Mental Models, Decision Rules, and Performance Heterogeneity

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ABSTRACT

This paper focuses on the role of managerial cognition as a source of heterogeneity in firm strategies and performance. We link differences in mental models to differences in decision rules and performance in a management simulation. Our results show more accurate mental models lead to better decision rules and higher performance. We also find that decision makers do not need accurate knowledge of the entire business environment; accurate mental models of the key principles are sufficient to achieve superior performance. A fundamental assumption in much of strategic management is that managers who have a richer understanding about organizational capabilities and the dynamics of industry structure can improve the performance of their firms. Our findings provide empirical evidence supporting this assumption and show that differences in mental models help explain *ex ante* why managers and firms adopt different strategies and achieve different levels of competitive success.

Keywords: mental models, decision rules, cognitive frames, heuristics, knowledge representations, schema

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Understanding why some firms and not others adopt strategies ultimately associated with competitive success is of central importance to strategy scholars. In addressing one aspect of this issue, research examining the role of managerial cognition has shown that managerial mental models are a critical determinant of strategic choices (Gavetti, 2005; Kaplan & Tripsas, 2008; Porac, Thomas, & Baden-Fuller, 1989; Reger & Huff, 1993; Simon, 1991; Walsh, 1995). Managerial mental models are simplified knowledge structures or cognitive representations about how the business environment works. There is substantial evidence that mental models influence decision making through managers' efforts to match strategic choices to their understanding of the business environment (Barr, Stimpert, & Huff, 1992; Porac *et al.*, 1995; Tripsas & Gavetti, 2000). There is limited empirical evidence, however, for the link between mental model accuracy and performance.

Advancing our knowledge about the relationship between mental model accuracy and performance is important. There are strong beliefs within strategic management that managers who have a richer understanding about the dynamics of industry structure and organizational capabilities can improve the performance of their firms (Cockburn, Henderson, & Stern, 2000). An alternative possibility is that complexity, uncertainty, and change in business environments overwhelm managers' capacity to take advantage of any richer understanding about the situation. Under such circumstances, competitive advantage would be driven by initial conditions, random environmental shocks, and lucky managerial responses rather than the result of accurate mental models underpinning managerial foresight or strategic insights (Stinchcombe, 2000). There has been very little empirical research examining whether managers with more accurate mental models of the business environment achieve superior performance outcomes.

This paper reports the results from an experimental study examining the relationships between differences in mental model accuracy and performance. We also investigate the impact of partial knowledge–in contrast to accurate mental models of the complete business environment–on performance outcomes. Recent simulation-based research suggests that even partial knowledge of the business environment may dramatically improve performance (Denrell, Fang, & Levinthal, 2004; Gavetti & Levinthal, 2000), but thus far we have scarce empirical evidence. To better understand the connection between mental models and performance outcomes, we also examine the relationship between mental model accuracy and the quality of decision rules. In the face of complexity and uncertainty, managers adopt rules of thumb and heuristics that are intended to be consistent with their simplified mental models of the business environment (Cyert & March, 1963; Levitt & March, 1988; March & Simon, 1958; Nelson & Winter, 1982; Simon, 1991).

In the experiment, we utilize a management simulation to investigate these relationships in a controlled setting. This enables us to investigate mental models and decision rules in a complex decision environment using an experimental design allowing more precise measures of constructs and testing of hypothesized causal relationships. Our analyses highlight several features of mental models and decision making not studied in previous research. The findings show that accurate mental models about causal relationships in the business environment result in superior performance outcomes. This provides systematic evidence that accurate mental models are an important source of superior performance outcomes in complex environments. Our results also show that decision makers do not need accurate mental models of the entire business environment, but rather an accurate understanding of the key principles of deep structure. We also find that decision makers with more accurate mental models are more likely to adopt higher quality decision rules. The different decision rules cluster into a relatively small number of distinct strategies, and these strategies are significantly related to mental model accuracy and performance. Connecting heterogeneity in mental model accuracy to differences in decision rules and strategies contributes to our understanding about how and why strategic decisions emerge as they do and why managers adopt different strategies.

THEORY AND HYPOTHESES

Managers have limited information processing capabilities and rely on simplified mental models of reality to organize their knowledge and make sense of the world (Cyert & March, 1963; March & Simon, 1958). Research in psychology shows that these knowledge structures impact perception, information processing, problem solving, judgment, learning, and decision making (e.g., Anderson, 1990; Johnson-Laird, 1983; Rehder, 2003). Prior research spanning psychology, administrative and organization theory, economics, political science, computer science and cognitive science has used a variety of terms for these knowledge structures, including: mental models, schemas, dominant logics, causal maps, cognitive maps, frames, and belief systems (Axelrod, 1976; Bettis & Prahalad, 1995; Hodgkinson, Maule, & Bown, 2004; Huff, 1990; Simon, 1991; Sterman, 1989b).

Management research provides extensive evidence that managerial mental models are heterogeneous and impact strategic choices (Barr *et al.*, 1992; Eden & Spender, 1998; Gavetti, 2005; Gavetti & Levinthal, 2000; Hodgkinson *et al.*, 1999; Huff, 1990; Jackson & Dutton, 1988; Kaplan & Tripsas, 2008; Porac *et al.*, 1989; Reger & Huff, 1993; Simon, 1991; Tripsas & Gavetti, 2000; Walsh, 1995). Much of the strategy research examining the content of mental models has focused on how managers perceive and categorize information about their organization or competitive environment (Hodgkinson & Johnson, 1994; Jackson & Dutton, 1988; Porac *et al.*, 1995; Porac *et al.*, 1989; Reger & Huff, 1993). In contrast, there has been very little research investigating decision makers' mental models of the causal relationships in business environments and how these affect strategic choices. Recent research in psychology provides strong evidence that beliefs about cause-effect relationships are particularly important in supporting strategic decision making since they serve as the basis on which decision makers infer the consequences of their actions and guide intervention efforts to reach desired targets (Rehder, 2003). For example, solving complex strategic problems requires managers to generate options about where and how to intervene in their business by forming expectations about the possible outcomes resulting from their decisions. This process of developing strategic prescriptions relies heavily on the inferred causal relationships that make up managers' mental models about their business environment. Therefore, it is crucial to examine decision makers' inferences about chains of cause-effect relationships linking specific decision options to outcomes in order to understand how managers make strategic decisions (Levitt & March, 1988).

Prior research on managerial cognition has also established that different managers often perceive the same objective business environment differently (Barr *et al.*, 1992; Bourgeois, 1985; Tripsas & Gavetti, 2000). Despite strong evidence of heterogeneity in mental models, there has been very little strategy research investigating the importance of accurate mental models on performance outcomes. This is surprising since a fundamental assumption in much of strategic management is that successful firms and managers purposefully adopt strategies–based on accurate mental models–that match or 'fit' the competitive environment. Most strategy scholars believe that managers who have a richer understanding of the dynamics of industry structure and organizational capabilities can take advantage of this knowledge to improve firm performance. Strategy courses at business schools are built on the basic idea that managers can advance their understanding (i.e., mental models) of the business environment through rigorous, disciplined analysis, and that these richer mental models will facilitate the development of winning strategies. "The worth of a strategy depends on management's ability to… identify and to evaluate correctly the [business] environment" (Hatten & Schendel, 1975: 196). However, we have little systematic evidence that this is true (Henderson, 2000).

An alternative explanation is that the success or failure of individual firms is primarily driven by initial conditions, random shocks, and luck (Stinchcombe, 2000). This could be the case if resource positions are randomly distributed among firms during founding and any initial advantages are maintained through unyielding path dependence. This alternative might also be the dominant explanation for performance heterogeneity if managers are so completely overwhelmed by the complexity, uncertainty, and dynamism of the business environment to the point that strategic choices are equivalent to gambles at the race track (Stinchcombe, 2000). In other words, performance differences among firms may simply be a function of the realized competitive environment favoring some resource positions and some strategies above others.

There is some evidence from fieldwork as well as limited empirical support that accuracy of managerial mental models plays an important role in firm success (Barr *et al.*, 1992; Bourgeois, 1985; Tripsas & Gavetti, 2000). In addition, recent simulation-based work suggests that more accurate mental models about the causal relationships linking actions to outcomes translate into better performance (Denrell *et al.*, 2004) and may play a central role in the discovery of superior strategic positions (Gavetti & Levinthal, 2000; Gavetti, Levinthal, & Rivkin, 2005). On the other hand, Weick speculates that "Accuracy [in mental models] is nice, but not necessary" (Weick, 1990: 6). Similarly, Sutcliffe (1994) suggests that inaccurate perceptions may lead to positive consequences for organizations if they enable managers to overcome inertial tendencies and propel them to pursue goals that might look unattainable when the environment is assessed accurately. In this line of reasoning, having an accurate mental model may be less important than having some mental map that brings order to the world and enables incremental and adaptive action.

Overall, prior strategy research suggests that accurate mental models are important, but no prior studies have empirically tested the value of mental model accuracy about the causal relationships of the business environment. Given the importance of this issue for strategic management, we need to improve our understanding about whether more accurate mental models enable managers *ex ante* to identify and interpret signals from their business environment that lead to superior strategic choices and performance outcomes.

We investigate this issue directly in this paper. Based on the research streams discussed above, we expect variation in the accuracy of decision makers' mental models as a result of their own individual, unique experiences and due to differences in their learning strategies and differing abilities to draw inferences. Within this diversity, we expect decision makers with more accurate mental models to make better decisions and to achieve higher performance outcomes. Of course, through good luck, vastly deficient and incorrect mental models may result in correct action in some circumstances. However, on average, we expect more accurate mental models will help direct managerial attention to the most relevant information and serve as a better guide for strategic decisions.

Managers with accurate beliefs about interdependencies between their firm, competitors, and the market have a better understanding of the market drivers, the likely effects of different actions, and the resources needed to ensure success in different strategic positions. They will better understand competitive reactions and time delays and therefore are less likely to abandon effective long run strategies prematurely or to remain committed to failing courses of action. In summary, decision makers with more accurate mental models have a more comprehensive understanding of the fit between different strategic options and the business environment, formulate more effective strategies, and better understand market information and other sources of feedback compared to decision makers with less accurate mental models.

> H1: More accurate mental models of causal relationships in the business environment result in higher performance outcomes.

As simplifications of reality, mental models will always be incomplete and inaccurate. In the complex organizational environments in which managers operate, making accurate causal inferences is often very difficult. Consequently, decision makers are unlikely to construct completely accurate mental models in even a moderately complex environment. Prior research on judgment and decision-making shows that complexity–including time delays, nonlinearities, feedback effects, and stock accumulation processes–impairs the formation of accurate mental models and undermines performance (Moxnes, 1998; Paich & Sterman, 1993; Sengupta & Abdel-Hamid, 1993; Sterman, 1989a). Although greater complexity degrades the fidelity of mental models, recent simulation-based research suggests mental model accuracy becomes more important as complexity increases (Gavetti & Levinthal, 2000). Accurate mental models, the rationale goes, help managers identify promising regions of the competitive landscape. Other simulation-based strategy work suggests mental model accuracy may not be especially helpful in very simple or very complex contexts, but is instead most beneficial in moderately complex situations (Rivkin, 2001). Very simple decision environments can be effectively navigated without accurate mental models, while highly complex environments impair the development of highly accurate mental models.

Overall, prior research suggests that the benefits of mental model accuracy increase as decision environment complexity increases, but that very high levels of complexity may degrade mental models so much that they are not helpful in making strategic choices. Based on these arguments, we expect the benefits of mental model accuracy will be moderated by complexity of the decision environment. Decision makers with low quality, inaccurate mental models may still achieve relatively high performance outcomes in low complexity decision environments. Low complexity means there are fewer determinants to consider, fewer options, and the effects of decisions are more immediate and more transparent. In these simple environments, accurate mental models may offer little competitive advantage as all managers can quickly understand feedback and adapt strategies appropriately from the limited options available. As environments become more complex, an accurate understanding of causal relationships can contribute to the quality of choices during the formulation, implementation and evaluation of strategies. More accurate mental models help managers identify promising regions of the competitive landscape and drastically reduce the feasible strategy choices, thus affording a significant competitive advantage over managers with less accurate mental models. We expect mental model accuracy will be more important for achieving high performance outcomes in more complex decision environments.

> H2: More accurate mental models of the causal relationships in the business environment have a greater positive effect on performance in more complex environments.

The discussion so far has focused on the benefits of accurate mental models of the complete business environment. However, recent simulation-based research suggests that even partial knowledge of the business environment may dramatically improve performance by playing an important role in seeding and constraining the process of experiential learning (Denrell *et al.*, 2004; Gavetti & Levinthal, 2000). In search processes, even a small amount of knowledge may provide significant performance advantages by cutting down the search space and thereby reducing an otherwise lengthy random search process. This raises the question about whether accurate mental models of the entire business environment are required or if partial knowledge results in superior performance outcomes.

Research findings on expertise provide some guidance about the performance benefits of partial knowledge. Specifically, research shows that experts have deeper, structural-level mental representations of problems, while novices typically represent problems based on detailed, situation-specific surface characteristics (Chi, Feltovich, & Glaser, 1981). Mental representations of the deep structure of a problem domain are composed of ‘chunks’ of knowledge about the important key principles at work (Chase & Simon, 1973; Gentner, Loewenstein, & Thompson, 2003). Mental models of the key principles enable experts to recognize common elements and patterns across a class of problems, to quickly generate and evaluate relevant options, and to systematically outperform novices whose mental models typically focus on inconsequential details rather than the deep structure. Recent strategy work has started to explore the related issue of how experienced senior executives–with rich mental models of the deep structure or architecture of a strategic problem–often draw on solutions from past experience dealing with analogous situations (Gavetti *et al.*, 2005).

Based on these strands of prior research, we expect accurate mental models of key principles of the deep structure will result in superior performance outcomes.

> H3: More accurate mental models of key principles of the deep structure of the business environment lead to higher performance outcomes.

METHODS

We use an interactive, computer-based simulation of managing new product launch and lifecycle dynamics as the experimental task in our study. MBA students with no prior experience on the management simulation were invited to participate. The 63 participants included 47 male and 16 female volunteers, with an average age of 30 and seven years of work experience. Participants were randomly assigned to either the low complexity (n = 31) or the high complexity (n = 32) group and remained in the same group throughout the experiment. Participants were paid for taking part in the experiment. In addition, a small donation was paid to a nominated charity for the 43 students who also participated in the delayed-testing stage fifteen weeks later.

Task and Procedures

The management simulation has been utilized in previous research and captures many well-established features of product lifecycle management (Paich & Sterman, 1993). The core dynamic of the simulation is the process through which potential customers become aware of and choose to adopt the product. The causal relationships driving this market diffusion process are well understood (Bass, 1969; Kalish & Lilien, 1986; Mahajan, Muller, & Bass, 1995; Roberts & Urban, 1988). Customer adoption increases the installed customer base. The installed customer base generates word of mouth resulting in additional sales, but also depleting the pool of potential customers. The customer base follows an S-shaped growth pattern where sales rise exponentially, then peak and decline to the rate of replacement purchases as the market saturates (Paich & Sterman, 1993).

Participants take on the role of Chief Executive Officer of the firm and make quarterly decisions, such as price and production capacity expansion, with the goal of maximizing cumulative profit from the sales of their product over a forty-quarter simulation. The business environment changes as a consequence of participants' decisions and includes a large number of interdependent variables with multiple feedback effects, time delays, nonlinear relationships, and stock accumulations (Paich & Sterman, 1993; Sterman, 1989a). These features of the management simulation also characterize the sort of complex environments that senior managers typically operate in while making strategic decisions.

Participants completed three phases: a learning phase, an immediate testing phase, and a delayed testing phase. The learning phase and immediate testing phases were completed in an initial laboratory session in groups of 15 to 20. Each participant was seated at a separate computer and could not see other screens. The learning phase included three blocks of 40 decision trials–120 decision trials in total–for participants to learn about and become familiar with the simulation. After each decision trial, participants received outcome feedback on their results for that trial plus their cumulative performance up to that point. This feedback was presented in both table and graphical format in order to control for the effects of feedback format (Atkins, Wood, & Rutgers, 2002). After each trial block of 40 quarters, the simulation was reset to the same initial values and the next trial block began. The simulated outcomes could be, and were, very different from one trial block to the next since different decisions result in different simulated responses.

Following the learning phase, participants were asked to complete a series of questionnaires to assess their self-efficacy and mental models of the task. After completing the questionnaires, participants proceeded to the immediate testing phase, in which they completed three more blocks of 40 decision trials on the same version of the task. Participants completed each phase at their own pace. On average, the initial experimental session took three hours. Upon completing the immediate testing phase, participants left the laboratory and were paid for their participation in the study. The delayed testing phase was completed fifteen weeks later, and involved logging into the simulation from remote locations and completing three more blocks of 40 trials on the exact same version of the task. This phase was used to test the stability of the relationships proposed in all of our hypotheses.

Task Complexity

There were two levels of task complexity associated with either a monopoly market or a competitive market. In the low complexity version of the task, there were two decision variables−price and target capacity−and 19 interdependent variables in the causal structure. There was no competitor in the low complexity version of the task. There were three decision variables−price, target capacity, and marketing spend−and over 30 interdependent variables in the causal structure of the high complexity version of the task. This included causal relationships for a competitor in the market. While it is difficult to characterize any decision as inherently strategic, the set of decisions required each quarter involve substantial capital, are made difficult by the complexity of the business environment, and have considerable potential to influence firm performance.

Measures

Performance. Performance was measured for each of the nine trial blocks by the cumulative profit at the end of the last decision trial for each block. The nine trial blocks of performance included three blocks completed during the learning phase, three blocks completed in the immediate testing phase, and three blocks completed in the delayed testing phase. The potential achievable cumulative profit was different in the high and low complexity task conditions, and therefore we divided the raw performance scores by benchmarks for the high and low conditions. The performance benchmarks were found through a modified Powell search optimization (Powell, 1998). Marketing Spend was fixed at 5% of revenue throughout the simulation. Capacity was determined by a perfect foresight rule in which capacity always matched demand. Finally, the single price level that optimized profits over the entire simulation was computed. Note that this pricing rule is very simplistic since price does not change throughout the simulation in response to changing capacity, backlog, order demand, or any other variable in the decision environment. Therefore, the calculated cumulative profit benchmark is not a global optimum for the task, but is instead a consistently calculated benchmark enabling comparison across the two complexity groups[1].

Mental Model Accuracy. We evaluated several methods for assessing the accuracy of decision makers' knowledge structures. We considered using the repertory grid technique (Reger & Huff, 1993), but this approach was not feasible given the number of variables in the management simulation. Over 900 response cells would have been necessary for the high complexity version of the task. We also considered facilitated interviews to develop individual causal loop diagrams (Huff, 1990; Sterman, 2000), but this approach was not practical for use in a large-sample experiment. Other scholars have used content analysis of written narratives to infer managerial mental models (Osborne, Stubbart, & Ramaprasad,

[1] We also analyzed alternative benchmarks including a behavioral rule previously used as a benchmark on the high complexity version of this task (Paich & Sterman, 1993). All of our results were robust to these alternative benchmarks.

2001), but this approach did not leverage the advantage of having direct access to decision makers in our study. We also evaluated the cognitive mapping approach in which individual decision makers draw their own cognitive maps directly (Axelrod, 1976; Hodgkinson *et al.*, 1999). After a pilot test, this measurement approach was ruled out since the participants in our study were not familiar with the cognitive mapping method. There is also evidence that actors often have poor insight into their own decision making processes and interpretive approaches may simply capture espoused theories rather than ‘theories in use’ (Argyris & Schon, 1974). Instead, we devised a knowledge test using a sample of questions about the causal relationships in the management simulation for which the answers were known.

The measurement of knowledge using standardized tests is a well-developed subdiscipline of education and psychology. An individual’s knowledge is measured by calculating the proportion of questions answered correctly (Borgatti & Carboni, 2007). A key advantage of our laboratory experiment is that we know the correct answers to the knowledge questions about causal relationships in the management simulation and can therefore distinguish between correct and incorrect answers. This avoids a tricky and difficult problem of measuring mental model accuracy in field settings.

One set of questions tested participants’ inferences about bivariate causal relationships between pairs of variables from the management simulation. The questions covered the exhaustive set of actual relationships in each of the complexity conditions along with several items for which no relationship existed in the decision environment. Participants answered 30 items on the relationships between variables that were common to both complexity conditions. Participants in the high complexity condition answered a further 24 items relating to the additional variables and relationships in the high complexity condition. For each question, participants drew a directed influence arrow between the two variables and indicated the polarity−sign of the slope−of the relationship if they believed a causal relationship existed (Sterman, 2000). In order to complete this first set of knowledge questions, participants were provided with a complete list of variables in the management simulation. Appendix A provides a segment of the instructions along with the first three items of this first set of questions. Figure 1 shows a diagram of the full set of causal relationships in the low complexity decision environment.

Insert Figure 1 Here

A second set of questions tested participants' knowledge of the relationships between a small set of simulation variables and their ability to infer the dynamics of this set of variables. Each question presented a graph of one or two variables over time from the management simulation, and subjects chose from a multiple choice of answers for the evolution of another variable in the management simulation. To answer correctly, participants had to draw on their experience with the management simulation and their knowledge of the causal relationships between variables in order to determine how the dynamic behavior of the first variable or variables influences the dynamic behavior of another variable. This second set of questions captures whether participants' mental models accurately simulate the interaction of small sets of variables to predict subsequent events. This is an important aspect of mental models since decision makers use their mental models to predict and understand the environment by 'running' their models mentally (Norman, 1983). Appendix B provides a segment of the instructions along with one example from this set of questions. The full knowledge test is available upon request from the authors.

Each item on the knowledge test was scored as correct or incorrect and each participant's mental model accuracy was the percentage of items on the knowledge test answered correctly. The possible scores range from 0-1, where a score of 1 indicates perfect knowledge of the tested aspects of causal structure and dynamic behavior of small sets of variables in the decision environment. It is important to note that achieving a high score on the knowledge test is no guarantee of success in the complex decision environment. Understanding bivariate causal relationships and correctly inferring the dynamics of small sets of interdependent variables supports the development of effective decision making in the complex system, but the application of this knowledge remains a difficult task.

Mental Model Accuracy of the Deep Structure. A subset of the causal relationships were identified from prior research as the key principles of deep structure for the new product launch and lifecycle simulation. The multidisciplinary literature on the diffusion of new products is extensive (for starting points see Mahajan, Muller, & Bass, 1990; Parker, 1994; Rogers, 1995) and shows that many new products follow roughly logistic or S-shaped growth trajectories. Much of the research has focused on identifying the causal relationships that underpin this S-shaped pattern of behavior. For example, prior research shows that an important factor driving the growth phase in new product diffusion is social contagion through word of mouth. As early purchasers of a new product tell their friends, work associates, and families about the new product, some of these potential customers are persuaded to buy it for themselves. Sales to potential customers increase the installed customer base and further reinforce the word of mouth effect. Another source of awareness and adoption identified in the literature is the level of marketing spend on advertising, promotion, public relations, and direct sales efforts. The combined effects of word of mouth and marketing spend drive the adoption rate from the pool of potential customers to the installed customer base. However, these growth processes cannot continue forever. Once the population of potential customers has been depleted, sales fall to the replacement level of purchases driven by the average useful lifetime of the product.

This set of causal relationships underpinning the market diffusion process is well-established as the key principles of deep structure underlying product lifecycle dynamics spanning numerous industries (Bass, 1969; Kalish & Lilien, 1986; Mahajan, Muller, & Bass, 1995; Roberts & Urban, 1988). We expect that accurate knowledge about these causal relationships will lead to a richer understanding about the dynamics of the market. In particular, decision makers with knowledge about these causal relationships, including an accurate understanding about the dynamics over time of this small set of interdependent variables, will realize that the customer base follows an S-shaped growth pattern where sales rise exponentially, peak, and then decline to the rate of replacement purchases as the market saturates. We expect this knowledge will be helpful in guiding decision making about capacity investments, prices, and marketing spending to avoid–or at least mitigate–the boom and bust dynamics common in new product introductions (Gary, Dosi, & Lovallo, 2008; Paich & Sterman, 1993). In contrast, decision makers who lack accurate knowledge about the market diffusion process will find it difficult to match capacity and demand over the product lifecycle and performance will suffer as a result.

A total of eleven items from the knowledge test, involving questions about inferred causal relationships and dynamic behavior of small sets of variables, assess participants' knowledge of this deep structure. Appendix C provides seven example items for this measure of deep structure accuracy. The remaining four items of the deep structure accuracy measure are graphical scenario questions covering a subset of the same relationships. The example graphical scenario question in Appendix B is one of those items. Each participant's mental model accuracy of the deep structure was the percentage of these eleven items answered correctly. The possible scores range from 0-1, where a score of 1 indicates perfect knowledge of the tested aspects of the key principles of deep structure.

Control Variables

Cognitive Ability. One potentially important individual difference among decision makers in our study is cognitive ability. Cognitive abilities have been shown to play a central role in problem solving, reasoning, and learning (Anderson, 1990). Participants' scores on the Graduate Management Aptitude Test (GMAT) were used as a proxy for general cognitive ability. The GMAT is widely used to assess general cognitive ability of applicants to MBA programs around the world. In the admissions process, GMAT scores are commonly used as a selection criterion and are thought to reflect the achievement and learning potential of applicants in the domain of management.

Perceived self-efficacy is an established motivational predictor of performance on complex tasks and the constituent processes−such as search, information processing and memory processes−that can affect learning (Bandura, 1997). Also, complexity levels have been shown to influence the motivational reactions to tasks (Wood, Bandura, & Bailey, 1990). Therefore, self-efficacy was incorporated to control for differences in performance attributable to motivational differences. Perceived self-efficacy was measured with a 10-item scale, available from the authors, covering a broad range of activities involved in managing the simulated firm. The format followed the approach recommended by Bandura (1997), which has been validated in numerous empirical studies. For each item, participants first recorded whether or not they understood what was required to manage the activity−yes or no −and then recorded their confidence in their capabilities on a 10-point scale where 1 = "very low confidence" and 10 = "very high confidence." The perceived self-efficacy score was computed by taking the mean confidence level across all ten items.

Mental Model Complexity. A number of prior studies have used mental model complexity as an indication of the richness and accuracy of managers' mental models. The basic idea is that more complex knowledge structures are necessary for coping with the multidimensional challenges of complex organizational realities, and enable managers to respond appropriately in complex environments. The complexity of top managers' mental models has also been positively linked to competitive success (McNamara, Luce, &

Tompson, 2002). Therefore, mental model complexity was included as a control variable in order to distinguish between the effects of complex mental models and accurate mental models.

The complexity of decision makers' mental models was measured by counting the number of inferred causal relationships in the set of knowledge questions assessing beliefs about bivariate causal relationships. Reported perceived relationships were included in the count whether or not these causal relationships were correct. The potential number of perceived bivariate relationships was different in the high and low complexity task conditions, and therefore we divided the raw counts by the correct number of causal relationships in each condition. The result assesses the complexity of decision makers' mental models relative to the complexity of the perfectly correct mental model. Possible scores range from 0 to values greater than 1, where a score less than 1 indicates less complexity than in the correct mental model and a score greater than 1 indicates more complexity than the correct mental model due to inaccurate beliefs.

Data Analyses

The relationships proposed in Hypotheses 1-3 were tested by estimating both Ordinary Least Squares (OLS) regressions and linear mixed models with repeated measures. In the OLS models, the dependent variable was performance at the end of either trial block six−the final trial block of the immediate testing phase−or trial block nine−the final trial block of the delayed testing phase. In the linear mixed models with repeated measures, performance for trial blocks 4-9 in the immediate and delayed testing phases were all dependent variables, increasing the statistical power and reducing bias in the estimates. Task complexity was a between-subjects fixed effect. A first-order, autoregressive correlation structure was specified for the repeated measures of performance across trial blocks. Trial Block was also included as a fixed effect. In addition, a random intercept was included for each participant. Linear mixed models provide the best linear unbiased estimates for unbalanced, correlated repeated measures data (Verbeke & Molenberghs, 2000).

RESULTS

Table 1 provides the correlations, means, and standard deviations for all study variables. Task complexity was coded such that 0 = low complexity and 1 = high complexity. Task complexity is negatively correlated with mental model accuracy and performance across all trial blocks. Mental model accuracy is positively correlated with performance across all trial blocks. In addition, mental model accuracy ranges from 0.32–0.81 with mean 0.56 and standard deviation 0.11, demonstrating substantial variance. Decision makers' in the low complexity condition have significantly more accurate mental models [$t(61) = 2.73$, $p < 0.01$] than the high complexity group. As expected, complexity impairs the development of accurate mental models.

Insert Table 1 Here

Figure 2 illustrates mean performance and 95 percent confidence intervals across all nine trial blocks for the high and low complexity groups. The learning phase includes trial blocks 1-3, the immediate testing phase includes trial blocks 4-6, and the delayed testing phase includes trial blocks 7–9. Performance in both complexity conditions improves considerably from trial block 1 to trial block 3, but plateaus relatively quickly in the experiment. Performance falls slightly in the delayed testing phase but the difference is not statistically significant. The 95 percent confidence intervals show there is considerable variation in performance across decision makers in the same version of the management simulation task.

Insert Figure 2 Here

Tests of Hypotheses

Models 1-3 of Table 2 test the impact of mental model accuracy of the business environment on performance proposed in Hypothesis 1. Model 1 provides the OLS estimates using performance on trial block six, the last immediate testing phase trial block, as the dependent variable. In support of Hypothesis 1, mental model accuracy is a significant predictor of performance ($b = 1.039$, $p < 0.05$) after controlling for task complexity, general cognitive ability, and self-efficacy. To help interpret the effect size, the standardized coefficient for mental model accuracy is equal to 0.30. If we increase mental model accuracy by one standard deviation from its mean–assuming all other variables remain at their mean levels–performance increases by 22 percent. Task complexity has a significant and negative main effect on performance ($b = -0.434$, $p < 0.001$), indicating that participants in the high complexity condition achieved significantly lower performance outcomes than participants in the low complexity group. General cognitive ability, self-efficacy, and mental model complexity were not significant predictors of performance.

Model 2 provides the OLS estimates using performance on trial block nine, the last delayed testing phase trial block, as the dependent variable. The results are the same as in Model 1. In fact, the effects of mental model accuracy on performance ($b = 1.668$, $p < 0.05$) are even stronger in the delayed testing phase than in the immediate testing phase. The standardized coefficient for mental model accuracy is 0.41, and increasing mental model accuracy by one standard deviation increases performance by 40 percent. This indicates decision makers' mental models of the management simulation remained stable fifteen weeks after the initial laboratory session and continued to impact performance. Model 3 provides linear mixed model estimates using repeated measures for performance on trial blocks 4–9, all of the immediate and delayed testing phases, increasing the number of observations to 315. Again, the results are the same as in Models 1 and 2 with a significant, positive relationship between mental model accuracy and performance ($b = 0.988$, $p < 0.01$) and a negative main effect of task complexity on performance ($b = -0.438$, $p < 0.001$).[2]

Model 4 includes the interaction of task complexity and mental model accuracy to test Hypothesis 2. The interaction term is not significant, indicating that more accurate mental models do not have a greater positive effect on performance in environments that are more complex. The data do not support Hypothesis 2. Overall, the results of Models 1–4 of Table 2 support Hypothesis 1 and provide empirical evidence that more accurate mental models of the business environment lead to higher performance outcomes.

Insert Table 2 Here

Models 1–3 of Table 3 test the impact of accurate mental models of the deep structure on performance proposed in Hypothesis 3. Model 1 provides the OLS regression estimates using performance on the sixth trial block as the dependent variable. Deep structure accuracy has a significant positive impact on performance ($b = 0.596$, $p < 0.05$). Decision makers' do not need an accurate mental model of the complete business environment, but rather accurate mental models of key principles of the deep structure. To help interpret the effect size, the standardized coefficient for deep structure accuracy is equal to 0.23. If we increase deep structure accuracy by one standard deviation from its mean–assuming all other variables remain at their mean levels–performance increases by 17 percent. As established previously, task complexity has a significant negative effect on performance ($b = -0.442$, $p < 0.001$). General cognitive ability and self-efficacy were not significant predictors of performance. Model 2 provides the OLS estimates using performance on trial block nine as the dependent

[2] To simplify the presentation, the fixed effects associated with each trial block and the three variance-covariance components for the random-effect intercept and the autoregressive structure of the repeated measures are not shown in any of our results tables. Trial block is not significant in any of our analyses due to the performance plateau which occurs after the learning phase (refer back to Figure 3). The repeated component of all models is significant, indicating that residual errors are correlated by trial block. In addition, the random subject intercept is also significant in all models, indicating that performance varies between individuals.

variable. The results are the same as in Model 1 and, as in the previous analysis with mental model accuracy, the effects of deep structure accuracy on performance ($b = 1.178$, $p < 0.01$) are even stronger in the delayed testing phase than in the immediate testing phase. The standardized coefficient for deep structure accuracy is equal to 0.39, and increasing deep structure accuracy by one standard deviation increases performance by 38 percent. Model 3 provides linear mixed model estimates using repeated measures for performance across trial blocks 4–9. The results are the same as in Models 1 and 2 with a significant and positive impact of deep structure accuracy on performance ($b = 0.555$, $p < 0.05$) and a negative effect of task complexity on performance ($b = -0.446$, $p < 0.001$).

To assess the importance of deep structure knowledge relative to partial knowledge about any subset of the competitive environment, we tested whether the improvement in R square when we add Deep Structure Accuracy to the models is significantly better than the change in R square obtained when randomly chosen partial knowledge variables are added to the model instead[3]. The unadjusted R square of Model 1 in Table 3 with Intercept, Task Complexity, Self efficacy, and GMAT included as independent variables and Performance on the 6th trial block as the dependent variable is .45. When Deep Structure Accuracy is added to the model, unadjusted R Square increases to 0.49. This change in R square of 0.04 is significant ($p < 0.05$).

Next, we generated 1,000 random samples of eleven knowledge test items–out of 69 items on the high complexity condition and 42 items in the low complexity condition–to compute 1,000 partial knowledge variables. Eleven items were used to measure Deep Structure Accuracy, so we kept this consistent when computing random partial knowledge variables. We ran Model 1 regressions separately for all 1,000 partial knowledge variables and computed the change in R square for each partial knowledge variable. The mean R

[3] We would like to thank an anonymous reviewer for this helpful suggestion.

square change across the 1,000 partial knowledge variables was 0.025 (N = 1,000; std dev = 0.022; std error = 0.00068) with a 95 percent confidence interval of [0.024–0.027]. The change in R square for Deep Structure Accuracy, 0.04, is significantly different from the mean change in R square for the 1,000 partial knowledge variables ($t = -19.98$, $p < 0.001$).

We repeated this analysis again for Model 2 in Table 3. The unadjusted R square of Model 2 with Intercept, Task Complexity, Self-efficacy, and GMAT included as independent variables and Performance on the 9th trial block as the dependent variable is 0.39. When Deep Structure Accuracy is added to the model, unadjusted R Square increases to 0.496. This change in R square of 0.106 is significant ($p < 0.01$). In addition, this change in R square for Deep Structure Accuracy is significantly better ($t = -38.40$, $p < 0.001$) than the mean change in R square across the 1,000 partial knowledge variables. Overall, these results show that accurate knowledge about key principles of the deep structure leads to superior performance.

Insert Table 3 Here

Decision Rules and Strategies

To further investigate the mechanisms linking mental models and performance, we performed supplementary analyses of participants' decisions. In the face of complexity, decision makers adopt satisficing rules of thumb and heuristics that are intended to be consistent with their simplified mental models of the business environment (Cyert & March, 1963; Levitt & March, 1988; March & Simon, 1958; Simon, 1991). Mental models encompass beliefs about what information is most relevant in a given situation and how much weight to give to different pieces of information when making decisions. Decisions resulting in favorable outcomes are repeated when the same situation is encountered again and, in due course, this leads to the development of rules of thumb for making decisions that managers have seen in the past (Cyert & March, 1963; Levitt & March, 1988). Over time, these decision rules are likely to be executed more and more automatically without high levels of cognitive effort or conscious processing (Argyris & Schon, 1974).

Research shows that linear models of decision making often provide good higher-level representations of underlying processes (Camerer, 1981; Cyert & March, 1963; Einhorn, Kleinmuntz, & Kleinmuntz, 1979; Levitt & March, 1988). Supported by post experiment interviews, analysis of participants' experimental logs, and the decision rules identified in previous research for this new product launch experimental task (Paich & Sterman, 1993), we identified linear decision rules for pricing and capacity investment decisions for each participant.

Participants' capacity investment decisions involved estimating future demand by extrapolating current demand using the recent growth rate, and then making adjustments to balance capacity with expected future demand. Capacity adjustments do not happen instantaneously in most organizational settings or in our management simulation. Instead, decision makers set a target capacity level and after a time delay the actual level of production capacity approaches this target value. This time delay in combination with the requirement for accurate expectations with respect to future demand, makes the capacity investment decision dynamically complex (Sterman *et al.*, 2007; Zajac & Bazerman, 1991). Equation 1 shows the form in which participants' capacity decision rules were estimated; where C* is target capacity, D is actual demand, g is fractional demand growth over the last two quarters, B is Backlog, C is Capacity, the subscript *t* is time, and the subscript *t*-1 is the current time lagged by one period. We estimated parameters for the intercept *c* and the information weights a_0, a_1, and a_2.

$$\log(C_t^*) = c + a_0 \log(D_{t-1}) + a_1 \log(1 + g_{t-1}) + a_2 \log(B_t / C_t) + \varepsilon_1 \qquad (1)$$

Participants' pricing decisions involved a markup from unit variable cost, with margin over cost driven by the ratio of demand to capacity. This markup pricing rule is consistent with behavioral pricing rules documented in organizations from a wide range of competitive environments (Cyert & March, 1963). Equation 2 shows the form in which this pricing decision rule was estimated; where P is price, UVC is unit variable cost, B is Backlog, C is Capacity, the subscript *t* is time, and the subscript *t*-1 is the current time lagged by one period. We estimated parameters for the intercept b_0 and the information weights b_1 and b_2.

$$\log(P_t) = b_0 + b_1 \log(UVC_{t-1}) + b_2 \log(B_t / C_t) + \varepsilon_2 \qquad (2)$$

The information weights for the capacity and pricing decision rules were estimated separately for each trial block for each participant using Prais-Winsten regressions to correct for first-order autocorrelation (Camerer, 1981; Einhorn *et al.*, 1979). These decision rules capture the majority of the variance in participants' decisions in both complexity conditions. The mean adjusted R square values for the high and low complexity conditions are 0.75 and 0.85 respectively for the Target Capacity rule, and 0.97 and 0.92 for the Price rule. For the capacity and pricing decision rules, we also computed the optimal information weights maximizing cumulative profit[4]. These should in no way be construed as the global optimal decision rules for the management simulation since the rules only incorporate a handful of information cues in accordance with the information processing constraints of boundedly rational decision makers. The optimal information weights for these rules were used to calculate how far participants' information weights deviated from the optimal values[5].

We estimated linear mixed models with repeated measures to investigate the relationships between mental models and decision rules using deviation from the optimal information weights across trial blocks 4–9 as the dependent variable. Larger deviations

[4] The optimal information weights were computed using the Powell algorithm with random multiple starts over more than ten million simulations.
[5] The deviations were adjusted by a weighting factor to account for the sensitivity of performance to each information cue, and then the absolute differences summed across all information cues in both decision rules.

indicate less effective decision rules and Models 1–3 of Table 4 show the results[6]. Model 1 shows that mental model accuracy of the business environment has a significant impact ($b = -3.40$, $p < 0.001$), with more accurate mental models reducing the deviation from optimal information weights. Task complexity also has a significant impact ($b = 2.64$, $p < 0.001$) indicating participants' decision rules in the high complexity condition deviate more from the optimal information weights than participants in the low complexity group. Model 2 shows that more accurate mental models of the deep structure result in more effective decision rules with significantly smaller deviations from the optimally computed information weights ($b = -2.14$, $p < 0.01$). Overall, these results provide evidence for a positive relationship between mental models and effective decision heuristics. Establishing the link between mental model accuracy and decision rules highlights one more mechanism connecting mental models and performance variation.

Insert Table 4 Here

Further analysis of participants' pricing and capacity decision rules shows rapid stabilization of the information weights for both rules. The evolution of decision rules were tested using ANOVA contrasts comparing the information weights between trial blocks with the data pooled across participants and analyzed separately for each level of complexity. For the capacity investment decision rules, there are some significant differences between information weights on the first four trial blocks. However, there are no significant differences between information weights in all subsequent trial blocks of the immediate testing phase. In the pricing decision rule, there are no significant differences between information weights throughout all trial blocks of the learning and immediate testing phases. These results provide evidence that participants formed decision rules rapidly and largely

[6] A total of 12 cases–out of 315 total repeated measures cases–were identified as extreme outliers across multiple information weights and removed for the analysis.

stabilized the information weights for these rules by the end of the fourth trial block with little adjustment thereafter. This speedy stabilization of the decision rules helps explain why average performance plateaus so rapidly.

Our analysis of decision rules shows a great deal of variation in participants' information weights. To the extent that there are distinctive patterns of decision rules, this could be evidence of different high-level policies or strategies. Recent strategy research suggests different configurations of specific choice and decision sets lie below the surface of higher-level policies and overarching strategies (Gavetti *et al.*, 2005). Managers and firms vary in terms of the overall strategies they adopt. For example, a firm that adopts a pricing rule to capture market share by dropping price as unit cost decreases over time (e.g., due to learning curve effects) and a capacity investment rule that rapidly expands capacity to fulfill demand could be characterized as adopting a 'Get-big-fast' cost leadership strategy (Sterman *et al.*, 2007). Different patterns of decision rules could similarly represent other generic strategies such as a premium price, niche strategy, as well as many other mixed strategies. These strategies may be the result of either rational ex ante planning or emergent behavior. Identifying different strategies by examining the observed patterns in decision rules is necessarily exploratory, but enables us to investigate heterogeneity in strategies and the relationships between mental models and strategies.

We used two-stage cluster analysis of the information weights to explore patterns in the decision rules. The first stage involved hierarchical analysis to identify outliers and centroid means, followed by K-Means nonhierarchical analysis to identify distinctive strategies (Ketchen Jr & Shook, 1996)[7]. As shown in Table 5, this analysis identified five distinct strategies for the low complexity task condition and four distinct strategies for the high complexity task condition. These strategies capture the range of observed patterns in the

[7] Analyses were run separately for each task complexity condition and the results were robust to using different distance algorithms for identifying clusters.

pricing and capacity investment decision rules. For example, the Tenacious Build and Hold strategy in the low complexity task combined building capacity to an initial forecast–as indicated by the large intercept for capacity investment–along with reducing price as unit costs fall; as indicated by a relatively large cue weight for unit cost. Figure 3 illustrates the different patterns of capacity investment decisions for the four distinct strategies in the high complexity condition. Similarly, Figure 4 illustrates the different patterns of pricing decisions associated with the five distinct strategies in the low complexity decision environment.

Insert Table 5 Here

Insert Figure 3 and Figure 4 Here

ANOVA shows there are significant differences in both mental model accuracy ($F = 5.372$, $p < 0.01$) and performance ($F = 14.745$, $p < 0.001$) between the four distinctive strategies in the high complexity decision environment. There are also significant differences in performance ($F = 3.064$, $p < 0.05$) and marginally significant differences in mental model accuracy ($F = 2.300$, $p = 0.06$) between the five distinctive strategies in the low complexity decision environment. Establishing these differences shows an additional mechanism connecting mental models and performance variation. Specifically, the accuracy of decision makers' mental models impacts the strategies they adopt and there are significant performance differences between the different strategies.

We also ran the complete set of pairwise tests of the differences in mental model accuracy and performance across the various strategies. The results show that decision makers with the most accurate mental models adopt the best strategies and achieve superior performance under both complexity conditions. However, at lower levels of mental model accuracy the connection between mental model accuracy, the strategies adopted and performance outcomes achieved, are not as straightforward. These findings suggest there may be threshold effects relating mental models to the selection of higher-level strategies. It is important to highlight that we are not suggesting that the highest performing strategies in the simulation are the optimal strategies for firms to adopt when launching new products and managing the lifecycle. Instead, these results demonstrate there are links between decision makers' mental models and the different strategies they adopt, and connect heterogeneity in mental model accuracy, decision rules, and strategies to variation in performance outcomes.

DISCUSSION

Our results provide empirical evidence for the links between mental models and performance outcomes and help explain why some managers and not others adopt strategies that are ultimately associated with competitive success. We found substantial variation in the accuracy of decision makers' mental models and in performance. While it is certainly true that perfect mental models are not necessary to reach high performance outcomes (Sutcliffe, 1994; Weick, 1990), our findings show that decision makers with more accurate mental models of the causal relationships in the business environment achieve higher performance outcomes. Further, this relationship not only remained stable but grew stronger between the immediate and delayed testing phases, providing evidence that decision makers' mental models of the experimental task were not ephemeral.

Our results are consistent with the limited prior empirical research findings about the importance of accurate mental models (Barr *et al.*, 1992; Bourgeois, 1985), and extend prior work by providing systematic evidence connecting differences in mental models of causal relationships with performance heterogeneity. Our findings also help address an important challenge facing the strategy field about whether more accurate mental models enable managers *ex ante* to identify and interpret signals from their business environment that lead to superior strategic choices and performance outcomes (Cockburn *et al.*, 2000). In our experimental study, variation in mental model accuracy is a key source of performance heterogeneity.

Our findings also show that managers do not need accurate mental models of the entire business environment. Accurate mental models about the key principles of the business environment lead to superior decision rules and performance outcomes. These results support recent theoretical work in strategy positing the benefits of partial knowledge (Denrell *et al.*, 2004; Gavetti & Levinthal, 2000), and extend this work by providing evidence that all partial knowledge is not equally valuable. The benefits of partial knowledge about the key principles far outweigh the benefits of other partial knowledge. Our findings are also consistent with prior research showing that experts with richer cognitive representations of the deep structure of problems outperform novices who typically focus on superficial features of problems (Chi *et al.*, 1981; Gentner *et al.*, 2003). An important implication is that managers do not need to develop perfect and complete mental models of complex business environments, but should instead focus on identifying and understanding the key principles.

We also find considerable variation in decision rules and that more accurate mental models and deep structure accuracy lead to more effective decision rules. These findings extend research examining the detrimental mean effects of decision biases and heuristics (e.g., Kahneman & Tversky, 2000; Sterman, 1989b; Zajac & Bazerman, 1991). Specifically, our results provide evidence of heterogeneity in decision rules and connect these differences to mental model accuracy. We also find a number of distinctive strategies or patterns in participants' decision rules. There are significant differences in mental model accuracy across these different strategies, and the different strategies account for significant variation in performance. These findings help us understand how variation in mental models and decision making underlies the origins of successful strategies.

We also find that decision rules stabilize rapidly and this explains why performance plateaus far below the potential achievable level. Rapid stabilization of decision rules is consistent with psychology research on complex problem solving that shows actors learning a new task or solving a novel complex problem quickly automate decision and action rules once they reach functional, satisficing levels of performance (Ericsson, Krampe, & Tesch-Romer, 1993). Our results are also consistent with research that finds managers typically interpret information to reinforce their current mental model rather than challenge and update their beliefs (Barr *et al.*, 1992). Similarly, another stream of simulation-based research suggests that in the face of complexity many firms reach suboptimal decision configuration “sticking points” from which they do not move (Rivken, 2000; Rivkin & Siggelkow, 2003).

We did not find evidence that more accurate mental models were more important in the higher complexity decision environment. However, compared with very simple tasks, both of our management simulations were fairly complex. Even the low complexity version of the new product launch simulation includes time delays, nonlinearities, and multiple feedback effects. Perhaps in truly simple competitive environments−with smooth payoff landscapes−mental model accuracy may be less important for achieving high performance outcomes (Gavetti & Levinthal, 2000). There may also be a level of complexity that overwhelms managers’ capacity to either accurately infer causal relationships in the business environment or apply their mental models to make effective strategic choices (Rivkin, 2001).

We also did not find a positive link between mental model complexity and performance. This is at odds with prior research findings on the benefits of more complex mental models (Lurigio & Carroll, 1985; McNamara *et al.*, 2002). However, there are important measurement differences that partially explain why our findings are different. Our focus on causal relationships led to an operationalization of mental model complexity that includes correct as well as incorrect cause-effect inferences. As expected, our results show that more complex mental models−that include incorrect causal inferences−do not enhance performance above simpler, more accurate mental models. We believe much of the prior research has used mental model complexity as a proxy for mental model accuracy, and this is not always the case. There is evidence that domain experts generally have more complex knowledge structures than novices (Lurigio & Carroll, 1985). However, expert knowledge is not a direct function of the number of years of experience a decision maker has in a domain.

Limitations and Future Research

Experimental findings linking differences in mental models, decision rules, and strategies to performance heterogeneity are not conclusive evidence of these links in real competitive environments. External validity is a common concern with experimental studies and ultimately can only be addressed through accumulating a stream of both experimental studies and field research replicating and extending our findings. However, recent meta-analyses comparing effect sizes from lab studies and field research reveals a correlation of .73-.97 suggesting a high degree of generalizability from laboratory to field (Anderson, Lindsay, & Bushman, 1999; Cohen-Charash & Spector, 2001). In the design of our study, we also made choices that we believe contribute to the potential external validity of our findings.

Dynamic decision making experiments using complex management simulations incorporating feedback, time delays, stock accumulations, and nonlinearities more closely approximate the decision making environments of senior managers than the experimental tasks typically employed in psychological and judgment and decision making research. Our management simulation represents a common real world strategic challenge of managing a new product over the entire lifecycle (Bass, 1969; Paich & Sterman, 1993; Roberts & Urban, 1988). In addition, decision makers in our studies had access to the same sort of information−through quarterly management reports about their simulated firm−that managers use in making similar decisions in real organizations (e.g., financial and operational reports).

Set against the potential limits to the external validity of our findings are the rigorous internal validity claims afforded by our experimental design. Our research design enabled us to measure attributes of decision makers' mental models–such as accuracy of causal inferences–that are notoriously difficult to measure in the field due to uncertainty about the objective cause-effect relationships. While our measure of mental model accuracy is certainly not ideal, the overall fit in the nomological network is supportive of construct validity (Schwab, 1980). A mental model of a problem domain contains direct representations of the entities observed in the environment and simulates the interaction of these entities through operators that predict subsequent events (Larkin, 1983). Our measure of mental model accuracy aims to capture both of these aspects of decision makers' mental models.

We are optimistic future research will continue to advance the measurement of mental models. An ideal measure would capture the formation and evolution of mental models over time, and would identify how knowledge about causal relationships informs beliefs about gestalt system behavior. There is also an opportunity for future research to identify different components of mental models and examine the conditions under which different sources of inaccuracy are important. In an exploratory analysis of our data, we identified two types of errors that significantly impacted performance in our study. Inferring a causal relationship between two variables when in reality no causal relationship exists is a superstitious belief (Levitt & March, 1988). Omitting a real causal relationship between two variables is a causal blind spot. We found that causal blind spots and superstitious beliefs about the business environment led to lower performance. We need more research investigating the types of misperceptions and errors in mental models that are most damaging.

Future research should assess the generalizability of our findings by testing the relationships between mental models, decision rules, strategies and performance, both in the field and in laboratory experiments across a variety of management contexts and decision makers. Recent developments in measuring knowledge in the field may provide opportunities to accurately estimate knowledge levels in domains where the objectively right answers are not known a priori (Borgatti & Carboni, 2007). Prior research also suggests possible ways to operationalize decision environment complexity in field settings (Sutherland, 1980), potentially providing a path for exploring the impact of complexity on mental models, strategic decisions, and performance in the field.

Our study also focused on individual decision makers and did not explore the enactment process in organizations where teams of executives come together to make decisions. Firm strategies and decisions are the product of a socio-political process embedded in an organizational setting involving multiple actors (Chattopadhyay *et al.*, 1999). However, ultimately it is individuals whose mental models form the substance of such collective deliberations. We believe isolating the cognitive aspects of decision making enables us to build solid microfoundations before we extend the scope to include social processes.

Our results suggest that addressing deficiencies in mental model accuracy will help improve performance outcomes. Fortunately, knowledge gaps are subject to remedial action. We believe learning laboratories using simulation models of common management challenges represent one promising approach to developing high-quality mental models of the deep structures (Gary *et al.*, 2008). Recent advances in interactive modeling and simulation tools provide an effective means for representing the causal structure of business and social systems and to learn about these complex, dynamic environments through simulation (Sterman, 2000). More work is also needed to isolate the small set of enduring causal relationships underpinning a wide range of management problems and challenges. Research is also needed on interventions to develop reflection and de-framing skills to help managers question their own mental models and decision rules. Such skills may prevent managers and firms from prematurely locking into inaccurate mental models and decision rules (Rivkin & Siggelkow, 2003; Tripsas & Gavetti, 2000).

There are also opportunities for research examining heterogeneity in the decision rules connecting high-level strategies with decision making processes on the front lines (Cyert & March, 1963; Simon, 1991). Research on decision errors and biases has primarily focused on identifying the mean or modal effects of specific types of errors (Camerer & Lovallo, 1999; Kahneman & Tversky, 2000; Paich & Sterman, 1993; Zajac & Bazerman, 1991). More work is needed to understand the heterogeneity in decision rules and heuristics and how differences in decision rules impact performance. This is particularly important for strategy scholars trying to explain heterogeneity in strategies and performance among firms. More research is also needed on the formation of decision rules and the links to mental models to help us better understand the origins of strategy.

Our findings provide much needed empirical evidence that differences in mental model accuracy explain why decision makers adopt different strategies associated with different levels of competitive success. This represents an important step forward and provides a number of opportunities for future research examining the cognitive aspects of strategy and identifying mechanisms to support better strategic thinking and decisions.

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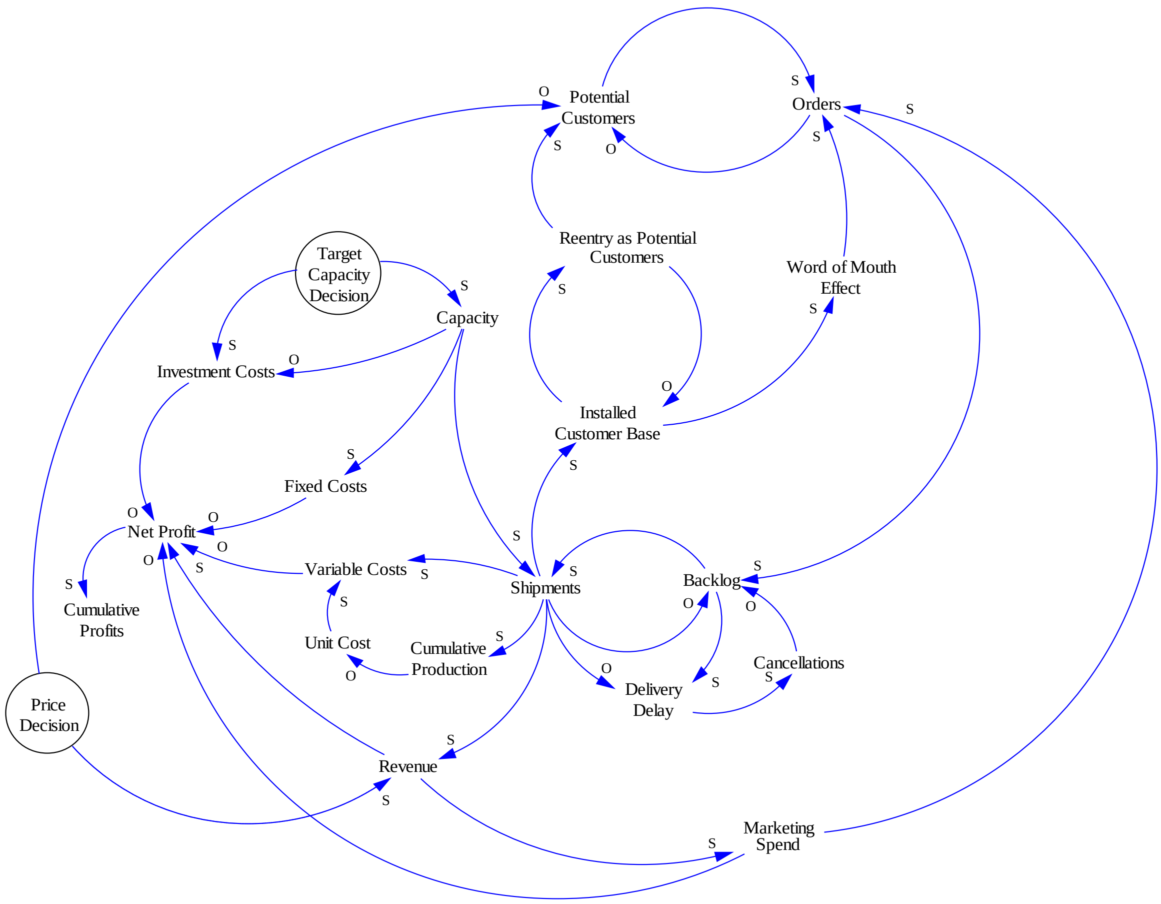


Figure 1 Causal relationships of the low complexity task[8]

[8] The arrows linking variables are defined formally as follows (Sterman, 2000):

$$x \xrightarrow{S} y \Rightarrow \frac{\partial y}{\partial x} > 0 \quad and \quad x \xrightarrow{O} y \Rightarrow \frac{\partial y}{\partial x} < 0$$

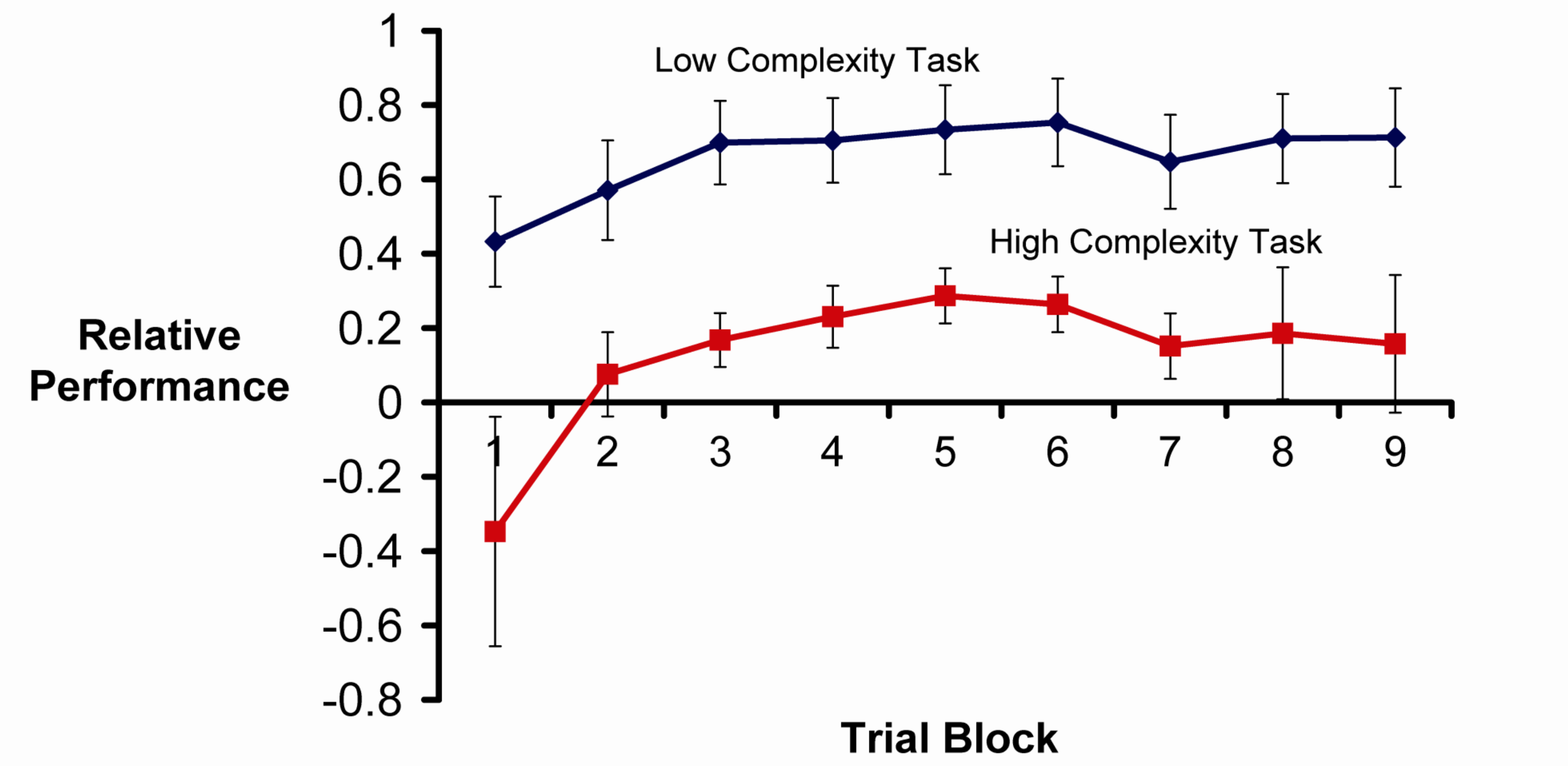


Figure 2 Mean performance relative to benchmark and 95% confidence intervals for low and high complexity groups across all nine trial blocks

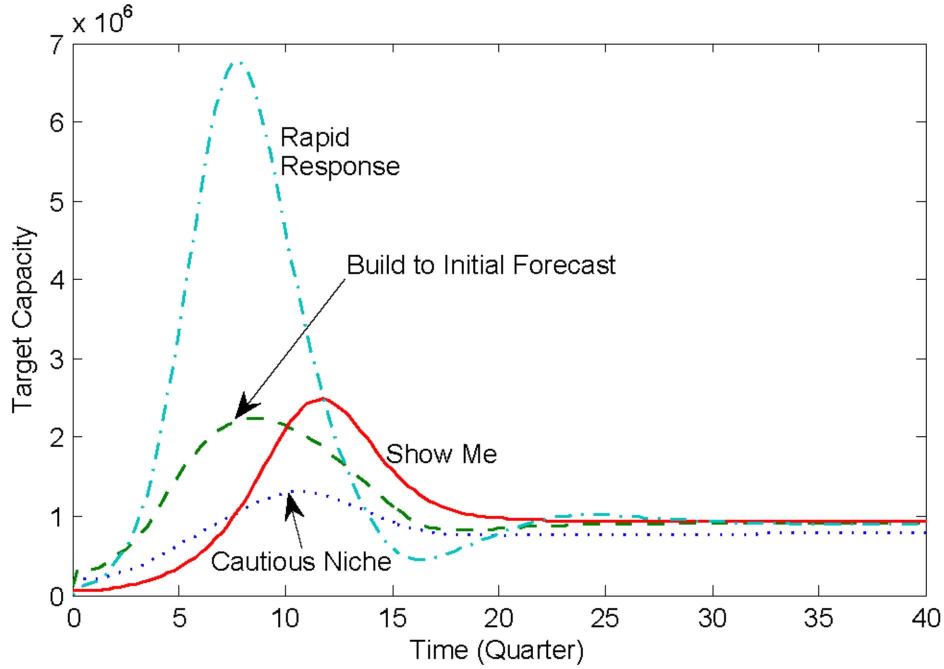


Figure 3 Different patterns of target capacity decisions for the four high complexity strategies

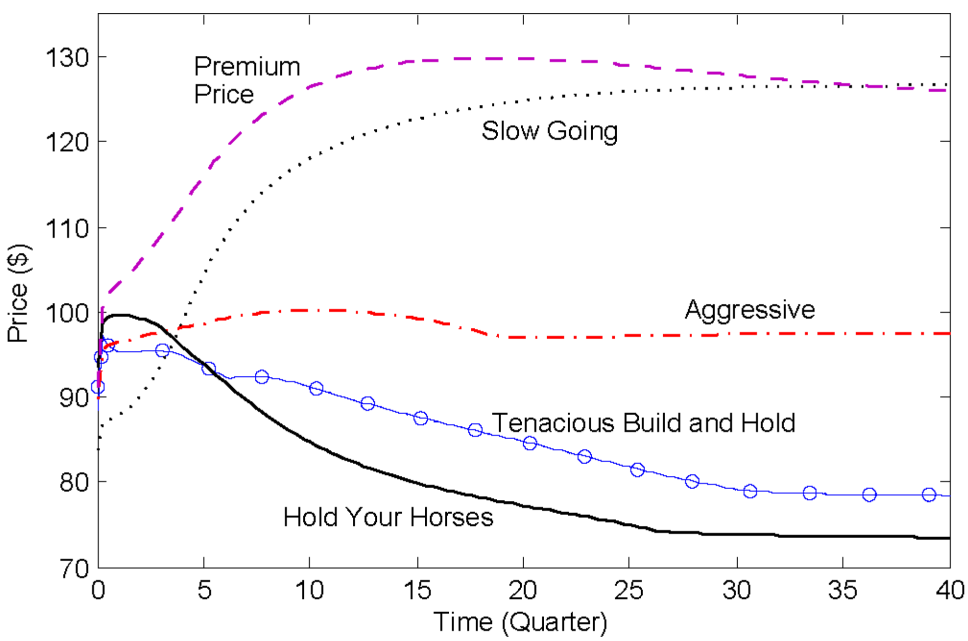


Figure 4 Different patterns of pricing decisions for the five strategies in the low complexity task

Table 1 Correlations, means and standard deviations for study variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. GMAT	1														
2. Task complexity	0.02	1													
3. Performance trial block 1	0.17	-0.50**	1												
4. Performance trial block 2	0.10	-0.58**	0.43**	1											
5. Performance trial block 3	0.03	-0.71**	0.45**	0.74**	1										
6. Performance trial block 4	0.17	-0.65**	0.47**	0.72**	0.87**	1									
7. Performance trial block 5	0.13	-0.63**	0.50**	0.74**	0.85**	0.92**	1								
8. Performance trial block 6	0.08	-0.66**	0.51**	0.75**	0.83**	0.87**	0.90**	1							
9. Performance trial block 7	-0.02	-0.68**	0.42**	0.55**	0.58**	0.63**	0.61**	.687**	1						
10. Performance trial block 8	0.13	-0.62**	0.39*	0.58**	0.66**	0.70**	0.66**	.737**	0.78**	1					
11. Performance trial block 9	0.14	-0.61**	0.46**	0.54**	0.59**	0.62**	0.63**	.709**	0.85**	0.79**	1				
12. Self-efficacy	0.14	-0.33**	0.27*	0.28*	0.25*	0.29*	0.27*	.281*	0.35*	0.40**	0.33*	1			
13. Mental model accuracy	0.37**	-0.33**	0.31*	0.43**	0.38**	0.37**	0.39**	.442**	0.37*	0.48**	0.53**	0.23	1		
14. Mental model complexity	0.11	-0.28*	0.18	0.23	0.15	0.08	0.13	.194	0.28	0.26	0.37*	0.30*	0.41**	1	
15. Deep structure accuracy	0.40**	-0.27*	0.40*	0.25*	0.26*	0.27*	0.30*	.387**	0.36*	0.56**	0.50**	0.28*	0.77**	0.31*	1
Total															
Mean	642.22	0.51	0.04	0.32	0.43	0.46	0.51	0.51	0.43	0.49	0.47	5.66	0.56	0.84	0.39
Std. Deviation	54.30	0.50	0.78	0.43	0.38	0.37	0.36	0.37	0.37	0.43	0.46	1.28	0.11	0.19	0.14
N	63	63	63	63	63	63	62	62	43	42	43	63	63	63	63
Low Complexity															
Mean	641.19		0.43	0.57	0.70	0.71	0.73	0.75	0.65	0.71	0.71	6.08	0.60	0.89	0.43
Std. Deviation	56.72		0.34	0.38	0.32	0.32	0.34	0.33	0.32	0.30	0.33	1.23	0.10	0.14	0.14
N	31		31	31	31	31	31	31	24	24	24	31	31	31	31
High Complexity															
Mean	643.22		-0.34	0.08	0.17	0.23	0.29	0.26	0.15	0.19	0.16	5.25	0.53	0.79	0.36
Std. Deviation	52.73		0.89	0.33	0.21	0.24	0.21	0.21	0.20	0.38	0.41	1.20	0.10	0.21	0.14
N	32		32	32	32	32	31	31	19	18	19	32	32	32	32

** $p < 0.01$, 2-tailed.
* $p < 0.05$, 2-tailed.

Table 2 Impact of mental model accuracy of the complete business environment on performance

Variables	Model 1[a]	Model 2[b]	Model 3[c]	Model 4[d]
Intercept	0.321	-0.091	0.168	0.098
	(0.437)	(0.624)	(0.371)	(0.405)
Task Complexity	-0.434***	-0.432**	-0.438***	-0.439***
	(0.078)	(0.128)	(0.067)	(0.067)
Self-efficacy	0.016	0.011	0.020	0.020
	(0.030)	(0.045)	(0.025)	(0.025)
GMAT (cognitive ability)	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Mental Model Complexity	-0.263	-0.038	-0.269	-0.286
	(0.216)	(0.364)	(0.185)	(0.190)
Mental Model Accuracy	1.039*	1.668*	0.988**	1.123*
	(0.392)	(0.619)	(0.335)	(0.456)
MentalModAcc X				-0.263
Task_Complexity				(0.593)
Adjusted R^2	0.470	0.434		
F	11.81	7.442		
Observations	61	42	315	315
Number of Parameters	6	6	14	15
-2 Restricted Log Likelihood			-7.041	-8.023
Akaike's Inf. Criterion (AIC)			-1.041	-2.023
Schwarz's Bayesian (BIC)			10.111	9.118

Notes:
Unstandardized coefficients with standard errors in parentheses
* p < .05; ** p < .01; *** p < .001

a Dependent variable is Performance on 6th trial block and the OLS model is:

$$Perf_6 = Intercept + B_1 TaskComplexity + B_2 SelfEff + B_3 GMAT + B_4 MentalModComplex + B_5 MentalModAcc + \varepsilon$$

b Dependent variable is Performance on 9th trial block and the OLS model is:

$$Perf_9 = Intercept + B_1 TaskComplexity + B_2 SelfEff + B_3 GMAT + B_4 MentalModComplex + B_5 MentalModAcc + \varepsilon$$

c Dependent variable is Performance on trial blocks 4-9 (repeated measures) and the linear mixed model is:

$$Perf_{it} = \beta_1 + \beta_2 TaskComplexity_i + \beta_3 SelfEff_i + \beta_4 GMAT_i + \beta_5 MentalModComplex_i + \beta_6 MentalModAcc_i + \beta_7 TrialBlk_{i4} + \beta_8 TrialBlk_{i5} + \beta_9 TrialBlk_{i6} + \beta_{10} TrialBlk_{i7} + \beta_{11} TrialBlk_{i8} + b_1 + \varepsilon_{it}$$

where β_1 - β_{11} are the fixed-coefficients (including the intercept term β_1), b_1 is the random-effect intercept capturing the variance among subject *i* intercepts, and ε_{it} is the error for observation *t* of subject *i* and is modeled using a first-order autoregressive structure to account for the correlation within individuals. Two parameters are estimated for the first-order autoregressive structure $\varepsilon_{it} = \phi\varepsilon_{i,t-1} + v_t$ where $v_t \sim NID(0, \sigma_v^2)$ and the autocorrelation between two errors one time-period apart is $\rho(1) = \phi$.

d Dependent variable is Performance on trial blocks 4-9 (repeated measures) and the linear mixed model is:

$$Perf_{it} = \beta_1 + \beta_2 TaskComplexity_i + \beta_3 SelfEff_i + \beta_4 GMAT_i + \beta_5 MentalModComplex_i + \beta_6 MentalModAcc_i + \beta_7 TrialBlk_{i4} + \beta_8 TrialBlk_{i5} + \beta_9 TrialBlk_{i6} + \beta_{10} TrialBlk_{i7} + \beta_{11} TrialBlk_{i8} + \beta_{12} MentalModAcc \times TaskComplexity + b_1 + \varepsilon_{it}$$

Table 3 Impact of mental model accuracy of the deep structure on performance

Variables	Model 1[a]	Model 2[b]	Model 3[c]
Intercept	0.480	0.428	0.305
	(0.440)	(0.624)	(0.377)
Task Complexity	-0.442***	-0.471***	-0.446***
	(0.076)	(0.121)	(0.066)
Self-efficacy	0.004	-0.005	0.008
	(0.030)	(0.044)	(0.026)
GMAT (cognitive ability)	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Deep Structure Accuracy	0.596*	1.178**	0.555*
	(0.286)	(0.417)	(0.245)
Adjusted R^2	0.454	0.443	
F	13.704***	9.36***	
Observations	61	42	315
Number of Parameters	5	5	13
-2 Restricted Log Likelihood			-4.479
Akaike's Inf. Criterion (AIC)			1.521
Schwarz's Bayesian (BIC)			12.682

Notes:
Unstandardized coefficients with standard errors in parentheses
* p < .05; ** p < .01; *** p < .001

a Dependent variable is Performance on 6th trial block and the OLS model is:

$$Perf_6 = Intercept + B_1 TaskComplexity + B_2 SelfEff + B_3 GMAT + B_4 DeepStrucAcc + \varepsilon$$

b Dependent variable is Performance on 9th trial block and the OLS model is:

$$Perf_9 = Intercept + B_1 TaskComplexity + B_2 SelfEff + B_3 GMAT + B_4 DeepStrucAcc + \varepsilon$$

c Dependent variable is Performance on trial blocks 4-9 (repeated measures) and the linear mixed model is:

$$Perf_{it} = \beta_1 + \beta_2 TaskComplexity_i + \beta_3 SelfEff_i + \beta_4 GMAT_i + \beta_5 DeepStrucAcc_i + \beta_6 TrialBlk_{i4} + \beta_7 TrialBlk_{i5} + \beta_8 TrialBlk_{i6} + \beta_9 TrialBlk_{i7} + \beta_{10} TrialBlk_{i8} + b_1 + \varepsilon_{it}$$

Table 4 Impact of mental model accuracy on deviation from optimal information weights

Variables	Model 1[a]	Model 2[b]
Intercept	3.170**	2.182*
	(1.004)	(1.068)
Task Complexity	2.640***	2.736***
	(0.190)	(0.189)
Self-efficacy	-0.062	-0.041
	(0.068)	(0.072)
GMAT (cognitive ability)	0.003	0.003
	(0.002)	(0.002)
Mental Model Accuracy	-3.398***	
	(0.883)	
Deep Structure Accuracy		-2.140**
		(0.702)
Observations	297	297
Number of Parameters	13	13
-2 Restricted Log Likelihood	767.896	772.923
Akaike's Inf. Criterion (AIC)	773.896	778.923
Schwarz's Bayesian (BIC)	784.874	789.901

Notes:
Unstandardized coefficients with standard errors in parentheses
* p < .05; ** p < .01; *** p < .001

Deviation from Optimal Information Weights on trial blocks 4-9 is the Dependent Variable

a $Dev\_from\_Opt\_Weights_{it} = \beta_1 + \beta_2 TaskComplexity_i + \beta_3 SelfEff_i + \beta_4 GMAT_i + \beta_5 MentalModAcc_i + \beta_6 TrialBlk_{i4} + \beta_7 TrialBlk_{i5} + \beta_8 TrialBlk_{i6} + \beta_9 TrialBlk_{i7} + \beta_{10} TrialBlk_{i8} + b_1 + \varepsilon_{it}$

b $Dev\_from\_Opt\_Weights_{it} = \beta_1 + \beta_2 TaskComplexity_i + \beta_3 SelfEff_i + \beta_4 GMAT_i + \beta_5 DeepStrucAcc_i + \beta_6 TrialBlk_{i4} + \beta_7 TrialBlk_{i5} + \beta_8 TrialBlk_{i6} + \beta_9 TrialBlk_{i7} + \beta_{10} TrialBlk_{i8} + b_1 + \varepsilon_{it}$

Table 5 Distinct strategies identified in the high and low complexity task conditions

Strategies	Description	N[a]	Perf[b]	Mental Model Acc[c]	Capacity Invest. Decision Rule[d] Intercept	Orders	Growth	Backlog/ Capacity	Pricing Decision Rule[e] Intercept	Cost	Backlog/ Capacity
Low Complexity Strategies											
[1] Tenacious Build & Hold	Build capacity to initial forecast and maintain position while reducing price	59	0.74	0.60	12.78	0.10	0.05	0.27	2.34	0.57	0.05
[2] Slow Going	Slow and cautious capacity investment with high price	47	0.72	0.62	11.87	0.09	0.04	0.18	7.18	-0.66	0.02
[3] Aggressive	Responsive capacity adj. to market demand while maintaining fixed price	28	0.92	0.64	7.28	0.48	0.38	0.53	4.51	0.02	0.02
[4] Hold Your Horses	Capacity investment lags demand with aggressive price cutting	40	0.74	0.56	5.04	0.65	-0.13	-0.03	2.19	0.60	0.03
[5] Premium Price	Charge price premium and avoid excess capacity by following demand	68	0.55	0.60	6.46	0.51	-0.10	0.01	5.83	-0.28	0.05
High Complexity Strategies											
[1] Cautious Niche	Raise margin when excess demand & cautious capacity expansion	62	0.16	0.50	8.69	0.33	0.04	0.08	-1.45	1.47	0.05
[2] Build to Initial Forecast	Build capacity to initial forecast and maintain constant margin	77	0.30	0.53	11.72	0.14	0.24	0.42	0.74	0.88	0.01
[3] Show Me	Invest in capacity only after seeing demand & drop prices as unit costs fall	76	0.02	0.52	2.35	0.79	0.02	-0.06	0.35	0.97	-0.01
[4] Rapid Response	Aggressive capacity adj. to match demand and drop prices as unit costs fall	16	0.49	0.62	10.13	0.23	1.22	1.62	0.73	0.88	0.00

Notes:
a Number of decision makers adopting each strategy over trial blocks 1-9

b Mean performance across trial blocks 4-9 for each strategy

c Mean mental model accuracy across trial blocks 4-9 for each strategy

d Mean information weights (cluster centroids) for the capacity investment decision rule for each strategy over trial blocks 1-9

d Mean information weights (cluster centroids) for the pricing decision rule for each strategy over trial blocks 1-9

Appendix A: Segment from the first set of knowledge questions about bivariate causal relationships

$$X \xrightarrow{S} Y$$

This arrow indicates that an increase in X results in an increase in Y above what it would have been (all else equal). On the other hand, a decrease in X results in a decrease in Y below what it would have been (all else equal). X and Y move in the SAME direction.

$$X \xrightarrow{O} Y$$

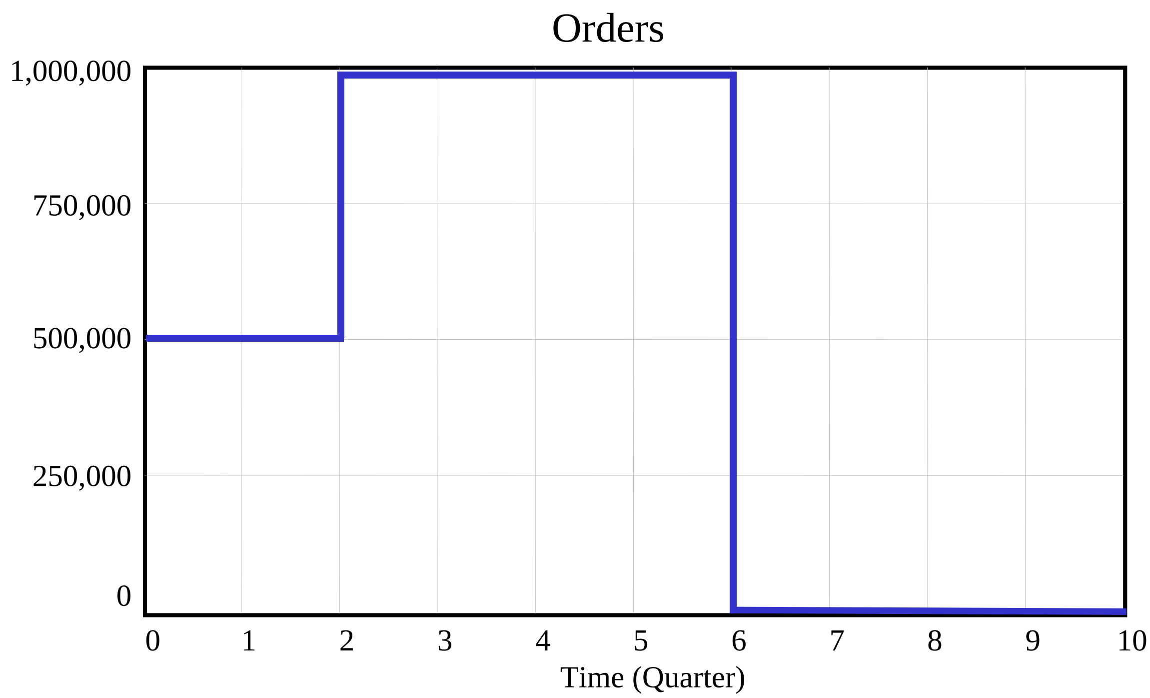
In contrast, this arrow indicates X and Y move in the OPPOSITE direction. For example, an increase in X results in a decrease in Y below what it would have been (all else equal). On the other hand, a decrease in X results in an increase in Y above what it would have been (all else equal).

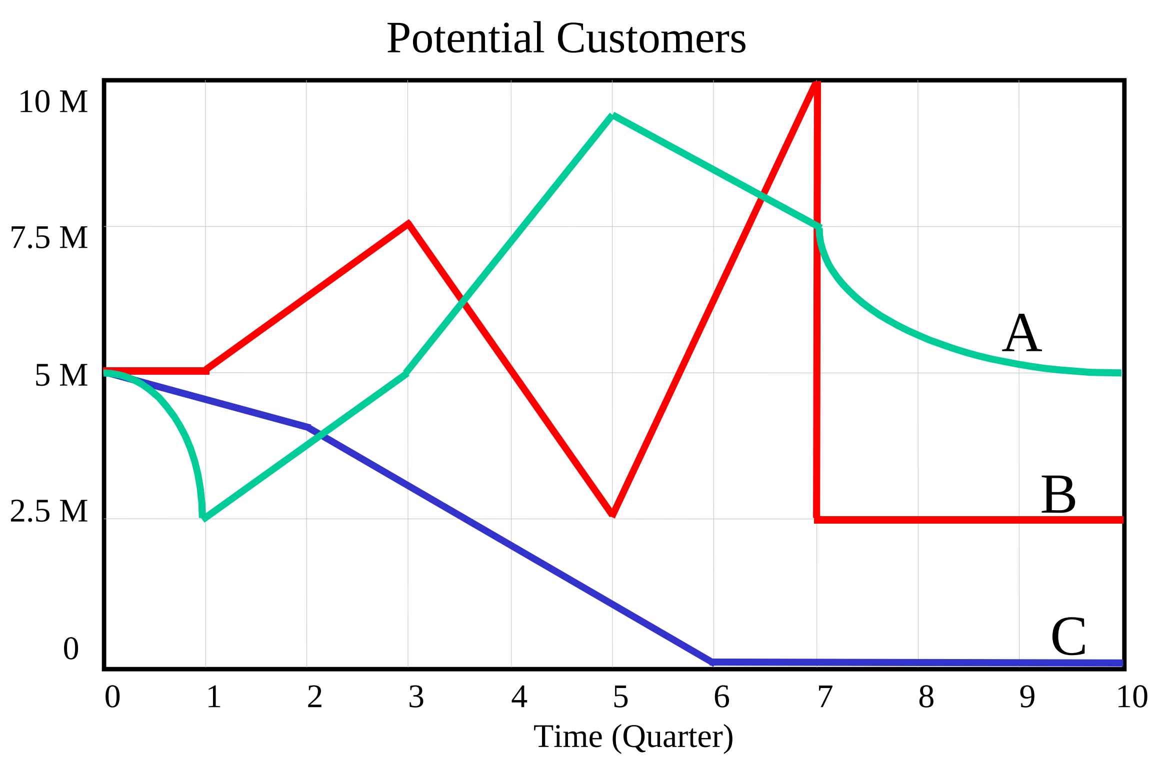
Think about the relationships between these variables that you believe are embedded in the simulator. Relying only on your experience with the simulated firm, draw the appropriate influence arrow(s) for each variable pair and indicate whether the causal influence is in the same or opposite direction using an ‘S’ or ‘O’ at the end of the arrow. Identify any cases in which there is two-way dependency between the variables by drawing the appropriate arrows representing the two-way loop of influence. Focus only on direct relationships and ignore any intervening variables that may result in indirect influence arrows. If there is no direct relationship between the variable pair, write ‘NONE’ between the two variables. If you do not have any idea about the correct answer, then write ‘Do Not Know’ instead of guessing randomly.

1.	Orders	Backlog
2.	Shipments	Backlog
3.	Backlog	Delivery Delay

Appendix B: Example graphical scenario question from the second set of knowledge questions

Using the time path of Total Industry Orders provided in the top graph below, select the letter of the appropriate time path for Industry Potential Customers on the bottom graph. Circle D if none of the lines in the bottom graph show the correct time path. Assume the initial value of industry Potential Customers is 5 million at Time 0. Also assume that no other variables affect industry Potential Customers over this time horizon.





Answer: A) B) C) D) None of the Above

Appendix C: Example questions assessing deep structure accuracy

The following are seven example items about bivariate causal relationships used to measure deep structure accuracy. See Appendix A for the instructions participants were given for answering these questions. Also note that these questions were randomly placed throughout the knowledge test and therefore the numbers along the left side of the table below do not reflect the order of the questions in the full knowledge test. The remaining four items of the deep structure accuracy measure are graphical scenario questions covering a subset of the same relationships. The example graphical scenario question in Appendix B is one of those items.

1.	Potential Customers	Orders
2.	Potential Customers	Reentry as Potential Customers
3.	Potential Customers	Price
4.	Installed Customer Base	Shipments
5.	Installed Customer Base	Reentry as Potential Customer s
6.	Installed Customer Base	Word of Mouth Effect
7.	Orders	Word of Mouth Effect