# An Experimental Investigation of Audit Decision-Making: An Evaluation Using System-Mediated Mental Models

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## Abstract

This paper has two purposes. The first is to present hypotheses generated by joining two foundation theories of decision-making. The first foundation theory is the mental model theory, which has its roots in cognitive psychology (Johnson-Laird 1983). The theory posits that individuals make inferences by constructing and integrating mental models, which are internal representations of external items. Decision-makers facing complex problems make predictable errors by failing to fully integrate their mental models of the inference task. The second foundation theory is the general systems theory, which argues that decision-makers need to understand the system as a whole in order to lessen the chances of overlooking important properties of the system (Bertalanffy 1968). Joining these two theories, we formulate a set of hypotheses referred to as System-Mediated Mental Model (SMMM) hypotheses. The SMMM hypotheses provide insights as to *how* systems thinking can lead to improved decision-making. In short, the SMMM hypothesis posits that systems knowledge will help DMs integrate multiple mental models more accurately, thus reducing systematic inference errors. The second purpose of this paper is to investigate the hypotheses using a laboratory experiment that compares "bottom-up data immersion" approach to decision-making (i.e., settings with no guideline for developing a framework to solve the problem) with "top-down big picture" approach to decision-making (i.e., settings with a guideline for developing a framework). Our results are consistent with the predictions of the SMMM hypotheses and indicate that a top-down systems approach can enhance the effectiveness of decision-making by reducing systematic errors that arise from not fully understanding the system underlying the problem. These findings have implications for the systems audit approach developed by Bell et al. (1997).

## INTRODUCTION

Bell et al. (1997) advance the argument that systems audits could enhance auditor decision-making. Under the systems audit (SA) approach, the auditor takes a "top-down big picture" orientation by first acquiring general knowledge about the client's underlying business activities and then using this knowledge as a guide for collecting evidence and drawing inferences (Kinney 2000; Knechel 2001). The SA approach has evolved, in part, because business models of clients have become increasingly complex and changeable, which in turn has increased demands on the auditor (Elliott 1994). The SA approach can be contrasted with a "bottom-up data immersion" approach, in which auditors immerse themselves in the details of accounting transactions and develop perceived relations between transactions and financial statements, but perhaps without specific knowledge of how the underlying business processes generate the transactions.[1] Currently, the largest audit firms are moving toward a greater top-down orientation (Eilifsen et al. 2001; Winograd et al. 2000). Our objective is to address the theoretical questions of *how* systems knowledge might improve auditors' decision-making, especially in changing environments. Thus, our goal is to provide a decision-making foundation to the Bell et al. (1997) framework.

We begin by presenting a set of hypotheses referred to as the System-Mediated Mental Model (SMMM) hypotheses. The SMMM hypotheses build on two related but distinct foundation theories. The first is the mental model theory (MMT), which has its roots in cognitive psychology (Johnson-Laird 1983). The MMT predicts that humans make inferences by constructing mental models that are internal (mental) representations of some external state of affairs. Decision-makers (DMs) who face complex problems and are boundedly rational (i.e., have limits on working memory or problem solving skills) are unable to construct and evaluate multiple mental models to arrive at an accurate integrated mental model, thereby making

[1] This characterization focuses on only one dimension of audits and we recognize that audits typically have some mix of the top-down and bottom-up approaches. Also audits can have other distinguishing features that are not considered in this analysis.

predictable errors (Johnson-Laird and Savary 1999).[2] We use the MMT as a benchmark theory to evaluate decision-making and to identify predictable decision errors.

The second input into the SMMM hypothesis comes from the general system theory (GST) proposed by Bertalanffy (1968). This theory emphasizes the importance of understanding the interactions of activities within an entity (such as the client's organization) and the interactions between the entity and its environment. The SA approach, as articulated by Bell et al. (1997) is consistent with GST.

Although MMT explains how DMs make systematic errors in their decisions, the theory offers no guidance for improvement. In contrast, the GST offers an approach for improving an individual's ability to solve complex problems, but it offers no explanation for how the approach helps DMs improve their decisions. By combining the MMT with the GST, the SMMM hypothesis posits that systems knowledge will help DMs integrate multiple mental models more accurately, thereby reducing systematic inference errors. The SMMM hypothesis helps explain *how* systems thinking can improve decision-making.

Our second purpose is to examine the SMMM hypotheses using a laboratory experiment. We use student subjects and follow the precepts of experimental economics, including providing subjects with salient and dominant rewards. The task performed by subjects has an information collection component and a reporting component, which is consistent with modeling approaches in auditing (Antle 1984; Dye et al. 1990).

We create two experimental audit approaches under two different environments. The first audit approach is a top-down big picture approach (denoted as TOP) that provides a guideline to the DM to develop an *organizing framework* for decision-making. The second audit approach is a bottom-up data immersion approach (denoted as BOT) that does not provide explicit guidance to the DM for developing an organizing framework. The task is designed so that if DMs are unboundedly rational (i.e., ability to create an accurate organizing framework without external guidance), the DM will perform equally well under both approaches. However, the MMT predicts that if DMs are boundedly rational, they are likely to commit systematic errors under the

[2] The words "mental model" have a different meaning in different fields, and sometimes even among different researchers in the same field. Our use of mental models follows that used by Johnson-Laird (1983). Subsequent research has led to refinement of the theory (Bara et al. 2001), but these refinements do not affect the basis of our theory.

BOT approach. The SMMM hypothesis predicts that the TOP approach will result in more effective decision-making by reducing the systematic inference errors. The two environments we created in the experiment are Static World (SW) and Dynamic World (DW) surrogating for a stable and an evolving business environment respectively. The two different environments allow us to investigate how the two approaches perform when the decision-making environment changes unexpected.

In general, our results are consistent with the predictions of the MMT and the SMMM hypotheses. Specifically, the results show that (1) subjects make predictable systematic errors in the absence of a guideline for developing an organizing framework, as predicted by the MMT; (2) the guideline provided by TOP reduces systematic errors, as predicted by the SMMM hypothesis; and (3) as predicted by the SMMM hypothesis, the TOP approach improves DMs' inference accuracy even when the environment affecting the decision variables changes unexpectedly.

Our research complements traditional behavioral auditing research (for reviews, see Gibbins and Swieringa 1995; Libby 1995; Messier 1995; Solomon and Shields 1995) and research addressing systems audits (Ballou et al. 2001; Blokdijk et al. 2001; O'Donnell 2001) by investigating psychology-based theory under controlled experimental economic conditions (Kachelmeier 1996; Kachelmeier and King 2002). Our findings add to auditing literature by providing a decision-making foundation to the System Audit approach as articulated by Bell et al. (1997). In addition, our research has implications for the decision aid literature in that systems thinking may aid auditors to develop big-picture judgment abilities, as opposed to "smaller" judgment capabilities, as discussed by Messier (1995). We view our research as a first step in a progression from theory development and refinement, to laboratory experimentation, and then to empirical investigation in natural settings.

In the next section we discuss the hypothesis development; in Section III we discuss the experimental design, task, and methods; and in Section IV, we present the procedures for testing the hypotheses. The results are presented in Section V, and Section VI provides a summary and discussion of future research.

## II. Hypothesis Development

Bell et al. (1997) advance the proposition that a successful audit is one that focuses on the client's systems dynamics, such as the interactions between the client and its suppliers, customers, competitors, regulators, strategic partners, and the capital markets. Such a focus is argued to improve the auditor's evidence collection efficiency and inference accuracy. Our objective here is to provide a theoretical underpinning of *how* systems theory could improve auditors' judgment using the System Mediated Mental Model (SMMM) hypotheses. Below we discuss the two components of the SMMM hypotheses; the mental model theory (MMT) and the general systems theory (GST) and present our three general hypotheses. We expand on these hypotheses below in the section titled 'hypotheses testing procedures.'

### *Mental Model Theory (MMT)*

The goal of the mental model theory is to provide a foundation to help explain the process of decision-making, to show how systematic errors could arise, and to predict the type of and the conditions for inference errors to occur. According to Johnson-Laird (1983), a mental model is an internally constructed representation of an event based on a set of premises and the general knowledge possessed by the DM. To illustrate, assume that the DM needs to make inferences based on two premises. The DM uses the first premise to construct one or more mental models; similarly, the DM uses the second premise to construct the corresponding mental model(s). The DM must then consider the different possible ways the mental models from the two premises could be combined to produce an integrated model, and draw temporary conclusions based on the integrated model. If the models are integrated correctly, the temporary conclusions will pass the process of falsification and the DM will have arrived at the correct inference (see Brown et al (1999) for a discussion of the falsification process).

Integrating mental models imposes a heavy burden on memory. To minimize this cognitive burden, the DM only considers some of the possible models based on the information, which could lead to decision errors (see Appendix A for an example illustrating the MMT). The MMT predicts that (1) more complicated problems require more mental models to be constructed and evaluated; and, (2) the more mental models the DM needs to process and integrate, the more errors the DM is prone to make. The errors are systematic and predictable due to improperly integrated mental models.

There is mounting evidence supporting the theory in the psychology literature; however, the theory has not been evaluated in combination with systems theory.[3] We initially investigate settings to test the MMT alone and use these settings as benchmarks for comparison to settings where MMT is evaluated in combination with systems theory.

Our first hypothesis deals with the benchmark settings and the null hypothesis is that DMs' decision errors are random and hence unpredictable. In contrast, the MMT posits that DMs make systematic and hence predictable inference errors (the specific type of errors is discussed in the hypotheses testing procedure section below).

**H1 (null):** The decision maker's inference errors are random.

**H1 (MMT):** The decision maker's inference errors are systematic, and hence predictable. The inference errors are consistent with those predicted under MMT.

***Systems-Mediated Mental Model Hypotheses***

Our second hypothesis deals with the application of systems theory to decision-making. Systems theory emphasizes the importance of understanding individual components as an integrated part of a system rather than as stand alone parts because the DMs are more likely to miss important interactions among different components in a system when the components are investigated independently. Auditing requires auditors to make inferences in complex environments. The external environment, such as the actions taken by suppliers, debtors, customers, government, and special interest groups, often have an important impact on the client's economic health, and hence an auditor who understands the client's business environment and strategies can increase efficiencies (see Bell et al 1997). That is, an understanding of the client's systems dynamics could help auditors to develop mental models that maps more accurately into the client's true financial condition. The auditor can use the developed mental models, which incorporate all vital factors, both internal and external, to form an *organizing framework*, a set of decision rules that maps various information signals from the audit to the validity of the client's financial statements. Information signals include signs of

[3] Empirically, MMT is well supported when tested against other theories of reasoning (Johnson-Laird and Byrne 1991; Johnson-Laird 1996; Goldvarg and Johnson-Laird 2001; Garcia-Madruga et al. 2001). The theory has been applied to explain systematic errors in reasoning (Johnson-Laird and Savary 1996, 1999) and differences in

GAAP compliance versus violations and/or coherence versus incoherence between the client's business strategy and its business environment (Bell et al. 1997). Auditors who develop a correct organizing framework are more likely to perform efficient and effective audit. If the systems audit approach helps auditors form more accurate expectations by helping them to develop a correct organizing framework, audits should be more efficient. We characterize systems technology as the acquisition of a guideline for developing an organizing framework (denoted as *guideline* hereafter). The SMMM hypothesis predicts that DMs who gain an understanding of the systems underlying a problem are more likely to integrate the mental models appropriately, leading to better decisions compared to DMs who do not have such an understanding. In an auditing context, the auditor acquires systems thinking by undertaking actions along the lines suggested by Bell et al. (1997). We do not investigate how SA provides such a guideline, or the challenges of developing the guideline. Rather we investigate how the provision of the guideline can improve decision-making in settings where DMs must integrate multiple mental models.

Our second hypothesis compares subjects' decision accuracy in settings with the guideline to settings without the guideline. The SMMM hypothesis predicts that DMs make less systematic inference errors in the presence of the guideline than in the absence of the guideline. Hence our second hypothesis stated in the alternative form is:

**H2 (SMMM):** Decision-maker's inference accuracy is higher in the presence of the guideline.

### *Changes in Business Process*

Our third hypothesis deals with one of the key strengths of the top-down approach to decision-making: inference accuracy in a changing environment. As articulated by Bell et al (1997), under the bottom-up approach, DMs focus more on understanding the interrelationships among reported data while under the top-down approach, auditors focus more on understanding the interrelationships among the client's business strategies and its environment. [4] The auditor forms expectations about the client's financial situation after gaining an understanding of these interrelationships and then compares the expectations to the reported data. Thus, auditors using

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inferential ability among different individuals (Johnson-Laird 1983). Recent work by Knauff et al. (2002) shows evidence supporting the MMT in a functional MRI study of the brain.

[4] In an auditing setting, the top-down approach has a business process focus instead of information process focus (Bell et al. 1997 p.72).

the top-down approach are more likely to perceive changes in the interrelation between the client's business strategy and its environment, leading to more accurate inference decisions in a rapidly changing business world.

In our last hypothesis, we compare DMs' decision accuracy both when the guideline is presence and absence when the interactions among the key components in a system change; that is when a different organizing framework is required. We expect DMs who use the bottom-up approach are less likely to develop a mental model that incorporates how changes in the environment could lead to different decision. Failure to develop a correct mental model under the bottom-up approach will increase inference errors. Hence, our last hypothesis stated in the alternative form is:

**H3 (Changing environment):** Inference accuracy is higher for DMs who use the top-down approach than for DMs who use the bottom-up approach even when the actual decision rule (unobservable) changes.

## III. EXPERIMENTAL DESIGN, TASK, AND METHODS

We design an experimental task that captures the essence of a stylized audit process to (1) test the predictions of the MMT and the SMMM hypothesis and (2) investigate the DMs' performance when the environment changes. We design two experimental audit approaches (TOP and BOT) under two different environments (Static World and Dynamic World). We use *TOP* and *BOT* to represent the experimental audit approaches that surrogate for the respective top-down and bottom-up audit approaches. We use *static world* (denoted as SW) to represent a stable client environment and *dynamic world* (denoted as DW) to represent a more dynamic client business environment.

There are four parts in each experimental session and 10 rounds in each part. We use a combination of within-and between-subject design in a $2 \times 2$ design. In the first treatment, we manipulated the order in which the subjects were given the audit approaches (TOP and BOT); half the subjects were given one of the audit approaches in part 1 while the same audit approach is given to the other half in part 2. We denote this treatment as the *ordering* treatment and the settings in this treatment are TOP-BOT and BOT-TOP. In the second treatment, we manipulated the environment, we denote this the *environment* treatment, and the settings in this treatment are SW and DW. Table 1 provides a summary of the treatments. The rows of Table 1 show the four

settings: TOP-BOT/SW; TOP-BOT/DW; BOT-TOP/SW; and BOT- TOP/DW and the columns show the design and treatment specific details used in each of the four parts.

{Insert Table 1 about here}

Table 1 also shows that subjects could choose either the BOT or the TOP approach in Parts 3 and 4. Providing subjects this choice allows us to investigate the extent to which the approach acquired by the subjects appears appropriate given their decision-making accuracy in Parts 1 and 2. We provide the treatment specific details in the experimental task section below.

## Subjects

Subjects are university business-school student volunteers, paid based on the outcome of their decisions. We conducted each experimental session on networked personal computers with privacy maintained. The instructions, available upon request, do not use terms with real-world connotations, such as *auditor*. The use of context in experimental settings can have important implications, as discussed by Haynes and Kachelmeier (1998). Our goal is to create a setting that has internal validity for the investigation of the underlying hypothesis. A total of 88 subjects participated in the experiment.

## Experimental Task

### *Objectives for the task*

The experimental task was designed to meet three basic objectives. First, the task must require the DM to make inferences within the purview of the SMMM hypothesis (i.e., it must be possible to characterize the task using systems). Second, the task needed to capture the important decision aspects of an audit, which we simplify to include (i) planning and executing the audit and (ii) issuing a report (a choice that could represent one component of the overall audit).[5] Third, the task had to be appropriately challenging so that subjects needed to construct and evaluate multiple mental models to make inferences.

[5] Our setting is a very simplified version of the native complexities of real-world auditing. However, our objective is to incorporate only those frictions that are most germane to testing the hypothesis. See Bloomfield (1997), Calegari et al (1998), Dopuch and King (1992), and Kachelmeier (1991) for examples of other experimental operationalizations of audits.

We designed the task with a single-person decision-theoretic orientation to insulate subjects from strategic interactions. We acknowledge that strategic issues between auditors and clients are central to auditing, but we consider this study to be a first step in assessing the predictions of the SMMM hypothesis.[6] In addition, our setting does not involve uncertainty (assuming an optimal solution), thus removing risk issues. We realize the design deviates from practice. However, we want a setting that is most appropriate for a controlled examination of the SMMM hypothesis. Lastly, we tied subjects' payoffs to their decisions, consistent with the method of experimental economics (as discussed below). It is particularly critical to induce subjects to exert effort in settings that are cognitively demanding in order to have confidence that subjects' decision errors are due to limitations in working memory, rather than errors caused by a lack of motivation.

***Conceptual overview of the task***

There are seven components of the experimental task, including: (1) *accounts*, (2) *data* (3) *states*, (4) *report*, (5) *logical expressions*, (6) *records*, and (7) *templates of logical expression configurations* (only under the TOP approach). Accounts are information sources containing data useable by the subject to draw inferences about the state. We use four accounts in the experiment; designated by the colors Red, Yellow, Green, and Blue.[7] Each account contains data that indicate either a positive (+) or a negative (–) sign. A positive sign is analogous to no errors/no red flags while the negative sign indicates errors/red flags in the account.[8]

A state represents the validity of the client's financial statement. There are two states: GOOD and BAD. In a GOOD state, the client's financial statements are accurately stated while in a BAD state, there are red flags/material misstatements in the client's financial report. A report represents the auditor's judgment about the state after investigating the data in the accounts. There are two types of reports: $\hat{G}$ and $\hat{B}$. If the subject expects the state to be GOOD

[6] See Bloomfield (1995) for a discussion of strategic dependence in an auditing setting.
[7] A real world parallel to our term 'accounts' could be any evidence source available to the auditor used to form and justify a report. We chose four accounts because it is consistent with our objective of having a task that is appropriately complex for our purposes (discussed above).
[8] With four accounts and two possibilities in each account, either a positive (+) or a negative (–) sign, we have a total of 16 ($2^4$) different data combinations.

(BAD), s/he should report $\hat{G}$ ($\hat{B}$). Logical expressions (LE) are the rules that map data (+ or – signs) from the four accounts into the two states. A LE is modeled here as the relations among the factors that determine the state. We limit the number of possible LEs with the following three conditions to obtain tractable analysis:[9]

1. We use the logical operators/connectors "AND", "OR", and "( )" only, but these logical operators/connectors could be used multiple times in a LE;
2. We use only negative sign(s) to contribute to a BAD state; and
3. We assume that the four accounts presented to subjects are the accounts that matter if a negative sign (alone or in combination) is found. Hence, each account must play a role, either alone or in combination with other account(s) leading to a BAD state. For tractability, we restrict each account to appear in the LE once and only once.

It is critically important to note that in the instructions, we told subjects these three conditions and that these conditions are necessary for them to infer the LE. An example of a LE used in the experiment (denoted as LE-1/1) is:

*If Yellow is - OR if (Blue AND (Green OR Red)) are -, then the state is BAD* ***(LE-1/1)***

LE-1/1 is interpreted as follows. If the Yellow account has a negative sign, then the state is BAD, however, the state could also be BAD if the Blue and either the Green or Red accounts are negative. In natural auditing settings, LE-1/1 could indicate that the Yellow account is individually critical in determining the appropriateness of the financial statements, but the effect of others is interactive. A loose illustration of LE-1/1 could be as follows: assume that a company competes in the market for high quality product. A negative sign in the Yellow account indicates a material departure from GAAP, a negative sign in Blue indicates an immaterial error in the revenue account, a negative sign in Green indicates an immaterial error in the inventory account, and a negative sign in Red indicates that the quality of the company's product is low relative to its competitors. Thus, a problem/error found in the revenue account, combined with a problem/error found in the inventory account or a factor contrary to the company's strategic objectives indicates a BAD state.

As mentioned above, we use three conditions to obtain tractability in the LEs. With these

[9] With these conditions, we are able to limit the LEs to 52 different possibilities.

conditions, we could classify the LEs into 10 different configurations based on the logical complexity of each expression. Each LE configuration contains LEs with the operators/connectors located in exactly the same position while each account serves a different role. Appendix B provides a summary for all LE configurations and an explanatory note on how to calculate the number of different LEs under each configuration. To control for task complexity, we only use the following two LE configurations in the experiment:

- A OR (B AND (C OR D))
- A AND (B OR (C AND D))

where A, B, C, and D represent the accounts in a generic manner. We use "LE-*number*" to denote the configuration and the extension "/*number*" to identify each specific LE in a configuration.[10]

To control for the complexity of the LEs across settings, we only use LEs with LE-1 configuration in Parts 1 and 2, and LE-1 and LE-2 in Parts 3 and 4. Table 1 shows the specific LEs we used in the experiment. We rotated the LEs used in Part 1 and 2 to achieve a balanced design. In other words, half of the subjects had LE-1/1 in Part 1 while the other half had LE-1/2 in Part 1. Subjects with LE-1/1 in Part 1 had LE-1/2 in Part 2 while the remaining half, who had LE-1/2 in Part 1 had LE-1/1 in Part 2. The rotation is designed to achieve high internal validity because learning under TOP and BOT could be different under different LEs. Table 1 columns three and four show the rotations described above in each setting.

Under SW, the LE configuration used in Parts 3 and 4 is the same as that used in Parts 1 and 2. Under DW, the LE configuration used in Parts 3 and 4 differs from the one used in Parts 1 and 2. By changing the LE configuration under the DW setting, we can evaluate auditors' performance under the TOP and the BOT approach when the data in the accounts are mapped into the state differently. We model a change in the LE configuration as a change in the environment. Changing from one LE to another with the same configuration does not constitute to a change in the environment in our setting because only changes in the configuration require a

[10] For example: *"If Yellow is - OR if (Blue AND (Green OR Red)) are -, then the state is BAD"* has the same configuration as: *"If Blue is - OR if (Red AND (Green OR Yellow)) are -, then the state is BAD"* but different configuration as: "*If Yellow AND (Blue OR (Green AND Red)) are -, then the state is BAD"*

change in the guideline. This difference is unexpected to the subjects.[11] We select LEs from LE-2 for Parts 3 and 4 in the DW because this LE configuration also has 12 different possibilities, similar to LE-1. Thus, the complexity of the LE is controlled for under SW and DW. There were no explicit economic differences between the SW and DW treatments.

We reference the computer screens display used in the experiment to discuss the report and the records below. We discuss the templates of logical expression configuration in the 'operationalization of the TOP approach' section below.

***Computer screens display***

Figure 1 Panels A and B show the screen displays used by subjects under the BOT and the TOP settings respectively. The screen display in each Panel has four windows: the "Payoff" window (upper left-hand side), the "History" window (upper right-hand side), the "Report and Information" window (middle left-hand side) and the "Outcome" window (bottom left-hand side). We begin by describing the records appearing in the History window. A record consists of two components: data in the accounts and state. For example, the second record in the History window contains a "+", "-", "+", and "+" sign in the Red, Yellow, Green, and Blue account respectively and the state is BAD. We use 'Red, Yellow, Green, Blue, State' = '+, -, +, +, BAD' as a more convenient way to describe a record.[12] We discuss how records can be used to infer the underlying LE in the Hypothesis Testing Procedures section below.

{Insert Figure 1 about here}

Each subject is given four records at the beginning of each part of the experiment. Two of the records have BAD states and the remaining two have GOOD states.[13] A timeline for a part in the experimental is summarized below:

1. Nature determines the LE, which is not announced to the subjects
2. Each subject observes four records that provide sufficient information to infer the LE
3. Nature determines data in the four accounts in a round (unobservable to the subjects

[11] A change in the LE configuration can be thought of as a change in the interactions among key factors both internal and external that determine the accuracy of the client's financial report.
[12] In natural settings, a record could be thought of either as the auditor's (1) knowledge about GAAS, and (2) understanding of the client's business strategy and its systems dynamic.
[13] We provide subjects with two GOOD and two BAD states to reduce subjects' attempts to infer the underlying probability of each state based solely on the reported states in the records.

unless they investigates the accounts). Hence the state (unobservable to the subjects) is also determined[14]

4. Each subject receives an endowment of resources (¥460) that can be used to investigate the accounts and to pay penalties if there is a reporting error
5. Each subject must investigate one account (at a cost of ¥60) before issuing a report
6. Each subject can investigate a second, third, or fourth account before issuing a report (each investigation costs ¥60)
7. Subjects provide a measure of their confidence in the accuracy of the reports
8. Each subject's payoff is determined for a round
9. Repeat steps 3-8 for rounds 2-10.

In other words, subjects are given an initial endowment of ¥460 in each round (¥ is used here to denote experimental currency) and they can use this endowment to investigate accounts and to pay sanctions when there is a reporting error. At each round, the subject must investigate at least one account before issuing a report. After investigating the desirable number of accounts, the subject issues either a $\hat{G}$ or $\hat{B}$ report corresponding to the subject's beliefs of a GOOD or BAD state.[15] A report is correct when the report matches the state and incorrect when the report does not match the state. The cost to investigate an account is held constant at ¥60 and a subject who investigates one account and reports correctly earns ¥400 for that round.

When the subject issues an incorrect report, s/he is assessed a penalty that depends on the type of reporting error. Specifically, if the state is GOOD and the subject's report is $\hat{B}$, the subject pays a fixed penalty of ¥400. This penalty represents the cost to the subject of being disciplined by the client for issuing $\hat{B}$ when the state is actually GOOD (the penalty imposed by the client is assumed to be independent of the subject's effort). On the other hand, if the state is BAD and the subject's report is $\hat{G}$, then the penalty depends on the number of accounts being investigated in that round. The more evidence the subject collects, the smaller the penalty for the reporting error. Specifically, if the subject reports $\hat{G}$ when the state is BAD, the penalty is 1061,

[14] All data are presequenced for control purposes.
[15] The report represents the auditor's expectation about the state (i.e., the validity of the overall financial statements), so a reporting error indicates a judgment error.

755, 558, and 400 for the four different levels of investigation. This pattern reflects the assumption that liability decreases with increases in audit effort (courts assess higher damages if the auditor collected less evidence). Table 2-Panel A and B show the payoff calculation under each scenario for the BOT and the TOP settings respectively. Table 2 indicates that the payoffs are the same for both types of errors given all four accounts are investigated. Thus subjects who investigate all four accounts and still do not know which report to issue would not have an incentive to merely pick the one with the lower penalty at that point. In short, the subject's payoff objective for each round is calculated as follows:

**Subject's payoff in a round = Initial endowment (¥460) - cost of investigating accounts (¥60 * number of accounts investigated) - reporting error losses (which depend on type of error) – cost of TOP (¥50, when applicable)**

A ¥50 fixed cost is deducted from the subject at the beginning of each round under the TOP setting;[16] and the payoffs shown in the payoff window in the subject's computer screen display (Figure 1) are the same as those shown in Table 2.

{Insert Table 2 about here}

**Operationalization of the TOP approach**

We take as a starting point the position of Bell et al. (1997) that the *process analysis templates* (PAT) within the knowledge acquisition framework serve as a method to develop a correct guideline for the audit task. Our implementation of TOP setting is a simplified characterization of the results of going through the PAT described in Bell et al (1997). Without first acquiring the guideline auditors are less likely to consider the signals from the client's business strategy and/or its systems dynamic and their impact on the client's financial statements.

We implement the TOP approach by providing subjects with a template of the corresponding LE configuration. For example, we have reproduced LE-1/1 below followed by the corresponding template of the logical expression configuration, LE-1.

[16] We assigned a cost for TOP because we assume the process of collecting systems related information on a client is costly and also because we wanted to assess the net value auditors place on the TOP approach in Parts 3 and 4 of the experiment.

*If Yellow is – OR if (Blue AND (Green OR Red)) are -, then the state is BAD* ***(LE-1/1)***

*If A is - or (B and (C or D)) are -, then the state is BAD* ***(LE-1)***

In other words, in the experiment, we provide the subjects with a template of the LE configuration, LE-1, as the guideline to help the subjects to infer the underlying LE using the records. Each configuration shows the types and locations of the logical operators/connectors (AND, OR, ()) without specifying the positions of the color accounts. Thus LE-1 informs the user that one account alone could trigger a BAD state, without indicating which account. LE-1 also indicates that a BAD state can be triggered by two other accounts combined in a certain manner. The template of the LE configuration represents the systems knowledge obtained under a systems audit approach (Bell et al. 1997; Eilifsen et al. 2001; Winograd et al. 2000).

## IV. HYPOTHESES TESTING PROCEDURES

Our setting requires subjects to: (1) use the records to develop a mental model about the unobservable LE; (2) use the mental model to form an organizing framework; and (3) use the organizing framework to guide them in deciding which account(s) to investigate and what report to issue. These procedures are created in the spirit of auditors making risk assessments by using their knowledge about GAAS together with an understanding of the client's business strategy and the environment in which it operates. The auditors use the organizing framework to guide them in performing the audit. Depending on the evidence (signs in the accounts that have been investigated), additional audit work maybe performed (investigate additional accounts if necessary). Finally, the report issued by a subject in our setting represents an audit judgment on the client's financial statement.

In our setup, all subjects received the four records prior to investigating any account in round 1. The records serve as the premises that the subject uses to infer the LE. With a complex LE, the construction and evaluation of several mental models are necessary before producing the final integrated mental model about the LE. We use the four records shown in the screen display in Figure 1 to indicate how the subjects could infer the LE using these records. As discussed above, a MMT agent is more likely to make predictable errors. Table 3 summarizes the mental process a DM is assumed to go through under different theories. We start our discussion with the unboundedly rational agent. The first six columns of Table 3 reproduce the data and the state in the four records given to the subject for the LE:

*If Yellow is – OR if (Blue AND (Green OR Red)) are -, then the state is BAD* ***(LE-1/1)***

Column 7 of Table 3, denoted "prediction with unbounded rationality", shows the mental process of an unboundedly rational agent.

{Insert Table 3 about here}

To illustrate how an unboundedly rational agent uses the records to infer the LE, we look at the information content of each record. In the first record, there are only positive signs and the state is GOOD. This record is not informative because subjects were instructed that only negative sign(s) could give rise to a BAD state. With no negative signs, the DM knows that the state will never be BAD. In the second record, there is a negative sign in the Yellow account and the state is BAD, indicating that a negative sign in the Yellow account alone is sufficient to produce a BAD state. Hence the DM form the following mental model:

*If Yellow is – OR (XXX), then the state is BAD* ***(MM-start)***

where XXX represents the unknown part of the LE yet to be determined. In the third record, there are negative signs in the Green and the Blue accounts, and the state is BAD. The DM reasons that a negative sign in either of these accounts or both accounts could trigger a BAD state. Hence the three possible mental models are:

*If Yellow is – OR if Green is – OR (XXX), then the state is BAD* ***(MM#1)***

*If Yellow is – OR if Blue is – OR (XXX), then the state is BAD* **(MM#2)**

*If Yellow is – OR if Green AND Blue are – OR (XXX), then the state is BAD* ***(MM#3)***

That is, MM#1 indicates the possibility that a negative sign in the Green account alone triggers a BAD state, MM#2 indicates the possibility that a negative sign in the Blue account alone triggers a BAD state and MM#3 indicates the possibility that both the Blue and Green accounts need to be negative to trigger a BAD state. In the fourth record, the signs in both the Red and the Green accounts are negative, and the state is GOOD. This structure allows the DM to realize that a negative sign in the Green account alone will not produce a BAD state, which eliminates MM#1 as a viable possibility, leaving only MM#2 and MM#3 as the remaining possibilities. However, an unboundedly rational agent will also eliminate MM#2 because the agent knows that each account is restricted to appear in the LE exactly once. The agent will eliminate the following possibility:

*If Yellow is – OR if Blue is – OR if (Green AND Red are –), then the state is BAD*

because the above expression is contradicted by record 4, leaving the final model developed from MM#3:

*If Yellow is – OR (Blue AND (Green OR Red)) are –, then the state is BAD*

as the only possibility that is consistent with all the given records and satisfies all three conditions imposed on the LEs. Analyzing the four records to infer the LE could be cognitively demanding.

Once the subject makes an inference on the LE to develop an organizing framework, the subject will implement an investigation strategy based on the organizing framework. Specifically, the optimal strategy for LE-1/1 is to investigate the Yellow account first. If it contains a negative sign, report BAD. If it contains a positive sign, investigate the Blue account. If it contains a positive sign, report GOOD and if it contains a negative sign investigate either the Green or Red account and report accordingly. Hence, the organizing framework serves as a guide to the auditor throughout the audit process. An unboundedly rational agent always collects information optimally and makes no reporting errors.

Refer again to Table 3, and to the column designated as "Prediction with MMT." In this column, we show how predictable errors could arise when DMs simplify the mental process by constructing fewer mental models than are appropriate to arrive at the correct inference. Specifically, the simplification takes place after the DM eliminates MM#1 (as discussed above). Under the MMT prediction, the DM is less likely to eliminate MM#2 because s/he is not able to construct and subsequently falsify the following possibility:

*If Yellow is – OR if Blue is – OR if (Green AND Red are –), then the state is BAD*

Instead, the DM simplifies MM#2 by dropping the XXX and ignoring the condition that each account appears in the LE once and only once and uses the following expression as the final model:[17]

*If Yellow is – OR if Blue is –, then the state is BAD* *(LE-MMT1)*

In this case, in a round with 'Red, Yellow, Green, Blue' = '+, +, +, -' the DM will erroneously conclude that the state is BAD and issue a $\hat{B}$ report (although the state is GOOD).

[17] Dropping the XXX could be similar to a TA auditor not knowing how to incorporate knowledge about the client's business into an audit even though the auditor realizes the importance of understanding the client's business.

Even if the DM is able to eliminate MM#2, s/he may not be able to integrate the mental models correctly to produce the final model using MM#3. Instead, s/he may drop the *XXX* and overlook the importance of the Red account, leading to the following erroneous organizing framework as the final mental model:

*If Yellow is – OR (Blue AND Green) are –, then the state is BAD* *(LE-MMT2)*

In this case, in a round with 'Red, Yellow, Green, Blue' = '-, +, +, -', a DM will incorrectly conclude that the state is GOOD when it is BAD. It is equally likely that a boundedly rational DM will use either *LE-MMT1* or *LE-MMT2* as the organizing framework to guide the accounting investigation process and the reporting decision.

Finally, the right-hand column (designated "Prediction with SMMM") of Table 3 shows how the inference process can be enhanced with the template LE-1 as a guideline for the DM. The second record indicates that A represents the Yellow account. From the last two records, the negative sign in Green leads to a BAD state in the third record but not in the fourth record; therefore, B can only be the blue account.

As noted earlier, there are four parts in each experimental session, and in each part, there are 10 rounds. We consider each part an audit and the subject's reporting accuracy in a part is used as an observation. Considering the subject's reporting accuracy out of 10 rounds as one observation allows us to (1) avoid the problem that the subject is correct just by chance (in any one round, there is a 50% chance that the report is correct); (2) evaluate the predictable errors based on the MMT. Table 4 shows these predictable errors under different LEs used in the experiment. The first column of Table 4 shows the LEs used in the experiment. The second column shows the organizing framework subjects could potentially use at if they fail to construct and integrate the final mental model properly. The third column shows the round number in a part that we expect to see subjects reporting incorrectly for the respective LE used. For example, for the LE:

*If Yellow is - OR (Blue AND (Red OR Green)) are -, then the state is BAD*

if the subject use the following organizing framework instead:

*If Yellow is - OR (Blue AND Green) are -, then the state is BAD*

we will observe subjects with a reporting error in round 5. If the subject uses the following organizing framework:

*If Yellow is - OR Blue is -, then the state is BAD*

then we will observe subjects making a reporting error in round 7. We denote these rounds as MMT-ERROR rounds, and the rest of the rounds as REGULAR.

{Insert Table 4 about here}

The first hypothesis predicts that DMs, in the absence of a guideline, will make predictable errors. To test this hypothesis we compare the percentage of reporting accuracy in the MMT-ERROR rounds to the percentage of reporting accuracy in the REGULAR rounds for each subject using the BOT approach in Parts 1 and 2. We expect a higher percentage of reporting error in the MMT-ERROR rounds than in the REGULAR rounds.

The second hypothesis posits that auditors who are given the template make fewer predictable errors. To test this hypothesis, we compare the percentage of reporting accuracy under the TOP approach to that under the BOT approach in the MMT-ERROR rounds in Parts 1 and 2. We also compare the percentage of reporting accuracy under the TOP approach to that under the BOT approach in the REGULAR rounds in Parts 1 and 2. Consistent with the prediction of the SMMM hypothesis, we expect that subjects are more accurate under the TOP approach than under the BOT approach in the MMT-ERROR rounds. We also expect no difference between subject reporting accuracy under the TOP approach and under the BOT approach in the REGULAR rounds.

Finally, we test the third hypothesis by evaluating subjects' reporting accuracy in Part 3 under the TOP and the BOT approaches where the LE configuration could be different. Consistent with the advocacy for systems audit and SMMM, we predict that subjects who selected the TOP approach in Part 3 will be more accurate in their reports than subjects who selected the BOT approach. Specifically, we expect that subjects selecting the BOT approach under the DW setting made more reporting errors than subjects who selected the TOP approach under the same setting. In addition, we expect that subjects who selected the BOT approach and performed poorly under the DW setting will switch and select the TOP approach in Part 4. As a rationality check, we further investigate whether subjects' experiences in both the TOP and BOT setting affect their choice between the TOP and the BOT approaches in Part 3. Although subjects may have cognitive limitations in their ability to make correct inferences with a complex task, their choices of audit approach may still be rational. We predict that subjects who made fewer predictable errors under the TOP approach than under the BOT approach (i.e. had higher

reporting accuracy in Parts 1 or 2 under the TOP approach) are more likely to select the TOP approach in Parts 3 and 4. We use a logistic regression to evaluate subjects' choices.

## V. RESULTS

In this section we present the results for the three hypotheses discussed above using the methods outlined in the previous section. In general, our results are consistent with the predictions of the MMT and the SMMM hypotheses. Specifically, the results show that (1) subjects make predictable and systematic errors in the absence of a guideline; (2) the template provided by TOP reduces systematic errors, as predicted by the SMMM hypothesis; and (3) when subjects face the changing environment, they make fewer errors if they have the guideline.

There were 22 subjects in each of the four settings, with each subject making decisions in 40 rounds (10 rounds in each of the four parts). We use subjects' decisions over the 10 rounds in each part as an observation, resulting in 88 observations for each part.

### *Results for H1: DMs make predictable reporting errors under the BOT approach*

Our results support the MMT hypothesis that subjects make systematic inference errors in the absence of a guideline. Figure 2 shows average reporting accuracy for different LEs used in Parts 1 and 2 over the 10 rounds. The MMT-ERROR round numbers are in parentheses after the LE. For example, the (5, 7) after the LE (*If Yellow is - OR (Blue AND (Red OR Green)) are -, then the state is BAD*) shown in the left graph of Panel A indicates that rounds 5 and 7 are the MMT-ERROR rounds. Panel A of Figure 2 shows the data for Part 1 and Panel B shows the data for Part 2. The MMT hypothesis predicts that reporting errors (denoted as MMT-ERROR rounds) is observed in rounds 5 and 7 for the LE corresponds to the graph on the left-hand side of Panel A and the right-hand side of Panel B. For the other two graphs, the hypothesis predicts higher percentage of errors in rounds 3 and 4. These graphs provide visual perspective of the data and quantitative analyses are summarized in Table 5. Panel A of Table 5 shows average reporting accuracy pooled across Parts 1 and 2 for the MMT-ERROR rounds and REGULAR rounds under the BOT and TOP approaches. For this hypothesis, we focus on the data under the BOT approach. The table indicates that subjects were correct 93.8% in the REGULAR rounds but only 47.7% in the MMT-ERROR rounds, a difference of 46.0% with a p-value of 0.000 using a t-test. Thus we find support for the first hypothesis, and conclude that subjects' reporting

errors are systematic under the BOT setting. The TOP data are discussed below.

{Insert Table 5 about here}

***Results for H2: Hypothesis on DMs' inferences errors with an organizing framework***

In general, we find support for the SMMM hypothesis that inference accuracy is higher in the presence of a guideline. Panel A of Table 5 provides a side-by-side comparison of the average reporting accuracy under the TOP and the BOT approaches. We find that under both the TOP and BOT settings, subjects were significantly more accurate in the REGULAR rounds than in the MMT-ERROR rounds (94.6% in the REGULAR rounds and 74.4% in the MMT-ERROR rounds with a 20.2% difference for TOP; $p < 0.0001$, and 93.8% in the REGULAR rounds and 47.7% in the MMT-ERROR rounds with a 46.0% difference for BOT; $p < 0.0001$). This also confirms the findings above that subjects made disproportionately more mistakes in the MMT-ERROR rounds under the BOT approach.

We perform a between subject comparison using data from Part 1 (comparing subjects' performance in the TOP setting with that in the BOT setting in Part 1), and a within subject comparison of subjects' performance in Parts 1 and 2. Table 5 Panel B provides a summary of the findings and the t-test results. Columns 2 and 3 of Table 5 Panel B show the mean and the standard deviation for the percentage of reporting accuracy for subjects under the TOP-BOT and the BOT-TOP setting respectively. The differences and the p-value for the t-test are shown in column 4.

In general, the results shown in Table 5 are consistent with the SMMM hypothesis that DMs have higher reporting accuracy under the TOP approach because they are more accurate in the MMT-ERROR rounds. Figure 3 Panel A shows subjects' average reporting accuracy under the TOP-BOT and the BOT-TOP settings in Parts 1 and 2 for all rounds. Under the BOT-TOP setting, the data in Table 5- Panel B shows that subjects' are more accurate in Part 2 than in Part 1 (8.2%; $p < 0.0001$). The increase in decision accuracy does not appear to be due to learning because we do not observe similar improvements in subjects' decision accuracy in the TOP-BOT setting. On the contrary, subjects performed better in Part 1 under the TOP-BOT setting than in

Part 2 (3.9% more accurate; p = 0.024).[18] Figure 3 Panel B shows subjects' average reporting accuracy under the TOP-BOT and the BOT-TOP settings in Parts 1 and 2 for the MMT-ERROR rounds and the REGULAR rounds. The graph reveals that subjects' improvements under the BOT-TOP setting comes primarily from an improvement in the subjects' decisions in the MMT-ERROR rounds while decline in subjects' perform under the TOP-BOT setting came primarily from subjects making more decision errors in the MMT-ERROR rounds. Interestingly, the between subject comparisons in Part 2 show no significant differences between the TOP and BOT settings for subjects' decisions accuracy.

We also find that the order in which subjects are exposed to the approach seems to matter. We compare results for subjects who had TOP in Part 1 with those who had TOP in Part 2. We find no significant differences in subjects' reporting accuracy (p = 0.20, result not shown in Table 5). However, we find that subjects are more accurate, 7.7%, in their reports in Part 2 of the TOP-BOT sequence than in Part 1 of the BOT-TOP sequence (p = 0.0003, result not shown in Table 5). Because there is no difference between subjects' performance under the TOP setting in Parts 1 and 2, we cannot attribute the difference in subjects' performance under the BOT setting in Parts 1 and 2 as due to subjects' learning about the task.

***Results for H3: Comparing DMs' reporting accuracy in the Static World setting with that in the Dynamic World setting***

We also find support for the third hypothesis. Figure 4 shows subjects' average reporting accuracy in parts 3 using the TOP and BOT approaches under the SW and DW setting. In general, we find that: (1) subjects who selected the TOP approach perform better than those who selected the BOT approach; (2) subjects performed better under the SW setting than under the DW setting; and (3) subjects who chose the BOT approach perform disproportionately worse under the DW setting than those who chose the same approach under the SW setting. Table 6 summarizes the average of subjects' decisions performance in Part 3. Subjects' reporting accuracy is 5.7% (p = 0.07) and 11.4% (p = 0.03) higher for those who chose the TOP approach

[18] *Ceteris paribus*, learning should lead to higher reporting accuracy in Part 2. The observed higher performance in Part 1 than in Part 2 under the TOP-BOT setting provides a stronger support for the SMMM hypotheses.

instead of the BOT under the SW and DW settings respectively. Overall, subjects' reporting accuracy is 7.3% (p = 0.02) higher under the SW than DW settings.

Table 6 reveals that: (1) there are no significant differences in subjects' performance under the SW and DW settings for subjects who selected TOP in both settings (p = 0.24); (2) subjects who selected the BOT approach under SW were on average 8.9% (p = 0.02) more accurate than those who selected the BOT approach under DW; and (3) subjects who selected the TOP approach under DW were on average 11.4% (p=0.03) more accurate than those who selected the BOT approach.

{Insert Table 6 about here}

Given that subject's choice of audit approach is endogenous in Parts 3 and 4, we also run a few logistic regressions to investigate the extent to which subjects select TOP or BOT in Part 3 are based on (1) their experiences in Part 1 and 2; and (2) economic motivation. Specifically, we investigate whether subjects' experiences across Parts 1 and 2 affected the TOP/BOT choice in Part 3. We use the reporting accuracy rather than payoff loss in the regression because the payoff loss function is non-linear.[19] We hypothesize that subjects' choice of the TOP approach depends on whether they had higher payoff and spent less time in each round under the TOP setting than under the BOT setting. The first logit model is based only on variables that we consider economic in nature. In all the logit regressions, the probability of selecting the TOP approach in Part 3 is modeled. The two economic explanatory variables we included in the regression are: (1) the percentage of correct reports under TOP minus the percentage of correct reports under BOT (denoted ?REP_ACC); and (2) the difference between the average amount of time (measure in seconds) a subject spent in a round under the TOP setting and the BOT setting (denoted ?TIME). The economic prediction is that subjects who have higher relative reporting accuracy under the TOP setting in Part 1 or 2 are more likely to select the TOP approach in Part 3; thus there should be a positive correlation between the probability of selecting TOP in Part 3 and the change in reporting accuracy, ?REP_ACC. If subjects also value their time as an important economic

[19] Apart from the number of correct report in each part, we also have data on the type of reporting errors, each subject's reported confidence about the selected report, and the number of second used in each round. These data allow us to calculate the payoff loss from each type of reporting errors and the total payoff loss in a round. However,

resource, the more time they spent under the TOP setting compared to the BOT setting in the first two parts of the experiment, the less likely they are to select the TOP approach in Part 3; thus we expect a negative relationship between the dependent variable and ?TIME. Table 7, column 2 shows the expected signs for the all the explanatory variables.

In the experiment, no time constraint is imposed on the subjects. As a result, even though time could be a valuable resource, it may not affect the subjects' choice. We estimated a second economic motivated model using ?REP_ACC as the only explanatory variable. We also notice that of the 44 subjects in the TOP-BOT setting, 34 (77%) chose BOT in part 3 while only 25 (57%) of the 44 subjects in the BOT-TOP setting chose BOT. Coupled with the results of higher subjects' reporting accuracy in Part 2 in the TOP-BOT setting, we also develop a third model to include two other variables, ?CONF and ORDER.[20] ?CONF is the difference of a subject's average confidence under the TOP setting (in either Part 1 or 2) and that under the BOT setting. ORDER is an indicator variable that equals 1 if the subject was given the TOP setting in Part 1 and 0 otherwise. The three models that we estimated are summarized below:

$$\log(P/1-P) = ß_0 + ß_1 ?REP\_ACC + ß_2\ ?TIME \qquad \text{(Model 1)}$$

$$\log(P/1-P) = ß_0 + ß_1 ?REP\_ACC \qquad \text{(Model 2)}$$

$$\log(P/1-P) = ß_0 + ß_1 ?REP\_ACC + ß_3\ ?CONF + ß_4\ ORDER \qquad \text{(Model 3)}$$

where P is the probability of choosing the TOP approach in Part 3.

Our results show that ? TIME is not significant in model 1. In other words, the relative amount of time subjects spent on the task in Parts 1 and 2 did not affect their choice of the audit approach in Part 3. We also find that apart from the economic factor such as ?REP_ACC, the psychological factor ?CONF and the treatment factor ORDER also affect subjects' choice of audit approach in Part 3. These variables add 9.3% (82.8% - 73.5%) to the predictive power over the ? REP_ACC variable (see Table 7). In short, we find that subjects' choices in Part 3 are consistent with their experiences in Part 1 and 2 (see Table 7).

{Insert Table 7 about here}

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we opt not to use the payoff loss function in the analysis because the payoff function is non linear, depending on the type of reporting errors and the number of accounts the individual chose to investigate.

## VI. SUMMARY AND CONCLUSIONS

Although the idea of a dynamic audit technology to meet current challenges had been discussed in the literature (Elliott 1994), the publication by Bell el al. (1997) has provided a concrete basis on which to discuss the approach. This publication has precipitated a number of research papers, including Ballou et al. (2001), Blokdijk et al. (2001), and O'Donnell (2001), and has generate a great deal of discussion, both in practice (Eilifsen et al. 2001; Winograd et al. 2000) and in the research arena (Ballou and Heitger 2001).

Our goal is to contribute to the understanding of *how* systems knowledge can improve audit decision-making and thus provide a decision-making foundation to the work of Bell et al. (1997). The SMMM hypothesis developed here predicts that systems knowledge reduces the cognitive demands of integrating the multiple mental models needed to solve a complex problem. The SMMM hypothesis predicts that the DMs who gain an understanding of the interactions among the components, both internal and external, of a system are more likely to integrate the mental models appropriately, leading to better decisions compared to DMs who do not have such an understanding. In an auditing context, the DM gains a system understanding by undertaking actions along the lines suggested by Bell et al. (1997). We also conduct an experiment to investigate the theory and find support for the hypothesis. In summary, we find that: (1) subjects make errors that are predicted by the mental model theory; (2) subjects perform better (i.e., higher reporting accuracy) under the TOP setting than the BOT setting, (3) subjects perform better under the TOP setting than the BOT setting in an environment that changes unexpectedly.

There are some noteworthy caveats to our study. First, our operationalization of the audit setting and audit approaches (TA and SA) is very stark relative to natural settings. However, we seek to create a setting that is simplified to focus on primitive decision-making issues that apply to the theory. A second caveat is that we use student subjects in our experiment, rather than audit practitioners. However, our subject pool choice and other experimental choices were chosen to enhance internal validity, which is a fundamental requirement of valid experimentation (Peecher and Solomon 2001). The last caveat is that we do not investigate how DMs might develop an

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[20] These variables were also selected by a model-selection procedure that determine the extent that other variables also help to predict auditors' choices in Part 3

understanding of a system. Rather, we investigate how a guideline for an organizing framework, such as systems knowledge, can be useful in settings where DMs are prone to making predictable errors.

One future research possibility is to refine the theory to evaluate the robustness of this theory when applied to other types of problems. A second possibility is to conduct experimental research to investigate the effects of adding a strategic element to the setting to investigate the emergence of biased decision-making. For example, Kadous et al. 2003 investigate decision-making under the mediating effect of the preference of others. This "motivated reasoning" could be a function of the extent to which systems are (mis)understood by auditor and that the negotiation stance that auditors take could be a function of their confidence in their understanding of the underlying systems.

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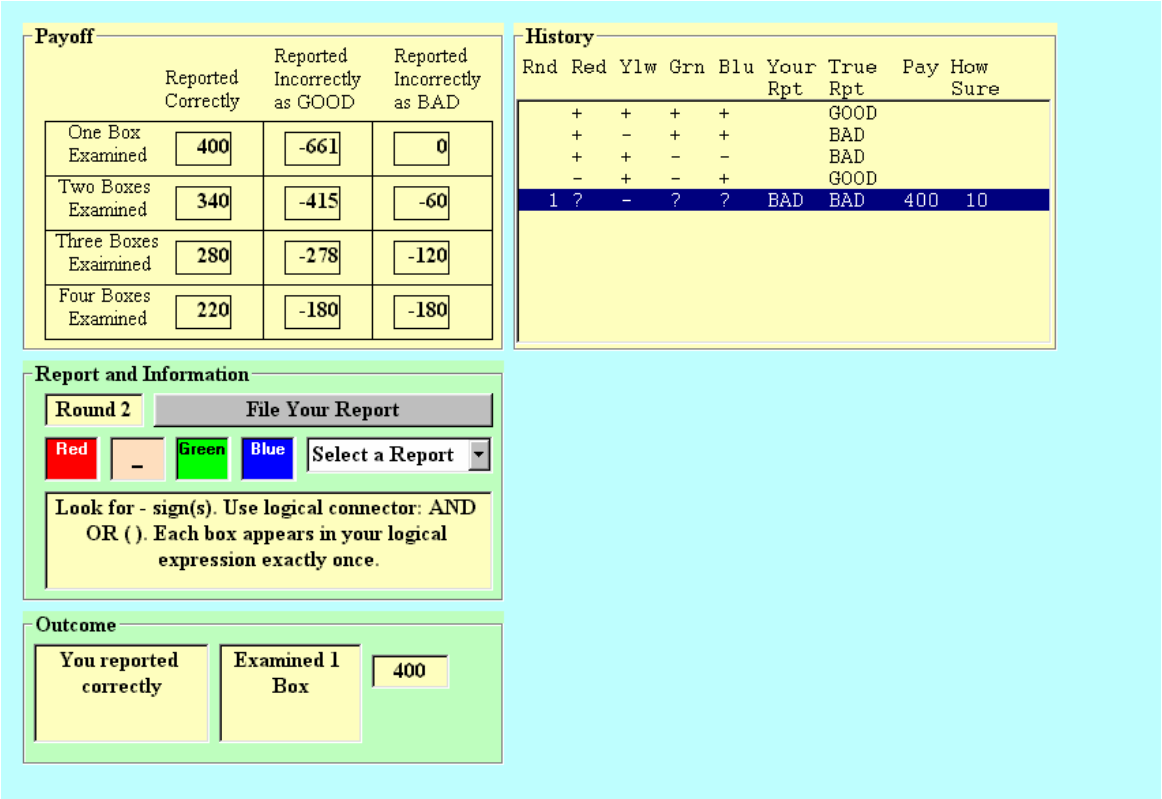
**FIGURE 1**

**Panel A: Auditor's Computer Screen Under the BOT Setting**




**Panel B: Auditor's Computer Screen Under the TOP Setting**

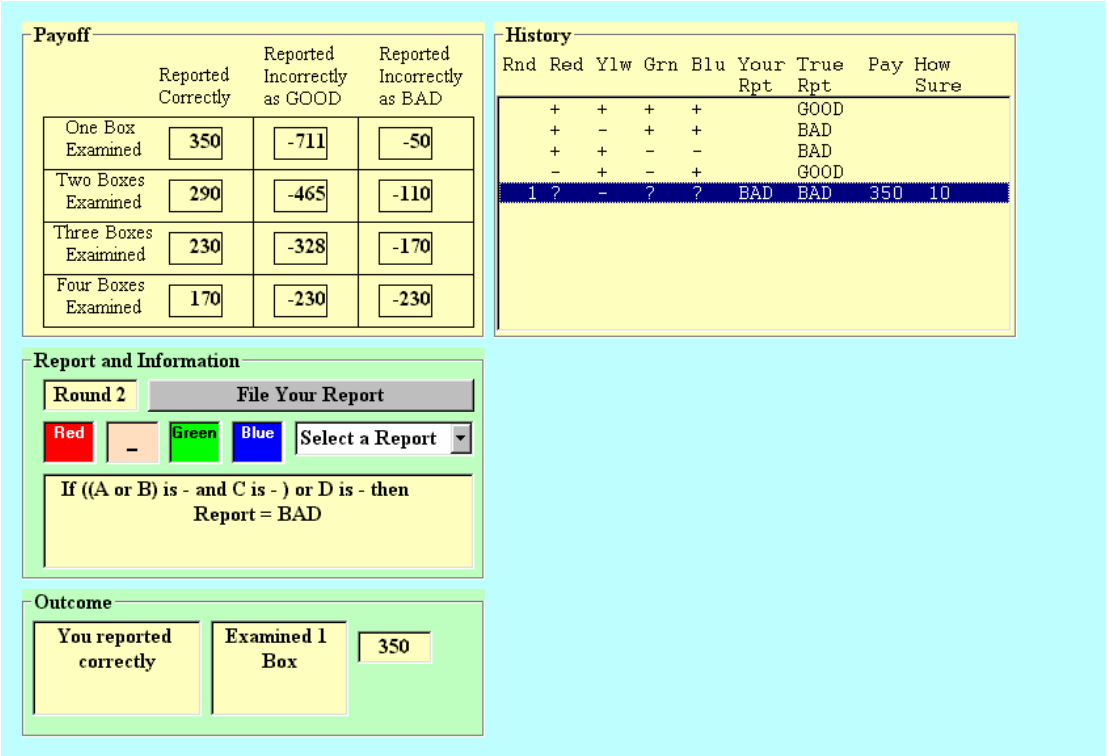
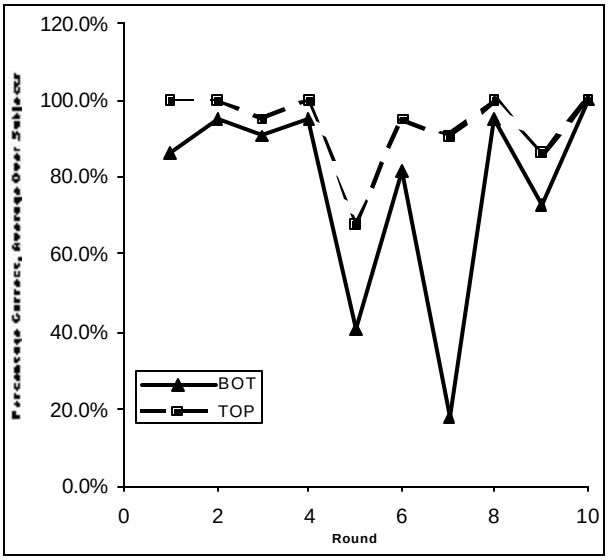
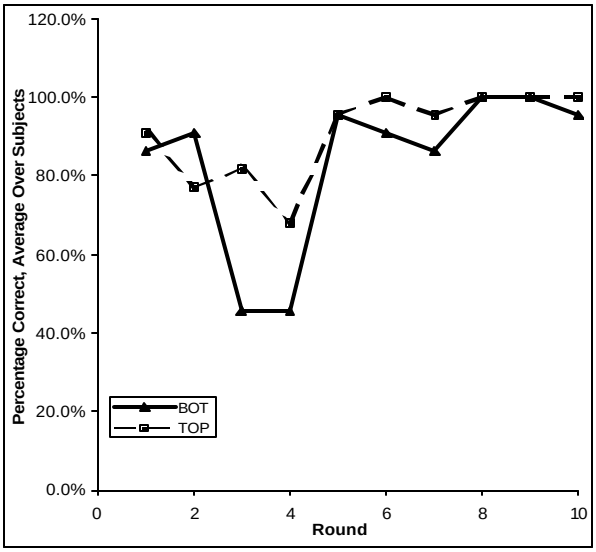


**FIGURE 2: Subjects' Reporting Accuracy Under TOP and BOT**
**Panel A: Part 1**

LE: If Yellow is - OR (Blue AND (Red OR Green)) are -, then the state is BAD (5, 7)*

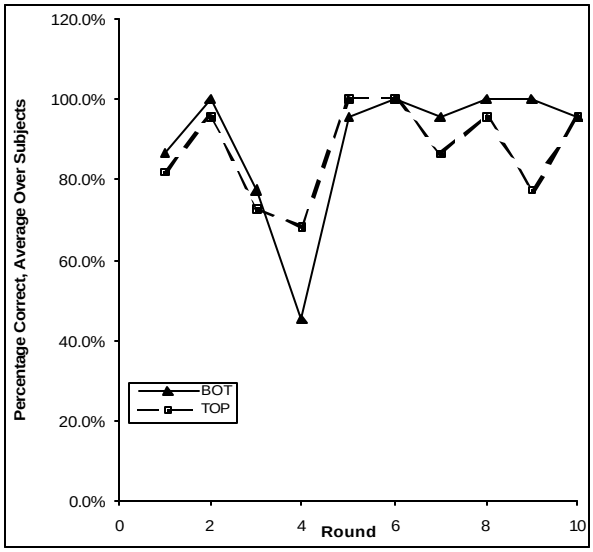



LE: If Blue is - OR (Green AND (Red OR Yellow)) are -, then the state is BAD (3, 4)

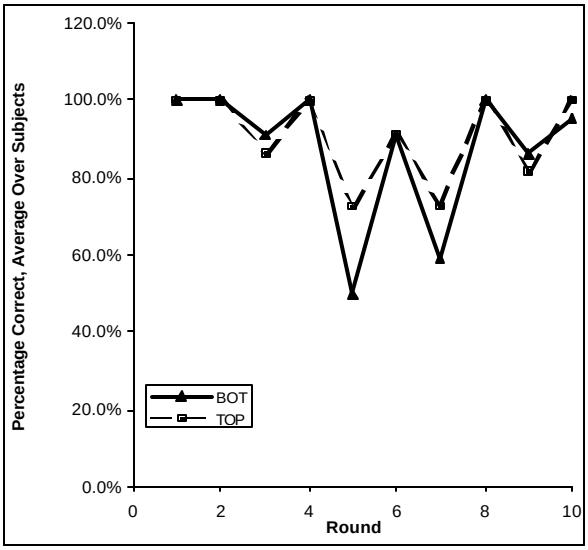



**Panel B: Part 2**

LE: If Blue is - OR (Green AND (Red OR Yellow)) are -, then the state is BAD (3, 4)



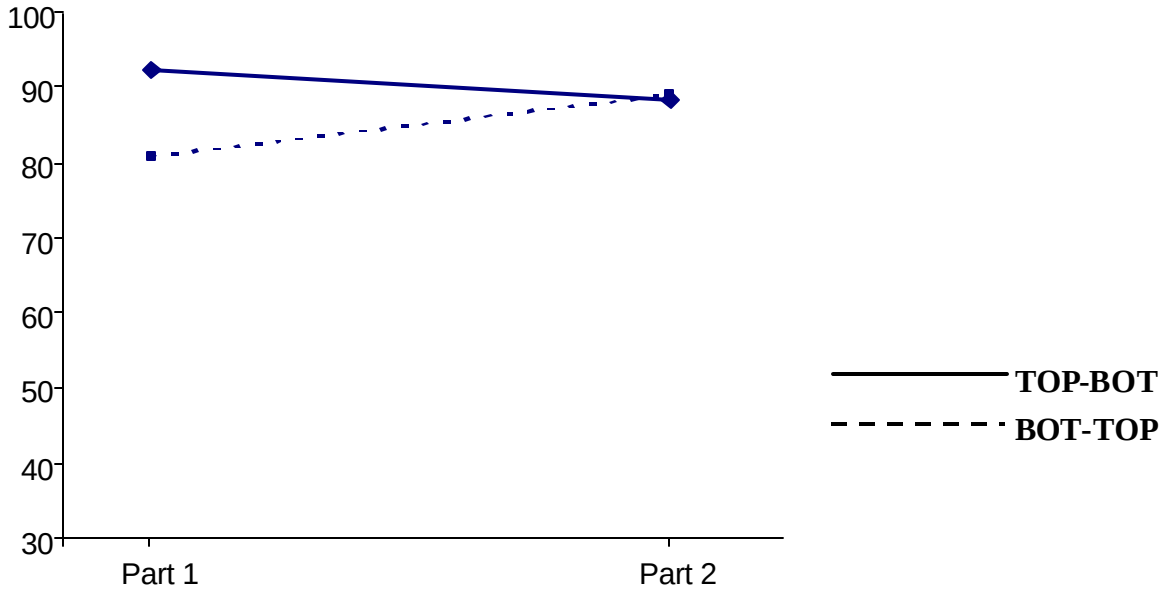

LE: If Yellow is - OR (Blue AND (Red OR Green)) are -, then the state is BAD (5, 7)




*MMT-ERROR rounds are in parentheses

**FIGURE 3: Subjects' Average Reporting Accuracy Under TOP-BOT and BOT-TOP in Parts 1 and 2**

**Panel A: All Rounds**




**Panel A: MMT-ERROR Rounds and REGULAR Rounds**

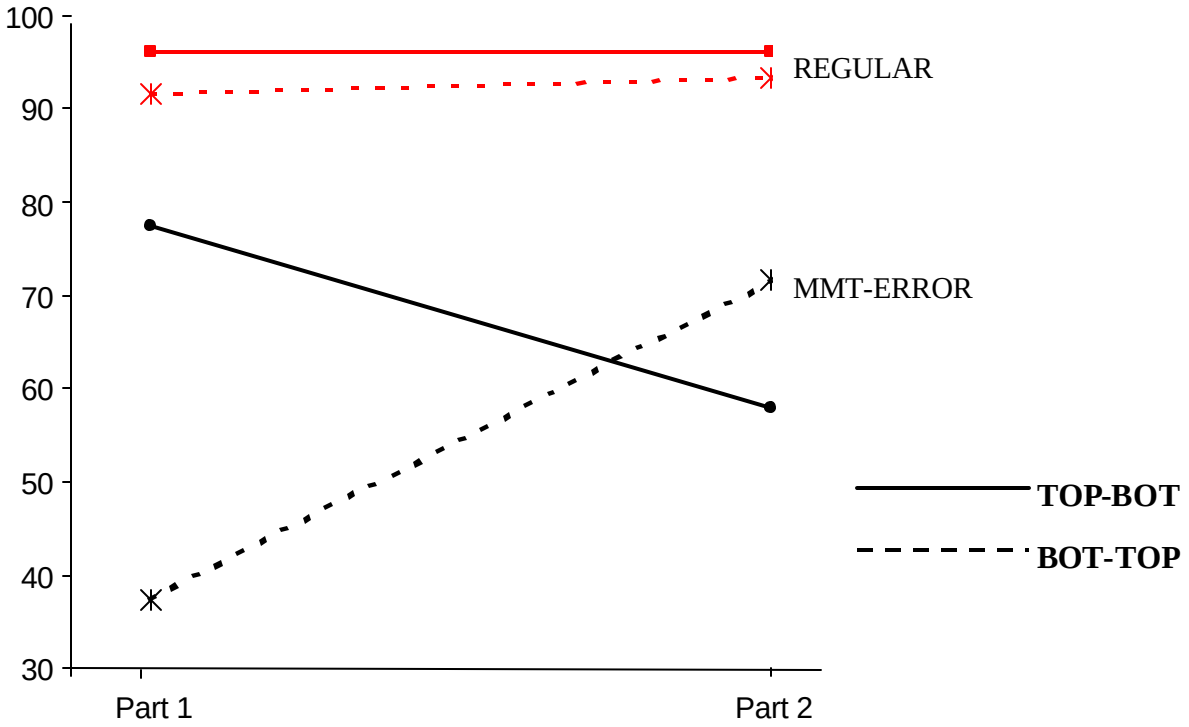


**FIGURE 4: Subjects' Average Reporting Accuracy Under TOP and BOT for SW and DW in Parts 3**

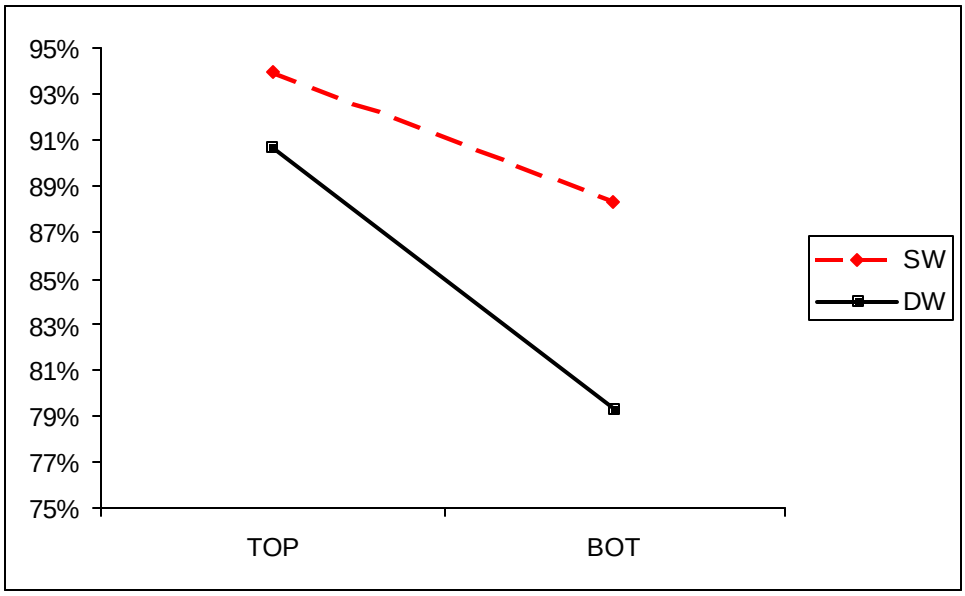


**TABLE 1**
**Design**

| Designations for the four settings (number of subjects) | | Part 1 (10 rounds) | Part 2 (10 rounds) | Part 3 (10 rounds) | Part 4 (10 rounds) |
|---|---|---|---|---|---|
| **1** | **TOP-BOT/SW** | TOP setting | BOT setting | Choice setting LE-1/3 | Choice setting LE-1/4 |
| | **11 subjects** | LE-1/1 | LE-1/2 | | |
| | **11 subjects** | LE-1/2 | LE-1/1 | | |
| **2** | **TOP-BOT/DW** | TOP setting | BOT setting | Choice setting LE-2/1 | Choice setting LE-2/2 |
| | **11 subjects** | LE-1/1 | LE-1/2 | | |
| | **11 subjects** | LE-1/2 | LE-1/1 | | |
| **3** | **BOT-TOP/SW** | BOT setting | TOP setting | Choice setting LE-1/3 | Choice setting LE-1/4 |
| | **11 subjects** | LE-1/1 | LE-1/2 | | |
| | **11 subjects** | LE-1/2 | LE-1/1 | | |
| **4** | **BOT-TOP/DW** | BOT setting | TOP setting | Choice setting LE-2/1 | Choice setting LE-2/2 |
| | **11 subjects** | LE-1/1 | LE-1/2 | | |
| | **11 subjects** | LE-1/2 | LE-1/1 | | |

TOP the top-down audit approach, operationalized by providing auditors with a template of the logical expression to be used with records to infer the underlying logical expression

BOT the bottom-up audit approach, operationalized by not providing auditors with a template of the logical expression and auditors only have records to infer the underlying logical expression

SW static world (use LE-1 in all 4 parts of the experiment)

DW dynamic world (use LE-1 in Parts 1 and 2 but LE-2 in Parts 3 and 4)

LE logical expressions

LE-1 template of the LE configuration A OR (B AND (C OR D))

LE-2 template of the LE configuration A AND (B OR (C AND D))

LE-1/1 logical expression with configuration LE-1 and the role of each account is specified in *If Yellow is - OR if (Blue AND (Green OR Red)) are -, then the state is BAD*

LE-1/2 logical expression with configuration LE-1 and the role of each account is specified in *If Blue is - OR if (Green AND (Yellow OR Red)) are -, then the state is BAD*

LE-1/3 logical expression with configuration LE-1 and the role of each account is specified in *If Green is - OR if (Yellow AND (Blue OR Red)) are -, then the state is BAD*

LE-1/4 logical expression with configuration LE-1 and the role of each account is specified in *If Yellow is - OR if (Red AND (Blue OR Green)) are -, then the state is BAD*

LE-2/1 logical expression with configuration LE-2 and the role of each account is specified in *If Green AND (Yellow OR (Blue AND Red)) are -, then the state is BAD*

LE-2/2 logical expression with configuration LE-2 and the role of each account is specified in *If Yellow AND (Red OR (Blue AND Green)) are -, then the state is BAD*

**TABLE 2**

**Panel A: Auditors' Payoffs Under the BOT setting, per round**

| Number of accounts investigated | Reported Correctly | Incorrectly report: Report G\|BAD | Incorrectly report: Report B\|GOOD |
|---|---|---|---|
| 1 | **400** (= 460 - 60) | **-661** (= 460 - 60 - 1061)* | **0** (= 460 - 60 - 400) |
| 2 | **340** (= 460 - 120) | **-415** (= 460 - 120 - 755) | **-60** (= 460 - 120 - 400) |
| 3 | **280** (= 460 - 180) | **-278** (= 460 - 180 - 558) | **-120** (= 460 - 180 - 400) |
| 4 | **220** (= 460 - 240) | **-180** (= 460 - 240 - 400) | **-180** (= 460 - 240 - 400) |

**Panel B: Auditors' Payoffs Under the TOP setting, per round**

| Number of accounts investigated | Reported Correctly | Incorrectly report: Report G\|BAD | Incorrectly report: Report B\|GOOD |
|---|---|---|---|
| 1 | **350** (= 460 - 50 - 60) | **-711** (= 460 - 50 - 60 - 1061) | **-50** (= 460 - 50 - 60 - 400) |
| 2 | **290** (= 460 - 50 - 120) | **-465** (= 460 - 50 - 120 - 755) | **-110** (= 460 - 50 - 120 - 400) |
| 3 | **230** (= 460 - 50 - 180) | **-328** (= 460 - 50 - 180 - 558) | **-170** (= 460 - 50 - 180 - 400) |
| 4 | **170** (= 460 - 50 - 240) | **-230** (= 460 - 50 - 240 - 400) | **-230** (= 460 - 50 - 240 - 400) |

*The first number (-661) is the net payout for the combination of investigating one account and reporting G, given a BAD state. The second number (460) is the beginning endowment, the third number (60) is the cost of investigating one account, and the fourth number (1060) is the cost of misreporting given one account was investigated.

**TABLE 3**
**An Example of the Mental Processes Under Different Theories**
**(If Yellow is negative OR if Blue AND (Green OR Red) are negative, then the state is BAD)**

| Records | | | | | | BOT approach | | TOP |
|---|---|---|---|---|---|---|---|---|
| | **Red** | **Yellow** | **Green** | **Blue** | **State** | **Prediction with unbounded rationality** | **Prediction with MMT** | **Prediction with SMMM (If A – OR B AND (C OR D) -, then BAD)** |
| **1** | + | + | + | + | GOOD | No negative sign, DM learns that if all four accounts are positive, the state will never be BAD | No negative sign, DM learns that if all four accounts are negative, the state will never be BAD | No negative sign, DM learns that if all four accounts are negative, the state will never be BAD |
| **2** | + | - | + | + | BAD | One mental model:<br>If Yellow – or (XXX), then BAD | One mental model:<br>If Yellow – or (XXX), then BAD | One mental model:<br>A = Yellow |
| **3** | + | + | - | - | BAD | Three mental models:<br>1. If Yellow – or Green – or (XXX), then BAD<br>2. If Yellow – or Blue – or (XXX), then BAD<br>3. If Yellow – or (Blue and Green) – or (XXX), then BAD | Three mental models:<br>1. If Yellow – or Green – or (XXX), then BAD<br>2. If Yellow – or Blue – or (XXX), then BAD<br>3. If Yellow – or (Blue and Green) – or (XXX), then BAD | Two mental models:<br>1. B = Green<br>2. B = Blue |
| **4** | - | + | - | + | GOOD | Eliminated the first model, leaving the following two:<br>1. If Yellow – or Blue – or (XXX), then BAD<br>2. If Yellow – or (Blue and Green) – or (XXX), then BAD<br>Must consider all accounts, leading to two possible integrated models:<br>1. If Yellow – or Blue – or (Red and Green) – , then BAD => failed the last record<br>2. If Yellow – or Blue and (Green or Red) – , then BAD => the only possibility | Eliminated the first model, leaving the following two:<br>1. If Yellow – or Blue – or (XXX), then BAD<br>2. If Yellow – or (Blue and Green) – or (XXX), then BAD<br>Fail to consider all accounts, leading to the following models:<br>1. If Yellow – or Blue –, then BAD<br>2. If Yellow – or (Blue and Green) – , then BAD | Eliminated the first model, and concluded that:<br>B = Blue<br>Since there are no ordering differences between C and D, the conclusion is:<br>If Yellow is – or (Blue and (Red or Green)) are – , then BAD |

**TABLE 4**
**Rounds with Expected Reporting Errors Under Each LE**

| LE used in the Experiment | Possible organizing framework used by subjects | Round with error |
|---|---|---|
| If Yellow is - OR (Blue AND (Red OR Green)) are -, then the state is BAD | If Yellow is - OR (Blue AND Green) are -, then the state is BAD | 5 |
| | If Yellow is - OR Blue is -, then the state is BAD | 7 |
| If Blue is - OR (Green AND (Red OR Yellow)) are -, then the state is BAD | If Blue is - OR Green is -, then the state is BAD | 3 |
| | If Blue is - OR (Green AND Red) are -, then the state is BAD | 4 |
| If Green is - OR (Yellow AND (Red OR Blue)) are -, then the state is BAD | If Green is - OR (Yellow AND Red) are -, then the state is BAD | 2 |
| | If Green is - OR Yellow is -, then the state is BAD | 7 |
| If Yellow is - OR (Red AND (Green OR Blue)) are -, then the state is BAD | If Yellow is - OR (Red AND Blue) are -, then the state is BAD | 3 |
| | If Yellow is - OR Red is -, then the state is BAD | 9 |
| If Green AND (Yellow OR (Red AND Blue)) are -, then the state is BAD | If Green AND Yellow are -, then the state is BAD | 5 |
| If Yellow AND (Red OR (Green AND Blue)) are -, then the state is BAD | If Yellow AND Red are -, then the state is BAD | 3 |

**TABLE 5**
**Panel A: Average Reporting Accuracy by Audit Approach in Parts 1 and 2, MMT-ERROR Rounds and REGULAR Rounds (in Percentage)**

| | **BOT (n = 88)** | | **TOP (n = 88)** | |
|---|---|---|---|---|
| **Pooling Parts 1 and 2** | Mean | Standard Deviation | Mean | Standard Deviation |
| All rounds | 84.5 | 10.3 | 90.6 | 12.4 |
| MMT-ERROR rounds | 47.7 | 33.8 | 74.4 | 34.7 |
| REGULAR rounds | 93.8 | 8.9 | 94.6 | 9.6 |
| REGULAR minus MMT-ERROR | 46.0 (0.000) [a] | | 20.2 (0.000) [a] | |

**Panel B: Average Reporting Accuracy by settings, in Parts 1 and 2, All rounds, MMT-ERROR rounds and REGULAR rounds (in Percentage)**

| | **BOT-TOP (n = 44)** | | **TOP-BOT (n = 44)** | | **Difference between individuals** |
|---|---|---|---|---|---|
| **Part 1** | Mean | Standard Deviation | Mean | Standard Deviation | BOT-TOP minus TOP-BOT |
| All rounds | 80.7 | 9.0 | 92.3 | 10.5 | -11.6 (0.000) [a] |
| MMT-ERROR rounds | 37.5 | 28.8 | 77.3 | 31.4 | -39.8 (0.000) [a] |
| REGULAR rounds | 91.5 | 9.6 | 96.0 | 7.5 | -4.5 (0.016) [b] |
| **Part 2** | | | | | |
| All rounds | 88.9 | 14.0 | 88.4 | 10.1 | 0.5 (0.431) [a] |
| MMT-ERROR rounds | 71.6 | 38.0 | 58.0 | 35.7 | 13.6 (0.043) [a] |
| REGULAR rounds | 93.2 | 11.3 | 96.0 | 7.5 | -2.8 (0.168) [b] |
| **Difference within individual (Part 1 minus Part 2)[a]** | | | | | |
| All rounds | -8.2 (0.000) [a] | | 3.9 (0.024) [a] | | |
| MMT-ERROR rounds | -34.1 (0.000) [a] | | 19.3 (0.003) [a] | | |
| REGULAR rounds | -1.7 (0.309) [b] | | 0.0 (1.000) [b] | | |

[a] P-value in parentheses is based on one-tailed t-tests.
[b] P-value in parentheses is based on two-tailed t-tests

**TABLE 6**
**Average Audit Accuracy, Confidence, and Time Used in Part 3, by SW and DW**

| | | **Overall** | **Choose TOP** | **Choose BOT** | **Difference TOP-BOT** |
|---|---|---|---|---|---|
| **SW** | Number of participants | 44 | 15 | 29 | (14) |
| | Average reporting accuracy (percentage) | 90.2% | 94.0% | 88.3% | 5.7% (0.07)[a] |
| **DW** | Number of participants | 44 | 14 | 30 | (16) |
| | Average reporting accuracy (percentage) | 83.0% | 90.7% | 79.3% | 11.4% (0.03)[a] |
| **Difference SW-DW** | Average reporting accuracy (percentage) | 7.3% (0.02)[a] | 3.3% (0.24)[a] | 8.9% (0.02)[a] | |

[a] P-value in parentheses is based on one-tailed t-tests.

**TABLE 7**
**Results for Predicting Auditors' Choice of TOP Approach in Part 3**

| | Dependent Variable = CHOICE_P3 | | | |
|---|---|---|---|---|
| | *Expected Sign* | *Model (1) Estimated Coefficients (Wald Chi-Square)* | *Model (2) Estimated Coefficients (Wald Chi-Square)* | *Model (3) Estimated Coefficients (Wald Chi-Square)* |
| $ß_0$ Intercept | +/- | -1.4186*** (16.9503) | -1.3602*** (16.4416) | -1.0995** (5.7226) |
| $ß_1$ ?REP_ACC | + | 0.7482*** (10.5409) | 0.8020*** (12.1444) | 0.7240*** (8.5319) |
| $ß_2$ ?TIME | - | -0.00686 (1.4715) | | |
| $ß_3$ ?CONF | + | | | 0.5843*** (8.7839) |
| $ß_4$ ORDER | - | | | -1.4427** (5.8280) |
| Likelihood Ratio | | 17.2089 (0.0002) | 15.7039 (<.0001) | 30.7323 (<.0001) |
| Max-rescaled R-Square | | 0.2472 | 0.2275 | 0.4102 |
| c | | 0.765 | 0.735 | 0.828 |

**, *** Indicates a significant level at 5 percent level or less, and 1 percent level or less respectively.

The variables are defined as follows:

CHOICE_P3 = 1 if TOP is selected; 0 otherwise
?REP_ACC = Percentage of correct reports under the TOP setting minus Percentage of correct reports under the BOT setting, using data from Parts 1 and 2 of the experiment
?TIME = Difference in the average minutes used under the TOP setting and that under the BOT setting, using data from Parts 1 and 2 of the experiment
?CONF = Difference in the average of an auditor's confidence in a round under the TOP setting and that under the BOT setting, using data from Parts 1 and 2 of the experiment
ORDER = 1 if the auditor was given the TOP setting in Part 1; 0 otherwise

## APPENDIX A

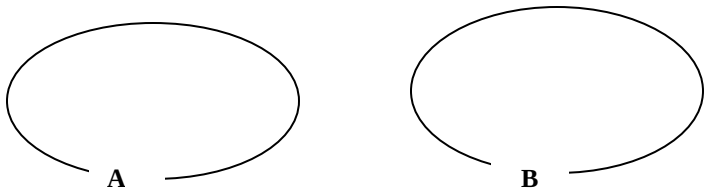
### Example to Illustrate the MMT with Pictorial Representation

Consider the following two premises:

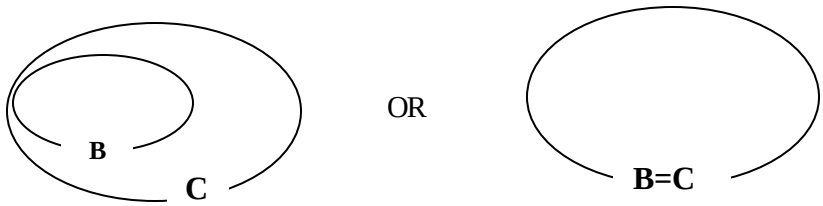
Premise 1: *None of A is a B*
Premise 2: *All Bs are C*
What can you conclude about A and C?

Johnson-Laird 2001 finds that DMs typically draw conclusions such as *None of A is a C*, which is incompatible with the premises because *Cs* that are not *Bs* could be *As*. DMs need to construct the mental model about the valid connection between *As* and *Cs*, which is 'Some of *Cs* are not *As*.' However, they may draw incorrect conclusions from the second premise to mean 'All the *Cs* are *Bs*.' A pictorial representation of the premises and the four possible mental models are shown below:

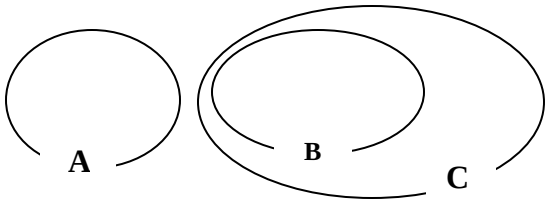
**Premise 1: None of A is B**



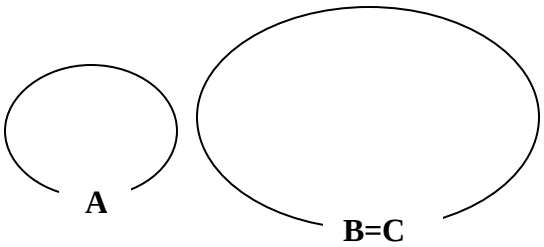

**Premise 2: All of Bs are C**



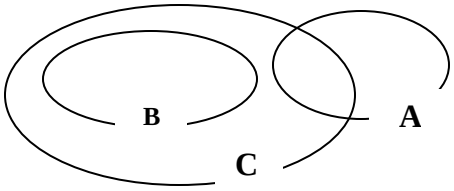

**What can you conclude about A and C?**



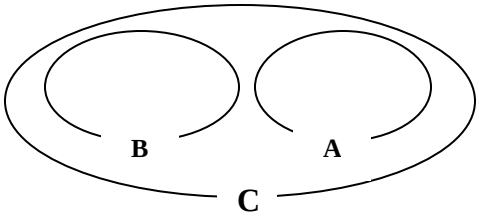

Case 1




Case 2




Case 3




Case 4

## APPENDIX B

### LE Configurations and the Number of LEs in Each Configurations

| LE configurations | Calculations for the number of LEs under each configuration[21] | Number of LEs under each configuration |
|---|---|---|
| LE-1: A OR (B AND (C OR D)) | ${}^{4}C_1 \times {}^{3}C_1 = 4 \times 3$ | 12 |
| LE-2. A AND (B OR (C AND D)) | ${}^{4}C_1 \times {}^{3}C_1 = 4 \times 3$ | 12 |
| LE-3. A AND B AND (C OR D) | ${}^{4}C_2$ | 6 |
| LE-4. A OR B OR (C AND D) | ${}^{4}C_2$ | 6 |
| LE-5. (A AND B AND C) OR D | ${}^{4}C_1$ | 4 |
| LE-6. (A OR B OR C) AND D | ${}^{4}C_1$ | 4 |
| LE-7. (A AND B) OR (C AND D) | ${}^{4}C_2 \div 2 = ((4 \times 3)/2) \div 2$ | 3 |
| LE-8. (A OR B) AND (C OR D) | ${}^{4}C_2 \div 2 = ((4 \times 3)/2) \div 2$ | 3 |
| LE-9. A AND B AND C AND D | ${}^{4}C_4$ | 1 |
| LE-10. A OR B OR C OR D | ${}^{4}C_4$ | 1 |
| Total | | 52 |

Let the letters A, B, C, and D represent the accounts in a generic manner. That is, let any of these four letters represent any one of the four accounts. Within each LE configuration, we generate a different LE by changing the positions of these accounts. By calculating the number of permutation within each configuration, we can find out the number of LEs in each configuration. For example, under configuration LE-1 (A OR (B AND (C OR D)), there exist 12 different LEs because there are four ways to choose A; and once A is chosen, there are three ways to choose B. Once A and B are chosen, the ordering of C and D does not matter. Hence we have 12 different LEs (${}^{4}C_1 \times {}^{3}C_1 = 4 \times 3 = 12$) under this LE configuration.

[21] ${}^{4}C_1$ is the number of combinations of four items, chose one.