option *i*, on trial *t*, differed based on whether the net outcome, *x(t)*, was positive or negative:

$$F_i(t) = \begin{cases} (1-\phi)\cdot F_i(t-1)+1 & if\, x(t)\geq 0 \\ (1-\phi)\cdot F_i(t-1)-1 & if\, x(t)<0 \end{cases} \quad (10)$$

The frequency value increases by 1 following a net gain or decreases by 1 following a net loss. Instead of using a separate parameter to capture the weight to previous information as in the VPP model, the EFP model utilizes the term: $1-\phi$. Here $\phi$ is the same as in Equation 9, accounting for weight given to recent information. Thus utilizing the same recency parameter for both the value updating function and the gain-loss frequency function increases the parsimony of the EFP model and restricts the model to assume that attention to recent outcomes is the same for both value and frequency information.

The *perseveration* term for chosen option *i*, on trial *t*, is determined by:

$$P_i(t) = \gamma \quad (11)$$

The tendency to perseverate or switch is denoted by $\gamma$ which varies between -100 and 100. Essentially this perseveration term simply gives a bonus or a reduction to the value of the option that was selected on the last trial, and thus indicates a general tendency to stay or switch to a different option on each trial. Note that in the VPP model tendencies to stay or switch were conflated with attention to the frequency of net gains versus

losses, while here the goal is to account for frequency and perseveration processes separately.

The overall value of each option was determined by taking a weighted average of the expected value and the frequency value plus the perseveration strength of each *j* option:

$$V_j(t) = \omega \cdot E_j(t) + (1 - \omega) \cdot F_j(t) + P_i(t) \tag{12}$$

where $\omega$ ($0 \leq \omega \leq 1$) quantifies the *weight* given to the expected value for each option versus the weight given to the frequency of losses versus gains provided by each option.

Finally, these overall values $V_j(t)$ were entered into a Softmax rule to determine the probability of selecting each option, *j*, on each trial, *t*:

$$Pr\big(G_j(t)\big) = \frac{e^{\theta(t) \cdot V_j(t)]}}{\sum_{j=1}^{4} e^{[\theta(t) \cdot V_j(t)]}} \tag{13}$$

I utilize a trial-independent action-selection rule:

$$\theta(t) = 3^c - 1 \tag{14}$$

Here *c* ($-5 \leq c \leq 5$) represents the response *consistency or exploitation* parameter. Lower values indicate more random responding over the course of the task.

In sum, the EFP model has five parameters: (a) the recency parameter $\phi$; (b) the response consistency parameter *c*; (c) the weight of the expected value $\omega$ versus the weight to the frequency values; (d) the loss aversion parameter $\rho$; and (e) the perseverative tendency $\gamma$. In comparison, the PVL models have four free parameters, while the VPP model has eight.

### 2.2.3 Method 1: Model Fits

The EFP, VPP, PVL-Delta, and PVL-Decay models were first compared regarding their post hoc model fits. A Baseline model[4] that assumes fixed choice probabilities was also considered (Gureckis & Love, 2009; Worthy & Maddox, 2012). To assess these models, I employed a large IGT dataset ($n$ = 504) of healthy participants from 7 independent experiments that collected data on the 100-trial version of the IGT (Steingroever, Fridberg, et al., 2015). Each participant's data were fit by maximizing the log-likelihood for each model's prediction on each trial. Bayesian Information Criterion (BIC; Schwarz, 1978) was used to examine the relative fit of the model. BIC penalizes models with more free parameters. For each model, $i$, $\mathrm{BIC}_i$ is defined as:

$$\mathrm{BIC}_i = -2\log \mathrm{L}_i + \mathrm{V}_i \log(\mathrm{n}) \tag{15}$$

where $\mathrm{L}_i$ is the maximum likelihood for model $i$, $\mathrm{V}_i$ is the number of free parameters in the model, and n is the number of trials. Smaller BIC values indicate a better fit to the data. The EFP model exhibited the smallest average BIC value (see Table 2), indicating that the EFP model provides a better fit to the data than other models. Also, note that the PVL-Decay model fits were close to those of the EFP model, followed by the VPP model. The PVL-Delta model had a poorer fit compared to these models.

[4] The baseline model has three free parameters that represent the probability of selecting Deck A, B, or C (the probability of selecting Deck D is 1 minus the sum of the other three probabilities).

**Table 2 Average BIC values for each model for the IGT data**

| Model | EFP | VPP | PVL-Delta | PVL-Decay | Baseline |
|---|---|---|---|---|---|
| Mean(SD) | **226.57(57)** | 229.93(56) | 242.53(48) | 227.95(57) | 258.96(33) |

*Standard deviations are listed in parentheses. Values in boldface are the minimum BIC values among these models.*

### 2.2.4 Method 2: Simulations

BIC indicates only comparative performance of candidate models in a given set. Thus, even if all the candidate models fit poorly, BIC cannot issue a warning of it. The second model comparison method evaluated how choices simulated from candidate models using participants' best-fitting parameters mimic human choices, which provides some evidence of the absolute performance of each model. 1000 simulations were run with each of the 504 sets of best-fitting parameter values. Each simulation generated a sequence of choices as a human participant. The proportion that each model selected each deck over the 100 trials was computed for each simulation and then an overall proportion of selecting each deck was computed for each model across all simulations, which indicates a model's prediction of how often each deck will be selected. Figure 1 displays the proportion of trials that participants and each model selected each deck. The EFP model's simulated choices most closely mimic participants' choices. The error bars for human choice behavior indicate 95% confidence intervals. Only the simulated proportions from the EFP model are consistently contained in these intervals. The EFP model produced almost the same proportion of selections of Decks A and B as did participants, while all other models under-predicted choices on Deck A and over-

predicted choices on Deck B and these departures make their predictions be out of the 95% confidence interval.

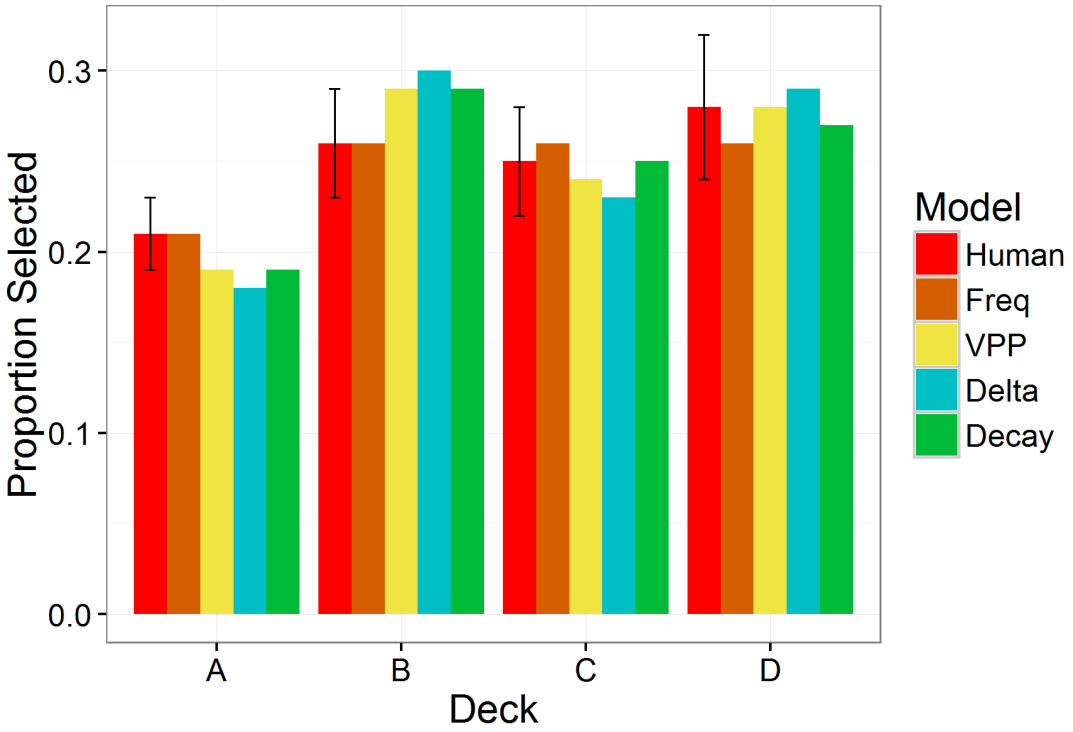


**Figure 1 Observed and simulated choices of each deck. Simulations were run with each set of best-fitting parameter values. The error bars for human choice behavior indicate 95% confidence intervals.**

### 2.2.5 Method 3: Generalization Criterion Method

The third method is a generalization criterion method which evaluates a model's ability to make a priori predictions of new conditions (Busemeyer & Wang, 2000). This method was applied to a data set from a within-subject experiment where each participant performed both the IGT and SGT with order counterbalanced ($n$ = 58). Each

model was first fit to the data for each task by maximizing the log-likelihood for each model's prediction on each trial to obtain the best-fitting parameters. The best-fitting parameters estimated from the first task, either the IGT or SGT, were employed to generate an entire sequence of choices in the second task, either the SGT or IGT, respectively. The observed probability of choosing each option on each trial was calculated across all participants, while the predicted probability was computed across all participants' simulation data. A mean square deviation score, comparing the observed and predicted probabilities, was computed for each model. A smaller difference score indicates better generalizability for a given model. Table 3 shows the results for this method. Clearly, the EFP and PVL-Decay model outperformed the VPP and PVL-Delta model when the IGT was used to predict the SGT. When the SGT was utilized to predict the IGT, the EFP and PVL-Decay model also exhibited slightly better generalizability than the other two models, although the four models all appeared to generalize well when predicting IGT performance from fits to SGT data.

**Table 3 Generalization criterion method outcomes for the IGT and SGT data**

| Target task | Model | Estimated Task | |
|---|---|---|---|
| | | IGT | SGT |
| IGT | EFP | | **33.49** |
| | VPP | | 50.08 |
| | PVL-Delta | | 72.81 |
| | PVL-Decay | | 34.12 |
| SGT | EFP | **22.80** | |
| | VPP | 24.92 | |
| | PVL-Delta | 26.82 | |
| | PVL-Decay | 22.83 | |

*Values in boldface indicate the best model for each method in each condition.*

## 2.3 Paradigm 2: Minimal Information Paradigm

### 2.3.1 Task Description

The second paradigm used to examine the frequency heuristic is a minimal information paradigm (Erev & Barron, 2005; Hertwig et al., 2004). It is often used to contrast with decisions from description. As discussed earlier, description-based decision problems are often given as simple gambles. Consider the following example,

*Choose between the two alternatives:*

*5% chance to get $32*

*50% chance to get $3*

In a minimal information task coupled with the description-based example given above, participants are also given two alternatives which have the same outcome distributions. However, they have no information about the outcome distributions and have to learn them through repeated choices and receiving feedback. Therefore, the only difference between the description-based and minimal information decision-making problems is the format of information presentation. This difference leads to a robust effect on choice behavior, which is called the description-experience gap (e.g., Camilleri & Newell, 2011; Hau, Pleskac, Kiefer, & Hertwig, 2008; Hertwig et al., 2004). In particular, decision makers often overweight rare events when making decisions from description, while they tend to underweight rare events when making decisions from experience. For instance, in the above example, 5% chance to get $32 is a rare event, participants tend to overweight it and prefer this alternative when the decision problem is given in a description-based format; in contrast, participants tend to underweight it and

prefer the other alternative (50% chance to get $3) when they learn the outcome distributions through experience.

Data from two minimal information tasks were used to investigate the frequency heuristic. Forty participants performed each task, and the data have not been published before. One task has two choices and the other has four choices. The two-choice task has two options with the same outcome distributions as the above example ($32, .05; $3, .5). The four-choice task was a modified version of the two-choice task that was derived by simply adding one of each type of option. Running two similar tasks allows for a generalization test for computational models. Behavioral results from both tasks replicated findings in the literature such that participants selected the option without rare events more often as if they underweighted rare events (e.g. Erev et al., 2010; Hertwig et al., 2004; Hills & Hertwig, 2010).

### 2.3.2 Model Description

For the minimal information paradigm tasks, a slightly modified EFP model was compared to a reinforcement learning (RL) model and a reinforcement learning plus perseveration (RLP) model, which have been often used to model choice data from the minimal information paradigm but do not take into account the frequency heuristic (e.g., Erev et al., 2010; Erev & Barron, 2005). The RL model assumes a delta learning rule with which it updates expected values $E_j(t)$ for each chosen option, *i*, on trial *t*:

$$E_i(t) = E_i(t-1) + \phi \cdot [x(t) - E_i(t-1)] \tag{16}$$

$\phi$ represents the recency parameter ($0 \leq \phi \leq 1$) that describes the weight given to recent outcomes in updating expectancies. This value-updating function is similar to

Equation 2 which is used in the PVL-Delta model. But here the utility function is an identity function (instead of discounting outcome values with a shape parameter or weighing gains and losses differently with a loss aversion parameter). The expected values from Equation 16 are then entered in a Softmax rule function (4) to compute the probability of selecting each option.

The RLP model additionally incorporated a perseveration term, $P_t(i)$. This term for option *i* is simply 1 if that option was chosen on the previous trial, and 0 otherwise:

$$P_i(t) = \begin{cases} 1, & if\ a_{t-1} = i \\ 0, & otherwise \end{cases} \tag{17}$$

The EFP model was slightly modified for modeling the minimal information tasks. Both tasks only yield gains or no reward. A loss aversion parameter in the utility function (8) is unnecessary, and hence removed for parsimony. As such, (8) is reduced to an identify function, same as the RL and RLP models. Accordingly, the frequency term in the EFP model was changed such that the frequency term for chosen option *i*, on trial *t*, differed based on whether the outcome, *x(t)*, was positive or zero:

$$F_i(t) = \begin{cases} (1-\phi)\cdot F_i(t-1)+1 & if\ x(t)>0 \\ (1-\phi)\cdot F_i(t-1) & if\ x(t)=0 \end{cases} \tag{18}$$

The frequency value increases by 1 following a gain or does not change following a zero outcome. Other aspects of the EFP model used for the minimal information tasks were the same as the one for the IGT and SGT.

### 2.3.3 Method 1: Model Fits

The EFP model was first compared to the RL model, the RLP model, and the baseline model on post hoc model fits. Each model was fit to each participants' data by maximizing the log-likelihood for the model's prediction on each trial, and an average

BIC value was computed for each model. Table 4 displays the average BIC value for each model. The EFP model exhibited the smallest BIC in both the two-choice task and four-choice task, indicating that the EFP model provides a better fit to the data than other models. Note that the RLP also provides a fairly good fit to the data.

**Table 4 Average BIC value for each model for the Minimal Information paradigm**

| Model | EFP | RLP | RL | Baseline |
|---|---|---|---|---|
| Two-Choice | **132.27(18.15)** | 135.70(18.24) | 142.15(11.87) | 133.35(13.38) |
| Four-Choice | **253.60(25.86)** | 259.78(28.29) | 264.82(25.61) | 273.60(45.52) |

*Standard deviations are listed in parentheses. Values in boldface are the minimum BIC values among these models*.

### 2.3.4 Method 2: Simulations

These models were then evaluated regarding their abilities to reproduce choices made by participants. The procedure was like the one for the IGT data. 1000 simulations were run with each set of best-fitting parameter values. Each simulation generated a sequence of choices. The proportion of trials that participants and each model selected the option with frequent gains was computed. In the calculation, the two options with frequent gains in the four-choice task were collapsed to facilitate comparison. Figure 2 displays the proportion of trials that participants and each model selected the frequent gains option. The choices simulated from the EFP model mirrored participants' choices better than did the RL model and RLP model. The problem of the last two models appears to be not considering participants' tendency to choose an option with frequent

gains. Thus, it is understandable they under-predicted the proportion of trials that participants selected the frequent gains options.

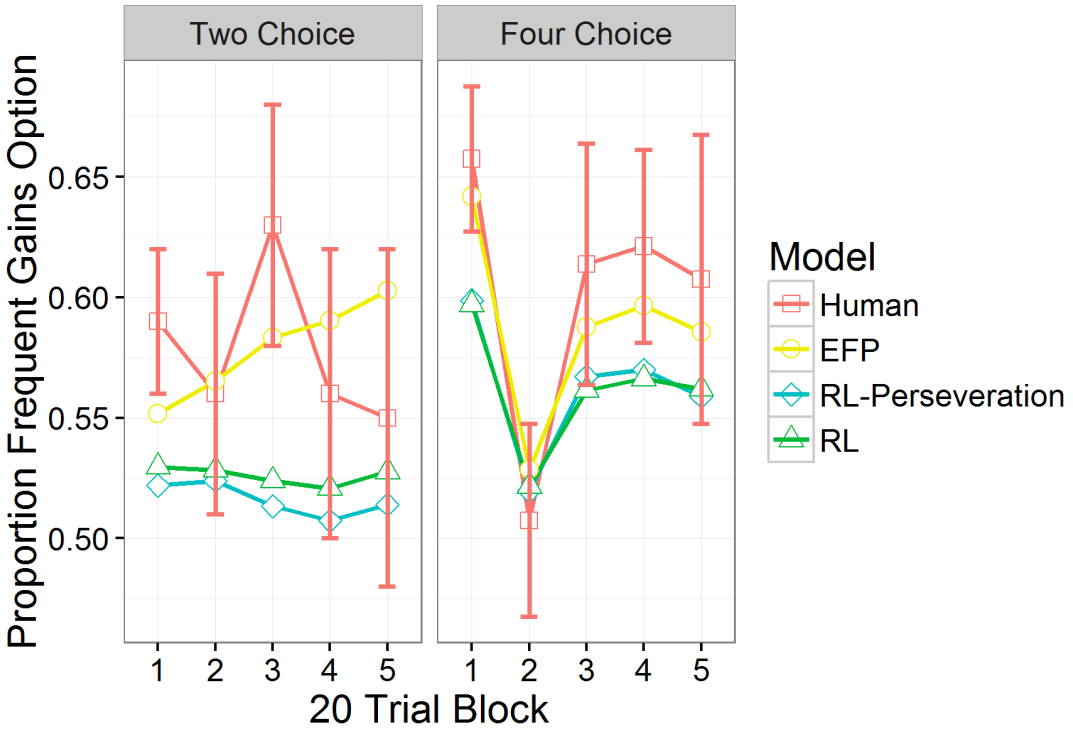


**Figure 2 Observed and simulated choices from the option(s) with frequent gains. Simulations were run with each set of best-fitting parameter values. The error bars for human choice behavior indicate 95% confidence intervals.**

### 2.3.5 Method 3: Generalization Criterion Method

The EFP model's ability to make a priori predictions of new conditions was evaluated against that of the RL and RLP models. The test procedure was the same as that used for the IGT and SGT data. The best-fitting parameters from the first task, either the two-choice or four-choice task, were utilized to simulate choices in the second task,

either the four-choice or two-choice task, respectively. A difference score, indicating a model's prediction ability, was computed accordingly. Table 5 summarizes the difference scores for all models and both tasks. It is evident that the EFP model outperformed the other two models when the best-fitting parameters for the two-choice task data were used to predict choices on the four-choice task. From the four-choice to the two-choice task, the EFP and RL models did better than the RLP model.

**Table 5 Generalization criterion method results for the Minimal Information paradigm**

| Target task | Model | Estimated Task | |
|---|---|---|---|
| | | Two-Choice | Four-Choice |
| Two -Choice | EFP | | **20.58** |
| | RLR | | 35.90 |
| | RL | | 33.85 |
| Four -Choice | EFP | **31.25** | |
| | RLR | 35.68 | |
| | RL | 31.79 | |

*Values in boldface indicate the best model for each method in each condition.*

## 2.4 Paradigm 3: Dynamic Decision Making Task

### 2.4.1 Task Description

In the previous two sections, results showed that frequency heuristic-based models outperformed other established models in terms of post hoc model fits, reproducing observed choices, and a priori predictions, indicating the significance of the frequency heuristic in experience-based decision-making. In the tasks that were examined in the previous sections, different alternatives have distinct frequencies of gains or losses. However, in some decision contexts, all alternatives produce gains or

losses with the same frequency. In these situations, the regular frequency heuristic is uninformative since all alternatives give gains or losses with the same frequency. Nevertheless, frequency of other task features could be informative and decision makers might employ them to make decisions.

Here I examined a dynamic decision-making paradigm which has been widely used to investigate various aspects of decision-making behavior. In contrast to the previous two paradigms where payoff structure is static and hinges only on the current choices, in a dynamic decision making paradigm the payoff on a trial depends not only on the current choices but also on the choices made on previous trials. In particular, I utilized two published data sets from two similar tasks (Pang, Otto, & Worthy, 2015). This is the first time that computational models have been applied to these data. In both tasks, participants chose from two options on each trial. One option is a *decreasing option* which consistently produces a larger immediate reward, although selecting it causes future rewards for both options to decrease. The other option is an *increasing option* which, when selected, causes rewards for both options to increase on future trials.

The only difference between the tasks is that in one task the two options have equivalent expected values (referred to as the Equal Task), while in the other task the decreasing option has higher expected value than the increasing option (referred to as the Decreasing Optimal Task). In both tasks, although choosing both options consistently yields rewards, selecting the increasing option results in an improvement on each trial before reaching its maximum; in contrast, choosing the decreasing option leads to a decrement on each trial before reaching its minimum. It is likely that participants might

track the frequency of positive changes, improvements, versus negative changes, decrements, and incorporate this information into their decision processes.

### 2.4.2 Model Description

To extend the EFP model for tracking the frequency of positive changes versus negative changes in payoffs, the frequency term was changed such that the frequency term for chosen option *i*, on trial *t*, differed based on whether the payoff change was positive or negative:

$$F_i(t) = \begin{cases} (1-\phi)\cdot F_i(t-1)+1 & \text{if } x(t)-E_i(t-1)\geq 0 \\ (1-\phi)\cdot F_i(t-1)-1 & \text{if } x(t)-E_i(t-1)<0 \end{cases} \tag{19}$$

where $x(t)$ is the payoff received on trial *t*, and $E_i(t-1)$ is the expected value of option *i* on last trial. The frequency value increases by 1 following a positive change or decreases by 1 following a negative change. Other aspects of the EFP model used for the dynamic decision-making tasks were kept the same.

A reinforcement learning (RL) model and an eligibility trace (ET) model are often utilized to model choices in dynamic decision making tasks (Gureckis & Love, 2009; Worthy et al., 2012). The RL model was the same as the one for the minimal information paradigm. The eligibility trace (ET) model is an extension of the RL model. The ET model assumes that an eligibility trace associated with each option encodes how often this option has been selected in the past. When expected values are updated, these eligibility traces allow for "credit" being assigned to not only the most recent chosen option but also to other options according to the respective choice history. In the dynamic decision-making task, if the decreasing option is selected on the current trial but was not chosen frequently in the past, and the increasing option was chosen quite

often in the past, the ET model reinforces selecting the increasing option more than choosing the decreasing option following this selection. Formally, the ET model assumes that each time an option, *i*, is chosen the eligibility trace for that option, $\varepsilon_t(i)$, is incremented according to:

$$\varepsilon_t(i) = \varepsilon_{t-1}(i) + 1 \tag{20}$$

The expected value updating rule extends the basic RL model to include the additional eligibility trace term:

$$E_t(j) = E_t(j) + \phi \cdot [E(t) - E_i(t-1)] \cdot \varepsilon_t(j) \tag{21}$$

here $\phi$ is a learning rate parameter as defined in (2). Instead of only updating expected value for the chosen option as in the basic RL model, the ET model updates expected values for all options, *j*.

On each trial, the eligibility trace, $\varepsilon_t(j)$, for every option, *j*, decays based on a decay parameter, $\zeta, 0 \leq \zeta \leq 1$:

$$\varepsilon_t(j) = \varepsilon_{t-1}(j) \cdot \zeta \tag{22}$$

Higher decay parameter ($\zeta$) values indicate less decay of memory traces for recent actions and more credit assignment to options that have been frequently selected in the recent past.

### 2.4.3 Method 1: Model Fits

The EFP model was compared against the ET, RL, and Baseline model. Following the procedure laid out in the previous sections, these models were compared in terms of the average BIC values. Table 6 displays the average BIC value for each

model. For both tasks, the EFP model exhibited a much smaller average BIC value than other models, suggesting a better fit the EFP model to choices in both tasks.

**Table 6 Average and BIC value for each model for the Dynamic Decision-Making tasks**

| | EFP | ET | RL | Baseline |
|---|---|---|---|---|
| Dec Optimal | **237.95(69.18)** | 278.13(72.63) | 292.89(68.22) | 295.43(58.06) |
| Equal | **232.97(78.73)** | 277.73(85.25) | 277.43(86.83) | 283.47(78.87) |

*Standard deviations are listed in parentheses. Values in boldface are the minimum BIC values among these models.*

### 2.4.4 Method 2: Simulations

Following the procedure from the previous sections, choices were simulated with the EFP, ET, and RL model. The proportion of times that participants and each model selected the increasing option within each 25-trial block was computed. The results are displayed in Figure 3. Clearly, simulated choices from the EFP model best mimicked observed choices. Nevertheless, all models failed to capture the initial trend of participants' choices. All models over-predicted the tendency to select the increasing option at the first and/or second block. The dynamic decision-making task is a complicated task. There might be mechanisms that this set of computational models did not capture. The goal of the EFP model is not to account for participants' decision-making processes completely but to investigate whether it can provide improved explanation over models that do not incorporate the frequency information. The EFP model obviously produced a choice pattern much closer to participants' choice pattern compared to the ET and RL model. The two latter models under-predicted the tendency

to select the increasing option. The increasing option consistently provided frequent improvements in payoffs. Participants might keep track of the frequency of the payoff improvement due to people's sensitivity to frequency information. The EFP model accounted for this frequency heuristic, thus resulting in a better fit to participants' choices.

### 2.4.5 Method 3: Generalization Criterion Method

Like previous sections, the best-fitting parameters from the first task, either the decreasing optional or equal task, were utilized to simulate choices in the second task, either the equal or decreasing optimal task, respectively. A difference score between observed and predicted probabilities of selecting the increasing option was computed for each model. Table 7 displays the scores for all models and both tasks. The EFP model outperformed the other two models. Also, it is worth noting the RL model performed better than the ET model in terms of the generalization criterion. Taken together, the enhanced complexity of the EFP model relative to the RL model was justified by the generalization criterion test, while the increased complexity of the ET model seemed to lead to overfitting.

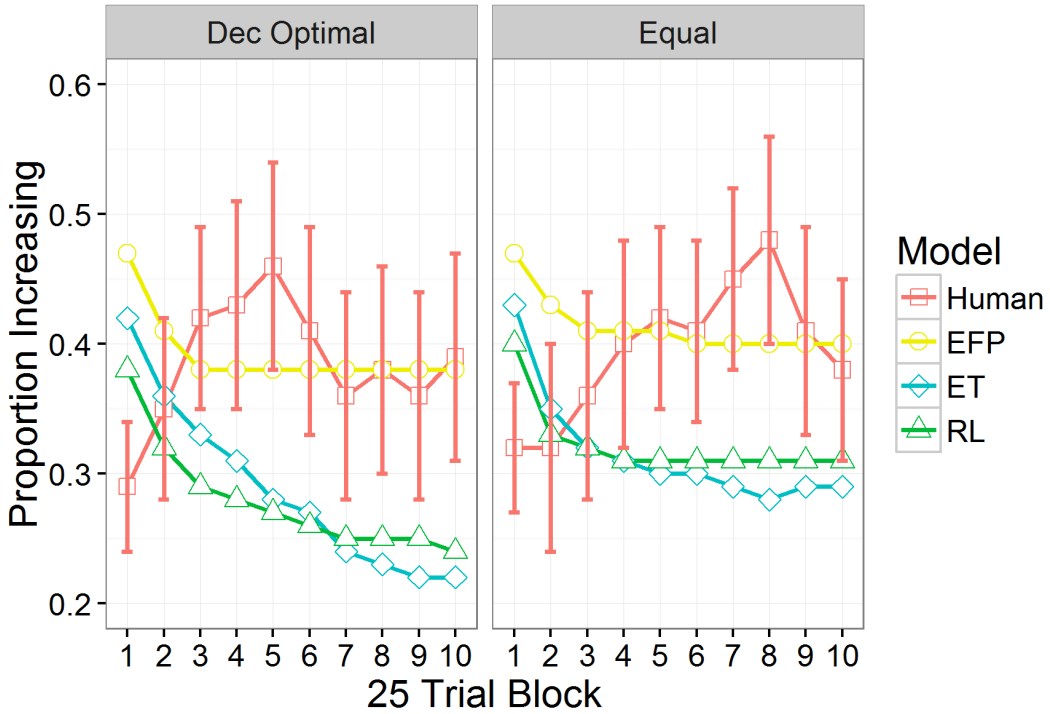


**Figure 3 Observed and simulated choices from the increasing option. Simulations were run with each set of best-fitting parameter values. The error bars for human choice behavior indicate 95% confidence intervals.**

**Table 7 Generalization criterion method results for the Dynamic Decision-Making tasks**

| Target task | Model | Estimated Task | |
|---|---|---|---|
| | | Dec Optimal | Equal |
| Equal | EFP | **68.30** | |
| | ET | 139.39 | |
| | RL | 113.87 | |
| Dec Optimal | EFP | | **97.32** |
| | ET | | 269.83 |
| | RL | | 211.83 |

*Standard deviations are listed in parentheses. Values in boldface are the minimum BIC values among these models.*

## 2.5 Discussion

Recently, more and more research focuses on decisions from experience (e.g., Hertwig, 2012; Hertwig, et al., 2004; Hills & Hertwig, 2010). In experience-based decision-making, frequency of gains and/or losses is often salient. Moreover, previous research demonstrates that people are highly sensitive to frequency information (e.g., Hasher & Zacks, 1984; Hasher & Zacks, 1979). Thus, frequency of gains versus losses might play an important role in experience-based decision-making. This study took a computational modeling approach to address this issue. A wide range of computational models have been established such as the PVL models (Ahn et al., 2008), the VPP model (Worthy et al., 2013) and the ET model (Gureckis & Love, 2009). These models mainly account for expected value, and some models also take into account perseveration (e.g., VPP). Extending from these models, EFP models which incorporated the frequency heuristic were developed for three major experience-based decision-making paradigms, and were compared to previous models thoroughly through three model comparison approaches.

Although they were not always superior to other models, the EFP models consistently performed well across different decision-making contexts and on different model performance indexes. The EFP models are more complex than some models but the generalization criterion results justified the slightly improved complexity, while some other complex models sometimes failed in the generalization criterion test. The consistently good performance of the EFP model supports the idea that people are highly sensitive to frequency information. More importantly, it indicates a critical role of gain-

loss frequency and the pervasiveness of the frequency heuristic in experience-based decision-making.

In addition, Study 1 contributes to the following studies by providing the EFP model to further understanding of choice data. Besides behavioral data analysis, applying the model to the data allows me to decompose the contributions of gain-loss frequency and expected value to choice behavior, thus providing more direct insight into the underlying psychological mechanisms of decision-making process.

# 3. STUDY 2

Study 2 was intended to assess the role of WM in the use of the frequency heuristic. WM load was manipulated by a dual-task paradigm. One group of participants performed the SGT only, while the other group performed the SGT and a WM-demanding task concurrently. Previous research on the relation between WM and the performance in the IGT yielded mixed results (e.g., Dretsch & Tipples, 2008; Li et al., 2010; Turnbull, Evans, Bunce, Carzolio, & O'Connor, 2005). In terms of frequency processing, prior work found that age, verbal ability, or intention did not impact frequency judgment accuracy (e.g., Hasher & Zacks, 1979; Zacks, Hasher, & Sanft, 1982), suggesting that frequency processing requires few WM resources, thus implying the absence of effects of WM load on the use of frequency heuristic. However, previous research where cognitive load was manipulated provided evidence that WM load impairs frequency processing (Mutter & Goedert, 1997; Naveh-Benjamin & Jonides, 1986; but see Zacks et al., 1982). Moreover, in prior studies, single task participants tended to use a simple heuristic, win-stay-lose-shift, while participants under WM load tended to make choices based implicitly tracked expected values (Otto et al., 2011; Worthy et al., 2012). I thus predicted that WM load would reduce the use of frequency heuristic in the decision-making task. Since reliance on the gain-loss frequency in the SGT is disadvantageous, it was also predicted that WM load would enhance the SGT performance.

## 3.1 Method

### 3.1.1 Participants

Eighty-three participants (49 females) recruited from an introductory psychology course at Texas A&M University participated in the experiment for course credit. Informed consent was obtained from all participants, and the experiment was approved for ethics procedures using human participants. Participants were randomly assigned to either the single task (ST; $n$ = 42) or dual task (DT; $n$ = 41) condition. My original goal was to collect 40 participants in each condition, but these numbers were slightly exceeded due to an oversight by the experimenters.

### 3.1.2 Materials and Procedures

Participants performed the experiment on PCs using Psychtoolbox for Matlab (version 2.5). Participants in the ST condition only performed the SGT (Chiu et al., 2008). They were informed that the game involved a series of selections from four decks of cards and each selection would always result in either gains or losses. Participants started off with 2,000 points and were instructed to try to finish with a total of at least 2,500 points. On each of 100 trials, four decks of cards appeared on the screen and participants were prompted to select one deck. Upon each selection the computer screen displayed the reward or penalty beneath the card decks. The cumulative total score was displayed on the right side of the screen. The task was self-paced, and participants were unaware of how many card draws they would receive. The schedule of gains and losses was identical to those used Chiu et al., 2008 (see Table 1).

In the DT conditions, in addition to the SGT participants performed a numerical Stroop task concurrently. The memory task required participants to remember which of two numbers was physically larger and which was larger in numerical value while performing the SGT. On each trial the four decks of cards were presented in the center of the screen. At the beginning of each trial, two numbers for the concurrent memory task were presented on each side of the screen, one number on each side, for 300 ms. Participants were then allowed to make a selection from among four decks of cards, followed by feedback as mentioned above. A new screen then appeared that queried participants with either *VALUE* or *SIZE*, and they selected either *Left* or *Right* to indicate which side had the number largest in either numerical value or physical size. Upon making a selection, they were told whether they were correct or not, and then the next trial began.

Following previous studies that have used the same concurrent task manipulation, participants were told that they should focus on achieving good performance on the numerical Stroop task and "use what you have left over" for the decision-making task (Waldron & Ashby, 2001; Worthy et al., 2012; Zeithamova & Maddox, 2006). To allow them to become familiar with the procedure, participants were given 10 practice trials. The practice trials were the same as the formal ones except that each selection on the SGT resulted in zero points regardless of which deck they selected.

## 3.2 Results

### 3.2.1 Behavioral Results

I first examined performance in the SGT which was computed as the proportion of advantageous minus disadvantageous deck selections. One hundred card selections were divided into five blocks of 20 trials. Figure 4 displays performance over five 20-trial blocks in each condition. A mixed ANOVA with WM load (ST versus DT) as a between-subjects factor and Block (five 20-trial blocks) as a within-subject factor revealed a significant main effect of WM load, $F(1, 81) = 6.50$, $p = .01$, partial $\eta^2 = .07$, and for block, $F(4, 324) = 14.76$, $p = .00$, partial $\eta^2 = .15$. The WM load X Block interaction was also significant, $F(4, 324) = 2.95$, $p = .02$, partial $\eta^2 = .04$. To examine this interaction, I looked at the simple effect of WM load within each block using *t*-tests. As can be seen in Figure 4, although participants in both the ST and DT conditions appeared to learn to perform better across the task, DT participants performed better compared to ST participants in the first three blocks (*p*s < .01), but ST participants reached a similar performance level as DT participants in the last two blocks (*p*s > .72). This result suggests that WM load affected decision-making early in the SGT such that WM load improved performance.

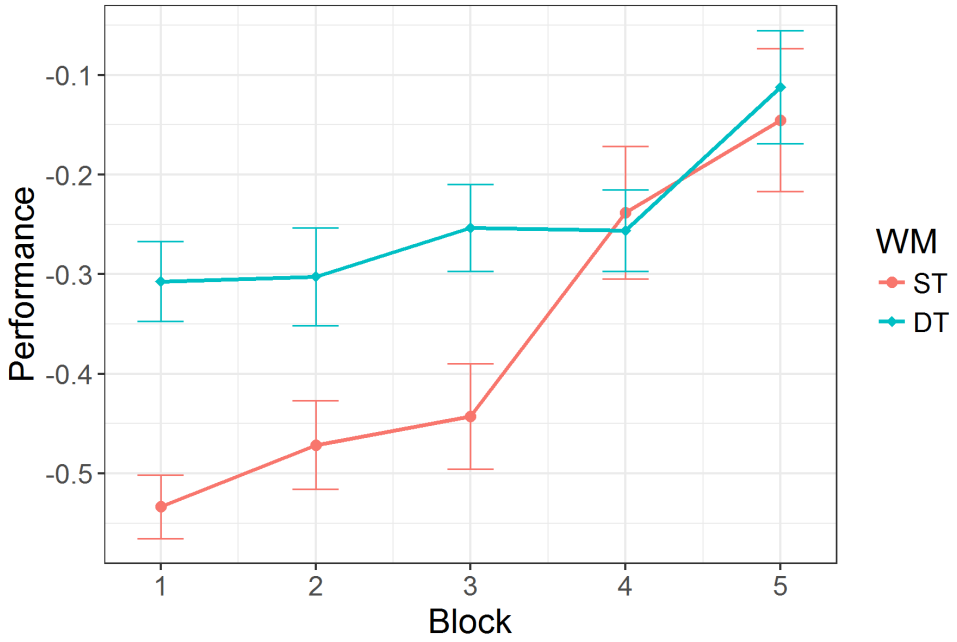


**Figure 4 Performance in the Soochow Gambling Task (SGT) by 20-trial blocks for each WM condition (ST versus DT) in Study 2. Error bars represent ±1 SE.**

I next conducted a similar mixed ANOVA for each deck. Figure 5 displays the proportion of trials that each deck was selected over five 20-trial blocks in each WM condition. For Deck A there was a main effect of block, $F(4, 324) = 9.87$, $p = .00$, partial $\eta^2 = .11$, suggesting that all participants learned to select Deck A less often over the task. No other significant results were observed (*p*s > .11).

The analysis for Deck B showed that ST participants ($M = .31$, $SD = .06$) selected disadvantageous Deck B more often than DT participants ($M = .23$, $SD = .08$), $F(1, 81) = 20.77$, $p < .001$, partial $\eta^2 = .20$. There was also a significant main effect of block, $F(4, 324) = 3.25$, $p = .01$, partial $\eta^2 = .04$, and a significant WM load X Block interaction, $F(4, 324) = 2.53$, $p = .04$, partial $\eta^2 = .03$. To examine this interaction, I looked at the

simple effect of WM load within each block using an independent samples *t*-test. ST participants chose Deck B more often in the first three blocks (*p*s < .01) than did DT participants, but they did not significantly differ in the last two blocks (*p*s > .14).

For Deck C, ST participants ($M$ = .17, $SD$ = .09) chose this advantageous Deck C less often than did DT participants ($M$ = .23, $SD$ = .09), $F(1, 81) = 7.71$, $p = .01$, partial $\eta^2 = .09$. It also revealed a significant main effect of block, $F(4, 324) = 9.81$, $p < .001$, partial $\eta^2 = .11$, suggesting that participants in both conditions learned to select Deck C more often as the task progressed. The interaction was not significant ($p = .10$).

For Deck D, there was a main effect of block, $F(4, 324) = 3.95$, $p = .00$, partial $\eta^2 = .05$, indicating that participants in both conditions learned to select Deck D more often. No other significant results were observed (*p*s > .22).

To summarize, the data from Study 2 indicated that participants under WM load performed better overall than ST participants, and that this advantage was due to better performance early on in the task. This pattern of behavior may have been due to participants who performed the task under the no-load condition being initially biased towards the disadvantageous decks because of their enhanced attention to the high frequency of gains and low frequency of losses provided by these decks. As the task progressed, ST participants learned to select the decks based on their expected values rather than their gain-loss frequencies.

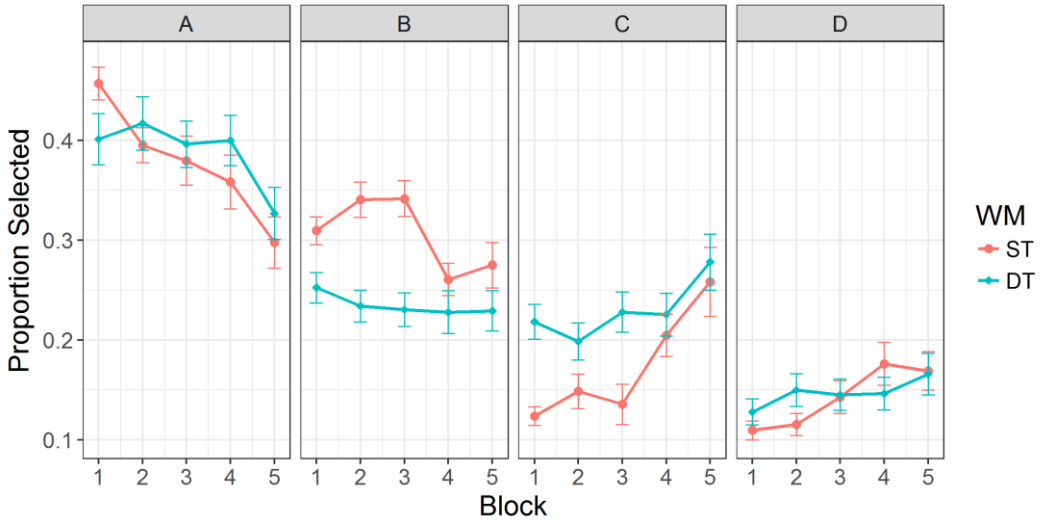


**Figure 5 Proportion that each deck was selected in the Soochow Gambling Task (SGT) by 20-trial blocks under each WM condition (ST versus DT) in Study 2. Error bars represent ±1 SE.**

### 3.2.2 Modeling Results

*Model Selection*

Five models were fit to the data, including the EFP model that was developed in Study 1, the two PVL models, the VPP model, and the baseline model (see Study 1 for detailed descriptions of these models). I fit each participant's data in each condition individually by maximizing the log-likelihood for each model's prediction on each trial. BIC was used to examine the relative fit of the models. Average BIC values for each model under each condition are listed in Table 8. In both WM conditions, the EFP model had the smallest average BIC values. Thus, these data suggest that the EFP model provides a better fit than other models to the choice behavior in the SGT.

**Table 8 Average BIC values for each model as a function of the WM condition in Study 2**

| Model | ST | DT |
|---|---|---|
| EFP | **246.02(33.09)** | **264.63(26.35)** |
| VPP | 249.11(33.77) | 271.89(26.97) |
| PVL-Delta | 264.12(21.38) | 269.23(25.82) |
| PVL-Decay | 250.23(25.66) | 267.49(24.88) |
| Baseline | 266.34(20.24) | 265.19(23.90) |

*Standard deviations are listed in parentheses. Values in boldface are the minimum BIC values among these models.*

*Comparison of Best-Fitting Parameters*

I next compared the parameter estimates of the EFP model between the ST and DT conditions to examine the effects of WM load on specific psychological processes related to decision-making. Table 9 lists the median best fitting parameter values of the EFP model under each WM condition. Nonparametric Mann-Whitney U tests were used because the best-fitting parameters were not normally distributed. ST participants exhibited lower values for the weight parameter than did DT participants, $U = 637$, $p = .04$. This suggests that participants with compromised cognitive resources were less likely to utilize the frequency heuristic in the SGT. Moreover, data from ST participants were best fit by higher learning rate parameter values than data from DT participants, $U = 626$, $p = .03$. This result suggests that ST participants were more attentive to recent outcomes, which might allow participants with intact WM resources to more actively update expectancies compared to participants under WM load. ST participants also exhibited higher perseveration values than did DT participants, $U = 435$, $p < .001$, suggesting that ST participants were more likely to perseverate with the choice previously chosen. I also found that ST participants showed lower consistency parameter

values than did DT participants, U = 629, p = .04, indicative of enhanced exploration among ST participants. Last, the difference in loss aversion parameter estimates was not significant, U = 730, p = .22.

**Table 9 Median parameter estimates from maximum likelihood fits as a function of the WM condition in Study 2**

| Parameters | ST | DT |
|---|---|---|
| Learning | 0.29 | 0.09 |
| Loss Aversion | 0.42 | 0.04 |
| Perseveration | 0.34 | −0.13 |
| Weight | 0.39 | 0.95 |
| Consistency | 0.77 | 0.90 |

### 3.3 Discussion

The behavioral and computational modeling results provide consistent evidence that WM plays a critical role in utilizing the frequency heuristic in experience-based decision-making. Participants under WM load performed better overall than participants with intact WM resources, and that this advantage was due to better performance early on in the task. Given that a preference to the high-gain-frequency and low-loss-frequency decks leads to inferior performance in the SGT, this pattern of behavior may be because participants who performed the task under the no-load condition were initially biased towards the disadvantageous decks due to their enhanced attention to the high frequency of gains and low frequency of losses provided by these decks, while participants under WM load did not form such a bias because attenuated attention did not allow them to utilize the frequency heuristic. As the task progressed, ST participants learned to select the decks based on their expected values rather than their gain-loss

frequencies. Computational modeling results provided further support to these implications. Participants under WM load exhibited greater weight to RL expected value versus gain-loss frequency than those in the no-load condition, providing direct evidence that WM load reduces attention to gain-loss frequency and thus prevents participants with compromised WM resources forming a bias towards the bad decks based on the frequency information. DT task participants might track expected values implicitly as suggested in Otto et al. (2011) and Worthy et al. (2012). Moreover, participants with intact WM resources exhibited higher learning rate than those under WM load, suggesting that ST participants were more attentive to recent outcomes. This could allow them to more actively update expected values and thus reach a similar level of performance as participants under WM load at later stage of the task.

# 4. STUDY 3

The results from Study 2 suggest that WM contributes to utilizing frequency information in decision-making. What is still unclear is whether WM load reduces the accuracy of gain-loss frequency estimation or undermines other components of the process of using frequency information. Some work in the frequency processing literature suggests that frequency judgment requires no or few WM resources (Hasher & Zacks, 1984; Zacks et al., 1982). It is thus likely that WM load does not impair frequency estimation but other components such as integrating frequency information and expected value. Study 3 served multiple purposes. The first one was to investigate whether WM load would diminish frequency judgment accuracy in a decision-making task, thus causing a problem to utilize the frequency information. Like in Study 2, one group of participants only performed the SGT and the other group did it and a numerical Stroop task concurrently. To examine frequency judgment, at the end of experiment all participants were asked to estimate the frequency of gains and losses for each deck. If WM load does not reduce the accuracy of estimating the gain-loss frequency, it would suggest that WM contributes to other components in the process of using frequency information in decision-making. Otherwise, it would suggest that at least one role of WM is to help reach an accurate judgment of gain-loss frequency, although WM might also contribute to other processes.

Moreover, Study 3 sought to replicate the results from Study 2. In Study 3, participants' working memory capacity (WMC) was also measured. One the one hand, it served as a covariate when the WM load effect was analyzed. On the other, I examined

the association between frequency judgment accuracy and WMC to seek convergent evidence for the role of WM in frequency processing.

Study 3 also address the issue of whether frequency judgment is based on an automatic frequency-processing process. Besides examining it in the decision-making task, I also investigated the effect of WM load on frequency judgment accuracy in a typical frequency processing task, a word frequency judgment task, which allows for directly comparing the current results to previous work on frequency processing. WM load manipulation for the word frequency judgment task was also done with asking participants to perform a numerical Stroop task concurrently. Prior work that directly manipulated WM load exhibited that enhanced WM load diminished the accuracy of estimating the frequency of words in a word list or pictures in a series of pictures (e.g., Naveh-Benjamin & Jonides, 1986; Sanders et al., 1987). Hence, I hypothesized that WM load would reduce frequency judgment accuracy in both the word frequency judgment task and the SGT.

The last purpose of Study 3 was to compare the effects of WM load on frequency judgment in the typical frequency processing task and the decision-making task. Decision-making is presumably a more complicated process than word frequency judgment. Thus, even if WM load does not reduce the judgment accuracy in the word frequency judgment task, it might diminish the accuracy in the decision-making task. Also, it is possible that frequency judgment is generally WM-dependent, and thus WM load would exhibit similar levels of effects on the judgment accuracy in the word frequency judgment task and decision-making task.

## 4.1 Method

### 4.1.1 Participants

One hundred and eighty participants (seventy-three females) recruited from an introductory psychology course at Texas A&M University participated in the experiment for course credit. Informed consent was obtained from all participants, and the experiment was approved for ethics procedures using human participants. Forty-five participants were randomly assigned to each of the four conditions where they performed the following tasks: the word frequency judgment task (word ST condition), the word frequency judgment and numerical Stroop task (word DT condition), the SGT (decision-making ST condition), the SGT and numerical Stroop task (decision-making DT condition). Four participants were excluded due to computer failure: 2 from the decision-making ST condition, 1 from the decision-making DT condition, and 1 from the word ST condition.

### 4.1.2 Materials and Procedures

All experiment tasks were implemented on PCs using Psychtoolbox for Matlab (version 2.5) except the frequency judgment part in the SGT and the word frequency judgment task. Participants completed the judgment part with pen and paper.

*SGT*

For the two groups of participants who performed the SGT, the materials and procedures are similar to those in Study 2. There was one difference. After finishing the decision-making task, participants in both the ST and DT conditions were asked to make

frequency judgments on gains and losses for each deck. Specifically, the questions they were asked are:

*Suppose you were to select 100 cards from Deck A*

*In how many of the 100 trials would you expect to get a loss?*

*In how many of the 100 trials would you expect to get a gain?*

*Word Frequency Judgment Task*

The pool of words used to construct the stimulus list consisted of 25 English nouns with a length of 5 to 7 letters and a frequency of 35 to 50 occurrences per 50,000 according to the Francis and Kucera's (1982) analysis of word usage frequency. Five of these words appeared twice in the list, another five words appeared three times, and so on, with the last five appearing six times. Together, there are 100 target stimuli (100 = 5*2 + 5*3 + 5*4 + 5*5 + 5*6; matching the 100 cards in the decision-making task). To absorb primacy and recency effects, 5 additional words were added to the beginning of the list and 5 to the end. In addition, 4 words were added to the beginning of the list for practice. Altogether, there were 114 words in the stimulus list for of this study. These words were presented at a rate of one word per 4s.

In the study phase of the task, ST participants only studied the words. On each trial, one word was presented on the computer screen for 4s. Participants were told to pay close attention to each word to prepare for an upcoming frequency judgment test. DT participants were told that they would perform two tasks during the presentation of the words. One task was to study the words and the other was to answer questions about numbers presented on each trial. The procedure was the same to that used in the

decision-making DT condition except that the SGT was replaced with the word study task. At the beginning of each trial, two numbers were presented for 300 ms, then a word was presented for 4s, and finally participants responded to questions about the physical size or numerical value of the numbers. Following Study 2, participants were instructed that they should focus on achieving good performance on the number memory task and "use what you have left over" for the word study task.

After studying the words under either a ST or DT condition, participants were asked to judge the frequency of occurrences of a list of 50 words. This list consisted of the 25 target words having appeared in the study phase and another 25 new words which have a similar word length and frequency in English usage. The 50 words were randomly mixed. Participants were given a sheet with these words and asked to write down a number for each word which represents the frequency of appearance of each word in the study phase. They were informed that some of these words were not appeared in the study phase. This design is modified based on Naveh-Benjamin and Jonides (1986) and Mutter and Goedert (1997).

*WMC*

At the conclusion of the experiment, participants from all conditions were asked to complete a task to measure their working memory capacity (WMC). The operation span task (OSPAN; Turner & Engle, 1989) was administered to measure WMC. In this task, participants were required to solve a series of math operations and remember unrelated words. In particular, they were first asked to solve a math problem (e.g., (8/2) + 2 = 5? respond yes or no) and then remember a word (e.g., bear). They were then to

solve another math problem, followed by another word. After a particular number (e.g., 3) of pairs of math-word problems (i.e., a set of pairings), they were asked recall the words in order presented in that set. The size of the set of math-word pairings ranged from 2 to 5 items. The OSPAN score was calculated by summing the number of words recalled for all correctly recalled sets.

## 4.2 Results

### 4.2.1 Decision-Making Behavioral Results

The analysis was like that in Study 2 except that WMC was included in the analysis. First, the overall performance was examined. Figure 6 displays performance over five 20-trial blocks in each WM load condition. I conducted an ANCOVA with WM load (ST versus DT) as a between-subjects factor, Block (five 20-trial blocks) as a within-subject factor, and WMC as a covariate. It revealed a significant main effect of WM load, $F(1,84) = 5.33$, $p = .02$, partial $\eta^2 = .06$. ST participants ($M = -.38$, $SD = .27$) performed worse than DT participants ($M = -.25$, $SD = .25$). No other main effects or interactions were significant, $p$s $> .25$. These results suggest that WM load improved overall performance in the SGT, consistent with the finding from Study 2.

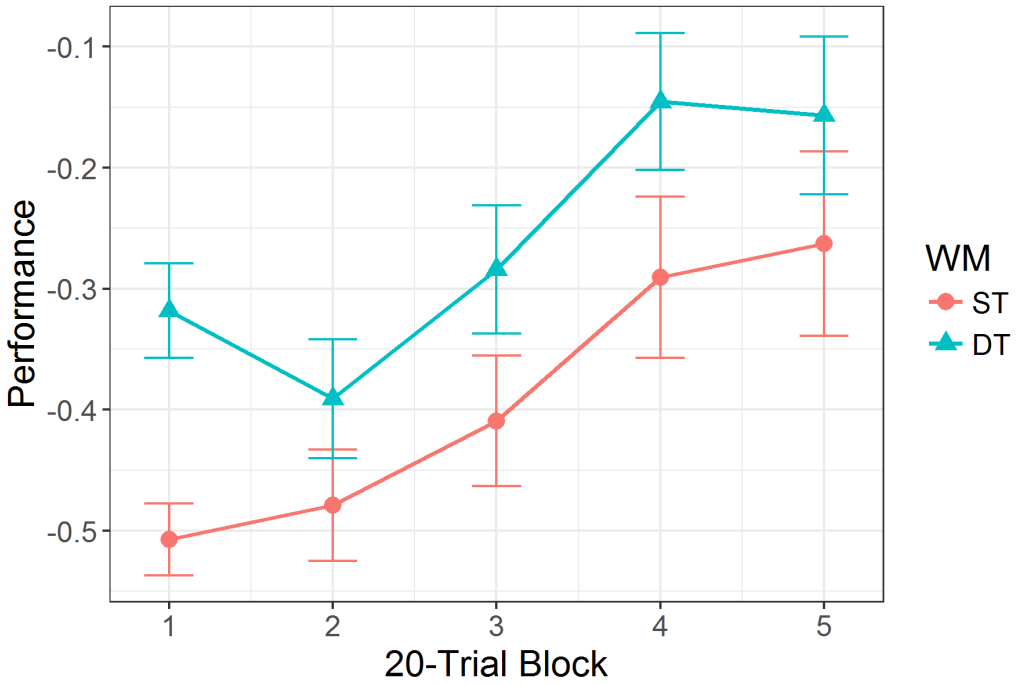


**Figure 6 Performance in the Soochow Gambling Task (SGT) by 20-trial blocks for each WM condition (ST versus DT) in Study 3. Error bars represent ±1 SE.**

I next conducted a similar ANOVA for each deck. Figure 7 displays the proportion of trials that each deck was selected over five 20-trial blocks in each WM condition. The analysis for Deck A did not reveal any significant effects, *p*s > .29.

For Deck B there was a main effect of WM load, $F(1, 84) = 8.51$, $p < .01$, partial $\eta^2 = .09$. ST participants ($M = .29$, $SD = .14$) selected disadvantageous Deck B more often than DT participants ($M = .23$, $SD = .12$). There were no other significant main effects or interactions, *p*s > .55.

The analysis for Deck C revealed a significant WM load X Block interaction, $F(4, 336) = 3.28$, $p = .01$, partial $\eta^2 = .04$. To examine this interaction, I looked at the simple effect of WM load within each block using an independent samples *t*-test. ST

participants chose Deck C less often in the first block ($p$ = .01) than did DT participants, but they did not significantly differ in the following blocks ($p$s > .25). No other significant results were observed ($p$s > .34).

For Deck D, ST participants ($M$ = .12, $SD$ = .09) chose this advantageous deck less often than did DT participants ($M$ = .19, $SD$ = .17), $F(1, 84) = 6.43$, $p = .01$, partial $\eta^2 = .07$. It also revealed a significant main effect of block, $F(4, 336) = 4.09$, $p < .01$, partial $\eta^2 = .05$. There were no other significant effects, $p$s > .13.

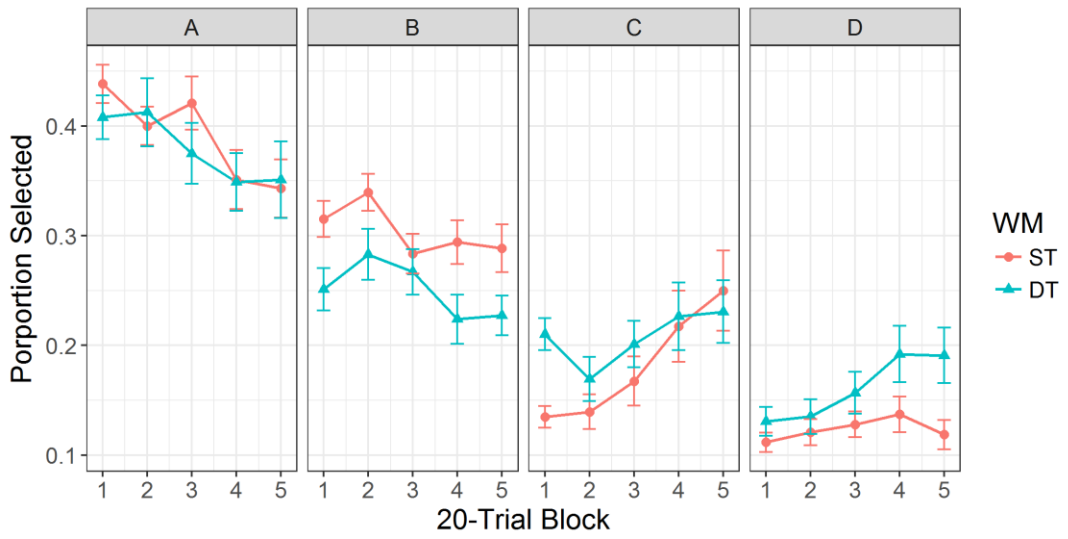


**Figure 7 Proportion that each deck was selected in the Soochow Gambling Task (SGT) by 20-trial blocks under each WM condition (ST versus DT) in Study 3. Error bars represent ±1 SE.**

### 4.2.2 Decision-Making Modeling Results

*Model Selection*

Five models were fit to the data, including the EFP model, the two PVL models, the VPP model, and the baseline model by the same maximum likelihood method as before. Average BIC values for each model under each condition are listed in Table 10. In both WM conditions, the EFP model had the smallest average BIC values. Thus, these data suggest that the EFP model provides a better fit than other models to the choice behavior in the SGT. Note that the VPP model also performed well for the data from ST participants.

**Table 10 Average BIC values for each model as a function of the WM condition in Study 3**

| Model | ST | DT |
|---|---|---|
| EFP | **241.39(39.78)** | **256.54(32.61)** |
| VPP | 242.14(38.09) | 263.56(31.54) |
| PVL-Delta | 256.77(29.07) | 264.79(29.26) |
| PVL-Decay | 252.79(30.98) | 267.34(28.19) |
| Baseline | 259.77(23.53) | 263.33(23.60) |

*Standard deviations are listed in parentheses. Values in boldface are the minimum BIC values among these models.*

*Comparison of Best-Fitting Parameters*

The parameter estimates of the EFP model between the ST and DT conditions were compared to examine the effects of WM load on specific psychological processes related to decision-making. Table 11 lists the median best-fitting parameter values of the EFP model under each WM condition. Nonparametric Mann-Whitney *U* tests were used because the best-fitting parameters were not normally distributed. ST participants

exhibited lower values for the weight parameter than did DT participants, $U = 881$, $p = .04$. This suggests that participants with compromised cognitive resources were less likely to utilize the frequency heuristic in the SGT, consistent with the behavioral results from this study and the findings from Study 2. No other significant differences were found between the WM load conditions, $p$'s >.15.

**Table 11 Median parameter estimates from maximum likelihood fits as a function of the WM condition in Study 3**

| Parameters | ST | DT |
|---|---|---|
| Learning | 0.14 | 0.11 |
| Loss Aversion | 0.22 | 0.09 |
| Perseveration | 0.00 | −0.07 |
| Weight | 0.68 | 0.97 |
| Consistency | 0.81 | 0.85 |

### 4.2.3 Gain-Loss Frequency Judgment Results

To measure frequency judgment accuracy, the slope of the linear regression relating frequency judgments[5] to actual frequencies was calculated for each participant. Since the slope of 1 indicates a prediction being absolutely accurate, the absolute value of the difference between each calculated slope and 1 was computed as a measure of each participant's judgment accuracy. A smaller number indicates a more accurate judgment. To avoid misunderstanding, I referred to this measure as a frequency judgment score. An ANCOVA was conducted with WM load as a between-subjects

[5] The gain frequency judgments were employed to calculate the accuracy score. Using the loss frequency judgments would yield the same results since the gain and loss frequency judgments were perfectly correlated (All participants knew Gain Frequency = 100 – Loss Frequency).

factor and WMC as a covariate. It revealed a significant main effect of WM load, $F(1, 78) = 7.58$, $p < .01$, partial $\eta^2 = .09$. ST participants ($M = .40$, $SD = .34$) made more accurate judgments than DT participants ($M = .59$, $SD = .40$). There was also a significant effect of WMC, $F(1, 78) = 6.79$, $p = .01$, partial $\eta^2 = .08$. Figure 8 illustrates the relationship between WMC and the frequency judgment score. Participants with higher WMC tended to make more accurate frequency judgments than participant with lower WMC. These results suggest that WM contributes to the process of frequency judgment in the decision-making task.

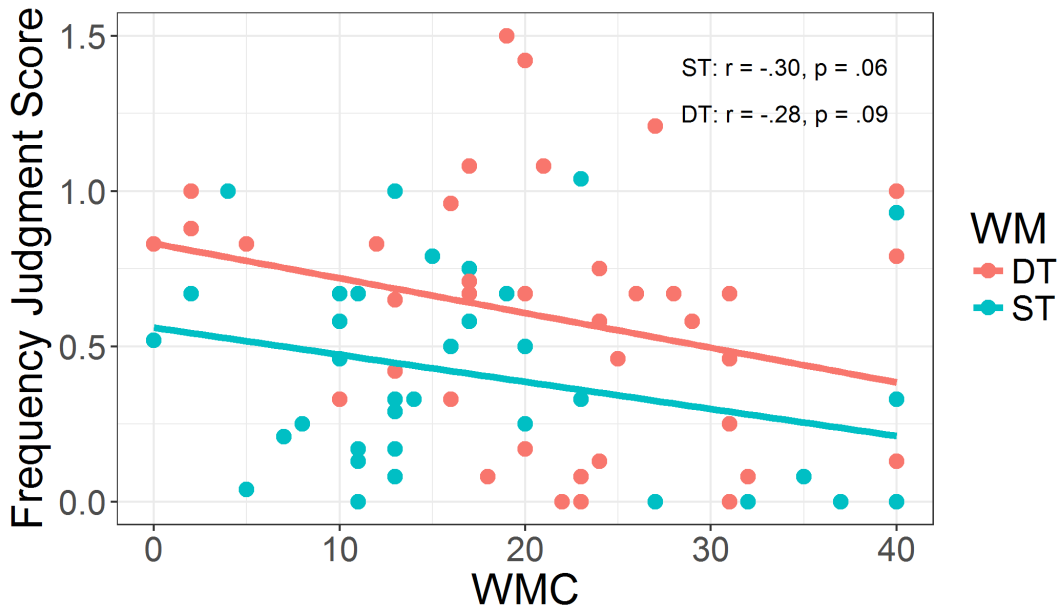


**Figure 8 Association between working memory capacity and frequency judgment scores in the SGT within each WM load condition (ST versus DT).**

### 4.2.4 Word Frequency Judgment Results

The same procedure was used to calculate the frequency judgment scores for the word frequency judgments. An ANCOVA was conducted on the scores with WM load as a between-subjects factor and WMC as a covariate. It revealed a significant main effect of WM load, $F(1, 86) = 5.04$, $p = .03$, partial $\eta^2 = .06$. ST participants ($M = .41$, $SD = .24$) made more accurate frequency judgments about the frequency of occurrences of words than did DT participants ($M = .52$, $SD = .23$). There was also a marginally significant effect of WMC, $F(1, 86) = 3.87$, $p = .05$, partial $\eta^2 = .04$. Figure 9 illustrates the relationship between WMC and the frequency judgment score. Participants with higher WMC tended to make more accurate frequency judgments than participant with lower WMC. These results from the word frequency judgment task are in line with the results from the SGT and confirmed the role of WM in frequency judgment.

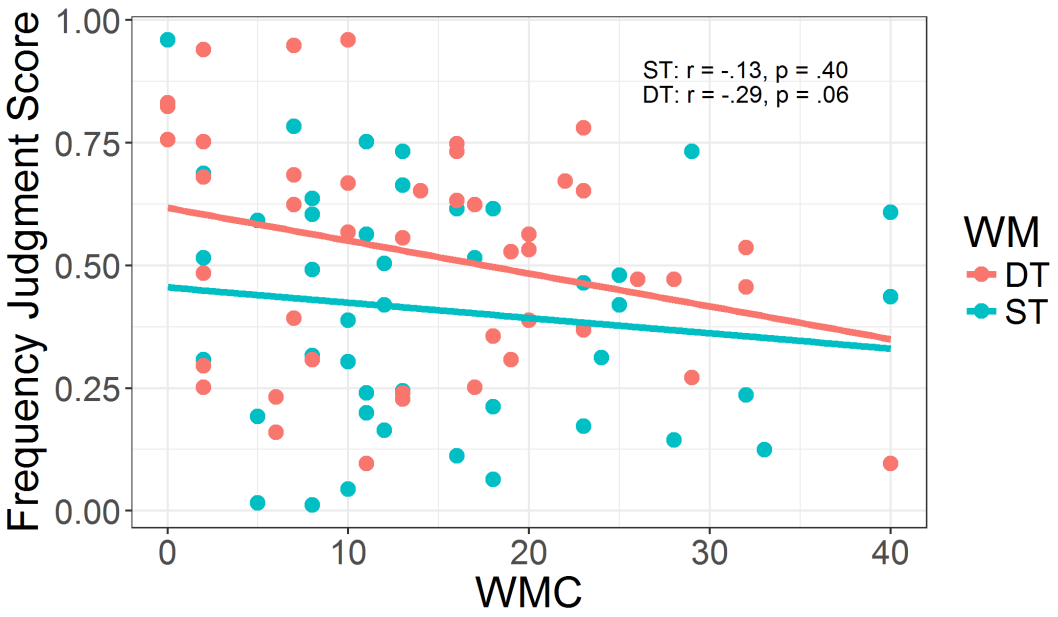


**Figure 9 Association between working memory capacity and frequency judgment scores in the word frequency judgment task within each WM load condition (ST versus DT).**

### 4.2.5 Comparison of WM Effects between the SGT and the Word Task

Considering that the frequency of gains and losses and the frequency of words were on different scales, the accuracy measures might not be comparable directly. Thus, these scores were standardized with the standard deviation for each score distribution before comparison. An ANCOVA was then conducted with Task (SGT versus Word Task) and WM load as between-subjects factors, and WMC as a covariate. It uncovered significant main effects of WM load and WMC, $F(1, 165) = 12.55$, $p = .001$, partial $\eta^2 = .07$, and $F(1, 165) = 10.75$, $p = .001$, partial $\eta^2 = .06$, respectively. These results are consistent with the results from separate analyses given above. No main effect of Task or

interactions were found, *p*s > .26. Thus, it seems that WM had similar effects on frequency judgment in the word frequency judgment task and the decision-making task.

### 4.3 Discussion

Study 3 replicated the main finding of Study 2: WM is critical in the use of the frequency heuristic in experience-based decision-making. Participants under WM load performed better overall and exhibited greater weight to RL expected value versus gain-loss frequency than participants with intact WM resources, both providing evidence that WM load reduces attention to gain-loss frequency. Nevertheless, while in Study 2 participants under the no-load condition were able to reach a similar level of performance as those under WM load at a later stage of the task, in Study 3 participants with intact WM resources consistently performed more poorly over the task than did those whose WM was taxed. To facilitate comparison, Figure 10 displays performance over five 20-trial blocks in each WM load condition in Studies 2 and 3. While DT participants in the two studies had different performance in Blocks 2 and 4, they exhibited similar trends of performance over the task and had similar performance at the last block. Participants under the no-load condition in the two studies also showed similar trends of performance across blocks, but participants in Study 3 did worse than those in Study 2 in the last two blocks, especially in Block 5. In Study 2, I proposed that although ST participants were biased to rely on the frequency heuristic early in the task, they were able to learn to select the decks based expected values at the later stage. ST participants in Study 3 did not appear to be able to switch their strategies, resulting in consistently poorer performance. This might be due to a semester-related timing effect

(Nicholls, Loveless, Thomas, Loetscher, & Churches, 2015). Study 2 was conducted early in semester, while Study 3 was done towards the end of a semester. Nicholls and colleagues (2015) found that participants who engaged late in semester showed decreased intrinsic motivation than those who did early. Hence, Study 3 participants might be less likely to switch to a strategy that relies on expected value instead of frequency information because of being less intrinsically motivated. Diminished motivation could make participants under the no-load condition less likely to detect an expected-value-based strategy and/or less willing to switch from a frequency-biased strategy, which may be their default strategy. In contrast, these effects would not affect DT participants much because they were not initially biased to the frequency heuristic.

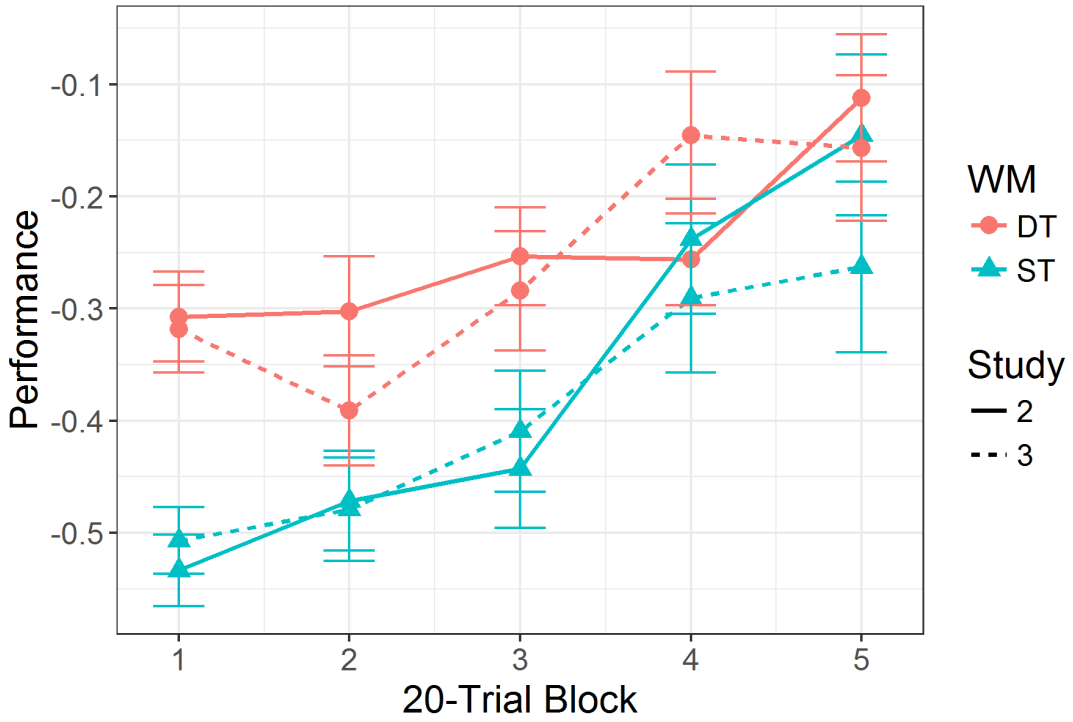


**Figure 10 Performance in the Soochow Gambling Task (SGT) by 20-trial blocks for each WM condition (ST versus DT) in Study 2 and Study 3. Error bars represent ±1 SE.**

Both Studies 2 and 3 suggest that WM contributes to utilizing frequency information in decision-making. One major goal of Study 3 was to delineate a more precise role of WM. Does WM load reduce the accuracy of gain-loss frequency judgments or undermine other components in the process of using frequency information? Study 3 found that WM load reduced the accuracy of gain-loss frequency judgments and higher WMC was associated with more accurate judgments, suggesting that one role of WM in the use of frequency heuristic is to help decision makers to make more accurate frequency judgments which could in turn form the basis of the frequency heuristic. Most WM models maintain that the main functions of WM are to direct and

control attention (Baddeley, 2012). It is likely that decision makers with greater WM resources[6] are able to direct more attention to frequency processing and protect related psychological operations from unrelated stimuli, resulting in more accurate frequency judgment. Also, it is worth noting that although it confirmed WM's contribution to frequency judgment, this work did not rule out the possibility that WM might also contribute to other processes of using the frequency heuristic.

Some prior work found that frequency judgment accuracy was invariant with respect to age, verbal ability, and intention (e.g., Hasher & Zacks, 1979; Zacks et al., 1982). Some theorists proposed an influential notion that frequency processing is effortless and automatic (Hasher & Zacks, 1984; see also Zacks & Hasher, 2002). Several following studies in which WM load was manipulated found that diminished WM resources led to poor frequency judgment, indicative of an important role of WM in frequency judgment. The current work added evidence to this idea. Study 3 found that WM load reduced the accuracy of frequency judgment in a typical frequency processing task, the word frequency judgment task, and the decision-making task. Further, this study revealed a link between higher WMC and more accurate frequency judgment in both the word frequency judgment task and the decision-making task. The convergent evidence lends strong support to the idea that the processes underlying frequency judgments depends on WM.

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[6] Following Schmeichel's resource account on executive control (2003), this work assumes that people with higher working memory capacity have more working memory resources available.

The last purpose of Study 3 was to test whether WM load would exhibit a stronger effect on frequency judgment in the decision-making task than in the word frequency judgment task. Because I reasoned that decision-making is presumably a more complicated process than word frequency judgment (e.g., decision-making requires integrating the frequency value and expected value for each option). However, the absence of an interaction between Task and WM load did not provide support to the hypothesis. The increased WM demand due to additional operations required by the decision-making task compared to the word frequency judgment task might be minimal when it is compared to WM taxed by a concurrent numerical Stroop task.

# 5. STUDY 4

Study 4 was aimed to evaluate aging effects on utilizing the frequency heuristic. The SGT was still used to examine this issue. Three group of adults, younger, middle-aged, and older adults, performed the SGT. Previous research suggests people tend to use heuristics more with advancing age (e.g., Carpenter & Yoon, 2011; Chen & Sun, 2003; Kim et al., 2005). Hence, older adults might also use the frequency heuristic more in the SGT. However, Studies 2 and 3 provide convergent evidence that using the frequency heuristic requires WM. Considering age-related decline in cognitive functioning, older adults' use of the frequency heuristic appears to depend on whether declined cognitive ability in older age would constrain the utilization of the frequency heuristic. Previous frequency processing research found that the accuracy of frequency judgment did not change with age (Attig & Hasher, 1980), implying that reserved WM capacity in older adults might suffice for frequency processing. I thus predicted that the use of frequency heuristic would enhance with age.

## 5.1 Method

### 5.1.1 Participants

Nighty-nine participants (30 females) recruited from the greater College Station, Texas, community and were paid $8 per hour for participation. 30 healthy younger adults (YA; mean age 24.83 years, range 18 – 38), 33 middle-aged adults (MA; mean age 49.24 years, range 40 – 59), and 32 older adults (OA; mean age 69.64 years, range 60 – 92) were included in the analysis. 4 additional participants were excluded due to computer failure. Written informed consent was obtained from all subjects according to

procedures approved by the Texas A&M University Internal Review Board. To determine whether older adults were functioning within the normal range for their age, they were administered a battery of neuropsychological tests measuring attention, verbal memory, visual memory, speed, and executive function. No older adults were excluded on these criteria.

### 5.1.2 Materials and Procedures

Participants performed the experiment on PCs using Psychtoolbox for Matlab (version 2.5). They performed the SGT among other experimental tasks.

## 5.2 Results

### 5.2.1 Behavioral Results

I first compared overall SGT performance between the three groups of participants (YA versus MA versus OA). Figure 11 displays performance over five 20-trial blocks for each age group. A one-way ANOVA did not reveal a significant effect of age on the overall performance, $F(2, 92) = .33$, $p = .72$, partial $\eta^2 = .01$. A similar analysis was also conducted on the proportion of selections for each deck. All analyses yielded non-significant results ($p$s > .31). Thus, the behavioral results suggest that choice behavior in the SGT does not change with age.

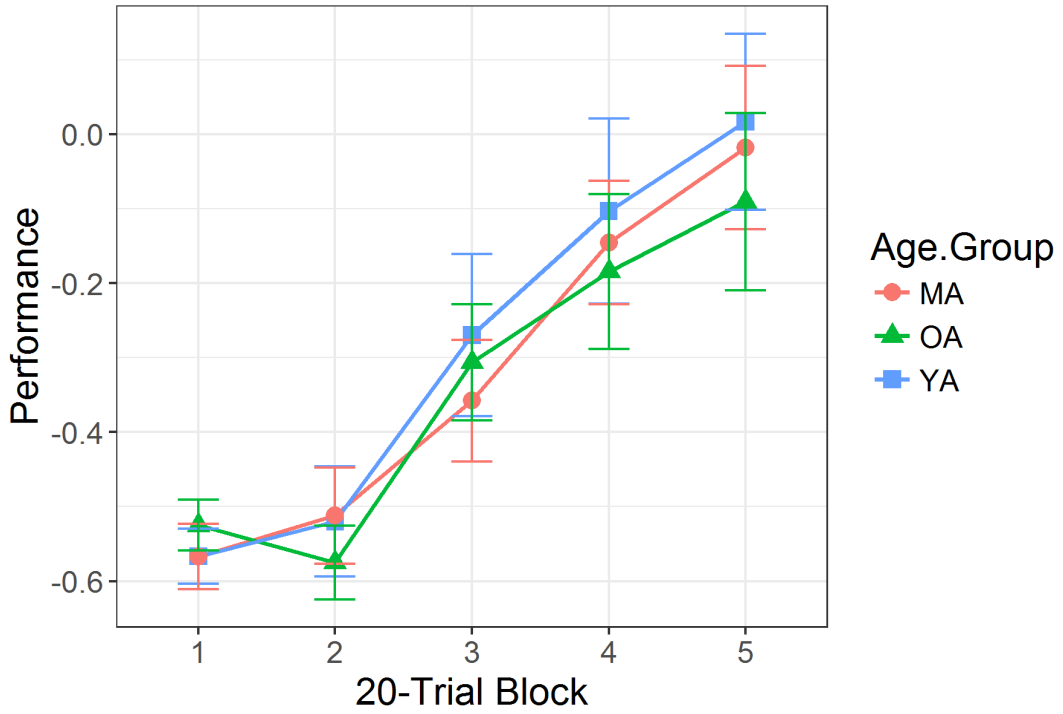


**Figure 11 Performance in the Soochow Gambling Task (SGT) by 20-trial blocks for each age group. Error bars represent ±1 SE.**

### 5.2.2 Modeling Results

Decision-making is a complex process and numerous psychological factors contribute to this process. Despite the lack of observed differences in the choice behavior in the SGT between the three age groups, it is likely that aging might cause some change of psychological processes involved in decision-making. I then applied computational modeling to understand the psychological processes.

*Model Selection*

The computational modeling analysis procedure is the same as in Studies 2 and 3. Five models were fit to the data, including the EFP model, the two PVL models, the

VPP model, and the baseline model. Average BIC values for each model for each age group are listed in Table 12. Across all age groups, the EFP model had the smallest average BIC values, suggesting that the EFP model provided a better fit than other models to this dataset.

**Table 12 Average BIC values for each model as a function of the age group in Study 4**

| Model | YA | MA | OA |
|---|---|---|---|
| EFP | **211.69(44.05)** | **211.58(43.16)** | **214.86(48.76)** |
| VPP | 214.64(43.99) | 216.63(41.32) | 222.25(48.46) |
| PVL-Delta | 241.33(46.89) | 254.33(31.57) | 252.99(37.56) |
| PVL-Decay | 221.72(42.00) | 223.35(27.71) | 222.57(37.05) |
| Baseline | 243.60(42.92) | 254.37(26.59) | 259.77(33.54) |

*Standard deviations are listed in parentheses. Values in boldface are the minimum BIC values among these models.*

*Comparison of Best-Fitting Parameters*

I next compared the parameter estimates of the EFP model between the three age groups to investigate the aging effects on specific psychological processes related to decision-making, especially the use of frequency heuristic. Table 13 lists the median best-fitting parameter values of the EFP model for each age group. Nonparametric Mann-Whitney *U* tests were used. Older adults exhibited lower values for the weight parameter than did younger adults, $U = 336$, $p = .04$. This suggests that older adults were more likely to utilize the frequency heuristic. Similarly, middle-aged adults showed lower values for the weight parameter than did younger adults, $U = 343$, $p = .03$, indicating enhanced use of the frequency heuristic by middle-aged adults compared to younger adults. There was no difference in the weight parameter value between older

and middle-aged adults, $U = 523$, $p = .95$. In addition, data from younger adults were best fit by higher consistency parameter values than data from older adults, $U = 319$, $p = .02$. This result suggests that older adults made choices less consistently than younger adults. A similar trend was also observed that middle-aged adults were less consistent on choices than younger adults, $U = 369$, $p = .08$. No significant aging effects were found on the best-fitting parameter values of the learning rate parameter, loss aversion, or perseveration.

**Table 13 Median parameter estimates from maximum likelihood fits as a function of the age group in Study 4**

| Parameters | YA | MA | OA |
|---|---|---|---|
| Learning | .10 | .13 | .20 |
| Loss Aversion | .37 | .01 | .10 |
| Perseveration | .46 | .78 | 1.36 |
| Weight | 1.00 | .89 | .82 |
| Consistency | 1.05 | .79 | .57 |

### 5.3 Discussion

Although a difference in the SGT performance was not observed, the computational modeling results revealed age-related changes in the psychological processes underlying decision-making. The weight parameter comparison result suggests that older and middle-aged adults are more likely to use the frequency heuristic than younger adults. Using the frequency heuristic in the SGT is disadvantageous, implying that older and middle-aged adults would have performed worse than younger adults. However, the modeling results also suggest that people in older age tend to respond more randomly. As a result, they did not keep choosing disadvantageous choices as often

as greater reliance on the frequency heuristic would imply. Together, increased use of the frequency heuristic and decreased consistency in older and middle-aged adults resulted in similar performance as younger adults. This study suggests that age-related cognitive decline does not limit the use of the frequency heuristic for people in older age. Therefore, they more likely utilize this heuristic than younger adults, consistent with previous findings that people tend to use heuristics with advancing age (Chen & Sun, 2003; Kim et al., 2005).

# 6. GENERAL DISCUSSION AND SUMMARY

## 6.1 Results Summary

Most decision models focus on the role of expected value (e.g., Ahn et al., 2008; Barron & Erev, 2003; Erev & Roth, 1998; Kahneman & Tversky, 1979; Sutton & Barto, 1998). The present work investigated the role of frequency information in experience-based decision-making. In Study 1, the EFP models which accounts for decision maker's reliance on frequency information were developed. In different decision-making tasks and on various model performance criteria, the EFP models consistently performed well and often outperformed other models without the frequency value component. Also, in the experimental studies (Studies 2 - 4), the EFP model also performed better than other models. Together, these results suggest a crucial role of frequency information and the pervasiveness of the frequency heuristic in experience-based decision-making. Studies 2 and 3 provided evidence that working memory (WM) plays an important role in the use of the frequency heuristic. Study 3 further showed that at least one role of WM is to contribute towards making accurate gain-loss frequency judgments, which forms a basis of applying this heuristic. Study 4 revealed a life-span trajectory of the use of the frequency heuristic, that is, people tend to utilize the frequency heuristic more with advancing age.

## 6.2 Why a Frequency Heuristic?

This work (especially Study 1) provides evidence for the prevalence of the frequency heuristic in experience-based decision-making, even when it is disadvantageous (e.g., in the SGT). Four reasons might account for the pervasiveness.

First, frequency information is critical in a variety of human behavior and people are highly sensitive to this information (e.g., Sedlmeier, 2002; Zacks & Hasher, 2002). Second, the frequency of gains and losses (and of other task features such as improvements and decrements in payoff) is salient in most of experience-based decision-making contexts. Third, as the naming of frequency *heuristic* suggests, it is a simplified strategy that ignores part of the information (e.g., the magnitude of gains and losses). People use it attempting to reduce effort despite its modest demands on WM (see discussions in 6.3). Fourth, while this heuristic is counterproductive in some tasks such as the SGT where the reward structure was designed to be so in order to examine the contributions of expected value versus gain-loss frequency, in real life the frequency heuristic could be efficient. Some prior work indicates the efficiency of a similar frequency heuristic. Dawes (1979) proposed Dawes's rule which sums up the number of pieces of positive evidence and subtracts the number of pieces of negative evidence, sharing the idea of the frequency heuristic formalized in this work[7]. Another study compared the predictive accuracy of Dawes's rule with multiple regression and found that this frequency-based simple rule performs better than multiple regression in some situations and not largely inferior in other situations (Czerlinski, Gigerenzer, & Goldstein, 1999; Einhorn & Hogarth, 1975). For instance, when the cues or pieces of

[7] The frequency tracking mechanism specified in the EFP model is similar to Dawes's rule. The difference is that the Dawes's rule simply tallies up the number of positive versus negative attributes and does not assume a memory decay mechanism since it is used to model description-based decision-making where all the attributes information is presented to decision makers all at once, while the frequency tracking function proposed in the current work is used to model experience-based decision making where positive and negative outcomes are gained gradually across the task.

evidence are highly correlated, Dawes's rule exhibits more accurate prediction. Hence a frequency-based strategy can be more efficient than a statistics-based strategy.

### 6.3 WM Demands of the Frequency Heuristic and Dual-Process Models

My studies that manipulated WM load provided evidence that using the frequency heuristic demands WM resources. What seems contradictory is that older adults with age-related cognitive decline were more likely to use the frequency heuristic. These seemingly contradictory results might suggest that WM is necessary to utilize the frequency heuristic but its demand is not heavy to the degree that diminished working memory capacity (WMC) in older adults constrains the utilization of this heuristic. The characterization of being WM-demanding makes the current results relevant to the dual-process models, which are popular in cognitive and social psychology and often used to account for various types of higher cognition such as judgment, decision-making, reasoning, and social cognition (e.g., Epstein, 1994; Kahneman & Frederick, 2007; Schneider & Schiffrin, 1977; for a review, see Evans, 2008). Despite numerous differences, these dual-process models have in common the distinction between two cognitive systems, here referred to as, System 1 and System 2 (Kahneman & Frederick, 2007). System 1 involves cognitive processes that are fast, automatic, unconscious, implicit, requiring low effort, independent of WM, and being default process. In contrast, System 2 entails cognitive processes that are slow, deliberative, conscious, explicit, require high effort, limited by WM, and inhibitory. It appears that the frequency heuristic shares some features of processing in both Systems 1 and 2, but is also dissimilar with other features of processing in each system.

Utilizing the frequency heuristic is limited by WM to a degree that concurrent WM demanding operations limit the use of it, which is a characteristic of System 2 processing. Like other heuristics, however, the frequency heuristic ignores part of the information (e.g., the gain and loss magnitude of an outcome) and is used for effort reduction, which seems to contradict the analytic and deliberative nature of System 2 processing. Another interesting phenomenon is that this heuristic appears to be a default choice for decision makers with intact WM resources even in a task where it is disadvantageous, but they could intervene the use of it and switch to a strategy based on expected value (single task participants in Study 2 and participants in Study 4). This process is the line with Evans's view (2008) on the relationship between Systems 1 and 2 (he called it default-interventionist; see Kahneman & Frederick, 2007 for a similar idea). In their terms, the phenomenon above can be described as: System 1 controls one's action according to a default choice (the frequency heuristic) unless System 2 detects an error or inefficiency and hence inhibits the default response. This view links the frequency heuristic to System 1.

Given the "irregular" position of the frequency heuristic on the map of the two systems, it seems to suggest a continuum nature of various dimensions of cognitive processes, in contrast to qualitative dichotomies assumed by dual-process models. For instance, WM demands of the frequency heuristic is medium, not either completely effortless or highly effortful. Also, this heuristic is based on a simple rule, not either associative or analytic. Two previous theories also share the notion of continua along aspects of cognitive processes (Hammond, 1996; Kruglanski et al., 2002). Dual-process

models provide a powerful framework to explain a wide range of psychological processes such as affect-based versus logic-based strategies (Evans, 2008), but the idea of continuum allowing for a “in-between” positions might be more effective in describing some phenomena such as the frequency heuristic.

On a relevant note, Hasher and Zacks (1984) examined frequency processing under an automatic and effortful processing framework and viewed it as an automatic process. Previous research (e.g., Maki & Ostby, 1987; Naveh-Benjamin & Jonides, 1986) and the present work both provide evidence that WM load diminishes frequency judgment accuracy. This work also uncovers an association between WMC and frequency judgment accuracy in a word frequency judgment task and decision-making task. These findings all speak against the automatic view on frequency processing. Considering some evidence that intention, age, and verbal ability do not influence frequency judgment accuracy, this work takes the same continuum view as above for general frequency processing, that is, it has a medium demand on WM.

### 6.4 Strategy use under a Single Task versus Dual Task Condition

In this work, I assumed that participants under WM load might track expected values through implicit processes, as suggested by prior work (Otto et al., 2011; Worthy et al., 2012). In fact, much evidence suggests that a prediction error, the difference between the outcome received and the expected value for a given option, is tracked by the ventral striatum, a subcortical region implicated in implicit, procedural learning (e.g., Hare, O’Doherty, Camerer, Schultz, & Rangel, 2008; Pessiglione, Seymour, Flandin, Dolan, & Frith, 2006). In many popular RL models, including models used in this work

(see Equations 2 and 9), these prediction errors are used to update the expected value for the option that was chosen on each trial (Busemeyer & Stout, 2002; Sutton & Barto, 1998; Yechiam & Busemeyer, 2005). Given the ability of subcortical regions to track expected value, people may be able to implicitly learn the expected value of options (although it is unclear about how accurate the learned expected values are when participants are under WM load). In short, dual task participants may make choices based on implicitly-tracked expected values, which are supposed to require little effort.

This work argues that one reason that single task participants use the frequency heuristic as a "default" strategy is because this heuristic ignores part of the information (e.g., magnitude of the gains and losses from an outcome) and hence utilizing it can reduce effort compared to other deliberative strategies. If so, why did single task participants not use the strategy employed by dual task participants? That should save much more effort. There are two conjectures. First, single task participants had access to the implicitly tracked expected values but were deeply uncertain regarding the validity of the expected values since they had no explicit access to how these values were learned. A choice of strategies or heuristics is considered as a result of an accuracy-effort-trade-off (Gigerenzer & Gaissmaier, 2011; Payne, Bettman, & Johnson, 1993). According to this view, because of great uncertainty about the accuracy of implicitly-learned expected values, single task participants did not use the implicit-processing-based strategy. Second, they might even have no conscious access to the expected values (both the learning process and learned outcome). In this case, dual task participants might make choices based on gut feelings which might in turn be informed by

implicitly-tracked expected values, such as “Hmm, I feel Deck A is good. Pick it!” If this is the case, the strategy used by dual task participants involved more uncertainty about its validity than in the first possibility. Single task participants would still not use expected value information because of uncertainty. Instead, the accuracy-effort-trade-off led to the frequency heuristic which seems to be valid in some real-life situations (Czerlinski et al., 1999; Einhorn & Hogarth, 1975) and is not highly effortful. Moreover, the salience of the relative frequency of gains versus losses encourages the use of this heuristic. Exploiting the trade-off idea further, this work argues that single task participants might give up the frequency heuristic and attempt to track expected values somewhat explicitly (implicitly-tracked expected values might facilitate this explicit process) when they discover that utilizing the frequency heuristic is inefficient.

To answer the question of why single task participants did not employ the strategy used by dual task participants, two strong assumptions are made: 1) having no conscious access to the learning processes of expected values leads to one’s great uncertainty regarding their accuracy; 2) people under WM load have no explicit access to learned expected values but just have some gut feelings which might be based on expected values. Future work might test these assumptions to understand the exact mechanisms of the choice of strategies by decision makers with intact WM resources.

## 6.5 Implications

### 6.5.1 Implications on Decisions from Experience

The predominance of the frequency heuristic may shed new light on a general finding in decisions from experience, that is, underestimation of rare events (Barron &

Erev, 2003; Hertwig, Barron, Weber, & Erev, 2004). Based on the findings from the current work, one possibility is that decision makers tend to use the frequency heuristic which engenders a behavioral pattern as if they underestimate rare events. For instance, in a choice problem in which one option yields 32 dollars with a probability of 2.5% and 0 dollars otherwise while choosing the other option produces 3 dollars with a probability of 25% and 0 dollars otherwise (32, .025 versus 3, .25). Hertwig and colleagues (2004) found that 88% of participants selected the option yielding rewards more frequently (3, .25) despite the sub-optimality of this option in this problem. This is a task of the minimal information paradigm. Study 1 results support the use of the frequency heuristic in this type of tasks. Hence, it is likely that most participants attentively track the frequency of rewards and choose the option with more frequent rewards but assign little attention to expected values. Although other mechanisms have been extensively studied (e.g., Rakow, Demes, & Newell, 2008; Ungemach, Chater, & Stewart, 2009; for a review, see Hertwig & Erev, 2009), for example, reliance on small samples or weighting functions, future work may particularly examine the role of the frequency heuristic in explaining the underestimation of rare events and its associations with other mechanisms.

### 6.5.2 The EFP Models

In this work, the EFP models were developed to parsimoniously capture three critical sources of choice behavior in decision-making tasks like the IGT and SGT: expected value, frequency of gains versus losses, and perseveration. The EFP models consistently performed well in a variety of tasks and on different performance criteria.

Given the validity of the EFP models, they have the potential to contribute to future research in providing a richer description of choice behavior and its underlying psychological processes such as attention to gain-loss frequency. For example, prior work has observed impaired performance in the Iowa Gambling Task (IGT) among patients with dorsolateral prefrontal cortex (DLPFC) deficits (Fellows & Farah, 2005; Manes et al., 2002), but has not revealed its mechanisms. Future research using computational models such as the EFP model for the IGT may pinpoint the detailed mechanisms that are disrupted by DLPFC damage.

### 6.5.3 Availability Heuristic and Frequency Heuristic

The EFP models assume that decision makers track the frequency of gains and losses. However, the availability heuristic, a much studied heuristic in the behavioral economics literature, assumes that frequency judgment is based on the ease of recalling relevant instances rather than tracking the frequency information *per se* (Tversky & Kahneman, 1973). It is illustrated by asking participants to estimate the frequency of names. Participants were presented a list consisting of 19 names of very famous men (e.g., Richard Nixon) and 20 names of less famous women (e.g., Lana Turner). Participants were then asked to write down as many as names as they could recall from the list or to judge whether the list contained more names of men or women. They found that participants recalled more names from the famous names than from the less famous names, and made incorrect judgment of relative frequency (i.e., more names of men). Tversky and Kahneman (1973) explained that this was because famous names are easier

to recall and frequency judgment of an event is based on the ease with which instances of that event come to mind.

Although this theory is popular, the frequency processing literature has much evidence speaking against it. First, the availability heuristic holds that frequency judgment is generally biased. However, in the frequency judgment literature, studies which exhibited biased frequency judgments are rare. Most studies provide evidence that people can make valid frequency estimates, either frequency of everyday life events (e.g., Lichtenstein et al., 1978; Shapiro, 1969) or of events in laboratory settings (e.g., Hintzman & Block, 1971; Mutter & Goedert, 1997). Second, the availability heuristic assumes that recall is the basis of frequency judgment. However, numerous studies indicate that frequency judgment is independent of recall (e.g., Bruce, Doyle, Dench, & Burton, 1991; Freund & Hasher, 1989). Taken together, people appear not to greatly rely on the ease of recall to make a frequency judgment. Instead, people track the frequency of events, as assumed in the EFP models, which forms the basis of frequency judgment. Also, the specification of the frequency tracking mechanism assumed in the EFP models can easily accommodate the "famous names" effect by allowing for different decay parameters to track the frequency of famous names and less famous names. As such, the frequency value of famous names might decay slower than that of less famous names, resulting in a higher estimate for the famous names.

## 6.6 Limitations and Future Directions

Some limitations of this work are already discussed in previous sections. For instance, this work did not provide an exact answer about why single task participants

did not use the strategy employed by dual task participants. Proposed reasons can be tested in future work.

Another unanswered issue is about the exact mechanisms of strategy switching. This work argues that people can change decision strategies during the task such as switching from a frequency-based strategy to an expected-value-based strategy. However, the exact mechanism of strategy switching is still unclear. It is evident that a primary goal of decision-making research is to help people make better decisions. Understanding the process that people change decision strategies from disadvantageous to advantageous ones is critical to reach the goal. According to the default-interventionist dual-process theory (Evans, 2008; Kahneman & Frederick, 2007), detecting inefficiency of the current strategy and inhibiting the use of it is responsible for strategy switching. Future work may follow this argument to examine this issue. For instance, do metacognitive monitoring and/or inhibitory control lead to effective strategy switching? Also, future work might consider other factors that can come into play. In this work, unlike single task participants in Study 2 (and participants in Study 4), single task participants in Study 3 failed to reach similar performance level as dual task participants. I explained that this might be attributed to diminished motivation because of a semester timing effect (Nicholls et al., 2015). Future work may investigate how motivation shapes strategy switching.

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