UNDERSTANDING THE ROLE OF RISK AND UNCERTAINTY IN SEQUENTIAL DECISION MAKING DURING INFORMATION ACQUISITION

By

Michael Thomas Braun

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

Psychology

2012

ABSTRCT

UNDERSTANDING THE ROLE OF RISK AND UNCERTAINTY IN SEQUENTIAL DECISION MAKING DURING INFORMATION ACQUISITION

By

Michael Thomas Braun

When employees are faced with novel situations it is often necessary for them to acquire new information. Unreliability of information sources and uncertainty regarding information usefulness make the information acquisition process analogous to a sequence of risky decisions. Prospect Theory (Kahneman & Tversky, 1979) and its generalizations are currently the dominant approach to the study of risky decision making in psychology and economics due to their ability to accurately describe the decision biases that are frequently document in the presence of risk and uncertainty. Using a lab-based computer simulation, CRONUS SOLO, common biases from the Prospect Theory literature are examined for sequential risky decision making during information acquisition. Additionally, common relationships between individual differences and sequential risky decision making as well as the effect of learning and feedback on risky decision making are explored. The biases present during the information acquisition process are not fully explained by Prospect Theory and its generalizations. Overall, individuals became more efficient and optimal decision makers over time. The effects of information reliability, information framing, and specific individual differences are presented. Finally, potential explanations for the current findings as well as implications for training are discussed.

ACKNOWLEDGEMENTS

I would like to extend my extreme gratitude to my advisor, Dr. Steve Kozlowski, for all of the time, effort, and support that he has given me throughout this research process. I am undoubtedly a better researcher, writer, and presenter thanks to his guidance.

I would also like to thank my committee members, Rick DeShon, Neal Schmitt and Georgia Chao, for providing excellent guidance and insight on improving my research.

Finally, thanks to all of my friends and family for all of the loving support they have always provided me. A special thanks to my parents for their continued love, encouragement, patience, and guidance.

Michael T. Braun gratefully acknowledges the Office of Naval Research (ONR), Command Decision Making (CDM) Program (N00014-09-1-0519, S.W.J. Kozlowski and G. T. Chao, Principal Investigators) for support of this research. Any opinions, findings, and conclusions or recommendations expressed are those of the author and do not necessarily reflect the views of ONR.

TABLE OF CONTENTS

LIST OF TABLES vi

LIST OF FIGURES viii

INTRODUCTION 1
Organizational Decision Making 5
Cognitive Decision Making 6
Behavioral Decision Making 8
Limitations of Organizational Decision Making 14
Prospect Theory: Describing Risky Decision Making 16
Prospect Theory 17
Cumulative Prospect Theory 25
The House Money Effect and Escalation of Commitment 28
Risky Decision Making during Information Acquisition 30
Prospect Theory Hypotheses 33
Individual Differences Hypotheses 37
Learning and Decision Making Hypotheses 40

METHOD 42
Sample 42
Procedure 42
CRONUS SOLO 43
Scenario Design 51
Measures 53
Demographics 53
Cognitive ability 53
Affect 53
Goal Orientation 54
Risk Propensity 54
Time Decision Making 54
Deviations from Optimal Decisions 55
Risky Decision Making 55
Performance 56
Data Analysis 58

RESULTS 60
Prospect Theory Hypotheses 60
Individual Differences Hypotheses 73
Learning and Decision Making Hypotheses 81

DISCUSSION 85
Limitations and Future Directions 92

Conclusion 96

APPENDIX A: Individual Differences Scales 98

REFERENCES 102

LIST OF TABLES

Table 1. Obstacle Properties in CRONUS SOLO 53

Table 2. Correlations among Focal Variables..57

Table 3. ICC(1) Values of Time-varying Covariates..58

Table 4. Average Proportion of High Probability Information Posted by Trial 61

Table 5. Proportion of Individuals who engaged in each Category of Posting Behavior for High Probability Information 62

Table 6. Differences in Proportion of High Probability Information Posted between Conditions 64

Table 7. Average Proportion of Low Probability Information Posted by Trial...........................65

Table 8. Proportion of Individuals who engaged in each Category of Posting Behavior for Low Probability Information..66

Table 9. Differences in Proportion of Low Probability Information Posted between Conditions 66

Table 10. Average Proportion of Moderate Probability Information Posted by Trial.................67

Table 11. Proportion of Individuals who engaged in each Category of Posting Behavior for Moderate Probability Information..68

Table 12. Differences in Proportion of Moderate Probability Information Posted between Conditions 69

Table 13. Effect of Risky Decision Making on Performance 71

Table 14. Effect of Negative Affectivity on Risky Decision Making 74

Table 15. Effect of Negative Affectivity on Performance 74

Table 16. Effect of Positive Affectivity on Positive Information Attended 75

Table 17. Effect of Positive Affectivity on Risky Decision Making...76

Table 18. Effect of Performance Avoid Goal Orientation on Risky Decision Making................77

Table 19. Effect of Performance Approach Goal Orientation on Risky Decision Making..........78

Table 20. Effect of Risk Taking Propensity on Risky Decision Making.....................................79

Table 21. Effect of Cognitive Ability on Risky Decision Making 80

Table 22. Effect of Cognitive Ability on Performance..80

Table 23. Effect of Time on Performance 82

Table 24. Effect of Time on Deviations from Optimal Probability..83

Table 25. Effect of Time on Time to Make Decisions 84

LIST OF FIGURES

Figure 1. Hypothetical value function for Prospect Theory 23

Figure 2. Hypothetical weighting function for Prospect Theory 24

Figure 3. Hypothetical weighting function for Cumulative Prospect Theory 27

Figure 4. Specialist Map screen for CRONUS SOLO. For interpretation of the references to color in this and all other figures, the reader is referred to the electronic version of this dissertation 46

Figure 5. Mission Info screen for CRONUS SOLO 47

Figure 6. Specialist Info screen for CRONUS SOLO 48

Figure 7. Mission Command screen for CRONUS SOLO 49

Figure 8. Feedback screen for CRONUS SOLO 50

INTRODUCTION

Organizational success often hinges on the ability of individuals to make correct decisions in the presence of high degrees of risk and uncertainty. Frequently, these decisions affect not only the organization but the community at large as well. For example, the United States intelligence community "gathers tremendous amounts of information based on a complex set of needs and requirements established by the policy makers it supports. …Much of these data are of questionable reliability and …is reviewed and evaluated by intelligence collectors and analysts who gauge its reliability and accuracy" (Permanent Select Committee on Intelligence: House of Representatives, 1996; p. 13). To properly identify relevant threats to national security, the intelligence collectors and analysts must make accurate decisions on what information is most reliable and what information is most important. Failure to do so can result in catastrophic disasters such as the terrorist attacks on September 11, 2001. Similarly, emergency medical personnel are bombarded with information on the patient they are treating such as medical history, reported symptoms, and physiological responses. To correctly diagnose and treat a patient, the individual must wade through the plethora of information and only attend to the data that are most likely relevant and most critical. Understanding the decision making process that individuals go through when presented with large quantities of uncertain, risky information is vital to the success of the organizations like those just described. Unfortunately, to date there is little research that directly studies this phenomenon.

Not surprisingly, given the impact that decision making can have on organizational success, there is an abundance of organizational research devoted to it. Unfortunately, like many areas of concentration in the organizational sciences, the study of decision making is plagued by an overreliance on cross-sectional and/or self report data. Additionally, many of the more recent studies of organizational decision making are focused at the team level. While understanding how teams make decisions is certainly important given the shift of organizations to utilize teams for problem solving, it is also necessary to understand how the building blocks of teams (i.e., individuals) integrate information to make decisions. Finally, most theories of organizational decision making are built on the assumption of a deterministic environment, ignoring the uncertain or stochastic nature of the real world. Therefore, to help organizations understand and improve sequential decision making, it is necessary to examine how individuals make a series of decisions over time in an uncertain environment with multiple risky outcomes.

The purpose of the current research is to understand the information acquisition process by modeling it as a series of risky decisions. More specifically, this dissertation categorizes the organizational decision making literature and highlights its shortcomings for understanding risky decision making. Additionally, the predictions of Prospect Theory, the dominant approach to risky decision making in other fields, are integrated with the type of decisions individuals make during information acquisition. Finally, relationships among individual difference variables, learning, and risky decision making that are commonly found in economics, cognitive psychology, and the organizational sciences are tested for the decisions made during the information acquisition process. Special attention is paid throughout the paper to the role of time in risky decision making and information acquisition.

The study of decision making under the conditions of risk and uncertainty is common in many scientific disciplines. In the social sciences, it is most frequently researched in economics and cognitive psychology. Initially, individuals were thought to be rational decision makers and were modeled accordingly with theories such as Expected Utility Theory (Atkinson, 1957;

Keeney & Raiffa, 1976). However, it was frequently documented that individuals deviate from rational choice when presented with risky uncertain outcomes (e.g., Kahneman & Tversky, 1979; Markowitz, 1952). As a result, an alternative class of models emerged which incorporated the heuristics and biases that people use in decision making, thus, making them better descriptors of actual behavior. Prospect Theory (PT) models decisions as a function of the relative gains and losses of each outcome weighted by the perceived impact of the outcomes (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). By incorporating perceptions and the unequal weighting of relative gains and losses, PT better describes human behavior than the original rational choice models. As a result, PT is currently the dominant approach to the study of decision making under risk and uncertainty.

Despite the ability of PT to describe actual decision making, its focus and application has been rather narrow in scope. In their initial presentation, Kahneman and Tversky state that "[Prospect] Theory is developed for simple prospects with monetary outcomes and stated probabilities" (1979; p. 274). Not surprisingly, then, the study of prospect theory has predominantly been in financial disciplines such as finance and economics. Even when other fields such as psychology have utilized the theory, it has primarily been done using monetary decisions (e.g., gambles). Similarly, Prospect Theory was created to explain single decisions. Little research exists that examines how the effect of learning or experience over a sequence of decisions would impact the accuracy of PT to describe actual behavior.

Despite the initially intended purpose of PT, Kahneman and Tversky (1979) recognize that "it can be extended to more involved choices" (p. 274). Recently, there have been arguments that time is a valuable resource similar to money, and that spending time on something can result in successes or failures equivalent to those in financial decisions (Cunha &

Caldieraro, 2009; Steel & Konig, 2006). Additionally, research has been conducted on possible boundary conditions of the predictions of prospect theory for sequential decisions (e.g., escalation of commitment; Staw, 1976; house money effect; Thaler & Johnson, 1990). As a result, PT and its generalizations provide a good framework to predict how individuals make a sequence of decisions in an uncertain, risky environment.

When acquiring new information, employees must quickly decide what information to attend to and what to ignore. Understanding this process is important because in organizations like those described earlier, workers are frequently bombarded with an extreme volume of information and the validity and usefulness of the information is not always certain. Choosing whether to attend to or ignore each piece of information has potential costs and benefits associated with it, and those costs and benefits each have a likelihood of occurrence. Since workers encounter both risk and uncertainty when deciding what to attend to, the information acquisition process becomes analogous to a sequence of risky decisions. While the organizational decision making literature lacks strong theories of decision making under risk, Prospect Theory and its generalizations provide a solid foundation for describing the risky decision making process that employees engage in when acquiring new information.

To determine whether prospect theory can accurately predict information searching under risky uncertain conditions, the paper is organized in the following manner: First, I review and categorize the organizational decision making literature, highlighting its shortcomings for understanding sequential decision making under risk and uncertainty. I then briefly define prospect theory, its origin, primary components, and its mathematical representation, including the generalization to cumulative prospect theory and the special cases of the house money effect and escalation of commitment. Next, I utilize the predictions of Prospect Theory and

Cumulative Prospect Theory to formulate specific hypotheses about the biases that individuals may demonstrate when engaging in the information search process. Additionally, common findings from the Prospect Theory literature are used to formulate predictions about what individual differences can affect the common biases in risky decision making. I also draw upon findings from the house money effect and escalation of commitment to understand how prior successes and failures could impact subsequent decision making. I then describe my sample, procedure, computerized task, operationalizations of risk, uncertainty, and information acquisition, and proposed data analytic strategy. Finally, I present results for each hypothesis followed by a discussion section summarizing the results, highlighting their implications, and discussing some limitations and future research directions.

Organizational Decision Making

Countless numbers of decisions are made in organizations each day. Not only do the quality and efficiency of decisions affect vital organizational outcomes (Shrode & Brown, 1970; Ziller, 1957) but they have also been shown to affect employees' affective reactions to the organization (Jackson, 1983, 1984; Ritche & Miles, 1970). There are numerous types of decisions that individuals can engage in, leading the study of decision making to encompass a wide range of scholarly work. The applicability of theories and prior research findings depends on the type of decision under investigation. The organizational decision making literature can be grouped into two broad categories, cognitive decision making and behavioral decision making. Cognitive decision making encompasses studies that investigate decisions where individuals or teams must complete some task of cognitive ability. These studies frequently operationalize decision making as either creativity or performance. Conversely, behavioral decision making defines studies where individuals must decide on an appropriate behavior to solve a particular problem, frequently without an obvious "correct" solution. Behavioral decision making incorporates a wide variety of decision types, including strategic decision making, dynamic decision making, open-ended choice problems, discrete choice problems, and gambles with monetary and nonmonetary outcomes. Each type of cognitive and behavioral decision making has unique properties related to the type of decision under investigation. As such, each type will be described and relevant relationships with organizational variables will be explained, followed by an overview of the limitations of the current organizational decision making literature to describe sequential decision making under risk and uncertainty.

Cognitive Decision Making

Cognitive decision making in the organizational sciences is frequently operationalized in two distinct ways. The first is by creativity tasks where individuals or teams are asked to make a list of all possible solutions to some question. The greater number of solutions the individual or team can generate, the higher the performance on decision making. Frequently, the quality of the potential solutions generated is completely ignored. A number of important constructs have been found to impact the quality of the creative decision making process. At the individual level, it was found that stress and time pressure inhibit the decision making process and fewer ideas are generated. Additionally, when questions are framed in an open-ended and ambiguous manner, individuals had greater difficulty effectively framing the problem and generating plausible solutions (Abualsamh, Carlin, & McDaniel, 1990). It has also been documented that initially suppressing emotions, so as to not interfere with the decision making process, had a positive effect on creativity (Guzzo & Waters, 1982).

At the team level, communication was found to be instrumental in increasing creative decision making in a number of important ways. The medium by which the team communicates is important, with face to face communication being more effective than computer mediated for idea generation. Along the same lines, as tasks become more interdependent, high quality team-member exchange (TMX) increases the decision making ability of the team (Alge, Wiethoff, & Klein, 2003). Additionally, during communication, the dissent of a minority opinion increases creativity and, thus, decision making (De Dreu & West, 2001). Finally, imposing structure on the communication of the group by forcing team members to first generate ideas independently and then discuss them as a group led to significantly better decision making processes (van de Ven & Delbecq, 1974).

The second type of cognitive decision making paradigm in the organizational sciences is to study decision making as performance. Given that performance is highly contextualized, there are as many ways to measure decision making as performance as there are scientific investigations of it. A few examples are studies that operationalize decision making through word memorization tasks, cognitive ability and problem solving tests, and tests of reading comprehension. Currently, the primary focus for studies on decision making as performance has been on teams. Not surprisingly, as seen in almost all team research, the type of task (e.g., Steiner, 1972) heavily influenced the decision making process. For disjunctive tasks, it was found that the highest performing member of the team dominated the task (e.g., Bonner, Baumann, & Dalal, 2002). For additive tasks that were more interdependent, teams consistently outperformed individuals and were able to perform better the longer they stayed together (Michaelsen, Watson, & Black, 1989; Vollrath, Sheppard, Hinsz, & Davis, 1989), becoming less reliant on their best team member over time (Watson, Michaelsen, & Sharp, 1991).

Studies on cognitive decision making are few in number and have not gained significant traction in the decision making literature. While the findings presented above are certainly important for organizations, they are not consistent with main stream operationalizations of decision making and, thus, better categorized in other areas of organizational psychology such as individual and team performance. As a result, the remainder of this paper focuses on behavioral decision making, the dominant approach to the study of decision making in the organizational sciences as well as other scientific disciplines (e.g., economics, cognitive psychology).

Behavioral Decision Making

As was the case with cognitive decision making, the behavioral decision making literature encompasses a wide variety of decision tasks. One type of task is strategic decision making. Strategic decisions are primarily focused at the organizational level. The actual decisions themselves are commonly ignored by aggregating to the level of the company. For a decision to be included, it must be critical enough that it can affect organizational growth and development. To date, little research exists examining this phenomenon. Initial evidence suggests that strategic decisions are most effective when made through a thorough investigation of all rational options, called procedural rationality, and made in the best interest of the corporate political structure, called politics (Dean & Sharfman, 1995). Similarly, effective strategic decisions are more likely made when companies have employees with a high level of organizational loyalty and a high degree of competence (Dooley & Fryxell, 1999).

A second type of behavioral decision making is decisions with open-ended solutions. This type of decision is similar to the cognitive decision making creativity tasks because individuals are asked to provide an answer to a particular problem without being provided a set of response options. However, it differs from the creativity tasks because the number of possible solutions is not considered; rather, the single solution provided is evaluated for its quality or consistency. The literature on open-ended decisions is primarily focused at the team level, specifically interested in the relationship between leadership and effective team decision making. It has been shown that teams are most effective when the team leader receives the problem from the leader's supervisor, interprets and frames the problem in a manner easily understood by team members, and provides structure to how the team responds (Miner, 1979). Additionally, involving subordinate team members in the decision process increases their positive affect (Richter & Tjosvold, 1980).

Another type of behavioral decision making is called dynamic decision making. The goal in studying dynamic decision making is to understand how individuals make decisions in a highly complex dynamic environment, focusing on learning and incorporating feedback. The tasks typically used to study this phenomenon simulate running a small company where money or other firm resources need to be allocated to different organizational departments (e.g., inventory, sales, staffing). After making a series of decisions, the individual receives feedback on the financial state of the company. The individual should then adjust his/her future decisions based on the feedback to improve corporate performance. This process is then repeated for several trials. With the goal of almost all of these studies to use feedback effectively to improve performance, results have been rather mixed. While some researchers have found that different modes of feedback lead to learning and increased performance (e.g., Atkins, Wood, & Rutgers, 2002), others have found that the complexity of the system overloads participants and, thus, feedback is ignored (e.g., Diehl & Sternman, 1995; Gonzalez, 2005).

Along with evaluating the usefulness of feedback, some researchers have used dynamic decision making to study the process of how individuals gain knowledge and formulate their decisions within each trial. Research has shown that people tend to evaluate all information and attempt to make rational choices (i.e., procedural rationality; Dean & Sharfman, 1995), even when it is to their disadvantage to do so because of time pressure (Kleinmuntz & Thomas, 1987). Additionally, it has been shown that some monetary choices in dynamic decision making trials can be described using Tversky and Kahneman's (1974) anchoring and adjusting heuristic.

Another paradigm that is very common in the organizational decision making literature is discrete choice problems. These problems can be on a variety of organizational topics including ethics (e.g., Detert, Trevino, Sweitzer, 2008), selection (e.g., Grove, 1981), marketing (e.g., Betsch, Haberstroh, Glockner, Haar, & Fiedler, 2001), and mergers and acquisitions (e.g., Pablo, 1994). Despite the wide range of topic areas, all discrete choice studies require participants to choose one "best" option from a list of possible choices in a deterministic environment. Research on discrete choice decisions is well established in the organizational sciences and has yielded numerous results.

At the individual level, a number of common biases have been documented in the way in which people make discrete choice decisions (Seale & Rapoport, 1997). Order of information presented is very important (Blakeney & MacNaughton, 1971), with people focusing heavily on early information (Dukerich & Nichols, 1991), and then seeking out additional information to confirm their initial decisions (Betsch, et al., 2001). Despite this bias, individuals are commonly unable to retrospectively determine which information or information gathering strategy they used to make their decision (Viswesvaran & Barrick, 1992). Additionally, individuals tend to use the majority rule heuristic (May, 1954; Russo & Dosher, 1983) to select an option when dealing with multiple sources of information, even if the overall rating of the options is identical (Zhang, Hsee, & Xiao, 2006). The impact of demographics on effective discrete decision making is far less solidified with some evidence that demographics are not related to decision effectiveness (Bridgeman & Marlowe, 1979) but other results suggesting that age and intelligence were positively related to decision making effectiveness while risk-taking propensity was negatively related to effective decision making (Taylor, 1975; Taylor & Dunnette, 1974).

Contextual factors also play a role in the discrete decision making process. For example, type of task, organizational culture, and corporate politics have been shown to impact decision effectiveness (Pablo, 1994). Similarly, when leaders provide advice to decision makers, leaders who are more supportive are listened to more often, thus, resulting in higher overall performance (O'Reilly, 1977). Over time, individuals who engage in procedural rationality by incorporating all information and attempting to make a rational choice make more effective decisions than those who make decisions based solely on prior success (Schweiger, Anderson, & Locke, 1985).

At the team level, communication is critical for discrete decision making success, similar to findings for the creativity tasks in cognitive decision making. The more information flow there is in a team, the more effective decisions the team makes (Holloman & Hendrick, 1972). Similarly, in conditions of distributed expertise, it is vital that individuals within a team share unique information (Stasser, 1992) so that team members will have greater team mental models and transactive memory structures for making effective decisions (van Ginkel & van Kippenberg, 2008, 2009). Finally, contrary to other types of decision making, stress was found to improve team decision making by making team members more receptive to information from one another (Driskell & Salas, 1991).

The final paradigm used to study behavioral decision making in the organizational sciences is gambles. Gambles are a special case of discrete decision making where individuals once again must select one option from a list of possible choices. Gambles, however, incorporate a stochastic component by adding uncertainty to the outcomes with given or hidden probabilities and a degree of risk associated with each possible choice. Each potential choice in a gamble is called a prospect. Each prospect has multiple outcomes associated with it and each outcome has a specific likelihood of occurrence represented by a probability ranging from zero to 100 percent. Typically, within a given prospect, the probabilities of the outcomes sum to 100 percent. Gambles can be created using either monetary or nonmonetary outcomes; though, the majority of gamble studies (even in the organizational sciences) utilize monetary outcomes because much of the decision making literature using gambles comes from economics and other financial fields. Despite the fact that most gamble studies are done utilizing lab tasks, evidence exists that results generalize well to real world decisions (e.g., Wiseman & Levin, 1996).

Across monetary and nonmonetary gambles, many common relationships have been discovered. At the individual level, one of the most consistent findings is that stress and affect impact the riskiness of decisions (Andrade & Ariely, 2009; Ordonez & Benson, 1997; Seo & Barrett, 2007). For example, individuals who exhibit signs of sadness tend to make riskier decisions while individuals higher on anxiety tend to be more risk averse (Raghunathan & Pham, 1999). This is analogous to many risky decision making studies done in clinical psychology using the Balloon Analogue Risk Task (BART) to assess an individual's level of riskiness. These studies frequently find that individuals with symptoms of depression (i.e., sadness) tend to be more risk seeking (e.g., Lejuez, Aklin, Jones, et al., 2003; Lejuez, Aklin, Zvolensky, & Pedulla, 2003; Lejuez et al., 2002; Lejuez, Simmons, Aklin, Daughters, & Dvir, 2004). In general, feedback has been found to increase individuals' ability to make effective decisions in the presence of uncertainty over time (Zeelenberg & Beattie, 1997). However, fear of regret has been found to ameliorate the effect of feedback on risky decisions such that individuals who fear regretting past decisions ignore feedback and perform worse on subsequent decisions (Reb & Connolly, 2009).

At the team level, the make-up of the team as well as the type of task has been shown to impact how teams engage in making decisions under conditions of risk and uncertainty. It is common for the riskiest member of the team to take the lead on tasks with a great deal of uncertainty (van Kippenberg, van Kippenberg, & van Dijk, 2000). In teams working individually as well as collectively, the effect of a loss experienced by a minority of team members will not impact future risky decision making (Kameda & Davis, 1990). However, if the majority of the team experiences a loss, future decision making of the team is impacted, making the team less likely to engage in risky decisions (Paese, Bieser, & Tubbs, 1993; Tindale, Sheffey, & Scott, 1993). Teams also tend to be more extreme than their individual members, with the effect of a loss or gain shared by the entire team impacting future decisions to a greater extent than if the loss or gain was experienced by any one individual (Whyte, 1993). Teams are better able to make effective decisions in conditions of risk and uncertainty if they are good at team communication, if minority opinions are expressed and discussed, if team leaders involve all members in the final decision, and if individual team members engage in procedural rationality (Colquitt, Hollenbeck, Ilgen, LePine, & Shepard, 2002; Hollenbeck, Ilgen, Sego, Hedlund, Major, & Phillips, 1995; Hollenbeck, Colquitt, Ilgen, LePine, & Hedlund, 1998; Park & DeShon, 2010). In contrast to other types of discrete decision making, when teams experience stress and time pressure, information flow becomes restricted, impeding performance (Gladstein & Reilly, 1985).

Limitations of Organizational Decision Making

While many interesting relationships between decision making and other processes have been documented, a number of limitations exist. Perhaps the most prevalent shortcoming is the unnatural way that most decision making is studied, making connections to the real world extremely difficult. With the exception of gambles, all other decision making paradigms treat the problem space as though the world is a perfectly deterministic closed system. By guaranteeing decision outcomes, studies grossly misrepresent the complex, stochastic environment in which employees operate. Creating a stochastic decision environment allows researchers to understand how decision makers actually weigh potential alternatives with respect to outcomes that are uncertain, mimicking real world problems.

In organizations, decision makers encounter a wide variety of problems that are commonly influenced by multiple sources, a level of complexity that most decision making studies ignore. Typically, even in stochastic decision making problems, participants answer a single (simple) question and then immediately receive feedback on the result of their decision. This once again lacks generalizability to the real world. Decisions in organizations rarely exist in a vacuum; often times many decisions must be made before an employee is able to determine the efficiency or effectiveness of their decisions. To represent this complexity, it would be beneficial to have individuals make a series of small, similar decisions that will affect a larger overall goal. This structure would better represent many common organizational problems like those of the emergency medical teams and U.S. intelligence community mentioned earlier.

Similarly, organizational decisions rarely exist at only a single moment in time. Like most topics in the organizational sciences, decision making studies suffer from an overreliance on cross-sectional data collection and self-report methods. To better represent real workplace decisions, it is necessary to collect data across multiple decisions over time to determine the trends that individuals exhibit in their decision making and to detect any potential long run biases. Likewise, tracking actual behavior rather than questionnaire responses to hypothetical situations provides a more true to life representation of how employees would behave at work. Overall, to best represent the stochastic, complex, dynamic nature of real organizational decisions, researchers must employ problems with probabilistic (not guaranteed) outcomes, many small decisions per trial related to an overarching goal, and have multiple trials to capture the dynamics of how individuals change their decision making strategies over time.

Along with misrepresenting the complexities of real organizational decisions, there are other shortcomings within the organizational decision making literature. One such problem is that there is little research on common themes or utilizing common decision making tasks. Unlike other areas such as clinical psychology which heavily rely on a common decision making paradigm, organizational studies almost entirely utilize unique methods of researching the decision making process. Compounding this problem is a lack of replication of findings within or between decision making types. With the exception of stress, communication, and affect, which have been studied in multiple decision making contexts, all other variables are unique to a particular study or a particular decision type. This makes it very difficult to make strong, confident recommendations about what organizational variables affect the decision making process and how that process affects important organizational outcomes. Not surprisingly, then, an additional limitation is that there are few tangible recommendations for organizations on how to impact decision making in ways that will likely increase organizational outcomes of interest.

The final major shortcoming with the decision making literature in the organizational sciences is the lack of attention paid to general decision making models that can describe the decision process. In other areas of study such as cognitive psychology and economics, much attention is paid to creating general models of decision making that can accurately capture the biases that individuals engage in when making certain types of decisions. Along with little theory on general decision making models, there is also rather limited attention paid to the descriptive decision models used in other scientific disciplines. While across different scientific fields the content of problems will certainly change, it is entirely possible that the underlying decision making process will remain constant. Therefore, it is important to incorporate decision models from related scientific fields and test their predictions and findings within an organizational context to better understand the process by which individuals make decisions. This will provide insight into potential systematic biases that decision makers exhibit in a variety of contexts, allowing researchers to potentially create training interventions to help employees make more optimal decisions.

Prospect Theory: Describing Risky Decision Making

Unlike decision making research in the organizational sciences, other fields frequently create mathematical models in an attempt to describe different decision making types. Gambles, in particular, have received significant attention in cognitive psychology and economics. Initially, individuals were modeled as purely rational beings that would always choose the best possible prospect despite the type of question asked. Under these assumptions, Expected Utility

Theory (Atkinson, 1957; Keeney & Raiffa, 1976) was the dominant rational choice model of human behavior. However, under conditions of risk and uncertainty, individuals were found to commonly deviate from making rational choices. As a result, Kanheman and Tversky (1979) created Prospect Theory in an attempt to explain some common biases in the choices people made when confronted with risky decisions. Prospect Theory was a significant improvement over Expected Utility Theory and other rational choice models, but was quite limited and still failed to accurately describe risky decision making over a sequence of decisions, could only incorporate a small number of prospects, and was found to inadequately account for the effect of question framing. Therefore, Tversky and Kahneman (1992) created a more general theory of risky decision making entitled Cumulative Prospect Theory. Additionally, Thaler and Johnson (1990) and Staw (1976, 1981) created extensions of Prospect Theory for how individuals make decisions over a sequence of decisions called the house money effect and escalation of commitment, respectively. Cumulative Prospect Theory and its generalizations have been shown to accurately describe many aspects of the risky decision making process and as a result are currently the dominant approach to the study of gambles. To understand how prospect theory and its generalizations could be used to predict risky decision making during information acquisition, each theory will be briefly explained, highlighting its origin, key features, and primary predictions.

Prospect Theory

Individuals exhibit many common tendencies when forced to make a decision that has multiple probabilistic outcomes (i.e., gambles). For example, one common bias in risky decision making is called the certainty effect (Allais, 1953). When individuals are forced to choose between a set of risky prospects and an equal probability outcome is removed from each prospect, the psychological effect of removing the probability is strongest for prospects that originally had certain (probability = 0% or 100%) outcomes. As a result, even though the ordering of prospect preference should not change by removing an equal outcome from all choices, individuals tend to switch preferences from a once certain outcome to one that was originally uncertain despite the fact that the once certain outcome is still objectively better (MacCrimmon & Larson, 1979; Slovic & Tversky, 1974). Additionally, when individuals are forced to choose between a set of high probability prospects with positive outcomes, the vast majority of people will select the most certain option even if it has a lower possible payout. Conversely, when individuals are forced to choose between low probability prospects, they will frequently choose the riskier option with the highest possible payoff (Kahneman & Tversky, 1979).

It turns out that the exact nature of the certainty effect is more complex and also depends on whether the prospects refer to positive or negative outcomes. When individuals are forced to choose between a set of prospects with negative outcomes, preferences systematically switch. For high probability prospects, individuals will choose the option with less certainty, in an attempt to avoid any loss. For low probability prospects, individuals will choose the outcome with more certainty, in an attempt to avoid the possibility of a really large loss. This preference reversal is called the reflection effect (Fishburn & Kochenberger, 1979; Markowitz, 1952; Williams, 1966). Taken together, the certainty and reflection effects create a pattern of behavior when deciding among risky prospects; outcomes with certainty are systematically over weighted, resulting in individuals being risk averse with positive outcomes and risk seeking with negative outcomes (Kahneman & Tversky, 1979). This is particularly important because these findings violate one of the key components of Expected Utility Theory, that individuals are always risk averse.

The final common bias that individuals demonstrate when making risky decisions is called the isolation effect (Kahneman & Tversky, 1979). When evaluating risky prospects, individuals tend to ignore aspects that the prospects have in common. This can be problematic because there is frequently more than one way to decompose a problem, potentially resulting in different preferences. More importantly, these findings suggest that decisions are not made solely by the anticipated final state that the individual will likely end up in. Rather, that decisions are made based on an anticipated change from the current state, or reference point, with which the individual begins the problem. These findings once again demonstrate that individuals violate the tenants of Expected Utility Theory in the presence of risky decisions because in Expected Utility Theory end states (not changes) are solely the basis for the selection of prospects.

The systematic biases that decision makers exhibit in the presence of risk demonstrates that Expected Utility Theory and other rational choice models of decision making inadequately describe human behavior. As a result, Kahneman and Tversky (1979) built an alternative mathematical representation of risky decision making, called Prospect Theory (PT), in the hope of accounting for biases like the certainty, reflection, and isolation effects. PT was originally created to describe how individuals make a single risky decision with two or three prospects and given probabilities. However, Kahneman and Tversky note that the model is generalizable to alternative, more complex decision types.

PT models the decision process as the result of two phases, the editing phase and the evaluation phase. The editing phase suggests that individuals psychologically frame and edit each potential prospect to simplify the decision making process through a series of rules prior to selecting the most desirable option. The first rule is called *Coding*, where individuals code each prospect in terms of potential gains and losses relative to a reference point. The second rule is called *Combination*, which states that individuals combine probabilities that are related to identical outcomes. The next rule is labeled *Segregation*, which is where individuals separate components of prospects with certainty from components with uncertainty. The final editing rule is *Cancellation*, when individuals will cancel shared components across prospects. The result of going through each rule of the editing phase is that each prospect has been reframed and simplified so that individuals can more easily make a decision as to the most desirable prospect.

At the conclusion of the editing phase, individuals begin the evaluation process of the newly framed prospects. The evaluation phase of PT introduces two new components of the risky decision making process that prior rational choice models did not include. The first is that each possible outcome in a given prospect is assigned a value, υ, which represents the subjective value of the outcome. Since outcomes are thought to be considered relative to a reference point, the value function measures the outcome in deviations (positive or negative) from that reference point. This suggests that the subjective representation of the prospect may not accurately reflect the stated problem.

The second new aspect of the risky decision making process is that the probability of each prospect is weighted by some weighting function, π. The weighting function indicates the impact of a given outcome probability on the overall probability of choosing the prospect. An important feature of the weighting function is that frequently, the weights within a given prospect do not sum to one, despite the fact that the probabilities they are weighting will sum to one. This allows for the common finding that individuals' psychological representation of probability does not perfectly match (a deterministic) reality (Edwards, 1962; Fellner, 1961).

Prospect Theory is designed to handle three specific types of decision making gambles. The first type is where all possible outcomes in all prospects are positive, called the strictly positive condition. The second is where all possible outcomes in all prospects are negative, called the strictly negative condition. Finally, the third condition is where both positive and negative outcomes are in each prospect, called the normal condition (Edwards, 1962; Markowitz, 1952).   Normal gambles are the most general and most studied type of risky decision making process and, thus, will be the focus of subsequent sections. In normal gambles, prospects are considered regular if they have an equal number of outcomes above and below zero. For example, if a prospect has two possible outcomes, X and Y, then the prospect would be normal if $X \leq 0 \leq Y$ or if $X \geq 0 \geq Y$. For regular prospects in normal gambles, the value function, υ, and the weighting function, π, are combined with each outcome and probability, respectively, within a prospect and then summed to give the overall value of the prospect. Equation 1 demonstrates this mathematically:

$$V(x, p;\ y, q) = \pi(p)\upsilon(x) + \pi(q)\upsilon(y), \qquad (1)$$

where V is the overall value of the prospect, x is the first possible outcome, p is the probability associated with outcome x, y is the second possible outcome, q is the probability associated with outcome y, υ is the value function for the prospect, and π is the weighting function for the prospect.

Both the value function and the weighting function have been found to have consistent qualities. As previously mentioned, the value function is designed to represent the magnitude of a given outcome in terms of deviations from some reference point. This is designed to replicate findings in the physical sciences that show that people frequently are poor judges of absolute values of physical stimuli like sound, light, and temperature. Rather, people are significantly better at judging the change in these states from some reference point (e.g., Helson, 1964). For both positive and negative outcomes, individuals weight the value of a deviation from the reference point larger, the closer it is to the reference point. For example, the difference between a loss of $10 and $20 is weighted with more impact than an equally large difference between a loss of $1000 and $1010. As a result, the slope of the value function decreases as it moves further away from the reference point. This leads to the common finding in risky decision making that the shape of the value function is concave above the reference point and convex below it (Galanter & Pliner, 1974; Kahneman & Tversky, 1979). Additionally, it is found that individuals weight negative outcomes greater than they do positive outcomes as indicated by the certainty and reflection effects mentioned earlier. As a result, the slope of the value function is greater below the reference point than it is above it (e.g., Barnes & Reinmuth, 1976; Grayson, 1960; Green, 1963; Halter & Dean, 1971; Swalm, 1966). Figure 1 shows a hypothetical value function for a normal gamble with regular prospects. The left side the figure shows the value function for negative outcomes and the right side of the figure shows the value function for positive outcomes. It can be seen that the slope for negative outcomes is steeper than the slope for positive outcomes and that for both types of outcomes, the slopes decrease with increased distance from the reference point.

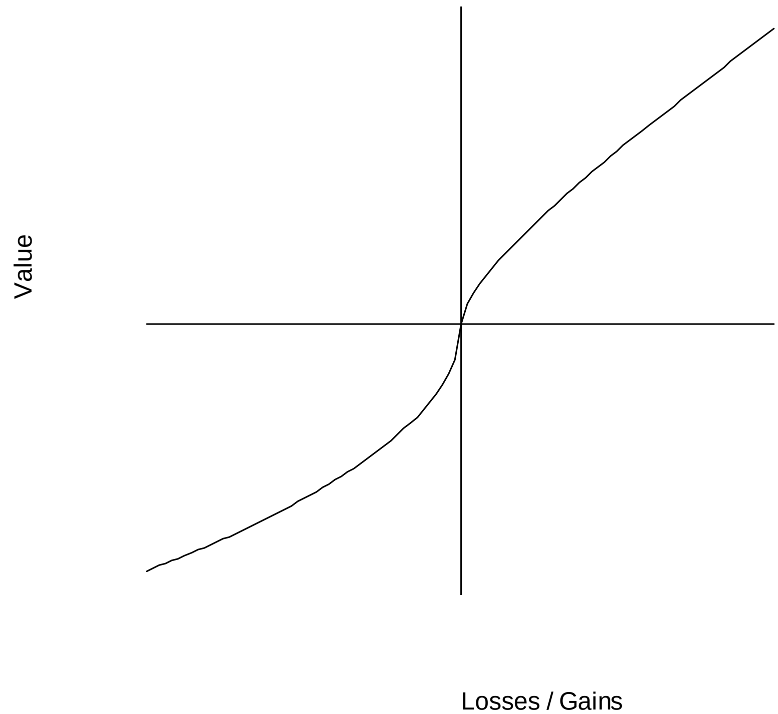

Figure 1. Hypothetical value function for Prospect Theory.

Like the value function, the weighting function has a number of unique properties. Although the weighting function is related to outcome probabilities, it is not considered a measure of the belief that a particular outcome will happen. This means that it is not a measure of perceived likelihood of an outcome but rather, it measures the perceived impact of the possible outcome on the overall desirability of a prospect. One common finding is that very low probabilities are over weighted (Kahneman & Tversky, 1979). It is important to note that the over weighting of a probability is distinct from the overestimation of the likelihood of that probability (see Kahneman & Tversky, 1973). Because the weighting function is a measure of impact, the overweighting of low probabilities means that individuals weight the impact of their happening greater than they should. This effect has the potential to interact with the overestimation of the likelihood of low probability events to seriously alter decision making behavior for very rare instances. Otherwise, individuals are found to underweight the impact of moderate to high probable events, which is why the total summed weighting function for a given prospect is likely less than one, despite the fact that the actual probabilities in the prospect sum to one. Figure 2 shows the hypothetical weighting function for a normal gamble with regular prospects. The dotted line represents the ideal situation where an individual perfectly weights the impact of the probability equal to the actual probability. Meanwhile, the solid line represents the proposed weighting function based on the biases predicted by PT.

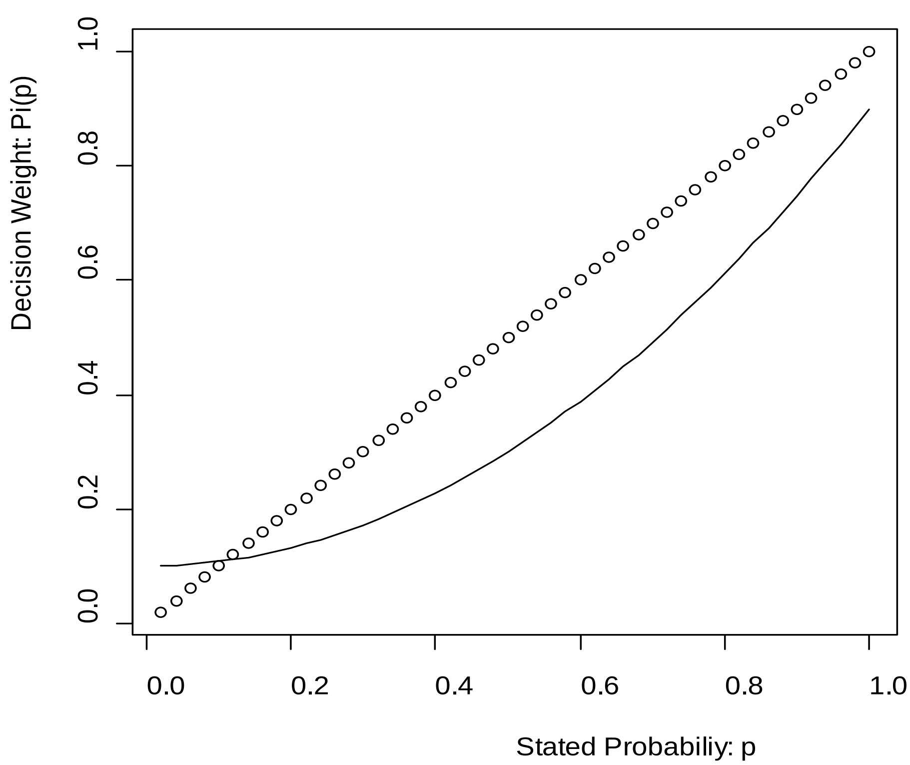

Figure 2. Hypothetical weighting function for Prospect Theory.

Overall, PT significantly advanced understanding of the decision making process under conditions of risk. The addition of an editing phase as well as the value function and weighting function in the evaluation phase allowed researchers a tool with which to model many of the common biases found in risky decision making such as the certainty, reflection, and isolation effects. As a result, it allowed for a better overall description of the process by which individuals decide which prospect is most desirable when making a gamble.

Cumulative Prospect Theory

After the creation of the original Prospect Theory, a number of limitations were discovered. First, Prospect Theory only can handle very simple gambles with two or three possible prospects. Also, the outcomes in each prospect must have stated probabilities, so Prospect Theory cannot properly predict decision making under situations of ambiguity (i.e., individuals are not told what the outcome probabilities are). Additionally, the strength of the effect of question framing was better realized. It became apparent that the way in which a question is worded can significantly affect the biases that individuals demonstrate in risky decision making (Tversky & Kahneman, 1986). Tversky and Kahneman also discovered that the effect that losses loom larger than gains was more significant than originally believed (Kahneman & Tversky, 1984; Tversky & Kahneman, 1991). As a result, many authors began to generalize Prospect Theory to include an infinite number of prospects, have different weighting functions for gains and losses, and handle situations of both risk and ambiguity (Quiggin, 1982; Schneidler, 1989; Weymark, 1981; Yaari, 1987). Therefore, Tversky and Kahneman (1992) built upon this work and created a more general form of Prospect Theory known as Cumulative Prospect Theory (CPT).

CPT is very similar to the original Prospect Theory in a number of ways. It once again has two phases, editing and evaluation, and can handle three types of gambles: all positive, all negative, or mixed (called normal in Prospect Theory). For mixed gambles, the overall value of a prospect is once again the summation of each outcome weighted by a value function and each probability weighted by a weighting function. However, the difference is that there are separate weighting functions for both positive and negative outcomes. Shown in Equation 2, the overall value of a prospect can be mathematically represented as:

$$V(f) = V(f^{+}) + V(f^{-})$$
$$V(f^{+}) = \sum_{i=0}^{n} \pi_i^{+} \upsilon(x_i), \; V(f^{-}) = \sum_{i=-m}^{0} \pi_i^{-} \upsilon(x_i). \tag{2}$$

$V(f)$ is the overall value of the prospect, $V(f^{+})$ if the overall value of all positive outcomes, $V(f^{-})$ is the overall value of all negative outcomes, n is the number of total positive outcomes, m is the number of total negative outcomes, π_i^{+} is the weighting function for each positive outcome, i, π_i^{-} is the weighting function for each negative outcome, i, υ is the overall value function for each outcome, and x_i represents each outcome.

Equation 2 demonstrates that the overall value of each prospect is the sum of all positive outcomes weighted by the overall value function and the individual outcome's probability and positive weighting function combined with the sum of all negative outcomes weighted by the overall value function and the individual outcome's probability and negative weighting function. Additionally, Equation 2 has the appealing mathematical property of having both the positive and negative weighting functions sum to one, without loss of generalizability.

Splitting the weighting function allows researchers to more accurately model the biases detected in risky decision making. One such finding that can be accurately modeled by CPT is that individuals are risk seeking for gains and risk averse to losses of low probability outcomes while being risk averse to gains and risk seeking for losses for high probability outcomes (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). The shape of the weighting functions is also different than in the original Prospect Theory, to be more consistent with empirical results (see Camerer, 1992 and Camerer & Ho, 1994 for reviews). Figure 3 shows a hypothetical weighting function in CPT. As in Prospect Theory, low probability outcomes are generally over weighted and moderate probability outcomes are generally underweighted. However, the weighting functions now more accurately predict that individuals accurately weight extremely low and high probability events so at the extremes the ideal (dotted) and hypothesized (solid line) functions are much closer.

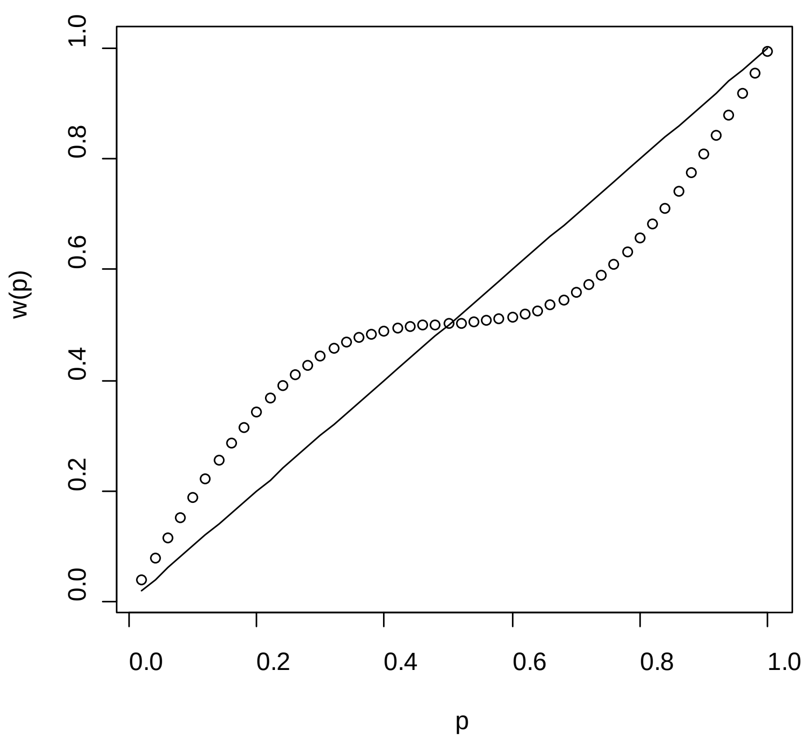

Figure 3. Hypothetical weighting function for Cumulative Prospect Theory.

The benefits of CPT above and beyond prospect theory are important when modeling complex decisions with many possible alternatives. Splitting up the weighting function for positive and negative outcomes as well as the ability to model an infinite number of prospects and outcomes allow researchers to use Cumulative Prospect Theory to study many different types of risky decision making. As a result, CPT is the dominant approach to modeling and studying decision making under conditions of risk.

The House Money Effect and Escalation of Commitment

While Cumulative Prospect Theory does an excellent job in modeling the decision making process of individuals confronted with situations of risk, it is designed to study only single decisions. Frequently in organizations, it is necessary for individuals to make a series of decisions over time toward the solution of a larger goal. It is likely that the results from prior decisions have an impact on how individuals make subsequent choices (Arkes & Blumer, 1985; Thaler, 1980). Research on the house money effect (Thaler & Johnson, 1990) and escalation of commitment (Staw, 1976, 1981) investigate how individuals update their risky decision making process based on successes and failures to prior risky decisions.

Thaler and Johnson (1990) extend Prospect Theory by the addition of a new editing rule called *Quasi-hedonic editing,* which suggests that individuals will edit potential prospects in the way that makes the individual happiest. This is supported by evidence that individuals will integrate or segregate prior positive and negative outcomes from subsequent decisions based on what is most psychologically pleasing. For example, people tend to prefer to spread out experiencing positive outcomes to separate the resulting happiness. Additionally, large losses desensitize an individual to subsequent smaller losses while small losses sensitize individuals to potential larger losses. As a result, small losses after a much larger one seem less disturbing and after a small loss individuals alter their behavior in an attempt to avoid any more unpleasant outcomes. Also, a small loss after a prior gain is immediately integrated into the gain, resulting in the loss having a minimal negative effect on the individual. All of these findings imply that individuals do not simply integrate prior outcomes into their reference point, as Prospect Theory would suggest, but rather they are separated and can directly impact subsequent decisions.

Perhaps the most common result of this process is what is termed the house money effect. After experiencing a positive outcome, individuals will become risk seeking in subsequent decisions, because they are essentially gambling with "house money." Combined with the finding that individuals become risk averse after experiencing a negative outcome, these findings are in direct contradiction to Prospect Theory and Cumulative Prospect Theory which have shown individuals to be risk averse for potential positive outcomes and risk seeking for negative outcomes. The house money effect has been quite robust and the pattern of results is the same for both real and hypothetical gambles, implying that the risky decision making process changes over time based on previous experience (Thaler & Johnson, 1990).

While the house money effect has been consistently demonstrated for positive outcomes, the evidence is more complex when dealing with prior negative outcomes. In fact, individuals have been shown to be incredibly risk seeking even after a series of very negative outcomes, directly contradicting the findings of the house money effect for negative outcomes. This phenomenon is called escalation of commitment (Laughhunn & Payne, 1984; Staw, 1976, 1981).

When individuals initially engage in a risky behavior that leads to negative outcomes, they may continue to engage in that behavior if the decision has the potential to lead to an eventual positive result, making up for all prior negative effects. While it was initially thought that individuals would only escalate their commitment if they chose the initial risky behavior (Staw, 1976), it was later found that even when forced to engage in the initial risk, some people will continue to invest resources if the potential is there to break even (Staw, 1981). Many possible explanations for this phenomenon have been explored, including that individuals may bias their view of the initial decision to be more consistent with the negative outcome, thus reducing cognitive dissonance and justifying their continued course of action (Aronson, 1968, 1972; Festinger, 1957). Additionally, it has been thought that individuals may engage in continued risky behavior due to the gambler's fallacy that the continued investment is bound to pay off eventually because they are "due for a win" (Lee, 1971; Staw, 1976).

Taken together, findings from the house money effect and escalation of commitment demonstrate that the risky decision making process changes when dealing with a dynamic environment in which individuals engage in multiple decisions and receive feedback of the results of those decisions. As a result, it is necessary to incorporate findings from these theories as well as from Prospect Theory and Cumulative Prospect Theory to fully understand and describe the risky decision making process over time.

Risky Decision Making during Information Acquisition

In organizations it is common for individuals to have to make decisions in content areas where they are not experts. As a result, they must first acquire relevant information before being able to deduce an appropriate solution. Unfortunately, like the intelligence officers and emergency medical staff described earlier, it can be unclear as to what information is most critical and most relevant. Therefore, when individuals engage in searching for new information, they are essentially engaging in a sequence of gambles with each decision to attend to a new piece of information being a unique gamble. Each of these gambles will likely have two potential prospects. The first prospect is that the individual chooses to attend to the piece of information. This prospect has two distinct outcomes, that the information was relevant and aided in the solution of the problem or that it was irrelevant and either simply wasted time or, even worse, provided misinformation that can bias the problem's solution. The second prospect is that the individual can ignore the piece of information. This prospect once again has two potential outcomes, that the individual correctly ignored an irrelevant piece of information, thus, not wasting time or acquiring misinformation or that the information was actually relevant and the individual will have insufficient knowledge for solving the problem, likely leading to an inefficient or ineffective solution.

Given the criticality of individuals being able to effectively make decisions for organizational success (e.g., Shrode & Brown, 1970; Singh, 1986; Ziller, 1957), it is imperative that researchers understand the process by which individuals choose what information to attend to and what to ignore. To date, no research exists that directly studies this important phenomenon. While the organizational decision making literature does contain important findings for understanding the process of decision making under risk and uncertainty, it lacks a general framework to describe the decision making process. Prospect Theory (PT) and its generalizations have been found to be predictive of the biases that individuals engage in when making risky financial decisions in a wide variety of organizational contexts such as firm resource allocation (e.g., Bromiley, 2009), organizational strategy (e.g., Bromiley, 2010), and performance testing (e.g., Bereby-Meyer, Meyer, & Budescu, 2003; Bereby-Meyer, Meyer, & Flascher, 2002). Additionally, time and information have been repeatedly argued to be valuable resources synonymous with monetary outcomes, which is the original outcome described by PT

(Ariely & Zakay, 2001; Cunah & Caldero, 2009; Katsikopoulos, Duse-Anthony, Fisher, & Duffy, 2002; Leclerc, Schmitt, & Dube, 1995). Therefore, PT provides a good foundation for understanding the process of making risky decisions while acquiring information in organizations.

The purpose of the current research is to understand the decision making process that individuals engage in when acquiring new information. In an attempt to fill the gaps identified in the organizational decision making literature, the study will integrate findings from organizational studies on gambles with the predictions of PT and its generalizations and common relationships found in the PT literature. Doing so will allow for understanding what general biases individuals engage in when making risky decisions related to information acquisition, a phenomenon that has previously not received attention in the literature. Additionally, using previous findings in the Prospect Theory literature as well as organizational studies with gambles provides insight into what individual differences play a role in impacting the risky decision making process. In addition, this study aims to understand how the decision making process changes over time and, thus, will explore how individuals make a sequence of small decisions related to a series of larger goals. This is important because it more closely represents the types of decision making problems that employees face in organizations.

Utilizing Prospect Theory and its generalizations to explain the decision making process individuals engage in when searching for new information has many potential benefits. It provides insight into the potential biases that people could make while deciding what information to attend to and what to ignore. Discovering these biases will inform researchers as to the types of training interventions necessary to help decision makers perform more efficiently and more effectively, likely resulting in higher overall performance. Similarly, understanding how this process unfolds over time will provide evidence about how feedback and prior decisions are incorporated and alter the decision making process. This once again has implications for how results from decision making tasks should be structured to help employees learn what are the most effective decision making strategies when acquiring new information.

Additionally, testing the predictions of prospect theory for the decisions necessary for information acquisition will also inform potential generalizations or boundary conditions of Prospect Theory. Since the vast majority of PT studies have been done with quantifiable outcomes (i.e., money and time), it is currently unknown whether the theory can describe the decision making process for prospects with more subtle successes and failures, like those encountered during information acquisition. Likewise, most studies on gambles use hypothetical questions rather than real behavior for understanding risky decision making. Using real behaviors will provide additional information to researchers as to the ability of PT to describe how individuals actually behave. Finally, few studies exist that thoroughly test the dynamics of the decision making process; rather, most studies that look at prior performance utilize only two or three time points (e.g., Staw, 1976, 1981; Thaler & Johnson, 1990). Having individuals engage in a long sequence of decisions will provide further evidence for how feedback and prior performance affect the biases commonly described by PT and its generalizations.

Prospect Theory Hypotheses

Despite the widespread use and acceptance of PT, it has never been used to describe decision making during information acquisition, with usefulness of information as an outcome. As a result, it is first necessary to determine if the common biases in decision making that PT describes are even present when making gambles about acquiring information. PT predicts specific patterns of behavior based on each of its components for individuals making gambles. The first behavioral prediction is based on the shape of the weighting function. The way in which a question is framed dramatically impacts behavioral decision making (Kahneman & Tversky, 1986; Kuhberger, 1998, van Schie & van der Pligt, 1995). As such, Cumulative Prospect Theory divided the weighting function into two separate components, one for positive outcomes and one for negative outcomes (Tversky & Kahneman, 1992). By having two separate functions it is possible to model the riskiness of positive and negative outcomes separately for high and low probability events. It has been found that individuals tend to be risk seeking for positive outcomes with low probabilities and for negative outcomes with high probabilities. Conversely, individuals tend to be risk averse for negative outcomes with low probabilities and positive outcomes with high probabilities (Abdellaoui, Vossman, & Weber, 2005; Camerer & Ho, 1994; Etchart-Vincent, 2004; Gonzalez & Wu, 1999). Therefore, it is probable that when individuals are presented with information framed positively with a high likelihood of being relevant, they will be risk averse.

Hypothesis 1a. Individuals will be risk averse when faced with positively framed information with a high likelihood of relevance.

Alternatively, it is likely that individuals will be risk seeking when they are presented with negatively framed information with a high likelihood of being relevant.

Hypothesis 1b. Individuals will be risk seeking when faced with negatively framed information with a high likelihood of relevance.

In addition, when individuals are presented with low probability information, they will most likely be risk seeking if the information is framed positively and risk averse when the information is framed negatively.

Hypothesis 1c. Individuals will be risk averse when faced with negatively framed information with a low likelihood of relevance.

Hypothesis 1d. Individuals will be risk seeking when faced with positively framed information with a low likelihood of relevance.

The shape of the value function in Cumulative Prospect Theory (Figure 1) implies that people value negative outcomes significantly more than positive outcomes, meaning that the effects of riskiness for negative outcomes will be larger than the effects for positive outcomes (Weber, 1994).

Hypothesis 2. The effects in hypotheses 1b and 1c will be greater than the effects in hypotheses 1a and 1d.

The shape of the weighting function in Cumulative Prospect Theory (see Figure 3) indicates that individuals have a tendency to overweight information that has a very low likelihood of being relevant, underweight information that has a moderate likelihood of being relevant, and approximately accurately weight information with a very high likelihood of being relevant (Bruhin, Fehr-Duda, & Epper, 2010). Additionally, individuals have a tendency to overestimate the likelihood of rare events, making them appear more likely than they really are (Kahneman & Tversky, 1973). These findings imply that individuals should attend to significantly more information that has a very low likelihood of relevance than is expected by the actual probability of relevance. Alternatively, individuals should attend to less information with a moderate likelihood of relevance than is expected by the actual probability of relevance. Finally, individuals should attend to the correct amount of information that has a high likelihood of relevance.

Hypothesis 3a. Individuals will attend to significantly more information of low relevance than the actual probability of relevance.

Hypothesis 3b. Individuals will attend to less information of moderate relevance than the actual probability of relevance.

Hypothesis 3c. Individuals will attend to an approximately equal amount of information of high relevance compared to the actual probability of relevance.

The prior predictions are designed to describe single decisions or general tendencies and do not account for changes in behavior over time. That said, it is commonly demonstrated that prior successes and failures can drastically alter the pattern of biases in risky decision making (Ansic & Keasey, 1994; Pietras, Locey, & Hackenberg, 2003; Staw, 1976, 1981; Thaler & Johnson, 1990). In particular, the house money effect has received significant support in the literature. It is commonly found that individuals are risk seeking for all types of outcomes after experiencing a prior success. Similarly, individuals have also been found to be more risk averse after experiencing a prior failure (Ackert, Charupat, Church, & Deaves, 2006; Akers, Joyner, Pezzo, Nash, Siegal-Jacobs, & Stone, 1994; Cowley, 2008; Hollenbeck, Ilgen, Phillips, & Hedlund, 1994). This finding contradicts the predictions of the escalation of commitment theory. It is possible that the escalation of commitment effect needs extremely specific circumstances to be witnessed, circumstances that are not often present. For example, it has been found that for escalation of commitment to occur, the decision must be one in which it is extremely difficult to change courses of action (Brehm & Cohen, 1962). In most gamble research this is not the case, which could explain why the predictions of escalation of commitment are commonly unsubstantiated (e.g., Weber & Zuchel, 2005; Zeelenberg & van Dijk, 1997). Therefore, it is likely that there will be a positive effect between prior outcomes and riskiness on subsequent decisions. When individuals experience a prior success, they will make more risky decisions. Alternatively, when individuals experience a prior failure, they will engage in less risky decisions.

Hypothesis 4a. After a prior positive outcome, individuals will make more risky decisions.

Hypothesis 4b. After a prior negative outcome, individuals will make less risky decisions.

Individual Differences Hypotheses

The literature on prospect theory as well as many organizational studies of risky decision making investigate how individual differences affect the riskiness and effectiveness of decisions. The relationship that has received the most attention in the literature is between affect and decision riskiness. However, affect is rarely examined at the trait level and has not been tested as to whether it has a main effect across time. Frequently, affect will be manipulated in a lab setting to determine its effect on the riskiness of decisions. Affect has been found to alter the weighting function in cumulative prospect theory, resulting in a change in the nature of biases (Rottenstreich & Hsee, 2001; Seo, Goldfarb, & Barrett, 2010). More specifically, it has been found that people who experience greater negative affectivity are more prone to make risky decisions (Raghunathan & Pham, 1999), and more likely to make less effective decisions (Taylor, 1975). Additionally, individuals who have experienced a positive emotion will be more likely to overestimate the probabilities of positively framed prospects and be more conservative overall, resulting in significantly more risk averse behavior (Nygren, Isen, Taylor, & Dulin, 1996). Thus, individuals who are higher on negative affectivity should make more risky decision as well as perform worse overall relative to those lower on negative affectivity. Conversely, individuals who are higher on positive affectivity should overweight positively framed prospects and be more risk averse relative to those who are lower on positive affectivity.

Hypothesis 5a. Individuals higher on negative affectivity will make riskier decisions relative to those lower in negative affectivity.

Hypothesis 5b. Individuals higher on negative affectivity will perform worse overall relative to those lower in negative affectivity.

Hypothesis 5c. Individuals higher on positive affectivity will choose to attend to more positively framed information compared to those lower on positive affectivity.

Hypothesis 5d. Individuals higher on positive affectivity will make less risky decisions compared to those lower on positive affectivity.

Another individual difference that has received significant attention is the effect of motivation and goals on decision making. Like affect, the effect of goal orientation as an individual difference is rarely considered and it is currently unknown as to the effect that goal orientation has across time. Goals are frequently manipulated in a lab setting to determine their effect on the riskiness and effectiveness of decisions. Not surprisingly, they have been found to be very important to decision making of both individuals (e.g., Heath, Larrick, & Wu, 1998) and teams (e.g, Lepine, Hollenbeck, Ilgen, & Hedlund, 1997). Specifically, regulatory focus (Higgins, 1997, 2000) has been found to drastically impact the pattern of risky decision making. In regulatory focus theory, individuals are considered to be either in a state of prevention or a state of promotion. The prevention state is where individuals do just enough to not fail. Alternatively, a promotion state is where individuals aim to exceed expectations. Individuals in a prevention state tend to be significantly more averse to negative outcomes, making them take fewer risks in decision making. Conversely, individuals in a promotion state tend to be more risk taking in hopes of achieving greater positive outcomes (Halamish, Liberman, Higgins, & Idson, 2008; Kluger, Stephan, Ganzach, & Hershkovitz, 2004; Scholer, Zou, Fujita, Stroessner, & Higgins, 2010). The concepts of prevention and promotion states of motivation in the regulatory focus literature are very similar to performance avoid and performance approach goal orientation in the organizational literature on motivation (Bandura, 1997; Locke & Latham, 2002). As such, it is likely that individuals who have a performance avoid goal orientation will be more loss averse and, thus, make fewer risky decisions. Individuals with a performance approach goal orientation, on the other hand, should take more risks in hopes of achieving greater success.

Hypothesis 6a. Individuals higher on performance avoid goal orientation will make fewer risky choices compared to individuals lower on performance avoid goal orientation.

Hypothesis 6b. Individuals higher on performance approach goal orientation will make more risky choices compared to individuals lower on performance approach goal orientation.

The final two individual differences that have been researched in relation to risky decision making are risk taking propensity and cognitive ability. The body of literature on these two constructs related to risky decision making is significantly less, however a few important relationships have been discovered. Not surprisingly, individuals who report a greater propensity for risk taking have been shown to take more actual risks (Taylor & Dunnette, 1974). However, this relationship tends to weaken when actual decisions are studied across time (e.g., Sitkin & Weingart, 1995). Therefore, individuals who report themselves as higher on risk taking propensity should take slightly more risks when acquiring information over time.

Hypothesis 7. Individuals higher on risk taking propensity will make more risky choices compared to those lower on risk taking propensity.

Cognitive ability has also been shown to impact risky decision making at both the individual (e.g., Taylor & Dunnette, 1974) and team (e.g., Lepine, 2003, 2005) levels, with those higher on cognitive ability taking fewer risks and performing better overall on risky decision making tasks. As a result, those higher on cognitive ability should take fewer risks and perform better.

Hypothesis 8a. Individuals higher on cognitive ability will take fewer risks compared to those lower on cognitive ability.

Hypothesis 8b. Individuals higher on cognitive ability will perform better than those lower on cognitive ability.

Learning and Decision Making Hypotheses

Despite the focus of a wealth of research on sequential risky decision making, very few studies have actually looked at the effect of learning. While findings such as the house money effect and escalation of commitment suggest that individuals do alter decision making strategies based on prior outcomes, they do not answer the question as to whether individuals learn or get better at making risky decisions over time. One potential reason for this is that most studies looking at sequential decision making utilize very few ($T < 5$) time points. That said, there is some initial evidence that suggests that as individuals make a long series of risky decisions, their choices begin to mirror the predictions of rational choice models (Aloysius, 2007), indicating that they learn to effectively navigate an uncertain environment over time. In addition, there is evidence that individuals can learn unstated probabilities over time and alter their decision making to better represent underlying probabilities (Pleskac, 2008; van de Kuilen & Wakker, 2006). This suggests that as individuals engage in making a series of decisions related to information acquisition they will improve over time. Also, these findings imply that individuals weighting function for probabilities will change over time such that the more decisions that are made, the closer individuals' decision weights will mirror the ideal rather than predicted weighting function from Prospect Theory (dashed line in Figure 2).

Hypothesis 9a. Individuals will perform better over time.

Hypothesis 9b. Over time, individuals will attend to information more closely to the proportion of time indicated by the true probability.

Finally, recent evidence exists that when individuals make a sequence of very similar decisions, eventually the decisions become automated. As a result, learning effectively stops after a certain point and the decision maker will always choose the same option from a given prompt (Pleskac & Wershbale, 2011). Given that individuals make a large number of risky decisions related to information acquisition, it is likely at some point the process will become automated and decision making time will significantly decrease and all decisions about similar prospects will become the same.

Hypothesis 10a. Over time, individuals will make decisions about similar prospects quicker.

Hypothesis 10b. Over time, individuals will make the same decision for all identical prospects.

METHOD

Sample

Data were collected from 245 undergraduate psychology students from a large Midwestern university. There were two conditions, a positively framed condition and a negatively framed condition. A total of 122 students participated in the positive condition and 123 students participated in the negative condition. A total of six students were dropped from the positive condition for failing to complete all required portions of the study. As a result the final sample consisted of 239 participants, 116 in the positive condition and 123 in the negative condition. Overall, the sample was 58 percent male and 42 percent female. Participants on average were 19.6 years of age (sd = 2.1) and had an average ACT score of 25.3 (sd = 3.4). All students were recruited through the online psychology Human Participation in Research (HPR) system and received research credit for participation in the study.

Procedure

Students logged into the HPR system using their unique HPR identifier and password. They then selected the “CRONUS SOLO” experiment from the list of all possible active psychology experiments. Upon selection of the “CRONUS SOLO” study, students were directed to an online consent form. After reading the form they electronically indicated their consent (or opted out of the experiment). At this point, students saw a list of possible in person lab sessions to sign up for. When students selected a given time and date, they were directed to a series of online questionnaires. The students then completed surveys for demographics, risk propensity, goal orientation, and positive and negative affectivity. At the conclusion of the individual differences measures, students were thanked for their participation and reminded of the in person lab time and date that they signed up for. The entire online portion of the experiment took approximately 30 minutes for which the students received one research credit.

When students arrived for the in-person lab session they were greeted by the experimenter, signed in, and were assigned a lab computer to work on. Students were randomly assigned to either the positive or negative frame condition. When all students arrived, they watched a short, approximately fifteen minute, training video on the basic functions as well as the rules and objectives of the computer task, CRONUS SOLO. At the conclusion of the training video, the participants logged into the computer task with their unique university identification number and completed up to 35 ($\bar{T} \approx 31$), five minute scenarios. After completion of all scenarios (or participation for 2.5 hours), the students were thanked for their participation, debriefed as to the purpose of the present research project, and assigned the remainder of their research credits (5).

CRONUS SOLO

Crisis Relief Operation Naval Unit Simulation (CRONUS) was originally designed to test a process model that was derived from the Fiore et al. model of Team Macrocognition (Fiore, Rosen, Smith-Jentsch, & Salas, 2010). CRONUS simulates a crisis relief effort that the Navy and other government organizations engage in after a natural disaster such as the devastating earthquake in Japan in 2011. It was built for a three person team with distributed expertise. As such, information was divided among three roles, Transport, Intel, and Engineer. For the purpose of this study, the task was amended for a single player, called CRONUS SOLO, where all information was available to each individual. For each scenario, individuals were presented with a map that had a number of potential routes from a starting point to some ending destination. Individuals had to search the map to discover potential obstacles on each route. Each obstacle had a given value for how much of an effect it had on the total time required to traverse the route. After determining the scores for each route, the individual must select a route to have his/her squad traverse the given terrain. The goal for each scenario was to choose the most efficient route (i.e., lowest score) in the least amount of time possible. There were four different game screens in CRONUS SOLO, each with information relevant to selecting the best route. The screens were the *Specialist Map, Mission Info, Specialist Info,* and *Mission Command.* The very bottom of each game screen had tabs with the names of all four screens to allow the participants to navigate between the screens. This was analogous to navigating multiple spreadsheets within a Microsoft Excel document.

The *Specialist Map* screen, shown in Figure 4, displayed an image of a map with a specified number of routes drawn on it. The map was divided into a 3 by 3 grid. Additionally, on the right side of the screen there was an information center on the top part of the screen and a bank of all possible obstacles on the bottom part of the screen. Clicking in a grid square on the map revealed the bank of potential obstacles and a text link in the information center located on the top right corner of the game screen that notes if any obstacles were present on the routes passing through that grid square. Each obstacle had its own unique text link, an example of which would be “Obstacle on route A.” If obstacles were present in the grid square and the text link appears, individuals could click on the link to reveal more information about the obstacle. Left clicking and holding down the mouse button revealed where on the route the obstacle was located (via an obstacle icon displayed on the map) as well as what obstacle was there (via text description and unique obstacle icon). An example of the text revealed by clicking on the obstacle link is “Route passes through a water obstacle” coinciding with a picture of the obstacle. Releasing the left mouse button closed the link and hid all obstacle information.

Participants were informed that to make an obstacle permanently visible on the map, so that they could easily remember what was there, they may post that obstacle to the route where the obstacle was located. Choosing to make an obstacle permanently visible equated to the individual attending to that piece of information because it was an indication that the obstacle would be incorporated into the final decision. Individuals could post obstacles by clicking on the relevant obstacle icon in the icon bank at the bottom right corner of the game screen. Clicking on an icon revealed the option to post that obstacle to any route passing through the selected grid square. Choosing the appropriate route made the obstacle icon permanently visible on the map in the location specified by clicking on the text link. Making obstacles permanently visible allowed participants to easily determine what obstacles are on each route when they had to calculate total route scores and decide which route is most efficient.

The goal on the *Specialist Map* screen was to locate all relevant obstacles by clicking in each grid square on the map, determining what obstacles were on each route in that grid square, and then posting those obstacles to the map so that they became permanently visible. Performing these steps allowed participants the best chance to make efficient, effective decisions.

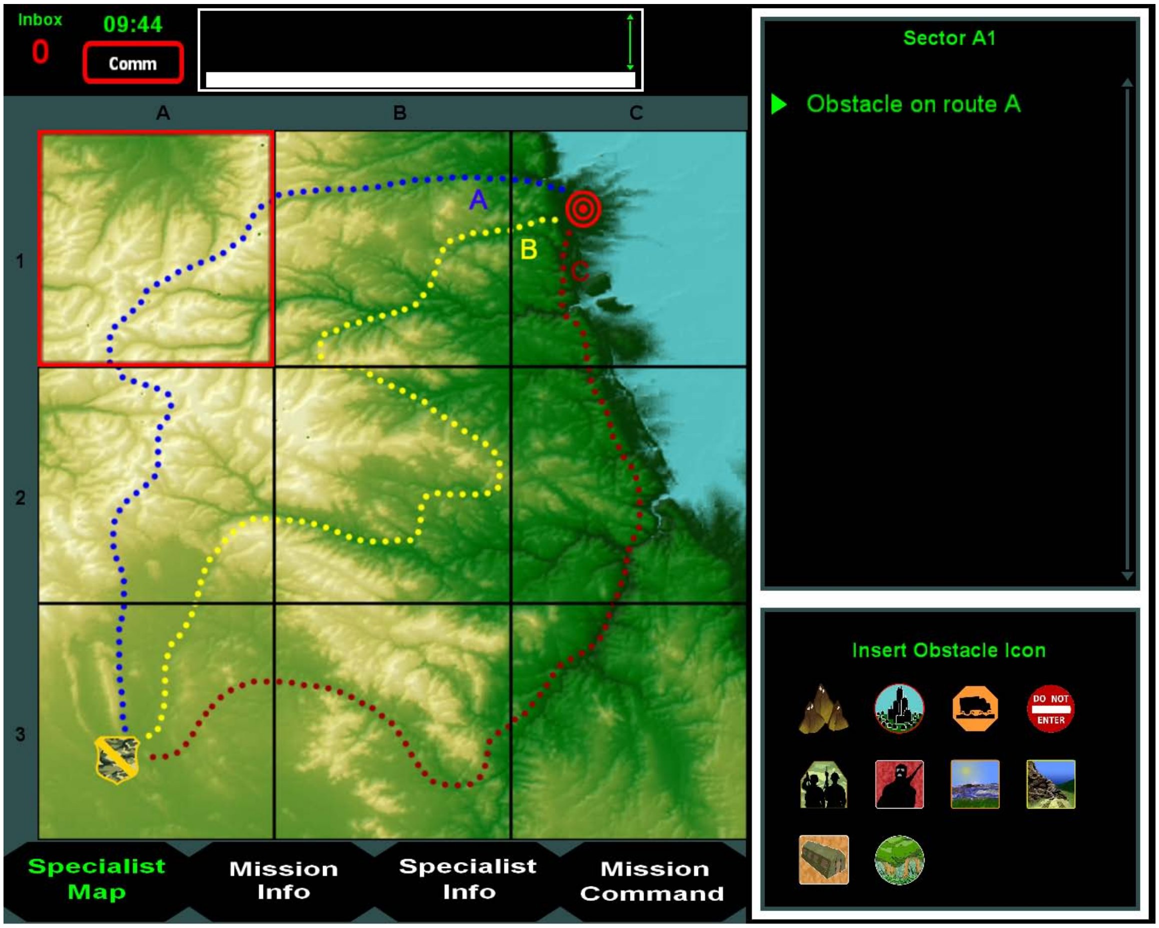

Figure 4. Specialist Map screen for CRONUS SOLO. For interpretation of the references to color in this and all other figures, the reader is referred to the electronic version of this dissertation.

The next game screen was the *Mission Info* screen, seen in Figure 5. This screen served as a training manual and displayed a list of text links with the names of each Microsoft PowerPoint slide from the training participants took part in prior to engaging in the task. Clicking on a text link displayed a picture of the PowerPoint slide. Participants could then close the picture by clicking the "Close" button or by choosing a different game screen by selecting a different tab at the bottom of the screen. This screen was designed to supplement the initial training and be a reference for participants if they forgot how to engage in any of the basic functions of the task.

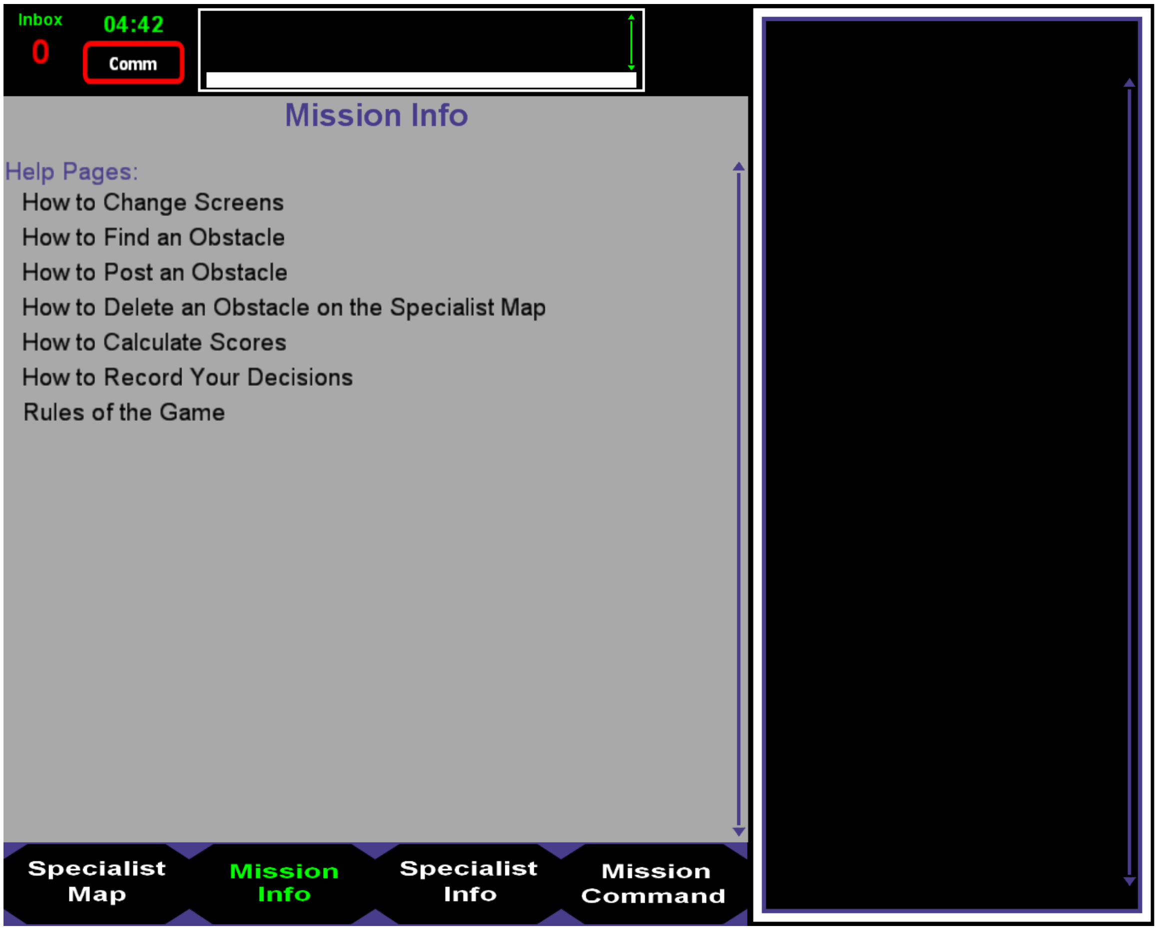

Figure 5. Mission Info screen for CRONUS SOLO.

As seen in Figure 6, the *Specialist Info* screen displayed information about the point value of each obstacle. The screen had a list of text links with the names of each obstacle. Left clicking and holding the mouse button on a link revealed the obstacle icon as well as the point value for that obstacle (higher numbers indicated more costly obstacles). Releasing the left mouse button hid the obstacle text. This screen allowed participants to learn how detrimental each obstacle was, so that they could accurately calculate predicted route scores and choose the most efficient route. It is important to note that obstacle point values remained constant across scenarios so individuals could learn the impact that each obstacle had on the total route time.

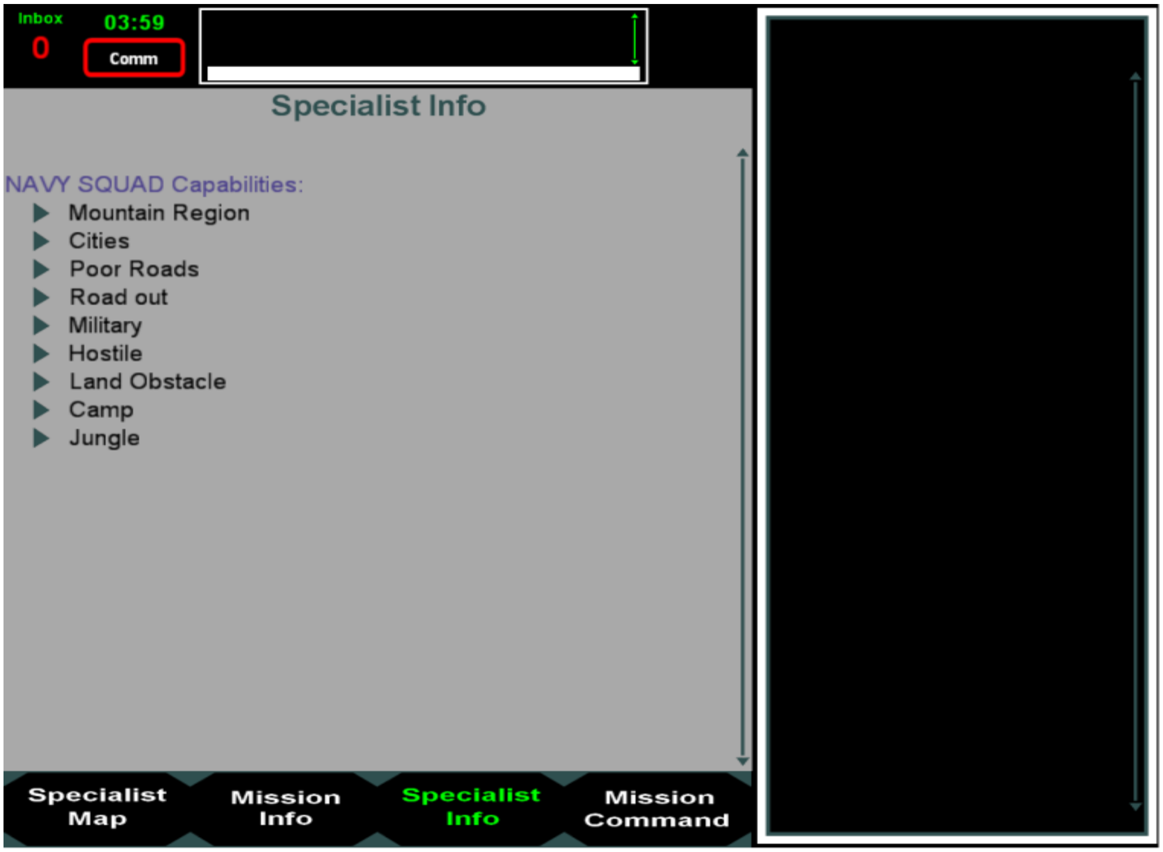

Figure 6. Specialist Info screen for CRONUS SOLO.

The final game screen in CRONUS SOLO was the *Mission Command* screen shown in Figure 7. This screen allowed participants to input predicted route scores for each route as well as select which route they choose to take. Each route had a designated row in a matrix with the name of the route. Next to the name of each route was a box where participants input the predicted route scores based on what obstacles were on each route and the obstacle point values obtained from the *Specialist Info* screen. Once participants had entered a predicted score for each route they selected their route choice by clicking a check box next to the route score of the preferred route. Once a route had been chosen, they could confirm their route choice by clicking the “Confirm Personal Choice” button located in the center of the right side of the screen. Clicking on the confirm route choice button brought up a pop-up box that asked participants whether they were certain that the route selected is the one that they wished to choose. Confirming their choice by selecting "Yes" ended the scenario.

Figure 7. Mission Command screen for CRONUS SOLO.

At the end of each scenario, participants could choose to look at a feedback page. This screen provided participants with overall feedback as well as detailed feedback for each obstacle on each route (shown in Figure 8). At the top of the feedback page was a matrix that displayed the overall number of obstacles correctly discovered for each route and the correct route choice compared to the route chosen by the participant. This information provided participants with general feedback on their overall effectiveness in the prior scenario. Scrolling down the feedback page revealed detailed feedback for each route. For a given route, the score input by the participant was displayed along with the correct route score based on the obstacles that were actually present in the game. In addition to route score, every obstacle on each route was displayed with feedback as to its presence in the game (based on given probability) and whether the participant correctly posted it (or not) on the specialist map. This information provided participants with detailed feedback as to what obstacles are commonly in the game and whether they were correctly identifying and posting those obstacles.

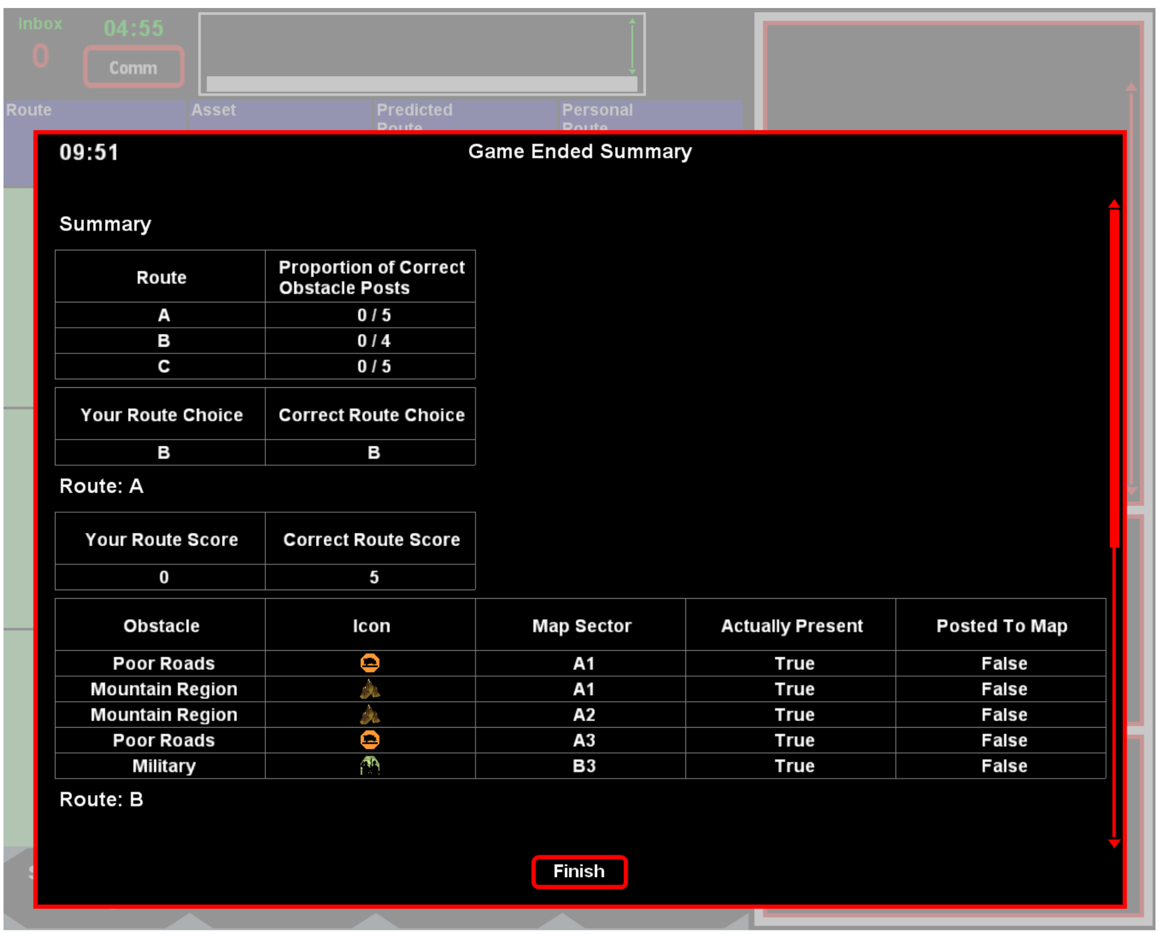

Figure 8. Feedback screen for CRONUS SOLO.

Scenario Design

Each of the 35 scenarios that participants engaged in was designed with the same basic architecture. A unique map displayed three routes that traversed the terrain from a starting point to a final destination. In some scenarios the destination point was the same for all routes; in other scenarios the destination was different for one or all routes. Prior to the location of any obstacles, all routes were considered to be equally efficient. The number of obstacles on each route changed across scenarios; however, the number of overall relevant obstacles within a given scenario remained constant at 18. Some scenarios also included distracter obstacles in addition to the 18 relevant ones. These obstacles were on a route but did not affect the overall efficiency of the route (i.e., had no point value and were not listed on *Specialist Info* screen). Within a given scenario there were three distinct types of obstacles, high probability, moderate probability, and low probability obstacles. There were six of each type of obstacle within each scenario; however, they were distributed across routes differently across scenarios. This basic design allowed each scenario to have the same overall difficulty while at the same time allowing each scenario to present a unique challenge.

The framing of the obstacle text depended on the condition. In the positively framed condition, information was presented in a way that made it seem as though the obstacle was not present and, thus, not affect the overall score (resulting in a more favorable outcome). For example, the obstacle text read “There is an 80% chance that your squad will NOT encounter hostile forces in the area.” Alternatively, in the negatively framed condition, the same obstacle information was phrased in a way that made it seem as though the obstacle was present, thus, making the route less efficient (resulting in a less favorable outcome). For example, the same obstacle text read “There is a 20% chance that your squad will encounter hostile forces in the area.”

There were a total of ten different obstacles in the game. Three of those obstacles were high probability, three were moderate probability, and three were low probability. The remaining obstacle is the distracter that had a probability of 100 percent and does not affect route score. The three high probability obstacles had a probability of approximately 0.80 (an 80% chance of affecting the total route score). The three moderate probability obstacles had a probability of approximately 0.55 (a 55% chance of affecting the total route score). Finally, the three low probability obstacles had a probability of approximately 0.20 (a 20% chance of affecting the total route score). In each scenario, there were six obstacles (except the distracter) with each given probability.

To test the effect of the impact of an outcome on the pattern of biases in risky decision making, the impact of each type of obstacle was systematically varied. One of each type of obstacle had a small impact on overall route preference (i.e., one point). Another of each type of obstacle had a moderate impact on overall route preference (i.e., four points). Finally, the last of each type of obstacle had a large impact on overall route preference (i.e., seven points). Completely crossing impact and probability with both positive and negative framing allowed for testing each type of prospect about which PT and CPT made predictions. Overall, the nine different types of relevant obstacles (for both the positive and negative frame condition) are shown in Table 1.

Table 1. Obstacle Properties in CRONUS SOLO

	Small Impact	Moderate Impact	Large Impact
High Probability (80%)	1	4	7
Moderate Probability (55%)	1	4	7
Low Probability (20%)	1	4	7

Measures

Demographics

Individual differences were assessed using questions on age, sex, academic major, and year in college.

Cognitive ability

Cognitive ability was assessed through self-report ratings of SAT/ACT scores. To equalize all participants on a common metric, all SAT scores were converted to the ACT scale.

Affect

To measure positive affectivity and negative affectivity the Positive and Negative Affect Schedule (PANAS) was administered (Watson, Clark, & Tellegen, 1988). The PANAS uses ten questions each to assess positive and negative affect. It is a Likert scale with 5 response options ranging from *never (1)* to *very frequently (5).* An example question from the positive affect scale is “How often to do you generally feel enthusiastic?” Similarly, an example from the negative affect scale is “how often do you generally feel upset?”

Goal Orientation

To measure goal orientation, a 16 item measure of goal orientation developed by VandeWalle (1997) was administered that utilizes a five point Likert scale from *strongly disagree (1)* to *strongly agree (5)*. This scale assessed individuals on the three primary types of goal orientation: mastery, performance-approach, and performance-avoid. A sample question from the scale is "I often read materials related to my work to improve my ability."

Risk Propensity

To assess risk taking propensity, a seven item measure was adopted from the Risk Propensity Scale developed by Meertens and Lion (2008). Responses were provided on a five-point Likert scale that ranges from *strongly disagree (1)* to *strongly agree (5)*. A sample item is "I prefer to avoid risks" (reverse coded). The complete scales for all constructs can be found in Appendix A.

Time Decision Making

To determine whether individuals made decisions more quickly across trials, the actual time spent making decisions was calculated. The CRONUS SOLO task monitored the total time that individuals spent left clicking and holding down their mouse button to observe obstacle texts. The cumulative time spent during each scenario that individuals spent observing this information was used as a proxy for the amount of time needed to decide whether to post or ignore an obstacle.

Deviations from Optimal Decisions

To determine how far from optimal that individuals made decisions, the overall posting behavior for each trial was utilized. To calculate optimal decision making, the overall probability of a prospect (0.80, 0.55, and 0.20) was multiplied by the overall number of each type of prospect (6). Then, the product of the three obstacle types was added together to determine the optimal number of posted obstacles per trial (9.3). That number was then divided by the total number of obstacles per trial (18) to create an overall probability for each scenario (51.7 percent). If performing optimally, individuals should have posted approximately that percentage of obstacles. The absolute value of the difference between the percentage of obstacles posted by an individual and the overall optimal posting percentage was calculated to determine each individual's deviation from optimal decision making for each trial.

Risky Decision Making

For each trial, the overall riskiness of decisions was calculated. Similar to the method of calculating deviations from optimal decisions, the posting behavior of an individual for each obstacle type (high, moderate, and low probability) within a trial was utilized. Decision making was considered risky if the percentage posted significantly exceeded the less likely outcome. For example, decision making was considered risky if an individual posted 35 percent of obstacles with a probability of 20 percent or posted 65 percent of obstacles with a probability of 80 percent. Similarly, decisions were considered risk averse (or conservative) if the percent posted significantly exceeded the more likely outcome. For example, decisions were conservative if an individual posted 90 percent of obstacles with a probability of 80 percent or posted 10 percent of obstacles with a probability of 20 percent. To calculate a risky decision making score for each person, the percent posted for each type of obstacle was subtracted from the more likely outcome of the obstacle probability. Then, the three obstacle types were summed to create an overall risky decision making score for each trial.

Performance

Individual performance for each trial was calculated by determining the number of obstacles that the individual correctly identified. More specifically, that is the number of obstacles that the individual posted that were actually present combined with the number of obstacles that the individual ignored that were actually absent. Means, standard deviations, and inter correlations among the focal variables can be found in Table 2.

Table 2. Correlations among Focal Variables

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11
1. Gender	0.58	-	-										
2. Age	19.55	2.10	-.046	-									
3. ACT	3.06	0.56	.062	-.195*	-								
4. Learning GO	3.22	0.61	.058	.159*	.114 ŧ	0.85							
5. Performance GO	3.06	0.62	.087	-.040	-.006	.122 ŧ	0.70						
6. Avoidance GO	2.83	0.72	-.049	-.098	.029	-.363**	.214*	0.80					
7. Negative Affect	2.41	0.43	-.085	-.112 ŧ	.079	-.240**	-.027	.162*	0.78				
8. Positive Affect	3.40	0.45	.032	-.048	.005	.447**	.121 ŧ	-.205**	-.419**	0.80			
9. Riskiness	2.94	0.64	.141*	-.029	.012	.164*	-.001	-.381**	-0.64	.149*	0.80		
10. Risky Decision Making#	-0.11	0.16	-.101 ŧ	.001	.002	-.023	.015	-.016	-.058	.055	.046	-	
11. Performance#	0.67	0.12	.033	.003	.001	.015	-.025	-.025	-.00	-.013	.00	-.443**	-

Note. ŧ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$, # time-varying covariates were averaged across time points, optimal decision making and time decision making were excluded because they were not hypothesized to relate to any other variables, reliabilities of individual differences variables are displayed on the diagonal.

Data Analysis

The data generated by the aforementioned design is at two distinct levels of analysis. Responses to gambles over time are nested within-person while individual differences data are inherently between-person. To account for the nested nature of the data, Hierarchical Linear Modeling (HLM) was used (Bryk & Raudenbush, 2002; Singer & Willet, 2003). HLM distinguishes between predictors at different levels of analysis. For longitudinal data, level 1 predictors are those that vary within a person over time. Level 2 predictors, on the other hand, are those that vary between people but are constant within a person across time points. As such, time decision making, total obstacle posts, deviations from optimal decisions, risky decision making, as well as dynamic performance are level 1 variables. Alternatively, demographics, cognitive ability, positive and negative affect, goal orientation, and risk propensity are all constant across time and, thus, are level 2 variables.

To justify the use of HLM, intraclass correlation coefficients (ICC(1)) were calculated for all level 1 variables. HLM divides the overall variance of the system into within- and between-person variance components. The ICC(1) is calculated by dividing the between person variance by the total variance (within plus between). As seen in Table 3, all time-varying processes showed a significant amount of between person variability, indicating that HLM is the appropriate analysis and that there is significant variance to predict.

Table 3. ICC(1) Values of Time-varying Covariates

	Overall	Positive Condition	Negative Condition
Time Decision Making	0.36	0.36	0.31
Total Obstacle Posts	0.49	0.44	0.52
Deviance from Optimal Decisions	0.32	0.29	0.35
Risky Decision Making	0.58	0.54	0.61
Performance	0.16	0.13	0.18

While HLM is well adept at determining growth trajectories, it is not well suited to predict more complex reciprocal relationships over time. It is anticipated that prior performance likely has a lingering effect on decision making. Conversely, it is also likely that trends in decision making will affect performance. To estimate this reciprocal relationship and model potential lag effects between decision making and performance, a Vector Autoregressive (VAR) model was used because VAR allows for simultaneous predictions of lag relationships over time (Enders, 1995).

RESULTS

Prospect Theory Hypotheses

The first three hypotheses are designed to determine whether the overall trends in risky decision making during information acquisition are consistent with the predictions of Prospect Theory and its generalizations. To do so, how people respond relative to the actual (true) probability is important to understand. Likewise, it is necessary to determine how the two conditions differ in their decision making trends. As a result, a series of t-tests was administered. There are two specific types of questions that can be tested with the current design. The first is the overall pattern across people for each time point and the overall pattern averaged across all time points. The second question is the proportion of people (averaged across all time points) that demonstrate the proposed bias.

To answer the first question related to Hypothesis 1a, data were collapsed across people at each time point in the positively framed condition for all high probability pieces of information. There are a total of six high probability pieces of information for each person for each time point with 116 people in the positively framed condition, yielding a sample of approximately 696 responses for each time point. The proportion of responses that are considered risk averse was calculated by dividing the total number of responses by the number of responses that chose the more likely (higher probability) option. That sample value was compared using a single sample t-test to the true value of 80% to determine if individuals are more risk averse than the true value would predict.

Table 4. Average Proportion of High Probability Information Posted by Trial

	Negative Condition			Positive Condition			Comparing Conditions		
Trial	DF	% Posted	p value	DF	% Posted	p value	DF	% Posted	p value
1	122	0.798	0.945	115	0.733	0.037	230	-0.065	0.123
2	122	0.924	0.000	115	0.886	0.000	188	-0.038	0.165
3	122	0.947	0.000	115	0.921	0.000	184	-0.026	0.228
4	122	0.931	0.000	115	0.940	0.000	232	0.009	0.655
5	122	0.932	0.000	115	0.934	0.000	225	0.002	0.933
6	122	0.916	0.000	115	0.941	0.000	232	0.025	0.245
7	122	0.882	0.000	115	0.892	0.000	228	0.010	0.690
8	122	0.924	0.000	115	0.915	0.000	195	-0.009	0.665
9	122	0.909	0.000	115	0.928	0.000	237	0.019	0.408
10	122	0.925	0.000	115	0.915	0.000	212	-0.010	0.640
11	122	0.925	0.000	115	0.927	0.000	227	0.001	0.952
12	122	0.924	0.000	113	0.933	0.000	229	0.009	0.652
13	122	0.912	0.000	115	0.930	0.000	234	0.018	0.396
14	121	0.929	0.000	114	0.930	0.000	229	0.001	0.941
15	122	0.907	0.000	115	0.908	0.000	232	0.002	0.944
16	122	0.905	0.000	114	0.914	0.000	234	0.009	0.689
17	119	0.899	0.000	113	0.923	0.000	226	0.024	0.319
18	121	0.919	0.000	114	0.925	0.000	231	0.005	0.815
19	121	0.919	0.000	112	0.944	0.000	228	0.025	0.194
20	120	0.902	0.000	112	0.923	0.000	230	0.021	0.373
21	105	0.925	0.000	103	0.941	0.000	208	0.016	0.476
22	105	0.904	0.000	98	0.944	0.000	203	0.040	0.055
23	103	0.913	0.000	96	0.943	0.000	194	0.030	0.225
24	103	0.947	0.000	96	0.928	0.000	187	-0.019	0.359
25	101	0.900	0.000	94	0.928	0.000	187	0.028	0.283
26	98	0.931	0.000	89	0.965	0.000	169	0.034	0.089
27	97	0.895	0.000	83	0.927	0.000	180	0.032	0.188
28	94	0.902	0.000	79	0.915	0.000	173	0.013	0.660
29	92	0.907	0.000	79	0.921	0.000	171	0.014	0.611
30	87	0.920	0.000	72	0.909	0.000	155	-0.012	0.669
31	85	0.924	0.000	70	0.941	0.000	151	0.017	0.486
32	83	0.905	0.000	68	0.925	0.000	149	0.020	0.451
33	83	0.917	0.000	60	0.918	0.000	122	0.001	0.963
34	77	0.921	0.000	56	0.953	0.000	133	0.032	0.208
35	73	0.887	0.000	52	0.918	0.000	102	0.031	0.319

Note. Comparison values created by Positive condition – Negative Condition

Table 4 shows that for all trials except the first, individuals attended to a significantly greater probability of positively framed information than the true probability would indicate. Additionally, across all trials individuals attended to positive information with high probability approximately 92 percent of time, significantly greater than the true probability of 80 percent ($p < 0.001$). Therefore, Hypothesis 1a was supported. These results indicate that individuals are risk averse, or overly conservative, when presented with high probability information framed in a positive way.

It is also possible to determine the percentage of individuals in the positive condition who were significantly risk averse. To do so, data were collapsed within each person across trials. There were six high probability pieces of information for each trial and on average individuals completed approximately 31 trials, resulting in about 186 decisions for each person. A single sample t-test was performed on each person comparing his/her distribution of decisions to the true probability of 80 percent.

Table 5. Proportion of Individuals who engaged in each Category of Posting Behavior for High Probability Information

Condition	Accurately Posted	Over Posted	Under Posted	Always Posted	Never Posted
Overall	0.130	0.799	0.071	0.063	0.000
Positive	0.138	0.810	0.052	0.069	0.000
Negative	0.122	0.789	0.089	0.057	0.000

Table 5 shows the percentage of people who accurately posted the proportion of information, the percentage that significantly over posted the information (risk averse) and the percentage of people that significantly under posted the information (risk seeking). Consistent with Hypothesis 1a, the results indicate that a significant proportion of individuals in the positive condition (81 percent) were risk averse. Additionally, approximately seven percent of the positive condition were extremely risk averse and always posted the high probability information, accepting an error rate of approximately 20 percent.

An identical procedure to that described for Hypothesis 1a was used to test Hypothesis 1b. As seen in Table 4, individuals in the negative condition were not significantly different from those in the positive condition. Contrary to the expectations of Prospect Theory, individuals did not tend to be risk seeking when presented with high probability information framed in a negative way. Rather, individuals still tended to be risk averse as demonstrated by the overall rate of posting which is 91 percent, significantly greater than the true probability of 80 percent ($p < 0.001$) and not significantly less than the amount posted by individuals in the positive condition ($p > 0.10$). However, Table 5 shows that the percentage of individuals who made risky decisions (under post) was greater in the negative condition (9 percent) than in the positive condition (5 percent). Similarly, the percentage of individuals who were extremely risk averse was lower in the negative condition (5.7 percent) than in the positive condition (6.9 percent). Although the trends present in table 5 provide evidence that individuals are more risky when presented with negatively framed information, Table 6 demonstrates that the observed relationships are not statistically significant. As a result, despite some trends indicating that individuals are more risk seeking with negatively framed information, overall, Hypothesis 1b was not supported.

Table 6. Differences in Proportion of High Probability Information Posted between Conditions

	Difference	DF	p value
Accurately Posted	0.016	234	0.715
Over Posted	0.022	236	0.676
Under Posted	-0.038	229	0.255
Always Posted	0.012	232	0.703
Never Posted	N/A	N/A	N/A

Note. Difference values created by Positive condition – Negative Condition

Hypotheses 1c and 1d were tested in an identical manner to 1a and 1b using data from low probability information. Consistent with Hypothesis 1c, when presented with low probability information that was negatively framed, individuals were risk averse, leading them to ignore more information than the true probability would suggest. As seen in Table 7, in almost all trials, individuals in the negative condition posted significantly less than the 20 percent true probability would suggest. Likewise, the overall percent posted across trials was 14 percent, significantly less than 20 percent ($p < 0.01$) and the majority of individuals (68 percent) exhibited risk averse decision making (see Table 8). As a result, Hypothesis 1c was supported.

Table 7. Average Proportion of Low Probability Information Posted by Trial

	Negative Condition			Positive Condition			Comparing Conditions		
Trial	DF	% Posted	p value	DF	% Posted	p value	DF	% Posted	p value
1	122	0.104	0.000	115	0.121	0.004	222	0.016	0.633
2	122	0.133	0.001	115	0.131	0.009	220	-0.002	0.951
3	122	0.130	0.001	115	0.098	0.000	232	-0.032	0.297
4	122	0.112	0.000	115	0.099	0.000	224	-0.013	0.666
5	122	0.218	0.402	115	0.165	0.147	233	-0.053	0.101
6	122	0.136	0.003	115	0.088	0.000	236	-0.048	0.099
7	122	0.154	0.025	115	0.105	0.000	236	-0.050	0.072
8	122	0.142	0.011	115	0.080	0.000	233	-0.062	0.036
9	122	0.102	0.000	115	0.069	0.000	223	-0.033	0.135
10	122	0.119	0.000	115	0.096	0.000	236	-0.023	0.322
11	122	0.138	0.002	115	0.091	0.000	233	-0.048	0.059
12	122	0.165	0.128	113	0.104	0.000	231	-0.062	0.038
13	122	0.117	0.000	115	0.065	0.000	216	-0.052	0.025
14	121	0.128	0.001	114	0.074	0.000	229	-0.055	0.041
15	122	0.176	0.249	115	0.109	0.000	234	-0.067	0.014
16	122	0.150	0.015	114	0.109	0.000	235	-0.042	0.127
17	119	0.132	0.001	113	0.086	0.000	224	-0.046	0.083
18	121	0.115	0.000	114	0.072	0.000	212	-0.042	0.105
19	121	0.112	0.000	112	0.052	0.000	200	-0.060	0.006
20	120	0.121	0.000	112	0.086	0.000	231	-0.036	0.155
21	105	0.134	0.002	103	0.082	0.000	203	-0.052	0.062
22	105	0.157	0.077	98	0.086	0.000	188	-0.071	0.016
23	103	0.136	0.003	96	0.065	0.000	177	-0.071	0.005
24	103	0.112	0.000	96	0.060	0.000	176	-0.052	0.040
25	101	0.212	0.577	94	0.130	0.001	195	-0.083	0.008
26	98	0.145	0.022	89	0.065	0.000	172	-0.080	0.006
27	97	0.150	0.039	83	0.085	0.000	172	-0.064	0.034
28	94	0.151	0.066	79	0.088	0.000	172	-0.063	0.070
29	92	0.127	0.004	79	0.075	0.000	169	-0.052	0.101
30	87	0.134	0.008	72	0.068	0.000	152	-0.066	0.028
31	85	0.145	0.047	70	0.082	0.000	149	-0.063	0.063
32	83	0.121	0.001	68	0.099	0.000	149	-0.022	0.490
33	83	0.095	0.000	60	0.060	0.000	142	-0.035	0.204
34	77	0.113	0.000	56	0.067	0.000	130	-0.046	0.176
35	73	0.108	0.000	52	0.069	0.000	116	-0.039	0.165

Note. Comparison values created by Positive condition – Negative Condition

Table 8. Proportion of Individuals who engaged in each Category of Posting Behavior for Low Probability Information

Condition	Accurately Posted	Over Posted	Under Posted	Always Posted	Never Posted
Overall	0.121	0.146	0.732	0.000	0.176
Positive	0.103	0.112	0.784	0.000	0.241
Negative	0.138	0.179	0.683	0.000	0.114

Contrary to the predictions of prospect theory and Hypothesis 1d, individuals presented with low probability information framed positively were not risk seeking. Rather, they consistently demonstrated more extreme risk averse decisions than the negative condition. Table 7 shows that in every trial individuals in the positive condition significantly under posted and overall they only attended to about 9 percent of the information. Similarly, Table 8 demonstrates that a reasonably high percentage (24) of individuals were extremely risk averse and never attended to the information, once again those individuals accepted an error rate of approximately 20 percent. However, as was the case with Hypothesis 1b, the differences between conditions in the percentage of individuals who were risk seeking, risk averse, and extremely risk averse, were not significantly different (Table 9).

Table 9. Differences in Proportion of Low Probability Information Posted between Conditions

	Difference	DF	p value
Accurately Posted	-0.048	228	0.014
Over Posted	-0.035	236	0.411
Under Posted	-0.067	233	0.143
Always Posted	N/A	N/A	N/A
Never Posted	0.102	236	0.076

Note. Difference values created by Positive condition – Negative Condition

Table 10. Average Proportion of Moderate Probability Information Posted by Trial

	Negative Condition			Positive Condition			Comparing Conditions		
Trial	DF	% Posted	p value	DF	% Posted	p value	DF	% Posted	p value
1	122	0.619	0.030	115	0.642	0.005	236	0.023	0.609
2	122	0.722	0.000	115	0.703	0.000	236	-0.020	0.622
3	122	0.703	0.000	115	0.744	0.000	236	0.041	0.285
4	122	0.728	0.000	115	0.724	0.000	234	-0.004	0.927
5	122	0.683	0.000	115	0.711	0.000	234	0.028	0.477
6	122	0.691	0.000	115	0.713	0.000	235	0.022	0.589
7	122	0.621	0.006	115	0.671	0.000	235	0.050	0.170
8	122	0.721	0.000	115	0.780	0.000	236	0.059	0.119
9	122	0.680	0.000	115	0.721	0.000	236	0.041	0.310
10	122	0.664	0.000	115	0.724	0.000	236	0.060	0.140
11	122	0.642	0.001	115	0.703	0.000	236	0.060	0.121
12	122	0.646	0.000	113	0.721	0.000	235	0.074	0.045
13	122	0.703	0.000	115	0.733	0.000	236	0.030	0.425
14	121	0.667	0.000	114	0.764	0.000	235	0.097	0.015
15	122	0.653	0.000	115	0.704	0.000	236	0.051	0.149
16	122	0.614	0.035	114	0.687	0.000	236	0.073	0.084
17	119	0.606	0.059	113	0.702	0.000	232	0.096	0.019
18	121	0.661	0.000	114	0.739	0.000	235	0.078	0.050
19	121	0.675	0.000	112	0.727	0.000	232	0.052	0.206
20	120	0.624	0.018	112	0.684	0.000	232	0.060	0.162
21	105	0.660	0.001	103	0.718	0.000	207	0.058	0.201
22	105	0.645	0.002	98	0.678	0.000	203	0.034	0.427
23	103	0.606	0.096	96	0.694	0.000	199	0.088	0.060
24	103	0.620	0.035	96	0.694	0.000	199	0.074	0.113
25	101	0.598	0.154	94	0.684	0.000	194	0.086	0.073
26	98	0.586	0.294	89	0.698	0.000	185	0.112	0.023
27	97	0.571	0.517	83	0.641	0.006	179	0.069	0.134
28	94	0.660	0.002	79	0.746	0.000	172	0.086	0.072
29	92	0.600	0.169	79	0.694	0.000	169	0.093	0.077
30	87	0.606	0.122	72	0.660	0.006	155	0.054	0.308
31	85	0.576	0.485	70	0.646	0.018	150	0.070	0.194
32	83	0.615	0.067	68	0.662	0.006	144	0.047	0.375
33	83	0.593	0.256	60	0.642	0.033	133	0.049	0.390
34	77	0.536	0.737	56	0.661	0.020	123	0.124	0.045
35	73	0.514	0.356	52	0.626	0.074	119	0.112	0.052

Note. Comparison values created by Positive condition – Negative Condition

Although there were not specific predictions about risky behavior for moderate probability outcomes, it is important to understand the pattern of biases present in decision making at all levels of probability. Table 10 shows that for moderate probability outcomes, individuals once again tend to be risk averse and attend to significantly greater amounts of information than would be suggested by the true probability (55 percent). Despite this general trend, there were large differences in the pattern of results across the two conditions. As seen in Table 10, individuals in the negative condition become better over time and began to attend to an accurate amount of information in later trials. Alternatively, individuals in the positive condition exhibit no such trend and are overly risk averse the entire time. This difference can also be seen in the total proportion of information attended to across trials. Individuals in the negative condition attended to approximately 63 percent of all moderate information while individuals in the positive condition attend to significantly more ($p < 0.05$), posting about 69 percent.

Not surprisingly, a similar pattern emerged at the individual level. There were a greater proportion of individuals in the negative condition that exhibited risky decision making compared to the positive condition. Conversely, there were significantly more individuals in the positive condition that were risk averse and extremely risk averse than in the negative condition (see Table 11). However, these differences were once again not significantly different (Table 12).

Table 11. Proportion of Individuals who engaged in each Category of Posting Behavior for Moderate Probability Information

Condition	Accurately Posted	Over Posted	Under Posted	Always Posted	Never Posted
Overall	0.213	0.582	0.205	0.021	0.000
Positive	0.198	0.638	0.164	0.026	0.000
Negative	0.228	0.528	0.244	0.016	0.000

Table 12. Differences in Proportion of Moderate Probability Information Posted between Conditions

	Difference	DF	p value
Accurately Posted	-0.029	236	0.581
Over Posted	0.109	236	0.087
Under Posted	-0.080	235	0.125
Always Posted	0.010	220	0.608
Never Posted	N/A	N/A	N/A

Note. Difference values created by Positive condition – Negative Condition

Hypothesis 2 tested whether the effects of negative framing are stronger than the effects of positive framing. In cases of both low and high probability information, both conditions showed similar tendencies to be risk averse. As a result, few significant differences between conditions were identified. Therefore, Hypothesis 2 was not supported. However, for moderate information, individuals in the negative condition did show a tendency to attend to significantly less information, especially with increased experience. Likewise, the percentage of people that exhibited risky behavior was greater (8 percent more likely) but due to small sample size that difference was not significant. These results suggest that there are different processes that individuals engage in due to the framing of information, but those differences may be less significant at the extremes than Prospect Theory would predict.

Hypothesis 3 examined whether individuals followed the same pattern of risky decision making for information acquisition as suggested by the weighting function in Cumulative Prospect Theory. The weighting function suggests that individuals over weight low probability information, underweight moderate probability information and about accurately rate high probability information. The decision making observed in information acquisition does not support this pattern of behavior, thus, not supporting Hypothesis 3. Individuals typically under weighted low probability information (see Table 7), slightly over weighted and at times accurately weighted moderate probability information (see Table 10), and tended to overweight high probability information (see Table 4).

A relationship that has received significant attention in the literature is the effect of outcomes of prior decision making on future decisions. Evidence from theories such as the house money effect (Thaler & Johnson, 1990) suggest that the riskiness of decisions should change based on the outcomes of past decisions. More specifically, it is thought that individuals who experience a prior positive outcome will make more risky decisions while individuals who experience a prior negative outcome will make more risk averse decisions. It is important to understand the relationship between prior outcomes and risky decision making because the riskiness of decisions drastically impacts performance on decision making tasks. Table 13 shows HLM results from a series of increasingly complex nested models. Models 4 and 5 demonstrate that when added, decision riskiness significantly predicts performance above and beyond the effect of experience and the control variables (which were excluded due to non-significance to conserve degrees of freedom). More importantly, as the riskiness of decisions increases performance significantly decreases, making it extremely important to understand what can lead to increased risky decision making.

Table 13. Effect of Risky Decision Making on Performance

	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed Effects					
Intercept	0.666**	0.661**	0.620**	0.623**	0.623**
Trial		0.001	0.001	0.000	0.000
Gender			0.002		
Age			0.007		
Risky decision making				-0.338**	-0.309**
Random Effects					
Residual	0.012	0.012	0.012	0.011	0.011
Intercept	0.002	0.002	0.002	0.000	0.002
Time		0.000	0.000	0.000	0.000
Risky decision making					0.013
ΔX^2		66.29**	0.00	947.14**	79.47**
Δdf		3	2	1	3

Note. * $p < 0.05$; ** $p < 0.01$

Prior research on the relationship between subsequent outcomes on future decisions has primarily been done using only one or two time points. The current design allows for a more thorough investigation of how performance and decision riskiness impact one another over time. To do so, a vector auto-regression (VAR) model was applied to the data. VAR simultaneously models a reciprocal relationship between prior time points of each variable. More specifically, both decision riskiness and performance were modeled as a function of their own prior realizations as well as prior realizations of the other variable. VAR is applied to only a single person's data, so all results presented are the average relationship across the entire sample.

When decision riskiness was regressed onto its prior time point and the prior time point of performance, a few common relationships emerged. Overall, the model explained a significant amount of variance in risky decision making. On average the R^2 value was 0.29. In 32 percent of individuals, prior risky decision making predicted subsequent risky decision making. For those 32 percent, the relationship between the two variables was positive ($\bar{\beta}_1$= 0.22), indicating that individuals who made more risky decisions on previous trials made more risky decisions on subsequent trials as well. In only 7 percent of individuals was the relationship between prior performance and subsequent decision making significant. In those 7 percent, performance was negatively related to risky decision making ($\bar{\beta}_2$= -0.07), suggesting that after prior poor performance individuals take a more risky strategy. While it is also possible that after receiving a positive outcome, individuals take a less risky strategy, it is unlikely because in general individuals tend to be so risk averse that becoming less risky would be extremely difficult due to a ceiling effect. These results do not support Hypothesis 4, but are partially consistent with the escalation of commitment literature (Staw, 1976, 1981) that proposes that after prior negative outcomes, individuals become more risky in an attempt to perform better.

Performance was also regressed on its prior realizations as well as prior realizations of risky decision making. Overall, the model did not fit the data particularly well, only explaining an average of about 9 percent of the variance in performance. Prior time points of performance only significantly predicted future time points for 5 percent of individuals, about what would be expected by chance. Prior risky decision making predicted subsequent performance for about 8 percent of individuals. It is likely that prior risky decisions are significantly related to performance because prior risky decisions are significantly related to subsequent risky decisions as demonstrated above and risky decisions are related to performance at the current time point (Table 13).

Although Hypothesis 4 was not supported, an important relationship was discovered. The pattern of results across the VAR model and HLM model suggests that for some individuals a reciprocal relationship between risky decision making and performance exists. For those individuals, performance at time t-1 impacts risky decision making at time t, which subsequently impacts performance at time t.

Individual Differences Hypotheses

Many individual difference variables have been linked to the decision making process. One of the most commonly studied relationships is between affect and riskiness of decisions. Hypothesis 5a tested whether there was a main effect of negative affect on risky decision making such that those higher on negative affect would make riskier decisions. Table 14 presents results from an HLM model where negative affect was inserted as a predictor. Models 1 through 3 are testing the unconditional means model, unconditional growth model, and control variables. Model 4 tests whether the insertion of negative affect predicts differences in risky decision making. The fixed effect estimate of negative affect (-0.027) was marginally significant ($p < 0.10$), indicating that on average, individuals higher in negative affect make significantly less risky decisions, contrary to the expectations presented above. Therefore, Hypothesis 5a was not supported.

Hypothesis 5b tested whether individuals higher in negative affect would perform worse overall. As demonstrated in Table 15 (Model 4), negative affect did not significantly predict differences in performance. As a result, Hypothesis 5b was not supported.

Table 14. Effect of Negative Affectivity on Risky Decision Making

	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Intercept	-0.110**	-0.112	-0.016	0.002
Trial		0.000	0.000	0.000
Gender			-0.028ŧ	-0.031*
Age			-0.004	-0.005
Negative Affectivity				-0.027 ŧ
Random Effects				
Residual	0.010	0.009	0.009	0.009
Intercept	0.015	0.015	0.015	0.014
Time		0.000	0.000	0.000
ΔX^2		795.88**	0.00	2.34
Δdf		3	2	1

Note. ŧ p < 0.10, * p < 0.05; ** p < 0.01

Table 15. Effect of Negative Affectivity on Performance

	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Intercept	0.666**	0.661**	0.620**	0.623**
Trial		0.001	0.001	0.000
Gender			0.002	
Age			0.007	
Negative Affectivity				0.001
Random Effects				
Residual	0.012	0.012	0.012	0.011
Intercept	0.002	0.002	0.002	0.000
Time		0.000	0.000	0.000
ΔX^2		66.29**	0.00	0.02
Δdf		3	2	1

Note. * p < 0.05; ** p < 0.01

It is also important to understand the effect that positive affect has on risky decision making. Hypothesis 5c investigates whether individuals higher in positive affect attend to more positively framed information. To test Hypothesis 5c a series of increasingly complex HLM models was applied to only data from the positive condition (N = 116). Table 16 (Model 4) shows that the relationship between positive affectivity and information attended to was not in the hypothesized direction (positive) and the effect failed to be significant. Therefore, Hypothesis 5c was not supported.

Table 16. Effect of Positive Affectivity on Positive Information Attended

	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Intercept	10.302**	10.310**	10.890**	11.032**
Trial		0.001	0.001	0.001
Gender			0.292	0.31
Age			-0.038	-0.046
Positive Affectivity				-0.292
Random Effects				
Residual	3.323	2.709	2.718	2.717
Intercept	2.618	4.350	4.380	4.316
Time		0.008	0.008	0.008
ΔX^2		459.79**	130.8**	0.677
Δdf		3	2	1

Note. ^{t} p < 0.10, * p < 0.05; ** p < 0.01

The final proposed relationship between affect and risky decision making is that individuals higher in positive affectivity will be lower in risky decision making (Hypothesis 5d). The relationship between positive affect and risky decision making is once again not in the proposed direction (negative) and is not significant (Table 17, Model 4). So, on average individuals higher in positive affect tended to exhibit riskier behavior, the effect was not statistically significant. As a result, Hypothesis 5d was not supported.

Table 17. Effect of Positive Affectivity on Risky Decision Making

	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Intercept	-0.110**	-0.112	-0.016	-0.020
Trial		0.000	0.000	0.000
Gender			-0.028ŧ	-0.029 ŧ
Age			-0.004	-0.004
Positive Affectivity				0.024
Random Effects				
Residual	0.010	0.009	0.009	0.009
Intercept	0.015	0.015	0.015	0.014
Time		0.000	0.000	0.000
ΔX^2		795.88**	0.00	2.06
Δdf		3	2	1

Note. ŧ p < 0.10, * p < 0.05; ** p < 0.01

Research has found that when individuals' goal orientation is manipulated, patterns of risky decision making change in systematic ways. To date, it is unknown whether the same systematic relationships exist between trait goal orientation and risky decision making. Hypothesis 6a examines whether individuals higher in performance-avoid goal orientation make significantly less risky decisions. Table 18 shows that although the proposed relationship is in the correct direction (negative), it was not significant. Therefore, while individuals did tend to slightly be less risky when higher in performance avoid goal orientation, the effect was minimal. As a result, Hypothesis 6a was not supported.

Table 18. Effect of Performance Avoid Goal Orientation on Risky Decision Making

	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Intercept	-0.110**	-0.112	-0.016	-0.012
Trial		0.000	0.000	0.000
Gender			-0.028ŧ	-0.029 ŧ
Age			-0.004	-0.004
Perf. Avoid GO				-0.006
Random Effects				
Residual	0.010	0.009	0.009	0.009
Intercept	0.015	0.015	0.015	0.015
Time		0.000	0.000	0.000
ΔX^2		795.88**	0.00	0.31
Δdf		3	2	1

Note. ŧ $p < 0.10$, * $p < 0.05$; ** $p < 0.01$

Unlike individuals high in performance avoid goal orientation; individuals high in performance approach goal orientation are thought to exhibit riskier behavior, making them more likely to engage in risky decision making. Table 19 (Model 4) shows that the relationship between performance approach goal orientation and risky decision making was trivial and non-significant. Therefore, Hypothesis 6b was not supported.

Table 19. Effect of Performance Approach Goal Orientation on Risky Decision Making

	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Intercept	-0.110**	-0.112	-0.016	-0.016
Trial		0.000	0.000	0.000
Gender			-0.028ᵗ	-0.028 ᵗ
Age			-0.004	-0.004
Perf. Approach GO				-0.003
Random Effects				
Residual	0.010	0.009	0.009	0.009
Intercept	0.015	0.015	0.015	0.015
Time		0.000	0.000	0.000
ΔX^2		795.88**	0.00	0.06
Δdf		3	2	1

Note. ᵗ p < 0.10, * p < 0.05; ** p < 0.01

A common finding in the decision making literature is that the individual difference trait of risk propensity is predictive of actual risky decision making. Little evidence of this link exists from a longitudinal perspective. As a result, Hypothesis 7 examines whether individuals higher in risk taking propensity make more risky decisions over time. Surprisingly, although the relationship between the two variables is in the hypothesized direction (positive), the relationship is not statistically significance (p = 0.12). Therefore, Hypothesis 7 was not supported (see Table 20, Model 4).

Table 20. Effect of Risk Taking Propensity on Risky Decision Making

	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Intercept	-0.110**	-0.112	-0.016	-0.017
Trial		0.000	0.000	0.000
Gender			-0.028ŧ	-0.032*
Age			-0.004	-0.004
Risk Taking Propensity				0.018
Random Effects				
Residual	0.010	0.009	0.009	0.009
Intercept	0.015	0.015	0.015	0.014
Time		0.000	0.000	0.000
ΔX^2		795.88**	0.00	2.24
Δdf		3	2	1

Note. ŧ p < 0.10, * p < 0.05; ** p < 0.01

The final individual difference variable that was measured was cognitive ability. It is predicted that people higher in cognitive ability will make fewer risky decisions (Hypothesis 8a) and perform better overall (Hypothesis 8b). HLM models were once again used to determine whether there is a significant main effect of cognitive ability for either risky decision making (Table 21) or performance (Table 22). Individuals higher in cognitive ability were found to make significantly fewer risky decisions ($p < 0.10$), marginally supporting Hypothesis 8a. Similarly, those higher in cognitive ability performed significantly better over time ($p < 0.05$), supporting Hypothesis 8b.

Table 21. Effect of Cognitive Ability on Risky Decision Making

	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Intercept	-0.110**	-0.112	-0.016	-0.008
Trial		0.000	0.000	0.000
Gender			-0.028ŧ	-0.023
Age			-0.004	-0.005
Cognitive Ability				-0.005 ŧ
Random Effects				
Residual	0.010	0.009	0.009	0.009
Intercept	0.015	0.015	0.015	0.015
Time		0.000	0.000	0.000
ΔX^2		795.88**	0.00	2.86 ŧ
Δdf		3	2	1

Note. ŧ $p < 0.10$, * $p < 0.05$; ** $p < 0.01$

Table 22. Effect of Cognitive Ability on Performance

	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Intercept	0.666**	0.661**	0.620**	0.615**
Trial		0.001	0.001	0.000
Gender			0.002	
Age			0.007	
Cognitive Ability				0.002*
Random Effects				
Residual	0.012	0.012	0.012	0.011
Intercept	0.002	0.002	0.002	0.000
Time		0.000	0.000	0.000
ΔX^2		66.29**	0.00	3.11*
Δdf		3	2	1

Note. * $p < 0.05$; ** $p < 0.01$

Learning and Decision Making Hypotheses

The final relationships tested are to determine whether individuals change or improve in their decision making strategy and process over time. Hypothesis 9 posits that individuals will perform better over time. This hypothesis is tested in two ways. First, an HLM model was performed analyzing whether over time, the number of correctly identified obstacles improved over time (Hypothesis 9a). Second, a separate HLM model was run that investigated whether over time individuals posted obstacles at a percentage closer to the actual stated probability. Table 23 shows results of the unconditional means model and unconditional growth model of performance over time. Model 2 demonstrates that on average individuals did not significantly improve in correctly identifying obstacles. However, despite the non-significance of the fixed effect, the unconditional growth model did significantly fit the data better than the unconditional means model. This finding indicates that there is significant variability in growth processes, meaning that individuals have unique growth trajectories. Therefore, Hypothesis 9a is partially supported because there is evidence of significant trends in performance over time, but it is not the consistent improvement that was hypothesized.

A post hoc analysis was conducted using cognitive ability as a predictor to determine whether there was either a main effect or moderation of ability on performance over time. Models 3 and 4 in Table 23 demonstrate that while there was, not surprisingly, a marginally significant main effect of ability, there was no moderating effect. These results indicate that while overall individuals higher in cognitive ability perform better, their performance trajectories are not significantly different.

Table 24 shows the unconditional means model and unconditional growth model for deviations from true probability. Model 2 highlights that over time, individuals became better at posting close to the true probability ($p < 0.05$), supporting Hypothesis 9b. Taken together, Hypothesis 9a and 9b demonstrate that over time the decision making process changes and individuals do become better decision makers, providing evidence of learning. These hypotheses also suggest that some individuals are more effective learners than others. Once again a post hoc analysis was performed to determine whether ability significantly predicted differences in either intercepts or slopes of deviations from optimal decisions. Models 3 and 4 in Table 24 demonstrate that ability does not significantly affect either the initial condition or changes in optimal decision making.

Table 23. Effect of Time on Performance

	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Intercept	0.666**	0.661**	0.612**	0.604**
Trial		0.001	0.000	0.000
ACT			0.002*	0.002 ŧ
Trial*ACT				-0.000
Random Effects				
Residual	0.012	0.012	0.012	0.012
Intercept	0.002	0.002	0.002	0.002
Time		0.000	0.000	0.000
ΔX^2		66.29**	0.00	0.20
Δdf		3	1	1

Note. ŧ $p < 0.10$, * $p < 0.05$; ** $p < 0.01$

Table 24. Effect of Time on Deviations from Optimal Probability

	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Intercept	0.124**	0.130**	0.144**	0.179**
Trial		-0.001*	-0.001 ŧ	-0.003 ŧ
ACT			-0.001	-0.002
Trial*ACT				0.000
Random Effects				
Residual	0.005	0.004	0.004	0.004
Intercept	0.002	0.004	0.004	0.004
Time		0.000	0.000	0.000
ΔX^2		664.51**	0.00	2.52
Δdf		3	1	1

Note. ŧ $p < 0.10$, * $p < 0.05$; ** $p < 0.01$

The final hypothesis examines whether individuals become more efficient decision makers over time and potentially automate the process. Table 25 shows the result of an HLM model designed to test whether the time spent making decision decreases with experience. Not surprisingly, Hypothesis 10a was supported because over time, individuals on average do become significantly faster at making decisions ($p < 0.01$). However, Model 2 also demonstrates that there is a significant amount of variability in growth trajectories, indicating that there is significant heterogeneity in the dynamic decision making process, indicating that some individuals become more efficient over time than others.

Table 25. Effect of Time on Time to Make Decisions

	Model 1	Model 2	Model 3	Model4
Fixed Effects				
Intercept	30.308**	46.885**	44.977**	50.708**
Trial		-1.071**	-1.08**	-1.355**
ACT			0.086	-0.140
Trial*ACT				0.011
Random Effects				
Residual	241.730	125.416	125.262	125.259
Intercept	136.300	278.140	281.745	281.219
Time		0.356	0.340	0.339
ΔX^2		4220.70**	2126.30**	0.74
Δdf		3	1	1

Note. * $p < 0.05$; ** $p < 0.01$

The final hypothesis (10b) posited that individuals would begin to automate the decision making process over time, thus beginning to make the same decision for all similar prospects. This hypothesis was not supported. As evidenced through Hypothesis 9b, individuals are continuing to improve in their decision making throughout the entire experiment, indicating that they do not settle on one strategy and stick with it. Similarly, individuals in general are not prone to make identical decisions for each type of prospect (always post or always ignore). It was very rare (< 10 percent) for individuals to choose to always make the same decision for identical prospects and even those individuals who did, tended not to do so with moderate probability information. Therefore, while it is possible that for some types of decisions (e.g., the BART), individuals will learn and adopt a consistent strategy, it appears that for information acquisition where each problem appears unique, individuals continually learn and improve. That said, it is possible that if observed over sufficient time points that individuals may begin to employ an identical strategy for all identical decisions.

DISCUSSION

The information acquisition process is critical to individuals' success in organizations. Whether it is for gathering and analyzing information as a United States intelligence officer, for accurately diagnosing and treating medical conditions as emergency medical personnel, or for solving any other organizational problem, the decisions made during information acquisition can drastically affect organizational outcomes. To date, little is known about how individuals make decisions about what information is most important to acquire. Since it is rare that what information is most critical to a solution is obvious, the decision to acquire information can be modeled as a gamble, where there is a given likelihood that each piece is relevant. Prospect Theory (PT) and its generalizations is the current dominant approach to the study of gambles for monetary and nonmonetary outcomes.

While the predictions of PT and its generalizations have been well documented for many types of risky decisions, most involving time and money, they do not perfectly predict the biases demonstrated by individuals during the information acquisition process. One of the main contributions of the PT literature above and beyond rational choice models of decision making is that PT accurately described instances where individuals were not risk averse. During information acquisition, however, individuals showed a strong tendency to be risk averse under all conditions, violating many of the PT predictions. These findings were consistent, however, with some research using PT to model decisions with time as an outcome where individuals tend to always be risk averse (Leclerc, 1995).

On the other hand, the rational choice models of decision making also do not accurately predict the biases demonstrated during information acquisition. Rational choice models of decision making (e.g., Atkinson, 1957; Keeney & Raiffa, 1976) do not account for differences in riskiness based on question framing or probability of relevance. A common finding during the information acquisition process was that individuals demonstrated slight differences in their decision riskiness depending on the probability of information relevance and the way in which the information was framed. More specifically, when information was framed in such as a way that made it seem as though something bad was going to happen (negative condition), individuals tended to be less risk averse for high, moderate, and low probability information. Likewise, a greater percentage of individuals tended to be risk seeking for all information probabilities in the negative condition. As a result, while the overall tendency was to be risk averse, those who received negatively framed information were less so and some even became risk seeking. Interestingly, individuals in the negative condition also tended to be more accurate, with a greater percentage of individuals accurately posting both moderate and low probability information. Similarly, for moderate probability information, individuals in the negative condition became much better over time and began to post at an accurate level in later trials, unlike those in the positive condition.

Prospect Theory and rational choice models of decision making do not predict that individuals will accurately weight uncertain information. However, it has been found that some individuals will accurately weight probabilistic information, thus choosing each prospect approximately the correct percentage of times (Bruhin, et al., 2010). This finding was replicated during information acquisition. For all three probability levels, some individuals correctly attended to the given proportion of information. Likewise, PT and rational choice models say nothing of improvement over time. However, it has been found that individuals make more optimal decisions with repeated experience (Aloysius, 2007), a finding that was replicated in some conditions for the information acquisition process. Therefore, it appears that some individuals, albeit a minority, are well attuned to the true decision weights in risky decision making and, thus, do not make the commonly found biases. Likewise, it appears that biases present in decision making may change over time. As a result, these findings demonstrate that Prospect Theory cannot accurately predict decision behavior in all cases. This is important because understanding the limitations and boundary conditions of PT and its generalizations allow for more accurate use of the theory in training manipulations.

PT and its generalizations explain biases in risky decision making by taking into account the perceptions and psychological representations of gambles that caused people to deviate from rational choice. It is possible that individuals perceive the gamble of information acquisition in such a way that differs from reality. However, the psychological representation of the prospects during information acquisition is not the same as the representation of the prospects during monetary gambles. This would account for the fact that individuals do not follow the exact predictions of Prospect Theory but also do not make purely rational decisions. These findings are important because understanding the common biases during information acquisition and their potential underlying causes will allow for better training manipulations to be created to make people more efficient, optimal decision makers.

Decision riskiness during information acquisition was found to significantly affect performance. As a result, it is important to understand the conditions under which individuals are more or less risky so that training programs can be designed to help individuals become more efficient, optimal decision makers. Despite the fact that Prospect Theory did not completely describe the biases in risky decision during information acquisition, it did provide a solid foundation to build upon for discovering the factors that influence risk taking. For example, the likelihood of relevance of a piece of information affected the risky decision making process. Likewise, the framing of information altered the process by which individuals made risky decisions. While discovering these two factors and how they impact decision riskiness is an important first step, additional research is needed to determine other factors that can affect the sequential risky decision making process during information acquisition.

The relationship between risky decision making and performance is likely not unidirectional. Theories such as the house money effect (Thaler & Johnson, 1990) and escalation of commitment (Staw, 1976) highlight the potential importance of prior decision outcomes (performance) on subsequent risky decisions. Although prior research has supported both the house money effect and escalation of commitment, it was thought that after performing poorly individuals would become more risk averse and after performing well, individuals would become more risk seeking (consistent only with the house money effect). Contrary to these expectations, it was found that for some people, after performing poorly, they began to make riskier decisions in an effort to increase performance (consistent with escalation of commitment). As a result, the timing and presentation of feedback are likely important components of the risky decision making process. Further research is needed to determine the effects of feedback and the manner in which feedback is presented on the riskiness of subsequent decisions.

There are likely many potential explanations for why the relationship between prior performance and decision riskiness was not in the expected direction. Most notably, almost all prior research on both the house money effect and escalation of commitment has been done looking at only two or three decisions. The current design used Vector Autoregressive (VAR) modeling to determine whether across all trials (mean = 31), the relationship between prior performance and subsequent risky decision making was significant for a given individual. This is a much more thorough test of the proposed relationship than in past studies and it is possible that while after one or two trials individuals followed the predictions of the house money effect, overall they altered their behavior when performing poorly by taking more risks in an attempt to perform better.

Many prior studies on risky decision making have utilized manipulations to determine whether affect and goal orientation had an effect on static decision riskiness. In organizations, it is less likely that manipulations for either of these constructs would be very useful during the information acquisition process. For workers such as the U.S. intelligence officer and emergency medical personnel, their entire job consists of acquiring information and making critical decisions under risk and uncertainty. Under these conditions, it would be nearly impossible to scientifically manipulate employee affect or goals on a consistent basis. As a result, it is important to determine how the trait forms of affect and goal orientation affect risky decision making during information acquisition over time.

Despite rather consistent results for the effect of affect and goal orientation on static risky decisions when manipulations were utilized, the traits of affect and goal orientation did not have a strong effect on risky decision making over time. Those higher in negative affectivity and performance avoid goal orientation did show a slight tendency to be overall more risk averse. Meanwhile, positive affectivity and performance approach goal orientation had no effect on either performance or decision riskiness. While these findings did contradict expectations, they are not without precedent. It has been shown that for organizational decisions, individual difference characteristics have minimal effects on decision making (e.g., Cooper & Wood, 1974). Similarly, affect and goal manipulations are likely to result in much more potent effects, especially in the short term, than personality traits would demonstrate on long run decision making patterns. These results are once again consistent with the idea that the short term and long term decision making biases and strategies used by individuals are not necessarily the same (e.g., Aloysius, 2007) and, thus, the findings and predictions from the Prospect Theory literature may not accurately reflect the dynamic decision making process. Despite affect and goal orientation not significantly predicting variability in risky decision making, there is significant variance left to be explained. As a result, further research is needed to determine what individual difference characteristics result in significantly different risky decision making behavior.

There is obvious conceptual overlap between the trait risk taking propensity and risky decision making. Not surprisingly, evidence has shown that those higher in risk taking propensity make more risky decisions (e.g., Taylor & Dunnette, 1974). However, the relationship between risk taking propensity and risky decision making over time was not significant despite being in the proposed direction. While this finding is counterintuitive it is perhaps not overly surprising. The relationship between risk taking propensity and risky decision making has been shown to become weakened when decision making is studied over time (e.g., Sitkin & Weingart, 1995). Similarly, risky decision making behavior has been shown to differ significantly depending on context (Barseghyan, Prince, & Teitelbaum, 2011), making it less likely that a stable trait will predict specific behavior. As a result, it is likely that those higher in risk taking propensity may be more likely to make risky decisions, whether they actually do will depend strongly on the context and measurement. This means that training interventions will likely be able to heavily influence the degree to which the predisposition to be risky actually materializes during information acquisition.

The final individual difference variable that was measured was cognitive ability. Cognitive ability has been consistently found to be negatively related to risky decision making and positively related to performance. Not surprisingly, these findings were replicated in the decisions made during information acquisition. As a result, individuals who are higher in cognitive ability will need less training to become more efficient, optimal decision makers.

As previously mentioned, how the decision making process changes over time has not received significant attention in the literature. As a result, how people learn and adapt their decision making strategy is still unknown. Over time, although overall individuals did not significantly improve in their decision performance, they did begin to attend to information at a more optimal level. Despite the fact that overall individuals did not significantly increase in their decision performance, there was significant variability in their slopes over time. This indicates that some individuals became better over time while others became worse. Further research is needed to determine what characteristics explain these slope differences. Additionally, the lack of increase in performance highlights a training or intervention need to help improve decision accuracy over time. Although there was a significant increase in optimality of decision making over time, the size of the increase was quite small. Therefore, further research is needed to determine training interventions to help boost optimal decision making at a quicker rate. Additionally, the time that individuals take during decision making did significantly decrease over time. As a result, individuals do become significantly more efficient decision makers during information acquisition over time.

Recent work by Pleskac and Wershbale (2011) has looked at whether the decision making process becomes automated with increased experience. Although decision makers on the BART task did show a tendency to automate their decisions, this tendency was not present during information acquisition. While time spent decision making and information attended to did change over time, the change never leveled off to a consistent pattern as would be expected if individuals automated the decision process. It is possible that on more realistic and complex decisions such as what information to acquire, people take time and consider each decision uniquely. Likewise, on decisions during information acquisition, it would be a suboptimal strategy to always choose the same prospect for all similar decisions, especially for moderate probability information. Therefore, as individuals become better decision makers they should take more information into account before choosing a prospect. While individuals can become faster at doing this, as demonstrated here, it is unlikely that they automate the process.

Limitations and Future Directions

Although the findings presented here are novel and interesting, a number of limitations exist. The primary limitation is the fidelity of the information acquisition decisions. Presenting individuals with stated probabilities of the relevance/ reliability of information is highly synthetic and unlike the real world. The decision was made to state probabilities to be consistent with the decision paradigm used in the prospect theory literature (e.g., Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Future research should increase the fidelity by initially presenting only qualitative statements about the relevance or reliability of information (see Dusenbury & Fennema, 1996; Gottleib, Weiss, & Chapman, 2007; Windschitl & Wells, 1996) and then increase further by only demonstrating the relevance or reliability of information through feedback (see Budescu, Kuhn, Kramer, & Johnson, 2002; Camilleri & Newell, 2009, Hao, Pleskac, & Hertwig, 2010; Liu & Colman, 2009; Rakow & Newell, 2010; Rode, Cosmides, Hell, & Tooby 1999; Trautmann, Vieider, & Wakker, 2011). Both of these scenarios have been shown to alter the biases in the decision making process. Another limitation related to fidelity is the use of a laboratory simulation. It is possible that motivation and the decision making process would be different under conditions in an actual organization. Future research should attempt to replicate these findings using a field sample to determine whether the same biases are present.

Another potential limitation is sample size. Some small effects between the individual difference variables and dynamic processes (e.g., risk taking propensity and risky decision making) were rather small and would have likely been found significant with a larger sample. Similarly, while an average of 31 time points is good in organizational research, many more time points are needed to apply VAR models with multiple predictors. Since VAR is run on a single individual's data, time points become the sample size of interest. It is generally accepted that for each predictor included in the model, researchers should have approximately 40 time points. This means that it is likely that the VAR relationships reported were under-powered and additional models including more continuous predictors could not be run.

The current research is descriptive in nature designed to understand the process that individuals go through when making decisions during information acquisition and document any potential systematic biases. Training has been shown to improve individuals' decision making performance and reduce the biases present in risky decision making (Barron, Leider, & Stack, 2008). The findings in this paper provide a solid foundation to help researchers design effective training interventions to improve the decision making process individuals go through during information acquisition. Further research is needed to determine the effectiveness of training intentions to improve decision making during information acquisition.

Given the limitations just described, a number of future studies are necessary to fully understand the phenomenon of risky decision making during information acquisition. Likewise, additional research is needed to better explain the current findings and to apply the relevant results to create training interventions to improve the information acquisition process.

The natural first step in this process is to improve the fidelity of the risky decisions that individuals must make when acquiring information. As previously mentioned, it is unlikely that in the real world employees would be given the reliability of information before making a decision. Rather, it is significantly more likely that they would either have a general qualitative understanding of the quality of information or would have no knowledge as to the information reliability until after the decision was made. To model these changes, two follow up studies will be conducted. The first will use general qualitative statements as to the source reliability such as "There is a high likelihood that…" which have been shown to alter the nature and severity of decision biases. The second study would include no descriptor of source reliability but rather just have deterministic statements about information and utilize only feedback to inform participants of the likelihood of information being relevant.

Studying decision types that are more realistic will also help determine whether the reciprocal relationship between performance and risky decision making is more likely in the real world than found in this paper. It is possible that because feedback in the current study only served to confirm the stated probabilities, individuals were less inclined to alter their decision making process based on it, resulting in only 8% of individuals demonstrating the proposed reciprocal relationship. When feedback is necessary to uncover the underlying reliability of information, it is possible that individuals will increasingly use feedback to alter their risky decision making.

Similarly, it is possible to model additional individual difference variables in future studies in an attempt to explain the observed heterogeneity in the decision making process. It was discovered that there was a significant amount of variability in the intercepts and slopes of risky decision making, performance, decision optimality, and efficiency. Although cognitive ability, affect, goal orientation, and risk taking propensity did not explain this significant variability, it is likely that there are alternative individual difference variables that could account for additional between person variance.

Along with studies to improve the fidelity of the information acquisition decisions, additional research should be done to investigate how changing the source of uncertainty in the information acquisition process affects decision biases. In the current design, all similar decisions (i.e., obstacles) had identical probabilities. In reality, it may not be that all similar decisions have identical probabilities but rather that all decisions based on information from a specific source have approximately equal probabilities. A follow up study will be conducted looking at how unreliability in information from the same source (e.g., Alpha) about different decisions (e.g., obstacles) affects the pattern of decision biases found in the current paper. Understanding how changing the source of unreliability affects biases is the first step toward generalizing the current findings to the team level, a common context in organizations.

The hope in discovering the nature and severity of decision biases during information acquisition is to utilize this information to develop training interventions to improve decision efficiency, optimality, and performance. After gaining a better understanding of the biases under different conditions by conducting the aforementioned follow-up studies, additional research will be conducted to develop effective training manipulations. A series of future studies will be conducted examining the effects of different training, agent-based real time feedback, and retrospective feedback manipulations on mitigating the biases demonstrated in this paper.

Conclusion

As has been documented with time and monetary decisions, individuals are biased during the information acquisition process if the information presented is uncertain or unreliable. Unlike the predictions of Prospect Theory, individuals showed an overwhelming tendency to be risk averse and changed their decision behavior over time. Despite these overall tendencies, individuals presented with negatively framed information showed a greater likelihood to be risk taking and performed better over time under certain conditions. Negative affect, performance avoid goal orientation, and cognitive ability were found to significantly predict risky decision making behavior. Alternatively, positive affect, performance approach goal orientation, and risk taking propensity were not found to significantly impact the decision making process. Overall, individuals become better decision makers over time, increasing in their efficiency as well as their optimality in terms of information acquired.

APPENDIX

APPENDIX A

Individual Differences Scales

Participant demographics and background. As noted below, this includes sex, age, class, self-reported GPA, and information regarding computer experience.

1. Sex: M F
2. Age:______________
3. Major:_______________
4. Class standing:

Freshman Sophomore Junior Senior Other

5. Your GPA:_______________; your SAT or ACT score:_______________

Negative Affectivity. From Watson, Clark, & Tellegen (1988). Answered on a five-point Likert scale with Never to Very Frequently anchors, with the question worded, "How often do you generally feel."

1. Distressed
2. Upset
3. Hostile
4. Irritable
5. Scared
6. Afraid
7. Ashamed
8. Guilty
9. Nervous

10. Jittery

Positive Affectivity. From Watson, Clark, & Tellegen (1988). Answered on a five-point Likert scale with Never to Very Frequently anchors, with the question worded, "How often do you generally feel."

1. Enthusiastic
2. Interested
3. Determined
4. Excited
5. Inspired
6. Alert
7. Active
8. Strong
9. Proud
10. Attentive

Goal Orientation. From Vandewalle, 1997. Answered on a five-point Likert scale with strongly disagree to strongly agree anchors.

1. I often read materials related to my work to improve my ability.
2. I am willing to select a challenging work assignment that I can learn a lot from.
3. I often look for opportunities to develop new skills and knowledge.
4. I enjoy challenging and difficult tasks at work where I’ll learn new skills.
5. For me, development of my work ability is important enough to take risks.
6. I prefer work situations that require a high level of ability and talent.
7. I would rather prove my ability on a task that I can do well at than to try a new task.

8. I’m concerned with showing that I can perform better than my coworkers.

9. I try to figure out what it takes to prove my ability to others at work.

10. I enjoy it when other at work are aware of how well I am doing.

11. I prefer to work on projects where I can prove my ability to others.

12. I would avoid taking on a new task if there were a chance that I would appear rather incompetent to others.

13. Avoiding a show of low ability is more important to me than learning a new skill.

14. I’m concerned about taking on a task at work if my performance would reveal that I had low ability.

15. I prefer to avoid situations at work where I might perform poorly.

16. When I don’t understand something at work, I prefer to avoid asking what might appear to others to be dumb questions” that I should know the answer to already.

Risk Propensity. Adopted from Meertens & Lion (2008). Answered on a five-point Likert scale with strongly disagree to strongly agree as anchors.

1. I prefer to avoid risks.
2. I take risks regularly.
3. I really dislike not knowing what is going to happen.
4. Safety first.
5. I do not take risks with my health.
6. I view myself as a risk taker.
7. I usually view risks as a challenge.

REFERENCES

REFERENCES

Abdellaoui, M. F., Vossman, F., & Weber, M. (2005). Choice-based elicitation and decomposition of decision weights for gains and losses under uncertainty. *Management Science, 51*, 1384–1399.

Abualsamh, R. A., Carlin, B., & McDaniel, R. R. (1990). Problem structuring heuristics in strategic decision making. *Organizational Behavior and Human Decision Processes, 45,* 159-174.

Ackert, L. F., Charupat, N., Church, B. K., & Deaves, R. (2006). An experimental examination of the house money effect in a multi-period setting. *Experimental Economics, 9,* 5-16.

Akers, H. R., Joyner, C. A., Pezzo, M. V., Nash, J. G., Siegal-Jacobs, K., & Stone, E. (1994). The psychology of windfall gains. *Organizational Behavior and Human Decision Processes, 59*, 331-347.

Alge, B. J., Wiethoff, C., & Klein, H. J. (2003). When does medium matter? Knowledge-building experiences and opportunities in decision-making teams. *Organizational Behavior and Human Decision Processes, 91,* 26-37.

Allias, M. (1953). Le comportement de l'homme rationnel devant le risqué, critique des postulates et axioms de l'ecole Americaine. *Economtetrica, 21,* 503-546.

Aloysius, J. A. (2007). Decision making in the short and long run: Repeated gambles and rationality. *British Journal of Mathematical and Statistical Psychology, 60,* 61-69.

Andrade, E. B., & Ariely, D. (2009). The enduring impact of transient emotions on decision making. *Organizational Behavior and Human Decision Processes*, *109,* 1-8.

Ansic, D., & Keasey, K. (1994). Repeated decisions and attitudes to risk. *Economics Letters, 45,* 185-189.

Ariely, D., & Zakay, D. (2001). A timely account of the role of duration in decision making. *Acta Psychologica, 108,* 187-207.

Arkes, H. R. & Blumer, C. (1985). The psychology of sunk costs. *Organizational Behavior and Human Decision Processes, 35,* 124-140.

Aronson, E. (1968). Dissonance theory: Progress and problems. In R. Abelson, E. Aronson, W. McGuire, T. Newcomb, M. Rosenberg, & P. Tannenbaum (Eds.), *Theories of cognitive consistency.* Chicago, Illinois: Rand McNally.

Aronson, E. (1972). *The social animal.* San Francisco, California: Freeman.

Atkins, P. W. B., Wood, R. E., & Rutgers, P. J. (2002). The effects of feedback format on dynamic decision making. *Organizational Behavior and Human Decision Processes, 88,* 587-604.

Atkinson, J. W. (1957). Motivational determinants of risktaking behavior. *Psychological Review*, *64*, 359–372.

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York, NY: Freeman.

Barnes, J. D., & Reinmuth, J. E. (1976). Comparing imputed and actual utility functions in a competitive bidding setting. *Decision Sciences, 7,* 801-812.

Barron, G, Leider, S, & Stack, J. (2008). The effect of safe experience on a warnings' impact: Sex drugs, and rock-n-roll. *Organizational Behavior and Human Decision Processes, 106*, 125-142.

Barseghyan, L., Prince, J., & Teitelbaum, J. C. (2011). Are risk preferences stable across contexts? Evidence from insurance data. *American Economic Review, 101*, 591-631.

Bereby-Meyer, Y., Meyer, J., & Budescu, D. V. (2003). Decision making under internal uncertainty: The case of multiple choice tests with different scoring rules. *Acta Psychologica, 112,* 207-220.

Bereby-Meyer, Y., Meyer, J., & Flascher, O. M. (2002). Propsect theory analysis of guessing in multiple choice tests. *Journal of Behavioral Decision Making, 15,* 313-327.

Betsch, T., Haberstroh, S., Glockner, A., Haar, T., & Fiedler, K. (2001). The effects of routine strength on adaptation and information search in recurrent decision making. *Organizational Behavior and Human Decision Processes, 84,* 23-53.

Blakeney, R. N., & MacNaughton, J. F. (1971). Effects of temporal placement of unfavorable information on decision making during the selection interview. *Journal of Applied Psychology, 55,* 138-142.

Bonner, B. L., Baumann, M. R., & Dalal, R. S. (2002). The effects of member expertise of group decision-making and performance. *Organizational Behavior and Human Decision Processes, 88*, 719-736.

Brehm, J. W., & Cohen, A. E. (1962). *Explorations in cognitive dissonance.* New York, NY: Wiley.

Bridgeman, D. L., & Marlowe, D. (1979). Jury decision making: An empirical study based on actual felony trials. *Journal of Applied Psychology, 64,* 91-98.

Bromiley, P. (2009). A prospect theory model of resource allocation. *Decision Analysis, 6,* 124-138.

Bromiley, P. (2010). Research notes and commentaries looking at prospect theory. *Strategic Management Journal, 31,* 1357-1370.

Bruhin, A., Fehr-Duda, H., 7 Epper, T. (2010). Risk and rationality: Uncovering heterogeneity in probability distortion. *Econometrica, 78,* 1375-1412.

Budescu, D. V., Kuhn, K. M., Kramer, K. M., & Johnson, T. R. (2002). Modeling certainty equivalents for imprecise gambles. *Organizational Behavior and Human Decision Processes, 88,* 748-768.

Camerer, C. E (1992). Recent tests of generalizations of expected utility theory. In W. Edwards (Ed.), *Utility Theories, Measurement and Applications*, Boston, MA: Kluwer Academic Publishers.

Camerer, C. E & Ho, T. (1994). Violations of the betweenness axiom and nonlinearity in probabilities. *Journal of Risk and Uncertainty, 8,* 167–196.

Camilleri, A. R., & Newell, B. R. (2009). The role of representation in experience-based choice. *Judgment and Decision Making, 4,* 518-529.

Colquitt, J. A., Hollenbeck, J. R., Ilgen, D. R., LePine, J. A., & Sheppard, L. (2002). Computer-assisted communication and team decision-making performance: The moderating effect of openness to experience. *Journal of Applied Psychology, 87,* 402-410.

Cooper, M. R., & Wood, M. T. (1974). Effects of member participation and commitment in group decision making on influence, satisfaction, and decision riskiness. *Journal of Applied Psychology, 59,* 127-134.

Cowley, E. (2008). The perils of hedonic editing. *Journal of Consumer Research, 35,* 71-84.

Cunha, M., & Caldieraro, F. (2009). Sunk-cost effects on purely behavioral investments. *Cognitive Science, 33,* 105-113.

De Dreu, C. K. W., & West, M. A. (2001). Minority dissent and team innovation: The importance of participation in decision making. *Journal of Applied Psychology, 86,* 1191-1201.

Dean, J. W. & Sharfman, M. P. (1995). Does decision process matter? A study of strategic decision-making effectiveness. *Academy of Management Journal, 39,* 368-396.

Detert, J. R., Trevino, L. K., & Sweitzer, V. L. (2008). Moral disengagement in ethical decision making: A study of antecedents and outcomes. *Journal of Applied Psychology, 93,* 374-391.

Diehl, E., & Sterman, J. D. (1995). Effects of feedback complexity on dynamic decision making. *Organizational Behavior and Human Decision Processes, 62,* 198-215.

Dooley, R. S., & Fryxell, G. E. (1999). Attaining decision quality and commitment from dissent: The moderating effects of loyalty and competence in strategic decision-making teams. *Academy of Management Journal, 42,* 389-402.

Driskell, J. E., & Salas, E. (1991). Group decision making under stress. *Journal of Applied Psychology, 76,* 473-478.

Dukerich, J. M., & Nichols, M. L. (1991). Casual information search in managerial decision making. *Organizational Behavior and Human Decision Processes, 50,* 106-122.

Dusenbury, R., & Fennema, M. G. (1996). Linguistic-numeric presentation mode effects on risky option preference. *Organizational Behavior and Human Decision Processes, 68,* 109-122.

Edwards, W. (1962). Subjective probabilities inferred from decisions. *Psychological Review, 69,* 109-135.

Enders, W. (1995). *Applied econometric time series*. New York: John Wiley & Sons.

Etchart-Vincent, N. (2004). Is probability weighting sensitive to the magnitude of consequences? An experimental investigation on losses, *Journal of Risk and Uncertainty, 28,* 217–235.

Fellner, W. (1961). Distortion of subjective probabilities as a reaction to uncertainty. *Quarterly Journal of Economics, 75,* 670-690.

Festinger L. (1957). *A theory of cognitive dissonance.* Stanford, CA: Stanford University Press.

Fishburn, P.C., & Kochenberger, G.A. (1979). Two-piece von Neumann-Morgenstern utility functions. *Decision Sciences, 10,* 503-518.

Galanter, E., & Pliner, P. (1974). Cross-modality matching of money against other continua. In H. R. Moskowitz, B. Scharf, & C. Stevens (Eds.), *Sensation and measurement.* Boston, MA: Reidel Publishing Company,

Gladstein, D. L., & Reilly, N. P. (1985). Group decision making under threat: The tycoon game. *Academy of Management Journal, 28,* 613-627.

Gonzalez, C. (2005). Decision support for real-timer dynamic decision-making tasks. *Organizational Behavior and Human Decision Processes, 96,* 142-154.

Gonzalez, R., & Wu, G. (1999). On the shape of the probability weighting function. *Cognitive Psychology, 38,* 129–166.

Gottlieb, D. A., Weiss, T., & Chapman, G. B. (2007). The format in which uncertainty information is presented affects decision biases. *Psychological Science, 18,* 240 -246.

Grayson, C. J. (1960). *Decision under uncertainty: Drilling decisions by oil and gas operators.* Cambridge, MA: Graduate School of Business, Harvard University.

Green, P. E. (1963). Risk attitudes and chemical investment decisions. *Chemical Engineering, 59.* 35-40.

Grove, D. A. (1981). A behavioral consistency approach to decision making in employee selection. *Personnel Psychology, 34,* 55-64.

Guzzo, R. A., & Waters, J. A. (1982). The expression of affect and the performance of decision-making groups. *Journal of Applied Psychology, 67,* 67-74.

Halamish, V., Liberman, N., Higgins, E. T., & Idson, L. C. (2008). Regulatory focus effects on discounting over uncertainty for losses vs. gains. *Journal of Economic Psychology, 29,* 654-666.

Halter, A. N., & Dean, G. W. (1971). *Decisions under uncertainty.* Cincinnati, OH: South Western Publishing Co.

Hao, R., Pleskac, T. J., & Hertwig, R. Decisions from experience and statistical probabilities: Why they trigger different choices than a priori probabilities. *Journal of Behavioral Decision Making, 23,* 48-68.

Heath, C., Larrick, R. P., & Wu, G. (1999). Goals as reference points. *Cognitive Psychology, 38,* 79-109.

Helson, H. (1964). *Adaptation-level theory.* New York, NY: Harper.

Higgins, E. T. (1997). Beyond pleasure and pain. *American Psychologist, 52,* 1280–1300.

Higgins, E. T. (2000). Making a good decision: Value from fit. *American Psychologist, 55,* 1217–1230.

Hollenbeck, J. R., Colquitt, J. A., Ilgen, D. R., LePine, J. A., & Hedlund, J. (1998). Accuracy decomposition and team decision making: Testing theoretical boundary conditions. *Journal of Applied Psychology, 83,* 494-500.

Hollenbeck, J. R., Ilgen, D. R., Phillips, J. M., & Hedlund, J. (1994). Decision risk in dynamic two-stage contexts: Beyond the status quo. *Journal of Applied Psychology, 79,* 592-598.

Hollenbeck, J. R., Ilgen, D. R., Sego, D. J., Hedlund, J., Major, D. A., & Phillips, J. (1995). Multilevel theory of team decision making: Decision performance in teams incorporating distributed expertise. *Journal of Applied Psychology, 80,* 292-316.

Holloman, C. R., & Hendrick, H. W. (1972). Adequacy of group decisions as a function of decision-making process. *Academy of Management Journal, 15,* 175-184.

Horvath, M., Scheu, C. R., & DeShon, R. P. (2001). *Goal orientation: Integrating theory and measurement.* Paper presented at the 16th annual conference of the Society for Industrial and Organizational Psychology, San Diego, CA.

Jackson, S. E. (1983). Participation in decision making as a strategy for reducing job-related strain. *Journal of Applied Psychology, 68,* 3-19.

Jackson, S. E. (1984). Correction to "Participation in decision making as a strategy for reducing job-related strain." *Journal of Applied Psychology, 69,* 546-547.

Kahneman, D., & Tversky, A. (1973). On the psychology of prediction. *Psychological review, 80,* 237-251.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47,* 263-292.

Kahneman, D., & Tversky, A. (1984). Choices, values and frames. *American Psychologist, 39,* 341-350.

Kameda, T., & Davis, J. H. (1990). The function of the reference point in individual and group risk decision making. *Organizational Behavior and Human Decision Processes, 46,* 55-76.

Katsikopoulos, K. V., Duse-Anthony, Y., Fisher, D. L., & Duffy, S. A. (2002). Risk attitude reversals in drivers' route choice when range of travel time information is provided. *Human Factors, 44,* 466-473.

Keeney, R. L., & Raiffa, H. (1976). *Decisions with multiple objectives: Preferences and value tradeoffs.* New York, NY: Wiley.

Kleinmuntz, D. N., & Thomas, J. B. (1987). The value of action and inference in dynamic decision making. *Organizational Behavior and Human Decision Processes, 39,* 341-364.

Kluger, A. N., Stephan, E., Ganzach, Y., & Hershkovitz, M. (2004). The effect of regulatory focus on the shape of probability-weighting function: Evidence from a cross-modality matching method. *Organizational Behavior and Human Decision Processes, 95,* 20-39.

Kuhberger, A. (1998). The influence of framing on risky decisions: A meta-analysis. *Organizational Behavior and Human Decision Processes, 75,* 23-55.

Laughhunn, D. J. & Payne, J. W. (1984). The impact of sunk outcomes on risky choice behavior. *Canadian Journal of Operational research and Information Processing, 22,* 151-181.

Leclerc, F., Schmitt, B. H., & Dube, L. (1995). Waiting time and decision making: Is time like money? *Journal of Consumer Research, 22,* 110-119.

Lee, W. (1971). *Decision theory and human behavior.* New York, NY: Wiley.

Lejuez, C. W., Aklin, W. M., Jones, H. A., Richards, J. R., Strong, D. R., Kahler, C. W., & Read, J. P. (2003). The Balloon Analogue Risk Task (BART) differentiates smokers from nonsmokers. *Experimental and Clinical Psychopharmacology, 11,* 26–33.

Lejuez, C. W., Aklin, W. M., Zvolensky, M. J., & Pedulla, C. M. (2003). Evaluation of the Balloon Analogue Risk Task (BART) as a predictor of adolescent real-world risk-taking behaviors. *Journal of Adolescence, 26,* 475–479.

Lejuez, C. W., Read, J. P., Kahler, C. W., Richards, J. B., Ramsey, S. E., Stuart, G. L., et al. (2002). Evaluation of a behavioral measure of risk-taking: The Balloon Analogue Risk Task (BART). *Journal of Experimental Psychology: Applied, 8,* 75–84.

Lejuez, C. W., Simmons, B., Aklin, W. M., Daughters, S. B., & Dvir, S. (2004). Risk-taking propensity and risky sexual behavior of individuals in residential substance use treatment. *Addictive Behaviors, 29,* 1643–1647.

LePine, J. A. (2003). Team adaptation and postchange performance: Effects of team composition in terms of members' cognitive ability and personality. *Journal of Applied Psychology, 88,* 27-39.

LePine, J. A. (2005). Adaptation in teams in response to unforeseen change: Effects of goal difficulty and team composition in terms of cognitive ability and goal orientation. *Journal of Applied Psychology, 90,* 1153-1167.

LePine, J. A., Hollenbeck, J. R., Ilgen, D. R., & Hedlund, J. (1997). Effects of individual difference on the performance of hierarchical decision-making teams: Much more than g. *Journal of Applied Psychology, 82,* 803-811.

Liu, H. & Colman, A. M. (2009). Ambiguity aversion in the long run: Repeated decisions under risk and uncertainty. *Journal of Economic Psychology, 20,* 277-284.

Locke, E. A. & Latham, G. P. (2002). Building a practically useful theory of goal setting and task motivation. *American Psychologist, 57,* 705-717.

MacCrimmon, K. R., & Larsson, S. (1979). Utility theory: Axiomes versus paradoxes. In M. Allais & G. M. Hagen (Eds), *Expected utility hypotheses and the Allais paradox.* Dordrecht, Holland: Reidel Publishing Company.

Markowitz, H. (1952). The utility of wealth. *Journal of Political Economy, 60,* 151-158.

May, K. O. (1954). Intransitivity, utility, and the aggregation of preference patterns. E*conometrica, 22*, 1–13.

Meertens, R. M. & R. Lion. (2008). Measuring and individual's tendency to take risks: The risk propensity scale. *Journal of Applied Social Psychology, 38,* 1506-1520.

Michaelsen, L. K., Watson, W. E., & Black, R. H. (1989). A realistic test of individual versus group consensus decision making. *Journal of Applied Psychology, 74,* 834-839.

Miner, F. C. (1979). A comparative analysis of three diverse group decision making approaches. *Academy of Management Journal*, *22,* 81-93.

Nygren, T. E., Isen, A. M., Taylor, P. J., & Dulin, J. (1996). The influence of positive affect on the decision rule in risk situations: Focus on outcome (and especially avoidance of loss) rather than probability. *Organizational Behavior and Human Decision Processes, 66,* 59-72.

O'Reilly, C. A. (1977). Supervisors and peers as information sources, group supportiveness and individual decision-making performance. *Journal of Applied Psychology, 62,* 632-635.

Ordonez, L., & Benson, L. (1997). Decisions under time pressure: How time constraints affect risky decision making. *Organizational Behavior and Human Decision Processes, 71,* 121-140.

Pablo, A. L. (1994). Determinants of acquisition integration level: A decision-making perspective. *Academy of Management Journal, 37,* 803-836.

Paese, P. W., Bieser, M., & Tubbs, M. E. (1993). Framing effects and choice shifts in group decision making. *Organizational Behavior and Human Decision Processes, 56,* 149-165.

Park, G., & DeShon, R. P. (2010). A multilevel model of minority opinion expression and team decision-making effectiveness. *Journal of Applied Psychology, 95,* 824-833.

Permanent Select Committee on Intelligence: House of Representatives. (1996). *IC21: The intelligence community in the 21st century.* Retrieved from http://www.access.gpo.gov/congress/house/intel/ic21/ic21_toc.html

Pietras, C. J., Locey, M. L., & Hackenberg, T. D. (2003). Human risky choice under temporal constraints: Tests of an energy-budget model. *Journal of the Experimental Analysis of Behavior, 80,* 59-75.

Pleskac, T. J. (2008). Decision making and learning while taking sequential risks. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 34,* 167-185.

Pleskac, T. J., & Wershbale, A. (2011). Making assessments while taking repeated risk: A pattern of multiple response pathways. *Unpublished manuscript.*

Quiggin, J. (1982). A theory of anticipated utility. *Journal of Economic Behavior and Organization, 3,* 323-343.

Raghunathan, R., & Pham, M. T. (1999). All negative moods are not equal: Motivational influences of anxiety and sadness on decision making. *Organizational Behavior and Human Decision Processes, 79,* 56-77.

Rakow, T., & Newell, B. R. (2010). Degrees of uncertainty: An overview and framework for future research on experience-based choice. *Journal of Behavioral Decision Making, 23,* 1-14.

Raudenbush, S. W. & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods.* Newbury Park, CA: Sage Publications.

Reb, J., & Connolly, T. (2009). Myopic regret avoidance: Feedback avoidance and learning in repeated decision making. *Organizational Behavior and Human Decision Processes, 109,* 182-189.

Richter, F. D., & Tjosvold, D. (1980). Effects of student participation in classroom decision making on attitudes, peer interaction, motivation, and learning. *Journal of Applied Psychology, 65,* 74-80.

Ritche, J. B., & Miles, R. E. (1970). An analysis of quantity and quality of participation as mediating variables in the participative decision making process. *Personnel Psychology, 23,* 347-359.

Rode, C., Cosmides, L., Hell, W., Tooby, J. (1999). When and why do people avoid unknown probabilities in decisions under uncertainty? Testing some predictions from optimal foraging theory. *Cognition, 72,* 269-304.

Rottenstreich, Y., & Hsee, C. K. (2001). Money, kisses, and electric shocks: On the affective psychology of risk. *Psychological Science, 12,* 185-190.

Russo, J. E., & Dosher, B. A. (1983). Strategies for multi-attribute binary choice. *Journal of Experimental Psychology, 9,* 676–696.

Schmeidler, D. (1989). Subjective probability and expected utility without additivity. *Econometrica, 57,* 571-587.

Scholer, A. A., Zou, X., Fujita, K., Stroessner, S. J., & Higgins, E. T. (2010). When risk seeking becomes a motivational necessity. *Journal of Personality and Social Psychology, 99,* 215-231.

Schweiger, D. M., Anderson, C. R., & Locke, E. A. (1985). Complex decision making: A longitudinal study of process and performance. *Organizational Behavior and Human Decision Processes, 36,* 245-272.

Seale, D. A., & Rapoport, A. (1997). Sequential decision making with relative ranks: An experimental investigation of the "Secretary Problem." *Organizational Behavior and Human Decision Processes, 69,* 221-236.

Seo, M., & Barrett, L. F. (2007). Being emotional during decision making – good or bad? An empirical investigation. *Academy of Management Journal, 50,* 923-940.

Seo, M., Goldfarb, B., & Barrett, L. F. (2010). Affect and the framing effect within individuals over time: Risk taking in a dynamic investment simulation. *Academy of Management Journal, 53,* 411-431.

Shrode, W. A., & Brown, W. B. (1970). A study of optimality is recurrent decision-making of lower-level managers. *Academy of Management Journal, 13,* 389-401.

Singer, J. D., & Willet, J. B. (2003). *Applied longitudinal data analysis modeling change and event occurrence*. New York: Oxford University Press.

Singh, J. V. (1986). Performance slack and risk taking in organizational decision making. *Academy of Management Journal, 29,* 562-585.

Sitkin, S. B., & Weingart, L. R. (1995). Determinants of risky decision-making behavior: A test of the mediating role of risk perceptions and propensity. *Academy of Management Journal, 38,* 1573-1592.

Slovic, P., & Tversky, A. (1974). Who accepts Savage's axiom? *Behavioral Science, 19,* 368-373.

Stasser, G. (1992). Information salience and discovery of hidden profiles by decision-making groups: A "thought experiment." *Organizational Behavior and Human Decision Processes, 52,* 156-181.

Staw, B. M. (1976). Knee-deep in the big muddy: A study of escalating commitment to a chosen alternative. *Organizational Behavior and Human Performance, 16,* 27-44.

Staw, B. M. (1981). The escalation of commitment to a course of action. *Academy of Management Review, 6,* 577-587.

Steel, P., & Konig, C. J. (2006). Integrating theories of motivation. *Academy of Management Review, 31,* 889–913.

Steiner, I. (1972). *Group processes and productivity.* New York: Academic Press.

Swalm, R. O. (1966). Utility theory – insights into risk taking. *Harvard Business Review, 44,* 123-136.

Taylor, R. N. (1975). Age and experience as determinants of managerial information processing and decision making performance. *Academy of Management Journal, 18,* 74-81.

Taylor, R. N., & Dunnette, M. D. (1974). Influence of dogmatism, risk-taking propensity, and intelligence on decision-making strategies for a sample of industrial managers. *Journal of Applied Psychology, 59,* 420-423.

Thaler, R. H. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior and Organization,1,* 39-60.

Thaler, R. H., & Johnson, E. J. (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Science, 36,* 643-660.

Tindale, R. S., Sheffey, S., & Scott, L. A. (1993). Framing and group decision-making: Do cognitive changes parallel preference changes? *Organizational Behavior and Human Decision Processes, 55,* 470-485.

Trautmann, S. T., Vieider, F. M., & Wakker, P. P. (2011). Preference reversals for ambiguity aversion. *Management Science, 57,* 1320-1333.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185,* 1124-1131.

Tversky, A.& Kahneman, D. (1986). Rational choice and the framing of decisions. *Journal of Business, 59,* 251-278.

Tversky, A.& Kahneman, D. (1991). Loss aversion in riskless choice: A reference dependent model. *Quarterly Journal of Economics, 107,* 1039-1061.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty, 5,* 297-323

van de Kullen, G., & Wakker, P. P. (2006). Learning in the Allais paradox. *Journal of Risk and Uncertainty, 33,* 155-164.

van de Ven, A. H., & Delbecq, A. L. (1974). The effectivenss of nominal, Delphi, and interacting groups decision making processes. *Academy of Management Journal, 17,* 605-621.

van Ginkel, W. P., & van Kippenberg, D. (2008). Group information elaboration and group decision making: The role of shared task representation. *Organizational Behavior and Human Decision Processes, 105,* 82-97.

van Ginkel, W. P., & van Kippenberg, D. (2009). Knowledge about the distribution of information and group decision making: When and why does it work? *Organizational Behavior and Human Decision Processes, 108,* 218-229.

van Kippenberg, D., van Kippenberg, B., & van Dijk, E. (2000). Who takes the lead in risky decision making? Effects of group members' risk preferences and prototypicality. *Organizational Behavior and Human Decision Processes, 83*, 213-234.

van Schie, E. C. M., & van der Plight, J. (1995). Influencing risk preference in decision making: The effects of framing and salience. *Organizational Behavior and Human Decision Processes, 63*, 264-275.

VandeWalle, D. (1997). Development and validation of a work domain goal orientation instrument. *Educational & Psychological Measurement, 57*, 995-1015.

Viswesvaran, C., & Barrick, M. R. (1992). Decision-making effects on compensation surveys: Implications for market wages. *Journal of Applied Psychology, 77,* 588-597.

Vollrath, D. A., Sheppard, B. H., Hinsz, V. B., & Davis, J. H. (1989). Memory performance by decision-making groups and individuals. *Organizational Behavior and Human Decision Processes, 43*, 289-300.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. Journal of Personality and Social Psychology, 54, 1063-1070.

Watson, W., Michaelsen, L. K., & Sharp, W. (1991). Member competence, group interaction, and group decision making: A longitudinal study. *Journal of Applied Psychology, 76,* 803-809.

Weber, E. U. (1994). From subjective probabilities to decision weights: The effect of asymmetric loss functions on the evaluation of uncertain outcomes and events. *Psychological Bulletin, 115,* 228-242.

Weber, M., & Zuchel, H. (2005). How do prior outcomes affect risk attitude? Comparing escalation of commitment and the house-money effect. *Decision Analysis, 2,* 30-43.

Weymark, J. A. (1981). Generalized Gini inequality indices. *Mathematical Social Sciences, 1,* 409-430.

Williams, A. C. (1966). Attitudes toward speculative risks as an indicator of attitudes toward pure risks. *Journal of Risk and Insurance, 33,* 577-586.

Windschitl, P. D., & Wells, G. L. (1996). Measuring psychological uncertainty: Verbal versus numeric methods. *Journal of Experimental Psychology: Applied, 2,* 343-364.

Wiseman, D. B., & Levin, I. P. (1996). Comparing risky decision making under conditions of real and hypothetical consequences. *Organizational Behavior and Human Decision Processes, 66,* 241-250.

Yaari, M. E. (1987). The dual theory of choice under risk. *Econorneotrica, 55,* 95-1 15.

Zeelenberg, M., & Beattie, J. (1997). Consequences of regret aversion 2: Additional evidence for effects of feedback on decision making. *Organizational Behavior and Human Decision Processes, 72,* 63-78.

Zeelenberg, M., & van Dijk, E. (1997). A reverse sunk cost effect in risk decision making: Sometimes we have too much invested to gamble. *Journal of Economic Psychology, 18,* 677-691.

Zhang, J., Hsee, C. K., & Xiao, Z. (2006). The majority rule in individual decision making. *Organizational Behavior and Human Decision Processes, 99,* 102-111.

Ziller, R. C. (1957). Four techniques of group decision making under uncertainty. *Journal of Applied Psychology, 41,* 384-388.