ROLE OF MENTAL REPRESENTATIONS AND EXPERIENCE IN DECISION MAKING AND ACQUISITION OF KNOWLEDGE

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ABSTRACT

Aleksandra Rebeka: Role of Mental Representations and Experience in Decision Making and Acquisition of Knowledge
(Under the direction of Richard A. Bettis)

The dissertation addresses the question of how to deal with problems where perfect rationality principles do not hold and optimization is not possible. I study the role of mental representations and experience in identifying and evaluating alternative solutions. I argue that actors can use different sources of information to set up reference points, or constraints, to guide search for strategies and acquire knowledge about strategies’ usefulness to solve a problem. In a computational model, I find that an exogenous goal has a curvilinear effect on the acquisition of knowledge and long-term performance. When the goal is set too low, actors often believe that inferior strategies are useful and do not explore enough. When the goal is set too high, actors explore too much but do not develop more accurate beliefs. The effect of using a competitor’s performance as an additional source of information is highly contingent on the goal level. In a laboratory experiment, I further study effects of competitor’s performance and find that differences between treatment conditions are not consistent across levels of analysis. Although an addition of competitor’s performance seems to hurt the acquisition of knowledge about the problem structure and the odds of achieving a challenging goal, it does not hurt decision making and performance nor does it influence exploration in predicted ways. Supplementary analysis of experimental data suggests that individual differences in the understanding of the problem structure are the primary driver of performance heterogeneity; however, the importance of
experience in developing this understanding is not evident. I find that participants in the study engage in a high level of exploration regardless of information on competitor’s performance but very few of them actually improve their understanding during the course of the game. The participants’ response to feedback does not appear to be consistent with the theoretical framework that is based on a simple model of reinforcement learning.
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I want to thank Jeff Edwards for providing invaluable guidance on experimental methodology. I would not have had such methodological freedom in my research, had it not been for Jeff. Scott Rockart has always made me think deeper about my assumptions and taught me to
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# TABLE OF CONTENTS

LIST OF TABLES .................................................................................................................. x

LIST OF FIGURES .............................................................................................................. xii

LIST OF ABBREVIATIONS AND SYMBOLS ........................................................................ xiv

INTRODUCTION .................................................................................................................. 1

BACKGROUND THEORY ...................................................................................................... 10

  *Rational decision theory* .................................................................................................. 10

  *Characteristics of strategic decision problems* ................................................................. 14

  *How do organizations deal with strategic decision problems?* ....................................... 17

THEORY DEVELOPMENT ..................................................................................................... 25

  *Knowledge — the missing pivot in Simon’s scissors* ......................................................... 25

  *Emergence and dynamic development of knowledge* ....................................................... 33

  *Implications of constraint specification for knowledge development and performance* ...... 40

A COMPUTATIONAL MODEL TO EXPLORE CONSTRAINT SPECIFICATION .................. 48

  *Multi-armed bandit model* ............................................................................................... 48

  *Model specification* ........................................................................................................ 54

  *Simulation experiment #1: Analysis of effects of exogenous goals* ............................... 57

  *Simulation experiment #2: Analysis of effects of competitor’s performance* ............... 64

AN EXPERIMENTAL STUDY: METHODOLOGY .............................................................. 70

  *Why a laboratory experiment?* ..................................................................................... 70
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overview of the analytical game</td>
<td>73</td>
</tr>
<tr>
<td>Experimental design</td>
<td>76</td>
</tr>
<tr>
<td>Main variables</td>
<td>78</td>
</tr>
<tr>
<td>Control variables</td>
<td>82</td>
</tr>
<tr>
<td>Experimental protocol</td>
<td>86</td>
</tr>
<tr>
<td>AN EXPERIMENTAL STUDY: RESULTS</td>
<td>88</td>
</tr>
<tr>
<td>Pilot study</td>
<td>88</td>
</tr>
<tr>
<td>Participants in the main study</td>
<td>90</td>
</tr>
<tr>
<td>Analysis of main effects</td>
<td>90</td>
</tr>
<tr>
<td>Discussion of results and supplementary analysis</td>
<td>100</td>
</tr>
<tr>
<td>DISCUSSION AND CONCLUSION</td>
<td>109</td>
</tr>
<tr>
<td>REFERENCES</td>
<td>164</td>
</tr>
</tbody>
</table>
LIST OF TABLES

Table 1 – Comparing model results from simulation experiment #1 to propositions ........... 117
Table 2 – Comparing model results from simulation experiment #2 to propositions ........... 118
Table 3 – Description and a sample realization of the game ........................................ 119
Table 4 – Treatment conditions in experimental design ............................................. 120
Table 5 – Power analysis using pilot data ..................................................................... 121
Table 6 – Descriptive statistics .................................................................................... 122
Table 7 – Distribution of participants across number of wins in the game ................. 124
Table 8 – Distribution of wins across groups .............................................................. 125
Table 9 – Estimating differences in likelihood of winning across treatment conditions ... 126
Table 10 – Estimating differences in absolute performance scores (APS) across groups ... 127
Table 11 – Estimating differences in decision making effectiveness (DME) across groups ... 128
Table 12 – Estimating differences in knowledge accuracy (KA) across groups ............ 129
Table 13 – Estimating differences in knowledge of structure (KS) across groups .......... 130
Table 14 – Estimating differences in heuristic knowledge (HK) across groups .......... 131
Table 15 – Estimating differences in problem awareness (PA) across groups
          treating round as a continuous variable ............................................................ 132
Table 16 – Estimating differences in problem awareness (PA) across groups
          treating round as a categorical variable ............................................................ 133
Table 17 – Estimating differences in exploration (EXPL) between groups .................. 134
Table 18 – Comparing results of an experimental study to propositions ....................... 135
Table 19 – Estimating differences in satisfaction and self-efficacy at the end
          of the game between groups ........................................................................... 137
Table 20 – Estimating differences in performance (APS), decision making
effectiveness (DME), and heuristic knowledge (HK) across groups
          with Group 2 being the omitted category ........................................................... 138
Table 21 – Estimating differences in the likelihood of correctly answering questions about the problem structure after Round 4 across groups......................... 139

Table 22 – Modeling wins in Round 5 and Round 6 as a function of decision making effectiveness and problem awareness.......................................................... 140

Table 23 – Predicted probabilities of winning in Rounds 5 and 6 at different levels of decision making effectiveness and problem awareness....................... 141

Table 24 – Change in problem awareness from Round 2 to Round 6 as a function of individual characteristics and treatment conditions.............................. 142
LIST OF FIGURES

Figure 1 – Using an exogenous goal as a constraint ..................................................................... 143
Figure 2 – Using competitor’s performance as a constraint ....................................................... 144
Figure 3 – Belief accuracy (left axis) and cumulative payoff (right axis) as a function of the goal level ($N=8$; $PS = (4,6)$; $\tau=0.25$) ................................................................. 145
Figure 4 – Standard deviations for belief accuracy (left axis) and cumulative payoff (right axis) across goal levels ($N=8$; $PS = (4,6)$; $\tau=0.25$) .............................................. 146
Figure 5 – Cumulative payoff distributions at goal levels $P*=5.25$ (left) and $P*=5.75$ (right). ($N=8$; $PS = (4,6)$; $\tau=0.25$) ................................................................................ 147
Figure 6 – Number of tried strategies (left axis) and cumulative payoff (right axis) across goal levels ($N=8$; $PS = (4,6)$; $\tau=0.25$) ................................................................. 148
Figure 7 – Number of tried strategies (left axis) and belief accuracy (right axis) across goal levels ($N=8$; $PS = (4,6)$; $\tau=0.25$) ................................................................. 149
Figure 8 – Cumulative payoff across goal levels – comparing effects of exogenous goals to combinations of exogenous goals and competitor’s performance ($N=8$; $PS = (4,6)$; $\tau=0.25$) ................................................................. 150
Figure 9 – Belief accuracy across goal levels – comparing effects of exogenous goals to combinations of exogenous goals and competitor’s performance ($N=8$; $PS = (4,6)$; $\tau=0.25$) ................................................................. 151
Figure 10 – Proportion of trials in which payoffs from using only exogenous goals are higher than payoffs from using a combination of exogenous goal and competitor’s performance ($N=8$; $PS = (4,6)$; $\tau=0.25$) ................................................................. 152
Figure 11 – Number of tried strategies – comparing effects of exogenous goals to a combination of exogenous goal and competitor’s performance ($N=8$; $PS = (4,6)$; $\tau=0.25$). Graph on the left compares scenarios at $P*=4.0$, graph in the middle compares scenarios at $P*=5.5$, and graph on the right compares scenarios at $P*=6.5$. ................................................................................. 153
Figure 12 – Cumulative payoff across goal levels – comparing effects of exogenous goals to a combination of exogenous goals and competitor’s performance ($N=8$; $PS = (4,6)$; $\tau=2.0$) ................................................................. 154
Figure 13 – Proportion of trials in which payoffs from using only exogenous goals are higher than payoffs from using a combination of exogenous goal and competitor’s performance ($N=8$; $PS = (4,6)$; $\tau=2.0$) ................................................................. 155
Figure 14 – Average absolute performance score across 6 rounds for all groups………………. 156
Figure 15 – Average decision making effectiveness across 6 rounds for all groups……………. 157
Figure 16 – Average knowledge accuracy for all groups at Round 4 and Round 6…………….. 158
Figure 17 – Average knowledge of structure (graph on the left) and average heuristic
knowledge (graph on the right) for all groups at Round 4 and Round 6…………………. 159
Figure 18 – Average problem awareness for all groups at Round 2, Round 4, and Round 6…. 160
Figure 19 – Average exploration across rounds for all groups……………………………….. 161
Figure 20 – Predicted probabilities of winning in Rounds 5 and 6 as a
function of decision making effectiveness and problem awareness…………………. 162
Figure 21 – Distributions of problem awareness scores after Round 2 for participants
that had high problem awareness scores after Round 6 (on the left) and for
participants that had low problem awareness scores after Round 6 (on the right)…… 163
# LIST OF ABBREVIATIONS AND SYMBOLS

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>APS</td>
<td>Absolute performance score</td>
</tr>
<tr>
<td>DME</td>
<td>Decision making effectiveness</td>
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<tr>
<td>EXPL</td>
<td>Exploration</td>
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<td>HK</td>
<td>Heuristic knowledge</td>
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<td>KA</td>
<td>Knowledge accuracy</td>
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<tr>
<td>KS</td>
<td>Knowledge of structure</td>
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<tr>
<td>PA</td>
<td>Problem awareness</td>
</tr>
<tr>
<td>PS</td>
<td>Problem space</td>
</tr>
<tr>
<td>C</td>
<td>Variance</td>
</tr>
<tr>
<td>N</td>
<td>Number of strategies</td>
</tr>
<tr>
<td>$P^*$</td>
<td>Threshold value of a constraint</td>
</tr>
<tr>
<td>$S_j$</td>
<td>Strategy $j$</td>
</tr>
<tr>
<td>$Q^*(S_j)$</td>
<td>True value (mean) of strategy $j$</td>
</tr>
<tr>
<td>$Q(S_j)$</td>
<td>Realized payoff of strategy $j$</td>
</tr>
<tr>
<td>$\varphi$</td>
<td>Weight parameter on new information in value/belief function</td>
</tr>
<tr>
<td>$\tau$</td>
<td>Temperature parameter in choice function</td>
</tr>
<tr>
<td>$V_{i,t}$</td>
<td>Vector of beliefs for actor $i$ at time $t$</td>
</tr>
<tr>
<td>$V_{i,t}(S_j)$</td>
<td>Value of strategy $j$ to actor $i$ at time $t$</td>
</tr>
</tbody>
</table>
INTRODUCTION

A theory of the firm is fundamentally a theory of how decisions are made (Simon, 1947 [1997]; Cyert and March, 1963). An organization can be viewed as a complex adaptive system that consists of agents making a myriad of interrelated decisions (Bettis and Prahalad, 1995). While some decisions are trivial, others are so profound that could potentially change the history of mankind. Firms’ choices affect firms’ chances of success and survival, and they could also affect the society at large. If there is such a thing as basic science in management research, a general theory of decision making is a key part of it. The validity of any model of organizational behavior and performance depends on the validity of a decision theory that it adopts as given.

Rational approach to decision making has been a long-standing paradigm in economics. A rational decision maker is assumed to have infinite computational abilities and complete information about the environment, which is then used to calculate the consequences of all available alternatives with surgical precision (Simon, 1955; 1956). This knowledge is used to form consistent and stable preferences that allow the decision maker to make an optimal choice. Simon (1955, 1979) referred to rationality used in the sense above as “perfect”, “global”, or “omniscient” rationality. Although good in theory, the application of perfect rationality to real problems has proven to be difficult, if not impossible. Savage (1954), who is considered to be the founder of modern Bayesian decision theory, stresses in his work that principles of perfect rationality hold only in type of decision situations whose problem spaces are well defined and
small enough for optimization to be feasible. However, strategic organizational decisions do not meet these requirements.

Strategic decisions are often characterized by a lack of readily available solutions, ambiguity about their values, uncertainty about future outcomes, and computational intractability (Simon, 1955; Arthur, 1992; Bettis, 2016). If potential solutions have to be sought, there is no guarantee that all of them are found prior to deciding which one is best. Even if all solutions are available at the time of making a decision, it may be difficult to compare their values because not all solution outcomes can be measured on the same scale. It could be difficult or even impossible to predict outcomes that are yet to occur, especially if they depend on other elements of the ecosystem surrounding a decision, for example, actions by actors in other parts of organization, actions by competitors, customers, investors, government, and other stakeholders. Finally, even if all solutions are known and can be evaluated unambiguously, their sheer number may prevent a decision maker from making an optimal decision due to the unreasonable amount of time it would take to conduct a rigorous and comprehensive analysis of all alternatives. Due to these characteristics of strategic decisions, it is simply inappropriate to apply deductive reasoning and optimization principles of rational decision theory in strategic decision situations.

Developing a theory of decision making that is appropriate for strategic problems in organizations should be a high priority on the agenda for research in strategic management. My ultimate aspiration is to contribute to this development. In this dissertation, my objectives are to build an understanding of what makes it impossible to optimize in strategic decision situations and then begin an exploration of how decision makers can deal with strategic problems in such a way that better decisions are made.
Previous research has sought to address some aspects of decision making in the contexts where optimization is not feasible. Three streams of research are particularly relevant here. The two streams, the Carnegie School and research on heuristics, build on the concept of bounded rationality introduced by Herbert Simon (1955; 1956). The Carnegie School tradition focuses on search for alternatives and rule-based behavior (Gavetti, Levinthal, and Ocasio, 2007). The seminal texts of “Administrative Behavior” (Simon, 1947[1997]), “Organizations” (March and Simon, 1958), and “A Behavioral Theory of the Firm” (Cyert and March, 1963) lay out fundamental ideas of how organizations actually make decisions – ideas that are radically different from prescriptions of rational decision theory. The Carnegie School tradition builds on Simon’s original ideas that organizations do not know all the alternatives but have to search for them. Although building on bounded rationality and satisficing, this research tradition has focused more on firms’ behavior around aspiration levels, than on studying how organizations select and evaluate alternatives when optimization is not possible. Due to heavy focus on established firms that deal with issues of organizational change, standard operating procedures and routines have come to dominate research within the Carnegie school tradition. However, the emergence and dynamics of standard operating procedures and routines are rarely, if at all, discussed.

While the Carnegie School tradition focuses on search for alternatives, research on heuristics focuses on search for cues that allow a decision maker to evaluate and differentiate between alternatives in an efficient manner (Gigerenzer and Selten, 2001). Identifying cues is the basic approach to forming a heuristic – a decision rule that ignores part of available information, facilitates fast decisions, and is often as accurate as more complex methods (Gigerenzer and Gaissmaier, 2011). Heuristics are meant to exploit the regularities in the environment’s structure.
making heuristics ecologically rational. However, the extant research has heavily focused on studying stylized and context-dependent heuristics. The issues of generalizability of stylized heuristics across different contexts, heterogeneity of heuristics across decision makers, and how heuristics emerge and evolve are not fully understood.

The third stream of research comes from a broad discipline of cognitive science and focuses on mental representations (Thagard, 2005). Taking the assumption that humans and organizations are information processing systems as given (Newell and Simon, 1972), research on cognition emphasizes the importance of knowledge structures that encode, organize and store information and knowledge in long-term memory (Anderson, 2000). The information in knowledge structures is not a perfect replication of reality. Knowledge structures help a decision maker organize the messy and complex real world and form a mental representation of it (Holland et al, 1986; Thagard, 2005). Although a real-world situation comes with enormous amount of information, the mental representation helps an actor isolate and attend only to information that she considers relevant to a given problem (Simon, 1997). How external information is encoded and converted into knowledge structures plays a big role in how this knowledge is then used for making decisions. While there is a good amount of research on cognition in the management literature (see Walsh (1995) and Kaplan (2011) for reviews), I have chosen to build on research in cognitive science because it recognizes issues of emergence and dynamics of mental representations more aptly than management literature does. While management scholars generally agree that cognition matters in decision making, what role it plays in selecting and evaluating alternatives is poorly understood. The issue of how decision makers develop beliefs about the structure of the environment and consequences of decisions is central in this dissertation.
By focusing on heterogeneous, dynamic, and incomplete nature of mental representations, I highlight the importance of knowledge in solving strategic decision problems. To be able to solve the problem, the actor needs to know at least something about the underlying structure of the problem and what solutions are effective for solving it. By using Nelson and Nelson’s (2002) definition of knowledge as “the content of mental representations”, I conceptualize knowledge as a hybrid of facts, beliefs, and values. I argue that knowledge of decision makers does not always reflect reality, changes with experience, and is better be thought of as a set of beliefs. Decision makers that acquire accurate beliefs about the structure of the problem and what solutions are appropriate are said to have veridical knowledge about the problem. Beliefs about the problem emerge from a decision maker’s experience with the problem. Therefore, it is plausible to assume that there could be different ways to experience the problem that could influence a decision maker’s ability to develop accurate understanding of the problem structure and make correct inferences about strategies that work best for solving the problem.

To explore the role of experience in the acquisition of veridical knowledge, I conceptualize problem solving as a search through a problem space — a decision maker needs to find operators that will allow her to move from initial state to a goal state (Newell and Simon, 1972; Simon, 1983; Anderson, 2000). Given that strategic decision problems have very large problem spaces, decision makers need to use heuristics to search through the problem space more efficiently (Newell and Simon, 1976). Heuristics exploit the knowledge about the structure of problem, but such knowledge is likely to be partially unavailable. If a decision maker has to solve the problem repeatedly, it makes sense to invest in developing the understanding of the problem structure. Decision makers can use various constraints to reduce the size of the problem.
space and guide their learning. Constraints, aspirations, reference points, and goals are used interchangeably and are in the spirit of Simon’s way of using the term “constraint” (Simon, 1997). They are defined as threshold values on variables of interest that determine what is relevant and what is not, or what is useful and what is not useful for solving the problem. The most common constraint that decision makers set up is the level of satisfactory performance. I suggest that even in the absence of any knowledge about the problem structure, decision makers can use external sources of information to set up constraints. These include exogenous goals and competitors’ performance. Although these metrics are well-known in the literature, their implications for the emergence and dynamics of mental representations have not been previously explored.

I examine how exogenous goals and competitor’s performance influence search when used for setting up constraints. Specifying a constraint is an important way to direct search and gather information but it also has its shortcomings in a way of limiting both the problem space and knowledge development. I develop a set of propositions to explore whether using an exogenous goal and competitor’s performance has a positive or negative effect on acquisition of accurate beliefs about the problem structure and long-term performance. I argue that an exogenous goal is useful as a constraint when it is challenging enough to prevent a decision maker from settling down on an inferior solution but not so challenging that it leads to a perfection syndrome when decision makers continue searching for better solutions because they discard everything they try as useless for solving the problem. I further argue that using the performance of a superior competitor as a constraint usually forces a decision maker to search more, because even superior strategies may be undervalued. Using the performance of an inferior competitor is believed to have an opposite effect, because the effectiveness of poorly-performing
strategies may be overestimated. If paying attention to performance of either superior or inferior competitor results in partially incorrect inferences, then I believe a combination of exogenous goal and competitor’s performance is a less effective constraint, than an exogenous goal alone.

To test propositions related to exogenous goals and competitor’s performance, I develop a computational model based on the multi-armed bandit. The multi-armed bandit is an important model to study dynamic learning from feedback in the presence of Knightian uncertainty (Arthur, 1991; Sutton and Barto, 1998). It is a simple model that is well-suited to study a specific type of strategic problems, in which consequences of alternatives cannot be computed with reasonable accuracy. The key feature of the model is that actors have to make decisions based on incomplete knowledge about the problem structure. Actors’ choices are driven by beliefs about relative value of available solutions, and beliefs are in turn influenced by outcomes of choices that actors make. In the model, I introduce changes to the belief updating function by assuming that actors use constraints to make inferences about usefulness of different strategies.

In line with propositions, results of simulation experiments show the following. First, the goal level has a curvilinear effect on the accuracy of beliefs and performance. Second, as the goal level increases, actors explore more because they are more likely to make inaccurate inferences that strategies they have tried are not useful. Third, actors that pay attention to a superior competitor explore more than actors that pay attention to an inferior competitor. However, several findings in simulation experiments were not aligned with propositions. First, I found that the most effective goal is not the one that isolates the optimal strategy but the one that isolates at least a couple of top-performing strategies. Such goal leads to better inferences about relative usefulness of strategies and more efficient search. Second, a combination of an exogenous goal and a competitor’s performance hurts the accuracy of beliefs and performance
only at some goal levels. When an exogenous goal is effective, paying attention to a competitor’s performance hurts. However, when the goal is extremely challenging, paying attention to inferior competitor helps neutralize some of the incorrect inferences that all strategies that have been tried are useless.

To further test propositions related to effects of competitor’s performance, I conduct a laboratory experiment. To capture the emergence and development of mental representations of a problem, I present study participants with a problem that they are unlikely to have experienced before. Participants are asked to play six rounds of a computer-based analytical game, which has an original design to ensure that participants do not have prior knowledge about the problem structure. The only way participants can win the game is if they learn about the underlying structure of the problem from their own experience and use that knowledge to identify the most efficient search strategy. Without the knowledge of the structure, the problem appears intractable and thus cannot be optimized, even though the optimal performance value is known. Participants in the study are randomly assigned to one of the four treatment conditions, where one group does not observe a competitor’s performance, and the other three groups observe different kinds of a “virtual competitor” (superior, similar, and inferior).

Some results of the laboratory experiment are in line with the propositions. Findings show that the odds of winning by participants that do not observe competitor’s performance are twice the odds of winning by participants that observe superior and inferior competitor. Participants that do not observe competitor’s performance also develop better understanding of the problem structure. However, some results are not in line with propositions. There are no significant differences in the level of exploration across treatment groups. Participants that observe inferior competitor make more effective decisions and achieve better absolute
performance scores than other groups, even though they are less likely to win the game. In the discussion, I develop several possible explanations that could reconcile inconsistent findings. These explanations could be tested in future research.

The remainder of this dissertation is structured as follows. I provide a brief review of background theory on rational decision theory, characteristics of strategic problems that prevent the application of rational decision theory, as well as concepts of search, heuristics, and cognition that have been useful for approaching decision making when optimization is not feasible. I then develop a conceptual framework for thinking about the nature of knowledge and role of experience in acquiring veridical knowledge. Next, I discuss how constraints can be used to approach a problem when knowledge about its structure is incomplete or even completely unavailable. I present propositions about effects of using exogenous goals and competitor’s performance as a constraint on search, development of beliefs, and performance. I then discuss the results of the computational model and the laboratory experiment. I conclude with a discussion on limitations, implications for theory and practice, and directions for future research.
BACKGROUND THEORY

The purpose of this dissertation is to study how decision makers can deal with problems in which principles of perfect rationality and deductive reasoning do not hold and optimization is not feasible. In this chapter on background theory, I first discuss principles of perfect rationality principles, under what conditions they hold, and briefly review how various economic theories propose to handle violations of rationality principles. Then I discuss specific characteristics of strategic problems that organizations face and conclude that rational decision theory, even after proposed fixes, is simply not appropriate for dealing with strategic problems. Finally, I review the three streams of literature that attempted to address the issue of strategic decision making in situations where optimization is not feasible. The core ideas of search, heuristics, and mental representations provide a foundation, on which I later build a theoretical framework of inductive decision making and acquisition of knowledge.

Rational decision theory

Decision making has been perhaps one of the most contentious areas of research on organizations specifically and human behavior more generally. An intellectual war has enthused between proponents of a rational approach and those who reject it as valid. Economic theorizing is predominantly based on the assumptions of perfect\(^1\) rationality and logic of deduction — that “human agents derive their conclusions by logical processes from complete, consistent and well-

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\(^1\) Simon (1956, 1979) used a number of different adjectives including global, omniscient, and perfect to describe rationality as it was used in economics. He used terms “bounded rationality” and “adaptive rationality” to describe how human actors actually make decisions (Newell and Simon, 1972; Simon, 1979).
defined premises in a given problem” (Arthur, 1992). A rational agent has complete knowledge or access to complete information about a given problem, has sufficient computational capabilities to evaluate consequences of all alternatives and select one that will lead to the optimal outcome (Simon, 1955; 1956). Rational decision theory implies intra-and inter-agent consistency of decisions, i.e. it predicts consistent choices from the same agent at different points in time and consistent choices from different agents at the same point in time. If taken to an extreme, rationality implies homogenous agents that never get surprising future outcomes. There is no room for error in rational decision theory; there is no room for variability.

Scholars across disciplinary borders have raised questions about the boundary conditions of deductive reasoning and perfect rationality. Savage (1954), who is often considered the pioneer of the modern Bayesian decision theory, has been very cautious about the applicability of the decision theory he was putting forward. As he states (Savage, 1954: p. 16):

“The point of view under discussion may be symbolized by the proverb “Look before you leap” and the one to which it is opposed by the proverb “You can cross that bridge when you come to it”. One must indeed look before he leaps, in so far as the looking is not unreasonably time-consuming and otherwise expensive; but there are innumerable bridges one cannot afford to cross, unless he happens to come to them.

Carried to its logical extreme, the “Look before you leap” principle demands that one envisage every conceivable policy for the government of his whole life (at least from now on) in its most minute details, in the light of the vast number of unknown states of the world, and decide here and now on one policy. It is utterly ridiculous, […] because the task implied in making such a decision is not even remotely resembled by human possibility. It is utterly beyond our power to plan a picnic or to play a game of chess in accordance with this principle, even when the world of states and the set of available acts to be envisaged are artificially reduced to the narrowest reasonable limits.

Though the “Look before you leap” principle is preposterous, if carried to extremes, I would none the less argue that it is the proper subject of our further discussion, because to cross one’s bridges when one comes to them means to attack relatively simple problems of decision by artificially confining attention to so small a world that the “Look before you leap” principle can be applied there.” (Emphasis added)

The term ‘small worlds’ was a succinct way for Savage to describe problems where rationality principles hold. The question is whether strategic problems that organizations face are a type of problems in which conditions for perfect rationality are met. Based on a substantial
amount of empirical evidence in psychology and organizations research we can infer that major decisions in organizations do not meet requirements of perfect rationality. Binmore (2009) used the term ‘large worlds’ to describe such problems.

Nevertheless, principles of perfect rationality have proven to be resistant to both empirical evidence and theoretical critics, and to date dominate the fields of economics, finance, accounting, and management science, especially in formal theory and modeling. Assumptions of perfect rationality permeate studies of critical organizational phenomena such as incentives of managers, R&D productivity, valuation, and markets for technology (e.g., Jensen and Meckling, 1976; Pakes, 1986; Serrano, 2010; Bloom, Schankerman, and Van Reenen, 2013). Proponents of rationality have attempted to demonstrate some empirical evidence that individual and organizational decision making is indeed based on deductive reasoning and rationality principles (Jorgenson and Siebert, 1968; Rips, 1986; Rust, 1992; Braine and O’Brien, 1998), but it is important to note that these findings are not the result of a direct comparison with behavioral models. The lack of comparison is interesting, given that economists are particularly keen on having high predictive validity of models they develop. In response to the critics of omniscience, economists have offered various “fixes” for uncertainty and incomplete information, while continuing to adhere to the rule of maximization. “Fixes” include introducing information and search costs, rational expectations, and game theory models to incorporate risk and competitive interactions (Stigler, 1961; Marschak and Radner, 1972; Muth, 1961; Baron and Diermeier, 2007; Bloom et al, 2013). Statisticians have also weighed in on the question of incomplete information by developing approaches broadly based on Bayesian probability theory (Carnap and Jeffrey, 1971; Daston, 1988). In response to the critics of infinite computational abilities, a research program in psychology has emerged to demonstrate that humans are not good at either
logical inferences or statistics. This program shows that human decision making deviates from predictions of optimal reasoning, with an underlying notion that human thinking is generally inferior to optimal reasoning in that it is less robust and less accurate (Kahneman and Tversky, 1973; Tversky and Kahneman, 1973; 1974). None of the approaches just described—in economics, statistics, and psychology—have abandoned deductive reasoning and optimization as ideal approaches to decision making.

Proponents of perfect rationality have demonstrated an unprecedented commitment to rational decision theory, which, as some scholars argue, can be explained in part by the fact that rationality allows for “nice mathematical models” and “beautiful solutions” (Arthur, 1992; Ghoshal, 2005). However, potential implications of using rationality in solving real-world problems go beyond just having a theory that does not adequately describe human behavior. The actual use of rational decision theory may have resulted in a few unfortunate practical outcomes that could be a concern for the society. For example, some scholars have argued that economists could not predict the 2008 financial crisis because economic models assume rational behavior for agents in the economic system (Colander et al., 2009). Other scholars have argued that maximization of shareholder value, one of the most impactful developments that came out of rational decision theory, is the reason why we observe so much unethical behavior (Freeman, Wicks, and Parmar, 2004; Ghoshal, 2005). Another example is concerned with the lack of experimentation in firms. “No room for error” condition of rationality stiffens exploration that is so much needed in research and development (Kahneman and Lovallo, 1993).

There is a need for continuous development of a decision theory as well as its rigorous testing, particularly in strategic situations that do not meet the requirements of perfect rationality. In the next section, I will discuss characteristics of strategic decision problems that make it
difficult to apply deductive logic and find optimal solutions for such problems. In the following section, I will review several existing approaches that deal with some of the issues of strategic decision problems.

**Characteristics of strategic decision problems**

The optimal solution to a problem can be found if all alternatives are known and feasible, their consequences can be computed unambiguously, and a decision-maker does not get any surprises in the future (Savage, 1954; Simon, 1979; Binmore, 2009). If these conditions are satisfied, a perfectly rational decision can be made. Major real-world problems, especially the ones that organizations face, generally do not satisfy these conditions. Therefore, we should consider what makes it difficult to find the optimal solution to a problem.

Is it possible to know all alternative solutions to solving a particular problem? For some trivial problems, it may be. For example, I want to buy a chocolate that costs $2.3 with tax. If I have only $2.0, then my alternatives are to walk away without a chocolate or buy something else that costs less than $2.0. If I have more than $2.3, then I have an alternative of buying a chocolate, buying something else, or buying nothing. Of course, if the chocolate is all I can think about (in other words, having a chocolate is my goal), then I have only one satisfactory solution in the latter scenario (to buy the chocolate), and I have no satisfactory solutions in the former scenario, because I do not have enough money. It seems that buying a chocolate is a well-defined problem that I should be able to solve through optimization.

However, I would pause here and ask myself the following question. In the first scenario, where I have only $2.0, have I really considered all possible alternatives? Is there really no other way for me to get the chocolate? It turns out that there are other possibilities. Maybe, I would
meet a friend who could lend me 30 cents so that I could buy the chocolate. Or maybe I could ask strangers in the store if they could give me 30 cents. Or maybe I could sing in front of the store and people would pay a few cents for my performance. Or maybe I could steal the chocolate when nobody is looking. If I now consider all these alternatives as feasible, how do I make a perfectly rational decision? What choice is the optimal one?

To make a rational choice, I will need to compute some kind of value for each alternative, so that I can compare values and choose an alternative with the highest value. How do I determine the value of each alternative? I have to take into account their consequences. For example, if I ask people in the store for 30 cents, will they publicly shame me or report me to the store security? If I sing in front of the store, will I have an overpowering feeling of anxiety and embarrassment? If I try to steal the chocolate, will I get caught? If I get caught, will the store call the police? If police is called, will an officer arrest me? If I truly want to put a value on each alternative and make a rational decision, I will have to consider all the consequences of all the alternatives. Even if I believed that there is such a thing as subjective expected utility, I would have a hard time calculating it.

If I ran into so many issues while trying to make an optimal decision in a simple chocolate problem, then what would happen to an organization if instead of 30 cents it was dealing with $300,000 (of a $2.3 million budget)? Bettis (2016) provides an excellent example of complexities that a division of an organization will face if it attempts to solve a strategic planning decision problem rationally. Following Bettis’ example, if the division considers only 20 variables (such as cost of beef, cost of potatoes, change in consumer preferences, moves of competitors, regulatory changes) and 5 possible levels for each variable, then there are over \(95 \times 10^{12}\) alternatives that the division will have to analyze. It is clear that even if we spend just
few minutes analyzing each alternative, it is going to take an impossible amount of time to analyze all of them. This is what Bettis (2016) has called the ‘organizational intractability’. Decisions can be intractable even in the absence of interdependencies among decisions (Levinthal, 1997; Siggelkow, 2001). For example, an R&D department and a marketing department may develop their strategies independently and each could face an intractable problem (analogous to Bettis’ example above). However, if an organization needs to coordinate decisions made by the R&D and marketing departments, interdependencies among strategic choices exponentially increase intractability of the firm’s overall strategy (Rivkin, 2000)².

It is important to recognize that organizational (or computational) intractability has nothing to do with limitations of the mind, especially in the modern world of computers. Some problems, known as NP-complete problems, cannot be solved in real time even by the fastest computers (Yanofsky, 2013), due to the sheer number of alternatives that need to be analyzed. It appears that most organizational problems are NP-complete.

The discussion above has not touched on the uncertainty of the future yet. Most of organization’s strategic decisions are made in the presence of uncertainty, the kind that is different from risk in a Knightian sense (Knight, 1921; Arthur, 2013). Unfortunately, organizations do not have a perfect foresight. If they did, we would not see failed acquisitions, failed clinical trials, or failed product launches, as we would not see organizations that fail and exit the market. The fact that we do see failures suggests that organizations take actions without complete knowledge of future outcomes. There is a clear implication of not knowing the future

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² Rivkin (2000) demonstrated how interdependency makes firm’s strategy computationally intractable. He specifically stated, that decisions become intractable when $k > 2$ (where $k$ specifies the extent to which decisions are interdependent in the NK model). To my knowledge, Bettis (2016) is the first to show that even a single decision, such as strategic planning for one division, can be computationally (and organizationally) intractable.
for rational decision making – the decision of a problem involving uncertainty cannot be optimized. As Arthur (2013: p. 4) states:

“[Fundamental uncertainty] has an important consequence to theorizing. To the degree that outcomes are unknowable, the decision problems they pose are not well-defined. It follows that rationality—pure deductive rationality—is not well-defined either, for the simple reason that there cannot be a logical solution to a problem that is not logically defined. It follows that in such situations deductive rationality is not just a bad assumption; it cannot exist. There might be intelligent behavior, there might be sensible behavior, there might be farsighted behavior, but rigorously speaking there cannot be deductively rational behavior. Therefore we cannot assume it.”

Therefore, I conclude that it is not feasible to find an optimal solution to a strategic decision problem, because the strategic problem exhibits at least one of the following:

- Not all alternative solutions are known.
- Consequences of alternatives cannot be computed with reasonable accuracy.
- All alternatives cannot be analyzed in a reasonable amount of time.

Uncertainty, computational intractability, difficulty to value and compare alternatives, and constantly changing environment that alters decision maker’s problem space are the realities of organizations. Despite all these issues, organizations make decisions every day. And some organizations are remarkably good at it.

In the next section, I will discuss several approaches that have been developed in the management literature to capture how organizations deal with problems which do not meet the requirements of perfect rationality.

**How do organizations deal with strategic decision problems?**

There are three theoretical approaches in the management literature that are pertinent to the issue of dealing with strategic decision problems in organizations – that of search, heuristics, and cognition. Despite the fact that they all attempt to address the issue of applying perfect rationality principles in strategic situations, they have gone in rather different directions and have
little overlap with each other. While all three approaches agree that most organizational decisions are not optimal in the purest sense of perfect rationality, non-optimality has a very different meaning in the three schools of thought.

**Search.** The concept of search has come into being with realization that a decision maker who deals with a strategic problem is not endowed with complete knowledge of all alternative solutions. She has to search for alternatives. If the exhaustive search is not possible within a reasonable amount of time and within the constraints of available resources, she will only continue searching until a satisfactory solution is found. A solution is deemed satisfactory if it meets criteria defined, implicitly or explicitly, by the decision maker\(^3\) (Simon, 1997). It means that the decision maker does not optimize – she satisfices\(^4\) (Simon, 1956; 1979).

The concept of search has taken roots most prominently within the behavioral tradition, also known as the Carnegie School (Simon, 1947 [1997]; March and Simon, 1958; Cyert and March, 1963), and has been further advanced in evolutionary economics (Nelson and Winter, 1982). The research stemming from the behavioral tradition has taken a major stance against the perfect rationality renaissance (Simon, 1979; Gavetti et al, 2007). However, Simon’s original ideas on how decisions are made have been significantly trimmed down to focus on a rather narrow set of issues that has taken the behavioral theory and evolutionary economics away from developing a more sound decision theory. Primarily driven by studies of established firms and their established practices, the behavioral theory has given a status quo a central stage, with focusing on standard operating procedures (or routines) and change that depends on

\[^3\] In an organization, it is likely that criteria for satisfactory solutions are set at one level of hierarchy, while solutions are identified at a lower level of hierarchy. This division has important implications, which would be addressed later in the dissertation.

\[^4\] Simon (1997) notes that satisficing is defined by the Oxford English Dictionary as “deciding on and pursuing a course of action that will satisfy the minimum requirements necessary to achieve a particular goal” and that is the meaning he has always implied in his writing.
organizational performance relative to aspirations. Standard operating procedures and routines help organizations save scarce and costly resources of time, efforts, and money. A standard operating procedure is a set of actions that is invoked in response to a stimulus – this is what March and Simon (1958) call a performance program. If such program is called for, the organization does not have to search for a solution – the performance program already contains one. These standard operating procedures are difficult to change, and the change, when it happens, is usually incremental (Gavetti et al., 2007; Gavetti and Rivkin, 2007). A trigger for change is a firm’s performance below an aspiration level, which “in the short run defines a utility function with essentially only two values – good enough and not good enough” (Cyert and March, 1963: p.10). Cyert and March (1963: p.123) proposed that organizational aspiration levels are weighted functions of past aspiration levels, past performance and competitive performance. These assumptions about aspiration levels persist to date, and the question of aspiration’s origins and antecedents has not received proper attention (Shinkle, 2012).

An over-simplified short version of the behavioral theory of search goes then as follows. Organizations rely on standard operating procedures, programs, and routines as long as environmental stimuli remain largely unchanged. In stable environments, organizations don’t have to search. In stable environments, the performance is also fairly stable, and thus historic performance (of both the focal firm and its competitors) serves as a good proxy for what to expect in the future. When the environment throws the firm a surprise, i.e. when the firm performance is below the aspiration level, the firm may consider changes to its routines.

Does the behavioral theory, in its over-simplified short version above, help explaining how strategic problems are solved? Unfortunately, only to some extent. Let’s go back to the example of strategic planning problem for a division that we discussed earlier. And let’s imagine
a firm solving this problem for the \( n \)th time period. If we think about a full set of alternatives to solve this problem, the theory slices it into two subsets – one containing the currently used solution and the other containing the rest of over \( 95 \times 10^{12} \) alternatives. The theory does not explain how the first subset, containing the currently used solution, has come into being, i.e. how a strategic planning problem for a division has become rule-based. As Simon (1997: p. 89) states:

“… the routines themselves are embodiments of “once and for all” decisions”, and applying them in particular circumstances is a decision, albeit often itself a routine one. When routines take over, our analysis must turn to the process that created them, and those that lead, from time to time, to questioning, reviewing and periodically revising them. Since Barnard, we have been aware that determining the occasions for decision (or for not taking a decision) is itself a key element in the decision process.”

If the problem had over \( 95 \times 10^{12} \) alternatives when the firm was solving it for the first time, how was the decision made in the first time period? The firm surely was not endowed with the routine – it had to create one, and that definitely took a long time. The theory has no explanation for the process of creation and evolution of a standard operating procedure, a routine, or a program. Furthermore, the theory tells us that we are more likely to consider an alternative from the second subset if the division’s performance was below the aspiration level but it does not tell us which alternative from the second subset we are going to choose\(^5\). The problem continues to be organizationally intractable, and the original meaning of satisficing, as discussed by Simon (1979; 1997), has been lost.

**Heuristics.** The research program on heuristics has also emerged from Simon’s original writings on bounded rationality (Simon, 1955; 1956). Heuristics are defined as “strategies that ignore information to make decisions faster, more frugally, and/or more accurately than more

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\(^5\) Computational models built on the idea of aspirations avoided this problem by reducing number of alternatives to just two (see, for example, Denrell and March, 2001).
complex methods” (Gigerenzer and Gaissmaier, 2011: p. 453). Heuristics can be a powerful way to make decisions (Gigerenzer, 2008), particularly suitable for strategic decision problems where perfect rationality and optimization are not appropriate. Like the behavioral tradition, the research on heuristics also draws on the concept of search. However, unlike the behavioral tradition that focuses on search for alternatives, research on heuristics focuses on search for cues – “reasons and predictors when decided between given alternatives” (Gigerenzer and Selten, 2001). Heuristics are designed to exploit the structure of the environment when it actually exhibits regularities and cue-goal relationships can be learned. In that sense, heuristics are ecologically rational because they adapt to the structure of the environment, but that also makes them highly domain-specific (Gigerenzer, 2001).

In management literature, research on organizational heuristics does not boast the same kind of legacy as does the Carnegie School. The situation is very different in the field of artificial intelligence where heuristics research is very prominent and its legacy is substantial (Newell and Simon, 1976; Pearl, 1984; Lucci and Kopec, 2013). However, the management literature on heuristics has been growing (see Loock and Hinnen (2015) for review). The focus of management scholars has been more on what heuristics managers use and less on whether heuristics that are used actually facilitate accurate decision making in organizations and are superior to more complex tools. For example, Bingham and Eisenhardt (2011) studied what heuristics IT firms learned during internationalization. They found that firms developed a portfolio of heuristics that was refined and simplified over time. And although Bingham and Eisenhardt (2011) have suggested that a set of learned heuristics constituted a competitive

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6 It is interesting that the NK modeling literature that has provided most promising insights on the structure of the environment and its effects on search has chosen a structure of the environment that is essentially random, i.e. it does not exhibit any regularities that firms can identify and exploit.
advantage to the firms in the sample, we cannot say whether the firms would have been better off otherwise, without explicit comparisons to more complex methods of decision making. There is, however, a study published in the *Journal of Marketing* that compares the performance of a heuristic used by retailers to the performance of a more sophisticated model (Pareto/NBD model) that predicts customer purchase (Wubben and Wangenheim, 2008). A Pareto/NBD model estimates a number of parameters, including purchase over lifetime and dropout rate, and makes distributional assumptions across customers. A heuristic that managers used was simply a recency of the last purchase: if a customer did not purchase anything in a certain number of months, she was considered inactive. It turned out that managers actually did not need to know the lifetime of customers’ purchases or purchase frequency. The accuracy of the heuristic was at least as good as the accuracy of the Pareto/NBD model.

However, is the “less-is-more” effect true for any organizational decision problem? The issue here is that strategic decision problems could be very different from each other; therefore, we have only barely scratched the surface in developing our understanding of which heuristics work for what kind of problems (in a normative sense) and the scope of their generalizability. When do we need to gather more information and when do we need to ignore some of the information we have in order to make a better decision? What influences these choices? Similar to routines and standard operating procedures in a behavioral theory, the origins and dynamics of heuristics are poorly understood.

**Cognition.** Despite significant interest in the role of cognition in decision making demonstrated by multiple disciplines, including cognitive psychology, artificial intelligence, philosophy, and neuroscience, cognition does not have a proper home in any of the prominent theories of decision making in organizations research. It does not have a place in rational
decision theory because complete information and infinite cognitive abilities are assumed. However, research streams on search and heuristics discussed earlier have also been surprisingly wary of incorporating cognition into their agenda and models. Both research streams have called for more attention to cognition (Gavetti et al., 2007; Loock and Hinnen, 2015).

Given that cognition is often vaguely defined in the literature and can mean different things to different people, it is important to state clearly assumptions and definitions that will be used and advanced in this study. Humans, and by extension organizations, are assumed to operate as information processing systems (Newell and Simon, 1972; Tushman and Nadler, 1978). The information and knowledge that exist in the world are perceived, encoded, and stored into knowledge structures in the long-term memory (Anderson, 2000). Information and knowledge come from events that we either experience ourselves or observe others experiencing them. We process and encode events differently; therefore, there is no such thing as an objective account of an event by a human observer. What we deal with is an internal, or mental, representation (Newell and Simon, 1972). Each of us has a mental representation of the world, but when we deal with a particular problem, we isolate knowledge structures that we believe to be relevant to the problem and create a mental representation of the problem.

The process of isolating relevant knowledge structures and creating a mental representation of the problem is essential for organizational decision making. As Simon (1997) states:

“Economic man purports to deal with the “real world” in all its complexity. The administrator recognizes that the perceived world is a drastically simplified model of the buzzing, blooming

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8 There is a debate on whether human cognition and inference are fragile and inferior to logic and rationality (Nisbett and Ross, 1980; Kahneman and Tversky, 1996) or robust and functional in the context of uncertainty and complexity that decision makers face (Holland et al., 1986; Gigerenzer, 1996). This study adopts the latter view.
confusion that constitutes the real world. The administrator treats situations as only loosely connected with each other – most of the facts of the real world have no great relevance to any single situation and the most significant chains of causes and consequences are short and simple. One can leave out of account those aspects of reality – and that means most aspects – that appear irrelevant at a given time.”

Mental representations are critical for dealing with strategic decision problems because they make problem spaces of strategic decisions smaller. When a problem is computationally intractable, mental representations influence what alternatives are considered first. The more the underlying structure of the problem is unknown to a decision maker, the more her beliefs about regularities in the structure become critical in directing her search for alternatives. When a problem involves uncertainty, beliefs about uncertain outcomes of various alternatives affect what alternatives are considered and which one is eventually selected.

The research on the role of mental representations in decision making is still in its infancy in the management literature, particularly with respect to understanding the emergence and dynamics of beliefs about the structure of the problem and about consequences of alternatives. Understanding how decision makers develop beliefs about strategic decision problems and their solutions is especially critical in organizational settings where many decisions are made repeatedly, over and over\(^9\). Why some organizations develop rigid beliefs and struggle to adapt while others remain flexible and nimble for change is important to reconcile theoretically. A dynamic view of mental representations and the associated inductive decision making offers a fruitful ground to do so.

\(^9\) It is interesting that the research on repetitive decision making resulted in the advancement of highly non-cognitive view in a way of routines and standard operating procedures. As discussed earlier, it is not clear how routines and standard operating procedures emerge in the first place. If they are the evidence of highly automated, non-cognitive behavior, there had to be a point in the past when making a decision for a particular problem has shifted from being a deliberate choice to being an automatic habitual behavior.
THEORY DEVELOPMENT

Knowledge — the missing pivot in Simon’s scissors

Let us consider faculty hiring decisions in universities. Each university department makes such decisions almost every year. These decisions are not trivial. Departments need to identify their needs, form a recruiting committee, advertise positions, screen applicants, interview candidates and select the ones to give offers to. It is unlikely that the process of candidate selection is entirely scripted. Some aspects of it could be standardized – for example, the application submission process is most likely to be standard from year to year. But there is likely to be a good amount of deliberation on which candidates to invite for interviews and, among the ones interviewed, which ones to give an offer to. How do departments make these choices? What do departments take into consideration when they decide? Do they consider the quality of a candidate’s training, number of publications, importance of a research topic, status of the candidate’s advisor, or other factors? How do these factors weigh into decisions?

Or let us consider patent renewal decisions in R&D intensive firms. Every firm that has been granted a patent in the United States is subject to paying a renewal fee at the end of 4, 8, and 12 years since the grant date. A number of patents for which renewal decisions are made can run into hundreds and thousands in some large firms, and these decisions are typically handled by the firm’s intellectual property office (Khanna, Guler, and Nerkar, 2016). A number of scholars suggest that a renewal decision is inherently related to the patent value (Pakes, 1986; Moore, 2005) but other factors such as an overall firms’ portfolio, competition, new
technologies, and interdependencies may play a role as well (Liu et al, 2008; Khanna et al, 2016). How do then firms weigh these different factors and make patent renewal decisions?

Both decisions, faculty hiring and patent renewal, are organizational problems, for which finding the optimal solution is not feasible. In both cases, organizations would like to select the best possible alternative – to hire the best candidate and to retain patents with the highest value while letting go useless ones. However, in both cases, evaluations of consequences of alternatives are complicated by uncertainty that stems from genuinely not knowing future outcomes. A university department has to judge the quality and future productivity of a candidate based on what she has accomplished to date, while the IP office of a firm has to judge future cash flows from a patent that may not even be a marketable technology yet. There is no way for university departments and IP offices to optimize their respective decisions, but can organizations make problem spaces of these decisions smaller? And if they can, then how?

Simon (1990) emphasized that in studying human problem solving and decision making it is important to consider both “the structure of the task environment and computational capabilities of the actor” – like the two blades of a scissors. The research that has grown out of Simon’s original writings on bounded rationality (Simon, 1955; Simon, 1956) has often focused only on one of the blades (Tversky and Kahneman, 1974; Levinthal, 1997; Fang and Levinthal, 2009), with just a fraction of research that has looked at both (e.g., Gavetti and Levinthal, 2000; Gigerenzer, 2008). While the use of the metaphor has been powerful in driving significant theoretical developments, taking it literally may have led researchers to discount the importance of another phenomenon in decision making and problem solving – that actors often vary dramatically in what and how much they know about the structure of the task environment and strategies useful in that specific environment.
Knowledge is the missing pivot in Simon’s scissors that actually holds blades together and allows the actor to “cut” through a problem space of a strategic decision problem and make it smaller. Actor’s cognitive abilities may not be sufficient to find the optimal solution, but they may be sufficient to extract useful information from the structure of the problem to find a better solution rather than worse. Newell and Simon (1976) called this ability intelligence. However, for an actor to act intelligently, she needs to know what useful information the structure of the problem can provide and what solutions are better than others given the structure of the problem. The key word here is “to know”. As Simon (1997 [1947]: p. 94) states:

“Rationality implies a complete, and unattainable, knowledge of the exact consequences of each choice. In actuality, the human being never has more than a fragmentary knowledge of the conditions surrounding his action, nor more than a slight insight into the regularities and laws that would permit him to induce future consequences from a knowledge of present circumstances.”

But where do “fragmentary knowledge… and slight insight” come from? Can we have more knowledge and better insights, and will they actually be helpful in solving a strategic problem? Also, what does it mean to know more in the context of solving strategic problems?

Before addressing the above questions, it is useful first to consider what knowledge is in general as well as in an organizational context. Although a common word, knowledge does not have a unique definition that unequivocally says – this is what knowledge is. Knowledge is difficult to define and even more difficult to measure, and it is true at both individual and organizational levels of analysis (Polanyi, 1958; Grandori and Kogut, 2002; Argote and Miron-Spektor, 2011). The term ‘knowledge’ is often used interchangeably with other terms, such as skill, competence, know-how, expertise, and capability (Winter, 1987; Simon, 1990; Kogut and

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10 By an actor, I mean an individual, a computer, or an organization. As argued before, strategic problems that organizations face are such that even a supercomputer cannot solve it optimally. Thus, it is not just a limitation of a human mind, and thus cannot be addressed by a calculating machine or multiple minds put together.

11 Checking various dictionaries yielded several definitions that were quite different in a conceptual sense.
Zander, 1992), which may or may not be appropriate for a specific context or research question. I will argue that in the context of solving strategic problems for which optimization is not feasible, it is appropriate to use these terms interchangeably, as long as we accept a proposition that knowledge is dynamic and may not be veridical at a given point in time. I elaborate on this below.

A definition useful to the conceptualization of knowledge advanced in this study can be found in Nelson and Nelson (2002: p. 721): “… knowledge is a general term referring to the content of all the long-term memory/representations humans possess”. Knowledge here is defined purely in cognitive terms – intentionally so. While I acknowledge the existence of knowledge externalized in procedures, programs, routines, manuals, reports, et cetera, I argue that such externalized knowledge is only a by-product of knowledge that resides in mental representations. When an actor decides to follow a known procedure, she makes a mental choice to forgo other alternatives, i.e. she makes a conscious or unconscious decision that following a procedure is the best action given what she knows. When the actor uses a report prepared by others to educate herself about the problem, the information in the report will be perceived, encoded, and stored in her mental representation, just as any other information, fact, or event that the actor experiences. The knowledge in the mental representation at a point in time will drive decisions that the actor makes.

If knowledge is the content of a mental representation, then what does a mental representation contain? The key aspect of the conceptualization developed here is that knowledge is a hybrid of facts, beliefs, and values. Information and facts from experience are interpreted by the actor and cannot be separated from her beliefs and values. In fact, the entire content of mental representations is better thought of as just a set of beliefs — some beliefs
coincide with facts, while others may not reflect the objective reality. However, this distinction holds true only if the objective reality can be identified as such. In the context of strategic decision problems that organizations face, the objective reality may not be readily available to actors for knowing. Let’s consider investment decisions to develop new technologies. Naturally, we will prefer to invest in technologies whose commercialization potential is higher. However, because technologies are not developed yet, their real commercial value is not known. As technology development progresses, we will know a little more about the relative potential of various technologies, but the true values will still be unavailable to us, because technological trajectory in part depends on the decisions made earlier in the development. We cannot know where we would have ended up had we taken the path we never travelled. For example, can we know what the world would have been like if Facebook had never started? In situations where values and their differences among social groups play a key role, the objective reality is also not obvious. Public policy is a prominent example of a decision space, where values cannot be separated from facts (Nelson and Winter, 1982: p.382), but for-profit organizations have also been gaining attention as battlegrounds of values. Commercialization of stem cell research is an interesting example in this regard, because apart from uncertainty associated with the technology itself, there is also much ambiguity about the greater good or greater evil of stem cells that is driven by religious arguments.

Knowledge is endogenous to a decision maker and thus can never be fully objective. Thinking of knowledge in this way has important implications for our treatment of human rationality. Can rationality be ever truly objective? Simon (1997 [1947]: p. 85) defined a decision objectively rational if “in fact it is the correct behavior for maximizing given values in a given situation”, and subjectively rational if “it maximizes attainment relative to the actual knowledge
of the subject”. However, the definition of an objectively rational decision is troubling, because it is not clear who has the authority to decide what the correct behavior for a given situation is. Is 180 degrees the correct answer to the question “What do angles of a triangle add up to?” Is 100 degrees the correct answer to the question “At what temperature does the water boil?” If the answers to such seemingly objective questions are not uniquely defined, then what can we say about less obvious situations such as the market shift from the analog photography to the digital photography? Was Polaroid wrong to believe that razor-blade model would work for the digital technology\textsuperscript{12}? Would we say that Polaroid was at least subjectively rational? Or was it not maximizing its value relative to what it knew at that point in time? This is a very difficult question to answer given the subsequent developments of the industry and the knowledge we have acquired since then – it is difficult to shake off the hindsight and ignore our personal beliefs about the industry and events that took place in the past.

What an actor knows then matters to how she solves problems. Typically, the actor has a vast amount of general knowledge in her long-term memory. However, when she faces a specific problem, only knowledge deemed relevant to the problem is assimilated into a mental representation of the problem. If the actor has never faced the problem, she is likely to know very little about its structure or what solutions exist to address it. If she has dealt with the problem multiple times, she may have developed some theories on what the underlying structure of the problem is and what solutions work for solving it. The mental representations of the problem are very different in these two cases. Research in cognitive psychology has demonstrated empirically that problem representations of novices and experts have very different knowledge content and structure for problems in chess, physics, programming, evaluation of

\textsuperscript{12} Tripsas and Gavetti (2000) is an in-depth case study of Polaroid at the time of transition to digital photography.

Having different knowledge makes experts perform better than novices in some contexts but not in others. Experts seem to have performance advantage in solving physics problems, programming, and chess. However, experts have failed to perform significantly better than novices in many other domains, including clinical psychology diagnosis, economic and financial forecasting, and evaluation of applicants’ merit for studies and jobs (Goldberg, 1959; Dawes, 1971; Armstrong, 1978; Johnson, 1988). These research findings raise an important question of what it means to be an expert in a particular domain. Is somebody an expert because of having experience or superior problem solving ability? Research in cognitive science historically had an implicit assumption that more experience translates into superior problem solving, but this bias can be partially explained by the fact that the domains that have been traditionally the focus of problem solving research (physics problems, programming) are the problems for which it is feasible to find the optimal solution. It is possible that in the context of problems for which it is not feasible to find the optimal solution – such as medical diagnosis, economic forecasting, or strategic decision making, experience does not always get translated into superior problem solving ability. Therefore, while actors may acquire more knowledge as they gain more experience, the knowledge may not be veridical.

Chess does not seem to fit the explanation above because chess is clearly a type of a problem which it is impossible to optimize. However, the puzzle of expertise in chess can be resolved by seeing that an expert in chess studied in the literature is somebody who has an enormous amount of experience (more than 10 years) and enormous amount of knowledge stored
in a mental representation (more than 50,000 patterns of chess positions). It is not quite clear what happens in between having no experience at all and having an enormous amount of experience. However, this is the space where most organizations find themselves in – most of the times they have to learn about the problem structure and solutions that work to solve the problem from a very small sample of decisions they have made or observed others make.

This discussion leads to the two important questions that we can ask in the context of repeated decision making. Faculty hiring and patent renewal decisions, discussed in the beginning of this chapter, are made repeatedly and present organizations with opportunities to gain superior knowledge about these strategic problems. The first question that we can ask is how to acquire the right kind of knowledge from a limited experience – the knowledge about the structure of the problem and solutions that are effective for solving it. Second, how much experience does one need to have with the problem to be able to solve it effectively?

Experience leads to more veridical knowledge about the problem and its solutions only when five conditions are met. First, the structure of the problem is not completely random, i.e. there are patterns and regularities in the structure that can be exploited to find better solutions. Second, the patterns and regularities can be discovered through experience. Third, the actor is not punished for failing to solve the problem and can continue to look for a better solution after failure. Fourth, the actor believes that there are regularities in the structure and makes an effort to look for them. And fifth, the heuristics that the actor chooses to search for solutions and choices that she makes do not limit the problem space to such an extent that regularities cannot be observed and better solutions cannot be discovered.

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13 That experts in chess store in their long-term memory nearly 50,000 patterns of chess positions that allow them to play at the superior level seems to be one of Simon’s favorite examples of expertise. It is mentioned in Simon (1990; 1996) and Newell and Simon (1976).
Emergence and dynamic development of knowledge

There are different ways to view problem solving as a cognitive activity (Thagard, 2005). Most popular metaphors include viewing problem solving as search, reasoning, or constraint satisfaction (Simon, 1983). I rely on the search metaphor and look at problem solving as search through a problem space, where one state corresponds to the initial state (where an actor is before solving a problem), one or more states correspond to a goal state (where the actor wants to be when she solves the problem), and there are many states in between (Newell and Simon, 1972; Anderson, 2000). The actor needs to find operators that allow her to move from one state to another, until she reaches the goal state (Simon, 1983).

A problem space could be thought of as either a set of alternatives or as a set of cues (or characteristics of the environment), or both. For example, in the chocolate problem discussed earlier, alternatives such as asking a stranger, singing, or stealing are states in the space of alternative decisions that an actor can take. The problem space for the chocolate problem could also be thought of as a set of alternative worlds depending on how things play out after the actor takes action. It could include a world (a) where the actor gets the chocolate but is embarrassed, (b) gets the chocolate but then is caught by the police, (c) gets the chocolate and is very happy after eating it, (d) does not get the chocolate and is angry, etc. In the strategic planning decision problem, also discussed earlier, variables such as cost of beef or changes in consumer preferences constitute cues that an actor may pay attention to while devising a strategy. Some of the variables may also serve as potential action points (e.g. we can negotiate a lower cost of beef as part of the strategy). Thinking of the problem space from different perspectives may potentially lead to finding better solutions to the problem — although this is an important research question and deserves a separate consideration, it is beyond the scope of this study. For
the purpose of this study, a problem space consists of a set of alternative solutions that have different payoffs. A goal state then is a solution whose payoff is above the threshold value specified by the goal. Even if an objective problem space exists for a given problem, each decision maker will search through a mental representation of the problem space — this is a crucial aspect of my view of problem solving, common with the view of problem solving in theories of complex adaptive systems, mental models, and induction (Holland et al, 1986; Cowan, Pines, and Meltzer, 1994; Johnson-Laird, 2006).

Problems that are computationally intractable or characterized by high levels of uncertainty often have extremely large problem spaces. Wandering blindly through different states in such problem spaces may not prove fruitful in a limited time span that organizations usually have to solve these problems. Decision makers are better off searching intelligently through the problem space — by using heuristics that allow them to get to a goal state in a shorter time, if at all (Newell and Simon, 1976). Heuristics exploit the knowledge about the structure of the problem space, but actors are unlikely to have such knowledge when they face the problem for the first time. Repeated exposure to the same kind of problem allows actors to accumulate information and revise their knowledge about the problem; however, even repeated problem solving does not guarantee that the knowledge emerging from experience is veridical or generalizable beyond specific problem instances. Faculty hiring and patent renewal decisions are interesting in this regard. On the one hand, the nature of decisions is the same every time period — faculty members need to be hired and patents need to be valued and renewed (or not). On the other hand, potential candidates are unique and different from the ones before, and so are the patents. What knowledge is generalizable and useful from one time period to another and what knowledge is too context-specific to be retained and be useful the next time? The issue of
generalizability and usefulness of knowledge is magnified when we try to apply knowledge accumulated from experience with one class of problems to a new class of problems. The phenomenon is known as analogical reasoning and is quite common in the business world (Gavetti and Rivkin, 2005; Gavetti, Levinthal, and Rivkin, 2005). An extensive research in cognitive psychology and a more recent research in management show that analogical reasoning is not always effective and may even backfire (Gick and Holyoak, 1983; Bassok and Holyoak, 1989; Markman and Gentner, 1993; Gavetti et al, 2005; Gary, Wood, and Pillinger, 2012). Major issues with using an analogy, if one was found and applied to the new problem, stem primarily from the fact that knowledge that is applied to the problem is simply not appropriate for it.

Therefore, if an organization has to solve a particular problem repeatedly, investing in understanding the problem and acquiring veridical knowledge about its structure and appropriate solutions is of paramount strategic importance to the organization. It could be thus argued that organizations that are more deliberate about learning the problem structure and its solutions will be better off long-term, than companies that are less deliberate and do not invest in such learning\(^\text{14}\).

Solving a new problem starts with creating a mental representation of a problem by pulling together current information from a given problem statement (whether explicit or implicit) and any previous knowledge that is deemed relevant to the problem. An actor attempts to understand the problem first – comprehend given information, analyze various problem elements and identify conceptual relationships between them (Hayes and Simon, 1974; Greeno,

\(^{14}\text{One could say that companies that are less deliberate are the ones that develop rigid routines or standard operating procedures for dealing with particular type of problems. However, as Nelson and Winter (1982) note on several occasions, companies may also have routines for deliberate learning, which does not contradict my argument. Therefore, I do not think that my view is in contrast with routine-based view of organizational behavior advanced in the Carnegie School tradition.}\)
From given information, the actor tries to extract specification of the goal, the distance from the initial state to a goal state, and constraints that need to be satisfied\(^{15}\). The reality of course is usually much more complicated than what is described above. Problems differ in the extent to which these elements of the initial problem representation are specified or present, which is driven both by the nature of the problem as well as by resources and capabilities of a problem solver (Simon, 1956; Simon, 1973; Jonassen, 2000; Anderson, 2000; Gavetti and Levinthal, 2000). There is heterogeneity among decision makers in what information they are able to extract from the problem statement, because processing new information is conditional on what is already known (Simon, 1983; Johnson-Laird, 2006). Some problems do not have well-specified goals (Cohen, March, and Olsen, 1972). If the actor does not know what the target is, it could be difficult to figure out how far she is from it. And even if the actor knows what the goal is, she may have a misunderstanding of where she is in the problem space. For example, managers and entrepreneurs often overestimate what they know and underestimate what they do not know (Cooper, Woo, and Dunkelberg, 1988; Kahneman and Lovallo, 1993; Schrage, 2015). Constraints are also often misidentified, especially among first-time entrepreneurs who often don’t recognize the bottlenecks that operations or finances can create. Another issue with objectives and constraints is that it is often difficult to disentangle them. In fact, Simon (1997: p. 154) suggests that we should think about problem solving as finding a solution that satisfies a set of goals or a set of constraints instead of a single goal.

\(^{15}\) Given that a problem space here is defined as a set of alternative solutions available to the actor, I assume that an actor is aware of possible operators if she is able to construct a problem space. While it is a strong assumption, it does not take away heterogeneity of operators available to different decision makers nor does it imply that decision makers use appropriate operators to solve the problem.
accompanied by a set of constraints. This view of multiple criteria for decision making is adopted here.

If an actor knows nothing about the problem structure, she does not have any knowledge about which directions of search will be more beneficial than others, i.e. she does not know which operators to use. Specifying a set of constraints could be a reasonable first step. The terms ‘constraint’, ‘goal’, ‘aspiration’, and ‘target’ are treated as synonyms here and refer to minimum (when more is better) or maximum (when less is better) threshold values that a decision maker establishes as satisfactory for variables of interest. In general, the variables of interest to the decision maker include both inputs and outputs. It could also be said that they include both cues and outcomes. For example, in the strategic planning problem, the organization can set up constraints on cue variables (e.g. cost of beef) and outcome variables (e.g. desired profitability next year). Similar to the issue of separating goals and constraints discussed above, separation of cue variables and outcome variables may also not be straightforward. Moreover, in the context of the current study, it is not critical to separate them. Therefore, going forward, constraints will be considered in a single vector, without explicit division in cues and outcomes.

A set of constraints serves multiple functions as it aids solving a problem with a large problem space. The first function is to direct search. Constraints help slice the problem space into smaller, more manageable segments, potentially converting a computationally intractable problem into a tractable one. In some cases, constraints can reduce the problem space so much that optimization becomes possible. My recent purchase of a car serves as a good example. By specifying a very strict (and quite idiosyncratic) set of constraints on what I want from a car, I rather quickly reduced a set of feasible alternatives to less than 10 and had no issue identifying the best alternative within that set. Was it an optimal choice among all possible alternatives? I
can almost guarantee that it was not, even with respect to my preferences. However, it was a choice that satisfied all criteria I wanted it to satisfy at the time of purchase – I did not have to compromise, which could by itself be considered a great accomplishment. Organizations rarely get away without compromising at least along some dimensions (Cyert and March, 1963).

The second important function of constraints is to help an actor evaluate usefulness of alternative solutions in order to gain knowledge about the structure of the problem. When a decision maker does not have the knowledge about true values of alternatives, constraints allow the actor to gather some useful information. Let us look at a simple problem, for which there is a set $S$ of $N$ strategies $S_j$ available to the actor for consideration. Each strategy has a true value $Q^*(S_j)$, but the true values are unknown to the actor. If the actor sets a threshold value $P^*$ for a desired outcome, such that a realized payoff $Q(S_j)$ should be at least as large as $P^* (Q(S_j) \geq P^*)$, then $P^*$ could be used to judge the usefulness of strategies that have been tried. If payoffs are deterministic and the actor has enough resources to try all $N$ strategies, then after $N$ trials, the actor can identify the best alternative, and there is no need to specify a constraint. However, if payoffs are non-deterministic and judgments have to be made over a limited number of trials, constraints allow for more efficient gathering of information about tried strategies. Specifically, strategies can be judged as useful or not useful for achieving a desired payoff. If the actor encodes strategies’ usefulness in some structured manner and stores in her memory, this knowledge can be used later as an input to deciding which strategy to pick. As long as the actor does not have a complete knowledge, the actor will be making a decision inductively.

Despite the virtues of constraints in directing search and aiding acquisition of knowledge, there are serious shortcomings of constraints that an actor should be aware of. First, constraints may severely limit the actor’s ability to find better solutions in later trials, if she has to solve the
problem repeatedly. By slicing the problem space and restricting the actor to only a part of it, constraints may prevent her from exploring other regions of the problem space (Simon, 1997: p.75). Second, constraints may also limit subsequent acquisition of knowledge, precisely because they played a role in initial acquisition of knowledge in the first place. As Johnson-Laird (2006: p. 176) states, “we reason in service of our goals”. While judging the usefulness of strategies relative to goals is an efficient way to gather information in a given context, using this information in a different context or under different set of constraints becomes increasingly difficult. Thus, there is always a tradeoff for the actor to solve the problem in short-term versus gathering information and developing knowledge about the problem structure in the long term.

Third, in organizations, there could also be an issue of hierarchical division of specifying constraints and searching for appropriate solutions. People at different levels of organizational hierarchy often have different knowledge bases. If constraints specified at one level are driven by the knowledge not available to the level below — a level that is responsible for finding a solution, the organization will not only have a problem that has not been solved, but also disappointed managers and frustrated employees.

There are few other important observations about constraints. First, constraints do not have to be inter-temporarily fixed. That means that a decision maker can alter existing constraints, remove some constraints, and add others, as she gains more knowledge. Second, constraints do not have to be precise or clear. In fact, as long as the actor’s knowledge about the structure of the problem remains largely imperfect, it will be impossible, if not foolish, to impose any sort of precise constraints. Third, a vector of constraints does not have to include an outcome variable, at least not in its traditional sense. That could seem as heresy to scholars of rational choice theory; however, there is value to be found even in undirected, or blind, search. Consider
for example, explorations by companies such as Alphabet or Facebook, or some of the scientific discoveries. Conceptually, these ideas have been displayed quite prominently in writings on decision making with ambiguous goals (e.g. March, 1978; Simon, 1996); however, there seems to be less appreciation of these ideas in vast empirical literature on aspirations.

Specification of constraints is itself a subject to the actor’s knowledge. Sometimes, the situation calls for some arbitrarily set values just to get things going. This is one of the reasons why constraints should never be viewed as fixed and precise. However, even in the absence of complete knowledge about the structure of the problem space, the actor can use information from the environment to specify values for constraints. My conjecture is that constraint specification could be one way for decision makers to change the way they experience problems and potentially improve acquisition of veridical knowledge. The question then is whether different ways of specifying constraints to direct search and gather information lead to differences in actor’s knowledge and subsequent performance. In the next section, I will discuss different sources of information that could be used to set constraints in order to search for solutions and learn about the problem structure in the absence of a complete mental representation of the problem.

**Implications of constraint specification for knowledge development and performance**

*Exogenous goal.* Let us start by considering the following situation. An actor is presented with an unfamiliar problem. There exist several alternative solutions that could be useful for solving the problem but the actor does not know how good payoffs of alternative strategies are. Because the problem is unfamiliar, the actor also does not know what level of payoff is possible to achieve in a given problem space. We often observe that actors use external
performance benchmarks for problems that they have never experienced before. One such external benchmark is an exogenous goal given to the actor by a third party. An example of an exogenous goal is a target issued by a higher level in an organization (e.g. a sales target) or a milestone set by an alliance agreement (e.g. very common in R&D alliances in the pharmaceutical industry).

Setting a goal is not an ordinary task. The goal serves as an efficient constraint if it allows an actor to differentiate between superior and inferior strategies. To differentiate correctly between superior and inferior strategies, the actor needs a goal that will lead to an inference that inferior strategies are useless to solve a problem, and superior strategies are useful. To visualize, let us continue with an abstract example introduced earlier. We assume that there are \( N \) available strategies with payoffs \( Q(S_j) \) distributed around true values \( Q^*(S_j) \). We further assume that true problem space is one-dimensional and such that it is limited by the true value of the worst strategy on the left, i.e. \( \min_{S_j} Q^*(S_j) \), and by the true value of the best strategy on the right, i.e. \( \max_{S_j} Q^*(S_j) \). In this problem set, setting the goal too low may lead to the development of false beliefs that many inferior strategies are useful (Figure 1, Scenario A). If the actor is given a low goal, and in her experience she comes across an inferior strategy that happens to produce a payoff that is above the goal level, the actor will infer that the strategy is useful and will be more likely to select this inferior strategy again in the future. Correcting this false belief and identifying a better strategy will be difficult, because finding a better strategy will require that the actor explore other alternatives. However, early inferences about inferior strategies’ usefulness will reduce the actor’s likelihood to explore other strategies. Therefore, when the goal is too low for a given problem space, actors are likely to settle on inferior alternatives.
Setting a goal too high will lead to the rejection of many alternatives, including superior ones (Figure 1, Scenario B). If an actor is given a very challenging goal and tries inferior strategies early in her experience, she will make inferences that inferior strategies are in fact inferior. Inferring that tried strategies are useless increases exploration and thus the likelihood of finding a better alternative. However, if superior strategies happen to produce a low payoff that falls below a challenging goal, they too will be considered useless, forcing the actor to continue exploring. Therefore, a very challenging goal leads the actor to explore too much and make her less likely to settle on any specific alternative. This argument suggests that there exists a level of a goal, which is neither too low nor too high, that results in superior knowledge development and superior performance outcomes. This level of goal also corresponds to the optimal balance between exploration, i.e. trying different strategies, and exploitation, settling down on a strategy that is believed to be the best. This leads to the following propositions:

**Proposition 1:** The effect of the goal level on accuracy of beliefs that the actor develops from experience is curvilinear. Accuracy of beliefs increases as the goal level increases but after a point it starts decreasing as the goal becomes more challenging.

**Proposition 2:** The effect of the goal level on performance is curvilinear. Performance increases as the goal level increases but after a point it starts decreasing as the goal becomes more challenging.

**Proposition 3:** Level of exploration increases linearly with the goal level.

**Proposition 4:** The exogenous goal will be the most effective in guiding search and knowledge development when it is in the neighborhood of the solution with best true value.

The discussion above and Propositions 1–4 suggest a mechanism that is different from the ones advanced in the goal-setting theory (Locke and Latham, 1990). The goal setting theory generally suggests that there is a linear relationship between goal level and performance\(^\text{16}\). The

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\(^\text{16}\) Research in goal-setting finds that task complexity serves as a moderator variable with effect sizes usually much smaller in complex tasks, than in simple tasks (Locke and Latham, 2002). However, the nature of the relationship
argument is that a hard and specific goal resolves the uncertainty of what is achievable in a given task (Locke et al., 1989). According to the goal-setting theory, there are four mechanisms that explain the effect of a difficult goal on performance (Locke and Latham, 2002). Goals (1) direct attention and effort, (2) energize, (3) improve persistence, and (4) prompt the actor to recall and use the knowledge and skills appropriate to the task. The arguments of these mechanisms hinge on the three important assumptions. First, it is assumed that a party that sets the goal has the knowledge of problem structure. In other words, the goal accurately indicates what is achievable in a given problem space. Second, it is assumed that the actor (a) has access to appropriate information about the problem and alternative strategies, (b) is able to convert this information into knowledge, and (c) uses it to solve the problem. Third, it is assumed that the actor’s experience provides unambiguous feedback. Even if the first assumption is true, there could be differences between knowledge held by the party who sets an exogenous goal and knowledge of the actor who is trying to solve the problem. In addition, if the actor has to learn from experience about the merit of different strategies, her learning becomes endogenous to the goal.

The goal-setting theory further argues that a very challenging goal in complex tasks hampers learning (Ordonez et al., 2009). The explanation is purely motivational — a challenging goal and failure to reach the goal decrease an individual’s desire to explore alternative solutions (Kanfer and Ackerman, 1989; Locke and Latham, 2002). However, my argument is that even if the actor’s motivation to solve the problem remains high, her ability to learn from experience is curtailed because her inferences are very likely to be wrong. Therefore, I suggest that it is not the failure to adequately explore the problem space but rather the failure to make correct inferences

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remains unchanged and has been explained by other factors (such as setting a learning goal or proximal goals) to keep the main idea intact.
about the merits of strategy that is the primary mechanism behind the negative effect of a very challenging goal on performance.

**Competitor’s performance.** In the real world, actors rarely operate in a vacuum where they are the only ones trying to solve a problem. In the business context, there are usually competitors who are likely to be dealing with the same kind of problems. Irrespective of whether the focal actor has information on what strategies are tried by a competitor, competitor’s performance alone may provide useful information about the problem. Competitor’s performance may indicate what is attainable within a given problem space. The information on competitor’s performance becomes particularly valuable when the actor is not familiar with the problem and does not know what level of performance is feasible.

The issue of competitor’s performance has long been studied in social psychology and management. In social psychology, it is considered in research on social comparisons, i.e. comparisons between self and others, which also include comparisons of who the others are and what they do. Social comparisons significantly influence individual judgments and behaviors (Corcoran, Crusius, and Mussweiler, 2011). When actors have access to information about others’ performance or achievements, they tend to relate this information to their own performance and achievements (Dunning and Hayes, 1996). In management and organizations research, competitor’s performance has a prominent place in the literature on learning from performance feedback (Greve, 2003), and on imitation and vicarious learning (e.g. Haunschild and Miner, 1997; Haunschild and Sullivan, 2002). These streams of research have been long concerned with how organizations select a comparison group to form a social aspiration point (Haveman, 1993; Porac *et al*, 1995; Greve, 1998b) and how decision making is affected by the organizational performance relative to this aspiration point (Cyert and March, 1963; Greve,
1998a; Baum et al, 2005; Baum and Dahlin, 2007; Iyer and Miller, 2008; Gab and Bhattacharya, 2012). The empirical findings suggest that competitor’s performance could be salient to a decision maker. However, we still know very little about exact mechanisms. The main limitation of the extant research is that proposed mechanisms cannot be directly observed or tested. In most situations, organizations are assumed to pay attention to a certain aspiration point which is based on competitive performance (e.g. industry average), but researchers do not know whether the companies actually are paying attention to that specific reference point. Moreover, research has shown that there is heterogeneity of attention to competitor’s performance across companies and across time (Blettner et al, 2014). This suggests that we still know very little about the effects of social aspirations on organizational learning, change, and performance. Therefore, here I consider whether using competitor’s performance as a constraint helps or hinders the acquisition of veridical knowledge and the achievement of high long-term performance.

Let us look at a couple of scenarios. Let us first consider that the actor faces a superior competitor, i.e. the actor’s own performance is below that of the competitor. If competitor’s performance is higher than a payoff the actors receives from trying a particular strategy, that strategy will be considered useless. In other words, superior performance of a competitor will indicate to the actor that there probably exist strategies with better payoffs. This inference will trigger the actor to explore other alternatives. If the actor continues to benchmark payoffs of various strategies against competitor’s performance, and competitor’s performance happens to be extremely high (such that it is beyond what is possible in the given problem space), most strategies will be considered useless for solving the problem (Figure 2, Scenario A). Paying attention to an unusually high performance of a competitor may prove to be counterproductive.
Seth Goldman and Barry Nalebuff, the co-founders of Honest Tea, discuss in their book how Jones Soda, another beverage company, was valued at 20 times their sales in 2007. Even though Honest Tea founders realized that Jones Soda was overvalued, they nevertheless tried to use the competitor’s performance as a benchmark in their negotiations with Coca-Cola. Thankfully, Coca-Cola did not take the bait (Goldman and Nalebuff, 2013: p. 246). Jones Soda’s stock plummeted in a matter of months, and is now selling for less than a dollar.

Facing an inferior competitor generally should have the opposite effect. Judging the usefulness of strategies by comparing their outcomes to the performance of the inferior competitor leads to the development of a false belief that many ineffective strategies are appropriate. This way of learning becomes pathological when performance of an inferior competitor falls below the true value of the worst strategy (Figure 2, Scenario B). If benchmarking against an unusually high performance of a competitor leads to excessive exploration, benchmarking against an unusually low performance of a competitor leads to insufficient exploration and high likelihood of settling on inferior strategies. This leads to the following proposition:

**Proposition 5:** Using performance of a superior competitor as a constraint results in higher level of exploration than using performance of an inferior competitor.

What happens when the actor is given an exogenous goal but also pays attention to competitor’s performance? I argue that the use of competitor’s performance as an additional constraint reduces the effectiveness of search and learning triggered by attention to the goal. When the actor faces a superior competitor, most tried strategies, including superior ones, will be judged as useless. If the actor has tried a strategy and found that it was helpful to meet the goal, she may nevertheless discard the strategy because it was not good enough to beat the competitor. Therefore, facing a superior competitor will lead to increased search even if strategies that meet
the goal have been identified. When the actor faces an inferior competitor, most tried strategies, including inferior ones, will be judged as useful. If the actor found a strategy ineffective for achieving the goal, she may nevertheless hold on to it because it was good enough to beat the competitor. Therefore, facing an inferior competitor will lead to insufficient search even if the goal requires a higher level of achievement. This discussion leads to the following propositions:

**Proposition 6:** Using an exogenous goal as a constraint results in higher accuracy of beliefs than using a combination of an exogenous goal and competitor’s performance, regardless of the level of competitor’s performance.

**Proposition 7:** Using an exogenous goal as a constraint results in higher performance than using a combination of an exogenous goal and competitor’s performance, regardless of the level of competitor’s performance.

**Proposition 8:** Using an exogenous goal as a constraint results in higher exploration than using a combination of an exogenous goal and performance of inferior competitor and in lower exploration than using a combination of an exogenous goal and performance of inferior competitor.
A COMPUTATIONAL MODEL TO EXPLORE CONSTRAINT SPECIFICATION

.Multi-armed bandit model

I develop ideas discussed in the previous section formally in the context of the multi-armed bandit model. The multi-armed bandit is an important model to study dynamic learning from feedback in the presence of Knightian uncertainty and has been widely used in disciplines as diverse as statistics, economics, computer science, and psychology (e.g. Gittins and Jones, 1974; Arthur, 1991; Sutton and Barto, 1998; Rieskamp and Otto, 2006). Even though the bandit model has been around for quite some time in the organizations literature (Lave and March, 1975; Denrell and March, 2001; Greve, 2002), the interest in it among management scholars has only recently experienced a considerable uptick (e.g. Posen and Levinthal, 2012; Stieglitz, Knudsen, and Becker, 2016; Puranam and Swamy, 2016; Lee and Puranam, 2016).

The multi-armed bandit is a sequential choice problem, where an actor has \( N \) alternative solutions (arms) with unknown payoff distributions. The only way the actor can learn the underlying payoff distribution of any arm is by trying it. Naturally, the actor would like to select the arm with the highest expected payoff at each time period but she will have to find it first, and the feedback she receives from each trial is ambiguous. At each time period, the actor has to make a decision based on the knowledge she has developed up to that point. However, the knowledge may or may not be veridical, and the actor may or may not be aware of that. The question, therefore, is how much to explore before settling on any particular arm. This is a classic exploitation – exploration tradeoff (March, 1991). This tradeoff becomes more critical,
when the ratio of number of arms to the number of available trials increases or when there is a likelihood for the actor to be selected out if she happens to draw a lower payoff. Each trial is an opportunity to gather more information to potentially benefit long-term performance if a better performing arm (or maybe even the best) is found; however, exploration can undermine short-term performance, threatening the actor’s survival. To take again the example of repeated patent renewal decisions, an organization would like to explore different ways of defining value of patents, but the risk of foregoing valuable patents and keeping useless ones is quite substantial.

The multi-armed bandit serves as a good simplified representation of a particular type of problem where deductive reasoning and perfect rationality do not work — the one where consequences of alternatives cannot be computed with reasonable accuracy. It is not well-suited for the other types of problems discussed earlier, namely when a complete set of alternatives is not known or cannot be evaluated in a reasonable amount of time. However, the uncertainty alone creates an obstacle to identifying the optimal solution. Solving the problem, and by solving I mean finding a satisfactory solution, depends on the quality and accuracy of knowledge that a decision maker has at a given point in time and her ability to recognize that what she knows may be wrong.

Therefore, the key element of the multi-armed bandit model is the specification of the choice function. There are three things to consider when specifying the choice function. First, to what extent can the actor take advantage of any information in a problem statement or general knowledge (Simon, 1983)? This will affect what information will be attended to at each trial and

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17 Computational intractability may arise even in the context of the bandit problem, if an actor forms a problem space that consists of numerous possibilities for potential values of each arm and then attempts to run scenarios to predict outcomes of picking an arm considering various possibilities. It may become even more computationally intractable if scenarios include sequences of time periods and not just evaluations of what to do in the next time period – what is known as the search for the optimal strategy (Gans, Knox, and Croson, 2007). This is, however, beyond the scope of the current study.
used for making decisions in subsequent trials. Second, how does the actor assimilate new information? How much weight is given to new information? This will define how existing beliefs are updated. And finally, how much does the actor trust that knowledge she has reflects reality? This will define how likely the actor is to act on her existing beliefs — in other words, how likely the actor is to select an alternative with the payoff currently believed to be the highest.

I use the multi-armed bandit to build an agent-based model. Scholars in economics and statistics are concerned with finding the optimal solution to the bandit problem, and a number of closed-forms solutions to special cases of bandit problems exist (e.g. Gittins and Jones, 1974). Agent-based models are not used, however, to find under what conditions the system is in equilibrium (Arthur, 2013). Instead, they allow a researcher to model the task environment, agents’ decision heuristics, and the updating process (how new information is assimilated into a decision heuristic) and then evaluate individual and population-level outcomes over time. The objective of building the agent-based model is thus to observe how agents’ behavior and task environment interact, how path dependency unfolds, and through that gain new insights about the system’s dynamic behavior.

The problem space in the bandit model is represented by a set of alternative strategies $S = [S_1, S_2, \ldots, S_N]$ and their payoffs. Depending on the chosen distribution for specifying payoff functions of each strategy, distribution parameters serve as cues for the actor to use them to build her decision heuristics and updating rules. For example, if outcomes of each choice are drawn from a normal distribution with mean $\mu$ and standard deviation $\sigma$, then both these parameters can be used by the agent to evaluate alternatives that have been tried. For any unknown parameter, an actor needs to make three decisions. First, she needs to decide whether to
pay attention to it, assuming that she is aware of it. Second, she needs to develop a method of estimating the parameter based on the imperfect information she receives from experience. Third, the actor needs to decide how to incorporate information about the parameter estimate into the choice function.

When specifying the bandit model, there are choices to be made about the type of distribution, distribution parameters and cues. I make several important assumptions. First, for each strategy $S_j$, payoffs are drawn from a normal (Gaussian) probability distribution with mean $Q^*(S_j)$ and variance $\sigma^2 = \mathcal{C}$. Therefore, I assume all strategies have the same variance that is also constant over time. Second, because variance is assumed to be constant and same across strategies, I also assume that agents do not pay attention to variance and do not attempt to estimate it. The only parameter from the problem space that the agents pay attention to is the estimate of the mean payoff for each arm.

As actors do not know the true values of strategies, they have to make decisions based on incomplete knowledge that they have at the time of making a decision. Actors develop and update beliefs about merits of each strategy based on their experience. There are few traditional ways to specify belief updating rules and choice rules that I will discuss below, before introducing new assumptions based on the discussion of constraints in the previous section.

Actor $i$ is assumed to have a set of beliefs at time $t$, $V_{i,t} = [V_{i,t}(S_1), V_{i,t}(S_2), ..., V_{i,t}(S_N)]$, where $V_{i,t}(S_j)$ is a vector of beliefs about the value of strategy $S_j$ at time $t$. In a traditional set-up, $V_{i,t}(S_j)$ is a scalar that captures an estimate of the mean payoff. It is estimated as a weighted function of the belief in a previous time period and a realized payoff in the current time period, such that:

$$V_{i,t}(S_j) = V_{i,t-1}(S_j) + \varphi \times (Q_{i,t}(S_j) - V_{i,t-1}(S_j)) \quad (1)$$
$Q_{i,t}(S_j)$ is a realized payoff for strategy $S_j$ if it was tried at time $t$. The parameter $\varphi$ regulates how much new information about a strategy contributes to the actor’s belief about the value of this strategy. A special case of this updating rule is a simple average of realized payoffs from all trials with strategy $S_j$.

The choice function could be specified to maximize with respect to existing beliefs or as a probabilistic choice rule (Puranam et al., 2015). Maximizing with respect to existing beliefs is known as greedy action selection rule in the artificial intelligence literature (Sutton and Barto, 1998). This choice rule makes the actor always pick a strategy that is believed to have the highest payoff at the time of making a decision, i.e. based on the information that the actor has gathered up to that point. Therefore, in accordance with the greedy method, actor $i$ picks up $\max_{S_j} V_{i,t}(S_j)$ at time $t+1$. Doing so is naturally incredibly myopic when the actor knows little about the problem. Therefore, the probabilistic choice rule may be more appropriate. In accordance with this rule, the probability of picking a particular strategy is proportional to its value to the decision maker. One probabilistic choice function established in the literature is known as softmax selection rule (Sutton and Barto, 1998), where probability of choosing strategy $S_j$ at time $t+1$ is defined as:

$$P_{i,t+1}(S_j) = \frac{e^{V_{i,t}(S_j)/\tau}}{\sum_{j=1}^{N} e^{V_{i,t}(S_j)/\tau}} \quad (2)$$

Apart from the relative values of strategies, the choice is also determined by a positive parameter $\tau$, called the temperature (Sutton and Barto, 1998). Low temperatures make the actor to put more weight on her current mental representation – in other words, the actor is more likely to act on current beliefs. When the temperature is sufficiently low ($\tau \to 0$), softmax selection rule is equivalent to greedy action selection rule. High temperatures could be thought of as
reflecting the actor’s awareness of the fallibility of her knowledge. The higher the temperature, the more current representations are discounted (Puranam et al, 2015). At very high temperatures, the actor is almost indifferent between alternatives and has nearly equal probability of selecting any alternative, irrespective of their values.

While the traditional approach in bandit models is to use actual payoffs in estimating strategies’ values, the research in psychology and management suggests that decision makers may judge the value of alternative solutions as successes and failures relative to the reference point (Holland et al, 1986; Levitt and March, 1988; Greve, 2003). By using Simon’s (1955) suggestions on simplifying value functions, the value of each strategy can be coded as a success or failure relative to a specified constraint. Compared to making calculations of actual payoffs and keeping track of them across time, the actor can instead only keep track of whether a particular strategy has been useful. If a strategy \( S_j \) has been useful in meeting the constraint \( P^* \) at time \( t \), the value of this strategy increases. If it has not been useful, its value decreases. More formally, we can specify the belief of actor \( i \) about the value of a strategy \( S_j \) at time \( t \) as follows:

\[
V_{i,t}(S_j) = \begin{cases} 
V_{i,t-1}(S_j) + 1, & \text{if } Q_{i,t}(S_j) \geq P^* \\
V_{i,t-1}(S_j) - 1, & \text{if } Q_{i,t}(S_j) < P^*
\end{cases}
\]

(3)

If the actor uses two constraints (\( P_1^* \) and \( P_2^* \)), then she is assumed to make two independent judgments of the strategy’ usefulness, which are then combined in the following way:

\[
V_{i,t}(S_j) = \begin{cases} 
V_{i,t-1}(S_j) + \alpha \times 1 + (1 - \alpha) \times 1, & \text{if } Q_{i,t}(S_j) \geq P_1^* \text{ and } Q_{i,t}(S_j) \geq P_2^* \\
V_{i,t-1}(S_j) + \alpha \times 1 + (1 - \alpha) \times (-1), & \text{if } Q_{i,t}(S_j) \geq P_1^* \text{ and } Q_{i,t}(S_j) < P_2^* \\
V_{i,t-1}(S_j) + \alpha \times (-1) + (1 - \alpha) \times 1, & \text{if } Q_{i,t}(S_j) < P_1^* \text{ and } Q_{i,t}(S_j) \geq P_2^* \\
V_{i,t-1}(S_j) + \alpha \times (-1) + (1 - \alpha) \times (-1), & \text{if } Q_{i,t}(S_j) < P_1^* \text{ and } Q_{i,t}(S_j) < P_2^*
\end{cases}
\]

(4)

If \( \alpha=0.5 \), then an actor pays equal attention to both constraints. The strategy value, once encoded in terms of successes and failures, is then used in the probabilistic choice rule based on
softmax action selection specification. By using this simplified value function, I want to study its effectiveness in the acquisition of the veridical knowledge and the achievement of long-term performance. I consider two simulation experiments. The first experiment explores how different levels of exogenous goal affect exploration, acquisition of accurate beliefs, and performance. With this, I address Propositions 1, 2, 3, and 4. The second simulation experiment adds performance of inferior and superior competitor as a second constraint, in a combination with an exogenous goal. With this, I address Propositions 5, 6, 7, and 8.

**Model specification**

A computational model based on multi-armed bandit requires specification of a set of parameters. In this section I describe the specification of parameters associated with (a) problem space, (b) choice function, and (c) value function.

**Specification of the problem space.** A problem space in the multi-armed bandit consists of a set of strategies and their associated payoffs. Number of strategies in the main simulation experiment are set to \(N=8\), while in the sensitivity analysis, I also explore \(N=4\) and \(N=12\). The expectation is that a larger number of strategies make it harder to locate better strategies. Payoffs for each strategy are drawn from the normal distribution with a mean that falls in the interval \(PS = (4, 6)\) and variance of 1 (\(C=1\)). Distributions from which payoffs are drawn do not change over time. With this specification, the problem of finding a superior alternative is sufficiently hard, because even the worst strategy may produce payoffs that fall anywhere in problem space. In other words, there is sufficient overlap in distributions of payoffs produced by different strategies. In the sensitivity analysis, I also explore a smaller interval \(PS = (4, 5)\) and a larger
interval $PS = (4, 8)$. The expectation is that a wider problem space makes it easier to locate superior strategies.

The problem space is given the following structure. The entire problem space is divided into 4 chunks, and means for 25% of strategies are drawn from a uniform distribution, corresponding to the chunk. For example, in the main experiment, with $N=8$ and $PS = (4, 6)$, means for 2 strategies are drawn from the uniform distribution $(4, 4.5)$, means for the next 2 strategies – from the uniform distribution $(4.5, 5)$, next 2 strategies – from the uniform distribution $(5, 5.5)$, and the last 2 strategies – $(5.5, 6)$. With this structure, the analysis always considers number of strategies to be a multiple of 4. Having such rigid structure allows me to ensure consistency across trials. In other words, keeping the structure constant, I can be sure that the differences in outcomes are driven by differences in constraint specification, and not by differences in the problem structure\textsuperscript{18}.

**Specification of the choice function.** The choice function is based on the softmax selection rule (Formula 2) and involves specifying the temperature $\tau$ – a parameter that regulates to what extent an actor acts on her current beliefs. The higher the value of $\tau$, the more the actor questions her beliefs. The parameter $\tau$ is sensitive to the magnitude of a belief $V_{t, x}(S_j)$ about the value of strategy $S_j$; it is also sensitive to the differences in beliefs between strategies. In the main simulation experiment, $\tau$ is set at 0.25. When $\tau=0.25$, the actor is most likely to choose a strategy that she believes to have the highest payoff based on her experience\textsuperscript{19}. In the sensitivity analysis, the following additional values for $\tau$ are considered: $\tau = (0.5, 0.75, 1.0, 1.5, 2.0)$.

\textsuperscript{18} Simulations were replicated on problem spaces without chunks. Results hold.

\textsuperscript{19} It is important to note that when $\tau=0.25$, an actor pursues greedy search strategy most of the times. However, on occasion, the actor may choose a different strategy if expected payoffs of different strategies are very close to each other. That makes a softmax action selection rule at $\tau=0.25$ work more like a $\varepsilon$-greedy search with a very small value of $\varepsilon$ (Sutton and Barto, 1998: p. 28).
**Specification of the value function.** The value function at time zero is equal to zero for all strategies and all agents. To update beliefs after each time period, I use Formula 3 and Formula 4. For this, I need to specify $P^*$. First, I consider exogenous goals. To comprehensively study the effect of exogenous goals, I specify a range of goals that cover the entire problem space in a given simulation. In the main experiment, where $PS = (4,6)$, I consider the following levels of exogenous goals: $P^* = (3.5, 3.75, 4.0, 4.25, 4.5, 4.75, 5.0, 5.25, 5.5, 5.75, 6.0, 6.25, 6.75)$. Once set, the goal level stays the same across the entire course of simulation.

Second, I consider competitive performance. I create two stylized competitors – an inferior competitor and the superior competitor. When an actor faces an inferior competitor, $P_{ic}^*$ is defined as $P_{ic}^* < \left< \left(\min_{S_j} Q^*(S_j) \right) \right.$ In the main experiment, $P_{ic}^* = 3$. When an actor faces a superior competitor, $P_{ic}^*$ is defined as $P_{ic}^* > \left(\max_{S_j} Q^*(S_j) \right)$. In the main experiment, $P_{ic}^* = 7$. In addition, I need to specify $\alpha$, which is equal 0.5 in all simulations.

**Other specifications.** Each scenario considers 100 agents sampling strategies for 100 time periods on the same problem space. All extracted measures are averaged first across 100 agents, and then across 2,000 replications\(^{20}\). Belief accuracy is calculated as the proportion of actors that at time $T=100$ believes that the best strategy in a given problem is in fact the best. Cumulative payoff is calculated as the sum of realized payoffs across 100 time periods, averaged across actors. Number of strategies tried across 100 periods is calculated as the number of unique strategies sampled across 100 time periods, averaged across actors. Number of strategies tried in the last 50 periods is calculated as the number of unique strategies tried in the last 50 time periods, averaged across actors.

\(^{20}\) In each replication, when goal level is varied, the problem space stays the same. Similarly, when testing the addition of competitor’s performance, results on the same problem space are compared.
Simulations are structured according to the following process. First, I generate a problem space. Second, within the problem space, I generate a certain number of groups with 100 agents in each that search according to different rules. In the first simulation experiment, where I consider exogenous goals, there are 13 goal levels. Therefore, I generate 13 groups of agents that search in the same problem space. In the second simulation experiment, there are 13 levels of goals and 3 scenarios (no competitor, inferior competitor, and superior competitor). Therefore, I generate 13×3=39 groups of agents that search in the same problem space. Third, I repeat the first and second steps 2,000 times.

**Simulation experiment #1: Analysis of effects of exogenous goals**

I begin the analysis of constraints by considering effects of setting up an exogenous goal. When an actor has very little knowledge about a problem, setting an exogenous goal could be very difficult. Without knowing what level of performance is feasible to achieve in a given problem space, it is impossible to say whether the goal is high enough to ensure that the actor does not settle with inferior strategies but also realistic enough for an actor to actually be able to achieve the goal. While this seems quite intuitive, what we do not know is where that threshold lies relative to the problem space.

I start by analyzing outcomes of bandit model for different levels of goals. Figure 3 captures belief accuracy and cumulative payoff as a function of the goal level. In this simulation scenario, the number of strategies is N=8, the interval for the problem space is PS = (4, 6), and τ=0.25. In line with Proposition 1, the goal level has a curvilinear effect on belief accuracy. Similarly, in line with Proposition 2, the goal level has a curvilinear effect on cumulative payoff. As the goal level rises, actors develop more accurate beliefs and achieve higher performance.
With higher goal level, actors are able to make better judgments about the merit of different strategies and are more efficient at discarding inferior strategies and retaining superior strategies. However, after a point, a higher goal starts having a detrimental effect on the quality of judgments that actors make about the merit of different strategies. When the goal is too ambitious, actors discard most strategies they try and continue searching for better strategies. This excessive exploration results in lower performance.

In Proposition 4, I suggested that the tipping point in curvilinear effects described above should be in the neighborhood of the solution with best true value. Although pretty close, it is not exactly the case. Actors do seem to develop more accurate beliefs the closer the goal gets to the state with the highest achievable outcome. However, the best outcomes are achieved when the goal isolates a couple of top-performing strategies, not just the best one. In Figure 3, we can see that the goal level of $P^*=5.5$ – the one that divides the problem space into one chunk with 2 highest performing strategies and the other one with remaining (lower performing) strategies – results in the highest belief accuracy. When a goal is set at this level, the evaluation of strategies is very efficient. Inferior strategies are deemed useless, while superior strategies are deemed useful for achieving the goal and retained. There is a disadvantage to setting a goal higher than that. Given that even the best strategy can sometimes result in a subpar performance, it seems that the goal that provides some buffer is better than a higher goal that is more rigid and has a higher likelihood of leading to an inference that the best strategy is not useful. Other than the development of wrong beliefs, setting a goal at very high levels has a more tangible disadvantage. At very high goal levels, the goal cannot actually be achieved. In this scenario, the goal is achieved as long as it is set at or below $P^*=5.5$ — a constraint that separates a top quartile of strategies.
As the goal level changes, it has different implications for knowledge accumulation and performance. As we can see in Figure 3, there is a zone in the problem space (approximately between 4.75 and 5.75), where substantial differences in belief accuracy are associated with much smaller differences in performance. This suggests diminishing returns to exploration. A higher goal leads to higher likelihood of rejecting strategies that have been tried. When actors try other strategies, they have a higher likelihood of finding a better strategy, but in the process of searching for it, performance may drop if inferior strategies are discovered.

Setting up goals at various levels also has different implications for variability of outcomes. Figure 4 depicts standard deviations of belief accuracy and cumulative payoff across 2,000 replications. There is a curvilinear effect of the goal level on variability of belief accuracy and cumulative payoff. Interestingly, the highest variability is observed when the goal is set very close to the state with the highest achievable outcome. When the goal is at $P^*=5.75$, actors are likely to discover a superior strategy, but they are also very likely to fail. It is informative to compare distributions of cumulative payoff at two goal levels: $P^*=5.25$ (the level at which the highest payoff is achieved) and $P^*=5.75$ (the level at which payoffs exhibit the highest variance).

Figure 5 compares histograms of cumulative payoffs for the two goal levels side by side. While maximum potential payoff is similar across two goal levels, the distribution has a longer and fatter left tail at $P^*=5.75$ where lower payoffs are much more likely.

I have argued in Proposition 3 that the knowledge and performance outcomes with respect to the goal level are driven by differences in exploration dynamics. Figure 6 shows how exploration changes across goal levels. As the goal level increases, actors sample a higher number of strategies, eventually sampling all of them across time at a very high goal level. Although I observe an increase in exploration as the goal level increases, the relationship is not
linear, unlike Proposition 3 states. We observe that as the goal level increases, there is an increase in number of strategies tried overall, but exploration declines rapidly in the last 50 periods, effectively resulting in exploitation of only one strategy. We observe this effect as long as the goal level \( P^* \leq 5.25 \). After this point, we observe a dramatic increase in exploration, which does not decrease with time. Therefore, the relationship between goal level and exploration has more of an S shape than a straight line.

Previous research using bandit models suggests that higher levels of exploration are usually beneficial for generating new knowledge, but are detrimental for performance (e.g. Posen and Levinthal, 2012). However, what I find here suggests that there could be a limit to which more intense exploration is beneficial — even for developing more accurate beliefs (see Figure 7). Whether more intense sampling of different strategies results in the acquisition of more accurate beliefs depends on how new information is encoded in knowledge structures and how those beliefs are formed. If it is true that we “reason in service of our goals” (Johnson-Laird, 2006), then it is possible that the quality of acquired beliefs is only as good as the goals are.

Higher level of exploration is only beneficial to an extent that it results in accurate inferences about the usefulness of different strategies. At high goal levels, many strategies, including good ones, are deemed useless, which prevents the actor from developing accurate beliefs about high performing strategies and forces her to explore other strategies. When an actor is able to differentiate efficiently between inferior and superior strategies, the values of different strategies become more distinct, exploration decreases, and the actor starts exploiting accumulated knowledge. However, we can see that exploration does not reduce efficiently at higher goal levels. On the other hand, we observe an efficient reduction in number of strategies sampled at lower goal levels. The higher performance results when a reasonably high number of strategies
are sampled initially, but then only one or two strategies are exploited in the later time periods. Therefore, what we want is balance between initial exploration and subsequent exploitation, where a sufficiently large number of strategies is sampled in early time periods, but only one or two strategies are exploited in later time periods.

I examined the sensitivity of results to changes in (a) the temperature $\tau$; (b) size of the problem space; and (c) number of strategies $N$. First, I consider changes in $\tau$. Main simulation experiment was based on a very small temperature ($\tau=0.25$), which means that actors are very likely to act on their current beliefs. In the sensitivity analysis, I analyze higher levels of $\tau$. With increase in temperature, actors are more likely to question their current beliefs. While performance declines as the parameter $\tau$ increases, it does so in a similar way across all goal levels, preserving the same kind of curvilinear effect that we observe in the main experiment.

Second, I consider changes in the size of the problem space. The main simulation experiment was based on $PS=(4,6)$. In the sensitivity analysis, I analyze the outcomes of decreasing ($PS=(4,5)$) and increasing ($PS=(4,8)$) the size of the problem space. Decreasing the size of the problem space increases the difficulty of distinguishing among the strategies. It pushes the optimal goal level downwards, but only slightly. When $PS=(4,5)$, $N=8$, and $\tau=0.25$, the optimal goal level falls in the middle of the problem space ($P^*=4.5$), as opposed to a top quartile we observed in the main experiment. All other outcomes are the same. The slight downward shift in the optimal goal level provides additional evidence that a more flexible goal is better than a more rigid goal (thus further contradicting Proposition 4). Third, I consider changes in number of strategies. In the main experiment, number of strategies was fixed at 8. In the sensitivity analysis, I analyze effects of decreasing ($N=4$) and increasing ($N=12$) number of strategies. Increasing number of strategies makes it more difficult to find better performing strategies and thus requires
more sampling. When \( N=12 \), we observe an increase in sampling, but overall results are the same as in the main experiment. Therefore, the sensitivity analysis suggests that effects of setting an exogenous goal on performance, knowledge, and exploration are robust across different levels of parameters.

Table 1 compares how model results stand against Propositions 1, 2, 3 and 4. While Propositions 1 and 2 are supported, Propositions 3 and 4 are not, but in a subtle way. Although I do find a curvilinear effect of the goal level on knowledge and performance, as suggested by Propositions 1 and 2, the optimal goal level is not in the neighborhood of the optimal solution, as suggested by Proposition 4. According to model results, the optimal goal level allows for inferences that at least a couple of top performing strategies are useful. This flexibility increases the chances of making correct inferences and decreases the likelihood of rejecting superior strategies. A higher goal level leads to a higher likelihood of rejecting strategies that have been tried and increases exploration, but at very high goal levels, exploration becomes excessive and does not reduce efficiently with time because actors are not able to identify superior strategies. While Proposition 3 suggests a linear increase in exploration, we observe more of an S shape, where actors explore too little at low goal levels and explore too much at high goal levels.

Theoretically, these results have several important implications. First, they suggest that there is more that we need to understand about the mechanism that explains the relationship between a goal level and performance. To be effective for finding superior solutions and achieving superior performance, a goal should help an actor distinguish between strategies with superior outcomes and strategies with inferior outcomes. If the goal is so high that it does not divide the problem space in an efficient manner, the quality of beliefs that actors develop about usefulness of strategies declines substantially, exploration increases, and performance declines.
Goal-setting theory attributes this effect to the drop in motivation and commitment when the actor perceives the goal as unattainable and explores less, reducing their chance of finding a better solution (Locke and Latham, 2002). However, results in simulation experiment #1 demonstrate that even if actors stay motivated and committed, a very challenging goal leads to subpar performance, solely because actors evaluate strategies relative to the goal level, find strategies that they try to be ineffective, and continue searching for better ones. A very challenging goal may lead to perfection syndrome, with which actors explore a lot but learn a little.

Therefore, the second theoretical implication is that these findings provide support to the following assertion made by March (1991, p. 71):

“Adaptive systems that engage in exploration to the exclusion of exploitation are likely to find that they suffer the costs of experimentation without gaining many of its benefits. They exhibit too many undeveloped new ideas and too little distinctive competence.”

However, I further extend March’s ideas on exploration by addressing the question of why actors explore more. I suggest that if goals are used to generate inferences about the problem structure, then exploration is an endogenous outcome of knowledge development. Actors only explore more because they believe they have not found the best strategy yet and thus continue searching. Whether actors’ beliefs are more or less likely to be accurate depends on the goal level.

This brings us to the third theoretical implication. I find that there is a strong positive correlation between quality of acquired knowledge and performance. However, both the knowledge and performance were a result of the process of making inductions based on experience relative to the goal level. In the simulation experiment, actors that paid attention to different goals had the same initial beliefs at time zero but eventually differed in the quality of knowledge they developed and performance they were able to achieve. The only difference was
the level of goal that they paid attention to. This suggests that we should give a more careful consideration to the context in which actors learn about the problem structure. It seems that performance advantage could arise simply because the goal happened to be set at the right level, which facilitated acquisition of accurate beliefs. The focus on the context in which actors learn complements previous research on the role of cognition in learning that mostly focused on characteristics of the problem, such as interdependencies, complexity, or feedback delays (e.g., Sterman, 2000; Denrell, Fang, and Levinthal, 2004; Gary and Wood, 2011).

Finally, the results have an implication for how we think about the virtue of optimization as an organizational objective in the context where the problem structure is unknown to actors. While the best performing strategy leads to superior performance if applied consistently, searching for the best strategy may prove counterproductive. Excessive exploration results in inferior performance, because the more actors search the more they are likely to come across inferior strategies than superior ones. It further implies that if the party that sets a goal has the knowledge what level of performance can be achieved in a given problem space, while actors do not know what strategy results in the highest performance, the party is better off setting a modest goal for actors rather than a challenging one. A modest goal will ensure that actors engage in sufficient exploration to increase chances of finding a better solution but do not develop a perfection syndrome in the process.

**Simulation experiment #2: Analysis of effects of competitor’s performance**

In the second experiment, I analyze the effects of using information on competitor’s performance for setting up constraints, in addition to exogenous goals. I introduce stylized inferior and superior competitors. It means that no matter what actors do, their performance is
always above the performance of a competitor (when there is an inferior competitor) or below (when there is a superior competitor). I compare 3 scenarios: (a) actors use only an exogenous goal to evaluate strategies; (b) actors use a combination of an exogenous goal and inferior competitor’s performance to evaluate strategies; and (c) actors use a combination of an exogenous goal and superior competitor’s performance to evaluate strategies.

Figure 8 shows cumulative payoffs and Figure 9 shows belief accuracy across these 3 scenarios and goal levels. The results suggest that there is only partial support to Propositions 6 and 7. Using an exogenous goal alone results in the highest cumulative payoffs and most accurate beliefs only within a specific region of the problem space. Specifically, Figure 10 captures proportion of trials in which cumulative payoff from a scenario where actors pay attention only to the exogenous goal exceeds cumulative payoffs from the two scenarios where actors also pay attention to competitor’s performance. We can see that only at some goal levels, Proposition 6 is supported in 100% of trials.

It seems that paying attention to competitor’s performance in addition to an exogenous goal has a negative effect on knowledge and performance only when the exogenous goal itself is effective. Particularly, using the exogenous goal as a constrain pays off really well when the goal is set in such a way that it allows to distinguish between inferior and superior strategies in an efficient manner. This is a zone where accurate inferences are most likely to be made. As the goal allows to make more accurate inferences, paying attention to competitor’s performance, in addition to the goal, hurts the actor’s performance in this zone. It hurts performance when the actor pays attention to a superior competitor, because superior strategies are undervalued, i.e. they are considered useless when comparing their payoffs to a superior competitor’s performance, thus reducing the efficiency of distinguishing between strategies. It also hurts
performance when the actor pays attention to an inferior competitor because inferior strategies are overvalued, i.e. they are considered useful when comparing their payoffs to an inferior competitor’s performance, again reducing the efficiency of distinguishing between strategies. Figure 11 (in the middle) shows that when the goal is set at $P^*=5.5$, paying attention to an inferior competitor results in insufficient number of strategies explored, while paying attention to a superior competitor results in persistent excessive exploration. Paying attention to only the exogenous goal at $P^*=5.5$ results in sampling a good number of different strategies initially that is later reduced to exploitation of only two strategies.

Second, it seems that paying attention to an inferior competitor is beneficial when the goal level is very high. To explain this result, one can think of it as a competitor’s performance serving as a reality check. When the goal is extremely high, almost all strategies are deemed useless for achieving the goal – we saw in the analysis of results from Simulation experiment #1 that at high goal levels actors continue to engage in excessive exploration over time. However, when they observe performance of an inferior competitor, actors have an additional information signal that strategies that they try may not be that useless — at least they are good for beating the competitor. In other words, strategies that are deemed useless when evaluated against a very high goal level are deemed useful when evaluated against a competitor’s performance. This double evaluation that provides opposite inferences reduces exploration in a more efficient manner, than an exogenous goal alone, as can be seen in Figure 11 (on the right).

Figure 11 provides indirect support to Proposition 5. Although I did not test the effects of using competitor’s performance alone, when competitor’s performance is combined with exogenous goal, actors that observe performance of superior competitor explore more than actors that observe performance of inferior competitor. This difference in the level of exploration holds
across different goal levels. Results provide only partial support to Proposition 8. Proposition 8 is supported only when the goal is set at a moderate level. When the goal is very high, there is not much difference in the level of exploration by actors that only use an exogenous goal and actors that use a combination of the exogenous goal and performance of a superior competitor. At a very high goal level, actors already reject virtually all strategies that they try and continue to explore; therefore, paying attention to a superior competitor does not make things any worse. At the same time, paying attention to an inferior competitor neutralizes some of the false inferences and results in efficient reduction of exploration as discussed above. When the goal level is very low, there is not much difference in the level of exploration by actors that only use an exogenous goal and actors that use a combination of the exogenous goal and performance of an inferior competitor. At a very low goal level, actors explore very little, because the very first one or two strategies that they try are likely to be found useful; paying attention to inferior competitor only reinforces these beliefs. However, at very low goal levels, paying attention to superior competitor results in an inference that there could be better strategies, thus forcing actors to explore more.

As I have done in Simulation experiment #1, I examined the sensitivity of results of Simulation experiment #2 to changes in (a) the temperature \( \tau \); (b) size of the problem space; and (c) number of strategies \( N \). First, I consider changes in \( \tau \). An increase in temperature makes it more likely that the actor will question her existing beliefs. Performance superiority of using only exogenous goal shifts downwards with respect to the goal level as the parameter \( \tau \) increases. Figure 12 shows cumulative payoff across the three scenarios and across goal levels when \( \tau=2.0 \). Figure 13 captures a proportion of trials in which cumulative payoff from a scenario where actors pay attention only to exogenous goal exceeds cumulative payoff from scenarios where
actors also pay attention to competitive performance when $\tau=2.0$. Interestingly, an increase in temperature does not have implications for relative dynamics in accuracy of beliefs and exploration. The odd result is that there is no high correlation between accuracy of beliefs and performance, particularly at lower goal levels when $\tau=2.0$. Actors that pay attention to both exogenous goal and performance of superior competitor develop more accurate beliefs than other groups but this knowledge advantage does not result in performance advantage. On the other hand, actors that pay attention only to exogenous goal develop less accurate beliefs but achieve a much better performance than the group that also pays attention to superior competitor. Second, I consider changes in the size of the problem space. Increasing or decreasing the size of the problem space does not have a substantive effect on the nature of results. Third, I consider changes in a number of strategies. Increasing or decreasing the number of strategies also does not have a substantive effect on the nature of results. Therefore, results are sensitive to changes in the temperature but robust to the size of the problem space and the number of strategies.

The comparison of results from Simulation experiment #2 with Propositions 5, 6, 7, and 8 is summarized in Table 2. While Proposition 5 is supported, Proposition 6, 7, and 8 only hold in specific circumstances. A theoretical implication of the results is that introducing an additional source of information that could be used to set up constraints does not just have a straightforward positive or negative effect. Whether having more information means better knowledge and better performance outcomes depends a lot on the quality of information sources themselves. I find that when the exogenous goal is set extremely high, it pays off to notice an inferior competitor. But when the goal itself is effective, paying attention to another source of information hurts performance. In a real-world situation, the challenge is of course to know when the goal is set right and when the competitive performance tells what’s realistic in a given space and what is
not. One possible way to deal with this challenge is to collect more information about distribution of outcomes in a given problem space. However, naturally, collection, analysis, and synthesis of data are not cheap. The issue of what information to pay attention to and how much data to collect is very important to continue to study.
AN EXPERIMENTAL STUDY: METHODOLOGY

In an experimental study, participants try to solve a problem that in reality has an optimal solution. However, in the beginning participants do not know anything about the structure of the problem or what solutions work to solve it; therefore, they may find it extremely difficult to optimize. The experimental design that has been chosen for this study allows me to explore effects of competitor’s performance on the development of knowledge, decision making, and performance. Participants are given an exogenous goal that indicates precisely the location of the optimal solution and some participants also have access to information about performance of other players. With this laboratory experiment, I explore Propositions 5, 6, 7, and 8. Below I discuss methodology and experimental design in detail.

Why a laboratory experiment?

Investigating effects of competitor’s performance on knowledge acquisition, decision making and performance of strategic decision makers is difficult in real-world settings because there are confounding effects of many other factors that are virtually impossible to control for. For example, I could have chosen to study effects of competitor’s performance on analysts in a knowledge process outsourcing (KPO) firm, as they work on projects for estimating the market size for new pharmaceutical products. As analysts work on more and more similar projects, they become more efficient in executing them. At the end of each project, they receive feedback on their work. In theory, this feedback should help them figure out how to improve their work. Hypothetically, I could introduce an experimental design in a company, so that some analysts
receive feedback only about their own performance, and others also become aware of the performance of others.

In such a field-based experiment, I would have to find a way to control for many contextual parameters on which analysts may exhibit heterogeneity. I would have to control for social dynamics in the firm, i.e. understand how analysts interact, who they are likely to compare themselves to, who they are likely to imitate and learn from. In other words, I will have to control for voluntary social comparisons. In addition, it will be impossible to differentiate effects of feedback from one’s own actions and effects of feedback from other’s actions. Moreover, there will be effects of changing environment and effects of changes in what optimal market sizing capability actually entails. For example, while analysts learn what final product of their market sizing project satisfies managers and customers the most, this optimal value of the product will also change over time. In this real world scenario with analysts in a KPO firm, it will be difficult to make causal claims, because there will be many factors affecting outcomes, which will be difficult or impossible to control for (Wilson, Aronson, Carlsmith, 2010).

Unlike this real-world setting, a laboratory experiment allows me to eliminate effects of some factors, randomize out effects of others, and make certain causal claims (Wilson et al, 2010). There are few major concerns that a lab experiment helps take care of or at least reduce their effect. First, I am concerned with being able to measure knowledge and performance objectively, thus many realistic tasks with interdependencies, noise, uncertainty, and feedback delays (e.g. a management game in Gary and Wood, 2011) pose a problem if a unique optimal solution does not exist. Therefore, in a laboratory experiment, I design a problem task that has a unique optimal solution which is feasible to find, but to participants, the underlying structure of the problem is unknown. Second, I am concerned about effects of identity and behavior
comparisons and social interaction patterns that always occur in a real world (Corcoran et al., 2011). These effects can be entirely eliminated through an experimental design. Third, I am concerned with effects of changing environment, changing nature of the problem, and changing optimal solution – the laboratory experiment allows to keep all these constant. There are still concerns about some individual characteristics of participants (such as intellectual abilities, motivation, and decision making style) that may confound effects of performance comparisons, but a random assignment of participants into treatment conditions allows us to diminish the likelihood of having this issue, as long as the sample size of each group is sufficiently large (Wilson et al., 2010). Even though I will randomize participants to treatment conditions, I intend to collect data on individual characteristics.

The experimental setting gives me an additional advantage of being able to collect data at the three levels of analysis – knowledge (mental representations), decision making behavior, and performance. To see these three levels of analysis in a single study is rare (see Gary and Wood (2011) for exception). Studies of cognition usually focus on mental models and decision making; studies of learning curves and performance usually focus only on performance and rarely consider behavior. Accessing information at all three levels is very challenging, especially in real-world settings, where we often deal with complex and ambiguous situations, or where no clear strategies exist, or where performance cannot be clearly attributed to decisions made. However, having information at all three levels is crucial in the current study. Therefore, it is important to choose a problem that can be solved with the use of clear analytical strategies and understanding of which participants can try to improve over time.

Based on the above, I have chosen to conduct a laboratory experiment, where participants play an analytical game on a computer. This experiment is low on mundane realism, because the
laboratory setting and activities in which I have engaged participants are hardly reflective of real life activities of decision makers in organizations. However, I believe that the experiment is high on experimental and psychological realism (Wilson et al., 2010). I believe that participants have taken the analytical game seriously and have been motivated to perform well. I also believe that the effect of competitor’s performance on search is the same in the lab as it is in the real world. I argue that the processes of forming mental representations, acquiring knowledge, and making decisions during the game are psychologically same as the ones that occur in real-world settings. In other words, the laboratory experiment, the way it is designed, captures the essential features of the phenomenon (Locke, 1986). The details of the experiment are described below.

**Overview of the analytical game**

For individuals to be able to learn from their experience and make relevant inferences, the problem they are facing should be neither too easy nor too complex. Previous research has shown that too much complexity impede learning (Levinthal, 1997; Gavetti and Levinthal, 2000; Sterman, 2000; Gary and Wood, 2011), while too easy problems are usually solved quickly and may not produce necessary performance heterogeneity across participants (Bandura and Jourden, 1991). Participants in the study are asked to play a game where they need to attempt to reach an optimal value of variable $Y$, which is set at 30,000, by adjusting values of the three decision variables $X_1$, $X_2$, and $X_3$. Each of the three $X$ variables can take 100 possible values, making 1,000,000 possible combinations of the $X$ variables, and only one combination corresponds to the optimal value of “$Y$”. Participants have only 20 attempts to find the optimal value of $Y$. At each attempt, participants can adjust values of as many $X$ variables as they like and receive immediate feedback about the value of $Y$ that has resulted from the last chosen combination of the three $X$
variables. To make this game sufficiently difficult for participants, I relate the three $X$ variables to the $Y$ variable through a deterministic quadratic function with equal weights, no interaction terms, and no temporal dependency. It can be expressed the following way:

$$Y = 30,000 - [(X_1 - a_1)^2 + (X_2 - a_2)^2 + (X_3 - a_3)^2]$$

(5)

$Y$ is a performance metric, $X_1$, $X_2$, and $X_3$ are decision variables, and $a_1$, $a_2$, and $a_3$ are optimal values of decision variables. Participants do not know the underlying function captured in Formula 5 and have to judge how their actions affect outcomes solely based on the feedback provided to them. Participants may employ various search strategies to achieve the goal. They may choose to adjust one decision variable at a time to observe its effect on the outcome variable, or they may choose to change more than one decision variable at a time. They may also choose to make small or large adjustments to the values of decision variables.

Given the structure of the problem, changing the values of variables one at a time is clearly the superior search strategy as it avoids confounding effects and superstitious learning. One interesting aspect of this strategy is that it often requires to forgo an immediate gain in order to have a long-term benefit, i.e. to experiment – something that organizations and decision makers within organizations are often reluctant to do (March, 1991). However, if the outcome of interest is the performance achieved at the end of a specified time period during which individuals can make several choices, we should reasonably expect that those individuals that employ “change one at a time” search strategy more consistently than others will achieve higher performance.

At the beginning of the game, participants are given the description and rules of the game. The game is described purely as a math problem challenge. The advantage of using this wording is that it presents a novel problem for participants to deal with. It enables participants to
work with a clean slate as they learn how to play the game and allows me to observe the
development of mental representations, learning from experience, and decision making – all
within the context of a problem that is new to all participants. While there may be concerns about
irrelevance of this problem to a business world, as I mentioned earlier, low level of mundane
realism is compensated by high level of experimental and psychological realism. A choice of a
problem is dictated by the need to observe development of knowledge about the problem from
scratch, therefore the more abstract the game is, the higher the likelihood is that participants will
not have any prior knowledge about the problem structure\textsuperscript{21}. Rules of the game read as follows:

“You have 3 decision variables (A, B, C) that you can manipulate to change the value of an
outcome variable Y. Each of the decision variables can take any integer value between 0 and 99.
Therefore, there are 1,000,000 combinations of values for A, B, and C. Only one of the
combinations corresponds to the optimal value of Y that is set at 30,000. As a starting point, you
are given a combination of values for A, B, and C that corresponds to Y=23,006. Can you find a
combination of values for A, B, and C that corresponds to the optimal value of Y in 20 attempts
or less? At each attempt, you can adjust as many variables as you like, and you will be given a
corresponding value of Y for every combination you select. [You will also see the performance of
another participant who played this instance of the game before you (we will call this person
Kasper).] If you reach the optimal value, you will win $10. Good luck!” (Note: Only participants
observing competitor’s performance will see the sentence in italics).

Participants are motivated to engage intellectually in the game through monetary rewards.
The rewards depend on participants’ ability to find the optimal value of “Y” – this, in turn,
depends on their ability to identify the most efficient way of adjusting the three “X” variables in
20 attempts. Without the use of efficient analytical strategies, participants are extremely unlikely
to find the optimal solution, given that there are 1,000,000 possible combinations of “X”
variables. The rewards are also structured as “all or nothing”, further motivating participants to
optimize, as opposed to satisficing. Each participant is asked to play 6 rounds of the game. The

\textsuperscript{21} The abstract novel problem does not preclude participants from using what Simon (1983) called common sense
knowledge.
reward system is structured as follows: each participant receives 10 dollars as a base reward and 10 dollars for each round of the game that he or she wins (i.e. whenever he or she finds the optimal value of 30,000). Therefore, each participant has an opportunity to get up to 70 dollars during the experiment. Table 3 summarizes the course of the game and provides an example.

**Experimental design**

Participants are randomly assigned to one of the 4 treatment conditions (see Table 4). Group 1 does not observe competitor’s performance. The remaining 3 groups observe competitor’s performance. During the game, participants in groups 2-4 do not only see their own performance, but also performance supposedly achieved by another participant, a so-called “virtual competitor”. This additional piece of information is the only thing that differentiates the treatment conditions, in which participants observe competitor’s performance, from the treatment condition, in which participants only observe their own performance. The performance of participants does not depend on the performance of a “virtual competitor”. However, performance values of a “virtual competitor” do depend on performance values of the participant.

Performance values for a “virtual competitor” will be calculated by the program to reflect one of the three scenarios in competitor’s performance conditions – inferior performance, similar performance, and superior performance. Given the original nature of the game, there are no existing benchmarks for defining inferior, superior, or similar performance. However, we could look at analogous research in organizational behavior and consumer behavior where scholars have studied perceptions of pay changes, income increases, and price changes (Uhl and Brown, 1971; Katona and Mueller, 1968; Rambo and Pinto, 1989). When we compare numbers, we can
definitively say which one is larger and which one is smaller; however, the difference between
the two numbers may not be meaningful in a cognitive sense. Research has used the idea of “just
noticeable difference” to identify what differences between numbers are large enough for people
to assign different cognitive labels to different amounts. “Just noticeable difference” can vary,
but over 80% of people notice 15% increase in price for a large range of products (Uhl and
Brown, 1968). Pay increases at 7-10% are perceived to be functionally meaningful (Rambo and
Pinto, 1989; Mitra, Gupta, and Jenkins, 1997). By using these findings as a benchmark and using
several iterations, I have created the following rules:

- When participants observe inferior performance of a competitor (Group 2), the computer
  program calculates the distance between the participant’s performance value and optimal
  value (i.e. 30,000) and does the following:
  - For distance > 100, randomly picks an integer between (Performance – 0.5*Distance)
    and (Performance – 0.2*Distance)
  - For distance < 100, randomly picks an integer between (Performance – 100) and 30,000
- When participants observe similar performance of a competitor (Group 3), the computer
  program calculates the distance between the participant’s performance value and optimal
  value (i.e. 30,000) and does the following:
  - For distance > 100, randomly picks an integer between (Performance – 0.2*Distance)
    and (Performance + 0.2*Distance)
  - For distance < 100, randomly picks an integer between (Performance – 100) and 30,000
- When participants observe superior performance of a competitor (Group 4), the computer
  calculates the distance between the participant’s performance value and optimal value (i.e.
  30,000) and does the following:
  - For distance > 100, randomly picks an integer between (Performance + 0.2*Distance)
    and (Performance + 0.5*Distance)
  - For distance < 100, randomly picks an integer between (Performance – 5) and 30,000

The key with simulating performance values of a virtual competitor is to make treatment
conditions sufficiently different. It is achieved by exposing participants to sufficiently large and
sufficiently small numbers in “superior performance” and “inferior performance” treatment
conditions respectively. In “similar performance” treatment condition, participants are exposed
to numbers both above and below the participant’s performance values (but close enough) to
indicate that the competitor is neither better nor worse than the participant.
The use of a “virtual competitor” in experimental studies is well-established (Burton and Obel, 1988; Bandura and Jourden, 1991) and allows the researcher to control the environment and test different conditions. It is necessary to control what kind of competitor’s performance (for example, superior vs. similar, or inferior vs. similar) participants observe for two reasons. First, as previous research in social psychology has shown that different patterns of performance comparisons may have a differential effect on self-efficacy, an important influence on attentional and cognitive processes of decision-making (Schunk, 1986; Brown and Inouye, 1978; Bandura and Jourden, 1991). Second, the importance of such differences has been demonstrated in the literature on learning from performance feedback (Baum and Dahlin, 2007; Gaba and Bhattacharya, 2012).

**Main variables**

The experiment will allow me to collect rich data across the three levels of analysis: mental representations, decision making behavior, and performance.

**Mental representations.** This study investigates whether exposure to different levels of competitor’s performance leads to differences in the knowledge that decision makers acquire about the problem they are trying to solve repeatedly. Previous literature offers a wide variety of techniques to measure the accuracy of knowledge22, including repertory grid technique (Reger and Huff, 1993), causal loop diagramming (Huff, 1990; Sterman, 2000), content analysis of written narratives (Osborne, Stubbart, and Ramaprasad, 2001; Nadler, Thompson, and Van Boven, 2003), cognitive map drawing (Hodgkinson et al, 1999), and use of a standardized test (Borgatti and Carboni, 2007; Gary and Wood, 2011). The most feasible techniques to apply in

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22 The studies that are cited use different terms of the same concept, including mental models, cognitive maps, and others.
this study are content analysis of written narratives and a test. The data for the first measure is collected thrice in the course of the game. After every two rounds of the game, participants are prompted to describe approaches that they have tried and their opinion on the best strategy. After Round 2, participants are asked the following questions:

1. After playing two rounds of the game, we would like to learn what insights you have gained. What do you think the most effective strategy to find the optimal value of the performance variable Y is? Please explain in a short paragraph (2-4 sentences).
2. In your opinion, what approaches are not effective in finding the optimal value of the performance variable Y? Please explain in a short paragraph (2-4 sentences).

After Rounds 4 and 6, participants are asked the following questions:

1. Now that you have had an experience of two more rounds, we would like to learn more about your insights about the game. (Variation for round 6: Now that you completed all six rounds, we would like to learn about your insights one last time.) What do you think the most effective strategy to find the optimal value of the performance variable Y is now? Please explain in a short paragraph (2-4 sentences).
2. What new approaches have you tried that you found helpful? Please explain in a short paragraph (2-4 sentences).
3. What new approaches have you tried that you did NOT find helpful? Please explain in a short paragraph (2-4 sentences).

Answers to these prompts were analyzed and coded to create a quantitative measure of *problem awareness*. The idea behind it is to capture what aspects of the problem and its solutions were salient to participants. It was done in the following way. First, I developed a taxonomy of characteristics of the problem structure and elements of solutions. Then, I checked which characteristics and elements participants actually mentioned in their answers. It was done in an iterative way, by first creating a preliminary set of categories and then by verifying them against the answers. In the process, some categories were omitted and others were added. The final list of categories is as follows:

1. Changing one variable at a time is helpful.
2. Changing two or three variables at a time is not helpful.
3. Random guessing does not work.
4. There is a curvilinear relationship between variables and performance.
5. Variables should be changed by large and small increments.
A participant was given a point for each category that was present in his or her response. The more the number of points the participant receives for a set of answers he or she has given at a point in time, the higher will be his or her score for problem awareness at that point in time.

The data for the second measure, knowledge accuracy, is collected twice, after Round 4 and after Round 6. The participants answer multiple-choice questions about the nature of the problem and potential solutions to solve it. The main reason for administering the test only once during the game is to avoid priming participants to think of the problem in a certain way, at least for the part of the game. Administering the test one more time, after all 6 rounds of the game are complete, allows me to observe changes in knowledge with a repeated measure. Questions in the tests are as follows:

1. What best describes the relationships between decision variables A, B, and C, and performance variable Y?
   a. Y is a linear function of A, B, and C.
   b. Y is a quadratic function of A, B, and C.
   c. Y is a cubic function of A, B, and C.
   d. There is no identifiable function. It is random.
2. Do changes in values of decision variables affect Y differently, depending on values of other decision variables? In other words, are there interactions?
   a. Yes, effects of changing A depend on values of B, and vice versa.
   b. Yes, effects of changing A depend on values of C, and vice versa.
   c. Yes, effects of changing B depend on values of C, and vice versa.
   d. All three variables (A, B, and C) interact with each other.
   e. No, variables are independent of each other. Change in one variable does not affect the other.
3. Do variables A, B, and C have different effects on the performance variable Y? In other words, do they have different weights?
   a. Variable A has a bigger weight than variables B and C.
   b. Variable B has a bigger weight than variables A and C.
   c. Variable C has a bigger weight than variables A and B.
   d. All variables have the same weight.
   e. All variables have different weights.
4. Is there a random component that contributes to the relationships between decision variables and the outcome variable?
   a. No, there is no random component.
   b. Yes, but its contribution is trivial.
   c. Yes, and it significantly outweighs effects of decision variables on the performance variable, essentially making the game a random guess.
5. How many decision variables should be changed at each step to get the best result?
   a. Only one variable at a time.
b. Two variables at a time.
c. All three variables should be changed at each step.
d. It should be a combination of the approaches above.
e. None of the above is a useful approach.

6. What is the best approach to changing the values of decision variables at each step?
   a. Changing them just by little amount (e.g. less than 10 points).
   b. Changing them by some amount, but not too drastically (e.g. by 10-20 points).
   c. Changing them drastically – exploring extreme values (e.g. from 1 to 100).
   d. Some combination of the first and second approaches.
   e. Some combination of the first three approaches.
   f. It does not really matter for winning the game.

A proportion of correct answers to these questions creates a measure of knowledge accuracy, which can also be split into two parts: knowledge of the structure (based on the first 4 questions) and heuristic knowledge (based on the last 2 questions).

**Decision making behavior.** As each decision made by a participant is being recorded, there is ample amount of data to work with. The objective here is to understand whether participants use more or less efficient search strategies, and whether exposure to competitor’s performance has an effect on the choice of strategies. Changing one variable at a time is the most efficient strategy for this game – in fact, the only one that can lead to finding the optimal value within 20 attempts (not counting pure luck). Therefore, the primary variable of interest is decision making effectiveness — the proportion of attempts at which only one variable was changed, calculated for each round. Another variable of interest is exploration. It is measured by counting a number of different strategies a participant used in each round. I assume that there are 4 possible strategies: not changing any variable, changing one variable, changing two variables, and changing three variables.

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23 A couple of participants found a way to solve the problem by using derivatives, which involves one step of setting all variables to zero (meaning that more than variable is changed at a time).

24 To calculate how many variables are changed at a time, I compare values at each attempt to the previous attempt. The measure of decision making effectiveness is conservative, because occasionally participants make a change relative to values chosen few attempts prior to that. The measure here does not include these changes as “one variable at a time” and instead treats them as changing multiple variables at a time.
**Performance.** Finally, I collect information on performance of each participant in each of the 6 rounds. This is again very rich data, as I will have performance data within each trial (for each 20 steps), as well as across trials. I consider two performance metrics: absolute scores and round wins. *Absolute performance score* captures the highest value of an outcome variable that a participant reaches in a round (in any of the 20 attempts). *Win* is a dichotomous variable that equals to one when a participant reaches 30,000 in a round and zero otherwise.

**Control variables**

**Perceived self-efficacy** is an individual’s belief in his or her ability to perform a task or tasks effectively (Payne, Youngcourt, and Beaubien, 2007). Research has demonstrated that perceived self-efficacy is an important factor for performance (Gary and Wood, 2011), motivation for change (Paglis and Green, 2002), use of effective strategies to solve problems (Bandura and Jourden, 1991), creativity (Gong, Huang, and Farh, 2009), and adoption of advanced technologies (Hill, Smith, and Mann, 1987). I develop a scale for perceived self-efficacy based on the approach proposed by Bandura (1997), which has been used in prior research (e.g., Bandura and Jourden, 1991; Gary and Wood, 2011). The scale includes 6 items preceded by a header question: “Please rate your effectiveness in the game on a 10-point scale (from 1 – “very little confidence” to 10 – “total confidence”) on the following aspects”. The items are as follows:

1. Applying the strategy that you described as the best
2. Setting appropriate values for decision variables A, B, and C
3. Consistently improving the value of performance variable Y
4. Tracking changes in values of decision variables A, B, and C
5. Tracking changes in values of performance variable Y
6. Finding optimal values of performance variable Y
**Goal orientation.** The motivation literature in psychology and management has paid a lot of attention to the construct of goal orientation and its role in what individuals are able to achieve and behaviors that individuals adopt in order to achieve desired outcomes. Goal orientation has been argued to be an important factor in performance and learning (Hofmann, 1993; Button, Mathieu, and Zajac, 1996; Seijts et al, 2004; Johnson, Shull, and Wallace, 2011), creativity (Hirst et al, 2011), effective selling (Sujan, Weitz, and Kumar, 1994), job satisfaction (van Yperen and Janssen, 2002; Janssen and van Yperen, 2004), feedback-seeking (Farr, Hofmann, and Ringenbach, 1993; VandeWalle and Cummings, 1997), goal setting (Farr et al, 1993; Seijts et al, 2004), adoption of learning strategies (Ames and Archer, 1988; Nolen, 1988; Ford et al, 1998), continuous improvement, and individual work role innovation (Farr and Ford, 1990; Farr et al, 1993). While several conceptualizations of goal orientation exist in the literature (DeShon and Gillespie, 2005), for the purpose of this study it will be defined as “a set of dispositional tendencies that cause individuals to strive toward certain types of implicit achievement goals in performance settings” (Hafsteinsson, Donovan, and Breland, 2007; p. 719). Goal orientation is considered to be a somewhat stable trait that can be, however, altered by context (Button et al, 1996; DeShon and Gillespie, 2005; Payne et al, 2007). With this in mind, questions related to goal orientation are administered to participants prior to the game. In the literature, there are multiple scales to measure goal orientation, focusing on both academic and work domain, but in this experiment, I will use a scale, which is best known as Patterns of Adaptive Learning Scales developed by Midgley and her colleagues (Midgley et al, 1996; Midgley et al, 2000), with an intention to assess students’ motivation in the classroom. This instrument, however, is reasonably adaptable to be used with adults as well and has been demonstrated to be better than other scales, in terms of distributional characteristics and
construct validity (Jagacinski and Duda, 2001). The goal orientation scale includes three sub-scales: learning, performance, and avoid performance. The items are preceded with the following question: “Please indicate to what extent you agree with the following statements”. The response format is a five-point Likert scale with the following anchors: 1 – “not at all true”, 3 – “somewhat true”, and 5 – “very true”. The scale includes the following items:

**Learning:**
1. It’s important to me that I learn a lot of new things this year.
2. One of my goals in my work/studies is to learn as much as I can.
3. One of my goals is to master a lot of new skills this year.
4. It’s important to me that I thoroughly understand the work I do.
5. It’s important to me that I improve my skills this year.

**Performance:**
1. It’s important to me that other people think I am good at what I do.
2. One of my goals is to show others that I’m good at my work/studies.
3. One of my goals is to show others that work/studies is easy for me.
4. One of my goals is to look smart in comparison to the other people.
5. It’s important to me that I look smart compared to others.

**Avoid performance:**
1. It’s important to me that I don’t look stupid in comparison to other people.
2. One of my goals is to keep others from thinking I’m not smart.
3. It’s important to me that others don’t think that I know less than they do.
4. One of my goals in my work/studies is to avoid looking like I have trouble doing the work.

**Use of intuition.** Intuition is a non-conscious ability to tap into one’s experience, identify relevant past information or decisions to facilitate more efficient current decision making (Simon, 1987; Agor, 1989; Wally and Baum, 1994). The important aspect of engaging intuition is a process of using heuristics, simple rules, rather than complex cognitive information processing, to come up with a solution to the problem (Wally and Baum, 1994). Researchers have explored how the use of intuition relates to creativity (Shirley and Langan-Fox, 1996), productivity (Agor, 1985; Agor, 1986), and decision making such as corporate planning, stock analysis, performance appraisal, capital investments, and product commercialization (Agor, 1986; Simon, 1987; Hayashi, 2001; Dane and Pratt, 2007). To measure the use of intuition, I use a modified scale developed by Wally and Baum (1994). The items will be preceded with the
following question: “Please indicate to what extent you agree with the following statements”.

The response format is a five-point Likert scale with the following anchors: 1 – “not at all true”, 3 – “somewhat true”, and 5 – “very true”. The scale includes the following items:

1. I never have vague feelings of unease that precede unexpected significant events.
2. Sometimes when I awaken, I have an answer to a problem that had troubled me.
3. I listen to my intuition while solving problems I face.
4. I usually get along better with realistic people, rather than creative types (reverse).
5. I prefer careful and thorough analysis to intuition (reverse).
6. I used intuition when I made some important decisions such as choosing a college.

**Attitude toward math.** Participants are asked the following question: “How did you feel about math classes in high school?” with the following options for answers:

1. These were my favorite classes.
2. Math classes were among my favorite.
3. Math classes were ok. I liked them.
4. Going to math classes was not my favorite activity in high school.
5. I was going to math classes just because I had to, but I really did not like them.

Variable favorable attitude toward math is a dichotomous variable coded as 1 if participants marked the first or the second option, and 0 otherwise.

**Familiarity with calculus.** Participants are asked the following question “Have you ever taken a calculus course?” with the following options for answers:

1. Yes, I have had several of them.
2. Yes, I have had a calculus course once.
3. No, I have never had a calculus course.

The variable several calculus classes is dichotomous coded as 1 if participants marked the first option and 0 otherwise.

**Other Control Variables.** In addition to the above measures, the survey also included questions to capture few additional individual characteristics. Participants were asked about their gender, age, current occupation, and self-satisfaction after performing a task.
Experimental protocol

Participants were invited to a laboratory to participate in an experiment on decision making and problem solving that lasts anywhere between 40 and 90 minutes\textsuperscript{25}, depending on how fast participants play the game. They were told that the experiment involved answering several survey questions and playing a game.

Upon arrival, participants were briefed about the experimental procedure, after which they signed a consent form. Each participant was given a sheet of paper that included a personal code (used to connect different parts of the experimental data), a game code (used to identify which treatment condition to launch in the game), and rules of the game. A random sequence of game codes was regenerated in Python, and a stack of sheets was prepared in advance. When a sheet of the paper was given to each participant, I delivered the following prompt:

“Thank you for taking time to participate in this study! Each of you has been given a sheet that has all information you will need. The first thing that you see is a personal code. This is something you will need to enter several times, so please hold on to the paper. When you get to the game, it will also ask you for the game code. You can see it on this sheet as well. As for the process, you will start with a survey. Once you complete it, you can close the browser and get to the game window. As you play the game, the surveys will pop up couple of more times. You can again just close the browser after completing surveys and be back to the game window. Rules of the game will be on the screen in the beginning of the game, but if you want to refer to them at any point in time, they are on the sheet as well. There are 6 rounds of the game, and it is pretty challenging, but there is a reward of 10 dollars for every round if you win. Even though the game is challenging, we have seen the wins before, and we are always looking for the next big win. If you experience any technical difficulties, feel free to call me any time. Now, unless you have any questions, let’s get started, and good luck!”

The prompt was delivered in a very positive and friendly manner. Smiling, establishing an eye contact, and animated delivery is believed to induce positive and pleasant emotions in participants (Bartel and Saavedra, 2000; Hakonsson et al, 2016), which in turn may facilitate

\textsuperscript{25} The time estimate was based on a pilot study with 20 participants. In the main experiment, there are few participants who spent more than 90 minutes.
more effective decision making and creativity (Fredrickson, 2003; Amabile et al, 2005; Davis, 2009).

Participants started with a Qualtrics survey that included questions intended to capture data for control variables outlined earlier (except for self-efficacy and self-satisfaction). After completing the first survey, the game, written in Python language, was launched. After every two rounds the web-based Qualtrics was called by Python to capture participants’ responses to questions related to measures of mental representations, self-efficacy, and self-satisfaction. After participants completed the study, they called me or a research assistant to display the results on a computer screen and were paid at their desk in a discrete manner. The debriefing was done via e-mail sent after the study was completed by all participants.
AN EXPERIMENTAL STUDY: RESULTS

I conducted an experimental study in the fall of 2016 using a participant pool of the Center for Decision Research at Kenan-Flagler Business School. The main advantage of the participant pool at the Center for Decision Research is that it also includes individuals other than undergraduate students. Therefore, in addition to undergraduate students, graduate students, university staff, and members of the community also participated in the study. This diverse mix of participants allows me to make some generalizations beyond the population of undergraduate students.

A pilot study was conducted in October of 2016 to test the protocol of the experiment. 20 participants were recruited; 19 participants completed the study. Based on the pilot study, few minor changes were made to how participants were briefed in the beginning of the study and to questions that were related to variables measuring knowledge. Data from the pilot study were also used to carry out power analyses. The main study was conducted in November-December of 2016. Totally, 143 participants were recruited; 142 participants attempted to play the game; 141 participants completed all 6 rounds.

Pilot study

20 people signed up to participate in the pilot study. The advertisement for the study only mentioned that the study was about decision making and problem solving in a computer game. I conducted 2 sessions – 12 people attended the first session, and 8 people attended the second
session. In the second session, one person quit the study during the first round of the game, saying that he had no idea what he was doing and did not want to continue. 19 participants completed all 6 rounds of the game. Out of 19 participants, 13 people did not win a single round. Out of 6 participants who won at least one round, 4 people won one round each, and 2 people won 2 rounds each. Given that the pilot study was the first time the game was tested on a group of individuals, the winning statistics provided some initial evidence that the game was very challenging to win. In fact, some participants of the pilot study commented that the game was tricky and impossible to win. One participant said “It was all a lie”, although in a joking tone.

Originally, the briefing of participants in the beginning of the study did not include any reference to how challenging the game is. However, after observing reactions of participants in the pilot study, I added a statement about the fact that the game is challenging but possible to win to a briefing prompt that I used in the main study. I refrained from providing specific odds of winning, which are quite low as we can see from the winning statistics described above.

Because the pilot study was the first study to test the game, the pilot study provided the only reasonable data to perform the power analysis. Table 5 summarizes differences in means, pooled standard deviation, standardized effect size, and estimated number of participants per group for a set of measures related to knowledge, decision making, and performance. A required sample size for each measure is calculated assuming $\alpha=0.05$ and 80% power. Differences in means are calculated as the mean of Group 1 (that does not observe performance of “another participant”) minus the mean of Group 2, 3 or 4 (that observes inferior, similar, and superior performance of ‘another participant”, respectively).

Of 19 participants who completed the study, 4 people were in Group 1, 6 people – in Group 2, 5 people – in Group 3, and 4 people – in Group 4. Although the sample size is very
small, it is important to note that effects for decision making effectiveness and absolute performance score and performance were in line with expectations (based on Propositions 6 and 7). Average decision making effectiveness in round 6, average change in decision making effectiveness across 6 rounds, average performance in round 6, and average change in performance across 6 rounds are higher for Group 1, than for either Group 2, 3, or 4. Average differences for knowledge are not consistent with Proposition 6. One of the reasons for this inconsistency is that questions for capturing knowledge measures suffered from several wording issues. For example, most multiple choice questions included an option “I don’t know” and many participants opted for this. Based on the pilot study results, questions were rephrased to make them clearer. The wording that was used in the main experiment has been described in the methodology section.

**Participants**

In the main study, there were 143 participants. There were 82 females (58%) and 59 males (42%). The age of participants ranged from 18 to 64 years, with median age of 21 years and mean of 23 years. There were 102 (72%) undergraduate students, 21 (15%) graduate students, and 19 (13%) members of the community. 70 participants (50%) had a favorable attitude toward math. 60 participants (42%) had taken several calculus courses. Table 6 provides the descriptive statistics.

**Analysis of main effects**

The lab study was designed to test the effects of competitor’s performance on knowledge, decision making, and performance. Therefore, the primary analysis is concerned with analyzing
differences in these metrics across groups. In line with Propositions 6 and 7, I expected wins, absolute performance scores, decision making effectiveness, problem awareness, and knowledge accuracy to be higher for Group 1 (that did not observe competitor’s performance) than for Group 2 (that observed inferior competitor) and Group 4 (that observed superior competitor). In line with Proposition 5, I expected exploration to be higher for Group 4 than for Group 2. In line with Proposition 8, I expected exploration for Group 1 to be higher than that for Group 2 but lower than that for Group 4. Group 3 serves as a control group, and I did not expect differences between this group and Group 1.

Of 143 participants, 141 completed all 6 rounds of the game. 36 participants won at least one round. Table 7 shows distribution of wins. As expected, winning the game is challenging, especially winning multiple rounds. I did not expect anyone to win all 6 rounds; however, there were 2 people who were able to do that, while 4 more were able to win 5 rounds.

Of the 142 participants who attempted to play the game, 34 subjects were in Group 1, 36 subjects – in Group 2, 40 subjects – in Group 3, and 32 subjects – in Group 4. Table 8 shows tabulation of wins in Round 1, Round 6, and across all 6 rounds. Even though, on the surface, some substantial differences exist across groups in Rounds 1 and 6, both the chi-square test and Fisher’s exact test show independence between round wins and treatment conditions. When we pool all rounds together, the chi-square test suggests there could be differences between groups ($p=0.037$). Consistent with Proposition 7, there were 13% of wins in Group 1, compared with 7% of wins in Group 2 and 6% of wins in Group 4. However, wins of each participant are not independent of each other. To adjust for that, I estimate a population average logistic regression with first-order, autoregressive correlation structure for residuals\textsuperscript{26}:

\textsuperscript{26} As a robustness check, I have also estimated a model with standard errors clustered by participant. $P$-values increase to 0.131 for $\beta_0$ and 0.11 for $\beta_3$ (considering one-tailed test).
\[
\text{logit}(\Pr(\text{win}_{ij} = 1)) = \beta_0 + \beta_{\text{inferior}} i + \beta_{\text{similar}} i + \beta_{\text{superior}} i + \epsilon_{ij}
\] (6)

Model 1 in Table 9 provides estimates for equation (6). Model 2 also includes fixed effects for the rounds. I interpret results using estimates of Model 1. The estimated odds of winning in Group 1 is \(e^{\beta_0} = 0.14\), with 95\% confidence interval (0.08, 0.25). The estimated odds of winning in Group 2, which observed performance of inferior competitor, is \(e^{\beta_0 + \beta_1} = 0.07\), with 95\% confidence interval (0.04, 0.15). The estimated odds of winning in Group 2 are 48\% lower than the estimated odds of winning in Group 1 \((p=0.09\), one-tailed test\27\). This result is consistent with Proposition 7. The estimated odds of winning in Group 3, which observed performance of similar competitor, is \(e^{\beta_0 + \beta_2} = 0.14\), with 95\% confidence interval (0.08, 0.24). There are no differences in odds of winning between Group 1 and Group 3 \((p>0.4)\). This result is consistent with my expectations. The group that observed performance of a similar competitor did not have additional information to be used for making inferences, thus I would not have expected differences in performance. The estimated odds of winning in Group 4, which observed performance of superior competitor, is \(e^{\beta_0 + \beta_3} = 0.07\), with 95\% confidence interval (0.03, 0.16). The estimated odds of winning in Group 4 are half of the estimated odds of winning in Group 1 \((p=0.08)\). This result is also consistent with Proposition 7. Predicted probabilities of winning are 0.12 for Group 1, 0.07 for Group 2, 0.12 for Group 3, and 0.07 for Group 4.

Next, I analyze differences in absolute performance scores (APS) across groups. Figure 14 illustrates mean performance across all 6 rounds for each treatment condition. APS appears to improve across rounds for all groups. Contrary to Proposition 7, APS of Group 2 (that observed inferior competitor) appears to be the highest among the groups across all 6 rounds. APS of Group 4 (that observed superior competitor) appears to be no different from APS of Group 1.

\footnote{All tests associated with propositions are one-tailed unless otherwise stated.}
Given that observations are correlated for each participant, I estimate the following generalized linear models with first-order, autoregressive correlation structure for residuals:

\[ APS_{ij} = \beta_0 + \beta_{1\text{inferior}_i} + \beta_{2\text{similar}_i} + \beta_{3\text{superior}_i} + \varepsilon_{ij} \]  

(7)

To evaluate whether performance improves over time and test for difference in performance trajectories across treatment conditions, I estimate the following generalized linear model with first-order, autoregressive correlation structure for residuals:

\[ APS_{ij} = \beta_0 + \beta_{1\text{inferior}_i} + \beta_{2\text{similar}_i} + \beta_{3\text{superior}_i} + \beta_{4\text{round}_i} + \beta_{5\text{inferior}_i \times \text{round}_{ij}} + \beta_{6\text{similar}_i \times \text{round}_{ij}} + \beta_{7\text{superior}_i \times \text{round}_{ij}} + \varepsilon_{ij} \]  

(8)

Model 1 in Table 10 provides estimates for equation (7). Model 2 adds round fixed effects. Model 3 provides estimates for equation (8). Based on estimates of Model 1, APS does not differ between Group 1 and Groups 3 and 4 (\(p>0.4\)). Group 2, which observed performance of inferior competitor, has performance higher than Group 1 by 263 points (\(p=0.06\)). Based on estimates of Model 3, performance in Group 1 improves with every round by about 74 points (\(p=0.08\)). Performance trajectories in Groups 2, 3, and 4 do not differ from the performance trajectory in Group 1. Coefficients \(\beta_5\), \(\beta_6\), and \(\beta_7\) from equation (8) in Model 3 are insignificant (\(p>0.2\)). The analysis of absolute performance scores does not provide support to Proposition 7.

Next, I analyze decision making effectiveness (DME). Figure 15 illustrates mean DME across all 6 rounds for each group. Similar to performance, DME improves across rounds for all treatment conditions, and DME of Group 2 (that has observed inferior competitor) appears to be the highest across all 6 rounds. This is contrary to Proposition 6\(^{28}\).

I estimate the following generalized linear models with first-order, autoregressive correlation structure for residuals:

\(^{28}\) In my theoretical framework, decisions are driven by beliefs, therefore decision making behavior could serve as a proxy for beliefs that participants hold when they make decisions.
Model 1 in Table 11 provides estimates for equation (9). Model 2 adds round fixed effects. Model 3 provides estimates for equation (10). Based on estimates of Model 1, DME does not differ between Group 1 and Groups 3 and 4 ($p > 0.3$). Group 2, which observed performance of inferior competitor, has DME higher than Group 1 by 0.08 ($p = 0.06$). Based on estimates of Model 3, DME in Group 1 improves with every round by about 0.03 ($p = 0.01$). DME trajectories in Groups 2, 3, and 4 do not differ from DME trajectory in Group 1. Coefficients $\beta_5, \beta_6,$ and $\beta_7$ from equation (10) in Model 3 are insignificant ($p > 0.3$). The analysis of decision making effectiveness does not provide support to Proposition 6.

Finally, I analyze measures related to mental representations. I start with the analysis of knowledge accuracy (KA), which is based on multiple choice questions administered after round 4 and round 6. Figure 16 shows average KA for each group measured after round 4 and after round 6. Group 1 has the highest KA in both rounds, which is consistent with Proposition 6. KA in Group 1 seems to decline from Round 4 to Round 6. Group 4, which observed performance of superior competitor, has the lowest knowledge accuracy in both rounds. Group 2, which observed performance of inferior competitor, seems to have the highest improvement in knowledge from round 4 to round 6.

I test for differences between groups by estimating the following generalized linear models with clustered standard errors, where observations from round 4 and round 6 are pooled together:

\[
KA_{ij} = \beta_0 + \beta_1 \text{inferior}_i + \beta_2 \text{similar}_i + \beta_3 \text{superior}_i + \epsilon_{ij},
\] (11)

\[
KA_{ij} = \beta_0 + \beta_1 \text{inferior}_i + \beta_2 \text{similar}_i + \beta_3 \text{superior}_i + \beta_4 \text{round}_{ij} + \epsilon_{ij}.
\] (12)
where \( \text{round6} \) is an indicator variable coded as zero for Round 4 and as one for Round 6. I also test for differences between Round 4 and Round 6 by estimating the following generalized linear model with clustered standard errors:

\[
KA_{ij} = \beta_0 + \beta_1\text{inferior}_i + \beta_2\text{similar}_i + \beta_3\text{superior}_i + \beta_4\text{round6}_i + \beta_5\text{inferior}_i \times \text{round6}_i + \beta_6\text{similar}_i \times \text{round6}_i + \beta_7\text{superior}_i \times \text{round6}_i + \epsilon_{ij}
\]  

(Model 1 in Table 12 provides estimates for equation (11), Model 2 – for equation (12), and Model 3 – for equation (13). Based on results in Table 12, there are no differences in knowledge accuracy between groups, and there are no differences across time periods either (for all tests, \( p > 0.2 \)). One exception is that knowledge accuracy for Group 2, which observed performance of inferior competitor, improved by 0.19 (\( p = 0.11 \)). If after Round 4, participants in Group 2 answered 1.94 questions out of 6 correctly on average, they answered 2.13 questions correctly on average after Round 6. Group 2 is the only group that showed some improvement in knowledge accuracy. Overall, the analysis of knowledge accuracy does not provide support to Proposition 6.

Figure 17 shows the patterns of knowledge if we divide it into knowledge of problem structure and knowledge of heuristics. There are few interesting observations. Group 1 seems to have better knowledge of structure of the problem than the knowledge of what strategies are better for solving the problem (heuristic knowledge). Group 2, which observed inferior competitor, is the other way around. It has the highest level of heuristic knowledge but lowest level of knowledge of the problem structure. Group 4, which observed superior competitor, seems to have improved its knowledge of structure from Round 4 to Round 6, while heuristic knowledge declined. Group 1 appears to have better knowledge of structure than Groups 2 and 4, which is consistent with Proposition 6. However, it does not appear to have better heuristic knowledge, which is inconsistent with Proposition 6.
I estimate the same type of models for knowledge of structure and heuristic knowledge as I did for knowledge accuracy. Results for knowledge of structure are presented in Table 13. I interpret the results using Model 3. After round 4, participants in Group 1, which did not observe competitor’s performance, had an estimated knowledge of structure at the level of 1.31 (out of 4), with 95% confidence interval (0.96, 1.67). Participants in Group 2, which observed performance of inferior competitor, had an estimated knowledge of structure at the level of $\beta_0 + \beta_1 = 0.83$, with 95% confidence interval (0.50, 1.17). The difference in estimated knowledge of structure between Group 1 and Group 2 after Round 4 is estimated at $-0.48$ ($p=0.03$).

Participants in Group 3, which observed performance of similar competitor, had an estimated knowledge of structure at level of $\beta_0 + \beta_2 = 1.33$, with 95% confidence interval (1.00, 1.67). There are no significant differences in knowledge of structure between Group 1 and Group 3 ($p>0.5$). Participants in Group 4, which observed performance of superior competitor, had an estimated knowledge of structure at the level of $\beta_0 + \beta_3 = 0.94$, with 95% confidence interval (0.58, 1.29). The difference in knowledge of structure between Group 1 and Group 4 after Round 4 is estimated at $-0.38$ ($p=0.07$). Overall, results for Round 4 are consistent with Proposition 6.

However, the situation with knowledge of structure is a little different after Round 6. Differences between levels of knowledge of structure shrink between treatment conditions.

Participants in Group 1, which did not observe a performance of a competitor, had an estimated knowledge of structure at the level of $\beta_0 + \beta_4 = 1.24$ (out of 4), with 95% confidence interval (0.86, 1.61). The estimated knowledge of structure after round 6 for Group 1 is not significantly different from the estimated knowledge of structure after Round 4 ($p>0.7$). Participants in Group 2, which observed performance of inferior competitor, had an estimated knowledge of structure at the level of $\beta_0 + \beta_4 + \beta_5 = 0.99$, with 95% confidence interval (0.66, 1.32). The estimated
knowledge of structure for Group 2 improved from Round 4 to Round 6 by 0.16 \((p=0.12)\). The difference in knowledge of structure between Group 1 and Group 2 after Round 6 is estimated at \(-0.24\) \((p=0.17)\). Participants in Group 3, which observed performance of similar competitor, had an estimated knowledge of structure at level of \(\beta_0 + \beta_2 + \beta_4 + \beta_6=1.35\), with 95% confidence interval \((1.03, 1.66)\). The estimated knowledge of structure after round 6 for Group 3 is not significantly different from the estimated knowledge of structure after Round 4 \((p>0.4)\). There are no significant differences in knowledge of structure between Group 1 and Group 3 \((p>0.6)\). Participants in Group 4, which observed performance of superior competitor, had an estimated knowledge of structure at level of \(\beta_0 + \beta_3 + \beta_4 + \beta_7=1.16\), with 95% confidence interval \((0.82, 1.51)\). The estimated knowledge of structure for Group 4 improved from Round 4 to Round 6 by 0.23 \((p=0.09)\). There are no significant differences in knowledge of structure between Group 1 and Group 4 \((p>0.3)\). The analysis of knowledge of structure after Round 6 does not provide support to Proposition 6.

Results for heuristic knowledge are presented in Table 13. I interpret results using estimates of Model 3. The heuristic knowledge of participants in Group 2, which observed performance of inferior competitor, is actually higher than the accuracy of heuristic knowledge of participants in Group 1 – with the estimated difference of 0.23 after Round 4 \((p=0.08)\) and 0.21 after Round 6 \((p=0.10)\). There are no differences in the accuracy of heuristic knowledge between Group 3 and Group 1 as well as Group 4 and Group 1 after Round 4 \((p>0.2\) for both tests). However, after Round 6, the accuracy of heuristic knowledge of participants in Group 3, which observed performance of similar competitor, is lower than the accuracy of heuristic knowledge of participants in Group 1 – with the estimated difference of \(-0.14\) \((p=0.18)\). The accuracy of heuristic knowledge of participants in Group 4, which observed performance of
superior competitor, is even lower – with the estimated difference of –0.18 ($p=0.14$). Group 4 is the only group where the accuracy of heuristic knowledge declined from Round 4 to Round 6, by estimated difference of –0.14 ($p=0.12$). Overall, the analysis of heuristic knowledge does not provide support to Proposition 6.

The second set of analyses related to mental representations involves problem awareness (PA) – a measure developed from the coding of open-ended questions about the strategies to win the game. Problem awareness was measured thrice – after Round 2, Round 4, and Round 6. Figure 18 shows empirical means of problem awareness across treatment conditions and time periods. There are a couple of interesting observations. First, groups that observed competitor’s performance visually seem very similar to each other in terms of evolution of problem awareness. Second, Group 1, that did not observe competitor’s performance, although very similar to other groups after Round 2, seems to have developed higher problem awareness by Round 6. This is somewhat consistent with Proposition 6.

I test for differences between groups by estimating the following generalized linear models with clustered standard errors:

$$PA_{ij} = \beta_0 + \beta_{1\text{inferior}i} + \beta_{2\text{similar}i} + \beta_{3\text{superior}i} + \beta_4\text{round}_{ij} + \beta_5\text{inferior}i \times \text{round}_{ij} + \beta_6\text{similar}i \times \text{round}_{ij} + \beta_7\text{superior}i \times \text{round}_{ij} + \epsilon_{ij}, \quad (14)$$

where variable $\text{round}$ is treated as a continuous variable, and linear trend is assumed.

And:

$$PA_{ij} = \beta_0 + \beta_{1\text{inferior}i} + \beta_{2\text{similar}i} + \beta_{3\text{superior}i} + \beta_4\text{round}_{4ij} + \beta_5\text{round}_{6ij} + \beta_6\text{inferior}i \times \text{round}_{4ij} + \beta_7\text{similar}i \times \text{round}_{4ij} + \beta_8\text{superior}i \times \text{round}_{4ij} + \beta_9\text{inferior}i \times \text{round}_{6ij} + \beta_{10}\text{similar}i \times \text{round}_{6ij} + \beta_{11}\text{superior}i \times \text{round}_{6ij} + \epsilon_{ij}, \quad (15)$$

where Rounds 2, 4, and 6 are treated as discrete time periods, and I include indicator variables for round 4 and round 6 in the model.
Model 1 in Table 15 provides estimates for equation (14), and Model 2 provides estimates for equation (14) with added first-order, autoregressive correlation structure for residuals. Table 16 provides estimates for equation (15). I interpret results using estimates from Table 16. After Round 2, the estimated problem awareness for Group 1 is 1.79 (out of 5), with 95% confidence interval (1.25, 2.34). The estimated problem awareness for Groups 2, 3, and 4 does not differ significantly from the problem awareness for Group 1 ($p > 0.5$ for all tests). After Round 4, the estimated problem awareness for Group 1 is 2.28, with 95% confidence interval (1.67, 2.90). For Group 1, the problem awareness improved from Round 2 to Round 4 by 0.49 ($p = 0.005$). After round 4, the estimated problem awareness for Groups 2, 3, and 4 also does not differ significantly from the problem awareness for Group 1 ($p > 0.5$ for all tests). Groups 2, 3, and 4 also saw improvement in problem awareness from Round 2 to Round 4 — by 0.33 ($p = 0.003$), 0.23 ($p = 0.05$), and 0.83 ($p = 0.002$) respectively. The analysis of problem awareness after Round 2 and Round 4 does not provide support to Proposition 6.

After round 6, the estimated problem awareness for Group 1 is 2.82, with 95% confidence interval (2.19, 3.45). It is an improvement of 0.54 from Round 4 to Round 6 ($p = 0.005$). The estimated problem awareness for Group 2 is 2.3, with 95% confidence interval (1.77, 2.83). It is 0.52 lower than problem awareness for Group 1 ($p = 0.108$) but is insignificant improvement of 0.11 from Round 4 ($p > 0.3$). The estimated problem awareness for Group 3 is 2.49, with 95% confidence interval (2.00, 2.98). It is an improvement of 0.42 from Round 4 ($p = 0.003$) but is not different from problem awareness in Group 1 ($p > 0.2$). The estimated problem awareness for Group 4 is 2.42, with 95% confidence interval (1.85, 3.00). It is 0.40 lower than problem awareness for Group 1 ($p = 0.18$) and also is an improvement of 0.25 from
Round 4 \((p=0.09)\). The analysis of problem awareness after Round 6 provides support to Proposition 6.

Finally, I analyze exploration \((EXPL)\) to address Propositions 5 and 8. Figure 19 shows average exploration across 6 rounds for each group. As we can see from the graph, there are no any visible differences in exploration between groups, which is inconsistent with both Proposition 5 and Proposition 8. To further confirm that, I estimate the following generalized linear model with first-order, autoregressive correlation structure for residuals:

\[
EXPL_{ij} = \beta_0 + \beta_{	ext{inferior}_i} + \beta_{	ext{similar}_i} + \beta_{	ext{superior}_i} + \varepsilon_{ij}
\]  

(16)

Model 1 in Table 17 provides estimates for equation (16). Model 2 also includes round fixed effects. Based on the estimates in Table 17, there are no significant differences in exploration between groups \((p>0.4\) for all tests). Propositions 5 and 8 are not supported.

**Discussion of results and supplementary analysis**

In my theoretical framework on effects of using competitor’s performance as a constraint, I argued that using an exogenous goal alone will result in better knowledge and higher performance than using a combination of the exogenous goal and competitor’s performance (Propositions 6 and 7). I further argued that this is the case because paying attention to inferior competitor leads to overvaluing low-performing strategies and under-exploring, while paying attention to superior competitor leads to undervaluing superior strategies and over-exploring (Propositions 5 and 8).

Table 18 summarizes analysis of results in comparison with Propositions 5, 6, 7, and 8. The first important finding that I should discuss is that there are no significant differences in exploration across groups; thus, there is no support for Proposition 5 and 8. One possible
The critical assumption in my theoretical framework is that actors actually notice information about competitor’s performance and use it to make inferences. However, in real-world situations this assumption may not always hold. Few participants explicitly commented on Kasper (a virtual competitor in the game), and some wondered whether information on Kasper’s performance was helpful. A few quotes are provided below:

“I still do not know the purpose of Kasper's numbers, unless the variables affect that number by some factor to output my Y variable. Seeing as I am not given the values he inputted to attain those numbers, it serves as little more than a distraction.”

“I'm not sure if I should be looking at the performance score or not of Kasper.”

“I have tried using Kasper's results as a base instead of coming up with something random. This has been helpful because it has gotten me a little closer to the number I was supposed to find.”

“I have an inkling my idea to form an equation from the first set was useless. I'm also wondering why "Kasper's" info is even included.”

“It wasn't helpful to look at Kasper's experience, obviously. It also didn't help to make wild swinging changes to all three at a time.”

“Paying attention to Kasper has not been part of my plan. There's no way of seeing what variables Kasper is using, so looking at that just makes you feel bad if you're not doing as well.”

Most likely, participants varied substantially in how much attention they gave to information on competitor’s performance and how they used it. However, it is a little surprising that Group 4, which observed superior competitor, did not explore more than other groups, especially because this group displayed the lowest level of satisfaction and had the lowest perceived self-efficacy at the end of the game (Table 19). If the satisfaction score in Group 1, which did not observe competitor’s performance, was 2.7, with 95% confidence interval (2.3, 3.1), the satisfaction score in Group 4 was 1.9, with 95% confidence interval (1.5, 2.3) — a difference of 0.8 ($p=005$). Given that satisfaction was measured on a 5-point scale, a difference of 0.8 is pretty substantial. Self-efficacy in Group 1 was 5.5, with 95% confidence interval (4.6,
6.4), while in Group 4 it was 4.5, with 95% confidence interval (3.5, 5.5). The difference of 1 point ($p=0.07$) is fairly large on a 10-point scale.

Group 4, which observed superior competitor, did not explore more than Group 1, which did not observe competitor’s performance. Its decision making effectiveness and absolute performance score also did not differ. These results do not lend support to Propositions 6 and 7. However, Group 4 was half as likely to win the game as Group 1. Group 4 also appeared to have developed mental representations of lower quality on some dimensions, compared to Group 1 (see Table 18). This provides some support to Propositions 6 and 7. However, if groups did not differ in the level of exploration, it is not immediately clear why we observed such outcomes. One possible explanation is that my measure of exploration is too limited and does not capture real exploration that participants actually engaged in. My measure of exploration only captures how many variables participants changed at a time. Other aspects could include exploration over rate of change, functional form, formulae, and others. For example, if participants change 3 variables together, it could be because they try to guess randomly or it could be because they try to find a functional trick. For example, there were 1,086 decisions, in which participants entered the same value for the 3 variables; participants entered (1, 1, 1) 108 times and (99, 99, 99) 90 times. In other words, participants may have explored the problem in ways other than just changing the number of variables they adjust at each attempt. This is very similar to the idea of searching among different representations (Holland et al, 1986; Nelson, 2008). One way to try to measure such cognitive exploration is to conduct a lab experiment using think-aloud protocols and then conduct text analysis of participant’s thoughts to capture how many different mental hypotheses participants have entertained.
Another finding is that Group 2, which observed inferior competitor, had the highest absolute performance score, decision making effectiveness, and heuristic knowledge, than other groups (Table 20). This is contrary to Propositions 6 and 7. The fact that the group that observed inferior competitor made more effective decisions and was better able to raise its performance score seems interesting in the light of my findings in Simulation Experiment #2, where I found that the group that observed inferior competitor performed the best when the goal was extremely challenging. It is plausible to think that the goal of the game was extremely challenging because it was the highest (optimal) possible score in the game, and only one of 1,000,000 combinations corresponded to that value.

However, I would be hesitant to claim consistency between a computational model and a lab study for two reasons. First, Group 2 had substantially higher decision making effectiveness even in Round 1. Therefore, it is possible that Group 2 just happened to have participants who started the game with more accurate beliefs about the right strategy (i.e. changing only one variable at a time), received feedback that this strategy is indeed working, and continued using it.

Second, even though Group 2 had higher absolute performance score and decision making effectiveness, this group was only half as likely to win the game and had lower knowledge of structure and problem awareness than Group 1, which did not observe competitor’s performance (Table 18). One possible way to reconcile this inconsistency across different metrics is to consider that the strategy that is effective for raising the absolute performance score may not be sufficient for winning the game. Changing one variable at a time is enough to get the score closer to 30,000, but actually hitting 30,000 in 20 attempts or less requires an understanding of the functional form that relates decision variables to the outcome variable. Table 21 provides estimates of differences across groups in the likelihood of correctly answering questions about
structural characteristics of the game (based on multiple-choice questions administered after Round 4), using logistic regressions. Group 2 was half as likely to correctly answer the question about the functional form (Model 1), as Group 1 ($p=0.13$). It was also half as likely to correctly answer the question about the interactions between variables ($p=0.085$) as Group 1 (Model 2). Group 2 was 73% less likely to correctly answer the question about a random component in the function ($p=0.009$), than Group 1 (Model 4). Provided below are two quotes from participants in Group 2:

“I found a lot of things that didn't work. Finding wildly different variables getting the same result made me think that there was more randomness in the game than I originally thought.” (Note: The same outcome for two different values is a clue that an optimal lies in the middle between the two)

“Honestly, I think this game is rigged. A variance from 0,0,1 =/= 50,50,51. As in they are scaled or this is to monitor how performance failure affects our mood as we go through this. Basically, actually using math is ineffective in finding the optimal value.” (Note: A different rate of change at different levels of value is a clue for a non-linear relationship)

It seems that although participants in Group 2 changed one variable at a time, they did not necessarily make right inferences about the outcomes of their decisions. Curiously enough, because of their experience, participants often stuck with their original beliefs. The participant who made a comment above about the game being rigged after Round 2, continued to believe that the game was rigged after Round 6 as well.

To further explore the idea that winning the game requires more than just changing one variable at a time, I estimated the following model:

$$\text{logit}(\Pr(\text{win}_{ij} = 1)) = \beta_0 + \beta_1 DME_{ij} + \beta_2 PA_i + \beta_3 DME_{ij} \times PA_i + \epsilon_{ij},$$ \hspace{1cm} (17)

where wins and decision making effectiveness are only for Round 5 and 6, and problem awareness is measured after Round 4\textsuperscript{29}. Model 1 in Table 22 shows estimates of equation (17). In

\textsuperscript{29} Results are qualitatively similar if we replace problem awareness with knowledge accuracy or with knowledge of structure.
Model 2, I add control variables, such as demographic characteristics participants, goal orientation, favorable attitude toward math, and use of intuition, as well as indicator variables for groups and Round 6. There are a couple of notable effects of control variables. Self-efficacy increases the likelihood of winning. With every additional point on self-efficacy scale, participants are 25% more likely to win \( (p=0.134, \text{two-tailed test}) \). Participants who indicated favorable attitude to math classes in schools are 3.67 times more likely to win than participants who thought that math classes were just ok or did not like them at all \( (p=0.003, \text{two-tailed test}) \).

To help interpret main effects of problem awareness and decision making on likelihood of winning in Rounds 5 and 6, I calculate predicted probabilities of winning at different levels of problem awareness and decision making effectiveness, using estimates from Model 1 (Table 23), and create a surface plot (Figure 20). The likelihood of winning increases with more effective decision making as well as more accurate understanding of the problem but the interaction between the two is the most interesting aspect. It appears that it is more important to have a better understanding of the game structure than just using a more effective strategy. For example, even if a participant’s decision making effectiveness is at 0.2 but her problem awareness is at 5 (maximum value), the estimated probability of winning is 0.359. However, if a participant’s decision making effectiveness is at 1 (maximum value) but her understanding of the problem is 1 (out of 5), the estimated probability of winning is only 0.175. As suggested before, I believe the main reason for higher importance of problem awareness for the likelihood of winning is that problem awareness captures understanding of multiple structural characteristics of the game, while decision making effectiveness captures only one of them – the fact that it is better to change only one variable at a time.
The question that I find most fascinating but most difficult to answer is to what extent experience with the game affected participants’ ability to develop an understanding about the problem structure and what solutions work to solve it, as opposed to initial beliefs that they held at the beginning of the game. Figure 21 shows distributions of problem awareness scores after Round 2. Graph on the left shows the distribution for 41 participants that had problem awareness scores of 4 or 5 after Round 6. Graph on the right shows the distribution for 93 participants who had the problem awareness score of 3 or less after Round 6. Although scores for 41 participants ranged between 0 and 5, the average problem awareness score for this group (that had high problem awareness score after Round 6) was 3.1 after Round 2. The average problem awareness score for the group that had low problem awareness score at the end of the game was only 1.2. So it seems that participants that had higher scores at the end of the game already had better understanding of the game just after two rounds. In other words they seem to have approached the game with the right assumptions or mental hypotheses. Provided below are quotes from participants:

One participant after Round 2: “There does not seem to be any local optimum. That means we just need to figure out optimum of every single variable. So, starting from one variable and subdivide the space in a binary way. As we have only 99 options, within 4-6 trials we can find the optimum of a single variable. Then the next variable.”

Another participant after Round 2: “This is an optimization problem and I believe the objective function is concave in all three parameters. There is a unique optimum.”

The second participant after Round 6: “I didn't try any other approach. I believed there is a unique optimal because otherwise (in case there are local optima), there is no systematic way of searching for the optimal solution. The only way in that case would be to search randomly, which is meaningless for measuring one's analytical skills.”

It is also informative to see how participants changed their understanding of the problem from Round 2 to Round 6. Out of 92 participants that had problem awareness score of 2 or lower after Round 2, 11 people had problem awareness score of 4 or higher at the end of the game. The rest (62 people out 92) continued to have a low problem awareness score. On the other hand, out
of 19 participants that had a problem awareness score of 4 or higher after Round 2, only 2 people decreased their problem awareness score after Round 6 (one person got a score of 2 and one person got a score of 3). Other 17 participants continued to have high problem awareness score at the end of the game. It seems that for majority of participants, their initial beliefs and mental hypotheses about the structure of the game mattered more than their experience during the game.

A small number of participants (11 people) dramatically improved their understanding of the problem structure during the game. However, it is not immediately clear how their experience contributed to this improvement. In the discussion on the use of an exogenous goal as a constraint, I argued that strategies whose performance falls below the goal are judged useless, leading to increased search behavior. Given that these participants mostly failed (there was only one win by one person in Round 2), it is plausible to assume that a failure led these individuals to realize that their initial beliefs were wrong. However, 62 individuals that did not improve their understanding during the game also mostly failed in the first 2 rounds. All individuals were engaged in high level of exploration. However, in case of some individuals, exploration resulted in better knowledge, and in case of others, it did not. Clearly, there is heterogeneity in how well individuals extract knowledge from their experience.

To check whether an improvement in the problem awareness score is associated with any individual characteristics, I run an ordinary least squares regression model where a dependent variable is a difference in problem awareness score after Round 6 and after Round 2. Table 24 provides estimates for this model. There are a couple of curious results. First, female participants

30 In a logistic regression, where a dependent variable equals 1 for a person who improved PA from less than 3 to more than 3, few individual characteristics differentiate the individuals who started out with low PA but improved substantially from those who started with low PA and did not improve. They include being an undergraduate student, taking several calculus classes, and learning goal orientation. It is plausible to assume that people who had a natural inclination and aptitude for math puzzles were more likely to improve their understanding even if they started with wrong assumptions.
improved their problem awareness by 0.5 more than male participants ($p=0.03$, two-tailed test).

Second, participants that had favorable attitude to math improved their problem awareness by 0.27 ($p=0.244$, two tailed test). Other individual characteristics did not have substantial effects.

In addition, as discussed earlier, participants in Group 1 improved problem awareness much more than participants in Group 2, 3, and 4. Variables included in the model explain only 10% of variance in the improvement of problem awareness. Understanding what differentiated individuals that improved their understanding of the problem from those who did not warrants further research.
DISCUSSION AND CONCLUSION

This dissertation is driven by a broad question of how to make better decisions in strategic problem situations where principles of perfect rationality do not hold and optimization is not feasible. Optimization requires complete knowledge of the problem structure, but in strategic situations that organizations face, the requirement of complete knowledge is almost never met. Actors make decisions based on mental representations of the problem, and I have set to explore how mental representations of the problem emerge and evolve. The objective is to study what affects a decision maker’s ability to acquire accurate beliefs from experience and achieve superior long-term performance.

The main focus is on effects of using constraints – setting threshold values on variables of interest in order to learn about the problem in a more efficient manner. Findings from a computational model and a laboratory experiment suggest that constraints have non-trivial consequences on knowledge and performance. However, I have also found that our current understanding of acquisition of knowledge is not sufficient to explain some results of the lab study. I discuss implications of my findings for theory and practice.

Results from simulation experiments #1 and #2 demonstrate that a significant heterogeneity in knowledge and performance arises even if we hold constant the structure of the problem and computational abilities of actors – the famous blades of Simon’s scissors (Simon, 1990). Performance heterogeneity is driven by differences in the process of acquiring beliefs, where constraints influence an actor’s ability to acquire accurate beliefs. When constraints allow
actors to differentiate between superior and inferior strategies efficiently, actors develop accurate beliefs. However, if constraints are inappropriate for a given problem space, actors may acquire inaccurate beliefs. The implication of this result is that actors may fail at making better decisions, even if actors are deliberate about learning. Organizations may do many things right – provide incentives to properly motivate decision makers, conduct rigorous analysis prior to making decisions, perform a post-mortem of decisions and their outcomes to extract lessons. However, actors may still develop inaccurate beliefs because of the choices of constraints. I consider what happens when actors rely on an exogenous goal and competitor’s performance to set constraints.

Goals are considered extremely important in organizations. Goals are critical for organizational change and drive search behavior (Cyert and March, 1963; Greve, 2003). The goal setting theory argues that challenging and specific goals improve performance (Locke and Latham, 1990). However, research also showed that extremely challenging goals may hurt performance due to actors’ decreased commitment to the goal and lack of exploration (Kanfer and Ackerman, 1989; Locke and Latham, 2002). In the simulation experiment #1, I find that accuracy of beliefs and performance declines when the goal is very challenging. However, the mechanism is not a decreased exploration. It is quite the opposite – actors explore more because they fail to achieve an impossible goal. An inappropriately high goal leads to incorrect inferences about the usefulness of the strategies that actors try.

Results from a lab study provide further support for this mechanism. Participants have been presented with a very challenging goal – the baseline probability of winning the game is less than 0.1. In line with theoretical framework, participants in the study have engaged in high level of exploration and continued to explore at a high level throughout the game, especially if they failed to win at least one round. This exploration, however, has not necessarily led to better
understanding of the underlying structure of the problem. Most participants have started with low understanding of the problem and continued to have low understanding at the end of the game.

Goals appear to shape mental representations by affecting inductions that actors make from their experience. This implies that although setting the right goal is important in general, it is especially critical when organizations face new strategic problems. Young firms that just begin to learn everything about business and established firms that venture into new markets, products, or technologies have to deal with the challenge of setting an appropriate performance objective. Succumbing to the usual pressure from investors to maximize returns may prove fatal for both firms’ ability to learn about new businesses or markets and achieve high performance in the long term.

Competitor’s performance has long been critical to understanding learning from performance feedback through the concept of social aspirations (Cyert and March, 1963; Greve, 2003). In this literature, competitor’s performance is theorized to influence search behavior in a similar way as historical aspirations would — organizations are more likely to engage in problemistic search if their performance is below the social aspiration level than if it is above the social aspiration level (Greve, 1998a). It is further assumed that organizations select their social comparison group (Haveman, 1993; Porac et al, 1995; Greve, 1998b). In previous research, it has been impossible to establish empirically whether competitor’s performance matters for firms when they try to establish a reference point, because firms also observe competitor’s actions. Here, I explicitly theorized the use of competitor’s performance in setting up a constraint and proposed that paying attention to superior competitor’s performance results in higher exploration than paying attention to inferior competitor’s performance. I further proposed that adding information on competitor’s performance to exogenous goals leads to increased exploration.
when there is a superior competitor and decreased exploration when there is an inferior competitor. While results of the simulation experiment #2 generally support this proposition, results from the lab study do not. It is possible that for a competitor’s performance to matter, an actor needs to have some idea about strategies the competitor uses. It is also possible that exogenous goal is powerful enough on its own that it diverts actor’s attention from competitor’s performance. The second possibility is slightly undermined by the fact that in the lab study participants that observed superior competitor were less satisfied with their performance and their perceived self-efficacy was lower. Therefore, lack of competitor’s effect on exploration does not seem to be the result of lack of attention. This issue requires further theorizing and empirical testing.

The lack of differences in exploration depending on competitor’s performance results in a theoretical puzzle to explain other results of the lab study. I found that participants that observed inferior competitor made better decisions and achieved higher scores in the game, yet they failed to develop better understanding of the game and had lower odds of winning the game than participants that did not observe competitor’s performance. Results of the simulation experiment #2 and the lab study do not allow me to draw unequivocal conclusions about the mechanisms behind the effects of competitor’s performance. The most plausible explanation is that individual differences in mental representations were much stronger in driving differences in performance than competitor’s performance. I elaborate on this point below.

I have argued in my theoretical framework that knowledge of the problem structure plays a critical role in an actor’s ability to solve the problem. Knowledge is potentially more important than the structure of the problem or actor’s computational abilities. The structure could be simple, but actors may not know it. Computational abilities could be infinite, but actors may not
know what to compute. Results of the lab study acutely demonstrate the power of veridical knowledge of the problem structure. Participants in the lab experiment faced a well-structured problem and yet varied widely in both decision making effectiveness and performance. Heterogeneity in decision making and performance emerged in the first round and persisted through all six rounds. In the lab experiment, knowledge accuracy explained up to 20% of variance in winning the game. A correct understanding of one additional aspect of the problem structure may double or even triple the odds of winning. The results complement the very limited previous research that demonstrated association of accurate mental representations with better decisions and higher performance (Barr, Stimpert, and Huff, 1992; Gary and Wood, 2011).

However, this study extends beyond previous research by tracking the evolution of mental representations. Results of the lab study show that majority of participants approached the problem with inaccurate assumptions about the problem structure. Most of them continued to have inaccurate beliefs after six rounds of the game. However, given the previous discussion on exploration, it was not for the lack of trying to find better solutions. This suggests that a simple model of reinforcement learning that lies at the foundation of organizational learning in the management literature (Levitt and March, 1988) and induction-based learning in cognitive science (Holland et al, 1986; Sutton and Barto, 1998) may be either insufficient or inappropriate to explain the dynamics of mental representations. To make accurate inferences about the problem structure, actors need to do more than just try out different strategies, observe their outcomes, and retain the ones that are judged useful for solving the problem. The simple model of reinforcement learning does not address two issues, which appear to have been critical in the lab study. First, the assumption in the theory is that actors have access to all available alternatives. However, it seems that participants in the lab study varied in what possibilities they
have considered. Therefore, in a real-world scenario, actors may never come across a strategy that is actually useful for solving the problem. It is therefore not surprising that many problems remain unsolved for long periods of time. For example, mathematicians could not find a solution to “Fermat's last theorem” for over 300 years. Second, the theory of reinforcement learning simply assumes that failed strategies are discarded and successful strategies are retained. However, in the lab study, participants varied in how they responded to feedback about success or failure of alternatives that they tried. Some have stuck with their beliefs despite failures. Few have improved their understanding of the problem despite not observing successes. These findings suggest that we need to give much more consideration to how experience actually affects acquisition of beliefs and decision making behavior.

Focusing on emergence and dynamics of mental representations and emphasizing knowledge of structure as one of the main drivers suggests many directions for future research. More in-depth theorizing and empirical testing is needed to develop better understanding of effects of challenging goals on development of beliefs about the problem structure. It is especially important to explore boundary conditions of effects observed in both simulation experiments and the lab study. The computational model holds many factors constant, and it is important to understand how changing these factors will affect the outcomes. Future research can focus on studying how incentives, social context, and interdependency among strategic decisions change the effects of challenging goals on acquisition of knowledge. The limitation of this study is that an organization is assumed to be a unitary actor. However, in reality, organizations consist of many agents making many simultaneous decisions.

Multiple issues with effects of competitor’s performance also need to be addressed. It appears that competitor’s performance is not just a reference point. The limitation of this study is
the treatment of a competitor as a faceless piece of information. In reality, it is never the case. It is possible that information on competitor’s performance only matters when competitor itself matters to the actor. In future research, factors such as presence of a competitor, competitor’s characteristics, and importance of competition for survival can be studied for their effects on using information on competitor’s performance as a constraint.

Finally, in future research, we need to continue expanding our understanding of how individuals and organizations acquire beliefs from experience. If a simple model of reinforcement learning is not sufficient, do we need a more complex model or do we need a different model altogether? More studies with in-depth longitudinal analysis of mental representations are needed in order to understand how mental representations evolve based on experience. The limitation of this study is that it attempts to measure beliefs at discrete points in time. A more fluid, continuous approach, for example, using think-aloud protocols, is required. This study has also been limited to individual decision making. Understanding how evolution of mental representations is different when individuals are situated within organizational context is of paramount importance. Differences in network structures, social context, or organizational culture are just a handful of factors that could have an effect on how beliefs of individuals and organizations emerge from experience.

It has long been acknowledged that decision makers in organizations are boundedly rational (Simon, 1955; 1956). However, the research in management has been slow in explicitly incorporating cognition in dynamic models of boundedly rational decision making. Despite many advances in understanding the dynamics of mental representations in cognitive science and in determining the critical importance of strategy for organizational performance in management research, this study demonstrates that there is still a long road ahead of us in developing a
comprehensive understanding of why some organizations are better at strategic problem solving than others and why some organizations have persistent performance advantages despite the fact that they have to operate in dynamic, uncertain, and complex environments.
Table 1. Comparing model results from simulation experiment #1 to propositions

<table>
<thead>
<tr>
<th>Proposition</th>
<th>Model results</th>
</tr>
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<tbody>
<tr>
<td>Proposition 1: The effect of the goal level on accuracy of beliefs that the actor develops from experience is curvilinear. Accuracy of beliefs increases as the goal level increases but after a point it starts decreasing as the goal becomes more challenging.</td>
<td>Supported.</td>
</tr>
<tr>
<td>Proposition 2: The effect of the goal level on performance is curvilinear. Performance increases as the goal level increases but after a point it starts decreasing as the goal becomes more challenging.</td>
<td>Supported.</td>
</tr>
<tr>
<td>Proposition 3: Level of exploration increases linearly with the goal level.</td>
<td>Supported overall – level of exploration increases as the goal level increases. However, the relationship has more of an S shape than a straight line.</td>
</tr>
<tr>
<td>Proposition 4: The exogenous goal will be the most effective in guiding search and knowledge development when it is in the neighborhood of the solution with best true value.</td>
<td>Not supported. The goal that helps isolate at least 2 top performing strategies is more effective than a higher goal that only isolates the best strategy. When it becomes more difficult to distinguish between strategies, having an even lower goal that isolates a few top performing strategies is more beneficial, than the goal that isolates only one or two top performing strategies.</td>
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</table>
Table 2. Comparing model results from simulation experiment #2 to propositions

<table>
<thead>
<tr>
<th>Proposition</th>
<th>Model results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposition 5: Using performance of a superior competitor as a constraint results in higher level of exploration than using performance of an inferior competitor.</td>
<td>Effects of using inferior or superior competitor are not tested directly. When competitor’s performance is combined with exogenous goal, the proposition is supported. The effect holds at different goal levels.</td>
</tr>
<tr>
<td>Proposition 6: Using an exogenous goal as a constraint results in higher accuracy of beliefs than using a combination of an exogenous goal and competitor’s performance, regardless of the level of competitor’s performance.</td>
<td>Only supported for a specific region of the problem space. Not supported at very low or very high goal levels.</td>
</tr>
<tr>
<td>Proposition 7: Using an exogenous goal as a constraint results in higher performance than using a combination of an exogenous goal and competitor’s performance, regardless of the level of competitor’s performance.</td>
<td>Only supported for a specific region of the problem space. Not supported at very low or very high goal levels. The effects are sensitive to changes in temperature.</td>
</tr>
<tr>
<td>Proposition 8: Using an exogenous goal as a constraint results in higher exploration than using a combination of an exogenous goal and performance of inferior competitor.</td>
<td>Only supported for a specific region of the problem space. At very low goal level, exploration using an exogenous goal as a constraint is not distinguishable from exploration using a combination of exogenous goal and inferior competitor, but both are lower than exploration using a combination of exogenous goal and superior competitor. At very high goal level, exploration using an exogenous goal as a constraint is not distinguishable from exploration using a combination of exogenous goal and superior competitor, but both are higher than exploration using a combination of exogenous goal and inferior competitor.</td>
</tr>
</tbody>
</table>
Table 3. Description and a sample realization of the game

<table>
<thead>
<tr>
<th>Prior to the game</th>
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<tbody>
<tr>
<td>Description of rules</td>
</tr>
<tr>
<td>Preset optimal value of “Y”</td>
</tr>
<tr>
<td>Preset optimal values of decision variables</td>
</tr>
<tr>
<td>Start game</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>During the game</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1</td>
</tr>
<tr>
<td>Step 2</td>
</tr>
<tr>
<td>Step 3-20</td>
</tr>
</tbody>
</table>

The participant receives a base payment of $10 for participating in the experiment. He/she has an opportunity to win $10 for each of the 6 rounds he/she plays. Therefore, the participant has an opportunity to win up to $70 during the experiment.
Table 4. Treatment conditions in experimental design

<table>
<thead>
<tr>
<th>Group 1</th>
<th>Group 2</th>
<th>Group 3</th>
<th>Group 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Does not observe performance of “another participant”</td>
<td>Observes competitor’s performance</td>
<td>Observes inferior performance of “another participant”</td>
<td>Observes similar performance of “another participant”</td>
</tr>
</tbody>
</table>
Table 5. Power analysis using pilot data

<table>
<thead>
<tr>
<th>Comparing Group 1 with...</th>
<th>Mean difference</th>
<th>Pooled standard deviation</th>
<th>Standardized effect size</th>
<th>Estimated number of people per group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge accuracy after round 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group 2 (inferior)</td>
<td>-0.17</td>
<td>1.37</td>
<td>0.12</td>
<td>1,014</td>
</tr>
<tr>
<td>Group 3 (similar)</td>
<td>0.25</td>
<td>0.97</td>
<td>0.26</td>
<td>238</td>
</tr>
<tr>
<td>Group 4 (superior)</td>
<td>-0.5</td>
<td>0.91</td>
<td>0.55</td>
<td>52</td>
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<tr>
<td>Knowledge accuracy after round 6</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group 2 (inferior)</td>
<td>-0.17</td>
<td>0.89</td>
<td>0.19</td>
<td>428</td>
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<tr>
<td>Group 3 (similar)</td>
<td>0.75</td>
<td>0.79</td>
<td>0.95</td>
<td>18</td>
</tr>
<tr>
<td>Group 4 (superior)</td>
<td>0.5</td>
<td>1.07</td>
<td>0.47</td>
<td>72</td>
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<tr>
<td>Decision making effectiveness in round 6</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group 2 (inferior)</td>
<td>0.26</td>
<td>0.23</td>
<td>1.12</td>
<td>12</td>
</tr>
<tr>
<td>Group 3 (similar)</td>
<td>0.42</td>
<td>0.27</td>
<td>1.57</td>
<td>6</td>
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<tr>
<td>Group 4 (superior)</td>
<td>0.2</td>
<td>0.24</td>
<td>0.84</td>
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<td>Decision making effectiveness – growth coefficient</td>
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</tr>
<tr>
<td>Group 2 (inferior)</td>
<td>0.11</td>
<td>0.07</td>
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<tr>
<td>Group 3 (similar)</td>
<td>0.11</td>
<td>0.04</td>
<td>2.75</td>
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</tr>
<tr>
<td>Group 4 (superior)</td>
<td>0.12</td>
<td>0.05</td>
<td>2.35</td>
<td>3</td>
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<td>Absolute performance score in round 6</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group 2 (inferior)</td>
<td>325</td>
<td>309</td>
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<td>14</td>
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<td>Group 3 (similar)</td>
<td>1,364</td>
<td>1,973</td>
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<td>Group 4 (superior)</td>
<td>664</td>
<td>857</td>
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<td>Absolute performance score – growth coefficient</td>
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<td>Group 3 (similar)</td>
<td>314</td>
<td>347</td>
<td>0.9</td>
<td>19</td>
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<td>Group 4 (superior)</td>
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Table 6. Descriptive statistics

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<tr>
<th>Variable</th>
<th>No. of observations</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
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<tbody>
<tr>
<td><strong>Mental representations</strong></td>
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<tr>
<td>Problem awareness after round 2</td>
<td>140</td>
<td>1.84</td>
<td>1.41</td>
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</tr>
<tr>
<td>Problem awareness after round 4</td>
<td>137</td>
<td>2.20</td>
<td>1.56</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>Problem awareness after round 6</td>
<td>134</td>
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<td>1.68</td>
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</tr>
<tr>
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<td>138</td>
<td>2.04</td>
<td>1.43</td>
<td>0</td>
<td>5</td>
</tr>
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<td>Knowledge of structure after round 4</td>
<td>138</td>
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<td>1.06</td>
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<td>4</td>
</tr>
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<td>Heuristic knowledge after round 4</td>
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<td>0.93</td>
<td>0.66</td>
<td>0</td>
<td>2</td>
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<td>1.19</td>
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<td>0.91</td>
<td>0.66</td>
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<td><strong>Decision making behavior</strong></td>
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<td>Decision making effectiveness in round 1</td>
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<td>0.26</td>
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<td>0.9</td>
</tr>
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<td>0.29</td>
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<td>0.54</td>
<td>0.31</td>
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<td>141</td>
<td>0.54</td>
<td>0.31</td>
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<td>1</td>
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<tr>
<td>Decision making effectiveness in round 5</td>
<td>141</td>
<td>0.59</td>
<td>0.29</td>
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<td>0.56</td>
<td>0.28</td>
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<td>1</td>
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Table 6 Continued

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<tr>
<th>Variable</th>
<th>No. of observations</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
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</thead>
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<tr>
<td><strong>Performance</strong></td>
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<td></td>
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<tr>
<td>Absolute performance score in round 1</td>
<td>141</td>
<td>29,218.5</td>
<td>1,140.6</td>
<td>23,386</td>
<td>30,000</td>
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<td>141</td>
<td>29,356.7</td>
<td>1,183.0</td>
<td>23,006</td>
<td>30,000</td>
</tr>
<tr>
<td>Absolute performance score in round 3</td>
<td>141</td>
<td>29,312.9</td>
<td>1,296.6</td>
<td>23,332</td>
<td>30,000</td>
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<td>Absolute performance score in round 4</td>
<td>141</td>
<td>29,438.2</td>
<td>1,047.7</td>
<td>23,429</td>
<td>30,000</td>
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<td>29,520.9</td>
<td>985.8</td>
<td>24,520</td>
<td>30,000</td>
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<td>29,433.8</td>
<td>1,152.9</td>
<td>23,389</td>
<td>30,000</td>
</tr>
<tr>
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<td>141</td>
<td>0.04</td>
<td>0.19</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Win in round 2</td>
<td>141</td>
<td>0.06</td>
<td>0.25</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Win in round 3</td>
<td>141</td>
<td>0.09</td>
<td>0.28</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Win in round 4</td>
<td>141</td>
<td>0.13</td>
<td>0.33</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Win in round 5</td>
<td>141</td>
<td>0.13</td>
<td>0.33</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Win in round 6</td>
<td>141</td>
<td>0.15</td>
<td>0.36</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td><strong>Control variables</strong></td>
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</tr>
<tr>
<td>Female</td>
<td>141</td>
<td>0.58</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
</tr>
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<td>Age</td>
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<td>18</td>
<td>64</td>
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<td>0.45</td>
<td>0</td>
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<td>Several calculus classes</td>
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<td>0.50</td>
<td>0</td>
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<td>0.66</td>
<td>2.4</td>
<td>5</td>
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<td>Performance goal orientation</td>
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<td>0.91</td>
<td>1</td>
<td>5</td>
</tr>
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<td>Avoid performance goal orientation</td>
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<td>2.96</td>
<td>0.97</td>
<td>1</td>
<td>5</td>
</tr>
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<td>Use of intuition</td>
<td>139</td>
<td>3.03</td>
<td>0.46</td>
<td>2</td>
<td>4.3</td>
</tr>
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<td>Self-efficacy after round 2</td>
<td>132</td>
<td>5.08</td>
<td>2.28</td>
<td>0</td>
<td>9.5</td>
</tr>
<tr>
<td>Self-efficacy after round 4</td>
<td>138</td>
<td>5.00</td>
<td>2.59</td>
<td>0</td>
<td>10</td>
</tr>
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<td>Self-efficacy after round 6</td>
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<td>5.44</td>
<td>2.72</td>
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<td>10</td>
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<tr>
<td>Self-satisfaction after the game</td>
<td>136</td>
<td>2.57</td>
<td>1.24</td>
<td>1</td>
<td>5</td>
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</tbody>
</table>
Table 7. Distribution of participants across number of wins in the game

<table>
<thead>
<tr>
<th>Number of wins</th>
<th>Number of participants</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>105</td>
</tr>
<tr>
<td>1</td>
<td>17</td>
</tr>
<tr>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>Total</td>
<td>141</td>
</tr>
</tbody>
</table>
### Table 8. Distribution of wins across groups

#### Round 1

<table>
<thead>
<tr>
<th>Number of participants</th>
<th>Group 1</th>
<th>Group 2</th>
<th>Group 3</th>
<th>Group 4</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>32</td>
<td>36</td>
<td>39</td>
<td>30</td>
<td>137</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>Total</td>
<td>34</td>
<td>36</td>
<td>40</td>
<td>32</td>
<td>142</td>
</tr>
</tbody>
</table>

**Proportions**

<table>
<thead>
<tr>
<th></th>
<th>None</th>
<th>Inferior</th>
<th>Similar</th>
<th>Superior</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>94%</td>
<td>100%</td>
<td>98%</td>
<td>94%</td>
<td>96%</td>
</tr>
<tr>
<td>1</td>
<td>6%</td>
<td>0%</td>
<td>3%</td>
<td>6%</td>
<td>4%</td>
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</table>

$\chi^2=2.7 \ (p=0.441)$  
Fisher’s exact test: $p=0.422$

#### Round 6

<table>
<thead>
<tr>
<th>Number of participants</th>
<th>Group 1</th>
<th>Group 2</th>
<th>Group 3</th>
<th>Group 4</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>30</td>
<td>31</td>
<td>31</td>
<td>28</td>
<td>120</td>
</tr>
<tr>
<td>1</td>
<td>4</td>
<td>5</td>
<td>9</td>
<td>3</td>
<td>21</td>
</tr>
<tr>
<td>Total</td>
<td>34</td>
<td>36</td>
<td>40</td>
<td>31</td>
<td>141</td>
</tr>
</tbody>
</table>

**Proportions**

<table>
<thead>
<tr>
<th></th>
<th>None</th>
<th>Inferior</th>
<th>Similar</th>
<th>Superior</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>88%</td>
<td>86%</td>
<td>78%</td>
<td>90%</td>
<td>85%</td>
</tr>
<tr>
<td>1</td>
<td>12%</td>
<td>14%</td>
<td>23%</td>
<td>10%</td>
<td>15%</td>
</tr>
</tbody>
</table>

$\chi^2=2.78 \ (p=0.426)$  
Fisher’s exact test: $p=0.483$

#### All 6 rounds

<table>
<thead>
<tr>
<th>Number of participants</th>
<th>Group 1</th>
<th>Group 2</th>
<th>Group 3</th>
<th>Group 4</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>177</td>
<td>201</td>
<td>211</td>
<td>174</td>
<td>763</td>
</tr>
<tr>
<td>1</td>
<td>27</td>
<td>15</td>
<td>29</td>
<td>12</td>
<td>83</td>
</tr>
<tr>
<td>Total</td>
<td>204</td>
<td>216</td>
<td>240</td>
<td>188</td>
<td>846</td>
</tr>
</tbody>
</table>

**Proportions**

<table>
<thead>
<tr>
<th></th>
<th>None</th>
<th>Inferior</th>
<th>Similar</th>
<th>Superior</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>87%</td>
<td>93%</td>
<td>88%</td>
<td>94%</td>
<td>90%</td>
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<tr>
<td>1</td>
<td>13%</td>
<td>7%</td>
<td>12%</td>
<td>6%</td>
<td>10%</td>
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</tbody>
</table>

$\chi^2=8.48 \ (p=0.037)$  
Fisher’s exact test: $p=0.037$
Table 9. Estimating differences in likelihood of winning across treatment conditions

<table>
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<tr>
<th></th>
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<th></th>
<th>Model 2</th>
<th></th>
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</thead>
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<tr>
<td></td>
<td>DV: win</td>
<td></td>
<td>DV: win</td>
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</tr>
<tr>
<td>Coef.</td>
<td>S.E.</td>
<td>P</td>
<td>Coef.</td>
<td>S.E.</td>
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<td>0.000</td>
<td>-3.03</td>
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<tr>
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<td>-0.64</td>
<td>0.47</td>
<td>0.170</td>
<td>-0.62</td>
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<tr>
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<td>0.40</td>
<td>0.946</td>
<td>-0.02</td>
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<td>-0.69</td>
<td>0.50</td>
<td>0.163</td>
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<td>848</td>
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<td>Number of participants</td>
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</table>
Table 10. Estimating differences in absolute performance scores (APS) across groups

<table>
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<th></th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
<th>Model 3</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>S.E.</td>
<td>P</td>
<td>Coef.</td>
<td>S.E.</td>
<td>P</td>
</tr>
<tr>
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<td>29,295.40</td>
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<td>0.000</td>
<td>29,153.26</td>
<td>143.86</td>
<td>0.000</td>
</tr>
<tr>
<td>Inferior competitor</td>
<td>263.44</td>
<td>173.60</td>
<td>0.129</td>
<td>263.48</td>
<td>173.02</td>
<td>0.128</td>
</tr>
<tr>
<td>Similar competitor</td>
<td>-38.17</td>
<td>169.33</td>
<td>0.822</td>
<td>-38.05</td>
<td>168.77</td>
<td>0.822</td>
</tr>
<tr>
<td>Superior competitor</td>
<td>36.50</td>
<td>179.48</td>
<td>0.839</td>
<td>37.89</td>
<td>178.88</td>
<td>0.832</td>
</tr>
<tr>
<td>Round</td>
<td>73.51</td>
<td>52.77</td>
<td>0.164</td>
<td>-2.44</td>
<td>73.59</td>
<td>0.974</td>
</tr>
<tr>
<td>Inferior competitor*Round</td>
<td></td>
<td></td>
<td></td>
<td>-52.77</td>
<td>71.78</td>
<td>0.462</td>
</tr>
<tr>
<td>Similar competitor*Round</td>
<td></td>
<td></td>
<td></td>
<td>-56.66</td>
<td>76.13</td>
<td>0.457</td>
</tr>
<tr>
<td>Superior competitor*Round</td>
<td></td>
<td></td>
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</table>

Round fixed effects: No, Yes, NA

Number of observations: 848, 848, 848
Number of participants: 142, 142, 142
Table 11. Estimating differences in decision making effectiveness (DME) across groups

<table>
<thead>
<tr>
<th></th>
<th>Model 1 DV: DME</th>
<th>Model 2 DV: DME</th>
<th>Model 3 DV: DME</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>S.E.</td>
<td>P</td>
</tr>
<tr>
<td>Constant</td>
<td>0.49</td>
<td>0.04</td>
<td>0.000</td>
</tr>
<tr>
<td>Inferior competitor</td>
<td>0.08</td>
<td>0.05</td>
<td>0.122</td>
</tr>
<tr>
<td>Similar competitor</td>
<td>-0.03</td>
<td>0.05</td>
<td>0.623</td>
</tr>
<tr>
<td>Superior competitor</td>
<td>-0.01</td>
<td>0.05</td>
<td>0.841</td>
</tr>
<tr>
<td>Round</td>
<td>0.03</td>
<td>0.01</td>
<td>0.015</td>
</tr>
<tr>
<td>Inferior competitor*Round</td>
<td>-0.01</td>
<td>0.02</td>
<td>0.743</td>
</tr>
<tr>
<td>Similar competitor*Round</td>
<td>0.00</td>
<td>0.02</td>
<td>0.838</td>
</tr>
<tr>
<td>Superior competitor*Round</td>
<td>0.00</td>
<td>0.02</td>
<td>0.838</td>
</tr>
</tbody>
</table>

Round fixed effects: No, Yes, NA

Number of observations: 848, 848, 848
Number of participants: 142, 142, 142
Table 12. Estimating differences in knowledge accuracy (KA) across groups

<table>
<thead>
<tr>
<th></th>
<th>Model 1 DV: KA</th>
<th></th>
<th>Model 2 DV: KA</th>
<th></th>
<th>Model 3 DV: KA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>S.E.</td>
<td>P</td>
<td>Coef.</td>
<td>S.E.</td>
</tr>
<tr>
<td>Constant</td>
<td>2.18</td>
<td>0.24</td>
<td>0.000</td>
<td>2.15</td>
<td>0.25</td>
</tr>
<tr>
<td>Inferior competitor</td>
<td>-0.15</td>
<td>0.31</td>
<td>0.633</td>
<td>-0.15</td>
<td>0.31</td>
</tr>
<tr>
<td>Similar competitor</td>
<td>-0.03</td>
<td>0.31</td>
<td>0.927</td>
<td>-0.03</td>
<td>0.31</td>
</tr>
<tr>
<td>Superior competitor</td>
<td>-0.30</td>
<td>0.33</td>
<td>0.359</td>
<td>-0.30</td>
<td>0.33</td>
</tr>
<tr>
<td>Round 6</td>
<td>0.06</td>
<td>0.10</td>
<td>0.530</td>
<td>0.06</td>
<td>0.10</td>
</tr>
<tr>
<td>Inferior competitor*Round 6</td>
<td></td>
<td></td>
<td></td>
<td>0.20</td>
<td>0.23</td>
</tr>
<tr>
<td>Similar competitor*Round 6</td>
<td></td>
<td></td>
<td></td>
<td>0.00</td>
<td>0.26</td>
</tr>
<tr>
<td>Superior competitor*Round 6</td>
<td></td>
<td></td>
<td></td>
<td>0.10</td>
<td>0.29</td>
</tr>
<tr>
<td>Number of observations</td>
<td>274</td>
<td></td>
<td></td>
<td>274</td>
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</tr>
<tr>
<td>Number of participants</td>
<td>141</td>
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Table 13. Estimating differences in knowledge of structure (KS) across groups

<table>
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<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DV: KS</td>
<td>DV: KS</td>
<td>DV: KS</td>
</tr>
<tr>
<td>Coef.</td>
<td>S.E.</td>
<td>P</td>
<td>Coef.</td>
</tr>
<tr>
<td>Constant</td>
<td>1.27</td>
<td>0.17</td>
<td>1.23</td>
</tr>
<tr>
<td>Inferior competitor</td>
<td>-0.37</td>
<td>0.23</td>
<td>-0.36</td>
</tr>
<tr>
<td>Similar competitor</td>
<td>0.07</td>
<td>0.23</td>
<td>0.07</td>
</tr>
<tr>
<td>Superior competitor</td>
<td>-0.23</td>
<td>0.24</td>
<td>-0.23</td>
</tr>
<tr>
<td>Round 6</td>
<td></td>
<td></td>
<td>0.07</td>
</tr>
<tr>
<td>Inferior competitor*Round 6</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Similar competitor*Round 6</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Superior competitor*Round 6</td>
<td></td>
<td></td>
<td></td>
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Number of observations: 274 274 274  
Number of participants: 141 141 141
Table 14. Estimating differences in heuristic knowledge (HK) across groups

<table>
<thead>
<tr>
<th></th>
<th>Model 1 DV: HK</th>
<th></th>
<th>Model 2 DV: HK</th>
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<th>Model 3 DV: HK</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>S.E.</td>
<td>P</td>
<td>Coef.</td>
<td>S.E.</td>
<td>P</td>
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<tr>
<td>Constant</td>
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<td>0.10</td>
<td>0.000</td>
<td>0.92</td>
<td>0.11</td>
<td>0.000</td>
</tr>
<tr>
<td>Inferior competitor</td>
<td>0.22</td>
<td>0.14</td>
<td>0.132</td>
<td>0.22</td>
<td>0.14</td>
<td>0.133</td>
</tr>
<tr>
<td>Similar competitor</td>
<td>-0.10</td>
<td>0.13</td>
<td>0.448</td>
<td>-0.10</td>
<td>0.13</td>
<td>0.447</td>
</tr>
<tr>
<td>Superior competitor</td>
<td>-0.07</td>
<td>0.14</td>
<td>0.605</td>
<td>-0.07</td>
<td>0.14</td>
<td>0.601</td>
</tr>
<tr>
<td>Round 6</td>
<td>-0.01</td>
<td>0.05</td>
<td>0.798</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inferior competitor*Round 6</td>
<td></td>
<td></td>
<td></td>
<td>-0.03</td>
<td>0.15</td>
<td>0.847</td>
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<tr>
<td>Similar competitor*Round 6</td>
<td></td>
<td></td>
<td></td>
<td>-0.09</td>
<td>0.15</td>
<td>0.547</td>
</tr>
<tr>
<td>Superior competitor*Round 6</td>
<td></td>
<td></td>
<td></td>
<td>-0.21</td>
<td>0.16</td>
<td>0.195</td>
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</table>

Number of observations 275 275 275
Number of participants 141 141 141
Table 15. Estimating differences in problem awareness (PA) across groups treating round as a continuous variable

<table>
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<tr>
<th></th>
<th>Model 1 DV: PA</th>
<th>Model 2 DV: PA</th>
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<tr>
<td></td>
<td>Coef.</td>
<td>S.E.</td>
</tr>
<tr>
<td>Constant</td>
<td>1.27</td>
<td>0.32</td>
</tr>
<tr>
<td>Inferior competitor</td>
<td>0.40</td>
<td>0.44</td>
</tr>
<tr>
<td>Similar competitor</td>
<td>0.22</td>
<td>0.41</td>
</tr>
<tr>
<td>Superior competitor</td>
<td>0.33</td>
<td>0.43</td>
</tr>
<tr>
<td>Round</td>
<td>0.26</td>
<td>0.05</td>
</tr>
<tr>
<td>Inferior competitor*Round</td>
<td>-0.15</td>
<td>0.08</td>
</tr>
<tr>
<td>Similar competitor*Round</td>
<td>-0.10</td>
<td>0.07</td>
</tr>
<tr>
<td>Superior competitor*Round</td>
<td>-0.12</td>
<td>0.08</td>
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<table>
<thead>
<tr>
<th>AR1 correlation structure</th>
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<tr>
<td>Number of participants</td>
<td>140</td>
<td>137</td>
</tr>
</tbody>
</table>
Table 16. Estimating differences in problem awareness (PA) across groups treating round as a categorical variable.

<table>
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<th>Coef.</th>
<th>S.E.</th>
<th>P</th>
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<tbody>
<tr>
<td>Constant</td>
<td>1.79</td>
<td>0.28</td>
<td>0.000</td>
</tr>
<tr>
<td>Inferior competitor</td>
<td>0.07</td>
<td>0.36</td>
<td>0.851</td>
</tr>
<tr>
<td>Similar competitor</td>
<td>0.05</td>
<td>0.36</td>
<td>0.885</td>
</tr>
<tr>
<td>Superior competitor</td>
<td>0.08</td>
<td>0.35</td>
<td>0.828</td>
</tr>
<tr>
<td>Round 4</td>
<td>0.49</td>
<td>0.19</td>
<td>0.010</td>
</tr>
<tr>
<td>Round 6</td>
<td>1.03</td>
<td>0.22</td>
<td>0.000</td>
</tr>
<tr>
<td>Inferior competitor*Round 4</td>
<td>-0.16</td>
<td>0.23</td>
<td>0.480</td>
</tr>
<tr>
<td>Similar competitor*Round 4</td>
<td>-0.26</td>
<td>0.24</td>
<td>0.269</td>
</tr>
<tr>
<td>Superior competitor*Round 4</td>
<td>-0.19</td>
<td>0.26</td>
<td>0.458</td>
</tr>
<tr>
<td>Inferior competitor*Round 6</td>
<td>-0.59</td>
<td>0.32</td>
<td>0.063</td>
</tr>
<tr>
<td>Similar competitor*Round 6</td>
<td>-0.38</td>
<td>0.27</td>
<td>0.150</td>
</tr>
<tr>
<td>Superior competitor*Round 6</td>
<td>-0.48</td>
<td>0.33</td>
<td>0.153</td>
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</tbody>
</table>

Number of observations: 411
Number of participants: 140
Table 17. Estimating differences in exploration (EXPL) between groups

<table>
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<th>Model 2</th>
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<th></th>
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</thead>
<tbody>
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<td>Coef.</td>
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<td>P</td>
<td>Coef.</td>
<td>S.E.</td>
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<td>0.000</td>
<td>2.87</td>
<td>0.06</td>
</tr>
<tr>
<td>Inferior rival</td>
<td></td>
<td>-0.01</td>
<td>0.07</td>
<td>0.897</td>
<td>-0.01</td>
<td>0.07</td>
</tr>
<tr>
<td>Similar rival</td>
<td></td>
<td>-0.02</td>
<td>0.07</td>
<td>0.809</td>
<td>-0.02</td>
<td>0.07</td>
</tr>
<tr>
<td>Superior rival</td>
<td></td>
<td>0.01</td>
<td>0.07</td>
<td>0.873</td>
<td>0.01</td>
<td>0.07</td>
</tr>
<tr>
<td>Round fixed effects</td>
<td></td>
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<td>Yes</td>
<td></td>
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<tr>
<td>Number of observations</td>
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<td>848</td>
<td></td>
<td>848</td>
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</tr>
<tr>
<td>Number of participants</td>
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<td>142</td>
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<td>142</td>
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</table>
Table 18. Comparing results of an experimental study to propositions

<table>
<thead>
<tr>
<th>Proposition</th>
<th>Prediction</th>
<th>Lab study results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposition 5: Using performance of a superior competitor as a constraint results in higher level of exploration than using performance of an inferior competitor.</td>
<td>EXPL*(Group 2)&lt;EXPL(Group 4)</td>
<td>No significant difference ($p&gt;0.4$).</td>
</tr>
<tr>
<td>Proposition 6: Using an exogenous goal as a constraint results in higher accuracy of beliefs than using a combination of an exogenous goal and competitor’s performance, regardless of the level of competitor’s performance.</td>
<td>KA*(Group 1)&gt;KA(Group 2)</td>
<td>No significant difference ($p&gt;0.2$).</td>
</tr>
<tr>
<td></td>
<td>KA(Group 1)&gt;KA(Group 4)</td>
<td>No significant difference ($p&gt;0.2$).</td>
</tr>
<tr>
<td></td>
<td>KS*(Group 1)&gt;KS(Group 2)</td>
<td>After round 4, knowledge of structure in the group that did not observe competitor’s performance is higher by half a point (on a 4-point scale) than knowledge of structure in the group that observed inferior competitor ($p=0.003$). After round 6, the difference is only quarter of a point ($p=0.17$).</td>
</tr>
<tr>
<td></td>
<td>KS(Group 1)&gt;KS(Group 4)</td>
<td>After round 4, knowledge of structure in the group that did not observe competitor’s performance is higher by 0.4 (on a 4-point scale) than knowledge of structure in the group that observed superior competitor ($p=0.07$). After round 6, no significant difference ($p&gt;0.3$).</td>
</tr>
<tr>
<td></td>
<td>HK*(Group 1)&gt;HK(Group 2)</td>
<td>The effect is reversed. After Round 4, heuristic knowledge in the group that observed inferior competitor is 0.23 (on a 2-point scale) higher than heuristic knowledge in the group that did not observe competitor’s performance ($p=0.08$). After Round 6, the difference is 0.21 ($p=0.1$).</td>
</tr>
<tr>
<td></td>
<td>HK(Group 1)&gt;HK(Group 4)</td>
<td>After Round 4, no significant differences ($p&gt;0.2$). After Round 6, heuristic knowledge in the group that did not observe competitor’s performance is higher by 0.18 (on a 2-point scale) than heuristic knowledge in the group that observed superior competitor ($p=0.14$).</td>
</tr>
<tr>
<td></td>
<td>PA*(Group 1)&gt;PA(Group 2)</td>
<td>After Rounds 2 and 4, no significant differences ($p&gt;0.2$). After Round 6, problem awareness in the group that did not observe competitor’s performance is 0.52 (on a 5 point scale) higher than problem awareness in the group that observed inferior competitor ($p=0.11$).</td>
</tr>
</tbody>
</table>
Table 18 Continued

<table>
<thead>
<tr>
<th>Proposition</th>
<th>Prediction</th>
<th>Lab study results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposition 6: Using an exogenous goal as a constraint results in higher accuracy of beliefs than using a combination of an exogenous goal and competitor’s performance, regardless of the level of competitor’s performance.</td>
<td>PA(Group 1)&gt;PA(Group 4)</td>
<td>After Rounds 2 and 4, no significant differences ($p&gt;0.2$). After Round 6, problem awareness in the group that did not observe competitor’s performance is 0.4 (on a 5-point scale) higher than problem awareness in the group that observed superior competitor ($p=0.18$).</td>
</tr>
<tr>
<td></td>
<td>DME$_i$(Group 1)&gt;DME$_i$(Group 2)</td>
<td>The effect is reversed. Decision making effectiveness in the group that observed inferior competitor is 0.08 (equivalent to 1 – 2 attempts) higher than decision making effectiveness in the group that did not observed competitor’s performance ($p=0.06$).</td>
</tr>
<tr>
<td></td>
<td>DME(Group 1)&gt;DME(Group 4)</td>
<td>No significant difference ($p&gt;0.3$).</td>
</tr>
<tr>
<td>Proposition 7: Using an exogenous goal as a constraint results in higher performance than using a combination of an exogenous goal and competitor’s performance, regardless of the level of competitor’s performance.</td>
<td>P(Win(Group1))&gt;P(Win(Group2))</td>
<td>The odds of winning in the group that did not observe competitor’s performance are twice the odds of winning in the group that observed inferior competitor ($p=0.09$).</td>
</tr>
<tr>
<td></td>
<td>P(Win(Group1))&gt;P(Win(Group4))</td>
<td>The odds of winning in the group that did not observe competitor’s performance are twice the odds of winning in the group that observed superior competitor ($p=0.08$).</td>
</tr>
<tr>
<td></td>
<td>APS$_i$(Group 1)&gt;APS$_i$(Group 2)</td>
<td>The effect is reversed. Absolute performance score in the group that observed inferior competitor is 263 points higher than absolute performance score in the group that did not observed competitor’s performance ($p=0.06$).</td>
</tr>
<tr>
<td></td>
<td>APS(Group 1)&gt;APS(Group 4)</td>
<td>No significant difference ($p&gt;0.4$).</td>
</tr>
<tr>
<td>Proposition 8: Using an exogenous goal as a constraint results in higher exploration than using a combination of an exogenous goal and performance of inferior competitor and in lower exploration than using a combination of an exogenous goal and performance of inferior competitor.</td>
<td>EXPL$_i$(Group 1)&gt;EXPL$_i$(Group 2)</td>
<td>No significant difference ($p&gt;0.4$).</td>
</tr>
<tr>
<td></td>
<td>EXPL$_i$(Group 1)&lt;EXPL$_i$(Group 4)</td>
<td>No significant difference ($p&gt;0.4$).</td>
</tr>
</tbody>
</table>

Note: *EXPL – exploration; *KA – knowledge accuracy; *KS – knowledge of structure; *HK – heuristic knowledge; *PA – problem awareness; *DME – decision making effectiveness; *APS – absolute performance score. All reported probabilities are for one-tailed tests.
Table 19. Estimating differences in satisfaction and self-efficacy at the end of the game between groups

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DV: Satisfaction</td>
<td></td>
<td>DV: Self-efficacy</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coef.</td>
<td>S.E.</td>
<td>P</td>
<td>Coef.</td>
</tr>
<tr>
<td>Constant</td>
<td>2.71</td>
<td>0.21</td>
<td>0.000</td>
<td>5.49</td>
</tr>
<tr>
<td>Inferior competitor</td>
<td>-0.04</td>
<td>0.29</td>
<td>0.894</td>
<td>0.05</td>
</tr>
<tr>
<td>Similar competitor</td>
<td>0.14</td>
<td>0.28</td>
<td>0.608</td>
<td>0.56</td>
</tr>
<tr>
<td>Superior competitor</td>
<td>-0.81</td>
<td>0.30</td>
<td>0.009</td>
<td>-1.01</td>
</tr>
<tr>
<td>Number of participants</td>
<td>136</td>
<td></td>
<td></td>
<td>137</td>
</tr>
</tbody>
</table>
Table 20. Estimating differences in performance (APS), decision making effectiveness (DME), and heuristic knowledge (HK) across groups with Group 2 being the omitted category

<table>
<thead>
<tr>
<th></th>
<th>Model 1 DV: APS</th>
<th>Model 2 DV: DME</th>
<th>Model 3 DV: HK</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>S.E.</td>
<td>P</td>
</tr>
<tr>
<td>Constant</td>
<td>29,558.84</td>
<td>77.71</td>
<td>0.000</td>
</tr>
<tr>
<td>No competitor</td>
<td>-263.44</td>
<td>183.37</td>
<td>0.151</td>
</tr>
<tr>
<td>Similar competitor</td>
<td>-301.61</td>
<td>170.08</td>
<td>0.076</td>
</tr>
<tr>
<td>Superior competitor</td>
<td>-226.94</td>
<td>148.44</td>
<td>0.126</td>
</tr>
<tr>
<td>Number of</td>
<td>848</td>
<td></td>
<td></td>
</tr>
<tr>
<td>observations</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of</td>
<td>142</td>
<td></td>
<td></td>
</tr>
<tr>
<td>participants</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 21. Estimating differences in the likelihood of correctly answering questions about the problem structure after Round 4 across groups

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>S.E.</td>
<td>P</td>
<td>Coef.</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.94</td>
<td>0.39</td>
<td>0.017</td>
<td>-0.13</td>
</tr>
<tr>
<td>Inferior competitor</td>
<td>-0.67</td>
<td>0.60</td>
<td>0.260</td>
<td>-0.70</td>
</tr>
<tr>
<td>Similar competitor</td>
<td>0.32</td>
<td>0.51</td>
<td>0.535</td>
<td>-0.18</td>
</tr>
<tr>
<td>Superior competitor</td>
<td>-0.12</td>
<td>0.57</td>
<td>0.836</td>
<td>-0.77</td>
</tr>
<tr>
<td>Number of participants</td>
<td>139</td>
<td></td>
<td></td>
<td>139</td>
</tr>
</tbody>
</table>

139
Table 22. Modeling wins in Round 5 and Round 6 as a function of decision making effectiveness and problem awareness

<table>
<thead>
<tr>
<th></th>
<th>Model 1 DV: win</th>
<th>Model 2 DV: win</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>S.E.</td>
</tr>
<tr>
<td>Constant</td>
<td>-8.07</td>
<td>1.72</td>
</tr>
<tr>
<td>Decision making effectiveness</td>
<td>6.14</td>
<td>2.21</td>
</tr>
<tr>
<td>Problem awareness</td>
<td>1.47</td>
<td>0.57</td>
</tr>
<tr>
<td>Decision making effectiveness × problem awareness</td>
<td>-1.09</td>
<td>0.74</td>
</tr>
<tr>
<td>Self-efficacy</td>
<td>0.22</td>
<td>0.15</td>
</tr>
<tr>
<td>Female</td>
<td>-0.68</td>
<td>0.54</td>
</tr>
<tr>
<td>Undergraduate</td>
<td>0.46</td>
<td>0.60</td>
</tr>
<tr>
<td>Several calculus classes</td>
<td>-0.01</td>
<td>0.58</td>
</tr>
<tr>
<td>Favorable attitude toward math</td>
<td>1.30</td>
<td>0.61</td>
</tr>
<tr>
<td>Learning goal orientation</td>
<td>0.14</td>
<td>0.40</td>
</tr>
<tr>
<td>Performance goal orientation</td>
<td>-0.25</td>
<td>0.27</td>
</tr>
<tr>
<td>Use of intuition</td>
<td>-0.74</td>
<td>0.58</td>
</tr>
<tr>
<td>Inferior competitor</td>
<td>0.64</td>
<td>0.61</td>
</tr>
<tr>
<td>Similar competitor</td>
<td>-0.17</td>
<td>0.72</td>
</tr>
<tr>
<td>Superior competitor</td>
<td>-0.72</td>
<td>0.63</td>
</tr>
<tr>
<td>Round 6</td>
<td>0.42</td>
<td>0.39</td>
</tr>
</tbody>
</table>

Number of observations 274 266
Number of participants 137 133
Table 23. Predicted probabilities of winning in Rounds 5 and 6 at different levels of decision making effectiveness and problem awareness

<table>
<thead>
<tr>
<th>Problem awareness</th>
<th>Decision making effectiveness</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0.000</td>
</tr>
<tr>
<td>1</td>
<td>0.001</td>
</tr>
<tr>
<td>2</td>
<td>0.006</td>
</tr>
<tr>
<td>3</td>
<td>0.025</td>
</tr>
<tr>
<td>4</td>
<td>0.101</td>
</tr>
<tr>
<td>5</td>
<td>0.327</td>
</tr>
</tbody>
</table>
Table 24. Change in problem awareness from Round 2 to Round 6 as a function of individual characteristics and treatment conditions

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Coef.</th>
<th>S.E.</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.66</td>
<td>1.04</td>
<td>0.526</td>
</tr>
<tr>
<td>Female</td>
<td>0.50</td>
<td>0.23</td>
<td>0.030</td>
</tr>
<tr>
<td>Undergraduate</td>
<td>-0.01</td>
<td>0.25</td>
<td>0.966</td>
</tr>
<tr>
<td>Several calculus classes</td>
<td>-0.12</td>
<td>0.23</td>
<td>0.606</td>
</tr>
<tr>
<td>Favorable attitude to math</td>
<td>0.27</td>
<td>0.23</td>
<td>0.244</td>
</tr>
<tr>
<td>Learning goal orientation</td>
<td>0.16</td>
<td>0.17</td>
<td>0.349</td>
</tr>
<tr>
<td>Performance goal orientation</td>
<td>-0.09</td>
<td>0.12</td>
<td>0.475</td>
</tr>
<tr>
<td>Intuitive decision making</td>
<td>-0.11</td>
<td>0.25</td>
<td>0.662</td>
</tr>
<tr>
<td>Inferior competitor</td>
<td>-0.65</td>
<td>0.31</td>
<td>0.041</td>
</tr>
<tr>
<td>Similar competitor</td>
<td>-0.47</td>
<td>0.31</td>
<td>0.135</td>
</tr>
<tr>
<td>Superior competitor</td>
<td>-0.53</td>
<td>0.33</td>
<td>0.114</td>
</tr>
</tbody>
</table>

R²: 0.1
Number of participants: 131
Figure 1. Using an exogenous goal as a constraint

**Scenario A**
- Worst $S_j$
- Exogenous goal
- Best $S_j$

Strategies judged as useless
Strategies judged as useful

**Scenario B**
- Worst $S_j$
- Exogenous goal
- Best $S_j$

Strategies judged as useless by exogenous goal
Figure 2. Using competitor’s performance as a constraint

**Scenario A**

Strategies judged as useless by benchmarking against competitor’s performance

**Scenario B**

Strategies judged as useful by benchmarking against competitor’s performance
Figure 3. Belief accuracy (left axis) and cumulative payoff (right axis) as a function of the goal level ($N=8; \ PS = (4,6); \tau=0.25$)
Figure 4. Standard deviations for belief accuracy (left axis) and cumulative payoff (right axis) across goal levels ($N=8$; $PS = (4,6)$; $\tau=0.25$)
Figure 5. Cumulative payoff distributions at goal levels $P^*=5.25$ (left) and $P^*=5.75$ (right). ($N=8; PS = (4,6); \tau=0.25$)
Figure 6. Number of tried strategies (left axis) and cumulative payoff (right axis) across goal levels ($N=8$; $PS = (4,6)$; $\tau=0.25$)
Figure 7. Number of tried strategies (left axis) and belief accuracy (right axis) across goal levels ($N=8$; PS = (4,6); $\tau=0.25$)
Figure 8. Cumulative payoff across goal levels – comparing effects of exogenous goals to combinations of exogenous goals and competitor’s performance ($N=8$; $PS = (4,6)$; $\tau=0.25$)
Figure 9. Belief accuracy across goal levels – comparing effects of exogenous goals to combinations of exogenous goals and competitor’s performance ($N=8; PS = (4,6); \tau=0.25$)
Figure 10. Proportion of trials in which payoffs from using only exogenous goals are higher than payoffs from using a combination of exogenous goal and competitor’s performance (N=8; PS = (4,6); τ=0.25)
Figure 11. Number of tried strategies – comparing effects of exogenous goals to a combination of exogenous goal and competitor’s performance ($N=8$; $PS = (4,6)$; $\tau=0.25$). Graph on the left compares scenarios at $P*=4.0$, graph in the middle compares scenarios at $P*=5.5$, and graph on the right compares scenarios at $P*=6.5$.
Figure 12. Cumulative payoff across goal levels – comparing effects of exogenous goals to a combination of exogenous goals and competitor’s performance ($N=8$; $PS=(4,6)$; $\tau=2.0$)
Figure 13. Proportion of trials in which payoffs from using only exogenous goals are higher than payoffs from using a combination of exogenous goal and competitor’s performance ($N=8$; PS = (4,6); $\tau=2.0$)
Figure 14. Average absolute performance score across 6 rounds for all groups
Figure 15. Average decision making effectiveness across 6 rounds for all groups
Figure 16. Average knowledge accuracy for all groups at Round 4 and Round 6
Figure 17. Average knowledge of structure (graph on the left) and average heuristic knowledge (graph on the right) for all groups at Round 4 and Round 6.
Figure 18. Average problem awareness for all groups at Round 2, Round 4, and Round 6
Figure 19. Average exploration across rounds for all groups
Figure 20. Predicted probabilities of winning in Rounds 5 and 6 as a function of decision making effectiveness and problem awareness.
Figure 21. Distributions of problem awareness scores after Round 2 for participants that had high problem awareness scores after Round 6 (on the left) and for participants that had low problem awareness scores after Round 6 (on the right)
REFERENCES


