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# Creating A More Ecologically Valid Decision Task

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CREATING A MORE ECOLOGICALLY VALID DECISION TASK

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# ABSTRACT

There has been a standing debate in the field regarding the effectiveness of frequencies and probabilities to accurately convey information. This study utilized a naturalistic sampling procedure to determine risk preferences on binary choice decision using time, sex, and goal deficit variables as predictors. Participants consisted of 110 undergraduate students enrolled in core psychology courses at Fort Hays State University. A web application was created to conduct this specific study that will be made available to other researchers. Significant effects existed for time and goal deficit variables that predicted risk preferences.

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# INTRODUCTION

In the Midwest, it is common to hear phrases such as, "I could be the weather man, that is the only job I know where you are paid to be wrong most of the time!" Maybe the forecaster is not wrong as often as one would think, but instead the typical interpretations of the forecast are inaccurate. Weather forecasters commonly present the likelihood of a weather event occurring as a percentage (e.g., a 50% chance of rain). However, the average person would have difficulty explaining what a 50% chance of rain actually means. This format of presenting a chance of rain gives a single-event probability, which does not accurately describe the scenario (Gigerenzer, Hertwig, van den Broeck, Fasolo, & Katsikopoulos, 2005). Instead, Gigerenzer et al. (2005) believe that a reference class should be attached to these forecasts to facilitate better understanding. Therefore, a forecast of a 50% chance of rain tomorrow should also include that it means that it will rain on 50% of days like tomorrow. In essence, it will either rain or it will not rain, but on days like tomorrow half of them will receive rain.

Correctly interpreting probabilistic statements, such as the weather forecast, can be improved in another manner. Presenting people with a frequency (e.g., 5 out of 10) instead of a probability or percent tends to improve performance (Brase, Cosmides, & Tooby, 1998; Gigerenzer et al., 2005; Hill & Brase, 2012). Therefore, instead of presenting a 50% chance of rain to the viewing public, it would be better understood when presented as 5 out of 10 days like tomorrow will receive rain (Gigerenzer et al., 2005; Hill & Brase, 2012). In this instance, it is easier to interpret that 10 days like tomorrow are being compared, and in five of them it rains.

Similar effects have also been observed in medical decision-making. When discussing side effects, patients may be unsettled to hear that there is a 30% chance that they will develop some side effect, but much more at ease when it is communicated as a frequency, or that 3 in 10 people develop this side effect (Gigerenzer et al., 2005; Reyna, Nelson, Han, & Dieckmann, 2009). Rather than interpreting they may experience this side effect 30% of the time while they are taking a prescribed medication, patients can more easily see that they may not develop a side effect at all unless they are one of the three people out of 10.

**Problems Evaluating Probabilities**

Humans tend to have difficulty comprehending the odds of an event occurring and there are several potential explanations that include decision weights (Fox & Tversky, 1998; Kahneman & Tversky, 1979), format of odds presentation (Brase et al., 1998; Gigerenzer et al., 2005; Hill & Brase, 2012), and framing effects (Tversky & Kahneman, 1981). These factors tend to skew probability estimates, resulting in choices that may be less than optimal. An optimal choice is defined as the one whose product of probability (ranging from 0 to 1) and outcome (e.g., gain or loss of a monetary outcome) minus the cost of the choice yields the greatest final value. This formula is similar to that found in expected-utility theory (Friedman & Savage, 1952), but includes a “cost to play” that is derived from energy requirements in optimal foraging theory (MacArthur & Pianka, 1966).

Kahneman and Tversky (1979) introduced a decision weight function that describes how people estimate given probabilities. The function illustrates an overestimation of low probability events occurring and an under-estimation of high probability events occurring. This would present a discrepancy between objective values of choices and subjective values of these choices when calculating expected value. Decision makers, utilizing this decision weight function, would then over-value choices with a lower probability and under-value choices with a higher probability. Depending upon the content of options presented, this could lead to sub-optimal decisions.

Humans tend to lack proficiency when interpreting probabilities and percentages, and are better equipped to interpret odds presented in a frequency format (Brase et al., 1998; Cosmides & Tooby, 1996; Gigerenzer, 1991; Gigerenzer & Hoffrage, 1995). People cannot directly observe probabilities in nature, instead events are viewed discretely as either occurring or not occurring and information about probabilities are synthesized. It has been suggested that human evolution has led to mechanisms that are sensitive to counting the frequency of events occurring and not occurring (e.g., Brase et al., 1998; Hill & Brase, 2012). Decisions can then be made based on these actual, whole-number observations. Interpreting a probability of some event occurring that is equal to .67 is more difficult than understanding that some event occurs two out of three times. Misinterpretations of these probabilities may also lead to sub-optimal decisions.

How a choice is framed has also been shown to affect interpretations of risk (e.g., De Martino, Kumaran, Seymour, & Dolan, 2006; Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). Prospect theory postulates that people avoid risk when a choice is framed as a gain, and people seek risk when the choice is framed as a loss (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). That is, certainty is desired to gain a reward even if approaching certainty decreases the amount of the reward. When all choice options would result in a loss, choice behavior shifts away from selecting the option that is closer to certainty and illustrates a desire to seek risk in an effort to prevent such a loss from occurring. For example, Kahneman and Tversky (1979) found that decision makers preferred choosing an option that presented an 80% chance of losing $4,000 over a sure loss of $3,000. This is despite the fact that the sure loss of $3,000 is of a higher expected value (-$3,000 * 1.0 = -$3,000 > -$4,000 * .80 = -$3,200). This seems to point to some level of emotional subjectivity involved in making decisions. De Martino et al. (2006) reported that there is heightened amygdala activity present during decisions, suggesting an emotional component involved in the decision making process. Framing a decision as a loss instead of gain (or vice versa) could result in a sub-optimal decision.

**Effects of Reference Points and Time**

Making an optimal decision based on expected utility may not always be the best decision in every circumstance. It is hypothesized that humans use points of reference to evaluate choices based on what is important to them. These reference points have included a minimum requirement that represents an amount of something (e.g., calories from food) that must be possessed for an organism to survive (MacArthur & Pianka, 1966; Stephens, 1981; Stephens, 1987; Stephens & Krebs, 1986), a status quo that represents a current state where falling below this level is a painful loss and exceeding it brings some pleasure (Kahneman & Tversky, 1979; Wang & Johnson, 2012), and a social comparison or goal reference point that represents some achievement of one’s peers

(Festinger, 1954; Hill & Buss, 2010). These reference points have been identified as affecting risk preferences in certain scenarios. Risk, in this context, shall be defined as a choice in a binary pair with the lowest probability of occurrence. In recent history, there has been research examining combinations of two or more of these reference points (e.g., Koop & Johnson, 2012; Wang & Johnson, 2012).

Optimal foraging theory (MacArthur & Pianka, 1966; Stephens, 1981; Stephens, 1987; Stephens & Krebs, 1986) predicts an organism will assume any risk necessary in order to survive. That is, when presented with two options, with only one option allowing for the minimum requirement (MR) for survival to be met, that should be the preferred option—even if its likelihood of occurrence is minimal and the other option presents a much greater likelihood. When the options are framed as gains, it presents a contradiction to predictions about risk preference in prospect theory (Kahneman & Tversky, 1979); where, when faced with a gain, the option that is closest to certainty would be preferred. Perhaps the organism faced with this choice reframes the decision as a loss where one option is a certain loss of life and the other presents some risk that could allow life to continue. This is logical, because the less risky option with a lower reward presents a choice that would certainly result in death, while the other option provides some chance at continuation of life. Though prospect theory does account for some editing processes to occur when evaluating choices (Kahneman & Tversky, 1979), these functions do not include an edit that allows reframing of the option (i.e., framing a gain as a loss instead, or framing a loss as a gain instead). It does seem that the MR reference point offers further predictive value that cannot be entirely explained by prospect theory.

Assuming that both options presented to an organism allow for the MR to be met, something must guide the decision at this point. Kahneman and Tversky (1979) proposed that decisions are made in reference to the status quo (SQ). The SQ generally refers to some amount of wealth (e.g., money or calories) that is currently held by the decision maker, or a zero point. Options that exceed the SQ are gains and options that fall short are losses. Since humans avoid risk in the face of gains and seek risk in the face of losses (Kahneman & Tversky, 1979), if both options exceed the SQ, choosing the one that presents the greatest probability of occurrence would be expected. If neither option meets the SQ, selection of the riskier choice would be expected; if one option exceeds the SQ and the other option does not, then the option that exceeds the SQ should be chosen despite any associated risk.

However, there are some problems with this model. If neither option meets the SQ, then risk is expected to be preferred according to prospect theory (Kahaneman & Tversky, 1979). But, what if this riskier option also presents a possibility of falling below the MR while the less risky option does not? Some researchers have proposed the combination of the MR and SQ into a single theory that could help to predict choices in this very circumstance (Koop & Johnson, 2012; Wang & Johnson, 2012).

In addition to the MR and SQ reference points, there is one additional point to consider. Social comparison theory (Festinger, 1954) states an individual may choose to assume some level of risk in order to outperform a peer. These decisions are understandable from an evolutionary perspective, as males higher in status have greater access to potential mates (Ha, Overbeek, & Engels, 2010). However, this kind of risk-seeking behavior is not predicted by prospect theory since it would require one to *seek* risk when faced with a gain. This social comparison reference point has been adapted and referred to as a goal (G) reference point (e.g., Koop & Johnson, 2012; Wang & Johnson, 2012).

Many previous decision-making studies have utilized single-event decision tasks where the effects of time are not evaluated (e.g., Kahneman & Tversky, 1979; Koop & Johnson, 2012; Thaler & Johnson, 1990; Wang & Johnson, 2012). However, in nature, time is a factor that may influence choices (MacArthur & Pianka, 1966). For this reason, a task that seeks high ecological validity should account for the effects of time. College students are faced with deadlines, such as rent and utilities, which may illustrate a modern-day survival problem. Failure to pay these bills before the deadline may result in loss of shelter, water, or heat. As the deadline for these bills becomes closer (i.e., amount of time decreases) there should be less risk taken that could result in failure to meet these deadlines, such as allocating current wealth to goods or services not necessary for survival. In this framework, this behavior would result in the preference for the option representing the greatest risk, in terms of probability of payout.

## THE PRESENT RESEARCH

The present study aims to evaluate risk preferences over a series of trials while manipulating the budget and goal amounts. A web-based program will be created that allows participants to select their preferred gambles, or prospects, and will be provided feedback about the outcome of their choice. This method will allow participants to naturally sample their environment and receive immediate feedback after each choice.

**Predictions**

Utilizing tri-reference point theory (Wang & Johnson, 2012), and incorporating a time component, should afford ecological validity to a decision task. Tri-reference point theory incorporates the MR from optimal foraging theory, the SQ from prospect theory, and the G from social comparison theory and predicts choices based on the relationship between the options presented and the value of each of these reference points (Wang & Johnson, 2012). By incorporating the time component, a task would better represent decisions that are made outside of a laboratory setting.

Several predictions can be made based on prior empirical findings. First, all effort will be given to meet a MR and survive (Caraco et al., 1980; MacArthur & Pianka, 1966; Stephens & Krebs, 1986). Second, if MR is met, risk will be avoided when the options presented are framed as gains (Kahneman & Tversky, 1979). Third, if SQ is met then risk may be taken to outperform competitors (Festinger, 1954; Hill & Buss, 2010). Fourth, interactions are expected between time and reference points. It is also expected that using a frequency format will result in optimal decisions more often than when using probability format (i.e., probabilities or percentages). These predictions lead to the following hypotheses:

*H1:* As budget-goal difference increases, preference for risk will also increase.

*H2:* As time passes (trials remaining decreases), preference for risk will increase.

*H3:* Males are expected to assume more risk than females.

*H4:* Budget-goal difference and time are expected to interact such that a large budget-goal difference at a later time (fewer trials remaining) will lead to greater preference for risk.

## REVIEW OF RELEVANT LITERATURE

### Expected Utility Theory

Expected values of a monetary choice can be calculated by determining the possible outcomes that would occur with equal chance, or determining how many wins and losses out of 100 could be expected, and summing the amounts awarded, or lost, in each outcome and dividing by the total number of outcomes, 100 (Bernoulli, 1954). Mathematically, this method of calculating risk would be equivalent to multiplying the possible rewards or losses by their respective probabilities of occurrence. This calculation of expected values is not unique to expected utility theory; other theories use this method for calculating expected values (e.g., Kahneman & Tversky, 1979).

Unique to expected utility theory is the idea that decision-makers assign a subjective value to potential gains or losses that varies as a function of their "lifetime wealth" (Bernoulli, 1954). The term utility, in this context, refers to the usefulness of a potential gain to the individual faced with the opportunity to make a risky decision, or a decision where there is a chance that they will not win a stated amount for sure. A wealthy person would gain less utility from $10 than a poor person would, as the $10 is more useful (i.e., has greater utility) to the poor person than it is to the wealthy person. Intuitively, this idea makes sense; someone who struggles to feed him or herself, or their family, may have the opportunity to do so with a $10 increase in wealth, whereas the wealthy person would only increase their own wealth by a very small percentage. The utility function is concave, but little additional information has been incorporated into previous works involving expected utility theory (Rabin, 2000). The concavity of this function predicts changes in subjective valuations of monetary amounts. For example, $10 may not actually be twice as attractive as $5 because of diminishing returns. For this reason, expected utility theory is not an appropriate lens to approach decisions in which each option presents differing monetary rewards.

Some literature has pointed to potential flaws in expected utility theory, specifically when it pertains to defining and measuring utility. Friedman and Savage (1952) reference this very problem suggesting that definitions of utility lack specificity and measurements of it lack validity. Nevertheless, the evidence in support of the theory outweighs the evidence against it, and no competing theories predicted decisions involving risk with significantly greater accuracy at the time of publication (Friedman & Savage, 1952). Despite these limitations, many elements in later theories (e.g., Kahneman & Tversky, 1979) closely resemble those introduced in expected utility theory.

**Prospect Theory**

Prospect theory was developed as a model to predict human behavior in tasks with simple prospects (gambles) that include stated probabilities of monetary payouts (Kahneman & Tversky, 1979). This iconic work uncovered several tendencies in human behavior. Notably, people prefer to avoid risk. In fact, the pressure to avoid risk is so strong that avoiding perceived losses seems to be more than twice as important as increasing wealth (Kahneman & Tversky, 1979). This statement should be interpreted with caution as effects of the frame of prospects can reverse this trend. That is, when a prospect is framed as a gain (chance of winning money) with moderate to large probabilities, the trend is toward risk avoidance. However, if the problem is framed as a loss (chance of losing money) with large to moderate probabilities of occurrence, the preference shifts towards risk-seeking (Kahneman & Tversky, 1979; Kaheman & Tversky, 1984; Tversky & Kahneman, 1981). These terms, gain and loss, illustrate another important concept from this theory; it is implied that the decision-maker either knows or creates a baseline wealth level to which they compare presented prospects. It is in comparison to this reference point where prospects are judged on the amount of a loss or gain that they represent. The previous examples have mentioned the requirement for moderate to large probabilities because if low probability prospects are presented, preferences shift toward the option with the larger monetary outcome even if expected values are equal. Expected value is calculated by multiplying the monetary outcome by the probability that it will occur and subtracting the cost to play (if cost is present in the task).

The following example illustrates these effects: when presented either an 80% chance of winning $4,000 (or $0 otherwise) or a 100% chance of winning $3,000, nearly 80% of people choose the certain outcome even though its expected value ($3,000) is actually less than the alternative ($3,200), but riskier, option (Kahneman & Tversky, 1979). If the frame of the same prospect is reversed, the outcome is quite different. So, when presented an 80% chance of losing $4,000 (or losing nothing otherwise) or a certain

$3,000 loss, then 92% of people choose the 80% chance of losing the larger amount even though the expected value (-$3,200) is less than the alternative (-$3,000) (Kahneman & Tversky, 1979). This particular example clearly illustrates the risk preferences described by Kahneman and Tversky (1979). The preference was for the certain option when the prospect was framed as gaining money, but the preference was for the uncertain option when the same prospect was framed as losing money.

**Decision weights.** Central to prospect theory is the idea that outcomes carry some amount of subjective weight. Kahneman and Tversky (1979) mapped this decision weight curve (*Figure 1*) to model that losses carry a psychological value larger than an equivalent gain.

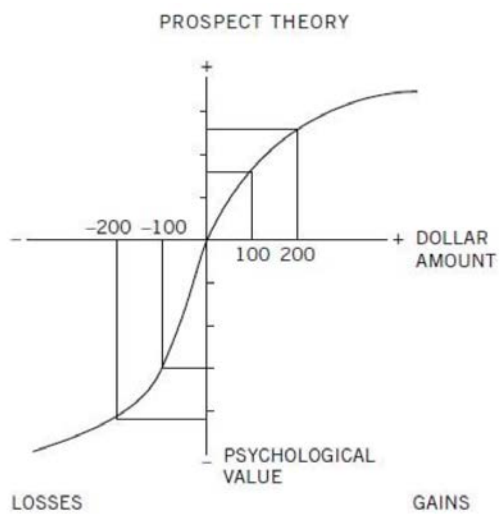


*Figure 1*. Decision weight curve (Kahneman and Tversky 1979). The psychological value of gains increases at a slower rate than the rate of decrease of the psychological value of equivalent losses.

This discrepancy in psychological values between losses and gains illustrate the idea that people avoid risk. Again, this only applies in positive frames with moderate to large probabilities. To understand this phenomenon Kaheman and Tversky (1979) considered how people perceive probability information. In general, people tend to overestimate low probabilities and underestimate high probabilities. For example, estimates and actual probabilities are equal at zero, and the estimate curve lies above the actual probability until approximately 35%, then falls and remains below the actual probability line until 100% where it again aligns with the actual probability line (*Figure 2*).

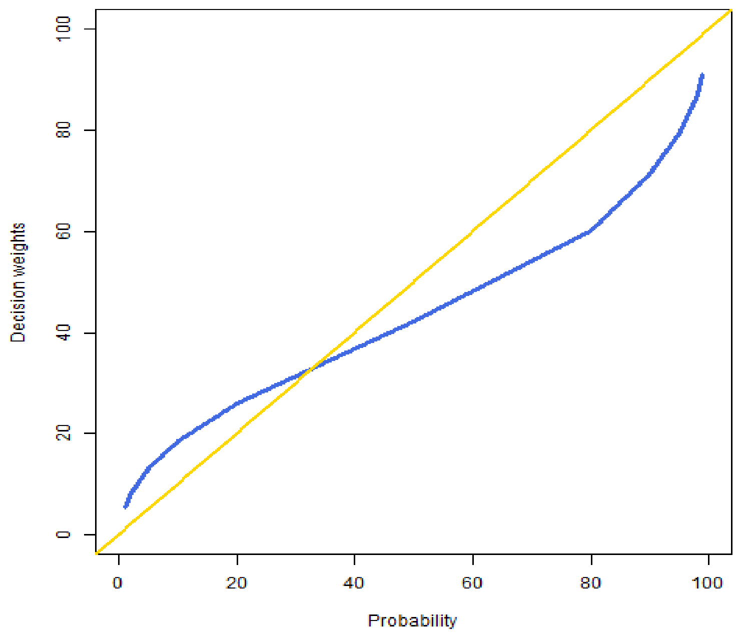


*Figure 2*. Probability estimates that contribute to decision weights as proposed by Kahneman and Tversky (1979).

The basic formula for prospect theory calculates a weighted value rather than a true expected value, which is based on decision weights (Kahneman & Tversky, 1979). This formula is illustrated as $V = \pi p(x)$, where $V$ is the subjective value of the prospect, $\pi$ is the decision weight assigned to the prospect by the decision-maker, $p$ is the probability that the prospect will pay out, and $x$ is the monetary award if the prospect pays out. Prospect theory would predict that the prospect with the largest $V$ will be the one preferred most often. Since $p$ and $x$ are held constant within a single prospect, $\pi$ is the only value that can change in the equation (from one person to the next) that would affect $V$ and, ultimately, which prospect is preferred.

It is important to note that decision weights are not a measure of perceived likelihood, but rather a relative impact the prospect would have on the decision-maker (Kahneman & Tversky, 1979). This means that the decision weights assigned to each prospect may not sum to one as probabilities will (i.e., there will be some outcome following a choice). Instead, these weights tend to reduce the value of a prospect below what would be calculated using expected-value theory (Kahneman & Tversky, 1979). The utility, or usefulness, and probability of payout are expected to influence decision weights assigned to a prospect. A prospect that presents a loss of money should increase the decision weight more, per unit increase in (the absolute value of) money, than a prospect that presents a potential gain (see *Figure 1*). Additionally, unit increases for low probability occurrences are expected to result in greater increases to decision weights than the same increase at higher probabilities (see *Figure 2*).

For example, the earlier prospect presented will be reexamined. The first option presents an 80% chance of winning $4,000 (and a 20% of winning $0) and the second option presents a 100% chance of winning $3,000. The first option, again, has an expected value (EV), the $p(x)$ part of the equation, of $3,200. This is calculated as follows: EV = (0.80)($4,000) + (0.20)($0) = $3,200. The second option has an expected value of $3,000, calculated by EV = (1.0)($3,000) = $3,000. However, Kahneman and Tversky (1979) noted that far more decision makers preferred the second option to the first. The idea for this choice is that the decision weight, $\pi$, assigned to each prospect differs enough to make the value, $V$, greater for the second prospect. Hypothetically, if a decision weight of 0.55 is assigned to the first option and a weight of 1.0 is assigned to the second, then the second option actually represents a greater subjective value: $V_1$ = (0.55)(0.80)($4,000) + (0.84)(0.20)($0) = $1,760 and $V_2$ = (1.0)(1.0)($3,000) = $3,000. Based on these values, calculated with decision weights, option two should now be the preferred option. If we look at the loss-framed example with the same decision weights, it becomes clear that option one, valued at -$1,760, is now greater than and should be preferred to option two, valued at -$3,000.

**Optimal Foraging Theory**

Prospect theory and optimal foraging theory, specifically risk-sensitive foraging, share some commonality in that the risk preferences depend on the current conditions facing the decision-maker (Houston, Fawcett, Mallpress, & McNamara, 2014). Prospect theory discusses current wealth, or status quo, as a reference point to judge against potential prospects (Kahneman & Tversky, 1979), while risk-sensitive foraging evaluates energy budgets of the decision-maker (Stephens & Krebs, 1986). It is from the comparison of these current state reference points to presented choices that risk-aversive or risk-seeking behaviors stem. For instance, when considering wealth, humans will make a risky choice in order to avoid falling below the status quo, but not to exceed this level; when considering energy budgets in animals, risk will be taken to gain enough calories to survive, but not to forage for excess calories (Houston et al., 2014; McDermott, Fowler, & Smirnov, 2008). This represents diminishing returns for gains above the status quo, in prospect theory, or the minimum calorie requirement, in risk-sensitive foraging.

**The risk-sensitive foraging model.** The following is a simple illustration of risk-sensitive foraging involving two squirrels. The first squirrel is in a low energy budget; therefore, it needs to forage for a large number of calories before the end of the day or it will certainly die. The second squirrel is in a high energy budget and only needs a small number of calories to survive. Both squirrels have the option to forage in two different patches, one which almost always provides a small number of calories; and one that infrequently provides an abundance of calories. The question becomes, which squirrel should choose which patch? Since the second squirrel is in a high energy budget, its best chances of survival would come from foraging in the first patch. This patch would almost certainly provide the small number of calories required by this squirrel. However, the first squirrel would not gain the number of calories it needs to survive by foraging in the first patch. The first squirrel's best chance for survival would come from foraging in the second patch where there is at least a possibility of gaining the number of calories it requires to survive, no matter how small the probability of successful foraging. This is risk-sensitive foraging in a nutshell.

Many terms used in the following descriptions revolve around the idea that foraging environments elicit varying rates of success and payoff amounts. This variability is also central to other decision models, including prospect theory (e.g., Kahneman & Tversky, 1979). Various studies describe providing two sources of food, one with a small but certain payout and another with a large but uncertain payout (e.g., Caraco, Martindale, & Whittam, 1980; Stephens, 1981; Stephens & Krebs, 1986). It is important to note that each option pays out the same mean amount, or expected value. That is, the average payout over several trials for each choice is mathematically equivalent. The difference lies in the single-event payouts or the likelihood that a specific option will pay out at the time it is selected. The following explanations will refer to risk as selecting the patch with the more variable payout schedule, not the risk of predation which is the common definition of risk in optimal foraging literature (Stephens & Krebs, 1986).

Important to the risk-sensitive foraging model for predicting risk preferences is the concept of energy budgets. Essentially, risk becomes preferred in expected low (or negative) daily energy budgets and risk is avoided in expected high (or positive) daily energy budgets (Caraco et al., 1980; Stephens & Krebs, 1986). For the present purposes, low energy budget shall be defined as a caloric requirement greater than can be provided by the certain or lower risk option presented in the time (i.e., number of trials) remaining. The high energy budget shall then be defined as a caloric requirement that can be met by the certain or lower risk option presented in the time remaining. These definitions closely resemble those described by Caraco et al. (1980).

Another consideration of risk-sensitive foraging is time pressure; energy budget and time act together to determine risk preferences (Caraco et al., 1980). For instance, when observing an animal with a low energy budget (high calorie requirement) at two different points in time during the day, its risk preference would likely differ. When there is ample time remaining in the day to forage for food this animal is expected to avoid risk in exchange for certain, or highly probable, food payouts. However, when time is scarce there is an expected shift toward risk preference to achieve a potentially higher food payout compared to the less risky option. This shift in risk preference may be due to framing effects posed in this foraging dilemma (e.g., Kahneman & Tversky, 1979; Kahneman & Tversky, 1984; Tversky & Kahneman, 1981). That is, early in the day foraging may be approached as gaining calories to continue life (a positive frame), while later in the day the same problem may be approached as gaining calories to avoid death (a negative frame). In this perspective it is assumed that gaining calories beyond a need level (or increasing wealth in prospect theory) presents less of a pressure to take risk than gaining calories to meet a need level (or avoid a loss in prospect theory). Logically, this makes sense as survival is assured if a need level is met, but death is certain if the forager fails to meet their need level. As time, or the number of opportunities to find food, decreases then the caloric requirement per unit of time must increase. If this need ratio (calories/time unit) exceeds what can be provided by the less risky patch, then the optimal survival choice would be to seek larger caloric payouts in a less certain patch.

**Social Comparison**

Humans are not solely motivated by their current wealth when it comes to making decisions. Comparison to peers who are similar in status has been proposed to explain why risk is sought when doing so is not the optimal, or most beneficial, choice (Festinger, 1954). Social comparison theory describes a shift towards risk preference when doing so presents a chance that the decision-maker can advance on the social hierarchy to achieve higher status than comparable peers. Dominance theory approaches the same question from an evolutionary perspective and has offered similar predictions and biological explanations for this behavior (e.g., Ermer, Cosmides, & Tooby, 2008; Hill & Buss, 2010). This theory explains the necessity of an equal status competitor to elicit risk taking.

Consider two animals in direct competition for a mate. If one animal is high in status and the other low, it would make little sense for either to engage the other in a fight. High status animals reach their rank by winning fights with others and are usually larger and more experienced than low status animals. The high status animal would gain very little by fighting a low status animal, but would risk losing its status. The low status animal, however, does have much to gain and little to lose, but defeating the high status animal in a fight presents a low chance of success and a chance of death. When this status mismatch is present, it is expected that neither animal will seek risk and would benefit more from remaining risk averse. However, when two animals that are equal in status have an opportunity to fight for status, risk-seeking behavior should be observed. That is, the opportunity to move up the social hierarchy is most salient in this scenario since size and experience mismatches are less likely to occur for animals equal in status.

There are three requirements for the shift from risk aversion to risk preference to occur; the more variable outcome must offer the chance to best competitors while the less variable one cannot, the choice must relate to the ability to solve a social problem, and the choices must be framed as gains rather than losses (Hill & Buss, 2010). It is also important to note, as stated above, that this shift in preferences only occurs in the context of competition with, or observation by, someone equal in status (Ermer et al., 2008).

This implies that the effect would not be seen when there is a status mismatch between the decision-maker under observation and either a competitor or the observer.

**Decisions Under Uncertainty**

When choosing between options that are equal, people tend to make a choice based on whether the probability information is stated or withheld, and favoring the option with stated probability (Rode, Cosmides, Hell, & Tooby, 1999). This effect results in decisions that may not be optimal and has been termed the *ambiguity effect*. This effect may best be represent by the work in Ellsberg (1961) where participants were offered a choice between two urns containing some proportion of red and black balls. One of the urns contained a known ratio of 50% red and 50% black balls, and the other contained an unknown ratio of 100 red and black balls. When offered a reward if a specific color was drawn, $100 if a red ball is drawn and $0 otherwise, participants prefer to select the urn with the 50-50 red to black ratio. Once the ball is returned they are again offered the same prize, $100 for a match and $0 otherwise, but this time for a black ball, and again the 50-50 urn is preferred. The probability of winning either the first time or the second time by choosing the 50-50 urn is 50%. Since there are two colors that are each selected to win once, this would represent the minimum probability of winning once by selecting the second urn with the unknown ratio. That is, if there were the same 50-50 distribution of red and black balls in the unknown urn then the probability would be the same. But, if the ratio were different then at least one of the two trials must present a chance greater than 50% of winning $100.

More recent work has found evidence to suggest that this effect is not always adhered to and can, in some cases, even be reversed (e.g., Rode et al., 1999). In this work, one experiment revealed that subjects were sensitive to outcome variables and selected the option with the lowest outcome variability, or risk, which in this case was the ambiguous option (Rode et al., 1999). This study was presented very similar to the one mention above in Ellsberg (1961), where there were boxes with black or white balls presented and monetary award for drawing the one matching a specified color. The major difference is that this choice was offered to each participant 10 times. In a subsequent experiment, Rode et al. (1999) examined preferences when there was a need level to be met. The problem was presented similar to the previous experiment (one box with a known distribution of black and white balls and the other with an unknown distribution) and participants were informed that they must draw a certain number of black balls to advance to the second stage of the lottery. When the minimum requirement was greater than the mean outcome, expected value, of the known distribution box, participants' preferences shifted to the ambiguous, or risky, box.

**Sex Differences**

Males and females have been found to differ in their individual preferences for risk. Typically, males exhibit greater risk-seeking behaviors than females across domains such as gambling, recreation, and health decisions (e.g., Eckel & Grossman, 2002; Harris et al., 2006). One explanation for this difference is perceptions of negative outcomes (higher for females) and expected enjoyment (lower for females; Harris et al., 2006).

Because of greater expectation of negative consequences and a lower level of expected enjoyment, females are not as motivated as males to engage in risky behaviors.

## HYPOTHESES

Risk sensitive foraging predicts that organisms will assume greater risk when facing an energy deficit (Stephens & Krebs, 1986). Additionally, tri-reference point theory predicts similar behavior in order to reach the next reference point (Wang & Johnson, 2012). These prior findings lead to the first hypothesis: as budget-goal difference increases, preference for risk will also increase.

As organisms face time pressure in order to reach a minimum aspiration level, they will take more risk in order to forage enough calories to survive (Stephens & Krebs, 1986). Assuming that the minimum aspiration level has not been met and all else remains constant, as time passes (trials remaining decreases), preference for risk will increase.

Since females expect more negative outcomes from taking risk and less enjoyment than males (Harris et al., 2006), males are expected to assume more risk than females.

Budget-goal difference and time are expected to interact such that a large budget-goal difference at a later time (fewer trials remaining) will lead to greater preference for risk. Risk sensitive foraging predicts that animals in a negative energy budget will seek more risk under time pressure than, both, the same animal without time pressure or and animal in a positive energy budget (Stephens & Krebs, 1986).

# METHOD

## Participants

Participants consisted of 110 undergraduate students (ideally half male and half female, though this is unlikely to occur) enrolled in a general education psychology course at Fort Hays State University. The mean age of participants was 19.92 years (*SD* = 2.98), and a majority of participants indicated their ethnicity as Caucasian (82.28%), followed by other/biracial (12.66%), followed by African-American (3.80%), and Native American (1.26%). The sample consisted of 51.25% males and 48.75% females. Participants received extra credit or partial fulfillment of research participation credit in their respective psychology course(s) for participating in this project; all identifying information was removed from the data. Acceptance of informed consent was collected using a radio button, therefore no identifying information was collected during informed consent procedures.

## Materials

**Web application.** The primary purpose of the study was to evaluate a software program (see Appendix A for a visual representation) that could be used to present decision tasks by other researchers. This task was programmed to allow flexibility in the information presented to participants, that can be easily adjusted by the researcher, and was a web-based program, coded using ASP.net in Microsoft® Visual Basic Community 2013, utilizing a Microsoft® SQL Server database back-end. The interface was designed to be simplistic and easy for participants to understand after very little instruction. Participants were presented a binary choice decision task in which the following information was displayed: number of trials remaining, running score (bank amount), goal amount, two gambles (Gamble A and Gamble B), payout amounts for each gamble, the cost to play each gamble, and feedback about the previous trial.

Participants began with a bank amount, a set goal amount, and a total number of trials. Each time a gamble was selected, the budget decreased based on the cost of the selected gamble. If the selection was a "win," the payout amount corresponding to that gamble was then added to the running score. If the selection was a "loss," then no points were added to the running score. Each time a selection was made, the remaining number of trials decreased by one until the last trial was completed.

Generally, people perform better on mathematic tasks when the problems are presented using frequencies (Hill & Brase, 2012). This phenomenon is known as the *frequency effect*, and this effect has many possible explanations such as the "frequency hypothesis" that states the world in which man evolved was one abundant with frequency information (e.g., Brase et al., 1998; Cosmides & Tooby, 1996; Hill & Brase, 2012). Following from this hypothesis, a laboratory test that could argue high ecological validity should present choice options in such a manner. The purpose of this study was to create such a measure where participants sample the given options, and probabilities are determined using naturalistic sampling techniques.

The task presented participants with a standard binary choice decision task. They began a certain number of trials in which they could test the two options for their payout frequencies. Participants then used this information to evaluate which option to choose with a given number of trials remaining in the task.

## Procedure

Participants were recruited by an announcement in their general education psychology course and asked to sign up for a specific date and time to participate in this study using Google® Forms. Upon arrival, they were informed of the purpose of the study and reminded of their rights as voluntary participants in research. Upon consenting, the study began. Participants were randomly assigned to one of four groups, determined by beginning budget (high or low) and goal amount (high or low; see *Table 1*). Gamble A presented a 100% chance of winning $100 with a $10 cost to play in every condition, and gamble B presented a 55% chance of winning $200 with a $20 cost to play in every condition.

| Condition | Budget | Goal | Difference |
|---|---|---|---|
| 1 | $50 | $1800 | -$1750 |
| 2 | $50 | $2700 | -$2650 |
| 3 | $950 | $1800 | -$850 |
| 4 | $950 | $2700 | -$1750 |

*Table 1*. Budget and goal amounts corresponding to each of the four conditions and the beginning budget-goal difference.

After reading and agreeing with the terms in the informed consent, demographic information was collected from each participant. Each participant then read an instructional page that described the computer application and its use in the study. Each piece of information that was presented in the task (e.g., budget, trials remaining, and goal amount) was explained prior to the start of the actual task. Once participants were comfortable with how the program works, they were directed to begin the computer task. Every participant completed 20 trials of the computerized decision task.

Upon completion, participants were debriefed and encouraged to ask questions about the study. Each participant was given the option to print a debriefing form that contained information about the study and contact information for the research team. They were given the option to request results of the study once data has been collected and analyzed. At the conclusion of debriefing procedures, participants were thanked for their time, excused from the lab, and the study concluded.

**Data Analysis**

For each trial in the computer task, every participant contributed data for trials remaining, bank amount (budget), observed probability of gamble A, observed probability of gamble B, expected value of gamble A, expected value of gamble B, and the selected gamble. Additional variables were calculated, including the difference between the budget and the goal (hereafter referred to as budget-goal difference; calculated by budget – goal), the expected values of gamble A and gamble B based on observed payout frequency (payout amount * observed frequency – cost to play), determination of the risky option based on observed payout frequency (hereafter referred to as risky option; lower payout frequency is the risky option), and determination of risky behavior (coded as 1 = risky and 0 = not risky; determined by matching the selection of gamble A or gamble B with the determined risky option).

Data were analyzed using a three-step multilevel hierarchical logistic regression. Main effects for budget-goal difference, trial number, and sex were entered in the first step as predictors and risky option was entered as the criterion. In the second step, all possible two-way interactions (trial number x budget-goal difference; trial number x sex;

budget-goal difference x sex) will be entered as predictors with risky option as the criterion. In the third step, the three-way interaction will be entered (trial number x budget-goal difference x sex) will be entered as the predictor and risky option as the criterion.

**A Primer on Multilevel Regression**

Researchers are sometimes interested in multiple levels of analysis. Consider, for example, a situation where we are interested in academic success of high school students from every high school in Kansas, and want to predict that success using prior test scores. This presents a unique scenario in which traditional data analysis techniques are unable to account for both individual-level variance (each student) and group-level variance (each high school) (Gelman & Hill, 2007). As an example, sex of the students would vary at the individual level (and may be a predictor of success), but funding for after-school programs would vary at the group, or school, level (and may also be a predictor of success for students attending each school). Traditional models can estimate group effects using an indicator variable (e.g., school “A” = 1, school “B” = 2), but this method does not allow variation between groups to be modeled. Simply stated, a multilevel regression model seeks to predict an individual outcome based on predictors unique to the individual (e.g., sex, age, grades) as well as predictors unique to the group to which the individual belongs (e.g., education level of faculty, after school program funding, socioeconomic status of school community) where coefficients at each level are allowed to vary.

Of particular value to the present research is the ability of multilevel regression models to handle repeated measures data (Gelman & Hill, 2007). In this case, time (trial number) would represent a group-level predictor, while sex and difference between budget and goal would represent individual-level predictors. In the main analysis, the dependent variable (choice of risky gamble; coded as risky = 1, not risky = 0) was regressed onto these predictors using the lme4 package in R©.

## RESULTS

Before performing the regression analysis, data were checked for impossible values (none found), coding errors, and missing values. Missing values were found for demographic variables for 30 participants. These participants were included in the main analysis, but demographic predictors, specifically sex, should be interpreted with caution as data for this variable was not present for all participants.

The trial number variable was also centered by subtracting the mean from each value. By centering the scale predictor variables, interaction effects are more easily interpreted.

Additionally, the budget-goal difference variable was calculated by subtracting the goal amount from the current budget. This allows negative values to be interpreted as a budget falling below the goal, and positive values indicate goal achievement. After calculating this variable, it was centered by subtracting the mean from all values. Then the variable was scaled by dividing by 1000 in order to scale the difference variable more similarly to the trial number variable.

**Main Analysis**

Data were analyzed using a three-step multilevel logistic regression. In the first step, risky choice (coded as risky = 1, not risky = 0) was regressed onto budget-goal difference, trial number, and sex (1 = male, 0 = female). In the first step, budget-goal differences (*Figure 3*) and trial number (*Figure* 4) were both unique predictors of risk preference, but sex was not a unique predictor (see Table 2 for analysis details).

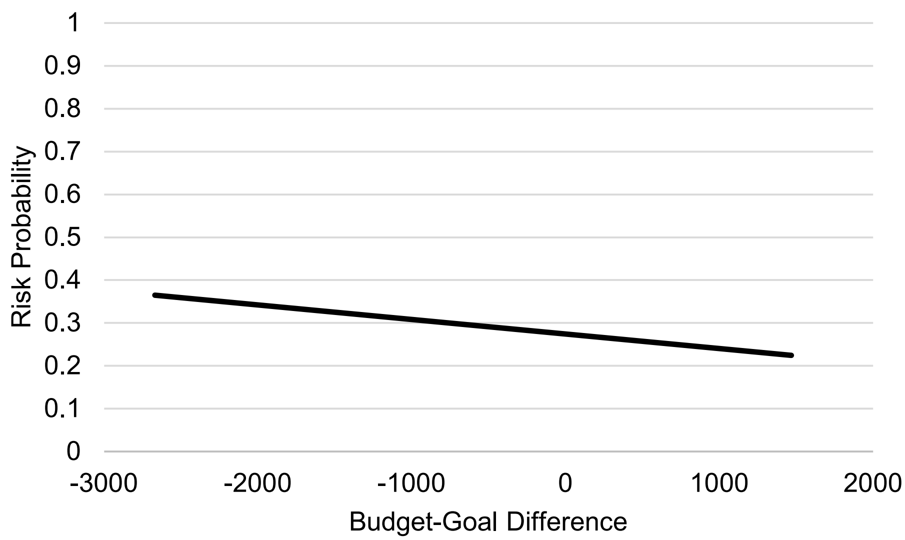


*Figure 3*. Probability of selecting the risky option predicted by budget-goal difference.

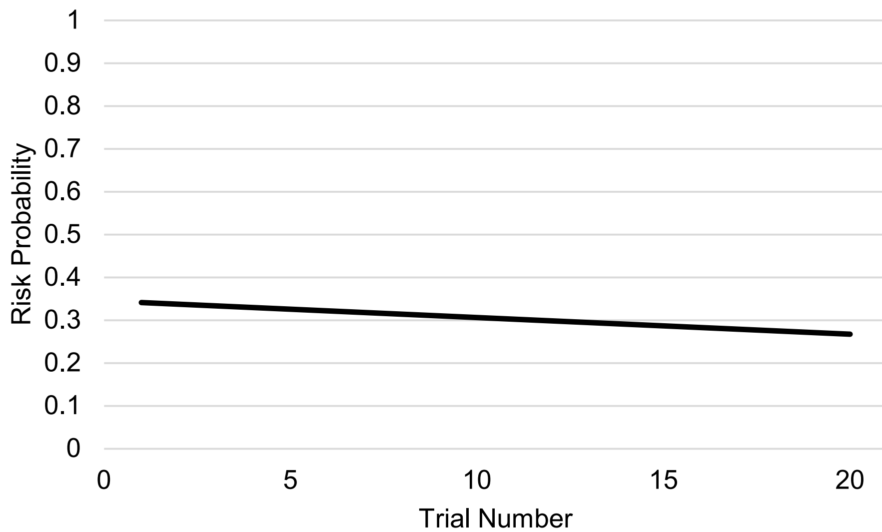


*Figure 4*. Probability of selecting the risky option predicted by trial number.

In step two, risky choice was regressed onto all possible two-way interactions: trial number X budget-goal difference, trial number X sex, and budget-goal difference X sex. None of the two-way interactions were unique predictors of risk preference (see Table 2 for analysis details). Additionally, the Akaike information criterion (AIC) increased from the first step to the second. This indicates that the model at step two did not show an improvement in model fit over step one (Gelman & Hill, 2007).

In the third step, risky choice was regressed onto the three-way interaction, trial number X budget-goal difference X sex. The three-way interaction was not statistically significant in step three. As in step two, the AIC increased in step three which indicates that fit did not improve with the addition of the three-way interaction.

| Step | Predictor | AIC | Coefficient | $p$ |
|---|---|---|---|---|
| 1 | --- | 1725 | --- | --- |
| | (Intercept) | --- | -1.53 | <0.001** |
| | B-G Difference | --- | 0.19 | 0.034* |
| | Trial Number | --- | -0.08 | <0.001** |
| | Sex | --- | 0.34 | 0.233 |
| 2 | --- | 1755 | --- | --- |
| | (Intercept) | --- | -1.80 | <0.001** |
| | TN * B-G Diff | --- | -0.01 | 0.712 |
| | TN * Sex | --- | 0.07 | 0.146 |
| | B-G Diff * Sex | --- | -0.02 | 0.932 |
| 3 | --- | 1773 | --- | --- |
| | (Intercept) | --- | -1.82 | <0.001** |
| | TN*B-G*Gen | --- | 0.01 | 0.744 |

*Table 2*. Summary of results from multilevel logistic regression analysis. * denotes $p < .05$, ** denotes $p < .001$

**Exploratory Analysis**

For exploratory purposes, the dependent variable was recoded to reflect choice for lower expected value (EV choice). The variable was coded as 1 (lower expected value) and 0 (higher expected value), and was analyzed using the same predictors as in the main analysis.

Data were analyzed using a three-step multilevel logistic regression. In the first step, EV choice was regressed onto budget-goal difference, trial number, and sex (1 = male, 0 = female). In the first step, only sex (*Figure 5*) was a unique predictor of EV choice (see Table 3 for analysis details).

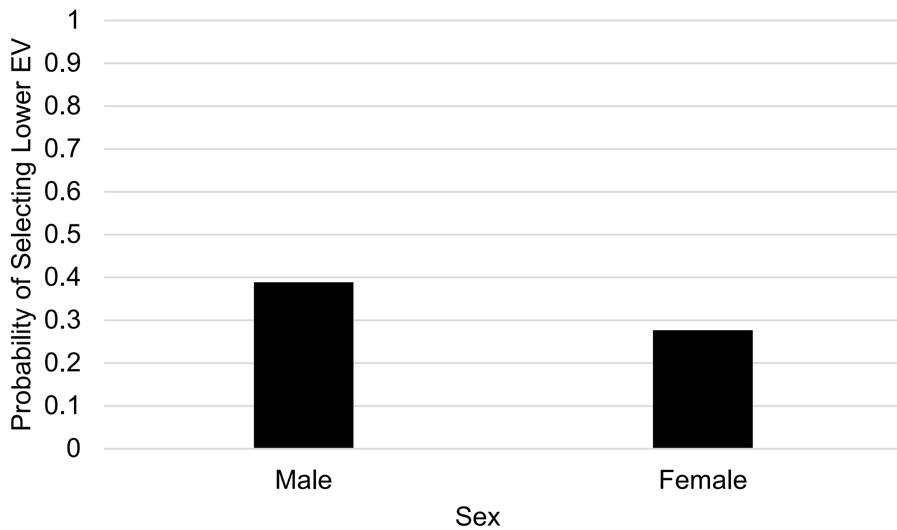


*Figure 5.* Selection of lower EV option predicted by sex.

In step two, EV choice was regressed onto all possible two-way interactions: trial number X budget-goal difference, trial number X sex, and budget-goal difference X sex. Only trial number X budget-goal difference was a unique predictor of EV choice (see Table 3 for analysis details). Additionally, the Akaike information criterion (AIC) increased from the first step to the second. This indicates the model at step two did not show an improvement in model fit over step one (Gelman & Hill, 2007).

In the third step, EV choice was regressed onto the three-way interaction, trial number X budget-goal difference X sex. The three-way interaction was not statistically significant in step three. As in step two, the AIC increased in step three which indicates that fit did not improve with the addition of the three-way interaction.

| Step | Predictor | AIC | Coefficient | *p* |
|---|---|---|---|---|
| 1 | --- | 1723 | --- | --- |
| | (Intercept) | --- | -1.49 | <0.001** |
| | B-G Difference | --- | 0.06 | 0.821 |
| | Trial Number | --- | -0.04 | 0.192 |
| | Sex | --- | 0.71 | 0.031* |
| 2 | --- | 1731 | --- | --- |
| | (Intercept) | --- | -2.02 | <0.001** |
| | TN * B-G Diff | --- | 0.08 | <0.001** |
| | TN * Sex | --- | 0.01 | 0.818 |
| | B-G Diff * Sex | --- | 0.61 | 0.157 |
| 3 | --- | 1749 | --- | --- |
| | (Intercept) | --- | -2.04 | <.001** |
| | TN*B-G*Gen | --- | 0.02 | 0.783 |

*Table 3*. Summary of results from exploratory multilevel logistic regression analysis. * denotes $p < .05$, ** denotes $p < .001$

## DISCUSSION

### Main Analysis

Budget-goal difference did predict risk preference, and the first hypothesis was supported. As the distance from the budget to the goal increased, the probability of selecting the risky option also increased. This finding aligns well with previous research on RST (e.g., Caraco et al., 1980; Stephens, 1981) and supports the idea that organisms are willing to assume a greater amount of risk if doing so increases the chance of survival (framed as meeting a goal in the present study).

As trial number increased (or trials remaining decreased) preference for risk actually decreased, which is the opposite of the prediction made in the second hypothesis. Though this finding is inconsistent with RST as described by Stephens and Krebs (1986), this finding should be interpreted with caution due to possible collinearity issues with trial number and budget-goal difference. Since both options presented positive EV values, the budget-goal difference should, mathematically, approach a surplus value over time. To address this limitation, future research should utilize choice options with expected values near zero. This would reduce collinearity between budget-goal differences and trial number and there would be no systematic change over time.

There was not a sex difference in regards to risk preferences, and the third hypothesis was not supported. This is contrary to several studies that find greater risk preferences exhibited by males than females (e.g., Eckel & Grossman, 2002; Harris, Jenkins, & Glaser, 2006). This does seem to fit with RST, as males and females should assume similar amounts of risk when a decision presents life-or-death consequences (e.g., starvation).

Finally, the main analysis also did not support hypothesis 4, there was no significant interaction between budget-goal difference and time. This makes logical sense as the main effect for time was in the opposite direction than expected, so the regression lines for budget-goal difference and time had similar slopes. Theoretically, however, this is in opposition to predictions from RST (e.g., Stephens, 1981; Stephens & Krebs, 1986) which states that an organism should take more risk under time pressure when a need level has not been met. This behavior could be a mechanism to prolong life (avoid starvation) by expending less of the available budget in hopes that an outside influence may provide the necessary income. For example, an organism on the brink of starvation may choose to conserve energy, if meeting a need level is no longer possible, in hopes of receiving sustenance from an altruistic neighbor. This would allow the organism to prevent furthering its energy deficit and requiring a smaller donation in order to survive.

**Exploratory Analysis**

Interestingly, when the dependent variable was coded for EV instead of risk, the unique predictors from the main analysis were no longer statistically significant. Additionally, sex and the interaction between budget-goal difference and time were unique predictors of choosing the option with the lower EV.

Males were more likely than females to choose the option with the lowest observed EV. This may suggest that females are more sensitive to outcomes in naturally sampled environments. It could also support the idea that males and females approach risk differently. Although the main analysis did not detect a sex difference for risk as it was operationally defined (i.e., the more variable of the two options), selecting an option with a lower EV could also be a viable definition for risk. Eckel and Grossman (2008) discuss several possible reasons for inconsistencies in findings regarding risk aversion and sex including task type and experiment setting. This finding may further the argument for the use of terms describing specific kinds of risk so that comparisons can be made across studies. One potential explanation for this effect, where females seem to be more sensitive to expected values of decisions, relates to ancestral foraging. Historically, there has been a sexual division of labor concerning the gathering of food resources; males have been responsible for hunting and females have been responsible for foraging (Silverman & Eals, 1992). New, Krasnow, Truxaw, and Gaulin (2007) discuss an advantage in navigation that females have over males when foraging for fruits and vegetables. Though not directly tested in this theory, sensitivity to greater caloric values in a single foraging session could moderate the effect of this navigational advantage in females. This effect should be directly examined in future research.

Interestingly, budget-goal difference and time interacted to predict the choice of the lower EV option. However, the effect was in the opposite direction of what should be expected. As budget-goal difference increased and time passed, the likelihood of choosing the lower valued option increased. A possible explanation for this effect is a lack of sensitivity to payout frequency or a lack of rationality on the part of decision makers (e.g., Kahneman & Tversky, 1979; Kahnemnan & Tversky, 1984). This could illustrate the lack of consequence for failure to meet the set goal amount, where participants lost interest in trying to reach the goal. In studies with other animals (e.g., Caraco et al., 1980), the failure of an animal to reach a minimum need level in terms of calories from food would likely result in death, a very serious consequence. Without a consequence for failure to reach the minimum level, the goal amount, participants in this study would not be motivated to avoid such a consequence.

**Limitations and Implications**

This study provided support for the frequency hypothesis. It appears as if decision makers were sensitive to the payout frequencies of the provided options, and chose the less risky option more often than the risky option. This would suggest that naturally sampled frequency information is more easily processed by the human mind than mathematical representations of probability.

Second, findings suggested a time component should be included in decision tasks, especially since many everyday decisions (e.g., paying rent on time or going out) carry with them a deadline of some kind. The data revealed a strong main effect for time on risk preferences, although not in the expected direction. This variable should be examined more closely as it is experienced universally. The present studied utilized only 20 time points, but a similar setup could collect many more data points from a single participant to establish an even more reliable estimate of the effects of time on risk preferences.

Finally, results supported the necessity of multiple reference points in a single decision tasks. Tri-reference point theory (Wang & Johnson, 2012) is one of the theories that attempts to analyze decision processes by using more than a single point of reference. The relationship between the budget and goal amounts was a significant predictor of risk preference, but only manipulated two of the three reference points described in tri-reference point theory. Future studies should incorporate all three as there is evidence to suggest an effect for two.

Most importantly, however, is that the software created for the purposes of this study could be used in future research. The area of judgment and decision-making seems to lack an agreed-upon tool by which to assess decision-making behavior. Many of the tasks created are similar, but better comparisons between studies could be drawn if scientists can compare results from the same task or set of tasks. This task adds the extra benefit of increasing ecological validity as it relates directly to the frequency hypothesis (e.g., Brase et al., 1998; Cosmides & Tooby, 1996; Hill & Brase 2012) by asking participants to naturally sample outcomes of the presented options in order to make their future decisions.

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**APPENDIX A**

The computerized gamble task:

**APPENDIX B**

IRB Approval Letter

FORT HAYS STATE UNIVERSITY

*Forward thinking. World ready.*

**OFFICE OF SCHOLARSHIP AND SPONSORED PROJECTS**

| | |
|---|---|
| DATE: | September 17, 2015 |
| TO: | Kevin Kenney |
| FROM: | Fort Hays State University IRB |
| STUDY TITLE: | [794833-1] Creating a More Ecologically Valid Decision Task |
| IRB REFERENCE #: | 16-007 |
| SUBMISSION TYPE: | New Project |
| ACTION: | DETERMINATION OF EXEMPT STATUS |
| DECISION DATE: | September 17, 2015 |
| REVIEW CATEGORY: | Exemption category # 2 |

Thank you for your submission of New Project materials for this research study. The departmental human subjects research committee and/or the Fort Hays State University IRB/IRB Administrator has determined that this project is EXEMPT FROM IRB REVIEW according to federal regulations.

Please note that any changes to this study may result in a change in exempt status. Any changes must be submitted to the IRB for review prior to implementation. In the event of a change, please follow the Instructions for Revisions at http://www.fhsu.edu/academic/gradschl/irb/.

The IRB administrator should be notified of adverse events or circumstances that meet the definition of unanticipated problems involving risks to subjects. See http://www.hhs.gov/ohrp/policy/AdvEvntGuid.htm.

We will put a copy of this correspondence on file in our office. Exempt studies are not subject to continuing review.

If you have any questions, please contact Leslie Paige at lpaige@fhsu.edu or 785-628-4349. Please include your study title and reference number in all correspondence with this office.