To the Graduate Council:

I am submitting herewith a dissertation written by Jefferson Toronto Davis entitled "Auditor Experience in Preliminary Control Risk Assessments: Neural Network Models of Auditors' Knowledge Structures." I have examined the final copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Business Administration.

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We have read this dissertation
and recommend its acceptance:

Accepted for the Council:

Associate Vice Chancellor
and Dean of The Graduate School

AUDITOR EXPERIENCE IN PRELIMINARY CONTROL RISK ASSESSMENTS: NEURAL NETWORK MODELS OF AUDITORS' KNOWLEDGE STRUCTURES

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ABSTRACT

Auditing pronouncements typically cite auditor judgment as an integral part of the audit process. Research in expertise suggests that increased experience in a specific task increases accuracy and efficiency of a decision maker's judgment. Contrary to these findings, the results from most internal control judgment research have not found that experience influences auditor judgment. However, none of these studies included all three integral elements of the decision process--selection of cues from the set of potential cues, cue processing and decision response--into one experiment or model. This study examines how experience influences auditors' abilities to select and use relevant cues to make efficient, appropriate preliminary control risk assessments (CRAs).

Using the preliminary CRAs of two auditor groups with differing levels of experience, this study developed two neural network models of auditors' CRA decision processes. The models provided a means of capturing and measuring auditors' selective attention, a cognitive concept describing a decision process that selects and uses cues based on cue dimensions, the different qualities or aspects of a cue perceived to provide a contrast in level of significance for making categorical decisions. The results showed that the typical experienced senior auditor exhibited a higher level of selective attention to cue dimensions. The experienced group also used fewer cues and exhibited less decision time than did the less experienced group. The results are consistent with the conclusions in the expertise literature (e.g. Anderson, 1983; Johnson, et al. 1984; Dreyfus & Dreyfus, 1986) that experience does

lead to a more top-down approach to cue selection and a more highly developed knowledge structure that provides more information content for relating the selected cues to the resulting decision response. However, decision error in relation to the firm's CRA solution was nearly the same for both groups and suggested that both groups could improve their CRA process. In order for the inexperienced seniors to adjust their control risk assessment to match the firm's solution, they need to use the information provided by their selected cue set better. Although the experienced seniors' CRAs were more consistent with their cue sets than the inexperienced seniors' CRAs were with their chosen cue sets, in terms of increasing consensus to the firm's prescribed solution, the experienced group may need to consider planning to rely more on internal controls and less on tests of account balances for this case that exhibited a fairly strong internal control structure.

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CHAPTER 1

INTRODUCTION

The first Generally Accepted Auditing Standard requires financial statement audits ". . . to be performed by a person or persons having adequate technical training and proficiency as an auditor." (See AICPA 1992, AU 150.) Audit firms rely on auditors' abilities to make effective and efficient audit decisions to plan and carry out the audit. The second standard of fieldwork addresses a crucial part of audit planning: "A sufficient understanding of the internal control structure is to be obtained to plan the audit and to determine the nature, timing, and extent of tests to be performed." (See Statement on Auditing Standards No. 55, Consideration of the Internal Control Structure in a Financial Statement Audit {SAS 55}, AICPA 1988, AU 319.) SAS 55 explains that consideration of a client's internal control (IC) structure for planning the audit includes (1) gaining an understanding of the control environment, accounting system and control procedures, and (2) assessing control risk based on the auditor's understanding of the IC structure. Auditors need more technical ability and proficiency to meet the second standard of fieldwork in understanding and assessing IC structures as computer and communications innovations change the nature of the IC structure by increasing accounting system complexity, using more electronic data processing (EDP) controls, and decreasing the visibility of accounting audit trails.

Audit staffing structure in most firms dictates that a senior level auditor make the planning stage control risk assessment (CRA), yet many seniors lack the expertise needed to make effective and efficient IC audit judgments. Einhorn (1976), Libby (1985), Ashton (1991) and Frederick (1991) suggest that finding ways to improve auditor judgment begins with a better understanding of how auditors organize, represent and use relevant data stored in memory. Accounting researchers have developed linear decision models and expert systems to measure how experience influences CRA performance and to help auditors improve their decisions. However, these linear decision models and expert systems have a limited ability to recognize relevant information for making accurate CRAs. The ability to recognize relevant cues is a hallmark of superior performance achieved by experienced decision makers (Johnson, Johnson and Little 1984).

PURPOSE OF THE STUDY

The purpose of this study is to examine how experience influences auditors' abilities to select and use cues to make efficient, appropriate preliminary control risk assessments (CRAs).[1] To examine experience effects of selecting and using cues, this study uses actual

[1]At the planning stage, an auditor performs a preliminary evaluation of the client's internal control environment, accounting system, and control procedures. The auditor then makes a classification judgment concerning level of reliance on the internal control structure. This decision is necessary for planning audit procedures and budgeting hours. This task is nearly always performed by a senior. Because of the complexity of the task, a senior who has been making these assessments for typically four or more years is expected to perform better than a senior who has made only a few CRAs. This planning stage CRA is called the preliminary control risk assessment in this paper following the terminology used by the AICPA in AU 8006.22 (Revised 1991). Although SAS 55 (AICPA 1988, AU 319) does not use this terminology, both sections of the standards have the same basic explanation of the auditor's CRA in the audit planning stage.

auditors' preliminary CRAs to develop two neural network based models of auditor knowledge structures[2] that represent two levels of expertise--(1) inexperienced decision makers represented by new audit seniors with approximately two years total audit experience, and (2) experienced decision makers represented by auditors who have been senior auditors for about three years and have approximately five years total audit experience. The models provide a means of capturing, measuring, and comparing selection and use of cues exhibited by each auditor group.

Selective attention is a cognitive concept describing a decision process of selecting and using cues based on cue dimensions, qualities or aspects of a cue perceived to provide a contrast in level of cue significance for making categorical decisions. From a measurement standpoint, a higher level of selective attention to cue dimensions results in a more uneven distribution (more variation or dispersion) of auditors' attention values (weights[3]) than a lower level of selective attention. More selective attention is consistent with a more top-down decision approach that uses general situation features to select cues from among the set of potential cues as opposed to a bottom-up decision approach that considers all the

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[2]Knowledge structure is defined as the organization and representation of data stored in memory. The term knowledge structure is usually used in relation to the context of a specific task.

[3]This study uses the term stimuli as the set of potential cues. A cue is defined as a piece of information selected by the decision maker as relevant to the decision. In this study, the stimuli are a large given set of controls and client characteristics that have potential use as relevant pieces of information for making a preliminary CRA. The cues are relevant controls and client characteristics selected by the auditors as relevant to the CRA decision process for the case. These cues are selected from the set of potential cues. Cue dimensions are features or qualities of a cue. The cue values represent whether the control is an existing control or a missing control. Cue weights represent the relative importance of or attention to the dimensions inherent in decision stimuli available for auditors' use in making their CRAs.

potential cues regardless of the situation features (Nosofsky 1984, 1986, 1987; Dreyfus and Dreyfus 1986). From an information theoretic perspective, more selective attention to cue dimensions means that the attention values (weights) used by the decision maker has more relevant information for making more efficient and accurate decisions.

To measure decision accuracy and efficiency, the auditor groups were also compared using three observable characteristics of decision performance--number of cues selected, decision time, and decision accuracy. These three observable characteristics of decision performance serve as consistency checks to the unobservable characteristic of attention to cue dimensions because selection of cues impacts decision efficiency and accuracy.

A secondary purpose of the study is to show how neural network models can function as knowledge based systems for planning stage CRAs. Knowledge based systems, often serve as expert systems that provide decision responses similar to human experts' decisions. Expert systems emulate to some degree the thinking process of decision makers who have become experts in a certain task.

IMPORTANCE OF THE STUDY

Modeling fallible human processes has two benefits. First, since many complex, ill-structured problems do not have an observable actual outcome,[4] models based on human

[4]Evaluation of decision accuracy in relation to actual outcomes is very difficult. Often actual outcomes are either unobservable, take a long time to occur, or are influenced by judgment decisions. Ashton (1985) and Wright (1988) discuss the use of decision consensus as a surrogate for decision accuracy. Wright suggests that judgment consensus in relation to an established expert is a better surrogate for accuracy than interauditor consensus. This study used established experts' decisions as the standard for evaluating decision accuracy of the two senior groups' control risk assessments.

experts' decisions provide the best available decision response predictions for use in decision aids. Second, decision modeling leads to increased understanding of the limitations and strengths of human processing. When observable decision responses resulting from decision variables are available, "as if" models of human knowledge structure can be used to test differences in judgment processes.

This study extends prior IC judgment research by combining into one model the auditor's process of selecting cues from a set of potential cues, processing selected cues, and making the decision response. This study incorporates auditor cue selection into the model building process by including 91 potential cues that represent the client's control environment, electronic data processing (EDP) controls, and accounting controls.[5] The neural network[6] modeling tool is capable of using large sets of interdependent decision variables while linear regression models are confined to a relatively small set of independent and identically distributed decision variables. Prior researchers were not able to include auditors' cue selection processes, an integral part of the whole decision process (Simon 1960), because linear regression models are limited to small sets of preselected cues.

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[5]These IC variables were taken from an IC documentation program produced by an international accounting firm. A large number of cues representing each of these IC aspects strongly contributes to the external validity of a study. External validity is very important if the model is to be used as an audit decision tool.

[6]Artificial neural networks are statistical information processing mechanisms (hardware or software) composed of many processing units or nodes that perform simultaneous computations and communicate using adaptable interconnections called weights. The pattern of connectivity between the processing units constitutes the network architecture. Artificial neural networks are loosely patterned after biological neural networks.

Research that does not model the complete CRA process may lead to incorrect conclusions about experience effects in auditors' judgments.

This study also proposes a neural network approach to building a knowledge based system that acquires and represents auditors' knowledge in such a way as to enable the system to simulate the flexible, robust, and intuitive pattern recognition processes of human experts rather than the mechanical, step-by-step processes that typify novice decision processes (Dreyfus and Dreyfus 1986; Smolensky 1988; MacLennan in press). Because traditional knowledge based systems have limited capability of recognizing relevant information, these systems often exhibit brittle behavior by failing when faced with novel situations or minor exceptions to the rules. However, like traditional expert systems, neural network expert systems potentially provide several benefits to auditors. Expert systems can help auditors by (1) preserving, replicating, and distributing expertise; (2) gaining new insights into the decision process; (3) supporting performance in complex domains; (4) maintaining consistency of performance; and (5) increasing productivity (Borthick and West 1987).

ORGANIZATION OF THE STUDY

Chapter 2 reviews literature in decision making and expertise, IC judgment, and pattern recognition to develop hypotheses concerning the effect of experience on auditors' CRAs. Chapter 3 explains the research methodology including model building and validation. Chapter 4 displays and explains results from hypothesis testing. Contributions, limitations and implications for further research are discussed in Chapter 5.

CHAPTER 2

LITERATURE REVIEW AND HYPOTHESES

Understanding auditors' IC judgment processes and knowledge structures begins with understanding how auditors perform the mechanics of CRA. Internal control research has described the complexity of the task and the information used by auditors to make a CRA. Felix and Niles (1988) explained the role of CRAs in planning and carrying out an audit. Walker and Pierce (1988) and Steinberg and Johnson (1991) described strategies for addressing control risk in a computer environment. Vaserhelyi (1980) identified controls, related client features, and categorical organizations of these controls and client features. Weber (1980) explained that to assess a client's IC structure, the use and interaction of EDP controls with accounting controls must be considered. The client's control environment also plays a large part in an auditor's judgment concerning the client's level of control risk (Haskins 1987). The control procedures and features identified in the literature serve as potential cues that auditors use in making each IC evaluation.With these cues, the researcher can experimentally test and model cue selection (identifying and selecting cues), cue processing, and auditor decision responses.[7] Results from research in decision making and expertise, IC judgment, and pattern recognition provide basic principles for developing

[7]The three parts of decision-making (cue selection, cue processing and decision response) are each complex. Each part is a necessary component of decision-making and influences the other two components (Simon 1960).

hypotheses concerning differences in auditor decision performance and knowledge structures for different levels of expertise.

DECISION MAKING AND EXPERTISE

Tversky and Kahneman (1974) concluded that human judgment is fraught with inconsistencies and biases that reduce decision accuracy. On the other hand, Shanteau (1989) suggested that experts' decisions are consistent and accurate when they operate in their own domain. Nonaccounting research in expertise supports Shanteau's conclusion. Johnson (1977), Johnson, et al. (1981), Bouwman (1982), Anderson (1983), Johnson, et al. (1984), and Dreyfus and Dreyfus (1986) suggested that the experienced decision maker is more adept than the novice at choosing the appropriate decision variables and recognizing the relationships among them. More experienced decision makers holistically recognize the general features of a given situation based on past situations and use these general features to select the specific cues they believe are relevant to the particular decision situation. The less experienced decision makers operate from the specific to the general by looking at all the potential cues and selecting the cues in an analytical fashion. In other words, expertise theory suggests that experts use a top-down approach to selecting information cues while novices use a bottom-up approach to selecting cues that are used to make decisions. Anderson (1983) called this holistic, top-down approach the intuitive approach. He called the analytical, bottom-up approach the rational approach. As a decision maker obtains more experience in a task, the decision process changes from a rational approach to an intuitive approach. Dreyfus and Dreyfus (1986) proposed five levels of skill acquisition that

explain how the decision process changes as a decision maker progresses from a novice to expert as more experience is obtained in a specific task. These skill acquisition levels are briefly summarized in Figure 1.

The nonaccounting researchers cited above also suggested that more experience in a task results in a more precise knowledge structure. A precise knowledge structure means that the appropriate cues are selected and the appropriate attention is paid to the selected cues. In essence the decision processes of cue selection and cue weighting are more parsimonious as experience increases. These researchers maintain that a more precise knowledge structure leads to more consistency and more accuracy in decision making. Essentially, experience is believed to translate into more intuitive, efficient and effective decisions. However, results reported by IC judgment researchers have generally concluded that experience effects are not found in the IC judgment domain.

INTERNAL CONTROL JUDGMENT RESEARCH

Internal control judgment research (summarized in Table 1) can be classified into two main categories--exemplar-based and explanation-based. Exemplar-based research has used a large set of judgment situations to build linear models that functionally relate the cues to the auditors' decisions. Explanation-based research tries to explain the IC judgment process by documenting and modeling the decision process with task experiments, protocol analysis, and knowledge-based systems.

Stage 1: Novice

The novice learns to recognize various objective facts and features relevant to the skill and acquires rules for determining actions based upon those facts and features. The new skill is usually learned through instruction. These facts and features are unambiguous and can be recognized without regard to the overall situation. These context-free features are manipulated by precise context free rules.

Stage 2: Advanced Beginner

Performance improves only after the novice has coped with considerably more real situations. In addition to using more context-free facts and more sophisticated rules, the learner begins to add situational elements. Situational awareness develops because the learner has experienced concrete situations and begins to recognize new situations in relation to actual situations stored in memory.

Stage 3: Competence

With more experience the number of recognizable context-free situational elements and rules becomes overwhelming. Hierarchical procedures or plans are developed that organize the situation as well as simplify and improve performance. To perform well requires choosing an effective organizing plan. Still, the decision process is a detached, almost mechanical process of manipulating elements with rules. The decision is only made by conscious choices of goals and decisions after reflecting upon various alternatives.

Stage 4: Proficiency

The proficiency stage is characterized by intuitive understanding followed by detached decision making. Intuition is described as holistic similarity recognition--the ability to use patterns without decomposing them into component features. Understanding effortlessly occurs upon seeing similarities with previous experiences. A related aspect of understanding is that certain features of the situation stand out as salient while others will recede into the background and be ignored. Although the proficient performer intuitively organizes and understands the task, the learner will still think analytically about what to do.

Stage 5: Expertise

The expert is characterized by both intuitive understanding and intuitive deciding. The expert does not see problems in some detached way and work at solving them. For example, we don't make conscious deliberative decisions when we walk, talk or socialize. An expert's skills have become so much a part of them, that they need not be more aware of it than they are of their own bodies. When time permits and outcomes are crucial, an expert will deliberate before acting. But this deliberation is not calculative problem solving; it is critical reflection on one's intuition.

FIGURE 1: DESCRIPTION OF DREYFUS AND DREYFUS' FIVE STAGES OF SKILL ACQUISITION

Adapted from Dreyfus and Dreyfus (1986). MIND OVER MACHINE: THE POWER OF HUMAN INTUITION AND EXPERTISE IN THE ERA OF THE COMPUTER. New York: Free Press, pp. 21-36.

TABLE 1

INTERNAL CONTROL JUDGMENT RESEARCH[a]

STUDY	CONSENSUS		EXPERI-ENCE EFFECT	PROCESS COMPONENT CONSIDERED IN RESEARCH			NUMBER OF CASES	NUMBER OF SUBJECTS	TASK SIZE & COM-PLEXITY
	DECISION	CUE USAGE		CUE SEARCH	CUE EVAL-UATION	DECISION RESPONSE			
EXEMPLAR-BASED RESEARCH									
Ashton 1974 (ANOVA)	high	high	no	no	yes	yes predict	32	63	low
Reckers and Taylor 1979 (ANOVA)	low	low	yes	no	yes	yes predict	5	36	high
Ashton and Brown 1980 (ANOVA)	high	high	no	no	yes	yes predict	32	31	low
Ashton and Kramer 1980 (ANOVA)	high	high	auditors more than students	no	yes	yes predict	32	30	low

[a]The task size and complexity for the research summarized in Table 1 was classified as low if the number of IC variables was less than 10. A medium value represents number of variables in the interval of 11 to 29. A high value represents 30 or more variables or case material that took at least an hour for the subjects to complete. Using auditors as subjects presents a distinct tradeoff between size and complexity of cases and the number of cases. A high number of cases can test many different situations but with very little external validity to the complexity of the IC judgment process. A large and complex task does not provide a way to measure many different situations for each decision maker, but the decision process is more realistic to audit judgment decisions made in actual audits.

TABLE 1 CONTINUED

STUDY	CONSENSUS		EXPERI-ENCE EFFECT	PROCESS COMPONENT CONSIDERED IN RESEARCH			NUMBER OF CASES	NUMBER OF SUBJECTS	TASK SIZE & COM-PLEXITY
	DECISION	CUE USAGE		CUE SEARCH	CUE EVAL-UATION	DECISION RESPONSE			
Hamilton and Wright 1982 (ANOVA)	high	high	no	no	yes	yes predict	32	78	low
Gaumnitz et al. 1982 (ANOVA)	high	high	no	no	yes	yes predict	20	35	low
Tabor 1983 (ANOVA)	high	n/a	yes	no	yes	yes predict	12	109	low
Libby et al. 1985 (ANOVA)	high	high	n/a	yes	yes	yes predict	16	12	high
Bonner 1990 Experiment 1 (ANOVA)	n/a	high	no	yes	no	no	2	64	medium
Bonner 1990 Experiment 2 (ANOVA)	high	high	yes	no	yes	yes predict	16	64	low
Nichols 1987 (Discriminant Analysis)	n/a	n/a	n/a	no	yes	yes predict	79-From work-papers	n/a	Low

TABLE 1 CONTINUED

STUDY	CONSENSUS		EXPERI-ENCE EFFECT	PROCESS COMPONENT CONSIDERED IN RESEARCH			NUMBER OF CASES	NUMBER OF SUBJECTS	TASK SIZE & COM-PLEXITY
	DECISION	CUE USAGE		CUE SEARCH	CUE EVAL-UATION	DECISION RESPONSE			
EXPLANATION-BASED RESEARCH									
Mock and Turner 1981 (Experimental)	n/a	low	n/a	yes	yes	yes	2	200	high
Niles 1987 (Experimental)	n/a	low	n/a	yes	yes	no	2	30	high
Biggs and Mock 1983 (Protocol)	n/a	low	n/a	yes	yes	yes	2	4	high
Biggs et al. 1987 (Protocol)	High--identified controls, sample sizes		n/a	yes	yes	yes	1	30+	high
Hansen and Messier 1986 (ES)	n/a	n/a	n/a	yes	yes	yes predict	n/a	n/a	high
Harper 1988 (AHP Model and Survey)	n/a	low	no	yes	yes	no	n/a	51	medium
Haskins 1987 (Survey)	n/a	low	n/a	yes	yes	no	n/a	146	medium
Frederick 1991 (Cue recall)	n/a	cue recall	yes	no	no	no	n/a	210	medium

Exemplar-Based Research

One goal of IC judgment research is to evaluate auditor decision making. The largest stream of IC judgment research focuses on the decision response of auditors' judgment processes. Ashton (1974) examined auditors' IC risk assessment judgments using linear modeling. Sixty-three practicing auditors assessed the strength of payroll system controls for 32 fictitious cases. The cases were the 32 possible combinations of 'yes' or 'no' values for the six controls provided to the auditors as input cues to their decisions. He found that the average correlation of an auditor's 32 judgments with all the other auditors' judgments was high (0.70). He also found that auditor disagreements on cue importance were associated with auditor decision disagreements. The results further indicated the auditors' judgment stability over time was high (average correlation was 0.86). Finally, he found that consensus and stability were not statistically related to experience or firm. However, he only tested auditors with one to three years of experience.

Several studies slightly altered this basic design. Ashton and Brown (1980) changed cue sets and studied different cue orders. Ashton and Kramer (1980) extended the study to include auditing students. Hamilton and Wright (1982) included more experienced auditors. Gaumnitz et al. (1982) and Tabor (1983) extended the research to include the next audit step of audit planning. The results of all these studies showed similar high levels of auditor

consensus. With the exception of Tabor (1983), no experience effects for practicing auditors were found.[9]

Research studies that used more complex and realistic situations (more cues) differed on the level of consensus. While Libby, Artman and Willingham (1985) found consensus to be high (interjudge correlation of 0.68), Reckers and Taylor (1979) found auditors' consensus to be low (interjudge correlation of 0.165). Reckers and Taylor also found experience effects. Libby, Artman and Willingham did not test for experience effects.

Frederick and Libby (1986) and Ashton (1991) suggested that differences in experience are task specific.[10] Bonner (1990) used a linear modeling approach to study experience consensus differences between internal control risk and analytical review risk tasks. She divided each audit task into two decision process components--search for cues and cue weighting--and tested each component using separate experiments. She found experience effects for cue search and cue weighting in the analytical review task. But, the IC judgment task exhibited experience effects only for the cue weighting decision component. Bonner suggested another reason that prior research often finds no experience effects--the

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[9]Ashton and Brown (1980) also found auditor judgment insight to be high. Ashton and Kramer (1980) did find statistical differences between auditors and students in consensus, stability, and judgment insight. Gaumnitz et al. (1982) found less variability (more consensus) in the audit time budget decisions made by more experienced auditors. Hamilton and Wright (1982) found firm effects concerning consensus, while Ashton and Brown (1980) did not.

[10]Judgment research that used other audit tasks found experience effects in bankruptcy prediction (Moriarity 1979) and materiality (Krogstad, Ettenson, and Shanteau 1984). Choo and Trotman (1991) examined the relationship of knowledge structure and judgments for experienced and inexperienced auditors in a going concern setting. They used memory recall experiments and found that experience influences the recall of typical and atypical data and the predictive judgments auditors made for the one case used in their study.

decision tasks used in the linear modeling studies did not include the whole decision process. However, she separated her study into two experiments, neither of which included the whole decision process. Her first experiment included only cue search and selection. Her second experiment included only cue weighting and the auditor's decision.[11]

Exemplar-based studies have not incorporated auditors' strategy for selecting the cues. Cues were preselected so that cue search and selection did not influence cue weighting and the decision response.

Explanation-Based Research

Researchers who used the explanation-based approach have included the cue selection process. However, because of the difficulty of evaluating auditor decisions with actual outcomes, some researchers have studied auditor processes without including the auditors' actual risk assessment decisions. These studies assessed group perceptions of the relationships of controls (cues) that auditors typically use in evaluating control risk.

Haskins (1987) identified over 40 control environment features from interviews with experienced auditors. In a survey, he had auditors rank these features for use in assessing control risk. To measure auditor consensus concerning the importance of the control environment features, Haskins computed the standard deviation of the ranks for each

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[11]Bonner's cue weighting task included cue processing of preselected cues and a decision response. Overall, Bonner found that the experience effects for the analytical review task were higher than the IC judgment task. She reasoned that auditors at the senior stage have the experience necessary to make a fairly accurate IC judgment but not an accurate analytical review judgment. Her study still has mixed results concerning the specific CRA task.

feature. Harper (1988) added to the IC judgment knowledge about cue usage, cue organization and relative cue importance by modeling the EDP control evaluation process. Using 17 EDP controls as cues, Harper used the Analytic Hierarchy Process (AHP) to structure cues into categories. This modeling allowed auditors to put relative values on the categories and on the controls in each category. He found that individual subjects exhibited high (average of 0.85 on a zero to 1 scale) consistency concerning relative importance of control pairs. He also found that EDP auditors had a variety of opinions concerning what controls and what control categories are more important in assessing EDP control strength. Finally, he found no experience effects based upon a 5-year experience cutoff.

Frederick (1991) found that auditors recall more IC features than students. Frederick organized the IC features into categoric lists and transaction flow lists. The results showed that auditors' memory structures incorporate more highly developed categoric and transaction flow representations of control features than the memory structures of audit students. His findings are consistent with the expertise literature that indicates experience leads to a more precise knowledge structure.[12]

Research that uses recall or does not use responses based on specific client situations does not describe or model the complete decision process nor does it evaluate decision

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[12]Tubbs (1992) investigated the nature of changes in the auditor's knowledge about accounting errors and irregularities as experience is acquired. He found that auditors with more experience recalled more possible accounting errors and fewer incorrect items for the revenue cycle of a typical wholesaling or manufacturing company. He also related accounting errors to IC objective features as causal explanations for errors. He found that violated IC objectives increase in salience as audit experience increased.

response accuracy. Explanation-based research that has considered the complete judgment process includes audit task experiments (Mock and Turner 1981; Niles 1987), protocol analysis (Biggs and Mock 1983; Biggs, Messier and Hansen 1987) and knowledge-based systems (Hansen and Messier (1986).[13] With the exception of Biggs, Messier and Hansen (1987), the task experiment and protocol analysis studies found variances in auditor decision judgments but did not examine experience effects. Using a case with a complex EDP environment, Biggs, Messier and Hansen found that three computer audit specialists, 14 new computer audit specialists and 20 group decisions were generally accurate when compared to the firm's suggested solution for identifying controls and selecting sample sizes for testing each identified control.[14] However, for controls where auditors' identification and sample sizes were not very accurate compared to the firm's solution, the experienced computer specialists were more accurate than the other two sets of subjects. The results also showed that auditors tended to rely on manual controls as opposed to EDP controls.

Although IC experimental studies and protocol analysis have not supplied predictive ability for novel cases, such research provides a valuable step in producing models that have the ability to make human-like IC judgments. Explicit rules used to develop traditional knowledge-based or expert systems were acquired by experimental and protocol analysis.

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[13]Other knowledge-based models dealing with internal controls include Bailey et al. (1985) and Meservy et al. (1986). These knowledge-based systems focus on documenting the internal controls of a client using computational modeling.

[14]Notice that identification of controls is a different task than evaluating a set of controls and making a reliance assessment based on the set of controls. This may account for the high decision consensus as opposed to low decision consensus in most other studies. A complete CRA would include identification of controls and evaluating the set of controls to obtain a risk level.

Summary of Internal Control Judgment Research

Exemplar-based research has failed to incorporate auditor selection of cues in developing models of auditor IC judgment. Explanation-based studies have explained the IC decision process, but either did not include decision response or did little if any measuring of experience effects. Prior IC judgment research has not agreed on the level of auditor decision consensus nor agreed whether experience is associated with higher consensus. However, the findings strongly established that decision variability is largely associated with variability of beliefs about the relative importance of cues in the IC judgment process.

PATTERN RECOGNITION

Pattern recognition is the process of associating an output response with observed input data relationships and features. Decision makers perform pattern recognition by identifying data features (dimensions) and relationships from attending to environmental stimuli. These identified features are then associated with a particular response according to the decision maker's knowledge structure.

The literature identifies two seemingly different approaches to pattern recognition--identification and classification (Shepard, et al. 1961; Luce 1963; Medin and Schaffer 1978). When the decision requires a category as the decision response, identification is the process of obtaining a certain response category when given a certain stimulus selected from among a set of comparable stimuli. Classification is the process that obtains a response category when given a whole set of comparable stimuli. Identification is a one-to-one stimulus to

response relationship while classification is a many-to-one stimuli to response relationship. Nosofsky (1984, 1986, 1987) explains that the categorization decision process is fundamentally the same as the identification decision process except that categorization processes use selective attention to dimensions of the stimuli. Identification is consistent with a bottom-up approach to pattern recognition and classification is consistent with a top-down approach to pattern recognition.

The identification implicitly requires equal attention to all dimensions so that small differences or relationships among stimuli[15] are accentuated. In the process of classification, some dimensions may be irrelevant, making equal weighting of dimensions inappropriate. Given that a subject's task is to make a decision based on patterns recognized among the stimuli and that attentional resources are limited, cue selections based on differential weighting schemes lead to more accurate predictions than cue selections based on equal weighting schemes. Response accuracy is increased because uneven cue weighting schemes allocate attention optimally to cue dimensions based on the dimensions' relative importance within the classification decision (Nosofsky 1984, 1986, 1987).

HYPOTHESES

Integrating Nosofsky's findings into Dreyfus and Dreyfus' progression of skill levels (see Table 2) implies that inexperienced auditors select the cues using more equal attention (equal weighting) to each dimension of the cues while experienced auditors select the cues

[15]Stimuli is defined as the set of potential cues for a particular situation.

TABLE 2

FIVE STAGES OF SKILL ACQUISITION

SKILL LEVEL		COMPONENTS[1]	PERSPECTIVE[2] (CUE SELECTION APPROACH)		DECISION	COMMITMENT
1.	Novice	Context-free	None	**BOTTOM-UP**	Analytical	Detached
2.	Advanced Beginner	Context-free & situational	Very limited	**CONTINUUM FROM BOTTOM-UP TO TOP-DOWN**	Analytical	Detached
3.	Competent	Context-free & situational	Chosen Plan		Analytical	Detached
4.	Proficient	Context-free & situational	Experienced[3]		Analytical	Intuitive & involved. Detached deciding
5.	Expert	Context-free & situational	Very Experienced	**TOP-DOWN**	Intuitive	Intuitive & involved

[1]As experience increases components used become more situational.

[2]Perspective of the problem is based more on experience, and the decision-maker approaches the problem by using the most important cue features while ignoring the irrelevant cue features. Approach is bottom-up (equal weighting of cues to cue features) or top-down (uneven weighting of cues to cue features).

[3]Intuitive processing also increases with experience.

Adapted from Dreyfus and Dreyfus (1986). MIND OVER MACHINE: THE POWER OF HUMAN INTUITION AND EXPERTISE IN THE ERA OF THE COMPUTER. New York: Free Press, p. 50.

using more optimal[16] attention (unequal weighting) to dimensions of the cues. The relationship of expertise (acquired through experience) to cue attention leads to a hypothesis concerning differences in auditor knowledge structures.

H1: More experienced auditors will exhibit a more uneven distribution of weights (more selective attention) to the cue dimensions than less experienced auditors.

Libby (1985) explains judgment as an interaction between environmental cues and a decision maker's knowledge structure. As an auditor has more practice with concrete situations, these events modify the salient features, the relative salience of features, the plans, and the expectations that are stored in memory and used to make a decision in an unstructured task. Stimuli from the current situation triggers memories of similar situations. When faced with a CRA task, a more experienced auditor will make the decision from some specific perspective based on memory of past situations. Because of the auditor's perspective, certain features of the situation will stand out as salient and others will recede into the background and be ignored. An auditor with very little experience does not have a highly developed situational perspective and has difficulty distinguishing between salient and irrelevant features of a particular situation. Because the inexperienced auditor does not ignore irrelevant features, cues that exhibit irrelevant features will be used in the decision making process. Experience should reduce the number of irrelevant pieces of information

[16]Optimal attention means that the auditor properly disregards irrelevant stimuli and concentrates on each of the selected cues to a level that he/she anticipates will provide the overall highest information content for making the decision.

used to make a decision. Thus, hypothesis two suggests that experience will reduce the number of cues used by auditors in decision making.

H2: More experienced auditors use fewer cues (decision inputs) to make classification decisions than less experienced auditors.

Use of fewer cues means that a more experienced auditor does not take the time to evaluate irrelevant information that an inexperienced auditor would take. Additionally, a more experienced decision maker will analyze the cues using a more highly developed intuitive ability to utilize patterns without decomposing them into component features. The inexperienced auditor will analytically decompose the patterns into component features and analyze the components in a step by step fashion that takes more time than the holistic similarity recognition process of an experienced decision maker. Hypothesis three states the expectations for auditor decision efficiency.

H3: More experienced auditors will make decisions faster than less experienced auditors.

The use of only relevant cues not only leads to faster decision making, but, in general, also to higher decision accuracy (Anderson 1983, and Dreyfus and Dreyfus 1986). Theoretically, the experienced auditor anticipates events similar to past situations and uses plans similar to plans that produced accurate decisions in the past. The knowledge structure becomes more tuned to making finer distinctions between features exhibited by the potential cues. The precise knowledge structure implies higher decision accuracy as stated in hypothesis four.

H4: More experienced auditors will exhibit higher decision accuracy than less experienced auditors.

The four hypotheses each assume a different measure of decision performance, but as a group, the hypotheses form a cohesive explanation of decision making expertise for preliminary CRAs. Each hypothesis serves as a consistency check on the other hypotheses. Together, the hypotheses are consistent with the notion of a top-down approach to decision making.

CHAPTER 3

RESEARCH METHODOLOGY

To measure auditors' attention to cue dimensions (H1), number of variables used (H2), decision time (H3), and decision accuracy (H4), this study used auditor CRAs and the cues (controls and environmental features) chosen by auditors from a case based on an actual public accounting firm client. Since H1 concerns a nonobservable decision performance attribute, two neural network-based decision models were developed. The inexperienced model was developed from the individual CRAs of the inexperienced senior auditors (inexperienced group), and the experienced model was developed from the individual CRAs of the experienced senior auditors (experienced group).

Each model was developed using a neural network as the modeling tool because this tool has the appropriate abilities to model and provide a means to measure auditors' attention to cue dimensions which other modeling tools lack. A neural network model was used instead of a traditional knowledge based system model because a neural network can "learn" from a set of auditors' decision cues and responses--examples of auditors' decisions. Analogous to a regression model, a neural network develops a statistical association between sample sets of the auditors' chosen cues and their control risk category. In regression the statistical association is captured as coefficients; in a neural network the statistical association is represented in the network's set of weights. The potential cues (inputs) of a

neural network can be viewed as independent variables in a regression model; the risk assessment decisions in the neural network are analogous to dependent variables in a regression model. However, the non-structured framework of a neural network provides an ability to model ill-structured decision tasks that regression models cannot match in terms of modeling large numbers of interdependent decision variables and the inherent dimensions of those variables.

The inexperienced model and the experienced model were each validated by analyzing their accuracy in predicting the CRAs of the inexperienced and experienced senior auditors, respectively. Analysis was performed for the training set and a holdout sample (test set) of each group. To test distribution uniformity (H1) the models were compared by measuring the variation of the values of each network's cue dimension weights. The weight set of each model represents what Nosofsky (1984, 1986, 1987) describes as the selective attention to cue dimensions exhibited by a typical auditor in each group when they make preliminary CRAs. Three directly observable measures of decision performance--number of cues chosen (H2), decision time (H3), and decision error (H4)--were also obtained from the experiment for each auditor. Group differences were tested using traditional statistical methods.

EXPERIMENTAL DATA COLLECTION

Thirty-seven new seniors with approximately two years of experience and 27 experienced seniors with approximately five years of experience completed the

experiment.[17] This study focused on the auditors' documentation and recording of the preliminary CRA. The IC structure of the case was already documented. The auditors had to review the documentation, record what controls they planned to rely on (key controls), and make their preliminary CRA. Tests of controls and CRAs based on the results of control testing were not in the scope of this study. The actual experiment was given to both groups at the end of approximately 16 hours of formal instruction by the firm's audit training staff on a newly developed computer program called INFOCUS. Each group met during a different week of the international firm's continuing educations sessions, but the instruction material was the same for both groups.

INFOCUS is a computer program developed by Grant Thornton to provide the firm's auditors with a general structure and mechanism for documenting client IC structures and accounting cycle CRAs using flowcharts, questionnaires, and lists of potential controls and for documenting their CRAs. Using INFOCUS, auditors document IC structure by flowcharting the accounting information processes and by identifying controls over these processes. The auditors also use INFOCUS to record the personnel who perform the accounting processes, the personnel who perform each control, and the control objective(s) satisfied by each control. The EDP environment is documented by completing a computerized questionnaire. If the auditor plans to rely on programmed controls, the program provides an EDP control questionnaire based on the answers to the EDP

[17]Forty-seven inexperienced senior auditors and 35 experienced senior auditors took part in the experiment. However, ten inexperienced auditors and 8 experienced auditors did not provide CRAs or decision time.

environment questionnaire. Once the IC structure is documented, auditors can use INFOCUS to document and record their preliminary CRAs, receive help in designing their tests of controls, and then adjust their CRAs based on control testing results.

The revenue cycle[18] IC documentation based on a real client was provided to each auditor. The client's IC structure was documented using the computer program and served as the experimental case. The case was chosen to present auditors with a situation where IC structure is consistent with relying on manual controls, programmed controls, and segregation of duties, but client size is compatible with a more substantive audit approach. The case involves a merchandising client with $14 million in revenue. The computer controls are strong and no major IC structure weaknesses exist. To match the firm's solution of moderate risk, an auditor should have planned to rely on programmed controls, or manual controls, or both in order to support such an assessment. Each auditor made a preliminary control risk assessment for the sales stream (initiation of sales to the recording of sales and accounts receivable in the general ledger) within the revenue cycle. The financial statement assertion group consisted of completeness, existence/occurrence, and gross valuation of sales transactions.

Using INFOCUS and printed output from the program, each auditor reviewed the documentation of the client's IC structure and selected cues from the set of potential cues which consisted of revenue cycle IC environmental features, EDP environment, and accounting controls documented for the client. Because the accounting controls operate

[18]The revenue cycle was chosen because of its importance in most audit situations.

within the framework of the revenue cycle IC environmental features, and any programmed accounting controls must operate within the limits of the EDP environment and controls, the revenue cycle IC environmental features and EDP environment and controls are an integral part of the CRA evaluation process. IC environmental features, EDP environmental features, accounting controls, and segregation of duties operate as interdependent parts of the IC structure. These variable types were included in the experiment and as interdependent variables within the model. Appendix A-1 presents the IC variables, ties these variables to the neural network input nodes, and explains the data values used to code the IC data into the neural network models.

The IC variables each auditor believed to be relevant to their preliminary CRA were recorded either using INFOCUS or on the case material. The recorded relevant IC variables were used as decision input cues for model building and to compare the number of cues (H2) used by auditors in each group. The auditors marked on the case material which general cycle characteristics and EDP environment and controls were relevant to their preliminary CRA. As part of the preliminary CRA process, auditors used INFOCUS to record whether the auditor planned to rely on manual controls, programmed controls, and segregation of duties. The auditors' plan to rely on any combination of these types of controls provides an indication of whether the auditor planned to use more tests of controls versus more substantive tests to reach an acceptable level of audit risk. Each auditor also used INFOCUS to record the existing controls that were selected as key controls. The missing

key[19] controls were recorded on the case material. Appendix A-2 presents the actual instructions and audit task procedures. Appendix A-3 presents the revenue cycle internal control workpapers used by the auditors for the experiment.

Each auditor then made a preliminary CRA. Auditors recorded their preliminary CRA in the computer program as well as on the case material. The auditors decision responses were used in model building and for testing group decision accuracy (H4). INFOCUS provides a choice of four risk categories--maximum, slightly below maximum, moderate, and limited. These risk categories are also consistent with case examples included in the SAS 55 Audit Guide (AICPA, 1989). Although the CRA of each auditor was recorded by the computer program as a categorical response, each auditor also recorded their CRA on the experimental material with a point estimate from 0 to 100 that corresponded to their categorical decision as follows:

Risk Category	Point Estimate Interval
Limited	0 - 25
Moderate	26 - 50
Slightly Below Maximum	51 - 75
Maximum	76 - 100

Using a number line, each auditor recorded their point estimate within the risk category they had chosen as an indication of how close to the category border their decision would be based on a percentage scale. The auditors' point estimates were all consistent with their categorical responses.

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[19]Key controls are defined as the controls that are relied upon for making the control risk assessment. Missing controls are controls the auditor would have relied on but did not exist. Missing controls are not a question of correct documentation of the client's IC structure.

A time budget of one hour was given to both groups. Each auditor recorded decision time (for testing H3) by writing on the experimental material the time at the beginning and end of the task. Once the decision task was finished, each auditor completed a demographic questionnaire.

DEMOGRAPHIC DATA COLLECTION AND ANALYSIS

Demographic data were collected from the auditors using the postexperimental questionnaire presented in Appendix B. The questions were developed from the IC judgment literature and from discussions with practicing auditors in the context of establishing levels of experience and controlling for confounding variables to CRA experience.

The results of t-tests and chi-square tests for data provided by the auditors in the postexperimental questionnaire are summarized in Table 3.[20] Grouping items from the

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[20]T-tests were used to evaluate the difference between the groups for each question that required a point estimate for amount of experience (questions 1, 12, 13, 14, and 15). Chi-square tests measured between group differences for client size experience (question 3), industry experience (question 4), experience with methods of IC documentation (question 7). T-tests were not used for these questions because t-tests are not appropriate for categorical data. Both t-tests and chi-square tests measured differences between the auditor group responses on questions that asked for an estimated range for types of audit task experience (questions 2, 5, 6, and 9). Auditors were asked to indicate the ranges of the number of times they had performed an audit task in their careers because pilot testing indicated that auditors had a difficult time providing a point estimate. The t-tests used the top number of the interval range as the point estimate for all auditors. Because the interval estimates technically divide each group into categories and t-tests are not appropriate for categorical data, chi-square tests were also performed to test association between the groups based on the experience categories within each group. Data for auditor beliefs and confidence (questions 8, 10, 11, 16, and 17) were obtained using a five point nominal scale. Both t-tests and chi-square tests were used to measure auditors answers for these belief and confidence questions. Fisher's exact test was also performed when the average number of observations in a contingency table was less than five.

TABLE 3

SUMMARY OF DEMOGRAPHIC STATISTICAL ANALYSIS

ITEM NO.	DESCRIPTION	MEAN Inexperienced Group	MEAN Experienced Group	T-TEST P-VALUE	CHI-SQUARE P-VALUE	FISHER'S EXACT TEST P-VALUE	STATISTICAL DIFFERENCE? (at alpha = .05)
AMOUNT OF EXPERIENCE							
1	Months of Experience	23.04	56.96	0.0001	n/a	n/a	yes
2	No. of Audits	22.70	47.41	0.0001	0.0000	0.0000	yes
5	No. Supervised	3.78	22.04	0.0001	0.0000	0.0000	yes
6	No. Documented	10.68	24.48	0.0307	0.2180	0.2750	yes (t-test)
9	**No. Preliminary CRAs**	**4.46**	**31.85**	**0.0001**	**0.0000**	**0.0000**	**yes**
TYPE OF EXPERIENCE							
3	Client Size	Small 40.0% Med 52.6% Large 7.4%	Small 33.7% Med 55.6% Large 10.7%	n/a	0.0020	n/a	yes
4	Industry	Merchandise 14.3% Mfg. 30.8% Other 54.9%	Merchandise 18.7% Mfg. 32.9% Other 48.4%	n/a	0.0000	n/a	yes
7	IC Documentation Method	Questionnaire 21.5% Narration 72.8% Flowchart 5.7%	Questionnaire 36.3% Narration 56.6% Flowchart 7.1%	n/a	0.0000 Flowchart only 0.474	0.0000	yes Flowchart only no

TABLE 3 CONTINUED

ITEM NO.	DESCRIPTION	MEAN Inexperienced Group	MEAN Experienced Group	T-TEST P-VALUE	CHI-SQUARE P-VALUE	FISHER'S EXACT TEST P-VALUE	STATISTICAL DIFFERENCE? (at alpha = .05)
AUDITOR CONFIDENCE AND BELIEFS							
8	Documentation Confidence[1]	3.14	3.46	0.0685	0.4444	0.4920	no
10	Preliminary CRA Confidence[1]	2.85	3.37	0.0040	0.0260	0.0350	yes
11	IC Propensity[1]	4.24	4.04	0.2396	0.6200	0.5540	no
EXPERIMENTAL INSTRUMENT FACTORS							
12	No. Document with INFOCUS	0.11	0.19	0.5426	n/a	n/a	no
14	No. CRAs with INFOCUS	0.14	0.07	0.6475	n/a	n/a	no
13+15	INFOCUS Training Hours	18.19	18.00	0.9189	n/a	n/a	no
16	INFOCUS Confidence[1]	2.36	2.59	0.2231	0.4130	0.3780	no
17	Like INFOCUS[1]	3.44	3.63	0.4271	0.4190	0.4080	no

[1]This question elicited a categorical response on a 5 point scale. A 5 corresponds to very high and 1 corresponds to very low.

questionnaire into amount of experience, type of experience, auditor confidence and beliefs, and experimental instrument factors makes demographic analysis easier to explain.

Amount of Experience

As expected, the experienced group has significantly more general audit experience as indicated by months of experience (57 to 23), number of audits in career (47 to 23), and number of audits supervised (22 to 4). The experienced group also has significantly more task specific experience in documenting clients' IC structure (24 to 11) and making preliminary CRAs (32 to 4). All of these experience differences were significant at probability values (p-values) less than 5 percent.

Type of Experience

The chi-square tests for between group association for type of experience with different sized clients ($p = .002$), different industries ($p = .000$), and methods of IC documentation ($p = .000$) revealed no statistically significant association. In other words the groups did not exhibit statistically similar levels of experience in these areas. The differences for client size, industry, and method of IC documentation are possible confounding variables to testing the hypotheses based on amount of experience alone. An analysis of the contingency table percentages (included in Table 3) in context of the case lends insight to the practical significance of client size experience, industry experience and documentation method experience on auditors preliminary CRA processes.

An examination of the experience percentages shows that for medium size clients the inexperienced group and experienced group (52.6% to 55.6%) are similar in practical terms given that for both groups the majority of experience is with medium size clients and experienced seniors have already performed more audits than inexperienced seniors. Similarly, the difference in percentage of experience with merchandizing clients for the inexperienced group (14.3%) and the experienced group (18.7%) is not of practical significance when considering that IC structure for the sales stream within the revenue cycle of the merchandizing client is usually similar to the sales stream IC structure of manufacturing firms. Again, percentage difference in experience with industries is very small compared to the difference in amount of absolute experience between the groups. Group differences in experience with client size and client industry were not of practical significance in affecting average group measures of auditors' decision processes and accuracy.

Different auditors may be more comfortable using different methods of IC documentation. INFOCUS predominately uses flowcharting and questionnaires for documenting IC structure. INFOCUS particularly incorporates questionnaires and control lists as tools for documenting the EDP environment, computer controls, and manual and programmed accounting controls. The statistical difference in auditors' experience with IC documentation methods occurs because the inexperienced and experienced groups differ in experience percentages using questionnaires (21.5% vs. 36.3%) and narratives (72.8% vs. 56.6%). However, no statistical difference was found between the groups' reported

experience with flowcharting (5.7% vs. 7.1%; $p = .47$). In each case, however, the experienced group had used each documentation type more times than the inexperienced group. Therefore for this case, the method of IC documentation is an unlikely confounding variable.

Auditor Confidence and Beliefs

The chi-square test on auditors reported confidence in their ability to document and understand IC structure results in no significant difference between the groups ($p = .44$). This result is not unexpected because new seniors probably document IC structure as frequently as experienced seniors do. Although not statistically different (*t-test* $p = .07$), experienced seniors exhibited higher confidence (3.46) in their ability to document IC structure than did the inexperienced seniors (3.14) on a five point scale.

The statistical test did reveal that experienced seniors were more confident (3.37) than inexperienced seniors (2.85) about their ability to make preliminary CRAs (*t-test* $p = .004$). The chi-square test for group differences ($p = .026$) agrees with the t-test results. These results are expected because the average auditor in the experienced group has made many more preliminary CRAs (32) than the average auditor in the inexperienced group (4). In addition, experienced seniors still regularly perform planning stage control risk assessments while inexperienced seniors are usually just beginning to perform this task.

Auditor beliefs about evaluating IC structure for a possible reduction of the CRA level are theoretically critical to whether an auditor plans to rely more on tests of controls versus reliance more on substantive tests. Without any IC structure evaluation, the auditor

must settle for a CRA of maximum and cannot reduce substantive tests. The chi-square test results indicate no statistical difference ($p = .62$) between the two groups' reported beliefs about going to the effort to make a preliminary CRA that is below maximum. Although, not statistically different, the means (4.24 to 4.04) show that inexperienced seniors might have a stronger belief about evaluating IC structure for making a lower CRA. Results from the experiment do show that only 1 of the 37 (less than 3%) inexperienced seniors took the automatic maximum CRA by not relying on any controls or segregation of duties, while 3 of 27 (11%) experienced seniors took this decision path.

Experimental Instrument Factors

Group differences related to the experimental instrument factors that might influence the results of hypothesis tests were tested using data from questions concerning INFOCUS. No statistical differences between the groups (inexperienced vs. experienced) were found in the auditors' reporting of the number of times INFOCUS was used to document IC structure in a live audit (0.11 vs. 0.19; $p = .54$), number of live audit preliminary CRAs (0.14 vs. 0.07, $p = .64$), and INFOCUS training hours (18.19 vs 18, $p = .92$). Chi-square tests showed no statistical differences between the groups' confidence in using INFOCUS as a tool for making preliminary CRAs ($p = .41$) and how well the auditors liked INFOCUS ($p = .42$). T-tests for INFOCUS confidence ($p = .22$) and how well auditors liked INFOCUS ($p = .43$) agreed with the chi square tests. Neither group had the advantage of being more familiar with the software.

Summary of Demographic Analysis

As expected group differences exist in months of experience, number of audits, number of audits supervised, number of times documented IC, and number of preliminary CRAs. The difference in amount of general audit experience, and more importantly, the specific task experience of making a planning stage CRA has been established between the sample groups. Analysis of the demographic data has shown that auditor experience with client size, industries, and method of IC documentation has little if any practical significance to the auditors' decision processes for this case. If any influence does exist, these possible confounding variables are overwhelmed by the amount of actual audit experience the experienced group has over the inexperienced group. Statistical measures of group differences in auditor confidence and beliefs and experimental instrument factors resulted in no statistical differences. The hypotheses can be analyzed based on the amount of experience in performing planning stage CRAs reported by auditors in each group.

HYPOTHESIS ONE: AUDITOR ATTENTION TO CUE DIMENSIONS

Influence of experience on auditor attention to cue dimensions for making control risk assessments can only be tested indirectly by analyzing cognitive models of the decision processes of auditors in each group. Therefore, to develop an "as if" model to measure the auditors' attention to cue dimensions while completing a decision task, an appropriate decision modeling tool must be used.

Decision Modeling Considerations

Methods of knowledge acquisition,[21] knowledge representation and data processing should be carefully considered to select an appropriate decision modeling tool that can accommodate the interrelated decision making components of cue selection, cue evaluation, and decision response. Table 4 provides a summary of knowledge acquisition and representation and model processing for traditional knowledge-based systems, linear regression models, and neural network models.

Knowledge acquisition in explanation-based research relies on obtaining rules directly from experts, observing experts' decision processes, or obtaining verbal protocols from experts as they perform a task. Exemplar-based models have built-in "learn by experience" mechanisms that acquire knowledge indirectly from a set of many different situations. Exemplar-based models capture and represent additional knowledge not incorporated in subjects' decision process descriptions nor in researchers' observations of the subjects' decision processes.

Expertise researchers favor models that process information in a manner that is characteristic of expert judgments. Characteristics of expert judgment include the ability to handle large numbers of cues, evaluation of cues using linear and nonlinear functions, and intuitive processing that recognizes the situation as a whole by using memory that is almost instantaneously sensitive to many situations (Dreyfus and Dreyfus 1986).

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[21]See Olson and Rueter (1987) for a review of knowledge acquisition methods.

TABLE 4

COMPARISON OF EXPLANATION-BASED AND EXEMPLAR-BASED MODELS

	KNOWLEDGE ACQUISITION	KNOWLEDGE REPRESENTATION	MODEL PROCESSING		
			IDENTIFICATION AND SELECTION OF RELEVANT CUES	EVALUATION USING THE CHOSEN CUES	DECISION RESPONSE
Traditional Knowledge-based Systems **(Explanation)**	Direct and Observed (Usually no learning)	Explicit, discrete rules. Approximate any function but don't know what the equation is.	Large set of preselected cues	Analytical & serial. Intermediate diagnostic signals[2]	Analytical[3]
Linear Regression Models **(Exemplar)**	Indirect (Static learning)	Implicit, continuous "rules." Approximate a limited set of functions.	Small set of preselected cues[1]	Intuitive & parallel. No intermediate diagnostic signals[2]	Intuitive & subject to strict statistical assumptions
Neural Network Models **(Exemplar)**	Indirect (Dynamic learning)	Implicit, continuous "rules." Approximate any function.	Large set of preselected cues	Intuitive & massively parallel. Intermediate diagnostic signals[2]	Intuitive[4]

[1]Regression models do not handle large numbers of input variables very well.
[2]Intermediate diagnostic signals are often based on relevant dimensions of the cues (e.g. type or purpose of the control).
[3]Decision explanation based on explicit rules instead of analysis of variable weights.
[4]Neural networks also have the advantage of graceful degradation and robust predictive ability in situations of missing data or noise.

Explanation-based models such as expert systems can incorporate large numbers of cues and approximate nonlinear functions. However, expert systems manipulate sets of logical (discrete) statements to arrive at a prediction using a step by step process. Dreyfus and Dreyfus (1986), Smolensky (1988) and MacLennan (in press) contend that explanation-based models, which use discrete rules, do not capture, represent, or process implicit (tacit), continuous "rules" which underlie the intuitive processing ability of human experts. Although expert systems can provide a computer trace of logical statements that give explanations of how the model arrived at the decision response,[22] exemplar-based models such as regression and neural networks, yield a functional (topological) "explanation" that can be mathematically measured more precisely than logical statement relationships. The ability to test H1 is better achieved by the knowledge acquisition, knowledge representation, and processing methods of exemplar-based models.

The methods and structures used to represent knowledge are key to determining which type of exemplar-based model is most appropriate for modeling and measuring functional relationships between auditors' usage (search and selection) of cues and decision responses. A neural network approach is favored over the linear regression model approach because of a network's ability to handle large numbers of potential cues and to find linear or

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[22]One reason that there are so many production rule systems is that people are more comfortable with systems that can give rule-like explanations of the decision. However, experts do not think using discrete, hard rules. Biggs, Messier and Hansen (1987) pointed out limitations of traditional expert systems. They found that reasoning processes were consistent with theories of reasoning by analogy and reasoning by assumptions, both of which rely heavily on experience of the decision-maker. They also found that very few explicit if-then statements could be written in production rules of the type required in expert systems such as the one developed by Hansen and Messier (1986).

nonlinear functions that map the subjects' chosen input cues to each decision response. Linear regression uses a small number of preselected cues, so auditors' search strategies for selecting cues are not considered. Libby (1985) suggested that the first step of a diagnostic process is to identify relationships among the cues. Inaccurate judgments can often be traced to subjects failing to recognize the relevant diagnostic cues (Slovic, Rorer, and Hoffman 1971). Einhorn (1974) concluded that experience improves a decision maker's ability to relevant information (cues). He also suggested that situational data help the auditor develop hypotheses that help structure the cue search. Frederick (1991) concluded that auditors' memory structures incorporate more highly developed taxonomic and schematic representations of control features than the memory structures of audit students. Linear models do not model auditors' utilization of perceived hierarchical relationships that provide important intermediate evaluation steps toward reaching the auditor's final decision.

Modeling nonlinear functions using a neural network does come at the expense of interpretibility of specific cue weights. However, measuring distribution uniformity of the model's weight set and not specific cue weight comparisons provides a way to compare how experience affects an auditor's ability to select cue sets with high information content that lead to accurate decisions. The neural network enables a researcher to incorporate into the cognitive model the weights between the cues and the dimensions of the cues while still considering the decision response. This feature is a key to measuring the knowledge structure differences suggested by the first hypothesis.

Neural networks provide several other advantages over traditional statistics that lead to a more detailed approximation of cognitive processes. Neural networks use an active process of adaptive modification over learning trials as different features enter into categorization judgments. For example, a neural network adjusts its current weight values based on each client IC structure and CRA presented as a data training record. A network is trained by going through the various states of experience similar to human skill acquisition. Regression does not go through these states. Networks also can make less stringent assumptions concerning the shapes of underlying data distributions than regression (Rumelhart and McClelland 1986a, 1986b; Lippman 1987).[23]

In summary, this study used neural network models instead of a traditional knowledge based system that uses symbolic "if-then" rules because of a network's ability to represent knowledge as implicit, continuous rules which take the form of interrelated weights that are acquired from auditors' CRAs. The weights can be measured for distributional differences between the two models representing the inexperienced and experienced groups. Neural network models were used instead of regression models because regression models cannot handle large sets of input cues nor model hierarchical or other intermediate data relationships which may help explain cue selection and decision response.

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[23]Neural networks have been compared to various statistical models. Previous research in financial prediction using neural network models has been successful in predicting failure or nonfailure of firms (Bell, Ribar and Verchio, 1990; Odom and Sharda, 1990) and predicting bond ratings (Dutta and Shekhar, 1989). Bankruptcy prediction models are built using financial information and actual bankruptcy outcomes. Each of these studies compared the network to logistic regression, multivariate analysis, or linear regression. The network performed as well or better in prediction accuracy against holdout samples in each case.

Model Building

The neural network-based models of auditors' control risk assessment processes were developed using the algorithm contained in Appendix C.[24] This algorithm is an appropriate algorithm because it utilizes each auditor's decision response to compute the network's decision error in relation to each auditor's decision. This algorithm can find a complex nonlinear equation that relates (maps) decision cue sets used by the auditors to their decision responses. Using the cues chosen and the risk decisions of the auditors, models of auditors' knowledge structure that map the chosen variables (inputs) into the risk category decisions were developed. Both network architectures were made up of 107 decision input nodes representing potential CRA decision cues numbered 1 through 107 in Appendix A-1, five middle layer or feature nodes[25] (cue dimensions), and one output node (decision response for the CRA). The data observations from each group of auditors were divided into a training set and a test set. One observation (data record) represents a single auditor's cue selections and CRA on the one client case used in this study. Since the number

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[24]The type of neural network that will be used for this study is a back-propagation network as described by Rumelhart, Hinton and Williams (1986) and first introduced by Werbos (1974).

[25]Middle layer nodes are not interpretable because all 107 input nodes feed values to each middle layer node. Finding the appropriate number of middle layer nodes used in a network is a matter of judgment. In general, if the number of middle layer nodes is too small, the network is likely to get trapped in a local minima. If the number of middle layer nodes is too high, the network memorizes the training set and does not generalize well to novel situations. Using ten middle nodes, the networks were very good at predicting CRAs using training set inputs. However, the models did not generalize well to the CRAs of the auditor decisions held out as the test set. The five middle nodes, representing five interrelated, noninterpretible IC cue dimensions, resulted in an acceptable balance of accurately predicting the auditors CRAs for both the training and test sets for both auditor groups. These accuracy results are reported and explained below in the validation section.

of observations in a training set may influence a network's learning process, the training sample sizes needed to be nearly the same. In order to have at least one third of the experienced senior observations held out as a test set, every third observation was included in the test set for the experienced seniors resulting in 18 training records and 9 test records. To get similar training sample size, the training set for the inexperienced group included every other data record, which resulted in 19 training records and 18 test records.

The inexperienced and experienced networks both started with the same set of randomized weights so that the change in weights of the two networks could be measured from the same point. Because a neural network uses an iterative gradient descent process of learning from the set of training observations, learning is considered complete when the weights settle toward an asymptote. The training criterion was set so that both the experienced and inexperienced networks would stop training when the average error between the networks' CRAs (computed output from the training set input values) and the auditors' CRAs reached 1 percent.[26]

Once the models--one model representing each senior group--were trained from the data, the resulting model weights represent the typical knowledge structure of an auditor in

[26]The inexperienced network reached root mean square error of less than .01 at 97 epochs (1843 record presentations) while the experienced model reached mean square error of less than .01 at 69 epochs (1242 record presentations). An epoch represents one presentation of each of the records in the training set. The presentation order was random within each epoch. The learning rate was set at 0.5, and changed to 0.25 after 1800 presentations.

each group.[27] Table 5 presents the model weights for both the experienced and inexperienced models that were used to test H1, difference between the groups attention to cue dimensions. These weights connect the input nodes that represent potential cues to the middle or feature nodes that represent cue dimensions. Table 5 lists the initial random weights, the trained weights, and the change in each weight that occurred during training of the inexperienced and experienced neural network models. The weights that did not change represent decision variables that were not selected as relevant by the auditor observations used in training the networks. Before using the models to test the difference between the groups for attention to cue dimensions, the models were validated to provide evidence that each model had approximated the control risk assessment decision process of a typical auditor in each group.

Validation of Network Models

The validation of each network model was performed by comparing the CRA decisions of the model to the CRA decisions of the auditors. Table 6 lists the CRAs for the inexperienced seniors and the corresponding CRAs made by the inexperienced model. Table 7 lists the CRAs for the experienced seniors and the corresponding CRAs made by the experienced model. Tables 6 and 7 also present the computed decision differences between each auditor's CRA and the model's corresponding CRAs for both the category CRAs and

[27]The neural network models implicitly combine subject decisions and obtain a group "average" of all the auditors' decisions for the case in this experiment. A neural network could also handle a set of different cases.

TABLE 5

NEURAL NETWORK CUE DIMENSION WEIGHTS

Middle Node	IC Cue No.	Inexperienced Model Initial	Change	Trained	Experienced Model Initial	Change	Trained
1	0	0.3910	0.0402	0.4312	0.3910	0.057	0.4480
1	1	-0.2744	0.1223	-0.1521	-0.2744	-0.0527	-0.3271
1	2	0.0322	-0.1223	-0.0901	0.0322	0.0528	0.0850
1	3	0.2146	0.1223	0.3369	0.2146	-0.0527	0.1619
1	4	-0.2962	0.0091	-0.2871	-0.2962	-0.028	-0.3242
1	5	0.1479	-0.009	0.1389	0.1479	0.028	0.1759
1	6	-0.3728	0.009	-0.3638	-0.3728	-0.028	-0.4008
1	7	-0.4983	0.0402	-0.4581	-0.4983	0.057	-0.4413
1	8	0.3118	-0.0578	0.2540	0.3118	-0.1327	0.1791
1	9	0.2715	0.0004	0.2719	0.2715	-0.026	0.2455
1	10	-0.3828	0.2059	-0.1769	-0.3828	-0.0865	-0.4693
1	11	0.1127	-0.2733	-0.1606	0.1127	-0.2104	-0.0977
1	12	-0.3823	-0.2675	-0.6498	-0.3823	-0.0243	-0.4066
1	13	0.1620	0	0.1620	0.1620	0	0.1620
1	14	-0.4048	0	-0.4048	-0.4048	0	-0.4048
1	15	0.2964	-0.1166	0.1798	0.2964	-0.0767	0.2197
1	16	0.3610	0	0.3610	0.3610	0	0.3610
1	17	0.2505	0	0.2505	0.2505	0	0.2505
1	18	-0.2233	0	-0.2233	-0.2233	0	-0.2233
1	19	0.0321	0	0.0321	0.0321	0	0.0321
1	20	-0.3149	0	-0.3149	-0.3149	0	-0.3149
1	21	0.3343	-0.0432	0.2911	0.3343	-0.0767	0.2576
1	22	0.3519	0	0.3519	0.3519	0	0.3519
1	23	-0.4947	0	-0.4947	-0.4947	0	-0.4947
1	24	-0.1709	-0.1299	-0.3008	-0.1709	-0.0766	-0.2475
1	25	0.4890	-0.1165	0.3725	0.4890	-0.0766	0.4124
1	26	0.2584	-0.1166	0.1418	0.2584	-0.1055	0.1529
1	27	0.3554	0.01	0.3654	0.3554	-0.0384	0.3170
1	28	-0.0887	-0.1107	-0.1994	-0.0887	-0.0385	-0.1272
1	29	-0.0128	-0.1299	-0.1427	-0.0128	-0.0767	-0.0895
1	30	-0.4081	-0.1165	-0.5246	-0.4081	-0.0767	-0.4848
1	31	-0.4621	-0.1166	-0.5787	-0.4621	-0.0767	-0.5388
1	32	-0.2281	0.0437	-0.1844	-0.2281	-0.0097	-0.2378
1	33	-0.1839	0.0099	-0.1740	-0.1839	-0.0385	-0.2224
1	34	0.3751	-0.1106	0.2645	0.3751	-0.0384	0.3367
1	35	0.1465	-0.1166	0.0299	0.1465	-0.0097	0.1368
1	36	0.3467	-0.1166	0.2301	0.3467	-0.0767	0.2700
1	37	-0.1111	-0.1299	-0.2410	-0.1111	-0.0767	-0.1878
1	38	-0.0983	0.1364	0.0381	-0.0983	-0.0767	-0.1750
1	39	0.0371	-0.0431	-0.0060	0.0371	-0.0767	-0.0396
1	40	-0.4622	-0.0432	-0.5054	-0.4622	-0.0767	-0.5389
1	41	-0.4567	-0.0431	-0.4998	-0.4567	-0.0767	-0.5334
1	42	0.3763	-0.0239	0.3524	0.3763	-0.0767	0.2996
1	43	-0.4008	0.066	-0.3348	-0.4008	-0.0269	-0.4277
1	44	0.0513	0	0.0513	0.0513	0.0444	0.0957

TABLE 5 CONTINUED

Middle Node	IC Cue No.	Inexperienced Model Initial	Change	Trained	Experienced Model Initial	Change	Trained
1	45	0.4210	0.0404	0.4614	0.4210	0.1596	0.5806
1	46	0.0675	0.0103	0.0778	0.0675	0.0309	0.0984
1	47	-0.4836	-0.15	-0.6336	-0.4836	-0.0033	-0.4869
1	48	0.1707	-0.0635	0.1072	0.1707	0.0023	0.1730
1	49	0.3208	0.0087	0.3295	0.3208	-0.0145	0.3063
1	50	-0.3063	0.0695	-0.2368	-0.3063	0	-0.3063
1	51	-0.1380	0.0776	-0.0604	-0.1380	-0.0292	-0.1672
1	52	-0.0655	0	-0.0655	-0.0655	-0.0671	-0.1326
1	53	0.1217	0	0.1217	0.1217	0	0.1217
1	54	0.2595	-0.0173	0.2422	0.2595	0	0.2595
1	55	0.3715	-0.1366	0.2349	0.3715	0	0.3715
1	56	-0.3131	0.0452	-0.2679	-0.3131	0.1143	-0.1988
1	57	0.3670	-0.0173	0.3497	0.3670	0	0.3670
1	58	0.0627	0	0.0627	0.0627	0	0.0627
1	59	0.2371	0	0.2371	0.2371	0	0.2371
1	60	0.4701	0	0.4701	0.4701	0	0.4701
1	61	-0.3959	0	-0.3959	-0.3959	0	-0.3959
1	62	0.0898	0	0.0898	0.0898	0	0.0898
1	63	0.2671	0	0.2671	0.2671	0	0.2671
1	64	0.2276	0	0.2276	0.2276	0	0.2276
1	65	0.0748	0.1603	0.2351	0.0748	0	0.0748
1	66	-0.4815	-0.0134	-0.4949	-0.4815	0.0666	-0.4149
1	67	-0.2455	0	-0.2455	-0.2455	0	-0.2455
1	68	0.2861	-0.0134	0.2727	0.2861	0	0.2861
1	69	-0.1515	0	-0.1515	-0.1515	0	-0.1515
1	70	-0.4533	0	-0.4533	-0.4533	0	-0.4533
1	71	-0.1016	-0.2209	-0.3225	-0.1016	-0.0292	-0.1308
1	72	0.0862	0	0.0862	0.0862	0	0.0862
1	73	-0.0081	0.0465	0.0384	-0.0081	-0.0208	-0.0289
1	74	0.2669	0.0998	0.3667	0.2669	0	0.2669
1	75	0.1214	-0.1476	-0.0262	0.1214	0	0.1214
1	76	-0.3706	0	-0.3706	-0.3706	0	-0.3706
1	77	-0.1290	0	-0.1290	-0.1290	0	-0.1290
1	78	-0.1972	0	-0.1972	-0.1972	0	-0.1972
1	79	0.1280	0	0.1280	0.1280	0	0.1280
1	80	-0.3893	0	-0.3893	-0.3893	0	-0.3893
1	81	0.1759	0	0.1759	0.1759	0	0.1759
1	82	0.4306	0	0.4306	0.4306	0	0.4306
1	83	0.0463	0	0.0463	0.0463	0	0.0463
1	84	-0.2942	0	-0.2942	-0.2942	0	-0.2942
1	85	-0.2341	-0.0698	-0.3039	-0.2341	0	-0.2341
1	86	-0.1012	0.1455	0.0443	-0.1012	0.0137	-0.0875
1	87	0.4977	0	0.4977	0.4977	0	0.4977
1	88	-0.0189	-0.0517	-0.0706	-0.0189	-0.0056	-0.0245
1	89	-0.0750	-0.0149	-0.0899	-0.0750	-0.0056	-0.0806
1	90	-0.3297	-0.0148	-0.3445	-0.3297	0	-0.3297

TABLE 5 CONTINUED

Middle Node	IC Cue No.	Inexperienced Model Initial	Change	Trained	Experienced Model Initial	Change	Trained
1	91	-0.0618	0.0559	-0.0059	-0.0618	0	-0.0618
1	92	-0.1049	0	-0.1049	-0.1049	-0.0344	-0.1393
1	93	0.1242	0	0.1242	0.1242	0	0.1242
1	94	0.3018	0.0472	0.3490	0.3018	0	0.3018
1	95	0.1148	-0.0532	0.0616	0.1148	0	0.1148
1	96	-0.1386	-0.0368	-0.1754	-0.1386	0.0472	-0.0914
1	97	-0.1165	0	-0.1165	-0.1165	0	-0.1165
1	98	-0.3192	0	-0.3192	-0.3192	0	-0.3192
1	99	-0.0191	-0.0368	-0.0559	-0.0191	0	-0.0191
1	100	-0.1599	-0.0149	-0.1748	-0.1599	-0.0056	-0.1655
1	101	-0.1737	0	-0.1737	-0.1737	0	-0.1737
1	102	0.3394	0.0236	0.3630	0.3394	0	0.3394
1	103	-0.0855	0.0343	-0.0512	-0.0855	-0.0097	-0.0952
1	104	-0.0726	-0.0133	-0.0859	-0.0726	-0.0802	-0.1528
1	105	-0.4777	-0.1738	-0.6515	-0.4777	0.0108	-0.4669
1	106	-0.4379	0	-0.4379	-0.4379	0	-0.4379
1	107	-0.4175	-0.1502	-0.5677	-0.4175	0	-0.4175
2	0	0.4124	-0.012	0.4004	0.4124	-0.0332	0.3792
2	1	0.2100	-0.2078	0.0022	0.2100	0.0663	0.2763
2	2	-0.4920	0.2077	-0.2843	-0.4920	-0.0664	-0.5584
2	3	0.2960	-0.2078	0.0882	0.2960	0.0663	0.3623
2	4	0.2688	-0.076	0.1928	0.2688	0.0216	0.2904
2	5	-0.0056	0.076	0.0704	-0.0056	-0.0216	-0.0272
2	6	0.0652	-0.076	-0.0108	0.0652	0.0216	0.0868
2	7	0.1988	-0.012	0.1868	0.1988	-0.0332	0.1656
2	8	-0.4483	0.0463	-0.4020	-0.4483	0.2945	-0.1538
2	9	-0.3868	-0.0506	-0.4374	-0.3868	-0.0303	-0.4171
2	10	-0.3437	-0.1358	-0.4795	-0.3437	0.2151	-0.1286
2	11	0.1344	0.1868	0.3212	0.1344	0.2742	0.4086
2	12	-0.3334	0.4223	0.0889	-0.3334	0.134	-0.1994
2	13	0.3650	0	0.3650	0.3650	0	0.3650
2	14	-0.2863	0	-0.2863	-0.2863	0	-0.2863
2	15	-0.4666	0.0874	-0.3792	-0.4666	0.1205	-0.3461
2	16	-0.0192	0	-0.0192	-0.0192	0	-0.0192
2	17	0.2926	0	0.2926	0.2926	0	0.2926
2	18	0.0440	0	0.0440	0.0440	0	0.0440
2	19	0.1677	0	0.1677	0.1677	0	0.1677
2	20	-0.2547	0	-0.2547	-0.2547	0	-0.2547
2	21	0.2173	0.0404	0.2577	0.2173	0.1205	0.3378
2	22	-0.2006	0	-0.2006	-0.2006	0	-0.2006
2	23	0.1116	0	0.1116	0.1116	0	0.1116
2	24	-0.2044	0.0886	-0.1158	-0.2044	0.1204	-0.0840
2	25	-0.2843	0.0874	-0.1969	-0.2843	0.1205	-0.1638
2	26	0.2756	0.0874	0.3630	0.2756	0.195	0.4706
2	27	-0.2420	-0.0689	-0.3109	-0.2420	0.0737	-0.1683
2	28	0.0007	0.0446	0.0453	0.0007	0.0737	0.0744

TABLE 5 CONTINUED

Middle Node	IC Cue No.	Inexperienced Model Initial	Change	Trained	Experienced Model Initial	Change	Trained
2	29	-0.3667	0.0886	-0.2781	-0.3667	0.1204	-0.2463
2	30	0.2540	0.0874	0.3414	0.2540	0.1204	0.3744
2	31	0.2292	0.0874	0.3166	0.2292	0.1205	0.3497
2	32	-0.0707	-0.0881	-0.1588	-0.0707	-0.0008	-0.0715
2	33	0.2298	-0.069	0.1608	0.2298	0.0737	0.3035
2	34	0.1085	0.0446	0.1531	0.1085	0.0738	0.1823
2	35	0.0288	0.0874	0.1162	0.0288	-0.0008	0.0280
2	36	-0.2986	0.0874	-0.2112	-0.2986	0.1204	-0.1782
2	37	-0.4517	0.0886	-0.3631	-0.4517	0.1205	-0.3312
2	38	0.3943	-0.1791	0.2152	0.3943	0.1205	0.5148
2	39	0.2775	0.0403	0.3178	0.2775	0.1204	0.3979
2	40	0.4933	0.0403	0.5336	0.4933	0.1204	0.6137
2	41	0.1039	0.0404	0.1443	0.1039	0.1205	0.2244
2	42	0.1372	-0.0036	0.1336	0.1372	0.1205	0.2577
2	43	0.3762	-0.0355	0.3407	0.3762	0.057	0.4332
2	44	-0.3330	0	-0.3330	-0.3330	-0.085	-0.4180
2	45	0.4825	-0.0906	0.3919	0.4825	-0.3016	0.1809
2	46	-0.4558	-0.0893	-0.5451	-0.4558	-0.0284	-0.4842
2	47	0.4418	0.1759	0.6177	0.4418	0.0007	0.4425
2	48	-0.0091	0.0441	0.0350	-0.0091	-0.0081	-0.0172
2	49	-0.0524	-0.0754	-0.1278	-0.0524	0.0367	-0.0157
2	50	0.3514	-0.0279	0.3235	0.3514	0	0.3514
2	51	0.3561	0.0298	0.3859	0.3561	0.1276	0.4837
2	52	-0.0798	0	-0.0798	-0.0798	0.1213	0.0415
2	53	-0.3545	0	-0.3545	-0.3545	0	-0.3545
2	54	-0.4697	0.0128	-0.4569	-0.4697	0	-0.4697
2	55	-0.2239	0.1747	-0.0492	-0.2239	0	-0.2239
2	56	0.4082	-0.0308	0.3774	0.4082	-0.1813	0.2269
2	57	-0.4963	0.0128	-0.4835	-0.4963	0	-0.4963
2	58	-0.4302	0	-0.4302	-0.4302	0	-0.4302
2	59	-0.0547	0	-0.0547	-0.0547	0	-0.0547
2	60	0.2139	0	0.2139	0.2139	0	0.2139
2	61	0.4174	0	0.4174	0.4174	0	0.4174
2	62	0.0531	0	0.0531	0.0531	0	0.0531
2	63	-0.3478	0	-0.3478	-0.3478	0	-0.3478
2	64	0.1780	0	0.1780	0.1780	0	0.1780
2	65	-0.1842	-0.1755	-0.3597	-0.1842	0	-0.1842
2	66	-0.2513	0.0012	-0.2501	-0.2513	-0.0955	-0.3468
2	67	0.1789	0	0.1789	0.1789	0	0.1789
2	68	0.4335	0.0012	0.4347	0.4335	0	0.4335
2	69	0.2039	0	0.2039	0.2039	0	0.2039
2	70	-0.0669	0	-0.0669	-0.0669	0	-0.0669
2	71	-0.4163	0.3339	-0.0824	-0.4163	0.1276	-0.2887
2	72	0.0205	0	0.0205	0.0205	0	0.0205
2	73	-0.2281	0.055	-0.1731	-0.2281	0.0491	-0.1790
2	74	0.1655	-0.1305	0.0350	0.1655	0	0.1655

TABLE 5 CONTINUED

Middle Node	IC Cue No.	Inexperienced Model Initial	Change	Trained	Experienced Model Initial	Change	Trained
2	75	0.1615	0.1219	0.2834	0.1615	0	0.1615
2	76	-0.1253	0	-0.1253	-0.1253	0	-0.1253
2	77	-0.3329	0	-0.3329	-0.3329	0	-0.3329
2	78	0.2319	0	0.2319	0.2319	0	0.2319
2	79	0.4255	0	0.4255	0.4255	0	0.4255
2	80	-0.3426	0	-0.3426	-0.3426	0	-0.3426
2	81	0.0219	0	0.0219	0.0219	0	0.0219
2	82	0.4776	0	0.4776	0.4776	0	0.4776
2	83	0.4543	0	0.4543	0.4543	0	0.4543
2	84	0.3956	0	0.3956	0.3956	0	0.3956
2	85	0.3308	0.0736	0.4044	0.3308	0	0.3308
2	86	0.2482	-0.1833	0.0649	0.2482	-0.0267	0.2215
2	87	-0.0522	0	-0.0522	-0.0522	0	-0.0522
2	88	0.4022	0.0254	0.4276	0.4022	0.0088	0.4110
2	89	0.2711	0.015	0.2861	0.2711	0.0088	0.2799
2	90	-0.3446	0.015	-0.3296	-0.3446	0	-0.3446
2	91	-0.1636	-0.1419	-0.3055	-0.1636	0	-0.1636
2	92	0.4438	0	0.4438	0.4438	0.0834	0.5272
2	93	-0.4392	0	-0.4392	-0.4392	0	-0.4392
2	94	0.3891	-0.0665	0.3226	0.3891	0	0.3891
2	95	-0.2143	0.0724	-0.1419	-0.2143	0	-0.2143
2	96	-0.3750	0.0104	-0.3646	-0.3750	-0.0599	-0.4349
2	97	-0.0527	0	-0.0527	-0.0527	0	-0.0527
2	98	-0.2085	0	-0.2085	-0.2085	0	-0.2085
2	99	0.4421	0.0104	0.4525	0.4421	0	0.4421
2	100	-0.0409	0.015	-0.0259	-0.0409	0.0088	-0.0321
2	101	-0.0794	0	-0.0794	-0.0794	0	-0.0794
2	102	-0.0841	-0.0905	-0.1746	-0.0841	0	-0.0841
2	103	-0.2373	0.0356	-0.2017	-0.2373	-0.0008	-0.2381
2	104	0.0922	0.0562	0.1484	0.0922	0.1356	0.2278
2	105	0.2448	0.2248	0.4696	0.2448	-0.0227	0.2221
2	106	-0.2160	0	-0.2160	-0.2160	0	-0.2160
2	107	0.2720	0.1344	0.4064	0.2720	0	0.2720
3	0	0.1507	0.2154	0.3661	0.1507	0.0457	0.1964
3	1	-0.0981	0.1877	0.0896	-0.0981	-0.0548	-0.1529
3	2	-0.4344	-0.1878	-0.6222	-0.4344	0.0548	-0.3796
3	3	-0.4092	0.1877	-0.2215	-0.4092	-0.0548	-0.4640
3	4	0.1812	-0.0792	0.1020	0.1812	-0.0217	0.1595
3	5	-0.4585	0.0792	-0.3793	-0.4585	0.0217	-0.4368
3	6	-0.1049	-0.0793	-0.1842	-0.1049	-0.0218	-0.1267
3	7	0.0801	0.2153	0.2954	0.0801	0.0457	0.1258
3	8	0.1496	-0.121	0.0286	0.1496	-0.1871	-0.0375
3	9	0.0298	-0.0867	-0.0569	0.0298	0.0135	0.0433
3	10	0.0466	0.1253	0.1719	0.0466	-0.2831	-0.2365
3	11	-0.0560	-0.3902	-0.4462	-0.0560	-0.3152	-0.3712
3	12	-0.0291	-0.5808	-0.6099	-0.0291	-0.1271	-0.1562

TABLE 5 CONTINUED

Middle Node	IC Cue No.	Inexperienced Model Initial	Change	Trained	Experienced Model Initial	Change	Trained
3	13	0.1924	0	0.1924	0.1924	0	0.1924
3	14	0.1846	0	0.1846	0.1846	0	0.1846
3	15	-0.3647	-0.0874	-0.4521	-0.3647	-0.1348	-0.4995
3	16	-0.4642	0	-0.4642	-0.4642	0	-0.4642
3	17	0.3437	0	0.3437	0.3437	0	0.3437
3	18	0.4099	0	0.4099	0.4099	0	0.4099
3	19	-0.0922	0	-0.0922	-0.0922	0	-0.0922
3	20	0.2056	0	0.2056	0.2056	0	0.2056
3	21	-0.3026	0.0781	-0.2245	-0.3026	-0.1348	-0.4374
3	22	-0.1811	0	-0.1811	-0.1811	0	-0.1811
3	23	0.3585	0	0.3585	0.3585	0	0.3585
3	24	-0.2592	-0.1195	-0.3787	-0.2592	-0.1348	-0.3940
3	25	0.2520	-0.0874	0.1646	0.2520	-0.1347	0.1173
3	26	0.2955	-0.0875	0.2080	0.2955	-0.1437	0.1518
3	27	-0.1963	0.2517	0.0554	-0.1963	-0.0611	-0.2574
3	28	0.1357	-0.0507	0.0850	0.1357	-0.0611	0.0746
3	29	0.2441	-0.1195	0.1246	0.2441	-0.1347	0.1094
3	30	0.2541	-0.0874	0.1667	0.2541	-0.1348	0.1193
3	31	0.3337	-0.0875	0.2462	0.3337	-0.1348	0.1989
3	32	0.3249	0.0955	0.4204	0.3249	-0.0523	0.2726
3	33	-0.2363	0.2518	0.0155	-0.2363	-0.0611	-0.2974
3	34	0.0529	-0.0508	0.0021	0.0529	-0.0612	-0.0083
3	35	0.3878	-0.0875	0.3003	0.3878	-0.0523	0.3355
3	36	0.2321	-0.0874	0.1447	0.2321	-0.1348	0.0973
3	37	-0.3738	-0.1196	-0.4934	-0.3738	-0.1348	-0.5086
3	38	0.2949	0.3299	0.6248	0.2949	-0.1347	0.1602
3	39	-0.3047	0.0782	-0.2265	-0.3047	-0.1348	-0.4395
3	40	0.1294	0.0782	0.2076	0.1294	-0.1348	-0.0054
3	41	0.0929	0.0782	0.1711	0.0929	-0.1347	-0.0418
3	42	-0.2623	0.147	-0.1153	-0.2623	-0.1347	-0.3970
3	43	0.4254	-0.1012	0.3242	0.4254	-0.0729	0.3525
3	44	-0.2241	0	-0.2241	-0.2241	0.0392	-0.1849
3	45	-0.4640	-0.0884	-0.5524	-0.4640	0.1836	-0.2804
3	46	0.0282	0.1329	0.1611	0.0282	-0.0038	0.0244
3	47	0.3896	-0.3331	0.0565	0.3896	-0.0076	0.3820
3	48	0.3043	-0.1415	0.1628	0.3043	0.0146	0.3189
3	49	-0.3603	0.1259	-0.2344	-0.3603	-0.0173	-0.3776
3	50	-0.0173	0.1223	0.1050	-0.0173	0	-0.0173
3	51	-0.3596	-0.0255	-0.3851	0.3596	-0.1359	-0.4955
3	52	0.3239	0	0.3239	0.3239	-0.0825	0.2414
3	53	0.2327	0	0.2327	0.2327	0	0.2327
3	54	-0.3687	-0.0348	-0.4035	-0.3687	0	-0.3687
3	55	0.3114	-0.301	0.0104	0.3114	0	0.3114
3	56	0.2101	0.0944	0.3045	0.2101	0.1235	0.3336
3	57	0.3454	-0.0347	0.3107	0.3454	0	0.3454
3	58	-0.2565	0	-0.2565	-0.2565	0	-0.2565

TABLE 5 CONTINUED

Middle Node	IC Cue No.	Inexperienced Model Initial	Change	Trained	Experienced Model Initial	Change	Trained
3	59	0.0393	0	0.0393	0.0393	0	0.0393
3	60	0.0475	0	0.0475	0.0475	0	0.0475
3	61	-0.4150	0	-0.4150	-0.4150	0	-0.4150
3	62	0.0560	0	0.0560	0.0560	0	0.0560
3	63	-0.1842	0	-0.1842	-0.1842	0	-0.1842
3	64	0.1958	0	0.1958	0.1958	0	0.1958
3	65	0.4234	0.1829	0.6063	0.4234	0	0.4234
3	66	-0.0799	-0.0322	-0.1121	-0.0799	0.0767	-0.0032
3	67	-0.3900	0	-0.3900	-0.3900	0	-0.3900
3	68	-0.0516	-0.0321	-0.0837	-0.0516	0	-0.0516
3	69	0.4897	0	0.4897	0.4897	0	0.4897
3	70	-0.4129	0	-0.4129	-0.4129	0	-0.4129
3	71	-0.3948	-0.3563	-0.7511	-0.3948	-0.1359	-0.5307
3	72	0.2507	0	0.2507	0.2507	0	0.2507
3	73	0.4643	0.0028	0.4671	0.4643	-0.1069	0.3574
3	74	-0.1473	0.2348	0.0875	-0.1473	0	-0.1473
3	75	0.3968	-0.3479	0.0489	0.3968	0	0.3968
3	76	-0.0519	0	-0.0519	-0.0519	0	-0.0519
3	77	-0.3360	0	-0.3360	-0.3360	0	-0.3360
3	78	0.2757	0	0.2757	0.2757	0	0.2757
3	79	-0.0095	0	-0.0095	-0.0095	0	-0.0095
3	80	-0.4680	0	-0.4680	-0.4680	0	-0.4680
3	81	-0.0836	0	-0.0836	-0.0836	0	-0.0836
3	82	-0.3070	0	-0.3070	-0.3070	0	-0.3070
3	83	-0.0509	0	-0.0509	-0.0509	0	-0.0509
3	84	-0.1474	0	-0.1474	-0.1474	0	-0.1474
3	85	-0.1863	-0.1814	-0.3677	-0.1863	0	-0.1863
3	86	0.2479	0.3648	0.6127	0.2479	0.0135	0.2614
3	87	-0.4719	0	-0.4719	-0.4719	0	-0.4719
3	88	-0.2329	-0.1369	-0.3698	-0.2329	-0.0223	-0.2552
3	89	-0.0584	-0.0392	-0.0976	-0.0584	-0.0223	-0.0807
3	90	-0.3497	-0.0391	-0.3888	-0.3497	0	-0.3497
3	91	0.1460	0.2628	0.4088	0.1460	0	0.1460
3	92	0.1924	0	0.1924	0.1924	-0.0311	0.1613
3	93	0.1765	0	0.1765	0.1765	0	0.1765
3	94	-0.1113	0.1369	0.0256	-0.1113	0	-0.1113
3	95	0.0318	-0.153	-0.1212	0.0318	0	0.0318
3	96	-0.4692	-0.0977	-0.5669	-0.4692	0.0411	-0.4281
3	97	-0.3549	0	-0.3549	-0.3549	0	-0.3549
3	98	0.1122	0	0.1122	0.1122	0	0.1122
3	99	0.3949	-0.0977	0.2972	0.3949	0	0.3949
3	100	-0.0626	-0.0391	-0.1017	-0.0626	-0.0223	-0.0849
3	101	0.4394	0	0.4394	0.4394	0	0.4394
3	102	-0.0997	0.165	0.0653	-0.0997	0	-0.0997
3	103	-0.0409	0.0118	-0.0291	-0.0409	-0.0523	-0.0932
3	104	0.3980	-0.0672	0.3308	0.3980	-0.1038	0.2942

TABLE 5 CONTINUED

Middle Node	IC Cue No.	Inexperienced Model Initial	Change	Trained	Experienced Model Initial	Change	Trained
3	105	-0.3185	-0.4703	-0.7888	-0.3185	0.0226	-0.2959
3	106	-0.3589	0	-0.3589	-0.3589	0	-0.3589
3	107	0.2064	-0.3053	-0.0989	0.2064	0	0.2064
4	0	0.0867	-0.027	0.0597	0.0867	-0.0297	0.0570
4	1	0.0321	0.0308	0.0629	0.0321	0.0191	0.0512
4	2	0.2355	-0.0308	0.2047	0.2355	-0.019	0.2165
4	3	0.1733	0.0308	0.2041	0.1733	0.019	0.1923
4	4	-0.0292	0.0311	0.0019	-0.0292	0.0108	-0.0184
4	5	0.2352	-0.0311	0.2041	0.2352	-0.0108	0.2244
4	6	-0.1546	0.0312	-0.1234	-0.1546	0.0108	-0.1438
4	7	0.1432	-0.027	0.1162	0.1432	-0.0298	0.1134
4	8	0.1333	0.0073	0.1406	0.1333	0.0543	0.1876
4	9	-0.2052	0.0068	-0.1984	-0.2052	0.0218	-0.1834
4	10	-0.0931	-0.024	-0.1171	-0.0931	-0.0229	-0.1160
4	11	0.0799	-0.0209	0.0590	0.0799	0.0259	0.1058
4	12	-0.2194	-0.0513	-0.2707	-0.2194	-0.0081	-0.2275
4	13	0.3754	0	0.3754	0.3754	0	0.3754
4	14	0.1251	0	0.1251	0.1251	0	0.1251
4	15	0.1441	-0.0239	0.1202	0.1441	-0.0019	0.1422
4	16	0.4042	0	0.4042	0.4042	0	0.4042
4	17	0.0212	0	0.0212	0.0212	0	0.0212
4	18	-0.3300	0	-0.3300	-0.3300	0	-0.3300
4	19	0.1386	0	0.1386	0.1386	0	0.1386
4	20	0.0660	0	0.0660	0.0660	0	0.0660
4	21	-0.2129	-0.0222	-0.2351	-0.2129	-0.0019	-0.2148
4	22	0.2931	0	0.2931	0.2931	0	0.2931
4	23	0.2238	0	0.2238	0.2238	0	0.2238
4	24	0.2750	-0.0196	0.2554	0.2750	-0.0019	0.2731
4	25	-0.1237	-0.0239	-0.1476	-0.1237	-0.0019	-0.1256
4	26	-0.4182	-0.0239	-0.4421	-0.4182	0.0279	-0.3903
4	27	-0.2502	-0.002	-0.2522	-0.2502	0.0067	-0.2435
4	28	0.4247	-0.0084	0.4163	0.4247	0.0066	0.4313
4	29	-0.1236	-0.0195	-0.1431	-0.1236	-0.0018	-0.1254
4	30	0.0717	-0.0239	0.0478	0.0717	-0.0019	0.0698
4	31	-0.4535	-0.0239	-0.4774	-0.4535	-0.0019	-0.4554
4	32	0.2598	-0.0187	0.2411	0.2598	-0.0231	0.2367
4	33	0.1899	-0.002	0.1879	0.1899	0.0066	0.1965
4	34	0.4348	-0.0084	0.4264	0.4348	0.0066	0.4414
4	35	-0.4833	-0.0239	-0.5072	-0.4833	-0.0232	-0.5065
4	36	0.3410	-0.0239	0.3171	0.3410	-0.0019	0.3391
4	37	0.2510	-0.0196	0.2314	0.2510	-0.0019	0.2491
4	38	0.4631	-0.0059	0.4572	0.4631	-0.0019	0.4612
4	39	-0.1243	-0.0223	-0.1466	-0.1243	-0.0019	-0.1262
4	40	-0.0237	-0.0222	-0.0459	-0.0237	-0.0019	-0.0256
4	41	-0.3762	-0.0222	-0.3984	-0.3762	-0.0019	-0.3781
4	42	0.0651	-0.011	0.0541	0.0651	-0.0019	0.0632

TABLE 5 CONTINUED

Middle Node	IC Cue No.	Inexperienced Model Initial	Change	Trained	Experienced Model Initial	Change	Trained
4	43	-0.1187	-0.0035	-0.1222	-0.1187	0.0012	-0.1175
4	44	-0.4117	0	-0.4117	-0.4117	-0.0149	-0.4266
4	45	-0.4248	0.0054	-0.4194	-0.4248	-0.0571	-0.4819
4	46	-0.0043	0.0131	0.0088	-0.0043	0.0041	-0.0002
4	47	0.3977	-0.0005	0.3972	0.3977	-0.0031	0.3946
4	48	-0.0146	-0.0014	-0.0160	-0.0146	-0.0029	-0.0175
4	49	0.2154	0.0092	0.2246	0.2154	0.0093	0.2247
4	50	-0.4637	-0.0065	-0.4702	-0.4637	0	-0.4637
4	51	0.1368	-0.033	0.1038	0.1368	-0.017	0.1198
4	52	-0.4939	0	-0.4939	-0.4939	0.0212	-0.4727
4	53	-0.1987	0	-0.1987	-0.1987	0	-0.1987
4	54	-0.1546	0.0041	-0.1505	-0.1546	0	-0.1546
4	55	-0.0784	-0.0048	-0.0832	-0.0784	0	-0.0784
4	56	-0.4943	0.0065	-0.4878	-0.4943	-0.0309	-0.5252
4	57	0.2954	0.0041	0.2995	0.2954	0	0.2954
4	58	0.1980	0	0.1980	0.1980	0	0.1980
4	59	-0.1859	0	-0.1859	-0.1859	0	-0.1859
4	60	0.1526	0	0.1526	0.1526	0	0.1526
4	61	-0.2257	0	-0.2257	-0.2257	0	-0.2257
4	62	-0.1685	0	-0.1685	-0.1685	0	-0.1685
4	63	0.4530	0	0.4530	0.4530	0	0.4530
4	64	0.0043	0	0.0043	0.0043	0	0.0043
4	65	-0.2193	0.0052	-0.2141	-0.2193	0	-0.2193
4	66	-0.3807	0.0044	-0.3763	-0.3807	-0.0191	-0.3998
4	67	0.4434	0	0.4434	0.4434	0	0.4434
4	68	0.3320	0.0043	0.3363	0.3320	0	0.3320
4	69	0.2126	0	0.2126	0.2126	0	0.2126
4	70	0.2878	0	0.2878	0.2878	0	0.2878
4	71	0.1434	-0.0208	0.1226	0.1434	-0.017	0.1264
4	72	-0.3393	0	-0.3393	-0.3393	0	-0.3393
4	73	-0.1574	-0.0242	-0.1816	-0.1574	-0.0241	-0.1815
4	74	0.3979	0.004	0.4019	0.3979	0	0.3979
4	75	-0.3090	-0.0084	-0.3174	-0.3090	0	-0.3090
4	76	0.4967	0	0.4967	0.4967	0	0.4967
4	77	0.0634	0	0.0634	0.0634	0	0.0634
4	78	-0.1913	0	-0.1913	-0.1913	0	-0.1913
4	79	-0.3856	0	-0.3856	-0.3856	0	-0.3856
4	80	-0.2929	0	-0.2929	-0.2929	0	-0.2929
4	81	-0.0504	0	-0.0504	-0.0504	0	-0.0504
4	82	-0.1573	0	-0.1573	-0.1573	0	-0.1573
4	83	-0.1290	0	-0.1290	-0.1290	0	-0.1290
4	84	-0.4752	0	-0.4752	-0.4752	0	-0.4752
4	85	0.2335	-0.0051	0.2284	0.2335	0	0.2335
4	86	-0.1297	0.0048	-0.1249	-0.1297	-0.0095	-0.1392
4	87	-0.3431	0	-0.3431	-0.3431	0	-0.3431
4	88	-0.3568	-0.0046	-0.3614	-0.3568	-0.0001	-0.3569

TABLE 5 CONTINUED

Middle Node	IC Cue No.	Inexperienced Model Initial	Change	Trained	Experienced Model Initial	Change	Trained
4	89	0.2853	0.0004	0.2857	0.2853	-1.0001	0.2852
4	90	-0.4665	0.0004	-0.4661	-0.4665	0	-0.4665
4	91	-0.1677	0.0138	-0.1539	-0.1677	0	-0.1677
4	92	0.3727	0	0.3727	0.3727	0.0296	0.4023
4	93	-0.3058	0	-0.3058	-0.3058	0	-0.3058
4	94	0.3267	0.0046	0.3313	0.3267	0	0.3267
4	95	0.3054	0.0011	0.3065	0.3054	0	0.3054
4	96	0.3259	-0.0049	0.3210	0.3259	-0.0097	0.3162
4	97	-0.4583	0	-0.4583	-0.4583	0	-0.4583
4	98	-0.2462	0	-0.2462	-0.2462	0	-0.2462
4	99	0.2197	-0.005	0.2147	0.2197	0	0.2197
4	100	-0.3984	0.0004	-0.3980	-0.3984	-0.0002	-0.3986
4	101	-0.0375	0	-0.0375	-0.0375	0	-0.0375
4	102	-0.2195	0.0087	-0.2108	-0.2195	0	-0.2195
4	103	0.2870	-0.0005	0.2865	0.2870	-0.0232	0.2638
4	104	-0.0657	-0.0114	-0.0771	-0.0657	0.0046	-0.0611
4	105	0.0867	-0.0051	0.0816	0.0867	-0.014	0.0727
4	106	-0.2004	0	-0.2004	-0.2004	0	-0.2004
4	107	0.1112	0.0036	0.1148	0.1112	0	0.1112
5	0	-0.2192	0.0619	-0.1573	-0.2192	0.0751	-0.1441
5	1	-0.0442	0.1414	0.0972	-0.0442	-0.0841	-0.1283
5	2	-0.1704	-0.1414	-0.3118	-0.1704	0.084	-0.0864
5	3	-0.1542	0.1415	-0.0127	-0.1542	-0.084	-0.2382
5	4	-0.1905	0.0145	-0.1760	-0.1905	-0.0504	-0.2409
5	5	-0.4925	-0.0144	-0.5069	-0.4925	0.0505	-0.4420
5	6	0.1634	0.0145	0.1779	0.1634	-0.0504	0.1130
5	7	0.0295	0.0619	0.0914	0.0295	0.0751	0.1046
5	8	-0.2355	-0.0435	-0.2790	-0.2355	-0.168	-0.4035
5	9	0.2228	-0.0077	0.2151	0.2228	-0.021	0.2018
5	10	0.1880	0.1334	0.3214	0.1880	-0.1263	0.0617
5	11	-0.0577	-0.1843	-0.2420	-0.0577	-0.1914	-0.2491
5	12	0.1695	-0.3383	-0.1688	0.1695	-0.0652	0.1043
5	13	-0.4717	0	-0.4717	-0.4717	0	-0.4717
5	14	-0.4078	0	-0.4078	-0.4078	0	-0.4078
5	15	0.3286	-0.0612	0.2674	0.3286	-0.0581	0.2705
5	16	-0.1557	0	-0.1557	-0.1557	0	-0.1557
5	17	-0.4510	0	-0.4510	-0.4510	0	-0.4510
5	18	-0.3182	0	-0.3182	-0.3182	0	-0.3182
5	19	-0.1728	0	-0.1728	-0.1728	0	-0.1728
5	20	-0.3011	0	-0.3011	-0.3011	0	-0.3011
5	21	0.3035	-0.0142	0.2893	0.3035	-0.0582	0.2453
5	22	0.0214	0	0.0214	0.0214	0	0.0214
5	23	-0.0443	0	-0.0443	-0.0443	0	-0.0443
5	24	-0.2235	-0.068	-0.2915	-0.2235	-0.0581	-0.2816
5	25	-0.0630	-0.0611	-0.1241	-0.0630	-0.0581	-0.1211
5	26	0.1204	-0.0611	0.0593	0.1204	-0.1076	0.0128

TABLE 5 CONTINUED

Middle Node	IC Cue No.	Inexperienced Model Initial	Change	Trained	Experienced Model Initial	Change	Trained
5	27	-0.0093	0.0739	0.0646	-0.0093	-0.0471	-0.0564
5	28	0.0136	-0.0326	-0.0190	0.0136	-0.0472	-0.0336
5	29	0.0852	-0.068	0.0172	0.0852	-0.0581	0.0271
5	30	0.3834	-0.0612	0.3222	0.3834	-0.0581	0.3253
5	31	-0.4120	-0.0611	-0.4731	-0.4120	-0.0581	-0.4701
5	32	-0.3155	0.0847	-0.2308	-0.3155	0.0024	-0.3131
5	33	-0.0379	0.0738	0.0359	-0.0379	-0.0472	-0.0851
5	34	0.0425	-0.0326	0.0099	0.0425	-0.0472	-0.0047
5	35	0.4872	-0.0611	0.4261	0.4872	0.0024	0.4896
5	36	0.0013	-0.0611	-0.0598	0.0013	-0.0581	-0.0568
5	37	0.2668	-0.068	0.1988	0.2668	-0.0581	0.2087
5	38	0.2911	0.167	0.4581	0.2911	-0.0581	0.2330
5	39	0.1441	-0.0142	0.1299	0.1441	-0.0581	0.0860
5	40	-0.1639	-0.0141	-0.1780	-0.1639	-0.0581	-0.2220
5	41	-0.4975	-0.0142	-0.5117	-0.4975	-0.0581	-0.5556
5	42	0.3373	0.0213	0.3586	0.3373	-0.0581	0.2792
5	43	-0.3661	0.0106	-0.3555	-0.3661	-0.0505	-0.4166
5	44	0.0357	0	0.0357	0.0357	0.0282	0.0639
5	45	-0.1994	0.035	-0.1644	-0.1994	0.1575	-0.0419
5	46	-0.4036	0.0579	-0.3457	-0.4036	0.0063	-0.3973
5	47	-0.3291	-0.165	-0.4941	-0.3291	0.001	-0.3281
5	48	0.2959	-0.0636	0.2323	0.2959	0.0146	0.3105
5	49	-0.1547	0.0458	-0.1089	-0.1547	-0.0267	-0.1814
5	50	-0.2594	0.0673	-0.1921	-0.2594	0	-0.2594
5	51	0.0854	0.0182	0.1036	0.0854	-0.0522	0.0332
5	52	0.0663	0	0.0663	0.0663	-0.0604	0.0059
5	53	-0.0093	0	-0.0093	-0.0093	0	-0.0093
5	54	-0.1756	-0.0152	-0.1908	-0.1756	0	-0.1756
5	55	-0.3947	-0.1581	-0.5528	-0.3947	0	-0.3947
5	56	0.4523	0.0212	0.4735	0.4523	0.1019	0.5542
5	57	0.1662	-0.0152	0.1510	0.1662	0	0.1662
5	58	0.2058	0	0.2058	0.2058	0	0.2058
5	59	0.2827	0	0.2827	0.2827	0	0.2827
5	60	-0.4160	0	-0.4160	-0.4160	0	-0.4160
5	61	-0.3388	0	-0.3388	-0.3388	0	-0.3388
5	62	0.4809	0	0.4809	0.4809	0	0.4809
5	63	0.4113	0	0.4113	0.4113	0	0.4113
5	64	0.4207	0	0.4207	0.4207	0	0.4207
5	65	0.3859	0.1457	0.5316	0.3859	0	0.3859
5	66	0.1502	-0.0069	0.1433	0.1502	0.0748	0.2250
5	67	0.2776	0	0.2776	0.2776	0	0.2776
5	68	0.4600	-0.0069	0.4531	0.4600	0	0.4600
5	69	-0.3009	0	-0.3009	-0.3009	0	-0.3009
5	70	0.2371	0	0.2371	0.2371	0	0.2371
5	71	-0.4094	-0.2776	-0.6870	-0.4094	-0.0522	-0.4616
5	72	0.3196	0	0.3196	0.3196	0	0.3196

TABLE 5 CONTINUED

Middle Node	IC Cue No.	Inexperienced Model Initial	Change	Trained	Experienced Model Initial	Change	Trained
5	73	0.3996	-0.0204	0.3792	0.3996	-0.0249	0.3747
5	74	-0.4244	0.1202	-0.3042	-0.4244	0	-0.4244
5	75	-0.0682	-0.1403	-0.2085	-0.0682	0	-0.0682
5	76	-0.3388	0	-0.3388	-0.3388	0	-0.3388
5	77	-0.0279	0	-0.0279	-0.0279	0	-0.0279
5	78	-0.0126	0	-0.0126	-0.0126	0	-0.0126
5	79	0.0709	0	0.0709	0.0709	0	0.0709
5	80	0.4243	0	0.4243	0.4243	0	0.4243
5	81	-0.3167	0	-0.3167	-0.3167	0	-0.3167
5	82	0.0652	0	0.0652	0.0652	0	0.0652
5	83	0.4911	0	0.4911	0.4911	0	0.4911
5	84	-0.1599	0	-0.1599	-0.1599	0	-0.1599
5	85	-0.3783	-0.087	-0.4653	-0.3783	0	-0.3783
5	86	-0.2165	0.1676	-0.0489	-0.2165	0.0197	-0.1968
5	87	-0.0338	0	-0.0338	-0.0338	0	-0.0338
5	88	0.1931	-0.0402	0.1529	0.1931	-0.0136	0.1795
5	89	0.2738	-0.0189	0.2549	0.2738	-0.0136	0.2602
5	90	-0.3463	-0.0189	-0.3652	-0.3463	0	-0.3463
5	91	-0.4652	0.1053	-0.3599	-0.4652	0	-0.4652
5	92	-0.2006	0	-0.2006	-0.2006	-0.0632	-0.2638
5	93	-0.2685	0	-0.2685	-0.2685	0	-0.2685
5	94	-0.3573	0.0595	-0.2978	-0.3573	0	-0.3573
5	95	-0.2856	-0.0765	-0.3621	-0.2856	0	-0.2856
5	96	0.1704	-0.0214	0.1490	0.1704	0.0415	0.2119
5	97	0.1243	0	0.1243	0.1243	0	0.1243
5	98	-0.4256	0	-0.4256	-0.4256	0	-0.4256
5	99	0.2997	-0.0213	0.2784	0.2997	0	0.2997
5	100	-0.1684	-0.0189	-0.1873	-0.1684	-0.0136	-0.1820
5	101	0.3694	0	0.3694	0.3694	0	0.3694
5	102	0.2317	0.0648	0.2965	0.2317	0	0.2317
5	103	-0.4114	-0.001	-0.4124	-0.4114	0.0024	-0.4090
5	104	-0.2365	-0.022	-0.2585	-0.2365	-0.0594	-0.2959
5	105	-0.1654	-0.2308	-0.3962	-0.1654	0.0216	-0.1438
5	106	-0.1205	0	-0.1205	-0.1205	0	-0.1205
5	107	0.3795	-0.166	0.2135	0.3795	0	0.3795

TABLE 6

INEXPERIENCED SENIOR AND MODEL CONTROL RISK ASSESSMENTS

Train or Test Set	Subject Number	Category Decision Auditor	Model	Error	Point Estimate (0 to 100%) Auditor	Model	Error
TRAIN	I1	SBM	SBM	0	0.4000	0.4206	0.0206
TRAIN	I4	MOD	MOD	0	0.5300	0.5183	0.0117
TRAIN	I6	SBM	SBM	0	0.3000	0.2939	-0.0061
TRAIN	I8	SBM	SBM	0	0.3000	0.3219	0.0219
TRAIN	I10	MOD	MOD	0	0.6000	0.6175	0.0175
TRAIN	I12	SBM	SBM	0	0.3500	0.3480	-0.0020
TRAIN	I14	MOD	MOD	0	0.5100	0.5164	0.0064
TRAIN	I16	SBM	SBM	0	0.3200	0.3541	0.0341
TRAIN	I18	SBM	SBM	0	0.4700	0.4703	0.0003
TRAIN	I20	MOD	MOD	0	0.5500	0.5145	-0.0355
TRAIN	I23	MAX	MAX	0	0.2000	0.2414	0.0414
TRAIN	I33	SBM	SBM	0	0.4800	0.4769	-0.0031
TRAIN	I38	SBM	SBM	0	0.2800	0.3393	0.0593
TRAIN	I41	LTD	MOD	-0.0309	0.8000	0.7191	-0.0809
TRAIN	I43	SBM	SBM	0	0.3600	0.3608	0.0008
TRAIN	I45	MOD	MOD	0	0.6200	0.5416	-0.0784
TRAIN	I47	MAX	MAX	0	0.2400	0.2172	-0.0228
TRAIN	I50	SBM	SBM	0	0.3500	0.3637	0.0137
TRAIN	I52	MOD	MOD	0	0.6300	0.6316	0.0016
TEST	I2	SBM	SBM	0	0.3900	0.4385	0.0485
TEST	I5	SBM	SBM	0	0.3900	0.3399	-0.0501
TEST	I7	LTD	MOD	-0.1539	0.7500	0.5961	-0.1539
TEST	I9	MOD	MOD	0	0.5000	0.6328	0.1328
TEST	I11	MOD	MOD	0	0.5300	0.5896	0.0596
TEST	I13	MOD	SBM	-0.0862	0.5200	0.4138	-0.1062
TEST	I15	MOD	SBM	-0.1064	0.5500	0.3936	-0.1564
TEST	I17	SBM	SBM	0	0.3500	0.4006	0.0506
TEST	I19	SBM	MOD	0.0170	0.4700	0.5170	0.0470
TEST	I21	SBM	SBM	0	0.4000	0.4429	0.0429
TEST	I32	SBM	SBM	0	0.4000	0.4639	0.0639
TEST	I36	SBM	SBM	0	0.2600	0.2681	0.0081
TEST	I39	SBM	MAX	-0.0677	0.3000	0.1823	-0.1177
TEST	I42	SBM	MOD	0.1151	0.4700	0.6151	0.1451
TEST	I44	SBM	MOD	0.1039	0.3800	0.6039	0.2239
TEST	I46	MOD	SBM	-0.0677	0.5500	0.4323	-0.1177
TEST	I49	SBM	SBM	0	0.3800	0.3663	-0.0137
TEST	I51	SBM	SBM	0	0.3000	0.4226	0.1226
Train average				-0.0016	0.4363	0.4351	-0.0012
Train standard deviation				0.0069	0.1542	0.1335	0.0344
Test average				-0.0137	0.4383	0.4511	0.0127
Test standard deviation				0.0635	0.1143	0.1206	0.1073
Total average				-0.0075	0.4373	0.4429	0.0056
Total standard deviation				0.0450	0.1363	0.1277	0.0791

Risk Category Intervals In Relation to 0 to 100% scale:			
Maximum (No Reliance)	0.0000	to	0.2500
Slightly Below Maximum (Low Reliance)	0.2501	to	0.5000
Moderate (Moderate Reliance)	0.5001	to	0.7500
Limited (High Reliance)	0.7501	to	1.0000

TABLE 7

EXPERIENCED SENIOR AND MODEL CONTROL RISK ASSESSMENTS

Train or Test Set	Subject Number	Category Decision Auditor	Model	Error	Point Estimate (0 to 100%) Auditor	Model	Error
Train	E1	LTD	MOD	-0.0314	0.8000	0.7186	-0.0814
Train	E3	SBM	SBM	0	0.3700	0.3187	-0.0513
Train	E5	SBM	SBM	0	0.4000	0.3776	-0.0224
Train	E6	MOD	MOD	0	0.5300	0.5874	0.0574
Train	E8	SBM	SBM	0	0.3000	0.3253	0.0253
Train	E9	SBM	SBM	0	0.4000	0.4385	0.0385
Train	E13	SBM	SBM	0	0.3500	0.3187	-0.0313
Train	E14	MOD	MOD	0	0.5200	0.5551	0.0351
Train	E16	SBM	SBM	0	0.3700	0.4273	0.0573
Train	E28	MOD	MOD	0	0.7200	0.6993	-0.0207
Train	E32	SBM	SBM	0	0.3000	0.4056	0.1056
Train	E33	SBM	SBM	0	0.4900	0.4847	-0.0053
Train	E35	SBM	SBM	0	0.4700	0.4237	-0.0463
Train	E36	MOD	SBM	-0.0124	0.5400	0.4876	-0.0524
Train	E38	SBM	SBM	0	0.3400	0.3620	0.0220
Train	E40	MAX	SBM	0.03691	0.2400	0.2869	0.0469
Train	E42	SBM	SBM	0	0.2700	0.2725	0.0025
Train	E43	SBM	SBM	0	0.3000	0.2881	-0.0119
Test	E4	SBM	SBM	0	0.2500	0.2975	0.0475
Test	E7	MOD	MOD	0	0.5200	0.7281	0.2081
Test	E12	SBM	SBM	0	0.3500	0.2566	-0.0934
Test	E15	SBM	SBM	0	0.4000	0.3519	-0.0481
Test	E29	MOD	MOD	0	0.5500	0.6601	0.1101
Test	E34	SBM	SBM	0	0.4800	0.4293	-0.0507
Test	E37	SBM	SBM	0	0.3000	0.3233	0.0233
Test	E41	MOD	SBM	-0.093	0.5300	0.4070	-0.1230
Test	E44	SBM	SBM	0	0.3500	0.3237	-0.0263
Train average				-0.0004	0.4283	0.4321	0.0038
Train standard deviation				0.0118	0.1476	0.1316	0.0470
Test average				-0.0103	0.4144	0.4197	0.0053
Test standard deviation				0.0279	0.1037	0.1528	0.0936
Total average				-0.0037	0.4237	0.4280	0.0043
Total standard deviation				0.0200	0.1346	0.1402	0.0686
Risk Category Intervals In Relation to 0 to 100% scale:							
Maximum (No Reliance)					0.0000	to	0.2500
Slightly Below Maximum (Low Reliance)					0.2501	to	0.5000
Moderate (Moderate Reliance)					0.5001	to	0.7500
Limited (High Reliance)					0.7501	to	1.0000

the point estimate CRAs. The computed differences provide the data for model validation tests.

The training sample, the test sample, and the total sample of each subject group were tested using paired difference t-tests and the Wilcoxon rank sum test[28] on how far the networks' CRA point estimates were from each auditor's point estimate CRAs and from each auditor's categorical CRAs.[29] A chi-square test was also performed that compared auditor's category decisions to the model's category decisions for the training set, test set, and training and total set. Table 8 presents the paired sample t-test results for the difference between the inexperienced seniors' and the "inexperienced" model's decisions. The average CRA point estimate differences (maximum possible of 1 or -1) for the training set (.0012), test set (-.0128), and total set (-.0056) shows that the network's decisions were similar to inexperienced seniors' decisions (t-test and sign rank test p-values were all greater than 0.5). The decision category difference (maximum of -.75 or .75) between the network model and the auditors for the training set (.0016), test set (.0137) and the total set (.0075) also shows a similarity between the auditors' and model's decisions (p-values greater than 0.3).

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[28]A nonparametric test is used due to the small sample sizes (below 20) for the test sets and the training sets.

[29]The category difference between the network's CRA category and each auditor's category was obtained by an "if-then" process. If the network's continuous value output was within the same risk category interval given by the auditor, then the difference was set to zero. If the network's output value was outside the auditor's risk category interval, then the difference was computed as the network's decision value minus the nearest interval endpoint of the auditor's risk category.

TABLE 8

INEXPERIENCED NETWORK VALIDATION SUMMARY

	TRAIN SET	TEST SET	TOTAL SET
NUMBER OF AUDITORS' DECISION RECORDS	19	18	37
CRA POINT ESTIMATE DIFFERENCE (model - auditor)			
Average	0.0012	-0.0128	-0.0056
T-test *p*	0.8832	0.6307	0.6748
Sign rank *p*	0.7938	0.6397	n/a
CRA CATEGORY DIFFERENCE (model - auditor)			
Average	0.0016	0.0137	0.0075
T-test *p*	0.3306	0.3876	0.3250
Sign rank *p*	1.0000	0.5469	n/a
CONTINGENCY TABLE ANALYSIS OF MODEL'S AND AUDITORS' CRAs	Model Auditor	Model Auditor	Model Auditor
Maximum	2 2	1 0	3 2
Slightly below maximum	10 10	11 12	21 22
Moderate	7 6	6 5	13 11
Limited	0 1	0 1	0 2
Chi-square *p*	0.783	0.545	0.496
Fisher's exact test *p*	1.000	1.000	0.708

The chi-square test indicates that association cannot be rejected for the training set (p = .78), test set (p = .55), nor total set (p = .49). However, the chi-square test may not be valid because 50% of the cells have expected counts less than five. Fisher's exact test was performed with the same conclusion of general association for all the observation sets. The network made only one category error (5% error) when tested against the training set and eight category errors (44% error) when tested with the test set. However, the test set errors were never more than one category different and when averaging the errors, the errors that are one category too high, nearly cancel out the errors that are one category too low. Since the goal was to develop a network that represents the relative importance of the cue dimension weights of a typical new senior auditor, the statistical tests based on averages are appropriate.

The same tests used to validate the inexperienced model were performed to validate the experienced model's CRAs in relation to the experienced seniors' CRAs. Table 9 summarizes experienced network validation results. The experienced network's decisions were similar to the experienced auditors' decisions as shown by the CRA point estimate differences, CRA category differences, and contingency table analysis of the experienced model's and experienced auditors' categorical CRAs (p-values all greater than 0.3). The experienced model made three category errors (17% error) on the training set and one category error (14% error) on the test set.

TABLE 9

EXPERIENCED NETWORK VALIDATION SUMMARY

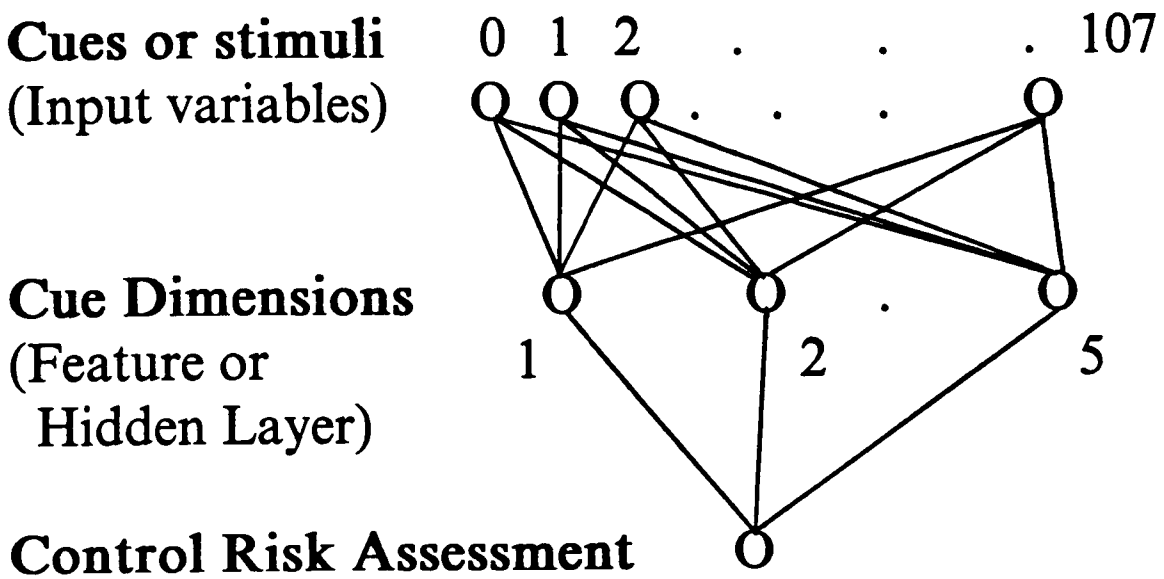
	TRAIN SET	TEST SET	TOTAL SET
NUMBER OF AUDITORS' DECISION RECORDS	18	9	27
CRA POINT ESTIMATE DIFFERENCE (model - auditor)			
Average	-0.0038	-0.0053	-0.0043
T-test *p*	0.7454	0.8833	0.7537
Sign rank *p*	0.7660	0.8203	n/a
CRA CATEGORY DIFFERENCE (model - auditor)			
Average	0.0004	0.0103	0.0037
T-test *p*	0.8943	0.3466	0.3536
Sign rank *p*	1.0000	1.0000	n/a
CONTINGENCY TABLE ANALYSIS OF MODEL'S AND AUDITORS' CRAs	Model Auditor	Model Auditor	Model Auditor
Maximum	0 1	0 0	0 1
Slightly below maximum	14 12	7 6	21 18
Moderate	4 4	2 3	6 7
Limited	0 1	0 0	0 1
Chi-square *p*	0.541	0.629	0.553
Fisher's exact test *p*	0.840	1.000	1.000

Implications of Validation Results

The validation results have important implications for using neural network models as an expert system for a CRA decision aid. The models were able to capture and represent auditors' CRA decision processes of relating relevant and irrelevant decision stimuli to the decision response. The results provide evidence that the neural network models have been able to acquire, represent, and store auditors' knowledge. In addition to accurately predicting the decision response of each auditor in the training set, the models were able to generalize to novel test cue sets. When the knowledge of the model that is stored as weights is combined with the input cue values, the result is a CRA that is representative of the auditors' decisions. The validation results provide evidence that the network weights are appropriate representations of attention to cue dimensions for the auditors in each group.

Measuring Model Weight Distribution Uniformity

To test differences in auditor attention to cue dimensions (H1), each neural network weight matrix of the cues (inputs) to the cue dimensions (network middle layer) was measured for distribution uniformity (dispersion or variation of the distribution). Figure 2 shows the structure of the neural networks and weight matrices that model the intermediate step of relating cues to cue dimensions that takes place as cues are evaluated to make decision responses. Consistent with research by MacLennan (1991), coefficient of



Weights from cues to cue dimensions form matrix **W**:

		Cues
		0 1 2 3 4 5 . . . 107
	1	
	2	
	3	
Dimensions	4	
	5	

FIGURE 2: NEURAL NETWORK STRUCTURE

variation[30] and entropy[31] were used to measure weight matrix distribution uniformity. These distribution measures can be interpreted in terms of auditors' approach to selecting cues. Entropy can also be interpreted as an assessment of the two groups' relative level of information content exhibited by the cue sets used by auditors in each group to make their decisions. The weight matrix with higher coefficient of variation and lower entropy represents the group with a more selective attention to cues. Lower entropy also represents higher information content exhibited by the set of cue dimension weights used by a typical auditor in each group to select cues for making a preliminary CRA. The models provide a way of capturing and measuring auditor knowledge structure differences as predicted by hypothesis one.

HYPOTHESES TWO THROUGH FOUR: NUMBER OF CUES, DECISION TIME, DECISION ACCURACY

T-tests were used to test for differences in central tendency between the two groups for number of cues chosen (H2), decision time (H3), and decision response accuracy (H4).

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[30]Coefficient of variation is a measure of relative variability defined as the ratio of the standard deviation to the mean expressed as a percentage.

[31]Entropy is viewed as a quantitative measure of the information content of an information system (Shannon 1948). In physics, entropy can be interpreted as a measure of the order of a system; high entropy values correspond to chaos; low entropy values to order (Toda, Kubo and Saito 1983). Entropy is computed as follows:

$$\sum_{i=1}^{N} w_i(\ln\frac{1}{w_i}),\ where \sum_{i=1}^{N} w_i=1$$

In this study, when entropy is low, the weights are distributed unevenly. Unequal weights support a top-down (classification) approach to the decision and a more precise knowledge structure.

Decision time and number of cues chosen were taken directly from the experimental case material and INFOCUS key control report that identifies which controls the auditor plans to rely on and test for compliance. An auditor's decision error was calculated by measuring how far the auditor's CRA point estimate was from the closest border of the correct risk category. Since the firm's solution was a CRA of moderate, if the auditor's CRA point estimate was between 25 and 50, decision error was zero. Levene's test for unequal variances[32] was also used to distinguish between the two groups for hypotheses two, three and four. Levene's test (Levene, 1960) serves as a measure of consensus exhibited by the two groups.

[32]Levene's test is a t-test on the mean variance of each group where the variance is the squared difference between each observation value and the mean of the observation values in the group.

CHAPTER 4

RESULTS

This chapter presents and explains the statistical results for the four hypotheses. The results of these hypotheses are based on the assumption that the experienced senior group has more preliminary CRA experience than the new senior group, and that possible confounding variables (type of experience, confidence and beliefs, and experimental instrument factors) to amount of preliminary CRA experience have been controlled for by the experiment. The demographic analysis results support both these assumptions. In addition to the demographic assumptions, hypothesis one is based on the assumption that each model has developed an appropriate set of weights to accurately predict the preliminary CRAs of auditors in the inexperienced senior group and experienced senior group, respectively. Validation results in Chapter 3 support this assumption.

HYPOTHESIS ONE: AUDITOR ATTENTION TO CUE DIMENSIONS

The neural network weights connecting the cues (IC variables) to the cue dimensions represent the selective attention to cue dimensions exhibited by the typical auditor in each group. The cue dimension weights of each model were measured for distribution uniformity using entropy and the coefficient of variation. Lower entropy and higher coefficient of variation mean less uniform distribution (more variation) of the cue dimension weights. More variation in the distribution of weights is consistent with a more top-down decision

approach that more properly disregards irrelevant decision variables and attends to selected cues to the level anticipated to provide the overall highest information content for making a CRA. Table 10 reports the statistical measurements of the distribution uniformity of the weights connecting the cues to the cue dimensions.

Since the first step in training a neural network is to randomize the weights, column 1 in Table 10 shows that the inexperienced network and the experienced network were started from the same point in the decision space. Each network was trained until it reached a root mean square error of .01. Columns 2 through 4 represent this level of training. The values in columns 2 through 4 differ because each column reports a different way of handling weights that did not change during the network training process. The occurrence of no weight change on a particular connection between an input layer node and a middle layer node indicates that no training set auditor used the particular cue variable in the CRA decision process. In other words, the variable was irrelevant to their CRA decision.

The values in column 2 are inappropriate for measuring the relative importance of the cues in relation to the cue dimensions because the irrelevant potential cues have the initialized random weight value even after training. This column is important, however, because it does show that when compared to column 1, entropy decreased and the coefficient of variation increased. Both networks exhibited decreased distribution uniformity and increased level of information content. This finding is consistent with the fact that as training occurred, the networks were able to improve prediction of the auditors' CRA decisions.

TABLE 10

SUMMARY OF HYPOTHESIS ONE: ATTENTION TO CUE DIMENSIONS

	INITIAL WEIGHTS (1)	TRAINED WEIGHTS (2)	TRAINED WEIGHTS (Irrelevant weights coded as zero) (3)	TRAINED WEIGHTS (Irrelevant weights deleted) (4)
NO. OF WEIGHTS IN DISTRIBUTION				
Inexperienced	540	540	540	345
Experienced	540	540	540	280
ENTROPY				
Inexperienced	6.1037	6.0814	5.6281	5.6281
Experienced	6.1037	6.0990	5.4269	5.4269
COEFFICIENT OF VARIATION				
Inexperienced	57.22	62.09	109.40	63.50
Experienced	57.22	58.39	128.90	61.63

Columns 3 and 4 represent two different viewpoints concerning how unchanged weights should be measured. Column 3 assumes that both relevant and irrelevant stimuli are meaningful for measuring auditors' attention to cue dimensions as represented by weight distribution uniformity. Weights attached to irrelevant stimuli are coded with a zero weight to represent attention to potential cues that have no significance to the auditors' preliminary CRA decisions for this case. Column 4 assumes that only relevant potential cues are meaningful for measuring auditors' attention to cue dimensions as represented by weight distribution uniformity. Column 4 presents the value of entropy and coefficient of variation when the zero weights are not included at all in the weight distribution. The value for entropy does not change in the last two columns because the zeros do not affect the amount of content information in a system. Coefficient of variation is different for columns 3 and 4 because elimination of zero weights and the reduction in number of weights in the distribution change the mean and the standard deviation--the two components of the coefficient of variation.

The results in column 3 indicate that for all the potential cues, both relevant and irrelevant, experienced seniors exhibited a more uneven distribution of weights (more selective attention) than the inexperienced seniors as measured by lower entropy (5.4269 to 5.6281)[33] and higher coefficient of variation (128.9 to 109.4).[34] These results are consistent

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[33]The possible range of entropy assuming 540 cue dimension weights (the number possible in the this experiment) is zero (maximum information content) to 6.29156 (lowest information content). Zero entropy is obtained when all but one cue dimension weight value approaches zero. The 6.29156 value for entropy is obtained when all the 540 cue dimension weights are equal. The large number of weight values makes a small difference in entropy meaningful for comparing two systems or models.

with hypothesis one.[35] The more uneven distribution of weights exhibited by the experienced seniors is consistent with a more top-down approach to selecting cues for making CRAs than the more even distribution of weights exhibited by the inexperienced seniors. In addition, the set of cue weights used by a typical experienced senior has more information content than the set of cue weights used by a typical inexperienced senior.

Since column 4 is a measure of the distribution of only relevant weights, the values for coefficient of variation suggest that the weight distribution of just relevant weights is not much different for the two groups. Taking this finding to the next logical step indicates that more uneven attention to cue dimensions would be consistent with using fewer relevant decision cues from a set of potential cues.

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[34]The possible range for coefficient of variation assuming 540 cue dimension weights (the number possible in this experiment) is 2321 (least uniform distribution) to zero (most even distribution). The 2321 coefficient of variation value is obtained when all but one weight value approaches zero. The coefficient of variation value of zero is obtained when all the 540 cue dimension weights are equal.

[35]Two extra inexperienced and two extra experienced networks were developed using the same training data and criteria as the original models except that two additional randomized weight sets were used. Entropy and coefficient of variation values corresponding to column 3 of Table 10 are as follows:

	Original	Extra 1	Extra 2
Entropy			
Inexperienced	5.6281	5.6151	5.6133
Experienced	5.4269	5.4195	5.4231
Coefficient of Variation			
Inexperienced	109.40	111.12	110.35
Experienced	128.90	129.55	127.33

No matter how the inexperienced and experienced models are paired for comparison, H1 is supported.

HYPOTHESIS TWO: NUMBER OF CUES

Hypothesis two directly tests whether a typical experienced senior would use fewer cues than a typical inexperienced senior. The results of the tests for this hypothesis are found in Table 11. The table shows that average number of variables used by the experienced senior group is significantly less than those used by the inexperienced group (16.2 to 10.5, $p = .010$). The breakdown of type of decision variables shows that the average number of revenue cycle environment variables was the same for both groups (3.9 to 3.9, $p = .42$), but that on average the experienced group used fewer EDP variables (3.4 to 7.4, $p = .026$) and internal controls (3.2 to 4.9, $p = .023$) than did the inexperienced group.

The finding that experienced seniors used fewer cues is consistent with the results found for hypothesis one. Use of fewer cues suggests that experience helps auditors select the cues which they believe will provide the most information for making their CRA. Levene's test for unequal variances compares the consensus of number of cues used by the auditors in each group. The experienced group had slightly more consensus for the total number of decision cues used (one-tail $p = .104$). Although the mean number of cycle environmental cues was the same for both groups (3.9), the inexperienced group exhibited more consensus (one tail $p = .091$). Consensus for number of relevant EDP variables favored the experienced group (one tail $p = .003$) while there seems to be no statistical difference between the two groups' consensus on number of relevant accounting controls (one-tail $p = .35$).

TABLE 11

SUMMARY OF HYPOTHESIS TWO: NUMBER OF CUES

	TOTAL	REVENUE CYCLE ENVIRONMENT	EDP	ACCOUNTING CONTROLS
NO. OF POTENTIALLY RELEVANT DECISION CUES	91	5	21	65
AVERAGE NO. CUES SELECTED				
Inexperienced N=37	16.2703	3.9729	7.4324	4.8649
Experienced N=27	10.5556	3.9259	3.4074	3.2222
T-test one-tail *p*	0.0101	0.4233	0.0261	0.0228
STANDARD DEVIATION				
Inexperienced	9.7258	0.8971	8.8554	3.3263
Experienced	9.2334	0.9971	7.3655	2.9656
Levene's test for unequal variances one-tail *p*	0.1038	0.0906	0.0029	0.3482

Table 12 presents the percentage of auditors in each group that marked IC variables (potential cues) as relevant to the preliminary CRA for this case. Although analyzing the usage of individual data variables is outside the scope of this study, the percentages of use by each group indicates which variables auditors in each group believed were most relevant to the preliminary CRA for this case. Both groups exhibited high usage percentages on IC environmental variables, while the inexperienced seniors' usage percentages of EDP environment and controls were higher than experienced seniors' usage percentages (approximately 30 to 40% versus 11 to 19%). The inexperienced seniors' cue usage percentages were not much different than the experienced seniors' cue usage percentages for each of the accounting controls (variables 43 - 107). However, for this study the most significant finding from accounting controls percentage usage is that of the 65 potential controls for the revenue cycle, 41 were listed as relevant by at least one inexperienced auditor, while only 24 were listed as relevant by at least one experienced auditor. This finding suggests that inexperienced seniors' selection of individual cues was more sporadic than experienced seniors' cue selections which is consistent with the finding that the experienced model weights exhibited more information content than the inexperienced model. The findings that experienced seniors used fewer cues and had greater consensus for the total cue count suggests that the experienced senior group had more similarity in their approach to making their decisions. In addition, a decision approach that is more concise in terms of number of variables used should lead to more efficient decision making. Hypothesis three tests decision efficiency.

TABLE 12

GROUP CUE USAGE PERCENTAGES

Variable Number and Description (Item numbers tie the variables {potential cues} to the neural network node)	Percentage of Group that Marked Potential Cue as Relevant to the CRA for this Case	
	Inexperienced (N=37)	Experienced (N=27)
Revenue Cycle Environment Variables		
Volume of transactions 1. High, 2. Medium, 3. Low	86%	59%
Dollar value of transactions 4. High, 5. Medium, 6. Low	86%	63%
7. Whether part of the cycle is automated	100%	100%
8. Whether management override is a concern	73%	81%
9. Whether client has an internal audit staff that works to prevent or detect material misstatements in the financial statements	51%	89%
Planned Reliance on Type of Controls		
10. Whether reliance is planned on manual controls	INFOCUS requires a yes or no decision on each of these items.	
11. Whether reliance is planned on programmed controls		
12. Whether reliance is planned on segregation of duties		

TABLE 12 CONTINUED

Variable Number and Description (Item numbers tie the variables {potential cues} to the neural network node)		Percentage of Group that Marked Potential Cue as Relevant to the CRA for this Case	
		Inexperienced (N=37)	Experienced (N=27)
EDP Control Objectives			
13.	Is computer system physical security adequate?	Based on the answers to the questions on the Computer Processing Overview (workpaper 94107.01 in Appendix A-3), these control objectives are not relevant to this case and INFOCUS did not generate EDP control questions on the General Controls Questionnaire (workpaper 94111s).	
14.	Is separation of EDP duties adequate?		
15.	Is access control over programs and data files adequate?	43%	19%
16.	Is control over PC-based applications adequate?	Based on the answers to the questions on the Computer Processing Overview (workpaper 94107.01 in Appendix A-3), these control objectives are not relevant to this case and INFOCUS did not generate EDP control questions on the General Controls Questionnaire (workpaper 94111s).	
17.	Is access control over source code adequate?		
18.	Is control over real-time updates to files adequate?		
19.	Is control over distributed processing applications adequate?		
20.	Is control over telecommunications and/or networks adequate?		
21.	Is control over computer generated transactions adequate?	38%	19%
22.	Is control of paperless audit trail adequate?	Based on the answers to the questions on the Computer Processing Overview (workpaper 94107.01 in Appendix A-3), these control objectives are not relevant to this case and INFOCUS did not generate EDP control questions on the General Controls Questionnaire (workpaper 94111s).	
23.	Is backup control adequate?		

TABLE 12 CONTINUED

Variable Number and Description (Item numbers tie the variables {potential cues} to the neural network node)		Percentage of Group that Marked Potential Cue as Relevant to the CRA for this Case	
		Inexperienced (N=37)	Experienced (N=27)
EDP Controls Questions Relating to Control Objective of Access Control over Programs			
24.	Are master lists of authorized personnel maintained, indicating restrictions on access?	38%	19%
25.	Are access and security features within the operating system utilized to restrict access to and amendment of files?	41%	19%
26.	Is terminal activity automatically monitored and rejected access attempts reported?	41%	19%
27.	Does the access control software identify each terminal via the logical address?	19%	11%
28.	Does the access control software identify each terminal via the physical address?	24%	11%
EDP Controls Questions Relating to Control Objective of Access Control over Data Files			
29.	Are master lists of authorized personnel maintained, indicating restriction on access?	38%	19%
30.	Are access and security features within the operating system utilized to restrict access to and amendment of data files?	43%	19%
31.	Is terminal activity automatically monitored and rejected access attempts reported?	43%	19%
32.	Is there encryption of all sensitive data files?	38%	15%

TABLE 12 CONTINUED

Variable Number and Description (Item numbers tie the variables {potential cues} to the neural network node)		Percentage of Group that Marked Potential Cue as Relevant to the CRA for this Case	
		Inexperienced (N=37)	Experienced (N=27)
33.	Does the access control software identify each terminal via the logical address?	24%	11%
34.	Does the access control software identify each terminal via the physical address?	27%	11%
35.	For database applications, is access to the data possible only through the DBMS?	38%	15%
36.	Is record of jobs actually run, and console logs, reviewed by supervisory personnel?	43%	15%
37.	Is the computer usage summary produced and reviewed?	32%	15%
EDP Control Questions Relating to Control Objective of Control over Computer Generated Transactions			
38.	Are the methods used in the program to generate the data nd related control record appropriate?	30%	19%
39.	Is there an adequate check over the accuracy of the data generated (e.g. reasonableness check, manual review of data generated, etc.)?	38%	19%
40.	Are the results of the check for accuracy reviewed and approved?	38%	19%
41.	Are controls such as computer sequence checks, computer matching or batch totals used to ensure the completeness of input and/or updates?	38%	19%
42.	Are exception reports investigated and reconciled?	35%	19%

TABLE 12 CONTINUED

Variable Number and Description (Item numbers tie the variables {potential cues} to the neural network node)	Percentage of Group that Marked Potential Cue as Relevant to the CRA for this Case	
	Inexperienced (N=37)	Experienced (N=27)
Potential Revenue Cycle Accounting Controls		
43. Balancing receivables subledger	24%	19%
44. Balancing run to run control totals	8%	11%
45. Balancing the G/L with the subledgers	43%	52%
46. Canceling original documents	11%	11%
47. Checking by computer for duplicate entries	11%	11%
48. Checking by computer the numerical sequence of a file	11%	7%
49. Checking for a third party signature	16%	7%
50. Checking manually the numerical sequence of a document, journal or report	22%	0%
51. Checking one-to-one	27%	26%
52. Comparing batch totals	0%	6%
53. Comparison of budgeted amounts to actual amounts	3%	0%
54. Comparison of cash receipts listing to deposit slips	8%	0%
55. Computer generation of transactions	3%	0%
56. Dual control over cash receipts	11%	11%
57. Electronic authorization	3%	0%
58. Independent review of edit reports for data file changes	3%	0%
59. Interactive dependency edit	0%	0%
60. Interactive document reconciliation	0%	0%
61. Interactive edit controls	0%	0%
62. Interactive existence edit	0%	0%
63. Interactive feedback edit	0%	0%
64. Interactive format edit	0%	0%
65. Interactive key verification	3%	0%
66. Interactive mathematical accuracy check	3%	7%

TABLE 12 CONTINUED

Variable Number and Description (Item numbers tie the variables {potential cues} to the neural network node)	Percentage of Group that Marked Potential Cue as Relevant to the CRA for this Case	
	Inexperienced (N=37)	Experienced (N=27)
67. Interactive prior data matching	0%	0%
68. Interactive reasonableness edit	3%	0%
69. Interactive range check edit	0%	0%
70. Interactive check digit	0%	0%
71. Matching to a previously validated document	46%	37%
72. Matching to a previously validated file	3%	0%
73. Matching to an authorized list	46%	26%
74. Monthly review of bank reconciliations	11%	0%
75. Monthly review of receivables	11%	0%
76. Non-interactive format edit	16%	7%
77. Non-interactive mathematical accuracy	0%	0%
78. Non-interactive edit controls	0%	0%
79. Non-interactive existence edit	0%	0%
80. Non-interactive dependency edit	0%	0%
81. Non-interactive range check edit	0%	0%
82. Non-interactive reasonableness edit	0%	0%
83. Non-interactive prior data matching	0%	0%
84. Non-interactive check digit	0%	0%
85. Performance of analytical procedures and investigation of unusual items	8%	0%
86. Periodic reconciliation of books to physical	11%	7%
87. Periodic revision of budgeted amounts based on updated information	0%	0%
88. Physical access controls	11%	7%
89. Physical safeguards	5%	7%
90. Reconciliation of manual totals to run totals	8%	0%
91. Reconciliation of master file balance to control account	14%	0%

TABLE 12 CONTINUED

Variable Number and Description (Item numbers tie the variables {potential cues} to the neural network node)	Percentage of Group that Marked Potential Cue as Relevant to the CRA for this Case	
	Inexperienced (N=37)	Experienced (N=27)
92. Reconciliation of master file balance to run totals	0%	7%
93. Reperformance	0%	0%
94. Restrictive endorsement of checks received	3%	0%
95. Reviewing adjustment transactions	11%	0%
96. Reviewing internal signatures	5%	7%
97. Reviewing permanent data file exception reports	0%	0%
98. Reviewing reference file data	0%	0%
99. Software access controls	3%	0%
100. Use of a lockbox	8%	7%
101. Use of prerecorded input (OCR,MICR,OMR)	0%	0%
102. Verifying mathematical accuracy	11%	7%
103. Other: Review & compare invoice adjusted for out of stock items with the packing slip.	19%	11%
104. Other: Driver gets signature on annotated sales invoice	24%	19%
105. Other: Cost of goods entry is calculated from sales invoices and calculations reviewed.	8%	4%
106. Other: Credit Check on invoice customer	3%	0%
107. Other: Compares amounts written off to aged trial balance and customer detail.	3%	0%

HYPOTHESIS THREE: DECISION TIME

The experienced seniors took an average of 56.22 minutes to make their CRA while the inexperienced group took an average of 64.46 minutes to complete the decision. The t-test results (one tail $p = .0025$) show that the inexperienced group took significantly more time than did the experienced group. Levene's test shows that there is no significant difference ($p = .52$) in the variation of the decision time for the two groups. The findings that experienced seniors take less time to make the control risk assessment supports the notion of more intuitive processing. Another explanation could be that since experienced seniors used fewer cues, they did not take the time to analyze what they judged as irrelevant control structure data.

The measures of decision processing have shown that consistent with a top-down approach, the experienced group selected cues using more selection attention, used fewer decision cues, and took less time to make the decision than the inexperienced group. Improved decision processing should lead to better decision accuracy.

HYPOTHESIS FOUR: DECISION ACCURACY

To test hypothesis four, decision accuracy was measured in terms of how far the auditors were from the firm's preliminary CRA of moderate.[36] The average auditor in the

[36]A preliminary CRA of moderate was supported by review from the firm's audit training personnel and was upheld by tests of controls in the live audit. The actual CRA was not for a first year client. For a case with no prior year workpapers, the auditors were counseled that a first-year CRA should be set no lower than slightly below maximum. In the experiment, once the auditors had made a CRA assuming a first-year client, each auditor was asked if they would make a different CRA for a second-year audit. This study used the auditors' second-year preliminary CRAs.

experienced group made a preliminary CRA of slightly below maximum and was 10 percentage points away from making a CRA of moderate. The average inexperienced senior also made a preliminary CRA of slightly below maximum and was 9 percentage points away from making a CRA of moderate. The t-test showed that decision accuracy was not statistically different between the two groups ($p = .71$). Levene's test showed that interauditor consensus within the experienced group was almost identical to the inexperienced group ($p = .99$). Although both groups were too conservative in making their CRA, the findings for hypothesis four should be discussed in the context of the planned level of compliance testing versus substantive testing. Decision accuracy results should also be discussed in relation to the decision processes used by the auditors in each group as indicated by results of the first three hypotheses.

The preliminary CRA dictates, subject to the results of IC testing, the decision as to how much the auditor plans to rely on internal controls and reduce substantive testing. If an auditor does not plan to rely on IC (CRA of maximum), substantive testing theoretically substitutes for the evaluation of IC structure and testing of controls that would be performed had the auditor relied more on internal controls. The preliminary CRA error found in this study does not necessarily mean that the auditors compromised audit effectiveness.

However, the trade-off of planning more tests of controls versus planning more substantive tests leads to an explanation of how the experienced seniors could exhibit more selective attention to cue dimensions, use fewer decision variables, and perform the decision

faster than the less experienced seniors, without coming closer to the "correct" CRA established by the firm. The experiment recorded whether each auditor planned to rely on manual controls, programmed controls, or segregation of duties. Experienced seniors tended to take a more substantive audit approach than did the inexperienced group. The percentages of auditors in each group who planned any reliance on manual controls, programmed controls, and segregation of duties are as follows:

Planned Reliance On	Inexperienced Group	Experienced Group
Segregation of Duties	89%	89%
Manual Controls	59%	41%
Programmed Controls	43%	19%

Although 89% of both groups planned to rely on segregation of duties, more inexperienced seniors planned to rely on any manual controls than did the experienced group (59% to 41%). Further, only 19% of the experienced seniors planned to rely on any programmed controls while 43% of the inexperienced seniors planned to rely on any programmed controls. The inexperienced seniors planned to rely more on tests of controls, but they did not make a lower preliminary CRA than did the experienced seniors. Given the audit approach of auditors in each group, the experienced seniors made a better preliminary CRA from the standpoint of audit efficiency and audit decision pedagogy.

SUMMARY OF RESULTS

In summary, two different measures, entropy and coefficient of variation, independently showed that the experienced seniors used more selective attention to choosing cues. This finding is consistent with a more top-down cue selection process. Entropy as a

measure of information content revealed that the cue sets chosen by the experienced auditors exhibited more information content in relation to their CRAs than did the cue sets of the inexperienced seniors. Experienced auditors also selected fewer cues and took less time to make their decisions. Both groups' average decision error was one control risk category too high (too conservative), but the inexperienced seniors' CRAs were less consistent with their planned compliance audit approach while the experienced seniors' decisions were more consistent with their planned substantive audit approach. The finding that the experienced seniors' decisions were more accurate than the inexperienced seniors in terms of audit planning pedagogy, is consistent with results from hypotheses one through three that measure cue selection and efficiency.

CHAPTER 5

CONTRIBUTIONS, LIMITATIONS AND RESEARCH IMPLICATIONS

This study makes three significant contributions to the auditing literature. The first contribution is the finding that experience changes auditors' abilities to select and use cues for making efficient, appropriate preliminary control risk assessments. The study found that experienced seniors exhibited more selective attention to choosing and weighting cues than did the inexperienced seniors. From an information theoretic perspective, the lower entropy value of cue dimension weights exhibited by the experienced seniors shows that they selectively attended to cue sets that provided more information content for their preliminary CRAs than the information content provided by the cue sets chosen by the inexperienced seniors for making their decisions. In other words, the lower entropy value means that the level of compatibility between auditors' decisions and their chosen cue sets was greater for the experienced seniors than for the inexperienced seniors. Experienced seniors also used fewer cues from the set of potential cues and used less decision time than did the inexperienced group. However, the experienced seniors' CRAs were not more accurate when compared to the firm's solution than were the inexperienced seniors. The study also found that the experienced seniors took a more substantive approach to the audit by relying less on manual and programmed controls than did the inexperienced group.

Together, the hypothesis tests and audit approach results support a conclusion that experience does influence auditors' CRA decision performance. The more uneven

distribution of attention to cue dimensions exhibited by the experienced seniors, their more parsimonious selection of cues and use of less decision time are consistent with a more top-down decision process. A more top-down approach suggests that experience leads to selecting cues more on situation features rather than considering all the potential cues regardless of the situation features. Although both groups were equally far from the firm's solution, the experienced group's CRAs were more consistent with their selection and use of relevant decision cues. The finding that the consistency between cue usage and decision response improves with experience is further supported by the fact that the experienced group planned to rely less on programmed and manual controls and made an appropriate CRA based on their level of reliance. The inexperienced group, on the other hand, planned to rely more on programmed and manual controls which is inappropriate to the average preliminary CRA recorded by the inexperienced seniors.

From an audit planning perspective, the results that experienced seniors did not plan to rely on manual and programmed controls as much as the inexperienced group suggests a possible uneasiness among the experienced seniors to perform and rely on tests of controls. Although the client is not a large entity, controls were in place to warrant reliance on programmed and manual controls. Results for reliance on manual controls indicate that experienced seniors were less willing to perform tests of controls (more willing to perform substantive tests) than inexperienced seniors.[37] Results for reliance on programmed

[37]This is in contrast to the results that the groups did not differ in their beliefs that an auditor should be willing to evaluate the internal control structure to decide whether the planned CRA can be reduced to some level below maximum risk.

controls suggest that the experienced seniors were less willing to "audit through the computer" than the inexperienced seniors. As even smaller clients exhibit more complex EDP environments, auditing around the computer becomes increasingly difficult and more risky.

The results of experience effects on preliminary CRAs suggest that both inexperienced and experienced seniors could improve their CRA decisions. In order for the inexperienced seniors to make their control risk assessment match the firm's solution, they need to use the information provided by their selected cue sets better. Although the experienced seniors' CRAs were more consistent with their cue sets than the inexperienced seniors' CRAs were with their chosen cue sets, the experienced seniors may need to consider planning to rely more on internal controls and less on testing account balances in order to make their CRA match the firm's prescribed solution. In either case, the auditors could use an expert system as a decision aid that would be a useful tool for training and for audit fieldwork.

The second contribution is that this study pioneers the development of a cognitive model that includes a more complete auditor decision process for making preliminary CRAs. The models developed in this study included a more complete CRA process by incorporating auditors' selection of cues, cue processing (weighting), and decision responses. This study overcomes the handicap of not being able to develop decision models to analyze decision accuracy in the context of cue selection and processing that are critical elements of expertise in domains that contain large sets of interrelated decision variables.

Neural network models approach knowledge acquisition inductively by providing a learning mechanism that can adapt to changing environments. Knowledge representation is also different from that of traditional knowledge based systems. Neural networks process and store information in a distributed and parallel fashion. This parallel distributed processing and the ability to adapt after each example is the main reason some cognitive scientists believe that neural networks provide closer approximations to human cognitive processes than traditional statistics or traditional knowledge based programs. The ability to acquire and represent finer features of human knowledge allows a neural network to simulate the accurate, intuitive and situational processing of human decision makers.

The third contribution is that this study demonstrates how neural network models can be developed for use as an expert system[38] for audit training and use in fieldwork. The validation results show that neural network models were able to acquire and represent the auditors' knowledge and accurately predict their preliminary CRAs. Although a neural network does not provide an "explanation" of its decision process like a traditional expert system does, Dreyfus and Dreyfus (1986) contend that traditional (rule consulting) expert systems are limited to the competence stage of skill acquisition. Neural network systems serve as an alternative or supplement to rule-consulting systems by performing beyond the competence stage of skill acquisition. Neural network systems have valuable potential as an

[38]In this study, the models acquire and represent auditor knowledge concerning preliminary review and evaluation of internal control systems. The models could then function as decision aids or expert systems, although an audit firm would really want a system based on the decisions of the best experts available for this task.

expert system to help auditors make critical audit judgments based on empirical results of many decision examples.

LIMITATIONS

Although the models were developed using actual subjects' decisions that are made in a complete decision making setting, the main limitation of this study is the inability to measure human knowledge structures directly. A neural network can only provide a representation of human knowledge structure, but it affords a way to model adaptive learning that takes place as auditors gain experience. Such models add to the understanding of differences in decision making at different levels of experience. The neural network models provide analyzable structures of auditor pattern classification processes that map cues (inputs) into features and then features into decision categories.

A limitation of the particular models used in this study is the inability to provide interpretation of the weights developed by the models. Such a research purpose was outside the scope of this study. The models in this study were specifically designed to measure distribution uniformity and information content of the cue dimension weights. This design does not provide interpretibility of specific cue weights. However, analysis of specific cue weights would be a fruitful next step for finding which selected cues improve or decrease decision accuracy. The ability to interpret specific cue weights would also provide a way to better explain the decisions made by the neural network model when used as a decision aid.

Generalizeability of the results to other client situations and auditors from other firms is the limitation related to measuring experience effects on decision making. However,

the case was chosen to partially overcome these limitations by presenting the auditor with a situation where IC structure is consistent with relying on manual controls, programmed controls, and segregation of duties, however, client size is compatible with a more substantive audit approach. Due to the nature of the case, the results are generalizable to smaller client situations where the computer environment may make tests of controls more efficient or where lack of such tests may compromise audit effectiveness. Planning and performing tests of controls is becoming more of an issue because auditing around the computer even for smaller clients may not lower detection risk enough to provide an acceptable level of audit risk due to innovations in computerized accounting information systems. Audit firms of all sizes perform these types of audit engagements.

RESEARCH IMPLICATIONS

Limited generalization does provide opportunities for further research concerning larger sized clients and auditors from more than one firm. Additional research in this area is worthwhile assuming additional auditor cue selection and CRAs can be obtained as exemplars for developing useful models.

This study only incorporated the preliminary CRA decisions of audit seniors. Studying the decisions made by audit managers, partners, and internal auditors may provide interesting results concerning the relationship of more general audit experience and different decision perspectives. For example, audit managers review CRAs of audit seniors, yet they do not go through the CRA decision process as often as seniors do.

The last limitation deals with the nature of the CRA used in this study. Since the CRA in this study is a categorical decision response, the hypothesis results are limited to classification problems.[39] However, Chandrasekaran (1987) suggests that classification is a generic cognitive task that is part of many decision tasks. Bruner, Goodnow and Austin (1956) suggest classification is used in nearly all tasks. The research approach and neural network based cognitive models may be useful for other auditor classification tasks such as materiality, analytical review, and total audit risk assessments for measuring the relationship between changes in selective attention and improved decision performance that results from auditor experience. The use of neural network based expert systems is also generalizable to other large, complex audit judgment tasks where decision exemplars can be obtained.

[39]Although the results concerning hypotheses are limited to categorical decisions, the neural network based models have the ability to handle categorical or continuous decision variables and responses and would not be limited to modeling only categorical decision tasks.

LIST OF REFERENCES

American Institute of Certified Public Accountants (AICPA) (1992). GENERALLY ACCEPTED AUDITING STANDARDS. New York: AICPA.

_____ (1988). STATEMENT ON AUDITING STANDARDS NO. 55: CONSIDERATION OF THE INTERNAL CONTROL STRUCTURE IN A FINANCIAL STATEMENT AUDIT. New York: AICPA.

_____ (1989). AUDIT GUIDE: CONSIDERATION OF THE INTERNAL CONTROL STRUCTURE IN A FINANCIAL STATEMENT AUDIT. New York: AICPA.

_____ (Revised 1991, First Issued 1981). RISK ASSESSMENT AND INTERNAL CONTROL. New York: AICPA.

Anderson, J. R. (1983). "A Spreading Activation Theory of Memory." JOURNAL OF VERBAL LEARNING AND VERBAL BEHAVIOR. June, 261-295.

Ashton, A. H. (1985). "Does Consensus Imply Accuracy in Accounting Studies of Decision Making?" THE ACCOUNTING REVIEW. April, 173-185.

_____ (1991). "Experience and Error Frequency Knowledge as Potential Determinants of Audit Expertise." THE ACCOUNTING REVIEW. April, 218-239.

Ashton, R. H. (1974). "An Experimental Study of Internal Control Judgments." JOURNAL OF ACCOUNTING RESEARCH. Spring, 143-157.

Ashton, R. H., and Brown, P. R. (1980). "Descriptive Modeling of Auditors' Internal Control Judgments: Replication and Extension." JOURNAL OF ACCOUNTING RESEARCH. Spring, 269-277.

Ashton, R. H. and Kramer, S. S. (1980). "Students as Surrogates in Behavioral Research: Some Evidence." JOURNAL OF ACCOUNTING RESEARCH. Spring, 1-15.

Bailey, A. D.; Duke, G. L.; Gerlach, J.; Ka, C.; Meservy, R. D.; and Whinston, A. B. (1985). "TICOM and the Analysis of Internal Controls." THE ACCOUNTING REVIEW. April, 186-201.

Bell, T. S.; Ribar, G. S.; and Verchio, J. R. (1990). "Neural Nets vs. Logistic Regression: A Comparison of Each Model's Ability to Predict Commercial Bank Failures." KPMG Peat Marwick Working Paper, May.

Biggs, S. F.; Messier, W. F., and Hansen, J. V. (1987). "A Descriptive Analysis of Computer Audit Specialists' Decision-Making Behavior in Advanced Computer Environments." AUDITING: A JOURNAL OF PRACTICE AND THEORY. Spring, 1-21.

Biggs, S. F. and Mock, T. J. (1983). "An Investigation of Auditor Decision Process in the Evaluation of Internal Controls and Audit Scope Decisions." JOURNAL OF ACCOUNTING RESEARCH. Spring, 234-245.

Bonner, S. E. (1990). "Experience Effects in Auditing: The Role of Task-Specific Knowledge." THE ACCOUNTING REVIEW. January, 72-92.

Borthick, A. F. and West, O. D. (1987). "Expert Systems--A New Tool for the Professional." ACCOUNTING HORIZONS. March, 9-16.

Bouwman, M. J. (1982). "The Use of Accounting information: Expert Versus Novice Behavior." In Ungson, Gerardo and Braunstein (Eds.) DECISION MAKING: AN INTERDISCIPLINARY INQUIRY. Boston: Kent Publishing Co.

Bruner, J.; Goodnow, J. and Austin, G. (1956). A STUDY OF THINKING. New York: Wiley.

Chandrasekaran, B. (1987). "Towards a Functional Architecture of Intelligence Based on Generic Information Processing Tasks." PROCEEDINGS OF THE TENTH INTERNATIONAL JOINT CONFERENCE ON ARTIFICIAL INTELLIGENCE. Milan, Italy, August, 23-38.

Choo, F., and Trotman, K. T. (1991). "The Relationship Between Knowledge Structure and Judgments for Experienced and Inexperienced Auditors." THE ACCOUNTING REVIEW. July, 464-485.

Dreyfus, H. L. and Dreyfus S. E. (1986). MIND OVER MACHINE: THE POWER OF HUMAN INTUITION AND EXPERTISE IN THE ERA OF THE COMPUTER. New York: Free Press.

Dutta, S. and Shekhar, S. (1989). "Bond Rating: A Non-Conservative Application of Neural Networks." Computer Science Division, University of California.

Einhorn, H. J. (1974). "Expert Judgment: Some Necessary Conditions and An Example." JOURNAL OF APPLIED PSYCHOLOGY. Vol. 59, 562-571.

_____ (1976). "A Synthesis: Accounting and Behavioral Science." JOURNAL OF ACCOUNTING RESEARCH. (Supplement) 196-206.

Felix, W. L., and Niles, M. S. (1988). "Research in Internal Control Evaluation." AUDITING: A JOURNAL OF PRACTICE AND THEORY. Spring, 43-60.

Frederick, D. M. (1991). "Auditors' Representation and Retrieval of Internal Control Knowledge." THE ACCOUNTING REVIEW. April, 240-58.

Frederick, D. and Libby, R. (1986). "Expertise and Auditor's Judgment of Conjunctive Events." JOURNAL OF ACCOUNTING RESEARCH. Autumn, 270-290.

Gaumnitz, B. R.; Nunamaker, T. R.; Surdick, J. J.; and Thomas, M. (1982). "Auditor Consensus in Internal Control Evaluation and Audit Program Planning. JOURNAL OF ACCOUNTING RESEARCH. Autumn, Part II, 745-755.

Hamilton, R. E. and Wright, W. F. (1982). "Internal Control Judgments and Effects of Experience: Replications and Extensions." JOURNAL OF ACCOUNTING RESEARCH. Autumn, Part II, 756-765.

Hansen, J. V. and Messier, W. F. (1986). "A Preliminary Test of EDP-EXPERT." Proceedings of the USC Symposium on Expert Systems and Audit Judgment.

Harper, R. M. (1988). "AHP Judgment Models of EDP Auditors' Evaluations of Internal Control for Local Area Networks." JOURNAL OF INFORMATION SYSTEMS. Fall, 67-86.

Haskins, M. E. (1987). "Client Control Environments: An Examination of Auditors' Perceptions." THE ACCOUNTING REVIEW. July, 542-563.

Hornick, K., Stinchcombe, and White, H. (1989) Multi-layer Feedforward Networks are Universal Approximators." NEURAL NETWORKS.

Johnson N. F. (1977). "A Pattern-Unit Model of Word Identification. In D. LaBerge & S. J. Samuels, BASIC PROCESSING IN READING: PERCEPTION AND COMPREHENSION. Hillsdale, NJ: Earlbaum, 91-125.

Johnson, P. E.; Duran, A. S.; Hassebrock, F.; Moller, J.; Prietula, M.; Feltovich, P. J. and Swanson, D. B. (1981). "Expertise and Error in Diagnostic Reasoning." COGNITIVE SCIENCE. Vol 5, 235-283.

Johnson P.E.; Johnson, M. G.; and Little, R. K. (1984). "Expertise in Trial Advocacy: some Considerations for Inquiry into Its Nature and Development." CAMPBELL LAW REVIEW. Fall, 119-143.

Krogstad, J. L.; Ettenson, R. T.; and Shanteau J. (1984). "Context and Experience in Auditors' Materiality Judgments." AUDITING: A JOURNAL OF PRACTICE AND THEORY. Vol. 4, 54-74.

Levene, H. (1960). "Robust Tests for the Equality of Variances." in CONTRIBUTIONS TO PROBABILITY AND STATISTICS. Ed. I. Olkin. Palo Alto, CA: Stanford University Press, 278-292.

Libby, R. (1985). "Availability and the Generation of Hypotheses in Analytical Review." JOURNAL OF ACCOUNTING RESEARCH. Autumn, 648-667.

Libby, R.; Artman, J. T.; and Willingham, J. J. (1985). "Process Susceptibility, Control Risk and Audit Planning." THE ACCOUNTING REVIEW. April, 212-230.

Lippman, R. (1987). "An Introduction to Computing with Neural Nets." IEEE ASSP MAGAZINE. April, 4-22.

Luce, R. (1963). "Detection and Recognition." In HANDBOOK OF MATHEMATICAL PSYCHOLOGY. New York: Wiley, 103-189.

MacLennan, B. J. (In Press). "Continuous Symbol Systems--The Logic of Connectionism." In Daniel S. Levine and Manuel Aparicio IV (eds.), NEURAL NETWORKS FOR KNOWLEDGE REPRESENTATION AND INFERENCE. Hillsdale, NJ: Lawrence Erlbaum.

_____ (1991). "Synthetic Ethology: An Approach to the Study of Communication." In D. Farmer, C. Langton, S. Rasmussen, and C. Taylor (eds.) ARTIFICIAL LIFE II, SFI STUDIES IN THE SCIENCES OF COMPLEXITY, Vol. XI. Addison Wesley.

Medin, D. and Schaffer, M. (1978). "Context Theory of Classification Learning." PSYCHOLOGICAL REVIEW. Vol. 85, 207-238.

Meservy, R. D.; Bailey, A. D.; and Johnson, P. E. (1986). "Internal Control Evaluation: A Computational Model of the Review Process." Working Paper, Carnegie Mellon.

Mock, T. J. and Turner, J. L. (1981). INTERNAL ACCOUNTING CONTROL EVALUATION AND AUDITOR JUDGMENT. New York: AICPA.

Moriarity, S. (1979). "Communicating Financial Information Through Multidimensional Graphics." JOURNAL OF ACCOUNTING RESEARCH. Spring, 205-224.

Munro, P. W. (1986). "State-Dependent Factors Influencing Neural Plasticity: A Partial Account of the Critical Period." In Rumelhart & McClelland's PARALLEL DISTRIBUTED PROCESSING, VOL 2. Cambridge, MA: The MIT Press.

Nichols, D. R. (1987). "A Model of Auditors' Preliminary Evaluations of Internal Control from Audit Data." THE ACCOUNTING REVIEW. January, 183-190.

Niles, M. (1987). "Auditors' Perceptions of Internal Control Characteristics." Working Paper, University of Arizona.

Nosofsky, R. (1984). "Choice, Similarity, and the Context Theory of Classification." JOURNAL OF EXPERIMENTAL PSYCHOLOGY: LEARNING MEMORY AND COGNITION. Vol 10, 104-114.

_____ (1986). "Attention, Similarity, and the Identification-Categorization Relationship." JOURNAL OF EXPERIMENTAL PSYCHOLOGY: GENERAL. Vol 115, 39-57.

_____ (1987). "Attention and Learning Processes in the Identification and Categorization of Integral Stimuli." JOURNAL OF EXPERIMENTAL PSYCHOLOGY: LEARNING, MEMORY AND COGNITION. Vol. 1, 87-108.

Odom, M. D. and Sharda, R. (1990). "A Neural Network Model For Bankruptcy Prediction." PROCEEDINGS OF THE INTERNATIONAL JOINT CONFERENCE ON NEURAL NETWORKS. Washington D. C.: INNS January, Vol II, 163-168.

Olson, J. and Rueter, H. (1987). "Extracting Expertise from Experts: Methods for Knowledge Acquisition." JOURNAL OF EXPERT SYSTEMS. August.

Reckers, P. M. and Taylor, M. E. (1979). "Consistency in Auditors' Evaluations of Internal Accounting Controls." JOURNAL OF ACCOUNTING, AUDITING AND FINANCE. Fall, 42-55.

Rumelhart, Hinton, and Williams (1986). "Learning Internal Representations by Error Propagation." In PARALLEL DISTRIBUTED PROCESSING. Vol. 1, Cambridge MA: The MIT Press. 318-362.

Rumelhart and McClelland (1986a). "PDP Models and General Issues in Cognitive Science." In PARALLEL DISTRIBUTED PROCESSING. Vol. 1, Cambridge MA: The MIT Press. 110-146.

_____ (1986b). "Learning the Past Tense." In PARALLEL DISTRIBUTED PROCESSING. Vol II. Cambridge, MA: The MIT Press. 216-271.

Shannon, C. E. (1948). "A Mathematical Theory of Communication," BELL SYSTEM TECHNICAL JOURNAL. Vol. 27, 379-623.

Shanteau, J. (1989). "Cognitive Heuristics and Biases in Behavioral Auditing: Review, Comments and Observations." ACCOUNTING ORGANIZATIONS AND SOCIETY. Vol. 14 165-177.

Shepard, R., Hovland, C. and Jenkins H. (1961). "Learning and Memorization of Classifications." PSYCHOLOGICAL MONOGRAPHS. Vol. 75 (13, Whole No. 517).

Simon, H. (1960). THE NEW SCIENCE OF MANAGEMENT. New York: Harper Row.

Slovic, P.; Rorer, L. G.; and Hoffman, P. J. (1971). "Analyzing Use of Diagnostic Signs." INVESTIGATIVE RADIOLOGY. January-February, 18-26.

Smolensky, P. (1988). "On the Proper Treatment of Connectionism." BEHAVIORAL AND BRAIN SCIENCES. II, 1-74.

Steinberg, R. M. and Johnson, R. N. (1991). "Implementing SAS No. 55 in a Computer Environment." JOURNAL OF ACCOUNTANCY. August, 60-68.

Tabor, R. H. (1983). "Internal Control Evaluations and Audit Program Revisions: Some Additional Evidence." JOURNAL OF ACCOUNTING RESEARCH. Spring, 348-354.

Toda, M. Kubo, R. and Saito, N. (1983). STATISTICAL PHYSICS. Springer-Verlag, Berlin.

Tubbs, R. M. (1992). "The Effect of Experience on the Auditor's Organization and Amount of Knowledge." THE ACCOUNTING REVIEW. October, 783-801.

Tversky, A. and Kahneman, O. (1974). "Judgment Under Uncertainty: Heuristics and Biases." SCIENCE. 185, 1124-1131.

Vaserhelyi, M. A. (1980). "A Taxonomization of Internal Controls and Errors for Audit Research." Auditing Symposium V, University of Kansas, Lawrence, Kansas, 40-58.

Walker, N. R. and Pierce, L. (1988). "The Price Waterhouse Audit: A State of the Art Approach." AUDITING: A JOURNAL OF PRACTICE AND THEORY. Fall, 1-21.

Weber, R. (1980). "Auditor Decision Making on Overall System Reliability: Accuracy, Consensus and the Usefulness of a Simulation Decision Aid." JOURNAL OF ACCOUNTING RESEARCH. Vol 18, 214-241.

Werbos, P. E. (1974). "Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences." Doctoral Dissertation, Applied Mathematics, Harvard University, November.

Widrow, G. and Hoff, M. (1960). "Adaptive Switching Circuits." IRE WESCON Convention Record, Part 4, August, 96-104.

Wright, W. F. (1988). "Audit Judgment Consensus and Experience." In K. R. Ferris (Ed.), BEHAVIORAL ACCOUNTING RESEARCH: A CRITICAL ANALYSIS. Columbus, Ohio: Century VII Publishing Company.

APPENDICES

APPENDIX A-1

DECISION VARIABLES

GENERAL CYCLE INFORMATION

In addition to having the general cycle information on the computer screen, the auditors marked on the task procedure worksheet whether they believed the information variable was relevant to making their planned control risk assessment. The possible data values, revenue cycle environment variables and planned reliance on type of controls are as follows:

Data Values

Yes (1)
No (-1)
Not Applicable or Not Relevant to CRA (0)

Revenue Cycle Environment Variables

1-3. Volume of transactions
   1. High 2. Medium 3. Low
4-6. Dollar value of transactions
   4. High 5. Medium 6. Low
7. Whether part of the cycle is automated
8. Whether management override is a concern
9. Whether client has an internal audit staff that works to prevent or detect material misstatements in the financial statements

Planned Reliance on Type of Controls

10. Whether reliance is planned on manual controls
11. Whether reliance is planned on programmed controls
12. Whether reliance is planned on segregation of duties

EDP ENVIRONMENT AND CONTROL OBJECTIVES

The Computer Processing Overview that documents the computer environment and the General EDP Controls Questionnaire (wp 94111) were already completed. The auditors reviewed the completed Computer Processing Overview, and marked on the overview workpaper the environmental features they believed were not relevant to making the CRA. If the auditors decided

to rely on programmed controls, they reviewed the EDP controls questionnaire, and marked which EDP control objectives were not relevant to the CRA. The general EDP control objectives listed on the controls questionnaire are neural network input variables. Since INFOCUS determines the controls listed on the questionnaire based on the computer processing overview questions, the EDP control objectives inherently include the computer environment. If the EDP environment questions are answered as no or listed as not relevant to the CRA, the input value for the corresponding EDP control objective will be zero (not applicable). The possible data values, computer processing overview questions, and EDP control objectives and variables are as follows:

Data Values

Yes (1)
No (-1)
Not Applicable or Not Relevant to CRA (0)

Computer Processing Overview Questions

Are the client's computers in a dedicated physical area or facility?
Is there a separate EDP department?
Can separate users access the system concurrently?
Is this application PC-based?
Does the client have the source code for the computer programs used in this accounting cycle?
Do multiple applications share the same databases (files)?
Are there real-time updates to files when transactions are entered?
Is the data processing function for this accounting cycle decentralized (Distributed processing)?
Are telecommunications or networks used in this accounting cycle?
Does the software in this accounting cycle generate transactions or pass information to other cycles?
Is there significant loss of visible audit trail in this accounting cycle?
Have there been any hardware or software malfunctions which resulted in a loss of data in this accounting cycle?

EDP Control Objectives

13. Is computer system physical security adequate?
14. Is separation of EDP duties adequate?
15. Is access control over programs and data files adequate?
16. Is control over PC-based applications adequate?
17. Is access control over source code adequate?

18. Is control over real-time updates to files adequate?
19. Is control over distributed processing applications adequate?
20. Is control over telecommunications and/or networks adequate?
21. Is control over computer generated transactions adequate?
22. Is control of paperless audit trail adequate?
23. Is backup control adequate?

EDP Controls Questions Relating to Control Objective of Access Control over Programs

24. Are master lists of authorized personnel maintained, indicating restrictions on access?
25. Are access and security features within the operating system utilized to restrict access to and amendment of files?
26. Is terminal activity automatically monitored and rejected access attempts reported?
27. Does the access control software identify each terminal via the logical address?
28. Does the access control software identify each terminal via the physical address?

EDP Controls Questions Relating to Control Objective of Access Control Data Files

29. Are master lists of authorized personnel maintained, indicating restriction on access?
30. Are access and security features within the operating system utilized to restrict access to and amendment of data files?
31. Is terminal activity automatically monitored and rejected access attempts reported?
32. Is there encryption of all sensitive data files?
33. Does the access control software identify each terminal via the logical address?
34. Does the access control software identify each terminal via the physical address?
35. For database applications, is access to the data possible only through the DBMS?
36. Is record of jobs actually run, and console logs, reviewed by supervisory personnel?
37. Is the computer usage summary produced and reviewed?

EDP Control Questions Relating to Control Objective of Control over Computer Generated Transactions

38. Are the methods used in the program to generate the data and related control record appropriate?
39. Is there an adequate check over the accuracy of the data generated (e.g. reasonableness check, manual review of data generated, etc.)?
40. Are the results of the check for accuracy reviewed and approved?
41. Are controls such as computer sequence checks, computer matching or batch totals used to ensure the completeness of input and/or updates?
42. Are exception reports investigated and reconciled?

ACCOUNTING PROCESS CONTROLS

The existing process descriptions and control descriptions were already documented for the auditors using INFOCUS. The control descriptions include the associated control objective(s), person performing the control, whether the control is preventive or detective, and whether the control is documented, not documented, or automatic (automated).

To record which controls the auditor believes are relevant to the control risk assessment, the auditors identified for each process or event in the revenue stream (1) what existing controls they believe are key controls, and (2) what controls they would classify as missing controls.

Existing Key Controls

Key controls are defined as those controls that will be used for relying on the control structure (assumes less than maximum risk). The auditors indicated key controls by going into the control description icon and designating which existing controls will be used as key controls. The program records which controls are selected as key controls.

Missing Controls

Each auditor reviewed the Missing Controls Report (wp 94104.01). This report identifies which control objectives are not satisfied for each particular process or event. However, if INFOCUS does not classify a control objective as missing, an auditor could still decide that an additional control is necessary to satisfy a particular control objective. The auditor was provided a workpaper (94105) that lists all potential controls and summarized which controls were being used by the client. Each auditor then marked on the workpaper what controls they believed were missing for each accounting process in the revenue stream. The auditors were also told that this workpaper would provide some of the information for the IC evaluation report to management.

The possible data values and accounting control variables are as follows:

Data Values

Key Control (1)
Missing Key Control (-1)
Not Applicable or Not Relevant to CRA (0)

Accounting Control Variables

43. Balancing receivables subledger
44. Balancing run to run control totals
45. Balancing the G/L with the subledgers
46. Canceling original documents
47. Checking by computer for duplicate entries
48. Checking by computer the numerical sequence of a file
49. Checking for a third party signature
50. Checking manually the numerical sequence of a document, journal or report
51. Checking one-to-one
52. Comparing batch totals
53. Comparison of budgeted amounts to actual amounts
54. Comparison of cash receipts listing to deposit slips
55. Computer generation of transactions
56. Dual control over cash receipts
57. Electronic authorization
58. Independent review of edit reports for data file changes
59. Interactive dependency edit
60. Interactive document reconciliation
61. Interactive edit controls
62. Interactive existence edit
63. Interactive feedback edit
64. Interactive format edit
65. Interactive key verification
66. Interactive mathematical accuracy check
67. Interactive prior data matching
68. Interactive reasonableness edit
69. Interactive range check edit
70. Interactive check digit
71. Matching to a previously validated document
72. Matching to a previously validated file
73. Matching to an authorized list
74. Monthly review of bank reconciliations
75. Monthly review of receivables
76. Non-interactive format edit
77. Non-interactive mathematical accuracy

78. Non-interactive edit controls
79. Non-interactive existence edit
80. Non-interactive dependency edit
81. Non-interactive range check edit
82. Non-interactive reasonableness edit
83. Non-interactive prior data matching
84. Non-interactive check digit
85. Performance of analytical procedures and investigation of unusual items
86. Periodic reconciliation of books to physical
87. Periodic revision of budgeted amounts based on updated information
88. Physical access controls
89. Physical safeguards
90. Reconciliation of manual totals to run totals
91. Reconciliation of master file balance to control account
92. Reconciliation of master file balance to run totals
93. Reperformance
94. Restrictive endorsement of checks received
95. Reviewing adjustment transactions
96. Reviewing internal signatures
97. Reviewing permanent data file exception reports
98. Reviewing reference file data
99. Software access controls
100. Use of a lockbox
101. Use of prerecorded input (OCR, MICR, OMR)
102. Verifying mathematical accuracy
103. Other: Review and compare invoice adjusted for out of stock items with the packing slip.
104. Other: Driver gets signature on annotated sales invoice.
105. Other: Cost of goods entry is calculated from sales invoices and calculations reviewed.
106. Other: Credit Check on invoice customer.
107. Other: Compares amounts written off to aged trial balance and customer detail.

INFOCUS' CONTROL OBJECTIVES

INFOCUS organizes the documentation of the control structure using three basic types of events which are documented using flowcharts. The objectives of the controls are related to the basic events as follows:

Boundary Events
- Boundary Objective (Event is valid, event is recorded)
- Authorization
- Integrity (automated data or file processing controls)

Intermediate Processing Steps

- Completeness
- Accuracy
- Authorization
- Integrity (programmed data or file processing controls)

General Ledger

- Reconcile and Review
- Budgetary
- Safeguard
- Other (Auditor Input)

Segregation of Duties

Violations are listed by the program based on a comparison of the employees who perform accounting processes as well as who performs the control function.

APPENDIX A-2

INSTRUCTIONS AND AUDIT TASK PROCEDURES

Participant No.

RICE LUMBER COMPANY

INSTRUCTIONS AND AUDIT TASK PROCEDURES

General Description of the Audit Task

As the in-charge on the job, you will make the planning stage control risk assessment associated with a financial statement assertion group consisting of completeness, existence/occurrence, and gross valuation for the general revenue (sales) processing stream within the client's revenue cycle. This is a first-year client in the merchandising business. No prior control risk assessments are available. The control structure of the revenue cycle is documented using INFOCUS.
In addition to this instruction and task procedures packet, you should have a floppy disk, revenue cycle internal control workpapers, and a questionnaire.

INFOCUS should already be loaded and ready for use. Please insert the floppy disk into drive A and do the following:

1. Using the mouse, move the pointer to **File**, click the left button once, and select **Client data path** by clicking the left button once.
2. Move the pointer to the **Drives** box and click on the selection arrow. Click the left button on the **A** drive symbol. Move the pointer to **OK** and click the left button.
3. Four files should appear on your screen. Move the pointer to the revenue folder for Rice.idb and select with a double click on the left button. (Do not select RiceM.idb, RiceP.idb nor RiceMP.idb at this time.)

After reading the general information about the client, complete the planned control risk assessment procedures that begin on the next page. The time budget for this task is one hour. Please work independently.

Rice Lumber Company General Information

Rice Lumber Co. is a lumber retailer with one location and has a total of 100 employees. The company is a nonpublic, closely held entity that is managed by Gary Rice, President & Chairman of the board, as well as two vice presidents and the treasurer. Gary Rice owns sixty percent of the company and understands the accounting aspects of the business. The treasurer, Larry Owens, heads up the accounting and data processing functions. He has been with Rice Lumber for five years. Top management has instituted control policies and procedures that are well documented. Even though there are no internal auditors, Gary Rice and Larry Owens review and test the policies and procedures to see that they are operating effectively.

RICE LUMBER COMPANY
PLANNED CONTROL RISK ASSESSMENT PROCEDURES
6-30-92

Record the time of day (hour:minutes) ___:_____ a.m. p.m.

1. Review of Internal Control Environment and Internal Control Structure For Making Control Risk Assessments for the Revenue Cycle

   Using INFOCUS interactively and/or printed output from INFOCUS that is contained in the revenue cycle internal control workpapers, gain a familiarity with the following client (filename Rice.idb) information:

   A. General characteristics of the client and the revenue cycle. Using the PROCESSING CYCLE INFO option within the CYCLE submenu, please answer the following questions:

      (1) Is the volume of transactions relevant to making a control risk assessment? **Yes___ No___**
      (2) Is the dollar value relevant to making a control risk assessment? **Yes___ No___**
      (3) Is automation or nonautomation of the accounting system relevant to making a control risk assessment? **Yes___ No___**
      (4) Is the question of management override relevant to making a control risk assessment? **Yes___ No___**
      (5) Is the existence or nonexistence of an independent internal audit staff (that evaluates effectiveness of controls for preventing or detecting financial statement misstatements) relevant to making a control risk assessment? **Yes___ No___**

   B. Computer processing environment. (workpaper {wp} 94107's) and the computer system hardware information (wp 94109.01). **As you review wp 94107.02 do the following:**

      Write NR next to the response for each question you believe is **not relevant** to making control risk assessments for financial statement assertions pertaining to the revenue cycle.

   C. The documentation of the Internal Control Structure of the Revenue Processing Stream. Review the information on the following worksheets and the general client information to make a decision on whether to rely on manual controls, programmed controls, and segregation of duties. **(Do only the Revenue Stream portion--sales order through G/L posting.)**

      (1) Flowcharts (wp 94100.01, 94101's)
          (Symbols within the Boxed off portion of the overview flowchart are the revenue stream processes.)
      (2) Process & Control Description (wp 94103's)
          (Items underlined in the Information Form column are the revenue stream processes.)
      (3) Missing Control Objectives Report (wp 94104's)
          (Items underlined in the Information Form column are the revenue stream processes.)
      (4) Incompatible Duties Report (Segregation of Duties) (wp 94106's)

D. Based on your review of client control environment and control structure, record below **and** in the processing cycle information screen your preliminary reliance decision.

__ No Reliance

__ Process Controls
- __ Manual Controls Only
- __ Programmed Controls Only
- __ Both Manual and Programmed Controls

__ Segregation of Duties

(1) Record any mitigating factors on the Incompatible Duties Report (wp 94106.01)
(2) Are the duties of accounting personnel appropriately segregated in relation to the size of the client? **Yes ____ No ____ Not Relevant to CRA ___**

E. **Record the time of day (hour:minutes) ___:_____ a.m. p.m.**

F. **Using the cycle menu, close the revenue cycle folder. Use the File, Save option to save the file.**

G. Based on your reliance decision in D above, choose and mark **ONE** of the following courses of action:

___ PLAN NOT TO RELY ON ANY PROCESSING CONTROLS NOR SEGREGATION OF DUTIES. The control risk assessment must be Maximum Risk. No testing of Controls will be done. Go to step 4.

___ PLAN TO RELY ONLY ON MANUAL PROCESSING CONTROLS WITH OR WITHOUT SEGREGATION OF DUTIES. Move the arrow to file RiceM.idb and open the revenue cycle folder. Enter the processing cycle information screen and **make sure the planned reliance decision for segregation of duties matches your decision in part D above.** Go to step 3.

___ PLAN TO RELY ONLY ON PROGRAMMED PROCESSING CONTROLS WITH OR WITHOUT SEGREGATION OF DUTIES. Move the arrow to file RiceP.idb and open the revenue cycle folder. Enter the processing cycle information screen and **make sure the planned reliance decision for segregation of duties matches your decision in part D above.** Go to step 2.

___ PLAN TO RELY ON BOTH MANUAL AND PROGRAMMED PROCESSING CONTROLS WITH OR WITHOUT SEGREGATION OF DUTIES. Move the arrow to file RiceMP.idb and open the revenue cycle folder. Enter the processing cycle information screen and **make sure the planned reliance decision for segregation of duties matches your decision in part D above.** Go to step 2.

___ PLAN TO RELY ONLY ON SEGREGATION OF DUTIES. Go to step 4.

2. Review of General Computer Controls Questionnaire (Do only if relying on programmed controls)

   To rely on programmed controls, the general controls questionnaire for computer processing has been completed. **As you review the questionnaire beginning on wp 94111.01, do the following:**

   A. The questionnaire documents whether the computer audit specialist believes each control objective has been satisfied or not. In the Reference/Comments column, write **NR** for each **EDP control objective** AND **EDP control** that you believe is **not relevant** to making control risk assessments for revenue cycle assertions.

   B. After reviewing general computer controls, decide whether you still plan to rely on programmed controls. Choose and mark **ONE** of the following courses of action.

      ___ PLAN NOT TO RELY ON PROCESSING CONTROLS NOR SEGREGATION OF DUTIES. The control risk assessment must be Maximum Risk. **Record no** planned reliance in the INFOCUS Processing Cycle Information screen. **Record the time of day (hour:minutes)** ___:____. **Go to step 4.**

      ___ STILL PLAN TO RELY ON PROGRAMMED CONTROLS OR BOTH PROGRAMMED AND MANUAL CONTROLS. **Record the time of day (hour:minutes)** ___:_____ **a.m. p.m. Go to step 3.**

      ___ PLAN TO RELY ON MANUAL CONTROLS AND NOT PROGRAMMED CONTROLS. Record planned reliance in the Processing Cycle Information screen. **Record the time of day (hour:minutes)** ___:_____ **a.m. p.m. Go to step 3.**

      ___ PLAN TO RELY ONLY ON SEGREGATION OF DUTIES. **Record planned** reliance in the Processing Cycle Information screen. **Record the time of day (hour:minutes)** ___:_____ **a.m. p.m. Go to step 4.**

3. Document Key Controls (Do only if relying on Manual or Programmed controls.)

   By recording the key controls, you document the controls that you will rely on for making a control risk assessment of slightly below maximum risk, moderate risk, or limited risk. Use INFOCUS to document the key controls for each process symbol in the revenue stream (within the box on wp 94100.01). **Using the computerized Overview Flowchart, do the following:**

   A. Activate the "key" tool by moving the pointer to the "key" symbol and click the left mouse button. Move the pointer to a process symbol in the revenue stream and click the left mouse button. The documented controls for the selected process will be listed.

   B. Decide which control or controls are to be used as key controls. Record the key controls by using the "make key" option. Record the key controls as key to the revenue stream.

   C. After recording the key controls, use the OK option to exit the process symbol. Repeat the above process for each process symbol in the revenue stream until key controls have been recorded for all the processes in the revenue stream.

   D. **Record the time of day (hour:minutes)** ___:_____ **a.m. p.m. Go to step 4.**

4. Identifying Missing and Redundant Accounting Controls

The missing controls report (wp 94104.01) provides a list of missing control objectives. However, if INFOCUS does not classify a control objective as missing, you may decide that an additional control is necessary to satisfy a particular control objective. (Items underlined in the Information Form column are the results of a revenue stream process.)

A. A list of potential controls is provided in the 94105's workpapers. The INFOCUS MANUAL or online INFOCUS Help provide descriptions of all these controls. To document the missing controls for making your control risk assessment and for use in preparing the management report, go to wp 94105.01 and follow the instructions.

B. **After completing the 94105's workpapers, record the time of day (hour:minutes) ___:_____ a.m. p.m.**

C. After Documenting Missing and Redundant controls, choose and mark ONE of the following courses of action:

__ PLAN NOT TO RELY ON ANY CONTROLS NOR SEGREGATION OF DUTIES. The planned control risk assessment must be maximum. Save the file by selecting File, Save. (Please save the file again even if you have not made any changes.) Go to step 7.

__ PLAN TO RELY SOLELY ON SEGREGATION OF DUTIES. Go to step 5.

__ PLAN TO RELY ON MANUAL OR PROGRAMMED CONTROLS WITH OR WITHOUT SEGREGATION OF DUTIES. Go to step 6.

5. Planned Control Risk Assessment Based Solely On Adequacy of Segregation of Duties

A. The planned control risk assessment can only be maximum or slightly below maximum when relying solely on Segregation of Duties. **Save the file by selecting File, Save.**

B. Based upon your review of the incompatible duties report (wp 94106's), mark an **X** on the number line to record your control risk assessment within your chosen risk category.

```
[   Slightly Below Max   ][       Maximum          ]
|----+----|----+----|----+----|----+----|----+----|
50   55   60   65   70   75   80   85   90   95 100
```

C. **Record the time of day (hour:minutes) __:_____ a.m. p.m.** Go to step 7.

6. Planned Control Risk Assessment Based On Adequacy of Manual or Programmed Controls and Adequacy of Segregation of Duties

To make your planned control risk assessment for the accuracy, existence/occurrence, and gross valuation assertions for the revenue processing stream, enter the strategy option and do the following:

A. Select the "Revenue" stream.

B. Click on the Box with the grouped assertions. From the four possible risk categories, select the planned control risk assessment that you believe is appropriate based on your review of internal control structure.

C. To exit the Control Risk Assessment window, move the pointer to the overview flowchart that is showing beneath the Control Risk Assessment window. Click once on the left mouse button.

D. Save the file by selecting File, Save.

F. Mark an X on the number line to record your control risk assessment. Make sure your mark is within the risk category you recorded using INFOCUS.

```
[          Limited          ][         Moderate          ]
|----+----|----+----|----+----|----+----|----+----|----+----|
0    5    10   15   20   25   30   35   40   45   50

 [  Slightly Below Max   ][          Maximum          ]
 ----+----|----+----|----+----|----+----|----+----|----+----|
 51  55   60   65   70   75   80   85   90   95  100
```

G. Record the time of day (hour:minutes) __:____ a.m. p.m. Go to step 7.

7. Decision Summary

A. Write a one paragraph summary to further document your control risk decision.

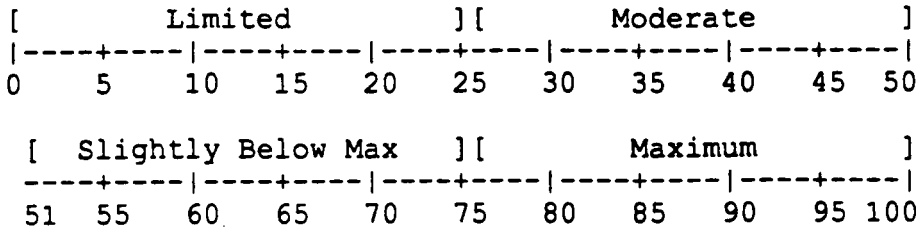
B. Record the time of day (hour:minutes) __:____ a.m. p.m.

C. Would you make a different control risk assessment if this was a second-year audit?

Yes___ Go to Step 8.
No ___ PLEASE COMPLETE THE AUDITOR QUESTIONNAIRE

8. Control Risk Assessment Assuming Second-Year Audit (Do only if your planning stage control risk assessment would be different than for a first-year audit.)

A. Mark an **X** on the number line to record your control risk assessment.



B. **Record the time of day (hour:minutes) __:____ a.m. p.m.**

C. **PLEASE COMPLETE THE AUDITOR QUESTIONNAIRE**

APPENDIX A-3

REVENUE CYCLE INTERNAL CONTROL WORKPAPERS

The workpapers in Appendix A-3 are actual INFOCUS printouts. INFOCUS was developed by Grant Thornton.

Participant No.

RICE LUMBER COMPANY

REVENUE CYCLE INTERNAL CONTROL WORKPAPERS

Done by:	Date:	Index:
Reviewer:	Date:	8410

GRANT THORNTON
INFOCUS
Information and Control Understanding System
6-30-92

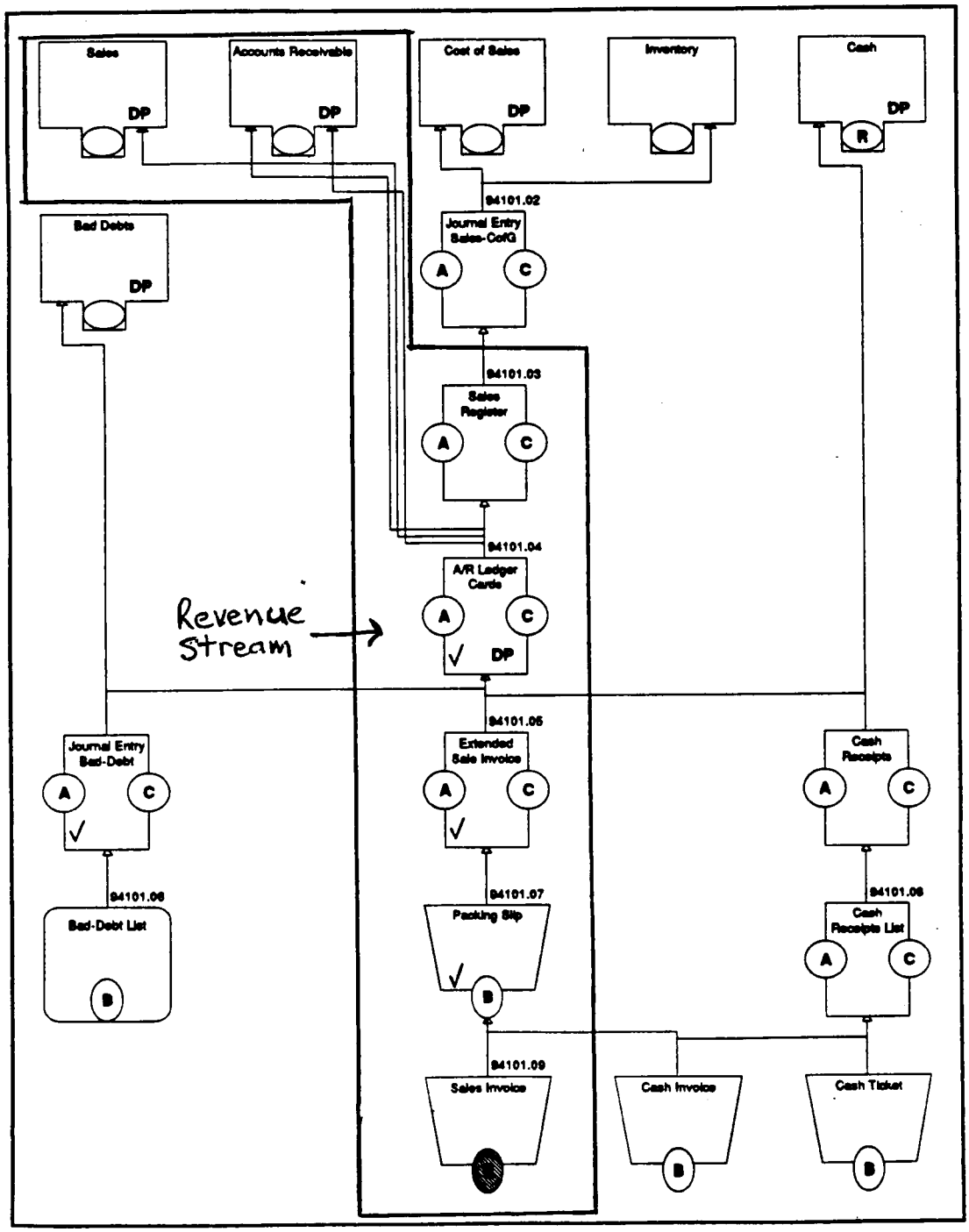
COMPANY NAME:	RICE LUMBER COMPANY
Processing Cycle:	Revenue
Period Ended:	6-30-92
Estimated Volume of Transactions:	$14,000,000
Estimated Number of Transactions:	15,000
INFOCUS File Names for this Client's Data:	A:\RICE.IDB

>> The planned assessment of control risk is maximum based on testing of no controls <<

A	Accuracy	○	No Control, No Compensating Control
B	Boundary (Boundary Event Symbols)	●	Compensating Control Exists
B	Budgetary (T-Account Symbols)	Ⓐ	Control Exists, not a Key Control
C	Completeness	(A)	Key Control
O	Other Controls (T-Account Symbols)		
R	Reconciliation (T-Account Symbols)		
S	Safeguard (T-Account Symbols)		
√	Authorization		
DP	Automated Process		
DP	Automated Process, with Integrity Controls		

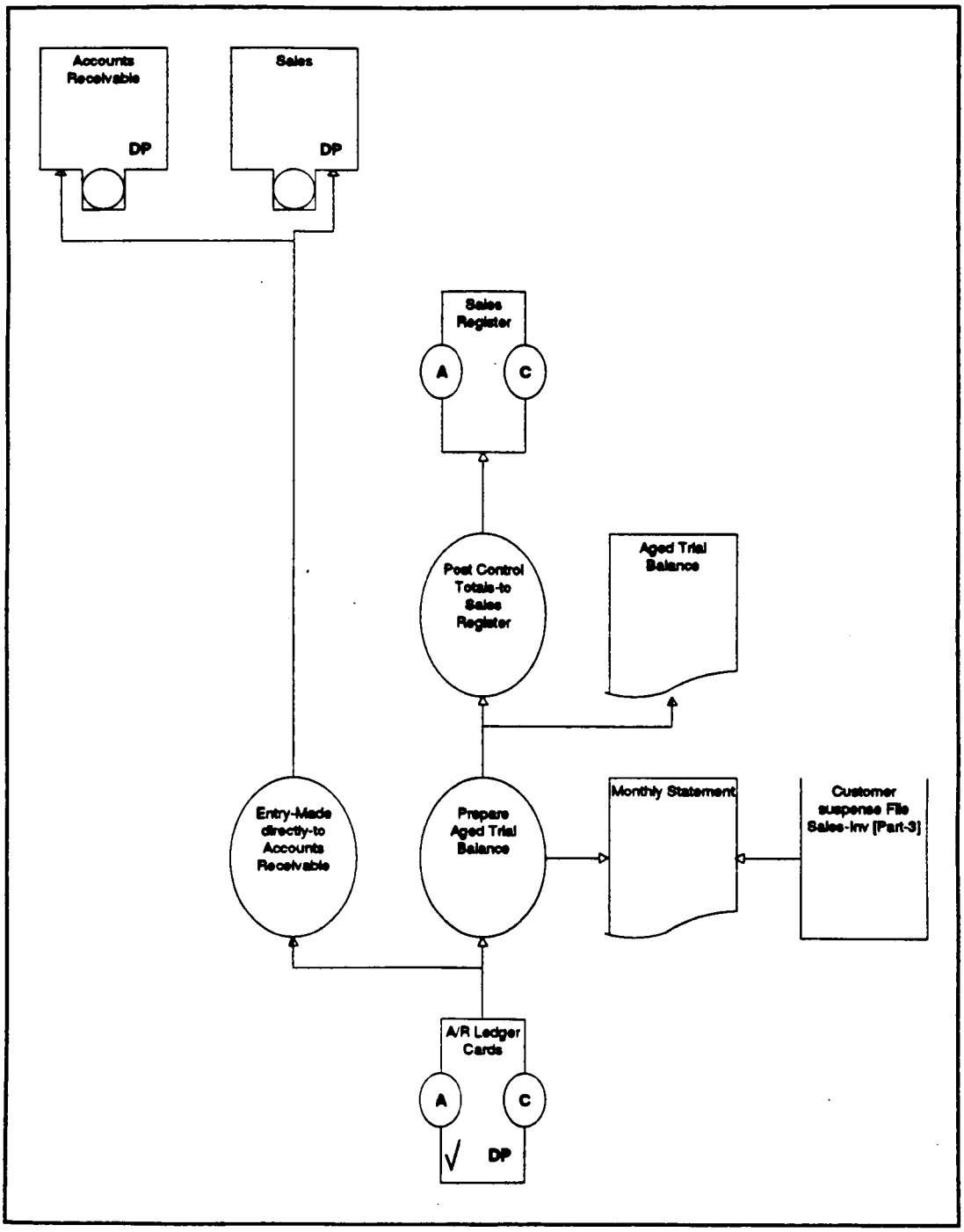
RICE LUMBER COMPANY
Revenue Cycle
Infocus Overview Flowchart
6-30-92

Done by:	Date:	Index:
Reviewer:	Date:	84100.01



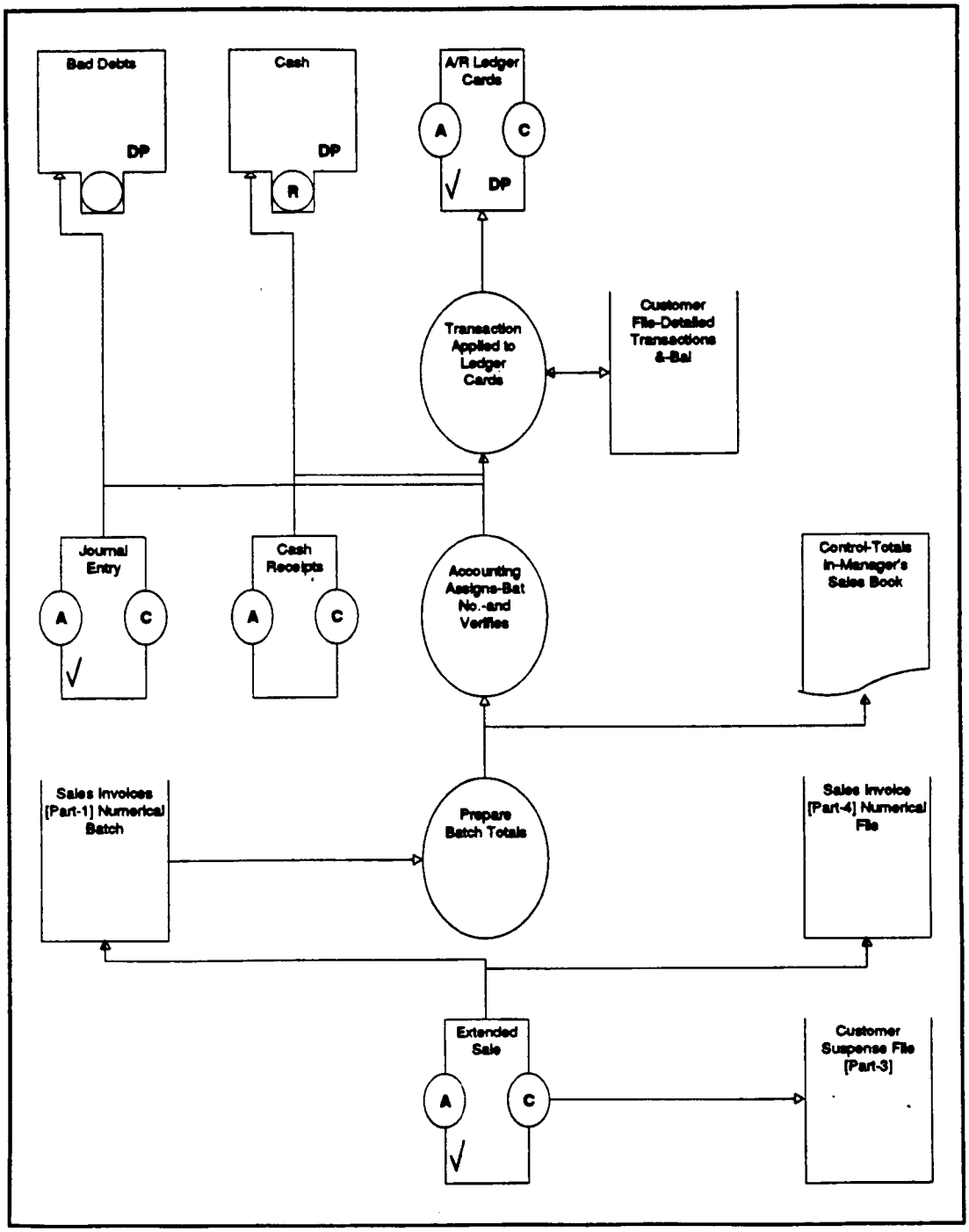
RICE LUMBER COMPANY
Revenue Cycle
Activity Level 1: Sales Register
6-30-92

Done by:	Date:	Index:
Reviewer:	Date:	84101.03



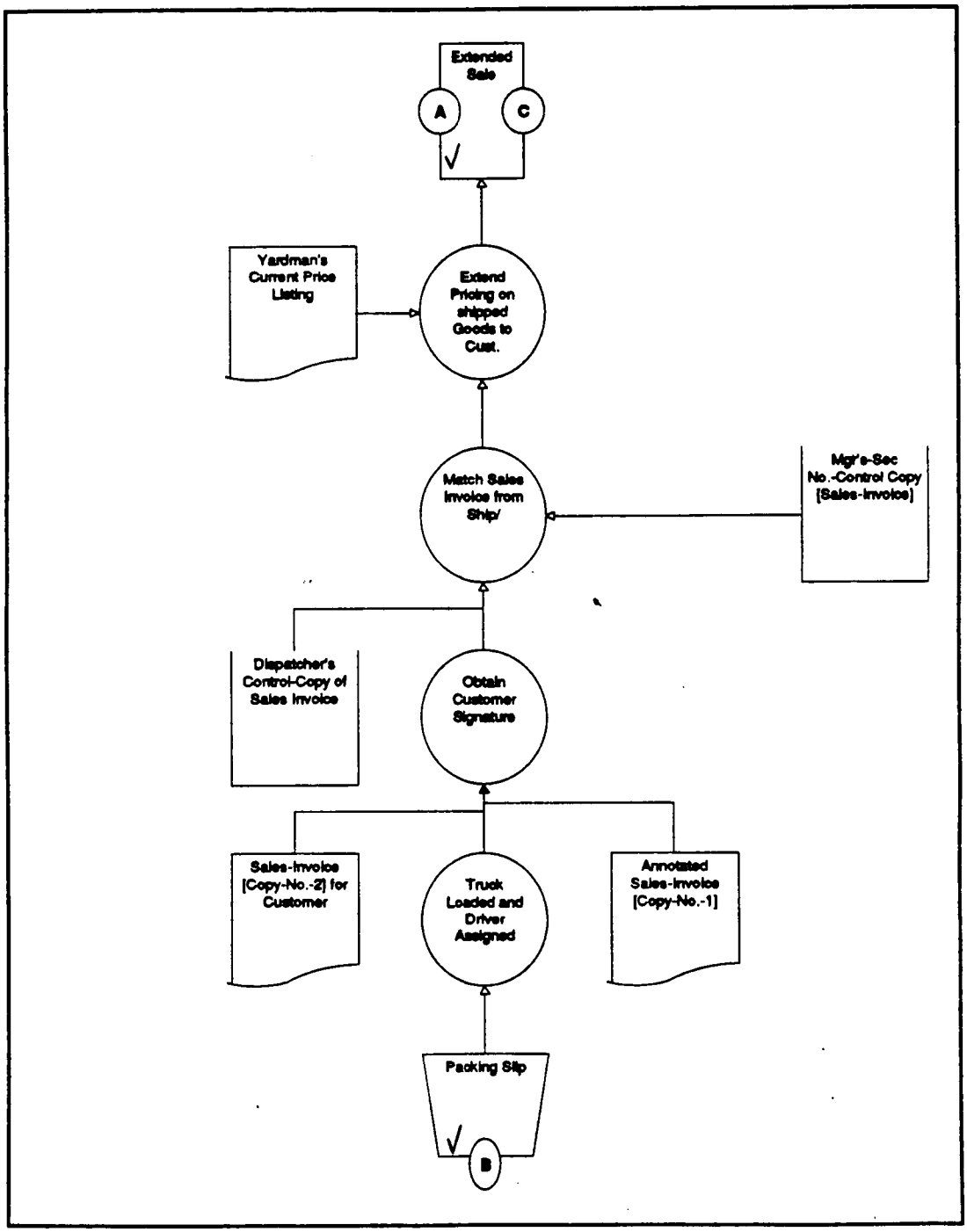
RICE LUMBER COMPANY
Revenue Cycle
Activity Level 1: A/R Ledger Cards
6-30-92

Done by:	Date:	Index:
Reviewer:	Date:	94101.04



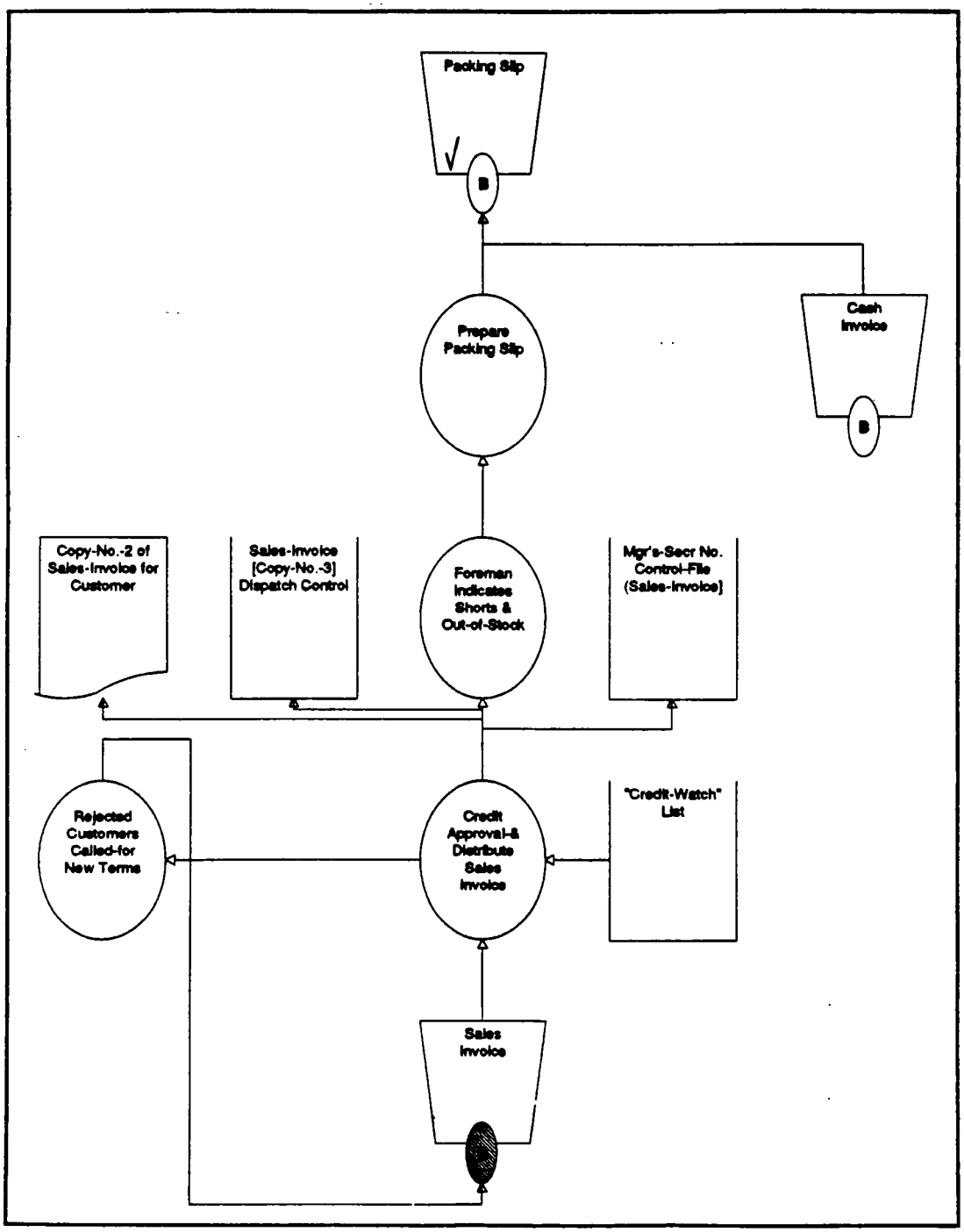
RICE LUMBER COMPANY
Revenue Cycle
Activity Level 1: Extended Sale Invoice
6-30-92

Done by:	Date:	Index:
Reviewer:	Date:	84101.06



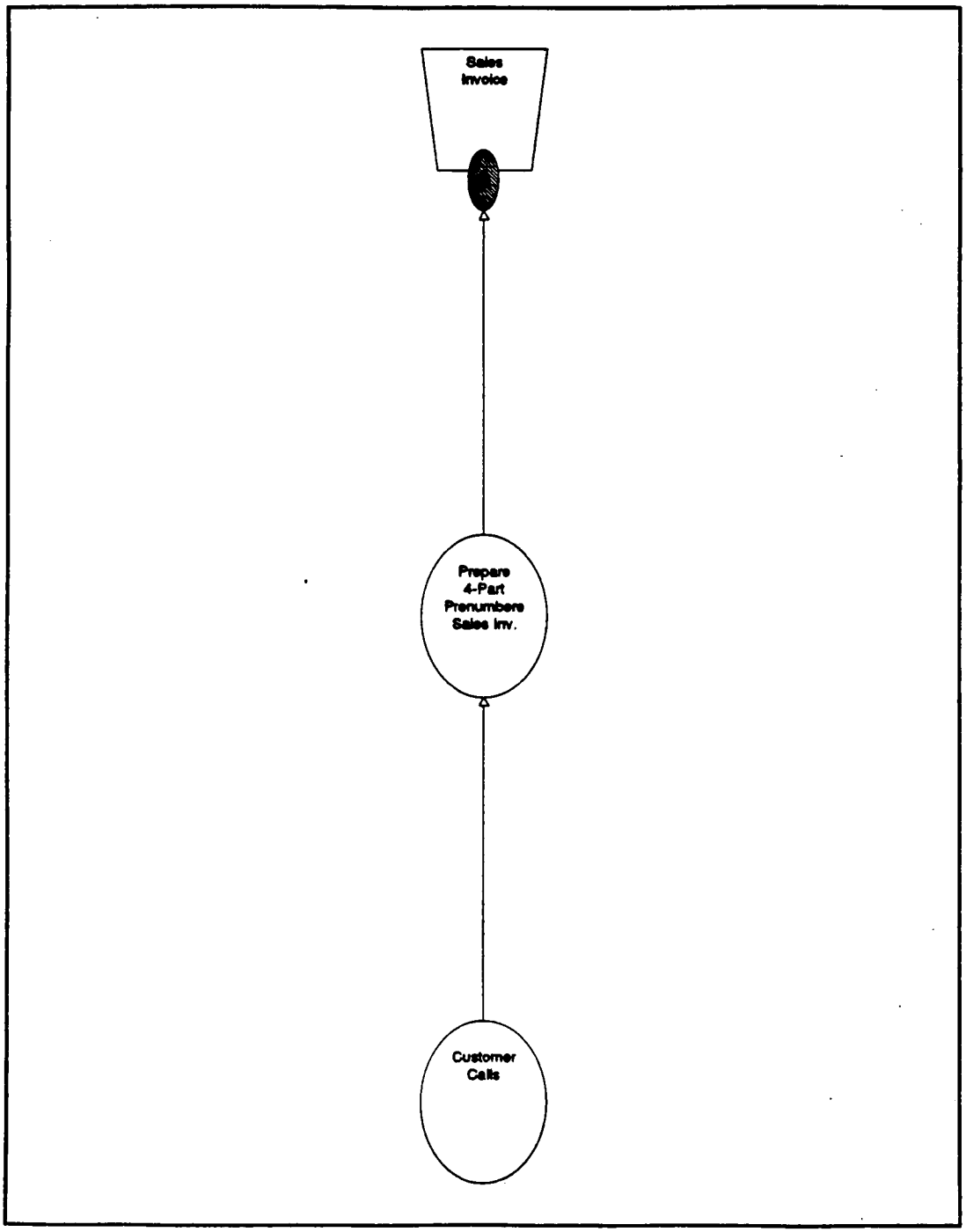
RICE LUMBER COMPANY
Revenue Cycle
Activity Level 1: Packing Slip
6-30-92

Done by:	Date:	Index:
Reviewer:	Date:	94101.07



RICE LUMBER COMPANY
Revenue Cycle
Activity Level 1: Sales Invoice
6-30-92

Done by:	Date:	Index:
Reviewer:	Date:	94101.00



RICE LUMBER COMPANY
Revenue Cycle
Process and Controls Description
6-30-92

Done by:	Date:	Index:
Reviewer:	Date:	94103.01

Information Form	Person Performing Process	Control Objective	Control Procedure	Person Performing Control	Preventive or Detective
Cash Invoice	Oglvie, Sherrill Sales Clerk	Boundary	Checking manually the numerical sequence of a document, journal or report	Fitzgerald, Stacy Yard Manager's Secretary	Detective
Packing Slip	Fitzgerald, Stacy Yard Manager's Secretary	Authorization	Matching to an authorized list	Pingree, Peter Yard Manager Wilson, George Ass't to Yard Manager	Preventive
	Various Yardmen	Boundary	Other: Reviews and compares sales invoice adjusted for out of stock items with packing slip	Mason, George Yard Foreman	Preventive
Cash Ticket	Pingree, Peter Yard Manager	Boundary	Other: - Checks are stamped "For Deposit Only" to Rice Lumber Yard account	Wilson, George Ass't to Yard Manager	Detective
Sales Invoice	Scott, Willy Sales Clerk				
Bad-Debt List	Pingree, Peter Yard Manager	Boundary	Matching to a previously validated document: - Aged Trial Balance	Jones, Jerry Ass't to Treasurer	Preventive
Journal Entry Bad-Debt	Jones, Jerry Ass't to Treasurer	Completeness Accuracy Authorization	Other: Compares amounts written off to aged trial balance and customer detail	Rice, Gary President & Chairman of the Board	Preventive
Cash Receipts List	Fitzgerald, Stacy Yard Manager's Secretary	Completeness Accuracy	Checking one-to-one: - Line items on listing to checks received and cash register tape of cash sales	Jones, Jerry Ass't to Treasurer	Preventive
Cash Receipts Journal	Smith, Rita Acc'ts Receivable Clerk	Completeness Accuracy	Matching to a previously validated document	Jones, Jerry Ass't to Treasurer	Detective
Journal Entry Sales-CofG	Jones, Jerry Ass't to Treasurer	Completeness Accuracy	Other: - Cost of Goods entry is calculated from sample of sales invoices. Calculations are reviewed	Owens, Larry Treasurer	Preventive
A/R Ledger Cards	Fitzgerald, Stacy Yard Manager's Secretary	Completeness Authorization	Matching to a previously validated document	Caldwell, Harry Vice-President	Detective
	Spiner, Susan Computer Input and Operator Clerk	Accuracy	Comparing batch totals	Smith, Rita Acc'ts Receivable Clerk	Detective
Sales Register	Smith, Rita Acc'ts Receivable Clerk	Completeness Accuracy	Matching to a previously validated document	Caldwell, Harry Vice-President	Preventive

RICE LUMBER COMPANY
Revenue Cycle
Process and Controls Description
6-30-92

Done by:	Date:	Index:
Reviewer:	Date:	94103.02

Information Form	Person Performing Process	Control Objective	Control Procedure	Person Performing Control	Preventive or Detective
Extended Sale Invoice [redacted]	Fitzgerald, Stacy Yard Manager's Secretary	Accuracy	Checking one-to-one	Caldwell, Harry Vice-President	Preventive
	Various Truck Drivers	Authorization	Other: - Driver obtains signature on annotated sales invoice	Wood, Walter Dispatcher	Detective
	Wood, Walter Dispatcher	Completeness	Matching to a previously validated document	Fitzgerald, Stacy Yard Manager's Secretary	Detective
Cost of Sales	Spiner, Susan Computer Input and Operator Clerk				
Cash	Spiner, Susan Computer Input and Operator Clerk	Reconciliation Review	Other: Comparison of cash receipts listing to deposit slips	Owens, Larry Treasurer	Detective
Accounts Receivable [redacted]	Spiner, Susan Computer Input and Operator Clerk				
Bad Debts	Spiner, Susan Computer Input and Operator Clerk				
Sales [redacted]	Spiner, Susan Computer Input and Operator Clerk				
Inventory					

RICE LUMBER COMPANY
Revenue Cycle
Missing Controls Report
6-30-92

Done by:	Date:	Index:
Reviewer:	Date:	94104.01

Information Form	Control Objective	Reportable Condition	Comments/Workpaper Reference
Sales Invoice	Boundary		Compensated by:Packing Slip
A/R Ledger Cards	Integrity		
Cost of Sales	Reconciliation Review		
	Integrity		
Cash	Integrity		
Accounts Receivable	Reconciliation Review		
	Integrity		
Bad Debts	Reconciliation Review		
	Integrity		
Sales	Reconciliation Review		
	Integrity		

Note: This workpaper is only used for this exercise and is not a Grant Thornton workpaper. However, the controls listed below were obtained from the online INFOCUS Help feature.

94105.01

RICE LUMBER COMPANY
Missing and Redundant Controls For Management Report
6-30-92

For each processing symbol in the revenue processing stream, the letters in the columns represent control objectives satisfied by the existing controls. (A = Accuracy; B = Boundary; C = Completeness; I = Integrity; O = Other; R = Reconciliation; S = Safeguard; U = Authorization)

The chart below provides a list of potential controls for the revenue stream. For each accounting process listed in the columns, document the controls that you believe are missing or redundant by doing the following:

Put a **K** in the appropriate accounting process column(s) if you believe the control is a missing key control (i.e. you would use it to rely on IC) for a particular process.

Put an **N** in the appropriate accounting process column(s) if you believe the control is a missing non-key control (i.e. you would add the control but it would not be used to rely on IC) for a particular process.

For controls that are in place, **CIRCLE** the appropriate accounting process column(s) if you believe the control is a redundant control and can be eliminated for a particular process. Be sure not to eliminate any key controls.

In the system environment column the **A** signifies the control could be used in an automated environment and the **M** signifies the control could be used in a manual environment.

Potential Controls

System Env.	Controls	Processes in Revenue Stream						
		Inv	Pack Slip	Ext Sale	S. Reg	A/R Sub	S.G/L	A/R G/L
AM	1. Balancing receivables subledger							
A	2. Balancing run to run control totals							
AM	3. Balancing the G/L with the subledgers							
AM	4. Canceling original documents							
A	5. Checking by computer for duplicate entries							
A	6. Checking by computer the numerical sequence of a file							
AM	7. Checking for a third party signature							
AM	8. Checking manually the numerical sequence of a document, journal or report							
AM	9. Checking one-to-one			A				
AM	10. Comparing Batch Totals					A		
AM	11. Comparison of budgeted amounts to actual amounts							
AM	12 Comparison of cash receipts listing to deposit slips							
A	13. Computer generation of transactions							
AM	14. Dual control over cash receipts							

Note: This workpaper is only used for this exercise and is not a Grant Thornton workpaper. However, the controls listed below were obtained from the online INFOCUS Help feature.

94105.02

RICE LUMBER COMPANY
Missing and Redundant Controls For Management Report
6-30-92

System Env.	Controls	Processes in Revenue Stream						
		Inv	Pack Slip	Ext Sale	S. Reg	A/R Sub	S. G/L	A/R G/L
A	15. Electronic Authorization							
AM	16. Independent review of edit reports for data file changes							
A	17. Interactive dependency edit							
A	18. Interactive document reconciliation							
A	19. Interactive edit controls							
A	20. Interactive existence edit							
A	21. Interactive feedback edit							
A	22. Interactive format edit							
A	23. Interactive key verification							
A	24. Interactive mathematical accuracy check							
A	25. Interactive prior data matching							
A	26. Interactive reasonableness edit							
A	27. Interactive range check edit							
A	28. Interactive check digit							
AM	29. Matching to a previously validated document			C	AC	CU		
A	30. Matching to a previously validated file							
AM	31. Matching to an authorized list		U					
AM	32. Monthly review of bank reconciliations							
AM	33. Monthly review of receivables							
A	34. Non-interactive format edit							
A	35. Non-interactive mathematical accuracy check							
A	36. Non-interactive edit controls							
A	37. Non-interactive existence edit							
A	38. Non-interactive dependency edit							
A	39. Non-interactive range check edit							
A	40. Non-interactive reasonableness edit							
A	41. Non-interactive prior data matching							
A	42. Non-interactive check digit							

Note: This workpaper is only used for this exercise and is not a Grant Thornton workpaper. However, the controls listed below were obtained from the online INFOCUS Help feature. 94105.03

RICE LUMBER COMPANY
Missing and Redundant Controls For Management Report
6-30-92

System Env.	Controls	Processes in Revenue Stream						
		Inv	Pack Slip	Ext Sale	S. Reg	A/R Sub	S. G/L	A/R G/L
AM	43. Performance of analytical procedures and investigation of unusual items							
AM	44. Periodic reconciliation of books to physical							
AM	45. Periodic revision of budgeted amounts based on updated information							
AM	46. Physical access controls							
AM	47. Physical safeguards							
AM	48. Reconciliation of manual totals to run totals							
A	49. Reconciliation of master file balance to control account							
A	50. Reconciliation of master file balance to run totals							
M	51. Reperformance							
AM	52. Restrictive Endorsement of Checks received							
AM	53. Reviewing adjustment transactions							
AM	54. Reviewing internal signatures							
A	55. Reviewing permanent data file exception reports							
AM	56. Reviewing reference file data							
A	57. Software access controls							
AM	58. Use of a lockbox							
A	59. Use of prerecorded input (OCR, MICR OMR)							
AM	60. Verifying mathematical accuracy							
AM	61. Other: Review & compare invoice adjusted for out of stock items with the packing slip		B					
AM	62. Other: Driver gets signature on annotated sales invoice			A				
AM	63. Other:							
AM	64. Other:							
AM	65. Other:							

RICE LUMBER COMPANY
Revenue Cycle
Incompatible Duties Report
6-30-92

Done by:	Date:	Index:
Reviewer:	Date:	94106.01

Information Form	Control Concern	Person Performing Process/Control	Mitigating Factors	Effects on Audit Program
There are no symbols or employees with incompatible duties.				

RICE LUMBER COMPANY
Revenue Cycle
CP Summary
6-30-92

Done by:	Date:	Index: 1220
Reviewer:	Date:	94107.01

Software Name	Planned Audit Approach	Design Factors	Simple/Advanced	Low Risk
	No Reliance	Integration with other applications	Advanced	No

RICE LUMBER COMPANY
Revenue Cycle
Computer Processing Overview
6-30-92

Done by:	Date:	Index: 1220
Reviewer:	Date:	94107.02

Question	Response
The first three questions relate to the company as a whole, while the remaining questions are specific to this accounting cycle.	
Are the client's computers in a dedicated physical area or facility?	No
Is there a separate EDP department?	No
Can separate users access the system concurrently?	Yes
Is access control software used to restrict access to the production programs?	Yes
Is access control software used to restrict access to the data files?	Yes
Are reports generated by such software reviewed by management?	Yes
The following questions are used to determine whether the application for this accounting cycle is simple or advanced. In addition, the answers for the next two questions are used to determine whether the environment is or is not low risk.	
Is this application PC-based?	No
Does the client have the source code for the computer programs used in this accounting cycle?	No
Do multiple applications share the same databases (files)?	No
Are there real-time updates to files when transactions are entered?	No
Is the data processing function for this accounting cycle decentralized (Distributed Processing)?	No
Are telecommunications or networks used in this accounting cycle?	No
Does the software in this accounting cycle generate transactions or pass information to other cycles?	Yes
Is there significant loss of visible audit trail in this accounting cycle?	No
Have there been any hardware or software malfunctions which resulted in a loss of data in this accounting cycle?	No

RICE LUMBER COMPANY
Revenue Cycle
Hardware
6-30-92

Done by:	Date:	Index: 1221
Reviewer:	Date:	94109.01

Location and Installation	Operating System	Fixed Disk Capacity	Floppy Disk Type	Tape Type	No. of Stations/ Systems	Other Equipment
Store Office - DEC - Minicomputer	Unix	600 MB		9 Track	15	

RICE LUMBER COMPANY
Revenue Cycle
General Controls Questionnaire
6-30-92

Done by:	Date:	Index: 1320
Reviewer:	Date:	94111.01

Controls	Placed in Operation (Y or N)	Operating Effectively (Y or N)	Does Not Exist	N/A	References/Comments
Control Objective: Access control over programs and data files is adequate.					
Are there adequate controls to achieve this objective? Yes ✓ No___					
Access control software used for production programs:					
1. Are master lists of authorized personnel maintained, indicating restrictions on access?		Y			
2. Are access and security features within the operating system utilized to restrict access to and amendment of program files?		Y			
3. Is terminal activity automatically monitored and rejected access attempts reported?		Y			
4. Does the access control software identify each terminal via the logical address?		Y			
5. Does the access control software identify each terminal via the physical address?		Y			
Access control software used for data files:					
1. Are master lists of authorized personnel maintained, indicating restrictions on access?		Y			
2. Are access and security features within the operating system utilized to restrict access to and amendment of data files?		Y			
3. Is terminal activity automatically monitored and rejected access attempts reported?		Y			
4. Is there encryption of all sensitive data files?		Y			
5. Does the access control software identify each terminal via the logical address?		Y			
6. Does the access control software identify each terminal via the physical address?		Y			
7. For database applications, is access to the data possible only through the DBMS?		Y			
Reports generated by access control software:					
1. Is the record of jobs actually run, and console logs, reviewed by supervisory personnel?		Y			

RICE LUMBER COMPANY
Revenue Cycle
General Controls Questionnaire
6-30-92

Done by:	Date:	Index: 1320
Reviewer:	Date:	94111.02

Controls	Placed in Operation (Y or N)	Operating Effectively (Y or N)	Does Not Exist	N/A	References/Comments
2. Is the computer usage summary produced and reviewed?		Y			
Control Objective: Control over computer generated transactions is adequate. Are there adequate controls to achieve this objective? Yes ✓ No					
1. Are the methods used in the program to generate the data and related control record appropriate?		Y			
2. Is there an adequate check over the accuracy of the data generated (e.g. reasonableness check, manual review of data generated, etc.)?		Y			
3. Are the results of the check for accuracy reviewed and approved?		Y			
4. Are controls such as computer sequence checks, computer matching or batch totals used to ensure the completeness of input and/or updates?		Y			
5. Are exception reports investigated and reconciled?		Y			

RICE LUMBER COMPANY
Revenue Cycle
Employee List Report
6-30-92

Done by:	Date:	Index:
Reviewer:	Date:	95801.01

Name	Title	EDP Duties	Comments
Caldwell, Harry	Vice-President		
Fitzgerald, Stacy	Yard Manager's Secretary		
Hales, Richard	Head Bookkeeper		
Jones, Jerry	Ass't to Treasurer		
Mason, George	Yard Foreman		
Oglvie, Sherrill	Sales Clerk		
Owens, Larry	Treasurer		
Pingree, Peter	Yard Manager		
Rice, Gary	President & Chairman of the Board		
Scott, Willy	Sales Clerk		
Shingles, Sam	Sr Vice-President & Secretary		
Smith, Rita	Acc'ts Receivable Clerk		
Spiner, Susan	Computer Input and Operator Clerk	EDP but no duties	
Various	Truck Drivers		
Various	Yardmen		
Wilson, George	Ass't to Yard Manager		
Wood, Walter	Dispatcher		

APPENDIX B

AUDITOR QUESTIONNAIRE

Participant No.

Auditor Questionnaire

Directions: Please answer the following 17 questions. Your answers to these questions will be confidential.

General Audit Experience

1. How long have you been working as an external auditor? _____ years and _____ months

   How long as an auditor for Grant Thornton? _____ years and _____ months

2. Approximately how many audits have you participated in during your whole career?

   1-10___ 11-20___ 21-30___ 31-40___ 41-50___ 51-60___ 61-70___ 71-80___

   81-90___ 91-100___ 101-125___ 126-150___ More than 150___

3. What is the percentage of audits that you have participated in that were:

Under $5 million in Revenue	_____ %
$5 to 100 Million in Revenue	_____ %
More than $100 Million in Revenue	_____ %
TOTAL	100 %

4. Audit Specialization--The percentage of audits that you have participated in that were in the following industries:

Commercial (Merchandising)	_____ %
Manufacturing	_____ %
Financial Institutions	_____ %
Governmental	_____ %
Other (Specify:_____)	_____ %
Other (Specify:_____)	_____ %
TOTAL	100 %

5. Approximately how many times have you supervised the audit fieldwork?

   0___ 1-5___ 6-10___ 11-15___ 16-20___ 21-25___ 26-30___ 31-35___ 36-40___

   41-45___ 46-50___ 51-60___ 61-70___ 71-80___ 81-90___ 91-100___

   101-125___ 126-150___ More than 150___

Experience Concerning Internal Control Structure Documentation

6. Approximately how many times have you personally documented a transaction cycle of a client's internal control structure in a live audit? (Count multiple transaction cycles in one audit.)

   0___ 1-5___ 6-10___ 11-15___ 16-20___ 21-25___ 26-30___ 31-35___ 36-40___

   41-45___ 46-50___ 51-60___ 61-70___ 71-80___ 81-90___ 91-100___

   101-125___ 126-150___ More than 150___

7. For the times you documented the internal control structure for a transaction cycle, what percentage of the time did you use the following forms of documentation? (Total percentage does not have to equal 100% because more than one type of documentation is often used in one transaction cycle.)

Questionnaires	_____ %	Manual Flowcharts	_____ %
Narrations	_____ %	Computerized Flowcharts	_____ %

8. What is your level of comfort concerning your ability to understand and document a client's internal control structure? (Please circle one.)

Very High High Medium Low Very Low

Experience and Beliefs Concerning Planning Stage Control Risk Assessments

9. Approximately how many times have you made a planning stage Control Risk Assessment (CRA) in a live audit? (Be sure to include multiple CRA's in one audit.) SAS 55 was effective January 1, 1990.

Pre SAS 55

0___ 1-5___ 6-10___ 11-15___ 16-20___ 21-25___ 26-30___ 31-35___ 36-40___

41-45___ 46-50___ 51-55___ 56-60___ 61-65___ 66-70___ 71-75___ 76-80___

81-85___ 86-90___ 91-95___ 96-100___ 101-125___ 126-150___ More than 150___

Post SAS 55

0___ 1-5___ 6-10___ 11-15___ 16-20___ 21-25___ 26-30___ 31-35___ 36-40___

41-45___ 46-50___ 51-55___ 56-60___ 61-65___ 66-70___ 71-75___ 76-80___

81-85___ 86-90___ 91-95___ 96-100___ 101-125___ 126-150___ More than 150___

10. What is your level of comfort concerning your ability to document and make planning stage control risk assessments? (Please circle one.)

Very High High Medium Low Very Low

11. How much do you agree with the following statement?

Once the client's internal control structure has been documented and understood, auditors should be willing to evaluate the internal control structure to decide whether the planned control risk assessment can be reduced to some level below maximum risk. (Please circle one.)

Strongly Agree Agree Neutral Disagree Strongly Disagree

Experience and Beliefs Concerning INFOCUS

12. How many times have you used INFOCUS to document client internal control structure for a transaction cycle in a live audit? _____

13. How many hours of training have you had using INFOCUS to understand and document client internal control structure? _____

14. How many planning stage control risk assessments have you made and documented using INFOCUS for a live audit? _____

15. How many hours of training have you had using INFOCUS to make and document planning stage control risk assessments? _____

16. What is your level of comfort concerning your ability to use INFOCUS to document and make planning stage control risk assessments? (Please circle one.)

    Very High High Medium Low Very Low

17. How well do you like INFOCUS for making and documenting planning stage control risk assessments? (Please circle one.)

    Strongly Like Like Neutral Dislike Strongly Dislike

PLEASE PUT THE FLOPPY DISK AND ALL THE PAPER MATERIAL INTO THE ENVELOPE AND CLOSE THE CLASP. THANK YOU FOR PARTICIPATING.

APPENDIX C

BACK-PROPAGATION ALGORITHM

The back-propagation algorithm is an iterative gradient descent process (Rumelhart, Hinton and Williams 1986; Lippman 1987) which minimizes the mean square error between the actual output of a multilayer feed-forward network and a desired target output. A feed-forward network architecture has connections only from one layer of nodes to the next layer. In other words, no connections between nodes in the same layer are used in the back-propagation algorithm, so node i must represent a node in the previous layer to node j. Usually each node in one layer is connected to every node in the next layer. A continuous differentiable activation function is required to compute the output value of each node in network layers other than the input layer. Usually a sigmoid function is used. The activation function is:

$$O_j = \frac{1}{1 + e^{-\Sigma[(W_{ij} \times O_i) + B_j]}}$$

where O_j is the output of the node being processed, W_{ij} is the weight of the connection going from node i to node j, and O_i is the output value from node i in the previous layer. The B_j is a bias term applied to node j that is similar to using a threshold. A sigmoid function is used because it approximates a threshold function that is used by a linear network (only an input layer and output layer of nodes or computational elements). Widrow and Hoff's (1960) convergence proof of a linear network used a threshold function. When the network becomes nonlinear (middle layers of nodes in addition to input and output layers), a function similar to a threshold function is desired, but the function must be continuous. A continuous function is desired because with a discontinuous function there is no advantage to having hidden units--the network would only have the limited power of a linear network.

Sigmoid functions such as the logistic function are continuous and approximate a threshold function. Hornick, Stinchcombe, and White (1989) provide a proof that the logistic function will always find a set of weights that will find the global minimum.[40] The logistic function is also easily computed and has the same salient features (threshold and monotonic approach to an asymptote) found in neuronal response characteristics in the brain (Munro 1986).

There are five steps to back-propagation learning:

1. Initialize the weights using random values (usually between 0 and 1).

2. Present the network with a pair a vectors. One vector is the input vector. The second vector is the corresponding target vector--the desired output values of each output node given the input vector. (The input vector is similar to the set of independent variables and the target vector is similar to the dependent variables in regression.)

3. Calculate the actual output vector using the activation function presented above. Notice that the output of each node (other than the input layer nodes) is based on the summation of the output value of previous layer nodes times the respective connection weight.

4. Change the weights using an adjusting function derived from the Delta Rule described by Widrow and Hoff. The adjustment of the weights start at the output node and adjust the connection weights back through the network layers of nodes. The equation is:

$$W_{ij}(t+1) = W_{ij}(t) + ND_jO_i$$

where $W_{ij}(t)$ is the weight from node i to node j at time t,[41] N is a learning rate, D_j is an error term for node j (the error only affects the weights and not the activation function), and O_i is the

---

[40]However, where the global minimum is or how one knows when the global minimum is found is still an unanswered question. The gauge used most in deciding when training is complete is the amount of error between the output and the target output.

[41]The incrementation of t can be done after each presentation of input/output vector pairs (not a true gradient descent) or after all data records (or a random set of data records) have been presented to the network during training. When t is incremented after a set of data records, the error described in step 4 is accumulated. The accumulated error is then used to adjust the weights. Adjusting of the weights based on accumulated error of a set of data records is called epoch learning. Epoch learning provides a true gradient descent. This study used epoch learning.

output from node i (i represents a node in the previous layer to node j). The error signal from the output layer to a middle layer is given by:

$$D_j=(TARGET_j-O_j)O_j(1-O_j)$$

where O_j is the value from the output node and $TARGET_j$ is the desired value for that same output node. The error signal D_j is replaced by D_i when the error signal is being passed back from a middle layer of nodes to another middle layer or to the input layer. The error signal from the middle layer to any previous layer is given by:

$$D_i=O_i(1-O_i)(\Sigma[D_j\times W_{ij}])$$

where O_i is the value from a middle layer node. The last term in the D_i equation is the summation of all the error signals from the output layer (or higher middle layer) coming back through the network, each multiplied by its respective weight (W_{ij}).

5. Repeat the process by going to step 2 (Lippman, 1987).

VITA

Jefferson Toronto Davis was born on October 9, 1959 in Salt Lake City, Utah to Eugene H. and Carol Toronto Davis. He attended Salt Lake City public schools and graduated from East High School in 1978. The next two years were spent serving as a missionary for the Church of Jesus Christ of Latter-day Saints in Northern England. After returning from England, Jeff majored in accounting at Utah State University and received his Bachelor of Science in 1985 and Master of Science in 1986. During the summers he was employed as a logistics specialist at Hill Air Force Base, Utah. After earning his master's degree, Jeff worked as an auditor in the Salt Lake City office of Grant Thornton Accountants and Management Consultants. While employed with Grant Thornton, he obtained his license to practice as a Certified Public Accountant (CPA). In 1988, Jeff began work on his Ph.D. at Ohio State University. In 1990, he continued doctoral work at the University of Tennessee--Knoxville, and completed all but his dissertation in 1992. He is currently employed at Clarkson University in Potsdam, New York as an accounting instructor. Jeff is married to Janet Brighton, of Sunset, Utah. Jeff and Janet have six children.