Conditions for Maximizing Expected Value in Repeated Choices from Experience

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Conditions for Maximizing Expected Value in Repeated Choices from Experience

by

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A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy
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Abstract

It is largely expected that people can learn from past experiences and use this knowledge to make better decisions in the future. However, there are aspects inherent in experiential learning which may affect the extent to which people can extract and use information from experiential feedback to make advantageous decisions. Three aspects inherent in experiential learning were identified: (1) it is reliant on memory, (2) information is gathered exclusively through outcome feedback, and (3) outcome feedback is inherently dynamic. The current investigation explored how each of these aspects may help shape experiential decision making, and examined how the presence of competing types of information might hinder the ability of experiential information to guide people towards advantageous choices.

A card-selection paradigm was used to examine learning about monetary outcomes from repeatedly sampling from two decks with different expected values (EVs, i.e., average payoffs). Effects on working memory were assessed by varying the number of outcomes within each deck and varying whether both decks had all-gain outcomes or one deck had some zero outcomes. Reliance on outcome feedback was manipulated by adding misleading (but technically correct) descriptive information which favored the less advantageous deck. To assess the impact of dynamic information, the dynamics of experience were contrasted with misleading dynamic descriptions. The primary dependent variable was the number of higher EV deck selections measured during the first and last 25 choices.
The results of the investigation revealed little strain on working memory, but found a surprise zero effect in which identification of the more advantageous option was noticeably disrupted when the better option contained possible zero outcomes. Participants seemed drawn to options that were less advantageous but had only gain outcomes. Misleading descriptions provided at the outset only disrupted advantageous choice when zero outcomes were involved, but outcome feedback was found to help overcome the initial bias toward the lower EV all-gain deck. However, when no description was available, the zero effect grew more intense with experience. Finally, when misleading dynamic descriptions were presented, disruptions in experiential learning were seen throughout. The implications of these results contribute to our understanding of which conditions are likely to support versus disrupt our ability to use experiential feedback to guide us towards advantageous choices.
Conditions for Maximizing Expected Value in Repeated Choices from Experience

“With age comes wisdom, but sometimes age comes alone.”

-Oscar Wilde

Whether hiring a new employee, or choosing a new doctor, his or her experience in the area is considered a favorable quality. It is presumed that with experience comes knowledge, and with knowledge comes the ability to make informed judgments and decisions. In other words, it is expected that people can learn from their experiences. By definition, learning is “the acquisition of novel information, behaviors, or abilities after practice, observation, or other experiences, as evidenced by change in behavior, knowledge, or brain function” (APA Dictionary, 2015; emphasis added). In this dissertation, I will investigate characteristics of repeated experience that may influence the ability to learn information and, as a result, to make advantageous decisions.

Over time, our experiences accumulate into a wealth of information from which we can learn. For example, grand chess masters are some of the most skillful chess players in the world. Part of their success is the ability to draw upon a repertoire of about 50,000 to 100,000 chess piece patterns that have been learned over decades of play (Chase & Simon, 1973; DeGroot, 1965). Thus, it is evident that, at least in some cases, people can and do learn from experience. However, more experience does not necessarily lead to learning. Some psychologists, such as Brehmer (1980) and Meehl (1954), have taken a skeptical stance on how well people can
typically learn from experience, noting several examples in which expert predictions are not very accurate. For example, Meehl found that clinical prognoses made by simple statistical models are often more accurate than those made by clinical psychologists with similar information.

Whether learning from experience is likely to be effective is partially dependent on the learning environment (Kahneman & Klein, 2009; Shanteau, 1992). If the environment is continuously changing and the relationship between cues and outcomes is unpredictable, learning from experience will be difficult if not impossible. Furthermore, if feedback is not readily available, it will be difficult to correct past judgments and predictions. For fields like clinical psychology, these unsteady learning environments are common. Yet, if the environment is stable and predictable, and there is timely and adequate feedback, such as in chess, learning from experience is likely to be much more effective (Shanteau, 1992).

One reason a steady environment with timely feedback supports learning is that outcome and probability information is more easily extracted when the relationship between cues and outcomes remains consistent (Brunswick, 1956; Einhorn & Hogarth, 1986; Kahneman & Klein, 2009). This promotes learning, which in turn may translate to a higher quality of decision making. To make accurate predictions that can support quality decisions, knowledge of the possible outcomes and their associated likelihoods is needed in order to evaluate and compare choice options.

When outcomes are non-numeric, determining the most advantageous outcome is somewhat subjective. For example, the choice between a new TV and a vacation may differ in utility, or personal value, based on the individual. However, when presented with two or more numeric options, the “gold standard” to more objectively determine which option is most
advantageous is expected value. Expected value (EV) refers to the average amount of earnings a given option is expected to yield if that option occurs or is experienced many times. To calculate EV, possible outcome values and associated probabilities must be known.

If all potential outcomes and associated probabilities are known, then identifying the option’s EV can be reduced to the following equation:

\[ EV = \sum [p_i(X_i)] \]

According to the equation, each potential outcome is multiplied by the likelihood of that outcome occurring. The sum of these values provides the EV for that option. For example, if given a gamble with a 50% chance of winning $10 and a 50% chance of winning $0, the expected value would be calculated by multiplying each outcome by .5, and then adding these values together. Thus, the EV for this example gamble would be $5.

Over time, the option with the highest EV will yield the highest accumulated earnings. Therefore, if decisions are being made repeatedly, adopting a decision strategy that maximizes EV would be in the decision maker’s best interest. When learning from experience, however, outcome and probability information are not explicitly stated. Rather, this information must be extracted by observing the outcomes of multiple choices and making inferences about outcomes and associated probabilities based on these observations. Thus, the accuracy of EV estimates for each option are partly dependent on how well we can extract outcome and probability information from experience. Consequently, this may impact the quality of decisions made from experience.
As noted earlier, the predictability of the environment and available feedback, may substantially impact how well outcome and probability information can be extracted and learned. Yet, even when environmental conditions are suitable for learning (i.e., steady environment with available feedback), the ability to extract outcome and probability information may be impacted by other characteristics that are inherent in learning from experience. Three of these characteristics are the focus of this dissertation. First, learning from experience is *heavily reliant on memory* – that is, all information is stored and integrated internally. Second, the *only available source* of information comes in the form of *outcome feedback*. Lastly, *choice feedback is dynamic* and accumulates with each new choice or experience.

In the current investigation, each of the abovementioned characteristics will be systematically examined to see how they affect extraction of probability information and the tendency to make advantageous decisions. This will be done in a decision environment that provides timely, regular feedback and has unchanging probabilities. Thus, the foundations that are generally conducive for learning from experience will be present.

Building on related literature, the current investigation employs a card-selection paradigm with two unmarked decks of cards as depicted in Figure 1. Within each deck of cards is a pre-determined sequence of monetary outcomes – one of which results in a greater amount of money earned (i.e., has a higher EV). To learn which deck is better, participants repeatedly draw cards from each of the two decks. The amount of money won for each draw is listed on the back of the card, which is flipped to become visible when the card is selected. This amount is added to a running total which accrues throughout the task. The extent to which participants drift towards, or come to prefer drawing from, the higher EV deck is used as the measure of learning from experiential feedback.
Using this paradigm, I will examine how fundamental aspects of experiential learning, including (1) working memory, (2) outcome feedback and (3) dynamic feedback help shape decision making. The results of this investigation will help provide insights as to the relative impacts of these aspects on learning and decision making, especially when misleading non-experiential information is also available.

**The Role of Memory in Outcome and Probability Learning from Experience**

Memory and learning are deeply intertwined with one another. In order for learning to occur, information must be (1) encoded into memory, (2) stored in memory, and (3) retrieved from memory (Melton, 1963). Of the various types of memory, *working memory* has been identified as an essential part of the decision-making process because it not only holds information, but actively manipulates and integrates new information gathered from sensory
systems with older information in long-term memory (Baddeley, 1986; Stolzfus, Hasher, & Zacks, 1996). Working memory comes closest to what might be described as ongoing thought. This active manipulation of information sets working memory apart from other types of memory. Working memory, therefore, play a particularly important role in experiential learning because it actively maintains, processes, and updates information about the decision environment in consciousness, which is fundamental to learning from experience (Bayliss, Jarrold, Baddeley, Gunn, & Leigh, 2005).

Although essential, the capacity of working memory is quite limited. On average, an individual can hold and manipulate about four pieces of information in working memory for only about two seconds without rehearsal (Cowan, 2001; Swanson, 2000). If the amount of information needed to be processes exceeds working memory capacity, deficits in learning and decision making may occur (e.g., Hinson, Jameson, & Whitney, 2002; Weiss-Cohen, Konstantinidis, Speekenbrink, & Harvey, 2018). In what follows, I will discuss how strains on working memory may affect how well outcome and probability information can be extracted from experience and integrated with existing memory, and the potential consequences this may have on maximizing EV in a repeated decision context.

**Outcome and Probability Learning from Experience**

*Frequency Learning.* Early studies of outcome and probability learning were typically described as frequency learning (e.g., Estes, 1976; Neimark & Shuford, 1959; Schmitt, Coyle, & King, 1976). These studies suggested that by repeatedly observing outcomes produced under similar circumstances, and encoding these outcome patterns into memory, people typically do develop knowledge of outcome frequencies. These frequencies are then thought to be translated
into probability estimates so that outcomes that are experienced more often are considered more likely than outcomes that are experienced less often (Estes, 1976).

Generally, studies of probability learning have found that, under the right circumstances, people can extract outcome and probability information from experience fairly successfully. For example, Neimark and Shuford (1959) conducted an experience-based experiment in which participants sampled through three decks of 100 cards. At the start of the task, participants were given a description of the possible letters that would appear in each deck and a target letter for which they would later have to estimate the frequency of occurrence. While sampling, participants made predictions about the next letter in the deck, and estimated the probability of the pre-specified target letter. The actual probability of the target letter occurring was .67. Analyses of the last 30 trials in each deck showed that people provided estimates of the target probability that closely approximated what was actually experienced; however, they also showed a bias toward over-predicting how often the target letter would appear. Thus, although not perfect, probability estimates learned through experience can be fairly accurate in some environments.

Part of the success in estimating outcome probabilities in these early studies, however, may be related to the relatively low number of event frequencies that needed to be learned. In Neimark & Shuford (1959), the frequency of one letter had to be learned and, in Estes (1976), no more than three outcomes had to be learned. If the number of unique potential outcomes were increased, the frequencies for each separate outcome would need to be held in memory. Such an increase could strain the capacity of working memory, which might in turn adversely affect outcome and probability extraction and retention, limiting the ability to make informed decisions.
The Somatic Marker Hypothesis. Early research into frequency and probability learning largely focused on the cognitive aspects of experiential learning. However, in more recent times, there has been a shift towards understanding the automatic and affective components that may also contribute to experiential learning. The Somatic Marker Hypothesis (SMH), proposed by Bechara, Damasio, and Damasio (1994), suggests that the brain’s reward system plays a role in assisting experiential learning by affectively “marking” options that result in favorable or unfavorable outcomes. As experience is gained, and outcome feedback accrues, these somatic markers strengthen so that options that frequently result in a favorable outcome are positively marked, encouraging subsequent selection. Conversely, if the option frequently results in an unfavorable outcome, the option is negatively marked which discourages subsequent selection. Over time, these somatic markers are hypothesized to help guide decision makers towards advantageous choices and away from disadvantageous choices.

Studies of the SMH have primarily used a card selection paradigm called the Iowa Gambling Task (IGT). In the IGT, participants are presented with four decks of cards (labeled A-D) from which they repeatedly sample (typically 100 samples/trials) (e.g., Bechara, et al., 1994). Each time a participant samples a deck, they receive feedback on the amounts won or lost, and these values are then added to or subtracted from a current running total. Two of these decks are advantageous in the long run (i.e., higher EV), resulting in net positive earnings or a net gain. The other two decks are disadvantageous in the long run (i.e., lower EV), resulting in net negative earnings or a net loss.

Over the course of 100 trials, healthy participants typically learned to avoid the disadvantageous decks and drift towards selecting the advantageous decks. However, participants with damage to the amygdala and/or ventral medial prefrontal cortex (VMP),
showed deficits in learning from experience (Bechara, et al., 1994; Bechara & Damasio, 2005). The amygdala is associated with processing emotion, while the VMP is thought to be responsible for pairing emotional states with stimuli.

Based on this evidence it was hypothesized by Bechara and colleagues (1994) that information from outcome feedback may be extracted automatically using an affective mechanism. Thus, healthy participants were able to identify the more advantageous deck because they formed stronger positive somatic markers towards the deck which resulted in money being gained, and were simultaneously deterred from decks that resulted in an overall loss. However, those with amygdala/VPM damage failed to identify the more advantageous deck because on an inability to link emotional states to environmental stimuli (Bechara, Damasio, & Damasio, 1994; Bechara & Damasio, 2005; Dunn, Dalgleish, & Lawrence, 2005).

If somatic markers are sufficient for differentiating between more and less advantageous options, then increased strain on working memory may not have much impact on identifying which deck has the higher EV. This is because somatic markers are thought to be affective and non-conscious, thus increases in cognitive load should not affect their formation.

Based on evidence presented above from studies of frequency learning, the SMH, and the limits of working memory, the following competing hypotheses have been formulated:

**H1 Working Memory Capacity Hypothesis:** Learning from experience will be more effective with only two potential outcomes per deck compared to when there are multiple outcomes per deck. Thus, participants will make more selections from the higher EV deck when there are two outcomes per deck than multiple outcomes. However, if this effect is not observed, and learning is strong regardless of whether there are only two
versus multiple outcomes per deck, this may suggest that the strength of somatic markers
is sufficient to differentiate decks.

**Two Types of Outcome Feedback Information: Valence and Magnitude**

Studies of frequency learning and the SMH demonstrate that choice feedback can be an
effective means of informing choice. However, it is difficult to discern which particular aspects
of feedback information are being used to guide choice. This is of interest because depending on
which aspects of feedback are being extracted, the information necessary to estimate EV may or
may not learned.

When outcomes are monetary, choice feedback provides both *valence* and *magnitude*
information about outcomes. For example, an outcome of $100 is positive in valence and has a
magnitude of 100. Estimates of EV, however, can only be inferred based on the frequency of
particular magnitudes (which subsumes valence but is much more specific). Magnitude
frequencies provide both outcome and probability information – and these are the two essential
components needed to calculate EV. Frequency of valence (i.e., positive or negative) alone is not
sufficient for estimating EV as it does not distinguish between greater or lesser magnitudes of
gains and losses. Therefore, if valence frequency is the type of information that is primarily
extracted with experience, estimates of EV may be inaccurate, leading to deficits in the ability to
make advantageous choices over time.

Classic studies of frequency learning primarily used non-monetary events. Therefore,
estimates of EV were not a factor in learning in these studies. In the IGT, monetary outcomes are
used, but it is not possible to untangle the effects of valence frequency versus magnitude
frequency. Although the decks differed in EV, on average, the higher EV decks had more gain
outcomes than the lower EV decks. Across the 100 trials of the IGT, the “bad” decks averaged 14 gains and 6 losses, whereas the “good” decks averaged 15.25 gains, 2.5 zeros, and 2.25 losses. Thus, it is unclear whether preferences for the advantageous decks in the IGT are a result of extracting magnitude frequencies, valence frequencies, or both (Chui, Lin, Huang, Lin, Lee, & Hsieh, 2008).

To help disentangle whether valence frequency contributes separately to somatic marker formation and decision making, an alternate version of the IGT was created, the Soochow Gambling Task (SGT; Chui, Lin, Huang, Lin, Lee, & Hsieh, 2008). In the SGT, valence frequency is manipulated so that disadvantageous decks (with lower EVs) have a higher frequency of gain outcomes, and advantageous decks have a lower frequency of gain outcomes. Thus, if somatic markers are more sensitive to magnitude frequencies than valence frequencies respondents should prefer the advantageous decks (as in the IGT). However, if valence frequency contributes separately to somatic marker development, preferences may be pulled towards decks which offer a higher number of gain outcomes even though they have a lower EV.

Using the SGT, Chui et al. (2008) found that participants more often preferred the disadvantageous options that offered a high frequency of gain outcomes over the advantageous options with fewer gain outcomes (see also Lin, Chui, & Huang, 2009). From these results, Chui et al. (2008) suggested that magnitude of outcomes may be a secondary factor in decision making from experience, and that valence frequency may be the primary driver of choice behavior when outcomes are monetary.
Using Valence Frequency to Guide Choice

Results from the SGT may be interpreted as suggesting that the reward system – which is affective and automatic – may be more sensitive to valence than magnitude. When measuring neural responses to gain and loss outcomes, people may be particularly sensitive to valence. For example, Gehrig & Willoughby (2002) found that neural activity near the medial frontal cortex (an area associated with decision making) was sensitive to the valence of the outcome but not whether it was a better or worse outcome. Therefore, it is possible that choice may be partially guided by an automatic process which is particularly sensitive to outcome valence. If so, this could result in a preference for options with a high frequency of gain outcomes, despite having a lower EV.

Evidence also suggests that there may cognitive factors which contribute to the attractiveness of high frequency gain options. Using descriptive choice tasks, in which choice outcomes and associated probabilities are fully described, it has been found that participants prefer options which offer a higher likelihood of a gain outcome over options that have a higher EV. Given that all the information about potential choice outcomes and probabilities are provided, preference for options that increase the likelihood of a gain outcome may reflect a more conscious choice strategy. Such a strategy has been termed the Pwin or Probability of Winning heuristic (e.g., Payne, 2005; Venkatraman, Payne, & Huttel, 2014).

For example, in Payne (2005) participants were given multiple described gambles and were then asked to make one modification to each of the gambles to make it more favorable (Payne, 2005). Most often, participants opted to increase the likelihood of a gain outcome rather than increase the EV of that gamble. In Venkatramen, Payne, & Huttel (2014), participants
selected between pairs of described gambles, one of which had a higher likelihood of a gain outcome, and the other had a higher EV. Again, participants preferred the gamble which resulted in a higher likelihood of a gain outcome. Therefore, in both types of paradigms, results provide evidence that preferences for maximizing the likelihood of a gain outcome are often stronger than preferences for maximizing EV.

Another interpretation of the Pwin phenomenon may be that options that more frequently result in reward are more attractive than those that result in a lower frequency of reward. Depending on the schedule of reinforcement (i.e., when and how often a behavior is rewarded), behaviors can be learned, and become extinct at varying rates. For example, studies of reinforcement learning have found that continuous reinternment schedules, in which a reward is provided each time a desirable behavior occurs, results in a faster acquisition of a learned behavior compared to a variable schedule of reinforcement, in which a reward is provided only some of the time a desirable behavior occurs (e.g., Ferster & Skinner, 1957; Skinner, 1969). In a new learning environment, this could suggest that people would prefer options that provide a higher rate of rewards as opposed to options with a lower rate of rewards. However, this result would suggest that learners may not take into account which may be more desirable in the long run.

The use of a strategy that maximizes the likelihood of a gain outcome is attractive for several reasons: (1) outcome valence may be easier to extract and process than expected value (Chui, et. al., 2008), (2) gains feel good, so increasing the number of gain outcomes is affectively pleasing (Thaler & Johnson, 1990), (3) the use of a heuristic can be an efficient way to make reasonably good decisions while saving cognitive resources (Tversky & Kahneman, 1974), and (4) maximizing the likelihood of a gain, rather than maximizing expected value, is sometimes a
more reasonable strategy. As noted by Lopes (1981), when decisions are made only once or a few times, the expected value may not be a good indicator of the amount of return that will be received. For example, in a 50/50 gamble in which you could win $0 or $10, one play will never yield the expected value of $5. Thus, when the number of choices are (or seem to be) limited, using a strategy that maximizes the likelihood of a gain outcome may be a useful approach, as it can help guarantee a gain amount if choices are limited.

However, in an experiential learning environment, where decisions are made repeatedly, maximizing the likelihood of a gain outcome is not typically the most profitable strategy. Only by selecting the highest EV option can a person maximize the likelihood of the highest possible profit.

**Influence of Working Memory on Magnitude/Valence Frequency Extraction**

The extent to which valence and magnitude frequency information is extracted from feedback and used to inform choice may depend on the level of strain imposed on working memory. Depending on the complexity of the choice environment, valence frequency information may be easier to extract and hold in working memory than magnitude frequency information. To extract and use valence frequency, only the number of gains and losses per option needs to be held in memory. To track magnitude frequencies, however, the number of items to be held in memory increases with the number of unique outcomes in a given option.

For example, if an option has only two possible outcomes, then the number of outcomes that need to be held in working memory would be similar for both valence (positive and negative) and magnitude (outcomes a and b). However, if the number of possible outcomes increases to five, then the number of outcomes to be held in working memory for valence
frequency remains the same (positive and negative), whereas the number of items needed to be extracted and held in memory for magnitude frequency would increase (outcomes a, b, c, d, and e).

As previously discussed, strain on working memory may adversely affect how well we can learn from experience, and in turn affect the ability to make advantageous decisions. Strain on working memory may also affect the type of information that is primarily extracted from experience. If extracting and maintaining magnitude frequencies in working memory becomes too cognitively demanding, valence frequency may be substituted as the primary type of information used to inform choice. Yet, as discussed earlier, valence frequency information is not sufficient for estimating EV. Therefore, if valence frequency is used as the primary source of information to guide choice, the higher EV option may not be identified as most preferable.

The current investigation will test how strains on working memory may affect the type of information (i.e., magnitude and valence frequency) that is extracted and prioritized based on experiential information involving options with numeric outcomes. Using a valence frequency manipulation similar to the one used by Chui, et. al., 2008, the outcomes of the two-deck card selection, depicted previously in Figure 1, were manipulated so that in some conditions the lower EV deck has a higher frequency of gain outcomes than the higher EV deck. Using this design, it can be inferred from the deck preferences whether magnitude or valence frequency is primarily being used to inform decisions. If preferences are more strongly driven by valence frequency, then participants should select from the lower EV deck more so than the higher EV deck. If, however, preferences are mostly driven by magnitude frequencies, participants are expected to maximize EV. In this case, there should be more selections from the higher EV deck than the lower EV deck.
Based on the evidence presented above, the following two hypotheses are proposed:

**H2 Valence Frequency Hypothesis:** If valence frequency information is the primary source of information used to guide choice, then the deck with the higher frequency of gain outcomes will be preferred even if it has a lower EV. Thus, when gain frequencies between decks are unequal, there will be a greater preference for the higher frequency gain deck (lower EV deck) compared to when there are no gain frequency differences between decks (i.e., equal gain frequency).

**H3 Valence Frequency and Working Memory Interaction:** If maintaining magnitude frequencies exceeds memory capacity due to an increased number of possible outcomes, valence frequency may be used as the primary type of information used to inform choice as it is easier to maintain in working memory. Thus, I predict that when working memory strain is high (i.e., 5 outcomes per deck), the tendency to prefer the higher gain frequency (lower EV) deck over the higher EV deck should be greater than when working memory strain is low (i.e., 2 outcomes per deck).

*Relative Impact of Outcome Feedback on Learning from Experience*

A second critical aspect of experiential learning is outcome feedback. In a purely experiential learning environment, all information is gained by observing the outcomes of past choices. Thus, learning and decision making would be completely dependent on extracting and integrating information from outcome feedback. However, in a more applied setting, it is rather unlikely that experience will be the only type of information available. For example, I may use my own experience to judge the chances of rain, but I may also consult a weather forecast to help decide whether an umbrella is needed. By incorporating the information from the forecast, my
When more than just outcome feedback is available, it is uncertain to what extent people will continue to rely on outcome feedback information. Therefore, a second area of focus of the current investigation is to examine the value of feedback information while learning from experience when other types of information are also available. Specifically, I will look at how the presence of descriptive information may affect the extent to which outcome feedback is used to inform choice.

Descriptive Information. Historically, descriptive information, and not experiential information, has been the focus of decision-making research. For the past 50 years, descriptions of non-repeated monetary gambles have been used as the predominant paradigm for studying decision making. Usually, participants are presented with a pair (or more) of monetary gambles, each with fully described outcomes and probabilities. The decision maker then selects the option they feel is preferable, often without receiving choice feedback (e.g., Kahneman & Tversky, 1979; Thaler & Johnson, 1990). Thus, choices between a given pair of options is made only once with no outcome feedback information to inform choice. An example of a described lottery pair is depicted in Figure 2.

<table>
<thead>
<tr>
<th>Which of the following would you prefer?</th>
</tr>
</thead>
<tbody>
<tr>
<td>A: 50% chance to win 1,000, 50% chance to win nothing;</td>
</tr>
<tr>
<td>B: 450 for sure.</td>
</tr>
</tbody>
</table>

*Figure 2.* Example of a traditional monetary gamble (Kahneman & Tversky, 1979).
By observing choice preferences from these monetary gambles, several theories of decision making under risk have been created, but the most acclaimed of these is prospect theory (Kahneman & Tversky, 1979). Prospect theory (PT) is a descriptive theory of decision making under risk which proposes that people are more risk-seeking in the loss domain and more risk-averse in the gain domain. However, more recent studies of risk taking have identified a description-experience gap (D-E gap; e.g., Hertwig & Erev, 2009; Ludvig & Spetch, 2011) in which risk-preferences seem to reverse depending on whether the decision is made based on descriptive or experiential information.

Rather than being risk-seeking in the loss domain and risk-averse in the gain domain (as prospect theory predicts), people tend to be risk-averse for losses and risk-seeking for gains when information is gathered from experience. Thus, it is possible that descriptive information may be processed differently than outcome feedback information. If so, the presence of both types of information may shape choice differently dependent on the extent to which outcome feedback versus descriptive information is used to inform choice.

**Impact of Descriptive Information when Learning from Experience**

There are at least a few studies which can help inform predictions about how descriptive and experiential information come together to shape choice. These studies examine the extent to which outcome feedback contributes to learning and choice typically when inaccurate descriptive information is also available (e.g., Jessup, Bishara, & Busemeyer, 2008; Lejarraga & Gonzalez, 2011; Weiss-Cohen, Konstantinidis, Speekenbrink & Harvey, 2016; Weiss-Cohen, Konstantinidis, Speekenbrink & Harvey, 2018). Generally, these studies have found that description has an initial impact on decision making, but that as experience accrues, choice
feedback tends to overwhelm the influence of descriptive information. Thus, over time, there appears to be a tradeoff between descriptive and experiential information as to which source of information is primarily used to inform choice.

*Short-Term & Long-Term Effects of Description.* When experience is absent or limited, such as at the beginning of a decision series, the presence of descriptive information may be especially impactful on choice. By nature, experiential learning is gradual. Therefore, when learning is just beginning, there may not be enough outcome feedback information to inform decisions. Therefore, if descriptive information is present, it is likely that people will rely on descriptive information to guide choice, as it is the only information readily available.

If accurate, descriptive information may assist learning from experience because it provides a summary of potential outcomes and associated probabilities. Thus, before outcome feedback is gathered, the decision maker may already have a sense of which option is more advantageous, and this initial assumption would be reinforced by outcome feedback. However, if description is misleading, or inaccurate, this could interfere with learning from experience. Not only does the decision maker have to extract information from outcome feedback as they would normally in experiential learning, but they would also have to overcome any initial preferences that may have developed from the misleading or incorrect description.

Despite the early influence descriptive information may have in a decision series, evidence suggests that the impact of misleading or incorrect descriptive information can be attenuated, over time, by experiential feedback. For example, Weiss-Cohen, et. al., (2016) found evidence that a false description initially impacted choice behavior, but as experiential feedback accrued, the effects of the misinformation lessened. In their task, participants repeatedly selected
between a single pair of two-outcome gambles that differed in EV. Depending on condition, participants were given (1) no description of gamble outcomes or probabilities (i.e., experience only), (2) a correct description of the gamble outcomes and probabilities, or (3) a description of the gamble outcomes with false probabilities. The false probability descriptions made the lower EV gamble appear to be the higher EV gamble.

Not surprisingly, when participants were given an accurate probability description people quickly identified the higher EV gamble, and continued to prefer this choice to the end of the decision series. Thus, it is unclear the extent to which descriptive versus experiential information contributed to choice as both types of information favored the higher EV option. When no descriptive information was provided (experience only), preferences still favored the higher EV gamble, though learning was slower. This is likely because outcome feedback needed time to accrue. Still, by the end of the decision series, the proportion of higher EV gamble selections for the experience only group was nearly equivalent to the proportion for those who were given a full accurate description of the gambles at the outset. Thus, from experience alone, participants were able to learn which gamble was more advantageous, about as well as when an accurate description was provided.

When given a false probability description, preference for the higher EV gamble at the beginning of the decision series was lower than conditions with an accurate description or experience only. Thus, it appears participants were mostly reliant on descriptive information at the beginning of the decision task. However, as outcome feedback accrued, preference for the higher EV gamble did gradually increase, but was still lower than the other two conditions by the end of the decision series. Thus, it appears that outcome feedback was able to discount the initial effect of descriptive information, though not overwhelm it completely.
To explain these results, Weiss-Cohen and colleagues (2016) proposed a Bayesian updating model in which probability information from description and feedback are averaged together. However, because there is greater accumulation of experiential information over time, experiential information contributes more to the updating process than description. This is especially evident in later trials in which there is a large amount of experiential information and only the single offering of descriptive information at the outset. Over time, this results in a discounted effect of the initial misleading description when experience is also available as a source of information.

**Experience Overwhelming (Misleading) Description?**

As found by Weiss-Cohen et. al., (2016) there is some evidence that initial descriptions, when misleading, can have a long-lasting, though gradually discounted, effect on choice. Yet, other studies, focusing on risk-taking behaviors, have suggested that the impact of description does not persist once enough experiential information has been gathered (e.g., Jessup, Bishara, & Busemeyer, 2008; Lejarraga & Gonzalez, 2011). That is, in the presence of enough experiential information, misleading descriptive information becomes overwhelmed and no longer has any influence on choice.

As briefly mentioned earlier, the description-experience gap refers to a finding in which opposite patterns of risk-taking behavior are found depending on whether information is gained from description or experience (e.g., Hertwig & Erev, 2009; Ludvig & Spetch, 2011). When information is gained from description, people tend to be risk-averse for gains and risk-seeking for losses. When information is gained from experience, people tend to be risk-seeking for gains
and risk-averse for losses. Thus, when both description and experience are present, the extent to which people rely on each type of information may be inferred through risk-taking preferences.

Using monetary gambles, Lejarraga and Gonzalez (2011) compared risk preferences choice preferences between the following experimental groups: (1) those with experiential and (accurate) descriptive information, (2) those with (accurate) description-only information (3) and those with experience-only information. Evidence from this study suggested that risk-taking behavior between the description-only group differed significantly from both the experience-only group and the experience with description group, but choices between the experience-only group and the experience and description group were nearly identical. Thus, risk-taking behavior when both experience and description were available more closely resembled what would be expected had only experience been present versus only description.

Due to the lack of differentiation in risky choice between those with experience-only information and those with experience and descriptive information, Lejarraga and Gonzalez (2011) proposed that descriptive information was completely overwhelmed when experiential information was available. They further posited that experiential information may be a preferable source of information because (1) probability information inferred from observing outcome frequencies are more easily processed than stated probabilities, and (2) descriptive probabilities represent a theoretical prediction of outcome frequencies whereas probability derived from observed outcomes is more empirical and offers more reliable information.

Although there were substantial differences in paradigms used between the Lejarraga and Gonzalez (2011) and Weiss-Cohen et. al., (2016) experiments, both studies found evidence suggesting that outcome feedback information continues to inform choice in the presence of
descriptive information. Whereas Weiss-Cohen et. al. (2016) found a continued (though discounted) effect of descriptive information if it contradicted experiential feedback information (i.e., a false description), Lejarraga and Gonzalez (2011) did not find evidence to suggest an effect of description when experiential information was available. Thus, there is still some uncertainty as to whether extended outcome feedback completely overwhelms descriptive information, or if both types of information contribute to decision making, but the influence of substantial outcome feedback is simply stronger.

**Evaluating Relative Contributions of Outcome Feedback**

One of the ways to examine the importance of outcome feedback in learning from experience is to compare its impact to that of other forms of information (i.e., description). To compare the effects of outcome feedback and descriptive information in an experiential learning environment, the card-selection paradigm introduced in Figure 1 will be augmented so that a description of the possible monetary outcomes will be listed above each deck. As shown in Figure 3, these descriptions – although true – create an appearance that always seems to favor the lower EV deck. This was done so that contributions of outcome feedback and description on decision making could be differentiated. To the extent that people are using outcome feedback to inform choice, the higher EV deck should be preferred. To the extent people are using descriptive information to inform choice, the lower EV deck should be preferred.
Figure 3  Example of card selection task with added outcome description. The blue deck has a lower minimum and maximum outcome, but the probability of the maximum outcome (although not shown) is higher in the blue deck than the red deck making it the higher EV deck.

Although the potential outcomes of each deck are available, this is not enough information to estimate EV. As noted earlier, outcomes and associated probabilities are needed to calculate EV, the latter of which still needs to be learned through experience. Thus, in both versions of this card-selection task (with or without description), estimates of EV can only be gained through experiential information. By comparing the number of selections from the higher and lower EV decks, with and without descriptive information, the relative impact of description in experiential learning and choice may be inferred.

Below I present two additional hypotheses regarding the short-term and long-term effects of descriptive information in a repeated-decision environment with outcome feedback.

**H4: Initial Impact of Description:** Towards the beginning of the card selection task, when experiential feedback is absent or limited, participants will rely mostly on descriptive information to make choices. Thus, when description favors the lower EV
deck, participants will prefer the lower EV deck more so than those who were not given descriptive information.

**H5: Experience Overwhelming Description:** After experiential information has accumulated, the effect of a misleading description is expected to be discounted, or completely overwhelmed, by experiential feedback information. Consistent with Weiss-Cohen et. al., (2016), if descriptive information is discounted over time, those with a description will end up with a lower number of selections from the higher EV deck compared to those who were given no descriptive information (experience only). Consistent with Lejarraga & Gonzalez (2011), if outcome feedback information completely overwhelms description, there should eventually be no difference in preferences for those with only experience information and those with both description and experience information. Moreover, the rate of learning which option is more advantageous based on outcome feedback will be the same regardless if description was available at the outset of the decision series.

**Power of Dynamic Information in Repeated Choice**

A third characteristic of experiential learning is that experiential outcome feedback is inherently dynamic. While learning from experience, new feedback events continue to accrue sequentially over time. A choice is made, feedback is received, and then information extracted from feedback is integrated with previous information and then used to inform the next choice. This process in repeated throughout the decision series. Thus, while learning from experience, there is a constant accrual of new information, making the process inherently dynamic.
As shown across several studies, experiential information appears to be a particularly powerful source of information in repeated decision studies (e.g., Jessup, Bishara, & Busemeyer, 2008; Lejarraga & Gonzalez, 2011; Weiss-Cohen et. al., 2018). Even when descriptive information is misleading or false (Weiss-Cohen et. al., 2016), decision makers seem to be able to get beyond the misinformation by using experiential information in a way that helps lead to advantageous choices. If this is true, such results prompt the question, what makes outcome feedback so powerful?

Greater Accumulation of Information. As mentioned previously, Weiss-Cohen and colleagues (2016) proposed a Bayesian updating model in which they suggested that experiential information gradually overwhelms descriptive information because there is greater accumulation of experiential information. Descriptive information, on the other hand, does not accumulate as there is only a single offering of information which does not change. Similar to calculating an average, when both sources of information are integrated, experiential information has larger effect on choice because there is more information. As a result, the effects of description would become discounted as more feedback information accrues.

Adaptation Capabilities. An additional possibility as to why experiential information may be a particularly powerful source of information is that dynamic information may be especially useful for choice adaptation. While in a repeated decision environment, the underlying structure of the decision environment may not be known. From the point of view of the decision maker it is uncertain whether the decision environment is subject to change. Thus, when making decision repeatedly, it may be more prudent to use the most current information to inform choice rather than relying on past information which may no longer be applicable to the current decision environment.
If the decision environment does change or evolve, this change will be reflected in outcome feedback because it is consistently providing new information about the current decision environment. Thus, the dynamic quality of outcome feedback can assist the decision maker in adapting to the new choice environment. However, if there are no changes in the decision environment, then newer information will continue to be consistent with past information. Thus, there is no little to no consequence of using dynamic feedback information if there is no change in the decision environment. In other words, dynamic information may be particularly useful in a repeated decision context because it can facilitate adaptation if needed.

The relevance of experiential information for adaptation is exemplified in a study by Rakow & Miler (2009). In their experiment, participants repeatedly sampled between two “money machines” that awarded differing numbers of points. The goal of the task was to obtain as many points as possible. Unbeknownst to the participants, however, the EVs of each machine gradually switched mid-way through the decision series. Thus, to earn as many points as possible, participants would need to reassess their choice strategy half-way through the task. A descriptive variable was also included in this study. In one condition, participants were provided with a running total of past outcomes, whereas in the other condition no such summary was given. Although this summary did have a dynamic component, it combined old and new information. Thus, the rate at which summary information changed was much slower than the rate by which outcome feedback information changed.

After the switch in EVs between the two money machines, participants readily adapted choice behavior, and modified choice preference in accordance with the higher EV machine. This adaptation, however, was significantly slowed by the presence of the summary history of past outcomes. It was suggested by Rakow and Miller (2009) that the presence of the summary
history slowed adaptation because it provided information that no longer was applicable to the current decision environment. This hinderance, however, gradually lost its effect towards the end of the decision series. It is therefore possible that participants relied on both the descriptive summary and outcome feedback to help inform choice, but once outcome feedback started to disagree with the descriptive summary, experiential feedback was the preferred source of information because it provides the most current information about the decision environment.

In the current investigation, the underlying probability distributions in each deck do not change. Still, the results of Rakow and Miller (2009) provide evidence that experiential feedback may be a particularly powerful source of information in a repeated decision context, and that the dynamic quality of experiential feedback may be particularly useful in repeated decision environments, as it can help facilitate adaptation if needed.

**Testing the Effect of Dynamic Information**

The dynamic quality of outcome feedback, although fundamental for experiential learning, is not exclusive to experiential learning. As shown in Rakow and Miller (2009) description may also have a dynamic quality. Therefore, to test whether the dynamic information has greater influence on choice while learning from experience than static information the current investigation will compare the effects of a static description versus a dynamic description. If the effect of a dynamic description on choice is larger than when the same information is presented statically, it may be inferred that dynamic information is more influential in repeated choice tasks.

To create a dynamic description, I introduced conditions in which a description of the next potential deck outcomes changes after each draw. Thus, just as experience provides new
feedback after each selection, new descriptive information will also be available before each new selection. As noted previously, this investigation is designed so that descriptive information always seems to favor the lower EV deck. This has been done to disentangle the effects of using descriptive information from experiential information. The same will apply to dynamic description, so that the presence of description will favor the lower EV deck.

The last hypothesis of the current investigation will focus on possible effect of dynamic descriptive information:

**H6: Dynamic Information**: When descriptive information is presented dynamically (i.e., changes after each decision), it will have a larger influence on choice than when it is presented statically. Therefore, if descriptive information favors the lower EV deck, preference for the lower EV deck should be greater with dynamic descriptive information than with static descriptive information.

**Present Research**

The primary goal of the current investigation was to study how characteristics inherent in experiential learning influence learning from experience and advantageous choice. To guide this investigation, three characteristics fundamental to experiential learning and decision making were identified: (1) it is heavily dependent on memory, (2) information is gathered through choice feedback, and (3) choice feedback is dynamic. Each of these characteristics was systematically examined to evaluate the extent to which they contribute to experiential decision making. Although all data for the current investigation were collected concurrently, the investigation is arranged as two experiments to facilitate comprehension of the various manipulations and subsequent results. The first experiment focuses on the relative importance of memory and outcome feedback, whereas the second experiment focuses on evaluating whether
dynamic information is a particularly powerful source of information in a repeated decision context.

Experiment 1 focused on assessing the effects of memory and choice feedback in experiential learning and decision making. The role of memory was tested by altering the number of potential outcomes in each deck. It was predicted that strain on working memory would be greater with a higher number of unique outcomes, and this would in turn negatively affect the extraction of information needed to estimate EV.

An additional area of interest was the type of information extracted from outcome feedback, valence or magnitude frequency, which is prioritized, and whether the priority differs depending on working memory strain. It was predicted that valence frequency information may be prioritized over magnitude frequency information, and that the reliance on valence frequency information to inform choice may increase when working memory resources are strained. Lastly, the relative importance of choice feedback was examined by testing the extent to which it continues to inform choice when descriptive information is also present. It was predicted that descriptive information would be most influential at the start of a decision series when outcome feedback is limited. Gradually though, the influence of description would lessen, or become completely overwhelmed by outcome feedback information.

Experiment 2 explored the possibility that dynamic information may be an especially powerful source of information when learning from experience. Because experience feedback is inherently dynamic, the differential of effects of static versus dynamic information were tested using description to determine whether this difference affects learning. It was predicted that
adding a dynamic quality to description would enhance the effect of descriptive information, compared to when the same information was presented statically.
Experiment 1

In Experiment 1, two of the three characteristics identified as being fundamental to experiential learning and decision making were evaluated: reliance on memory and outcome feedback.

Strain on Working Memory. It was previously argued that working memory is a necessary component for the extraction and updating of EV information. Therefore, imposing strain on working memory may negatively affect experiential learning and advantageous choice. To compare how different levels of strain on working memory may affect learning, as evidenced by advantageous choice, the number of possible outcomes per deck were manipulated: 2-outcomes or 5 outcomes per deck. It was expected that learning and decision making would be more effective with fewer possible outcomes because it would be necessary to hold and update fewer items in working memory. Given that this manipulation presumably changed the difficulty of the choice environment, this manipulation was referred to as complexity.

Experiment 1 also examined which type of outcome information is more likely to be extracted and used to inform decision making, and whether this is dependent on the level of complexity within the decision task. To test whether magnitude or valence frequency was the primary type of information extracted to inform choice, the number of gain outcomes within a pair of decks was manipulated to be equal between decks, or to favor the lower EV deck.
When gain frequencies were equal, and there was no difference in valence frequencies between decks, it was expected that people would be forced to use magnitude frequencies to inform choice. When gain frequencies were unequal, and the lower EV deck was assigned a higher number of gain outcomes than the higher EV deck (with the remaining outcomes being 0), it was predicted that people would prefer the deck with more gains (lower EV deck), more so than when gain frequencies were equal between decks. Such a result may indicate that valence frequency is more influential in shaping choice preferences than magnitude frequency information. Additionally, it was predicted that the effect of gain frequency would be stronger when there were more outcomes per deck. Due to increased working memory strain, valence frequency information may be an easier type of information to extract and hold than magnitude frequency.

*Outcome Feedback.* Experiment 1 also tested the extent to which choice feedback continues to contribute to experiential learning and decision making when other sources of information (i.e., descriptions) are available. To do this, a manipulation of initial information was included. Participants either had no initial information and had to gather information exclusively through outcome feedback (experience only; E-Only) or were provided at the outset an additional static description of potential deck outcomes (description-static with experience; DS+E).

To determine the relative impact of the experiential versus the descriptive information in choice, the provided description always appeared to favor the lower EV option whereas experience naturally favored the higher EV option. Thus, all else equal, the extent to which participants prefer the lower EV option can be attributed to the effect of descriptive information, while the extent to which they prefer the higher EV option can be attributed to the effect of
outcome feedback. It was expected that the presence of a description would have a large influence at the beginning of the decision series (when feedback had not yet accrued), and that gradually this influence would be lessened, or completely overwhelmed, by outcome feedback information.

Experiment 1 Methods

Participants

A total of 387 participants were recruited for Experiment 1. Prior to recruitment, power analyses were conducted to calculate the minimum number of participants needed to detect a medium effect size ($\eta^2 = .06$) with power $=.80$ and $\alpha = .05$ for eight between-subjects groups. According to G*Power version 3.1.9.2 (Faul, Erdfelder, Lang & Buchner, 2007), a minimum of 240 participants (30 per between-subjects condition) were needed to be powered sufficiently. However, to increase power for interaction effects, and to ensure that the minimum required number of participants were met in the event of any participant exclusions or drop-outs, an excess of 240 participants was recruited.

All participants were recruited through the University of South Florida’s SONA systems, an online platform used to schedule participants for studies in exchange for class credit. To ensure anonymity demographic information was not recorded, however the population which the sample was recruited from consists mostly of undergraduate psychology majors, the majority of which are female between the ages of 18 to 24.
Design

Experiment 1 utilized a 2x2x2x4 Complexity x Gain Frequency x Initial Information x Block mixed factorial design. Complexity, gain frequency and initial information were included as between-subjects variables, while block was included as a within-subjects variable.

All between-subjects variables had two levels. Complexity altered the number of unique outcomes per deck: 2-outcomes per deck or 5-outcomes per deck. Gain frequencies within a deck pair were either equal with both decks having all gain outcomes, or unequal with the lower EV deck resulting in more gain outcomes than the higher EV deck. Initial information was manipulated by providing only outcome feedback information, experience only (E-only), or providing an additional static description of potential outcomes at the outset of the decision series (DS+E). Finally, block was included to divide the experiment into 4 equal parts with 25 trials in each. For the purposes of the current experiment, only the first and last block of trials (Blocks 1 and 4) were included for analysis.

The primary dependent variable was the extent of advantageous choice measured by the number of selections from the higher EV deck out of the 25 choices in one block of trials. Secondary dependent variables were also included. At the end of the experiment, participants were explicitly asked to identify which of the two decks they believed would result in the most money if played repeatedly, and how confident they were in that selection. Confidence ratings were presented as 5-point Likert-type scale ranging from “I had to guess” to “Very confident.” Participants were also asked to estimate the number of times they received each possible outcome in each deck. This was included to help gauge how accurately participants were able to extract magnitude frequencies. For exploratory purposes, participants were given a free response
section in which they were asked to describe their choice strategy and any changes in choice strategy during the card-selection task.

**Stimuli**

Experiment 1 utilized two versions of four separate pairs of decks. To incorporate the initial information manipulation, one version provided only outcome feedback information (E-Only), and the second version included a static description of the possible outcomes above each deck on every trial (DS+E). The creation of outcomes within each pair of decks was guided by the four conditions required from crossing the complexity (2-outcomes and 5-outcomes per deck) and gain frequency (equal and unequal) variables. Within all four deck pairs, one deck had a higher expected value than the other deck.

*Incorporating Initial Information.* The manipulation of initial information was incorporated into the card-selection task by providing or not providing additional information about the potential outcomes in each deck in the form of a description. As shown in Figure 4, when a static description was available with 2-outcome decks, both outcomes were listed above each deck one each trial with an “or” between the two potential outcomes. With 5-outcome decks a range of possible outcomes was listed above each deck (only 5 of which would actually ever occur but always included the endpoints). When only outcome feedback was available (E-Only), the space above the decks was left blank.
To ensure that the added description would seem to favor the lower EV deck, outcomes were chosen so that the lower EV deck had a higher minimum and maximum outcome than the higher EV deck. For all four deck pairs, the lower EV deck had a maximum outcome that was greater than the maximum outcome of the higher EV by $2. However, the probability of getting the maximum outcome in the lower EV deck was lower than in the higher EV deck. Thus, despite having a higher minimum and maximum, the likelihood of receiving the maximum outcome was lower, which made the EV less than the other deck.

**Deck Outcomes and Probabilities.** By crossing the complexity and gain frequency variables, four deck pairs were created. Two deck pairs had 2-outomes per deck, with either equal or unequal gain frequencies across decks. The other two deck pairs had 5-outcomes per deck with either equal or unequal gain frequencies across decks. Several considerations went into
developing the outcomes and associated probabilities in each type of deck pair. A summary of these values for each of the four deck pairs is provided in Table 1.

Table 1. Deck Stimuli with Outcome Probabilities for Each Possible Outcome per Deck

<table>
<thead>
<tr>
<th>Outcome</th>
<th>2-Outcome Decks</th>
<th>5-Outcome Decks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Unequal Gain Frequency</td>
<td>Equal Gain Frequency</td>
</tr>
<tr>
<td></td>
<td>Hi EV(^1)</td>
<td>Lo EV(^1)</td>
</tr>
<tr>
<td>0</td>
<td>0.32</td>
<td>0.30</td>
</tr>
<tr>
<td>1</td>
<td>0.02</td>
<td>0.40</td>
</tr>
<tr>
<td>2</td>
<td>0.68</td>
<td>0.32</td>
</tr>
<tr>
<td>3</td>
<td>0.18</td>
<td>0.02</td>
</tr>
<tr>
<td>4</td>
<td>0.68</td>
<td>0.10</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>0.68</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>0.32</td>
<td>0.68</td>
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<tr>
<td>10</td>
<td></td>
<td></td>
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<tr>
<td>11</td>
<td></td>
<td></td>
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<tr>
<td>12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EV</td>
<td>4.76</td>
<td>4.24</td>
</tr>
</tbody>
</table>

*Note.* Higher EV and lower EV columns with the same superscript were shown together as a pair of side-by-side decks.

As shown in Table 1, when gain frequencies were unequal, one of the deck outcomes was zero. In these conditions, a zero outcome (non-gain outcome) was necessary in the higher EV deck so that the number of gains in the lower EV deck would always be higher. To help ensure comparability between the 2-outcome and 5-outcome deck pairs when gain frequencies were unequal, the probability of receiving the zero outcome was calculated so that the number of experienced zeros would be nearly identical. Out of 50 selections, 2-outcome decks with unequal gain frequencies had a total of 16 zeros (.32 probability), and 5-outcome decks with unequal gain frequencies had a total of 15 zeros (.30 probability). For decks with equal gain frequencies, all of
the outcomes were gains. Additionally, within all four deck pairs, the probabilities of receiving
the better or worse outcomes within the higher EV deck were reversed in the lower EV deck.
This was done so that the variance within a pair of decks would remain the same.

In preparation for this experiment, several sets of stimuli were tested to finalize the size
of EV difference between deck pairs. The difference in EV between decks needed to be
sufficiently large enough to discriminate, but not so large that the higher EV deck would be
readily apparent. This was done to help avoid any ceiling or floor effects that might have
occurred from the deck EV differences being too easy or too hard to discriminate. Based on the
pilot data collected prior to this experiment, a difference of $0.52 per trial was deemed to be
enough for discrimination without being too obvious as to which deck was better or worse. This
difference was the same in all four deck pairs. Thus, on average, the higher EV deck earned .52
cents more per trial than the lower deck.

*Outcome Orderings.* The order in which outcomes were presented were carefully
designed to ensure that any 10 consecutive outcomes within a deck would be within +/- $1 of the
expected value of that deck. This was done to help ensure that the experienced expected value
through sampling would be similar to the actual expected value of each deck. Additionally, the
number of better or worse outcome streaks was equivalent across all four deck pairs. This was
done to help control for any biases that might develop which could affect participants’ beliefs
about whether a better (or worse) outcome was more likely (hot hand effect) or less likely
(gambler’s fallacy) to occur on the next trial (Ayton & Fischer, 2004; Croson & Sundali, 2005).
Procedure

In each session, prior to participant arrival, computers were set up by a lab research assistant to run one of the 10 possible conditions.\(^1\) Conditions were randomized by session, as instructions varied depending on experimental condition, and sessions were randomly counterbalanced, so that each condition was run once within any 10 consecutive sessions. As participants entered, they were given free choice of seating at one of eleven laboratory computers. Once seated, participants read the informed consent on the computer screen and were asked to check a box signifying that they agreed to participate. Once all participants had agreed to consent, instructions for the task were read aloud by the research assistant.

Depending on the type of initial information present (experience only, static description or dynamic description), one of three verbal scripts were read. There were minor wording changes between scripts to acknowledge differences between various deck pair presentations. In the instructions, it was explicitly stated that the goal of the task was to make as much money as possible, and that one of the decks was worse than the other. It was also clarified in the instructions that, just as in real decks of cards, the order of the outcomes would not change once the task had begun. Participants were not told how many selections they would have to complete. To help motivate participants to try to gain as much money as possible, participants selected a “gift” colorful pen or pencil of their choice at the beginning of the study, but were told that they may or may not be able to keep it depending on their performance. However, unbeknownst to the participants, everyone who completed the study was able to keep their pen or pencil.

\(^1\) Experiments 1 and 2 were run contemporaneously.
After all instructions were read, and any questions were answered, participants began the computer task. They first completed 100 choices by repeatedly selecting a card from one of two decks, presented side-by-side. To balance any effects of how decks were presented, the side (left or right) and color (red or blue) of the higher EV deck were randomized across participants. As depicted in Figure 5, on each selection, the topmost card of the selected deck would flip over revealing the amount won for that trial. After each selection, earnings were added to a running total at the top of the screen.

![Figure 5. Three screenshots showing the sequence within a single trial in an experience-only deck pair. Panel A: View of deck pairs prior to any selection. Panel B: View after selection of the left (red) deck resulting in a gain of $2. Panel C: View of update in total earnings to reflect the gain of $2, along with the prompt to the participant to make another selection (i.e., begin the next trial).](image)

After the 100th draw, participants were notified that the first part of the experiment had concluded and were then asked to select which deck they thought would result in the most money if played repeatedly. The research assistant then changed the computer screen to a different program so that participants could respond to a few additional items. Once changed, participants were asked to confirm which deck they thought would result in the most money if played repeatedly, and they rated their confidence in their choice. Participants were then shown
an image of the two decks they had seen in the primary task. Below this image, participants were asked to estimate the number of times they had received each outcome from each deck. A screenshot of this estimation task is shown in Appendix A.

Once completed, a message appeared instructing participants to see the researcher before they left. The researcher informed participants that they could keep the pen or pencil they had selected at the beginning of the study and provided a brief information sheet about the experiment.

**Experiment 1 Results**

Analyses for Experiment 1 were performed to evaluate the effects of (1) complexity, (2) gain frequency, and (3) initial information on advantageous decision making when learning from repeated experience. The primary analysis conducted was a 2 x 2 x 2 x 2 Complexity (2 or 5 outcomes) x Gain Frequency (equal or unequal) x Initial Information (E-Only or DS+E) x Block (Block 1 and Block 4) mixed ANOVA. Complexity, gain frequency, and initial information were included as between-subjects variables, and block was included as a within-subjects variable. The primary dependent variable was the number of selections from the higher EV deck out of 25 choices in Block 1 and Block 4.

Additionally, to test for preferences that differed significantly from chance, a number of single-sample t-tests were conducted in Blocks 1 and 4. For all single-sample t-tests, sample means were compared to a test value = 12.5 higher EV selections (equal preference for both decks). Means statistically greater than 12.5 indicated preferences for the higher EV deck, while means statistically lower than 12.5 indicated preferences for the lower EV deck.
Prior to analysis, data were screened to ensure that (1) participants were engaged in the
card-selection task and sampled from both decks of cards, and (2) participants could see the
different color of the two decks (i.e., they were not color-blind). No participants were excluded
for lack of sampling between decks. There were five participants who never sampled from the
higher EV deck, however all these participants were in a description condition which favored the
lower EV. Therefore, the lack of sampling may be attributed to the manipulation, and not lack of
interest in the study. Additionally, no participants were excluded for color blindness. Two
participants indicated that they were “unsure” if they were color blind, but confirmed that they
could distinguish the color difference between the red and blue deck.

**Working Memory: Effects of Complexity and Gain Frequency on Advantageous Choice**

**Complexity.** It was predicted in the *working memory capacity hypothesis* (H1) that greater
complexity in the card-selection task would strain working memory which would adversely
affect experiential learning and advantageous choice. The main effect of complexity, however,
was not significant, $F(1, 379) = 1.59, p = .21$. There was no evidence to suggest that the number
of higher EV choices was influenced by the number of outcomes within each deck. Thus, no
support for the *working memory capacity hypothesis* (H1) was present.

No main effect of Block, $F(1, 379) = 2.94, p = .09$, was present either. From Block 1 to
Block 4 there was no discernable change in the average number of higher EV selections. Thus,
no overall effect of learning from Block 1 to Block 4 could be documented.

It was possible that the lack of complexity and learning effects were being masked by
differential effects of learning within the two levels of complexity (2-outcome or 5-outcome
decks); however, no Complexity x Block interaction was present, $F < 1$. Therefore, the lack of
complexity and learning effects held across conditions. The grand mean for all conditions combined was $M= 13.03$, $SE=.23$.

While complexity did not seem to affect experiential learning, an even more striking result was the lack of evidence of learning over time. These initial results suggested that participants were not able to differentiate well between decks even after outcome feedback had been accrued. However as revealed by subsequent analyses, an effect of learning was being masked by differential effects of gain frequency while learning.

Gain Frequency. It was predicted in the valence frequency hypothesis (H2) that the number of higher EV deck selections would be lower in the unequal frequency condition than when gain frequencies were equal between decks. This is because when gain frequencies were unequal, the lower EV deck had a greater number of gain outcomes than the higher EV deck. Thus, if valence frequency information had greater influence on choice than magnitude frequency information, people should be drawn to the deck with more gain outcomes despite having a lower EV.

In support of this prediction, a significant, but small, main effect was found for gain frequency, $F(1, 379) = 10.75, p < .01$, partial $\eta^2=.028$. On average, when gain frequencies were equal ($M=13.73$, $SE=.32$) there were more selections from the higher EV deck than when they were unequal ($M= 12.24$, $SE=.33$). Thus, in the unequal gain frequency condition, it appears that people may have been particularly drawn towards the deck which resulted in only gain outcomes (despite having a lower EV).

As reported earlier, the main effect of block was not significant, thus there was no evidence to suggest learning occurred from Block 1 to Block 4. However, this result was
qualified by a Gain Frequency x Block interaction, $F(1, 379) = 5.97, p=.02$, partial $\eta^2=.017$, which indicated that learning was dependent on the level of gain frequency. This interaction is depicted in Figure 6.

![Figure 6](image)

**Figure 6.** Effects of gain frequency across block. The red dashed line represents equal preference for the lower EV and higher EV deck (12.5 selections from higher EV deck). Error bars represent ±1 standard error from the mean.

Simple effects analyses revealed that when gain frequencies were equal, there was a significant, yet small, increase in the average number of selections from the higher EV deck from Block 1 ($M=13.09, SE=.30$) to Block 4 ($M=14.37, SE=.45$), $F(1,379)= 9.16, p<.01$, partial $\eta^2=.023$. A single-sample t-test confirmed that in Block 4, those with equal gain frequencies between decks showed a small preference for the higher EV deck, $t(201)=4.24, p<.01, d=.30$. When gain frequencies were unequal, however, the number of selections from the higher EV deck did not noticeably change from Block 1 ($M=12.35, SE=.31$) to Block 4 ($M=12.12, SE=.47$), $F<1$, nor was there evidence of a systematic preference for the lower or higher EV deck in either Block 1 $t(185)=-.20, p=.84$, or Block 4, $t(185)=-.78, p=.44$. 
Based on these results, there was at least some support for the valence frequency hypothesis (H2). When gain frequencies were equal, and all outcomes from both decks were gains, learning from experience was effective, suggesting that people may have been trying to use magnitude frequency information to identify the higher EV option. However, when the lower EV deck had all gain outcomes but the higher EV deck had some zero outcomes, no observable effect of learning was present. Thus, it seems that participants were influenced by valence frequency information, which competed with magnitude frequency information, making it harder to distinguish the lower EV option from the higher EV option.

A Valence Frequency x Working Memory interaction (H3) was also predicted, in which the influence of gain frequency was predicted to be greater in 5-outcome decks versus 2-outcome decks. It was hypothesized that strain on working memory would be greater when there were more outcomes per deck than fewer. Such an increase in working memory strain may increase the likelihood that valence frequency information would be used to inform choice because it is easier to hold in working memory than magnitude frequency information. If so, people might be especially attracted to the deck with only gain outcomes when there is more strain on working memory (5-outcome decks) compared to when there is less strain on working memory (2-outcome decks).

No evidence was found to support this hypothesis. A Complexity x Gain Frequency interaction could not be documented, $F < 1$; nor was there a significant Complexity x Gain Frequency x Block interaction, $F(1,379)=1.50$, $p=.23$. Thus, there was no evidence to suggest that complexity influenced the degree to which valence frequency was used to inform choice.
Short-term and Long-term Effects of Initial Information

It was predicted in the *initial impact of description hypothesis* (H4), that when descriptive information was present, there would be fewer selections from the higher EV deck at the start of the decision series (Block 1), compared to when only experiential information was available (E-Only). This is because descriptive information was manipulated to make the lower EV appear better. It was also predicted in the *experience overwhelming description hypothesis* (H5), that the initial impact of descriptive information would be discounted or perhaps completely overwhelmed by choice feedback information by Block 4. If so, similar rates of learning should be seen in E-Only and DS+E conditions.

No main effect of initial information was found, $F < 1$. However, this result was not surprising as it was predicted that the effect of initial information would be most prominent in Block 1. More importantly, an Initial Information x Block interaction was present, $F(1, 379)=10.98, p < .01$, partial $\eta^2=.028$, suggesting differential effects of initial information within Blocks 1 and 4. However, this too was qualified by the higher order interaction of Initial Information x Gain Frequency x Block, $F(1,389)=4.38, p=.04$, partial $\eta^2=.011$. Therefore, the effects of initial information differed dependent on the level of gain frequency and differed across block.

To evaluate the description-related hypotheses (H4 and H5), results of the 3-way interaction were interpreted. Additionally, given that initial information qualified the gain frequency effect, the interpretation of the valence frequency hypothesis (H2) needed to be
reassessed. A depiction of this 3-way interaction is shown in Figure 7.

**Figure 7.** Combined effects of gain frequency, initial information, and block on advantageous choice. The left panel shows the effects of gain frequency by block when only outcome feedback information is available. The right panel shows the effect of gain frequency by block when a static description was provided along with outcome feedback. The red dashed line represents equal preference for the lower EV and higher EV deck (12.5 selections from higher EV deck). Error bars represent ±1 standard error from the mean.

*Effects of Gain Frequency on Learning: Experience Only.* A Gain Frequency x Block simple interaction effect was found at the experience only level of initial information, \( F(1, 196) = 10.57, p < .01, \text{partial } \eta^2 = .051 \). This suggested that when only outcome feedback was available (E-Only; see left panel Figure 7), the effects of learning (change in preferences from Block 1 to Block 4) were moderated by the gain frequency manipulation.

Simple comparisons revealed that, when gain frequencies were equal between decks, the increase in preferences for the higher EV deck from Block 1 (\( M=13.40, \text{SE}=.35 \)) to Block 4 (\( M=14.29, \text{SE}=.58 \)), was not significant, \( F(1,93)=2.75, p=.10 \). Thus, no clear effect of learning was detected. Nevertheless, a single-sample t-test confirmed that the higher EV deck was favored in both Block 1, \( t(103)=2.58, p=.01, d=.25 \) and Block 4, \( t(103)=3.06, p<.01, d=.30 \). Therefore, despite the lack of an appreciable increase in the number of higher EV selections from
Block 1 to Block 4, there was some evidence to suggest that participants may have been able to use outcome feedback even early on to move toward identifying the more advantageous deck.

When gain frequencies were unequal between decks, simple comparisons revealed a small, but significant decrease in higher EV preferences from Block 1 (M=13.46, SE=.37) to Block 4 (M=11.52, SE=.73), $F(1,93)=7.74$, $p<.01$, partial $\eta^2=.08$. Thus, a small effect of learning was found, but preferences unexpectedly moved in the direction of the lower EV deck. Single-sample t-tests revealed that in Block 1 there was a small, initial, preference for the higher EV deck, $t(93)= 2.56$, $p=.01$, $d=.26$. Yet, as feedback accrued, the presence of the potential zero outcome seemed to push preferences away from the higher EV deck. Although average preferences moved in the direction of the lower EV deck, a single-sample t-test could not verify a significant preference for the lower EV deck in Block 4, $t(93)=-1.33$, $p=.19$. Still, the decrease in higher EV selections from Block 1 to Block 4 suggests that people may have been moving toward reliance on valence frequency information to inform choice based on outcome feedback, consistent with the valence frequency hypothesis (H2).

**Effects of Gain Frequency on Learning: Static Description with Experience.** No Gain Frequency x Block simple interaction effect was present when a static description was provided along with experiential feedback (see Figure 7, right panel), $F<1$. However, as can been seen in Figure 7 (right panel), it appears that a similar rate of learning was present in both the equal and unequal gain frequency conditions. Simple comparisons confirmed that a small increase in the average number of higher EV selections from Block 1 to Block 4 for when gain frequencies were equal, $F(1,96)=6.61$, $p=.01$, partial $\eta^2=.06$ and when they were unequal, $F(1,91)=5.67$, $p=.02$, partial $\eta^2=.06$. Therefore, it appears that at least a modest amount of learning was occurring through outcome feedback both when gain frequencies were equal and unequal. However, unlike
the E-only condition, participants did learn in the direction of the more advantageous deck, when the higher EV deck contained a zero outcome.

Although similar rate of learning was found between the equal and unequal frequency conditions when a static description was present, the presence of a zero outcome in the higher EV deck caused participants to start in a position that favored the lower EV deck. When a zero outcome was present in the higher EV deck, there was an slight initial preferences for lower EV deck in Block 1, \( t(91) = -2.44, p = .02, d = .25 \), however as experience accrued preferences shifted towards the higher EV deck, but were still largely mixed in Block 4, \( t(91) = .42, p = .68 \). When a static description was present, and all outcomes were gains, initial preferences were not pushed either towards or away the higher EV deck. A single-sample t-test confirmed that initially (in Block 1), deck preferences were largely mixed, \( t(96) = .50, p = .63 \), but by Block 4 participants appeared to prefer the higher EV deck, \( t(96) = 2.93, p < .01, d = .30 \).

When description was available, there was mixed support for the initial impact of description hypothesis (H4). It was expected that the presence of a misleading description which appeared to favor the lower EV deck would cause participants to develop initial preferences (Block1) towards the lower EV deck. As can been seen in Figure 7 (right panel, Block 1), when both decks contained only gain outcomes, there was no discernable effect of a misleading description pulling preferences towards the lower EV deck. However, if a zero was present in the description, participants did (slightly) prefer the lower EV deck early on. Thus, the initial impact of a misleading description could only be seen when there was a zero outcome in the higher EV deck.
Evaluating the Experience Overwhelming Description Hypothesis. There were two ways in which the *experience overwhelming description hypothesis* (H5) could be evaluated: (1) assessing the rate of learning between Block 1 and Block 4 between the E-Only and DS+E conditions, and (2) comparing preferences for the higher EV deck in Block 4. If rates of learning and final preferences are similar between the E-Only and DS+E conditions, it may be inferred that, over time, experiential information may have larger influence on choice than descriptive information.

As can be seen in Figure 7, when gain frequencies were equal, the rate of learning was similar in the E-Only and DS+E conditions (as confirmed by similar learning effect sizes). In both Block 1 and Block 4, preferences between the E-Only and DS+E conditions did not significantly differ. No effect of a misleading description was present to begin with, therefore there was no bias that outcome feedback needed to overcome as a result of a misleading description. Thus, when gain frequencies were equal there is no evidence that experience overwhelmed description – though it is clear that experience had more influence on choice than descriptive information. By Block 4, preferences for both the E-only and DS+E conditions favored the higher EV deck.

When gain frequencies were unequal, the relative contributions of descriptive and experiential information on choice were unclear. As can been seen in Figure 7, in Block 4, there were no significant difference in preference for the higher EV deck, \( F(1, 185) = 1.68, p = .20 \), however, learning slopes from Block 1 to Block 4 were very different. It was previously assumed that outcome feedback would always lead participants towards the higher EV deck. Yet, when only outcome feedback was available, participants were pulled towards the lower EV deck when the higher EV deck had zeroes in it. This may reflect a gradual learned aversion towards the deck
that sometimes resulted in a zero outcome (the higher EV deck). Yet, when description was available, preferences were initially pulled towards the lower EV deck, but then gradually shifted in the direction of the higher EV deck. This initial aversion is likely due to the descriptive information immediately informing participants that one deck has a potential zero and the other only contains gains. Over time, however, people may have learned that the deck with only gain outcomes most often resulted in worse outcomes. After realizing this, participants may have started to sample more from the deck with the described zero outcome and learned that they were receiving the better outcome more often.

**Final Selection Analyses**

At the end of the card-selection task, participants were asked twice to make a final selection indicating which of the two decks they thought would make the most money if played repeatedly. This was asked once right after the 100th card draw, and again moments later at the beginning of the questionnaire portion as a reminder before asking details about the card-selection task.

A series of chi-square goodness of fit tests were conducted to analyze whether the frequency of higher EV selections differed significantly from chance depending on the combined effects of gain frequency and initial information. Complexity was not included as there was no effect of complexity within the primary analysis. Prior to analysis, consistency in responses between the first selection and second selection was checked. There were 19 participants who did not have matching responses. These data from these participants were not included in the chi-square analyses because it could not be determined which deck they thought made more money.
in the long run. Analyses were conducted with the remaining 368 participants. Figure 8 depicts the percentage of higher and lower EV selections within each group.

![Figure 8](image)

Figure 8. Percentage of higher EV and lower EV final selections for combined effects of gain frequency and initial information. * = higher EV selections were greater than chance.

As can be seen in Figure 8, when gain frequencies were equal, there was a higher than chance rate of selection of the higher EV deck in both the E-Only, $\chi^2 (1, N= 100)= 10.24, p < .01, \phi=.37$ and DS+E, $\chi^2 (1, N= 90)= 17.79, p < .01, \phi=.44$, conditions. The effect size was medium is both cases. The pattern of preferences observed here is consistent with results from the primary analysis, and suggests that people were able to effectively learn from outcome feedback when both decks had all gain outcomes.

When gain frequencies were unequal and the higher EV deck had several zero outcomes, the rate of selection for the higher EV deck was not different from chance in either the E-Only ($\chi^2 (1, N= 88)= 2.22, p = .13$) or DS+E ($\chi^2 (1, N= 90)= 1.6, p = .21$) condition. Again, these
results are consistent with the primary analysis, and suggest that having unequal gain frequencies may have disrupted learning from outcome feedback.

**Card-Selection Process Analyses**

To help gain a better understanding of factors which shape deck exploration, and whether exploration strategy affect advantageous choice behavior, several post-experimental exploratory analyses were conducted. These included an analysis of initial search strategies, as well as an analysis of the propensity to alternate deck selections.

The presence of an initial description was designed to favor the lower EV (less advantageous) deck. It was therefore of interest to investigate whether this description resulted in an initial bias towards selecting the lower EV deck, and whether such bias would endure over time. To test the effect of initial description on card selection, two Chi-Square tests of independence were conducted to test whether the frequency of higher EV selections on the first and second selection differed between those who were given a description and those who learned from experience only. As could be expected, the presence of a description (favoring the lower EV deck) led participants to prefer the lower EV deck in their first selection, $\chi^2 (1), = 6.15, p = .01$. When a description was available, 63% of participants selected the lower EV deck as their first choice, whereas those with experience only selected the lower EV deck 51%. Yet, by the second selection there were no longer any differences in the percentages, with a similar number of lower EV selections between the descriptive (54.5%) and experience only (49%) groups, $\chi^2 (1), = 1.18, p = .31$. Thus, while description did have an effect on initial choice strategy, the effect seemed to be relatively weak and very short-lived.
A separate analysis was conducted to explore whether the degree of deck exploration was related to advantageous choice. Those who switch decks more often towards the end of the decision task (Block 4) may not have yet identified the more advantageous deck, whereas those with fewer alternations may have learned (or already suspected) which deck was more advantageous. A cursory look at the relationship between advantageous choice and number of alternations revealed that the relationship was non-linear with fewer alterations at both extremes. A median split was therefore used to create two groupings of results based on deck preferences in Block 4; an advantageous group ($\geq 14$ higher EV deck selections) and a disadvantageous group ($\leq 13$). A one-way ANOVA was then conducted using the two preference groupings as the predictor variable and the number of alterations in Block 4 as the dependent variable. No systematic difference in the number of alternations could be documented between the advantageous and disadvantageous groups, $F < 1$. Thus, there was no evidence that the degree of switching between decks was related to the likelihood of making advantageous or disadvantageous choices.

Lastly, for exploratory purposes, a $2 \times 2 \times 2 \times 2$ Complexity (2 or 5 outcomes) x Gain Frequency (equal or unequal) x Initial Information (E-Only or DS+E) x Block (Block 1 and Block 4) mixed ANOVA, was conducted using the number of alterations in Blocks 1 and 4 as the dependent measure. This was done to test whether the degree of exploration was influenced by the deck characteristics, and whether the degree of exploration changed over time. For example, in the beginning of the decision series it may be expected that participants would want to gather information about each deck by switching often between decks. After information has been gained, participants may settle on a single deck resulting in less switching.
A small main effect of complexity was found, $F(1, 379)= 10.10$, $p < .01$, partial $\eta^2=.03$. Participants with 5-outcome decks made slightly more alterations (M=9.8, SE=.30) than those with 2-outcome decks (M=8.4, SE=.31). This may suggest that more information inside the decision space (i.e., all possible options in a given decision) may have led participants to explore the decision space longer, resulting in more alterations. However, as noted earlier, complexity was not found to be related to advantageous choice. Thus, while the tendency to switch decks may be influenced by complexity, this may not be related to the likelihood of making advantageous choices.

A main effect of Block was also found, $F(1, 379)= 36.46$, $p < .01$, partial $\eta^2=.09$. From Block 1 (M=9.9, SE=.23) to Block 4 (M=8.3, SE=.28), the number of alterations between decks decreased slightly. Such a pattern could be expected if at the beginning of the decision series participants were more likely to explore between the two decks, and towards the end of the decision series participants started to settle – and continuously select from the same deck. Still, the number of alterations was rather high (1 switch for every 3 selections), which may suggest that participants were still exploring the decks by Block 4. All other main effects and interactions were not found to be significant.

Based on the results of the above analyses, it appears that the tendency to alternate between decks was not related to the likelihood that people will make advantageous choices. Yet, given that the average number of alterations were still fairly high by Block 4, it may be that participants were still in “exploratory mode,” and were still trying to gather information as to which deck is most advantageous. This would also help explain why, in several conditions, people did not overwhelmingly prefer either the higher or lower EV decks by Block 4.
Summary

The results of Experiment 1 suggest that learning from experience to make advantageous choices seems influenced by the frequency of gain outcomes within an option, and the presence of external (misleading) information, but not by the number of outcomes within an option (2-outcomes versus 5-outcomes).

Overall, results of Experiment 1 provided relatively strong support for the valence frequency hypothesis (H2), which hypothesized that valence frequency would be used to help guide choice while learning from outcome feedback. When the lower EV deck had a higher number of gain outcomes than the higher EV deck (unequal gain frequency), learning from experience was negatively affected. These results are consistent with results from SGT experiments (Chui et. al., 2008), which suggested that experiential learning is particularly sensitive to differences in valence frequency between options. However, when gain frequencies were equal between decks, learning from experience was not as strong as expected. Still, the presence of learning when all outcomes were of the same valence (i.e., all gains) may suggest that magnitude frequencies were also used to differentiate decks, but that the relatively small EV difference between the higher and lower EV decks may have been difficult to detect within the allowed number of samples. If more sampling had been allowed, it is possible that differences in magnitude frequencies would have been clearer to participants.

Additional support for the valence frequency hypothesis (H2) was found in Block 1 when description informed participants of a potential zero outcome in the higher EV deck. Immediate knowledge of the potential zero outcome made participants particularly averse to the higher EV deck. This may be reflective of a conscious Pwin choice strategy (Payne, 2005), where people
preferred the deck that maximized the likelihood of a gain outcome. Although there were no
predications for an effect of gain frequency in Block 1 while learning from experience only,
results of the primary analysis confirmed that there was no evidence to suggest valence
frequency differences had an early effect on choice preferences (Block 1). This is likely a result
of not having gathered enough information from feedback to know that one deck consistently
had a zero outcome and the other never did (see, e.g., Hadar & Fox, 2009).

The finding that participants were particularly averse to the presence of a zero outcome
when described also helped support the initial impact of description hypothesis (H4). This
hypothesis predicted that participants would be initially biased towards the lower EV deck if it
was described more favorably. However, this initial impact was only seen when a zero outcome
was described in one of the decks. When all described outcomes were gains, no effect of initial
information was found. This was somewhat surprising as the lower EV deck had a higher
minimum and maximum value. It could be that people were not as sensitive to differences in
values when they are within the same valence (e.g., all gains), as when values cross valence (e.g.,
gain or no gain). Thus, it is possible that descriptive information was not attended as strongly
when all outcome were gains because the outcomes did not appear very different between decks.

Results of Experiment 1 provide partial support for the experience overwhelming
description (H5) hypothesis. As mentioned above, when description was present, and the higher
EV deck had a zero-outcome listed in the description (unequal gain frequency), participants
initially preferred the lower EV deck. However, as outcome feedback accrued the effect of the
initial description was discounted, and an effect of learning in the direction of the higher EV
deck was found. However, the effects of learning where not overwhelming. By Block 4
participants were still rather mixed in their deck preferences.
Evaluation of the *experience overwhelming description* (H5) was less clear when only gain outcomes were available (equal gain frequency). An effect of learning was present, however, there was no effect of and initial description. As revealed by the process analysis conducted on the first and second card selections, the effect of description on choice was very short-lived. The bias introduced by description seemed to have faded, and perhaps become overwhelmed by outcome feedback. As a result, there was a slight preference for the higher EV deck (in Block 4) when learning from experience only, and when a description was also available.

*Lack of Complexity Effect.* Contrary to prior predictions, no effect of complexity could be documented. Thus, no support for the *working memory capacity hypothesis* (H1) or the *valence frequency and working memory interaction* (H3) was found. However, given that in many conditions deck preferences were largely mixed, it is possible that participants had trouble differentiating decks regardless of any additional strain that complexity may have had. Thus, it is difficult to assess (1) whether manipulation of complexity was strong enough to cause strain on working memory, and (2) whether such strain would have a negative effect on learning from experience. If, for example, somatic markers had been used to help differentiate, such strain may not have had much impact of choice preferences (Bechara, Damasio, & Damasio, 1994).
Experiment 2

In Experiment 2, the last of the three characteristics identified as being fundamental to experiential learning was evaluated: the inherently *dynamic* nature of outcome feedback. The purpose of Experiment 2 was to test whether dynamic information is a particularly influential source of information when making decisions from repeated experience. Experiment 2 also explored whether differences in gain frequency would affect learning when a dynamic description was present.

It was predicted that the addition of a dynamic description would enhance the influence of descriptive information on choice, compared to when description is presented only statically. Although no specific hypothesis was developed originally for the possible interaction between initial information and gain frequency, findings from Experiment 1 suggested that the effect of learning within different levels of initial information may be moderated by differences in gain frequency. Therefore, when learning only from gain frequency, it is predicted that over time participants would learn to favor the higher EV deck when gain frequencies were equal between decks, and that when the higher EV deck contained a possible zero outcome (unequal gain frequencies) participants would learn to prefer the lower EV deck. The presence of a static description is expected to have an additive effect of gain frequency. Thus, it is possible that with the addition of a dynamic description, an additive effect of gain frequency may also be observed.
As it was not possible to manipulate outcome feedback from experience to be static, descriptive information was instead manipulated to be dynamic. Thus, the influence of dynamic information may be inferred by comparing the effects of static versus dynamic descriptive information. Two levels of initial information were used in Experiment 2; a static description (DS+E) with data provided from the 5-outcome DS+E condition from Experiment 1, as well as a new dynamic description (DD+E) condition in which outcome descriptions from 5-outcome decks were presented dynamically (DD+E). After each selection, the description of the potential outcomes from the next card changed, giving description a dynamic element that is usually associated only with experiential information (i.e., outcome feedback over time). As in Experiment 1, the presence of description in Experiment 2 always favored the lower EV deck.

The results of this experiment may help determine whether the dynamic element inherent in experience is one reason why experiential feedback information may be especially effective in repeated choice environments.

**Experiment 2 Methods**

**Participants**

An additional 103 participants were recruited for the dynamic description (DD+E) conditions in Experiment 2. Data from these participants were analyzed along with the data collected in Experiment 1 for the 94 participants in the DS+E conditions with 5-outcome decks.

Prior to recruitment, power analyses were conducted to calculate the minimum number of participants needed to detect a medium effect size ($\eta^2 = .06$) with power = .80 with $\alpha = .05$ for four between-subjects groups. According to G*Power version 3.1.9.2 (Faul, Erdfelder, Lang &
Buchner, 2007), a minimum of 180 participants (45 per between-subjects condition) were needed to be powered sufficiently. However, to increase power for interaction effects, and to ensure that the minimum required number of participants were met in the event of any participant exclusions or drop-outs, an excess of 180 participants was recruited.

As in Experiment 1, participants were recruited through the University of South Florida’s SONA systems. To ensure anonymity demographic information was not recorded, however the population which the sample was recruited from consists mostly of undergraduate psychology majors, the majority of which are female between the ages of 18 to 24.

**Design**

Experiment 2 utilized a 2x2x4 Initial Information x Gain Frequency x Block mixed factorial design. Initial information and gain frequency were included as between-subjects variables, while block was included as a within-subjects variable.

There were two levels of initial information: static description (DS+E) or dynamic description (DD+E). In the DS+E condition, in addition to experiential feedback, participants were given a static description of the potential outcomes in each deck. In the DD+E condition, in addition to experiential feedback and a static description, participants were given a dynamic description of the potential outcomes for the current pair of cards. As in Experiment 1, gain frequency had two levels; equal or unequal. When gain frequencies were equal, both decks had all gain outcomes. When gain frequencies were unequal, the lower EV deck had a higher frequency of gain outcomes than the higher EV deck as the latter had several 0 outcomes. Lastly, block was included to divide the experiment into 4 equal parts with 25 trials in each. For the
purposes of the current experiment only the first and last block of trials (Blocks 1 and 4) were included for analysis.

Primary and secondary dependent variables were the same as Experiment 1. The primary dependent variable was the extent of advantageous choice measured by the number of selections from the higher EV deck out of the 25 choices in one block of trials. Secondary dependent variables included: (1) final selections of which deck would result in the most money over time, (2) confidence ratings in these selections, (3) outcome frequency estimates for each deck, and (4) a free response section to describe decision strategies used throughout the primary task.

**Stimuli**

Experiment 2 utilized two versions of two separate deck pairs which were directly adopted from a subset of stimuli used in Experiment 1. Data from the two 5-outcome decks (equal and unequal gain frequencies) used in Experiment 1 were reanalyzed in Experiment 2. Outcomes and orderings of these decks remained the same as in Experiment 1.

To incorporate the new initial information manipulation, a version of the decks was created to provide a dynamic description of the possible outcomes in addition to the static description and outcome feedback (DD+E).

*Initial Information- Dynamic Description.* Experiment 2 featured a new level of initial information, *dynamic description* (DD+E). This additional level of initial information was created by augmenting the DS+E condition. In addition to presenting a static range of potential outcomes above each deck, the DD+E condition presented a pair of possible outcomes which represented outcomes that could occur on the current draw. As depicted in Figure 9, after a card
was drawn, the pair of potential outcomes for the subsequence card would change, giving description a dynamic quality. The unchoosen deck did, however, did not change as the stimuli still represented the same card.

Figure 9. Example of the dynamic description (DD+E) manipulation with blue deck selection. Deck range information stays static throughout all trials. Possible pairs of outcomes change trial-by-trial.

To create the changing pairs of outcomes featured in the DD+E condition, each pair featured one possible outcome that would be selected on the next draw, as well as a “decoy” possible outcome which the computer never selected. The sequence of pre-determined outcomes that was experienced by participants was the same as in Experiment 1. The sequence of decoy outcomes was chosen so that the higher EV deck always had a lower minimum and maximum pair of possible outcomes for the next card than the lower EV deck. Table 2 shows the frequency
with which selected outcomes and decoy outcomes was shown in a block of 50 trials. The frequency of selected outcomes was the same as in the DS+E condition.

Table 2. Dynamic Description Outcome Pair Stimuli

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Unequal Gain Frequency</th>
<th>Equal Gain Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Higher EV</td>
<td>Lower EV</td>
</tr>
<tr>
<td></td>
<td>Selected</td>
<td>Decoy</td>
</tr>
<tr>
<td>0</td>
<td>15</td>
<td>18</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>2</td>
<td></td>
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<tr>
<td>12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EV</td>
<td>5.76</td>
<td>5.24</td>
</tr>
</tbody>
</table>

Note. Frequency and order of selected outcomes in the DD+E condition was the same as in the DS+E condition.

Procedure

All conditions for both Experiment 1 and 2 were run contemporaneously. Conditions for both experiments were randomized across sessions. Thus, the procedure described in Experiment 1 is the same for Experiment 2.

Experiment 2 Results

Analyses for Experiment 2 were performed to evaluate the effects of (1) initial information (including dynamic description) and (2) gain frequency on advantageous decision
making when learning from repeated experience. The primary analysis conducted was a 2 x 2 x 2 Initial Information (DS+E, or DD+E) x Gain Frequency (equal or unequal) x Block (Block 1 and Block 4) mixed ANOVA. Initial information and gain frequency were included as between-subjects variables, and block was included as a within-subjects variables. The primary dependent variable was the number of selections from the higher EV deck out of 25 choices in Block 1 and Block 4.

As in Experiment 1, a number of single-sample t-tests were conducted in Blocks 1 and 4 to determine whether there was a systematic preference for the lower or higher EV deck. Prior to analysis, data were screened to ensure that participants who were color-blind were not disadvantaged in being able to distinguish between the two decks. No participants were excluded for color blindness. One participant indicated that they were color blind, but confirmed that they could distinguish the color difference between the red and blue deck.

Due to overlap between conditions in Experiment 1 and 2, a subset of data used in Experiment 1 was reanalyzed in Experiment 2. This includes the DS+E condition with both levels of gain frequency (equal and unequal).

**Effects of Dynamic Descriptive Information and Learning**

*Dynamic Description.* It was predicted in the dynamic information hypothesis (H6) that dynamic descriptive information added to a static description would have a greater influence on repeated choice compared to a static description alone. Because descriptive information was manipulated to favor the lower EV deck, it was predicted that if a dynamic component were added to description, this would make the influence of description more powerful and would
result in fewer selections from the higher EV deck compared to the DS+E and E-Only conditions.

As predicted, a significant, though small, main effect of initial information was found, $F(1, 193)=4.97, p=.03$, partial $\eta^2=.025$. As predicted, participants with an additional dynamic description (DD+E; M=11.77, SE=.45), made fewer selections on average from the higher EV deck than those with only a static description (DS+E; M=13.15, SE=.43), $F(1, 195)=4.56, p=.04$, partial $\eta^2=.022$. This result was in line with the dynamic description hypothesis (H6). However, a single-sample t-test revealed that choice behavior in the DD+E condition was still largely mixed, and did not favor either deck overall, $t(93)=-1.49, p=.14$. Thus, there was some support that the presence of a dynamic description enhanced the effect of description on choice, though the effect was very small.

A main effect of block was also present, $F(1, 193)=5.38, p=.02$. From Block 1 (M=11.96, SE=.31) to Block 4 (M=12.96, SE=.44), there was a small, but significant, increase in the average number of higher EV selections, suggesting a small effect of learning. No Initial Information x Block interaction was present, suggesting that learning rates were similar in both the DS+E and DD+E conditions, $F(1, 193)=1.71, p=.19$.

*Gain Frequency.* As in Experiment 1, a valence frequency hypothesis (H2) was predicted in which the number of higher EV deck selections would be lower in the unequal frequency condition than when gain frequencies were equal between decks. In Experiment 1, gain frequency was one of the most prominent effects. A visual inspection of the data suggested that overall, those with a possible zero outcome (unequal gain frequency; M=11.86, SE=.44) made fewer selections from the higher EV deck than those with only gain outcomes (equal gain
Surprisingly, no main effect of gain frequency was discernible, $F(1, 193)=3.73, p=.06$. Nor was there a Gain Frequency x Block interaction which could qualify the lack of main effect, $F(1,193)=1.30, p=.26$. The lack of gain frequency effect in Experiment 2 may be because the effect of gain frequency is not as strong in the presence of description.

The Initial Information x Gain Frequency x Block 3-way interaction was also not significant, $F(2, 283)=1.07, p=.34$. However, because gain frequency moderated effects in Experiment 1, it was of interest, at least for exploratory purposes, to see how learning with static versus dynamic initial information might be differentially affected by the gain frequency manipulation. A depiction of the differences in effects of static and dynamic initial information is shown in Figure 10.

![Figure 10](image)

*Figure 10.* Combined effects of static versus dynamic initial information, gain frequency and block on advantageous choice. The lefthand panel shows the effects of initial information and block when all outcomes in both decks are gains. The righthand panel shows the effects of initial information and block when the higher EV deck has some outcomes of zero. The red dashed line represents equal preference for the lower EV and higher EV decks (12.5 selections from higher EV deck). Error bars represent ±1 standard error from the mean.
As noted earlier, the 5-outcome decks from Experiment 1 were included in Experiment 2. Thus, the pattern of learning for DS+E remained largely the same (though not exactly as the 2-outcome results were not included here).

**Static versus Dynamic Description for Equal Gains.** When gain frequencies were equal, there was an effect of learning in the DS+E condition. From Block 1 (M=12.56, SE=.62) to Block 4 (M=14.88, SE=.86), the mean number of higher EV selections increased significantly, $F(1,49)=7.13, p=.01$, partial $\eta^2=.13$. Results of single-sample t-tests confirmed that in Block 1 deck preferences were mixed $t(49)=.09, p=.93$, but by Block 4 preferences favored the higher EV deck, $t(49)=2.76, p < .01, d=.39$. As noted in Experiment 1, these findings provide evidence in support of the *experience overwhelming description hypothesis* (H5).

When dynamic description was present, there was no evidence of learning with equal gain frequencies, $F < 1$. From Block 1 to Block 4, although it looks like a slight upward trend, there was no discernable change in the number of higher EV selections. With equal gains, static description showed movement toward the higher EV deck with outcome feedback, but dynamic description did not. This provides support for the *dynamic information hypothesis* as gradual learning from experience did occur with a static description but not when dynamic description was added.

Evidence of the *initial impact of description hypothesis* (H4) should have been evident for both kinds of description in Block 1. As already noted above, preferences for equal gain decks with static descriptions did not significantly favor either the lower or higher EV deck in Block 1 and neither did those for dynamic description. Thus, there was not convincing evidence
for the *initial impact of description hypothesis* (H4) for either static or dynamic descriptive information in 5-outcome decks with all-gain outcomes.

**Static versus Dynamic Description for Unequal Gains.** When gain frequencies were unequal in the DS+E condition, the original effect of learning was no longer significant, $F(1,52)=1.22$, $p=.28$. This is likely the result of the fact that the sample size for this condition was about half the size it was in Experiment 1. No discernable preference for either deck was found in Block 1, $t(49)=.09$, $p=.93$, and even after feedback had accrued these preference were still did not favor the either the higher or lower EV deck, $t(49)=.65$, $p=.52$. Likewise, when dynamic description was present, there was no evidence of learning with unequal gain frequencies, $F < 1$. Initially (in Block 1) there was a slight preference for the lower EV deck, $t(42)=-2.25$, $p=.03$, $d=.34$, however, by Block 4 the tendency could no longer be substantiated, $t(42)=1.24$, $p=.22$.

Evidence of the *initial impact of description hypothesis* (H4) for unequal gains should have been evident in Block 1. When analyzed in Experiment 1, the presence of a static description worked to pull choice preferences towards the lower EV deck in the unequal frequency condition. However, with only the 5-outcome decks, preferences in Block 1 did not significantly favor either the lower or higher EV deck. In contrast, for dynamic decks with unequal gains, there was a small preference in Block 1 for the lower EV deck. Thus, when a zero was present, there was weak evidence of the *initial impact of description hypothesis* (H4) in 5-outcome decks for dynamic but not necessarily for static descriptions.
Final Selection Analyses

A series of chi-square goodness of fit tests were conducted to analyze whether the frequency of higher EV selections differed significantly from chance depending on the combined effects of gain frequency and initial information. At the end of the card-selection task, participants were asked to make a final selection as to which deck they thought made the most money if played repeatedly. This question was asked once immediately after the card-selection task and once again before the questionnaire portion to help aide memory of the card-selection task. For comparison purposes data from the E-Only, 5-outcome decks, from Experiment 1 were analyzed along with the DS+E and DD+E conditions in Experiment 2.

Prior to analysis, consistency in responses between the first selection and second selection was checked. There were 15 participants who did not have matching responses. These participants were not included in the chi-square analyses because it could not be determined which deck they thought made more money in the long run. Analyses were conducted with the remaining 275 participants. Figure 11 depicts the percentage of higher and lower EV selections within each of these groups.
Figure 11. Percentage of higher EV and lower EV final selections for combined effects of gain frequency and initial information. *= higher EV selections were greater than chance.

The left and center panels show the 5-outcome subset of data from the E-Only and DS+E conditions reanalyzed from Experiment 1. Thus, the pattern of preferences is largely the same.

As can be seen in Figure 11, when gain frequencies were equal between decks, participants selected the higher EV deck at a greater than chance rate in the E-Only group, $\chi^2 (1, N= 48) = 12.00, p < .01, \phi=.50$, and the DS+E group, $\chi^2 (1, N= 46) = 10.52, p < .01, \phi=.48$. Both of these effects were medium-large, suggesting that at the end of the study, learning was mostly effective for these groups. Only when dynamic misleading descriptions continually occurred, experience did not make the higher EV deck apparent by the end of the task even when all-gain outcomes were involved.
When gain frequencies were unequal, and the higher EV deck included many 0 outcomes, which apparently disrupted learning for all levels of initial information. By the end of the card-selection task, participants were largely split or uncertain in their views of which deck would make more money in the long-run (all $\chi^2 < 1$). This too is consistent with the primary analysis, and provides additional evidence of a tendency to rely on valence frequency information to help guide choice.

**Summary of Experiment 2 Results**

The primary purpose of Experiment 2 was to examine whether dynamic information is a particularly powerful source of information in a repeated decision context. To assess the influence of dynamic information, the relative influence of static versus dynamic descriptive information was compared. Consistent with the dynamic description hypothesis (H6), the influence of descriptive information was greater when presented dynamically versus statically. Overall, there were fewer selections from the higher EV deck when description was presented dynamically than when description was presented statically, particularly by Block 4.

Not only did dynamic description appear to increase the influence of description within the choice task, but it also may have disrupted learning from choice feedback. When descriptive information was presented statically, learning was somewhat effective when gain frequencies were equal, consistent with the experience overwhelming description hypothesis (H5). However, when this same information was presented dynamically, there was no evidence to suggest that participants preferred either the lower or higher EV deck even by the end of the task.
General Discussion

The current investigation found evidence that learning from experience and subsequent choice were sensitive to the effects of differential gain frequencies, initial outcome descriptions, and dynamic outcome descriptions, but not outcome complexity. While learning from experience, participants seemed particularly sensitive to the number of gain and non-gain (zero) outcomes in each deck. Decks with a potential zero outcome were apparently found to be particularly aversive – despite being more advantageous in the long run. The presence of a misleading description had an initial effect on choice, but only when a potential zero outcome was present in the misleading description. At the beginning of the decision series, participants seemed especially avoidant of the deck with a potential zero outcome in the description. If the description was static and unchanging, the initial influence of the misleading description was gradually discounted after outcome feedback had accrued. The only circumstance where the misleading description may have had a more long-term effect was when description was presented dynamically, and changed trial-by-trial.

At the start of this investigation, three aspects were identified as being fundamental to experiential decision making: (1) it is reliant on memory, (2) information is acquired through outcome feedback, and (3) outcome feedback is inherently dynamic. The goal was to assess the relative impacts each of these aspects has on experiential learning and advantageous choice. In what follows, I will elaborate on how these aspects contribute to shape experiential choice, and
under what conditions learning from experience and advantageous choice may be supported or disrupted.

Assessing Effects of Working Memory in Experiential Decision Making

Working memory has been implicated as being an integral part of learning and decision making, and has been associated with actively maintaining and integrating information in consciousness (e.g., Baddeley, 1986; Bayliss, Jarrold, Baddeley, Gunn, & Leigh, 2005). The capacity of working memory, though, is limited. It was predicted that strain on working memory, by increasing the number of outcomes per option, would lead to deficits in experiential learning as well as the quality of choice. However, there was no evidence to suggest that the number of outcomes within each deck had any influence on how well participants were able to extract and use information from outcome feedback, nor was there evidence that it affected the type of information that was primarily used to inform choice (valence or magnitude frequency information).

Although an effect of learning was observed in some conditions, the extent to which people preferred the more advantageous deck was limited. Even in the most successful learning conditions, the average number of higher EV selections was about 15 out of a possible 25. There appeared to be general difficulty in learning which deck was more advantageous, regardless of any extra strain that may have been imposed by an increase in the number of outcomes. Given that preferences for the decks were not very strong either way, there may not have been enough differentiation in preferences to detect an effect of complexity. The results of this investigation cannot therefore provide conclusive evidence as to whether the increase in number of outcomes
strained working memory, and whether such strain may have impacted information extraction and integration while learning from outcome feedback.

*Dimensions of Complexity and Working Memory Strain.* It is possible that no effect of complexity was found because the difference between 2 outcomes and 5 outcomes was not sufficiently large enough to impose a noticeable strain on working memory. In a recent study on experiential decision-making and advantageous choice (Weiss-Cohen., et. al., 2018), two dimensions of complexity were examined: the number of unique outcomes per option (2 vs. 4 vs. 6), and the number of options (2 decks, 4 decks, and 6 decks). In this complex design, the increase in the number of options or alternatives was found to have a deleterious effect on advantageous choice; however, the number of outcomes per option did not. This could suggest that increases in the number of options induces more strain on working memory than a similar increase does in the number of outcomes.

As suggested by Weiss-Cohen and colleagues (2018), an increase in the number of options within a decision may substantially increase cognitive demand because there are more options that need to be explored before a single option can be identified as being superior. For example, if there are only two decks, a single choice provides updating information for half of the available options. When there are six available options, a single choice provides updating information for only 1/6 of available options. Although a similar increase in number of unique outcomes may theoretically make EV estimation more difficult because there are more unique outcomes to keep track of, it may not have such a dramatic effect on the differentiation process.

*Using Somatic Markers to Guide Choice.* While it is unclear from the current results whether or when increases in the number of potential outcomes may negatively affect
experiential learning and decision making, there is also the possibility that somatic markers may have played a role in guiding choice. While strain on working memory was predicted to negatively impact the cognitive aspects of experiential decision-making, automatic processes like the formation of somatic markers may not have been affected. As noted earlier, the Somatic Marker Hypothesis (SMH) proposed by Bechara, Damasio, and Damasio (1994), offers an affectively based explanation for how people acquire information from experiential feedback, and use this information to guide choice. To the extent that somatic markers are sufficient to guide choice, increases in strain on cognition (e.g. working memory), may not have had an observable impact on learning from experience and decision making.

When experience was the only source of information, and both decks contained only gain outcomes, learning was found to be mostly effective. Yet, even in this condition an increase in the number of outcomes per deck did not negatively impact learning. As outcome feedback accrued, participants gradually moved toward preferring the higher EV deck. This lack of complexity effect may lend indirect support to the possibility that somatic markers may have developed and were helpful if not sufficient to guide choice towards the more advantageous deck.

Sensitivity to Valence and Magnitude Information in Experiential Decisions

Assessing Impacts of Valence vs. Magnitude. When decks contained only gain outcomes, and information was acquired only through outcome feedback, there was some evidence to suggest that magnitude frequency, extracted from outcome feedback, helped guide preferences towards the more advantageous deck. As mentioned earlier, magnitude frequency provides all the information needed to estimate EV. However, when a non-gain (zero) outcome was present
in the higher EV deck, learning was largely disrupted. While learning from experience only, participants seemed to gradually increase their aversion toward the higher EV deck because it contained a possible zero outcome, and instead moved toward preferring the lower EV with gain only outcomes. This aversion to the deck with the zero outcome, I will refer to as the zero effect.

The pattern of results found in the experience only condition when the more advantageous deck contained a possible zero outcome closely resembles results from the Soochaw Gambling Task (SGT; Chui, et. al., 2008). As noted previously, the SGT features four deck of cards that vary in EV and gain frequency. The two “bad” decks resulted in a loss of money over time, whereas the two “good” decks resulted in money gained over time. As in the current investigation, the lower EV decks in the SGT had a higher frequency of gain outcomes, while the higher EV decks had a lower frequency of gains. While learning from experience only, participants tended to prefer decks that resulted in a higher frequency of gain outcomes, even though the EV was lower. As suggested by Chui, et. al. (2008), these results may indicate that experiential choice is primarily driven by valence frequency information, and that magnitude valence (EV) information is used secondarily. Furthermore, they suggested that the formation of somatic markers may be particularly sensitive to valence information, which could help account for why experiential learning seems especially sensitive to valence frequency information.

The finding that people seem more influenced by valence frequency information than magnitude frequency information while learning from experience only does introduce some complications with relying on experience alone to make advantageous decisions. Valence frequency alone does not provide enough information to accurately estimate EV. Thus, if people primarily use valence frequency information to inform decisions, rather than magnitude frequency information, while learning from experience, there is the potential that people may
systematically pick options that are not the most advantageous. If the higher EV option also has a higher number of gain outcomes, then identifying the most advantageous option may be facilitated by valence information. However, in situations in which the higher EV option does not coincide with the higher gain frequency option, identifying the most advantageous option may be more difficult.

**Differential Zero Effects with Static Description.** In nearly all conditions in which valence frequencies were unequal between options, the presence of a (non-gain) zero outcome made the higher EV deck less attractive, and as a result, pushed preferences away from the more advantageous deck. Interestingly, the strength of the zero effect differed across the decision series depending on whether a description of the potential deck outcomes was provided or if decision makers had to learn about the potential zero outcome from outcome feedback alone. While learning from experience only, an aversion towards the option with zero outcomes gradually developed over time and showed no sign of abating. However, when a static description was present, and knowledge of the potential zero was immediately known, there was an initial aversion to the option with zero outcomes, but this aversion diminished as experience accrued.

It is possible that the description of the possible zero outcome directed attention towards sampling the less advantageous option initially because it was known that there was no zero outcome in that deck. However, after sampling, it was learned that the worse outcome(s) were occurring relatively frequently. This may have prompted participants to go back to explore the potential zero deck, in which they started to learn that the better outcome(s) occurred more often, and the zero outcome was relatively uncommon. Those learning from experience only, however, did not have the advantage of the certain knowledge that one deck contained only gain outcomes.
and the other had (a relatively infrequent) zero outcome (e.g., Hadar & Fox, 2009). Thus, previous knowledge of the potential outcomes could have assisted in creating a mental framework to better organize outcome feedback information, and to be in a better position to gradually pay attention to differences in outcome frequencies.

The finding that foreknowledge of a possible zero outcome resulted in an initial aversion towards the more advantageous deck may also have implications in understanding why decisions made based on descriptive information often differ from those made based on experiential information, i.e., the experience-description gap (D-E gap; Hertwig & Erev, 2009; Wulff, Mergenthaler-Canseco, & Hertwig, 2018). It has been previously theorized that the D-E gap is a result of underweighting rare events when learning from experience, and overweighting rare events when learned from experience (Hertwig & Erev, 2009). However, as proposed by Hadar & Fox (2009), the D-E gap may also be attributed to an information asymmetry, apart from differential weighting of probabilities.

As explained by Hadar and Fox (2009), descriptive information provides the decision maker with expressed knowledge about the set of possible outcomes. While learning strictly from experience, the possible outcomes of a decision remain unknown until they have been sampled by the decision maker, and it is never certain whether all possible outcomes have been experienced. This creates an information asymmetry when making decision from description versus experience. When making decisions from description there is complete knowledge regarding the possible outcomes and associated probabilities, whereas with experience there is never complete certainty.
In the current investigation, the effect of asymmetric knowledge between descriptive and experiential choices was isolated with respect to possible outcome. For both descriptive and experiential decisions probability was learned through outcome feedback, therefore the only asymmetry between description and experience was the level of uncertainty between possible outcomes. With description, knowledge of a possible zero outcome dissuaded participants from choosing the more advantageous choice initially because it was a known outcome. Those learning from experience only were initially unaware of such a possibility and therefore had no aversion towards sampling the deck with a potential zero outcome at the beginning of the decision series.

This difference in choice behavior between experience and description was found independently of how probability information was learned. Probability learning in all conditions was through outcome feedback. This finding demonstrates that a D-E gap can also be caused by asymmetric knowledge of outcomes. Thus, separate from probability weighting, choice behavior can differ depending on whether outcome information is explicit and certain from description, or whether outcome information is gradually acquired, but never 100% certain.

**Influence of Static versus Dynamic Descriptive Information**

It was originally predicted that outcome feedback may be an especially useful form of information in a repeated decision context because it is inherently dynamic. Not only may dynamic information result in *more* information (Weiss-Cohen, et. al., 2016), but it can assist with choice adaptation in uncertain choice environments (Rakow & Miler, 2009). The dynamic nature of outcome feedback may also be partially responsible for why experiential information
tends to overwhelm static descriptive information in the long run (e.g., Jessup, Bishara, & Busemeyer, 2008; Lejarraga & Gonzalez, 2011; Weiss-Cohen et.al., 2016).

As it was not possible to make experiential information static, descriptive information was instead manipulated to be either static or dynamic. By comparing the influence of static description versus dynamic descriptive information in a repeated decision environment. I aimed to infer whether the dynamic quality of outcome feedback made it a particularly influential source of information. Consistent with previous predictions, the results of the current investigation provided evidence that a dynamic description may be more influential in repeated choice than a static description.

Although all observed effects of dynamic description were small, the results of Experiment 2 provided at least some evidence that dynamic descriptions may be more influential than static descriptions. Overall, the number of higher EV choices when description was presented dynamically was lower than when presented statically. Thus, the effect of a misleading description seemed to be enhanced by the addition of a dynamic description compared to when description was only presented statically.

When comparing effects of learning, no effect of learning was present when description was dynamic, whereas when presented statically, there was a slight learning effect in the direction of the higher EV deck (especially in Experiment 1). This may suggest that the presence of dynamic description interfered with the extraction of magnitude frequency information from outcome feedback.

In what follows, I propose that the addition of a dynamic quality to description may make this information especially salient to the decision maker at the time of choice. By
increasing the saliency of this information, attentional resources may have been drawn towards evaluating descriptive information, leaving less resources to process outcome feedback information.

*Saliency in Pre-decisional vs. Post-decisional Information.* When both description and experiential feedback are available, there is a fundamental difference in *when* they are most salient in the decision-making process. Descriptive information is largely a *pre-decisional* piece of information. That is, it is available *before* a decision is made. Experiential information (i.e. choice feedback), however, is fundamentally *post-decisional*. That is, it can only be gained *after* a decision is made.

According to Svenson’s (1992; 2003) *differentiation and consolidation theory* (Diff-Con), before a decision is made a *differentiation* process occurs which uses pre-decisional information in the choice process to determine which option is superior. Because description is always available pre-decision, it may be especially salient within the differentiation process. Thus, the likelihood it will be used to inform choice may be increased because of its temporal location within the decision-making process.

If descriptive information is static and unchanging, then it may only need to be used in the differentiation process once. As it cannot provide any new information, attentional resources may be redirected to incorporating other sources of information, such as post-decisional outcome feedback. Yet, if descriptive information keeps changing, then a new differentiation process may be required for each separate choice. If so, attentional resources may have stayed directed at evaluating the changing pre-decisional aspects of each decision, while attention may have been directed away from evaluating other aspects of the decision environment, like choice feedback.
from previous selections. This could help account for why dynamic descriptive information
seems to be more influential than static information, and why choice feedback information did
not seem to influence choice as much as when description was static.

Limitations and Future Directions

Although effects of learning from experience were detected in some experimental
conditions, there were no conditions in which the effects of learning were particularly strong.
There appeared to be general difficulty in learning which deck was more advantageous, and this
may have masked some potential effects (e.g., complexity). As revealed by the process analysis,
this may be because participants were still exploring the decks to gather information, rather than
settling on a single deck. Additionally, in may be that the EV differences was too small for most
people to identify in less than 100 trials. A focus of future research may be to examine how
sensitive people are to the size of differences in expected value between options, and the amount
of sampling required to identify such differences. As evidenced by the current research,
advantageous choice is sensitive to aspects of outcome feedback such as valence and magnitude.
Advantageous choice will undoubtedly also be influenced by how difficult (or easy) it is to
discriminate these differences. The sensitivity to these magnitude differences may reveal that we
are vulnerable to missing large differences in expected value between options. Such an oversight
could result in a substantial loss of money. In contrast, it may reveal that people are sensitive to
relatively small differences in magnitude, in which losses due non-differentiation between
outcomes may be trivial.

The lack of complexity effect may also suggest that the manipulation used in the current
investigation (2-outcome vs. 5-outcome decks) did not strain working memory differentially for
a noticeable effect on choice to be observed. This may be because the number of outcomes within a choice may not strain memory to the same degree as the number of options within a choice. As shown by Weiss-Cohen et. al., 2018, a similar difference in the number of options did have a negative effect on advantageous choice, but the same differences in the number of outcomes had almost no effect on advantageous choice.

One possibility to explain this difference involves somatic markers (Bechara, Damasio, & Damasio, 1994). It may be that somatic markers assist with processing and integrating post-choice outcomes inside of an option. Because this process is automatic, it does not consume cognitive resources. This automatic process, however, cannot assist in processing the number of unique options. For each option, a new somatic marker must be created. Yet, once created, somatic markers within each option are updated and strengthened by choice feedback without taxing working memory. Thus, the tax on working memory from integrating outcome information is mitigated within options because the process is at least partially automatic. This interplay between number of options and number of outcomes, and the potential roles for automatic and controlled processes in learning, is rich area for discovering more about the learning process.

An additional future direction is to further explore the zero effect as a more general phenomenon in choice. If in a more naturalistic choice environment, people are averse to advantageous options that contain possible zero outcomes, there is the possibility that decisions could be set up to swindle people for monetary gain. If such a “blind spot” in choice were present, it would be priority to discover means to mitigate this vulnerability. As shown in the current investigation, it may be possible that additional experience could help lessen the aversion towards an advantageous choice with potential zero outcomes. Yet, even so, by the time
experience is gained, money may have already been lost. Future research may help find other methods, perhaps with descriptive information, which could lessen this effect in a timelier manner.

The zero effect in the gain domain suggests that people may be averse to options with non-gain outcomes even when they are advantageous. Investigating this effect in the loss domain may be of even greater interest because of people’s exceptionally strong aversion to losses. As outlined in prospect theory (Kahneman & Tversky, 1979), choice behavior in the positive domain can be expected to systematically differ from choice behavior in the negative domain. In fact, these preferences may often reverse.

In the negative domain, we may also see a reversal of the zero effect. When surrounded by negative outcomes, a possible zero outcome would seem relatively positive. Thus, compared to an option with all-loss outcomes, an option with a potential zero outcome may be especially attractive. The implication of a “reverse” zero effect is that choice may be guided by the attraction to a zero, rather than the expected value of each option. This would also demonstrate that attraction or aversion to a potential zero outcome is dependent on the contextual valence of surrounding outcomes (see, e.g., Schneider, Kauffman, & Ranieri, 2016).
Conclusion

There is no single context in which people learn from experience. As long as outcome feedback is available, there is the potential that people may extract information from feedback and use it to inform future decisions. In a real-world setting, it is uncertain as to what kind of feedback will be received, and whether other sources of information will also be available. Even when feedback is readily available, and the environment is stable and predictable, the quality of experiential learning may depend on surrounding information as well as the characteristics of the outcome feedback itself.

Perhaps most notable, the results of the current investigation suggest that experiential choice seems especially sensitive to differences in valence frequency. Although it has been demonstrated previously that experiential learning could be sensitive to differences in gain and loss outcomes (Chui et. al., 2008), the current study expands on this by demonstrating a zero effect in which people also seem averse to options that contain a non-gain (zero) outcome when the other option has all gains. This may represent a vulnerability that could lead to disadvantageous choice in some contexts. When there are no disruptions from valence differences, outcome feedback based on experience may be more likely to reliably guide the decision maker towards advantageous options even in the presence of initial misleading descriptive information.
The current investigation also provides pioneering evidence as to the effects of dynamic descriptive information in repeated decisions from experience. Results suggest that dynamic information can have a more lasting effect on choice behavior than similar information presented in a static form. This may be because dynamic information continuously provides up-to-date information about the decision environment, and may be seen as more relevant to the decision at hand. However, in the event that dynamic descriptive information competes with dynamic outcome feedback, the ability to learn from experience may be impeded. As a result, people may have more difficulty in identifying which option is most advantageous.

The results of this investigation help detail obstacles in experiential learning. Some of these we seem to be generally robust to, such as number of outcomes within an option as well as misleading information in the form of a static description. For example, if initial misinformation is presented, perhaps by the media or a colleague, adequate experience may be able to overcome initially introduced biases. Other obstacles may be generally harder to overcome. For instance, the ability to learn from experience may be hampered if options with fewer gains have better long-term benefits. While choosing investments, for example, a person may be inclined to prefer an investment that pays out regular, smaller, dividends, than one that pays only occasional dividends, but with a higher net return. In such a scenario, this person would be missing an opportunity to maximize their earnings because of an aversion to occasionally not getting any money. This might help explain why people tend to be risk averse in many decisions.

The findings of this investigation highlight the importance of surrounding information and type of feedback when learning from experience. As these influences are confirmed in future research, we can gain the ability to recognize when these potential obstacles could negatively influence choice behavior.
References


Appendix A: Screenshot of Estimation Task Questionnaire

Of the 100 deck selections you just made, please estimate the number of times you received each of the following outcomes in the blue and red decks. If you did not receive the outcome type in "0." Make sure that the total for both decks combined is equal to 100.

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# Appendix B: Table of Means and Standard Deviation for Experiments 1 and 2

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Appendix C: Institutional Review Board Approval and PI Change Letter

July 15, 2016

Sandra Kaufman, M.A.
Psychology
4202 East Fowler Ave.
PCD 418G
Tampa, FL 33620

RE: Exempt Certification

IRB#: Pro00026644
Title: Understanding decisions from experience

Dear Ms. Kaufman:

On 7/15/2016, the Institutional Review Board (IRB) determined that your research meets criteria for exemption from the federal regulations as outlined by 45CFR46.101(b):

(2) Research involving the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior unless:

(i) information obtained is recorded in such a manner that human subjects cannot be identified directly or through identifiers linked to the subjects; and (ii) any disclosure of the human subjects’ responses outside the research could reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects’ financial standing, employability, or reputation.

As the principal investigator for this study, it is your responsibility to ensure that this research is conducted as outlined in your application and consistent with the ethical principles outlined in the Belmont Report and with USF HRPP policies and procedures.

Please note, as per USF HRPP Policy, once the Exempt determination is made, the application is closed in ARC. Any proposed or anticipated changes to the study design that was previously declared exempt from IRB review must be submitted to the IRB as a new study prior to initiation of the change. However, administrative changes, including changes in research personnel, do not warrant an amendment or new application.

Given the determination of exemption, this application is being closed in ARC. This does not limit your ability to conduct your research project.

We appreciate your dedication to the ethical conduct of human subject research at the University of South Florida and your continued commitment to human research protections. If you have any questions regarding this matter, please call 813-974-5638.

Sincerely,

Kristen Solomon, Ph.D., Vice Chairperson
USF Institutional Review Board
August 20, 2018

Hello,

My name is Sandra Kauffman. I am currently the principal investigator for IRB PRO000026644 (Understanding decisions from experience). I am writing this letter to change the principal investigator from myself to Andrea Ranieri, effective immediately.

Thank you,

Sandra Kauffman
Appendix D: Informed Consent
Understanding Decisions from Experience
IRB Study PRO26644

This study will take **approximately 30 minutes**, and completion of the study will earn you 1 SONA credit, which will be rewarded to you after completion of the study. Please completely read through the follow informed consent. If you do consent to participate please click the box at the bottom of the page and press “continue”. If you decide that you would not like to participate in this study you may leave now.

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| Your privacy and research records will be kept confidential to the extent of the law. Authorized research personnel, employees of the Department of Health and Human Services, the USF Institutional Review Board and its staff, and any other individuals acting on behalf of USF, may inspect the records from this research project. Your name will not be associated with any of your study responses. |

| The results of this study may be published. However, your data will be combined with data from others in the publication. The published results will not include your name or any other information that would personally identify you in any way. |

| It is possible, although unlikely, that unauthorized individuals could gain access to your responses. Confidentiality will be maintained to the degree permitted by the technology used. No guarantees can be made regarding the interception of data sent via the Internet. However, your participation involves risks similar to a person’s everyday use of the Internet. |

| If you have any questions or concerns regarding the research, a copy of this agreement along with contact information for the principal investigator and the IRB office can be provided to you at your request. This project presents no risk or harm to you, and there are no anticipated benefits. Your participation in this experiment is entirely voluntary, and you |
may leave at any time should you feel uncomfortable with the procedures. Your decision to participate or not to participate will not affect your status or course grade. Do you want to participate in the study today?

PI Contact information:
Name: Andrea Ranieri
Phone: 813-974-9168
Email: ayr@mail.usf.edu

IRB Contact Information:
Phone: 813-975-5638

☐ I certify that I give my consent to participate and I am at least 18 years old.