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Abstract

ABSTRACT

The broad issue addressed in this paper is the effect of experience on an auditor's potential for expert performance in the future. The specific aspect of this issue examined is the effect field experience has on certain measures of an auditor's knowledge that can be used to anticipate changes in the level of that auditor's expertise in performing future tasks. The paper builds on extensive prior research by Russo to further expertise research in auditing in two ways. First, it extends previous findings from the realm of realized expertise in a current task to that of an auditor's potential for greater expert performance in an arbitrary future task. Second, it examines the relationship between experience and its differential effects on the types of knowledge that drive an auditor's expert-like behaviors during performance of field tasks.

A descriptive model of auditor behavior and learning during performance of a field task is presented that shows how the effects of experience on an auditor's potential for further expert development can be quantified. Expectations of the future level of expertise are modeled as functions of the magnitude and pattern of change in knowledge properties induced by current task experience. The model is then applied to an analysis of the task behaviors of four first-year auditors who performed audit-related tasks in simulated environments. Findings reported reveal both the highly individualistic effects of experience on knowledge driving expert behavior and analytical differences between effects along the structural and substantive dimensions of knowledge. The findings also provide diagnostic information about the progress of expert development and insight into limits on the rate at which expertise is acquired.

I. INTRODUCTION

The broad research issue examined in this paper is the effect of experience on an auditor's potential for expert performance in the future. I believe there is universal agreement that expertise develops through field experience. If it is also accepted that expert behavior is knowledge-driven, then we must conclude that field experience alters an auditor's knowledge base in such ways as to ultimately raise the level of expert performance during field tasks. What, then, does field experience do to an auditor's knowledge that changes the level of expert performance in future tasks and how can these effects be observed and quantified?

The ostensible explanation for the first part of the preceding question is that exposure to a variety of practice situations produces auditors who know more and whose knowledge is better organized, as consequence of which they produce better outcomes. As to the second part of the question, an extensive literature has evolved documenting attempts to observe and quantify these effects through comparative studies of expert/novice differences in substantive knowledge content, task strategy, and the cognitive processes by which knowledge content affects auditor judgments and decisions (See Arnold & Sutton, 1997; Ashton & Ashton, 1995 for reviews). However, while these studies provide useful state information, a comprehensive quantitative model of the expert-development process has so far failed to emerge. In a 1989 review of expertise research in auditing, Bèdard (1989:128) suggested that future research in expertise examine the way expert knowledge and its organization change as auditors acquire expertise. In a similar review almost a decade later, highlighting a glacial rate of progress, Bouwman & Bradley (1997: 120) conclude that little is actually known about what is involved in becoming an expert. Perhaps, as Russo (1997b) suggests, what is needed to stimulate progress is a new approach.

Russo (see references), in a departure from the dominant cognitive-based judgment/decision making paradigm of recent auditing behavioral research, approaches the study of expert development from a perspective that is more strictly behavioral in that it explores the development of expertise in novice auditors by examining the effects of their experience performing simulated audit-related field tasks on their observed expert-like task behavior.[1] Adapting the behavioral psychologist's definition of *learning* as any relatively permanent change in behavior resulting from experience (Reber, 1985), and employing the widely accepted notion of automaticity in the performance of a task as indicative of expertise (Alba & Hutchinson, 1987; Anderson, 1982, 1987; Mayer, 1992, p.305; Davis & Solomon, 1989; Bedard, 1989), Russo shows that experienced-induced changes in the properties of the knowledge demanded by an auditor's task behaviors are responsible for changes in that auditor's observed expertise during performance of a field task. The properties of knowledge examined are its organization, content, and availability. Russo's research demonstrates how the link between experience, learning, and an auditor's task behaviors can be exploited as a quantitative tool for acquiring insight into the process by which expertise evolves.

This paper builds on Russo's work to further expertise research in two ways. First, it extends Russo's (1999b) findings from the realm of *realized* progress in expertise in a specific task to that of an auditor's *potential* for greater expert performance in an arbitrary future task. Second, it examines the relationship between experience and its differential effects on the types of knowledge that drive auditors' expert-like behaviors during performance of field tasks. The model proposes that experience changes the knowledge driving task behaviors along two dimensions: knowledge structure, which addresses the properties of the knowledge demanded by task performance, and substantive content, which addresses its purpose and intentionality. Effects along the structural dimension are discussed more fully elsewhere (see Russo, 2000); this paper presents empirical evidence about how experience performing a task affects knowledge along the substantive content dimension. The research question posed is: What can be learned from observations of an auditor's behavior in a current task that can be used to anticipate performance in future tasks? This question is answered by proposing an augmented version of Russo's descriptive model of auditor behavior during performance of a field task. The augmented model is then applied to an analysis of the task behaviors of four first-year auditors who performed audit-related tasks in simulated environments to show how experience affected their knowledge along the substantive dimension.

This paper presents basic research contributing to an understanding of the process of expert development. The model shows how the effects of experience on an auditor's potential for further expert development can be quantified. Findings reported reveal both highly individualistic effects of experience on the knowledge driving expert behavior and analytical differences between effects along the structural and substantive dimensions of knowledge. The findings also provide diagnostic information about the progress of expert development and insight into limits on the rate at which expertise is acquired.

The balance of this paper is organized as follows: Section II presents an augmented version of Russo's model of auditor behavior during performance of a field task. The null hypotheses are developed in Section III, followed by a description of the experimental procedure in Section IV. Findings are presented in Section V, and discussed in Section VI. Section VII concludes the paper with suggestions for further research.

II. MODEL

Overview

The model proposed in this paper is an augmented version of the model proposed by Russo (1999) and consists of two major components: a behavior module and a learning module. The behavior module operationalizes the properties of an auditor's knowledge and how the effects of experience are quantified. The learning module proposes a process whereby new information acquired as a result of task experience is assimilated into an auditor's knowledge base[2] and, thereby, influences subsequent task behavior.

The Behavior Module

Task behavior is modeled as a sequence of observable target behaviors (reading, inquiry, calculating, writing, etc.) mediated by episodes of subconscious (automatic) and conscious (cognitive) mental activity. Measures of the properties of knowledge are based on analysis of the mental activity components of mediating episodes. *Experience* is operationalized as repetition in performing the various target behaviors. Russo's methodology for measuring the effect of experience on knowledge separates the task behavior sequence chronologically by behavior, and within behavior, by semi-frequency, producing two groups of equal frequency for each target behavior. Behaviors in the below-median group are the inexperienced or "naive" instances, and those in the above-median group are the experienced instances. The type and properties of knowledge utilized in the episodes of mental activity mediating the transition between the observed behaviors in each group are identified and enumerated. The effect of experience on each knowledge property is measured by the ratio of the experienced group's property metric to that of the inexperienced group.

The Learning Module

The model proposes that learning occurs in a three-stage process. When a knowledge base is stimulated by cue reception, the state of the knowledge at each stage is marked by a response, a distinctive form of mental activity. On an initial exposure to cues failing to elicit a consistent knowledge base response (stage 1), new knowledge may be acquired. However, evidence of the presence of that knowledge requires that there be a subsequent occasion for it to be accessed. Should such an occasion arise, it is evidenced by cognitive activity (stage 2). Further, with additional utilization in the task, access to that knowledge becomes more automatic as it is gradually assimilated into the knowledge base (stage 3). This process is, of course, subject to variation. For example, it is possible that considerable well-organized knowledge may already exist in memory, but given the context of the moment, lack accessibility. In such cases, a single cognitive episode, evoked by a single cue received from the task environment, may be sufficient to immediately bring that knowledge to an available state (stage 3), bypassing the intermediate state (stage 2) in which cognition is required for access.

In the next sections, each module is developed in detail.

The Behavior Module

Knowledge Base Response

Each instance of a behavior testifies to a demand for the information necessary for its instantiation and execution. When such demands are made, three forms of knowledge base response can be identified, each form revealing the stage in the learning process at which required knowledge rests. The three response forms and the stage each reveals are: subconscious transitions to target behaviors (stage 3), cognitive responses indicating a positive search of the knowledge base (stage 2), and cognitive responses indicating that sought knowledge is either not accessible or not present in the knowledge base (stage 1). The first of these responses is referred to as being *automatic*. The two kinds of cognitive response mentioned are referred to as, respectively, *analysis and planning* cognition and *uncertainty* cognition, terms that are roughly descriptive of their tenor and content.

The sum of automatic and analysis and planning responses is a measure of *accessible knowledge content*. The number of responses making up a cognitive episode is that episode's *complexity*, and is negatively related to the extent to which knowledge is organized in the knowledge base.

Knowledge Base Probes and Response Sampling

During an auditor's performance of a task, each instance of a behavior performed serves as a probe of that auditor's knowledge base. These probes and their related knowledge base responses, when aggregated by target behavior, produce the response samples that, in turn, are the basis for drawing inferences about the effects of experience on the properties of knowledge (Russo, 1997a). The model proposes that change in a knowledge base is manifest in task behavior in various ways, depending on how the properties of knowledge organization, accessible content, and knowledge availability are affected by repeated accesses to knowledge required during performance of a task. Data for measuring the level of each knowledge property over any set of target behaviors is derived from an analysis of the knowledge base responses that form episodes of mental activity mediating transitions to those behaviors.

"Global" and "Knowledge-Type" Phenomena

The model can be applied to analysis of knowledge base properties and responses at two levels. When applied at the level of the knowledge base without regard to the type of knowledge accessed, then this form of application will be termed a "global" analysis. When applied at a more micro level, to the analysis of knowledge base properties and responses reflecting access to a specific type of knowledge (i.e., strategic or environmental, as previously defined), then this application will be termed a "knowledge-type" analysis. The term "knowledge-type" is employed as a high-level, generic descriptor of substantive content, and consists of two nominal categories: *environmental knowledge*, an auditor's knowledge of entities, relationships, and processes present in the task environment, and *strategic knowledge*, an auditor's knowledge of task demands and objectives, and the behaviors appropriate to their realization. The distinction as to knowledge type is based on the purpose and intentionality[3] of each cognitive response. Because both strategic and environmental knowledge are required to perform any purposeful and intentional behavior, at the knowledge-type level, automatic responses are considered to be of both knowledge types, while at the global level, the distinction as to knowledge type is irrelevant.[4]

In the sections that follow, the properties of an individual auditor's knowledge base are defined. To avoid complicating mathematical notation, the equations are presented in global form. Extension to the knowledge-type level involves simply including an additional subscript, T, to indicate the particular knowledge type.[5] The additional notation will be included when required to avoid ambiguity.

Knowledge Base Properties

The model defines three primary knowledge properties: knowledge organization, accessible knowledge content, and available knowledge content, and one derivative property, mean knowledge accessibility.

Knowledge organization describes the amount of cognitive searching of a knowledge base required before an observable behavior is evoked. Knowledge organization (*S*) is negatively related to the mean complexity of mediating episodes (see equation 1).

$$S_j^P \equiv n_{sj}^P / n_j^P$$

In equation (1), *P* indicates data set, *N* for the naive set and X for the experienced set, n_{sj} is the sum of all knowledge base responses (uncertainty, analysis and planning cognition, and automatic responses) mediating transitions to target behavior *j*, and n_j is the frequency of those transitions.

Accessible knowledge content refers to the capacity of a knowledge base to respond positively to a demand for information required to support a given target behavior. Automatic responses and analysis and planning cognition are indications of positive knowledge base responses. Accessible knowledge content (*C*) is measured by the proportion of all knowledge base responses that are positive, as shown by equation (2), where n_{cj} is the frequency of positive knowledge base responses.

$$C_j^P \equiv n_{cj}^P / n_{sj}^P$$

Knowledge availability refers to the capacity of a knowledge base to automatically supply on demand the information supporting a given target behavior. Knowledge availability (*V*) is indicated by the proportion of positive knowledge base responses that are automatic, as shown by equation (3), where n_{vj} is the frequency of automatic responses.

$$V_j^P \equiv n_{vj}^P / n_{cj}^P$$

The product of these properties, averaged over all *b* categories of target behaviors, produces the *mean knowledge accessibility* of set *P*, a measure of the capability at experience level *P* of an auditor's knowledge base to respond automatically to an arbitrary demand for knowledge (see equation 4).[6]

$$c = \frac{1}{b} \sum^b S_j C_j V_j$$

Effects of Experience on Knowledge Base Properties and Accessibility

$$A_S = \frac{\sum^j S_j^X}{\sum^j S_j^N} (a) \quad A_C = \left(\frac{1}{A_S}\right)\frac{\sum^j S_j^X C_j^X}{\sum^j S_j^N C_j^N} (b) \quad A_V = \left(\frac{1}{A_S A_C}\right)\frac{\sum^j S_j^X C_j^X V_j^X}{\sum^j S_j^N C_j^N V_j^N} (c)$$

The effect of experience on each knowledge property is the ratio of its experienced to inexperienced measure. However, as implied by their definitions and equation (4), knowledge properties are serially related, so that the sequential products, S_j, S_jC_j, and $S_jC_jV_j$, measure the cumulative effect of their components on mean knowledge accessibility. Therefore, in order to isolate the unconditional effect of experience on any individual property, it is necessary to remove from the cumulative product the effects of any precedent properties. Following this procedure, equations (5a) through (5c) show the unconditional effects of experience on each knowledge property.

A_S, A_C, and A_V are collectively the *knowledge properties effects*. In equation (5), A_S measures the effect of experience on knowledge base organization, A_C the effect on knowledge base content, and A_V the effect on knowledge availability. The product of the three knowledge property effects produces the *knowledge accessibility effect*, a measure of the effect of experience on the mean knowledge accessibility of the knowledge base, as shown by equation (6).

$$A = A_S A_C A_V$$

With regard to the interpretation of equation (6), it should be noted that because episode complexity is employed as a proxy for knowledge organization, A_S is negatively related to changes in knowledge accessibility. Further, because of the serial dependence of the knowledge properties, when complexity declines, accessible knowledge content increases. It can easily be shown that equation (6) is consistent with the change in mean knowledge accessibility given by the ratio of the

$$A \equiv \frac{c^X}{c^N}$$

mean knowledge accessibility of the experienced behaviors to that of the inexperienced behaviors (equation 7).

The Learning Module

The learning module requires a somewhat more specific understanding of certain terms, concepts, and notions than what is generally conveyed in conventional usage. These requirements are discussed in the following sections. A clarification of terms having time-like connotations, such as "long-term," when used in the context of the model is presented first. Then follows a discussion of the nature of an arbitrary future task and notions of realized and potential expertise, all concepts central to the model. Finally, the relationships between changes in knowledge properties, potential expertise, and the measure of learning are examined.

Time Horizon and Its Implications

The term "time horizon" refers to the future point in time at which the realization of expert potential will be observed. Consistent with the previously given operationalization of experience, in this discussion, the expression "long-term" is to be understood in the sense of "the fullness of experiences" rather than "with the passage of time," and "near-term" in the sense of an auditor's (arbitrary) next task. Further, in comparisons among different scenarios affecting the time horizon to realizations of expert potential, the terms "sooner," "later," "nearer," "more distant," and others of similar connotation are to be understood in the sense of an ordinal relationship in cumulative experience rather than in the sense of a relative duration of chronologically delimited periods

The Nature of an "Arbitrary Future Task"

The concept of expert potential relates to expectations in performance of an arbitrary future task. Observed automaticity in any task is dependent upon both the current state of an auditor's knowledge and the auditor's current task strategy, i.e., the mix of behaviors followed.[7] However, in the most general of circumstances, it is not possible, *a priori*, to know what tasks will be faced or what mix of behaviors will constitute task strategy; all behaviors must be considered as being equally likely.[8] With this consideration in mind, the term *arbitrary future task* is adopted to describe a task in which all behaviors are equally probable.

Realized vs. Potential Expertise

Realized expertise and realized gains are *ex post* concepts related to the automaticity observed during performance of an auditor's most recently completed task. Potential expertise, on the other hand, is an *ex ante* concept related to the automaticity with which an auditor is expected to perform an arbitrary future task. This potential is generally realized in the long-term in the actual automaticity observed during performance of a current task. The time horizon to realization of a potentially greater level of expertise depends upon how quickly knowledge progresses through the stages of the learning process described in the model overview. Movement from stage 1 to stage 2 produces increases in accessible knowledge content ($A_C > 1$), but not necessarily decreases in episode complexity (i.e., A_S may either increase or decrease). However, in the long-term, with the greater number of knowledge access opportunities afforded by the accumulation of experience ("learning opportunities"), knowledge eventually progresses to stage 3, where it is manifest as automatic task behavior (increased knowledge availability, $A_V > 1$) and decreasing episode complexity ($A_S < 1$).

Changes in Knowledge Properties and Expert Potential

An increase in expert potential occurs when there is a change in the state of an auditor's knowledge base that increases the probability of observing greater task automaticity in the future.[9] While Russo has shown that assessments of *realized* (i.e., currently displayed) increases in expert-like behavior can be validly based on changes in the automaticity of current task performance, assessments of greater expert *potential* (i.e., probable greater automaticity in an arbitrary future task) must be based on fundamental changes in the properties of knowledge that define the state of an auditor's knowledge base at any moment in time. It is the state of an auditor's knowledge after each task experience that carries over to future tasks and, ultimately, to expert realization in the long-term. The knowledge accessibility and knowledge properties effects of the model presented above are defined by an unconditional (equiprobable) behavior mix and for this reason directly capture the post-current-task state of the knowledge base that unconditionally determines the automaticity of future task behaviors.

Comprehensive Learning

As discussed above, realized gains in expertise are fostered by increases in knowledge organization ($A_S < 1$), accessible knowledge content ($A_C > 1$), and knowledge availability ($A_V > 1$). However, as pointed out by Russo (1999b: 207-8), the path to expertise in the long-term may necessitate unlearning, restructuring, and making other alterations to existing knowledge, changes that, in the near-term, can manifest themselves as effects that are inimical to current and near-term realization of improvements in task automaticity and to one or more knowledge properties. Therefore, from a long-term perspective, increased potential for further expert development is indicated by current knowledge accessibility and knowledge properties effects that vary in either direction from unity.

This conclusion appears to suggest a set of tests based on a null hypothesis that each effect is equal to unity. However, such an approach presents two very significant interpretive difficulties. First, it is equivalent to using the mean knowledge accessibility effect (A) as a comprehensive indicator of the effect of current task experience on an auditor's potential for future expert development. The major objection to using A in this way is that increasing and decreasing properties metrics offset, raising the possibility that A may misstate the effect of experience on an auditor's knowledge. Second, although the knowledge properties effects (A_S, A_C, and A_V) are interpretable individually, doing so does not provide a comprehensive, objective, and quantitative measure of learning whose consistency across observers can be assured and that is also comparable across time, tasks, or auditors.

In light of these difficulties, it is proposed that the effects of current task experience on expert potential be based on measures of *comprehensive learning*, *L*, defined as the positive root of the mean squared change in knowledge properties, as shown by equation (8).[10]

$$L \equiv \sqrt{\frac{\sum^{k} (A_k - 1)^2}{3}}, k \in \{S,C,V\}$$

Comprehensive learning is a computationally objective synthesis of effects that takes into account all changes in knowledge properties resulting from the current task experience, regardless of direction. In so doing, as a comprehensive measure of the effects of experience on knowledge, *L* overcomes the limitations of mean knowledge accessibility mentioned in the preceding paragraphs.

III. NULL HYPOTHESES

Having now completed the presentation of the model, I turn to the first part of the question raised in the introduction: What does field experience do to an auditor's knowledge that changes the expectation of increasing expert performance in future tasks? In this discussion, the term "global learning" will be used to represent comprehensive learning without regard to the type of knowledge utilized during performance of task behaviors, while "learning," when qualified by a particular knowledge type, will refer to comprehensive learning with respect to that knowledge type only. When unqualified in any way, "learning" will refer to both global and knowledge-type learning. The following notation is used: $k \in \{S, C, V\}$, where k indicates knowledge property and S, C, and V retain their previous meanings, and T indicates knowledge type, $T \in \{1, 2\}$, where 1 and 2 indicate strategic and environmental knowledge, respectively.

Hypothesis 1: Global Learning

Learning at the global level is the most relevant measure of changing expert potential because, in a given task, it is the accessibility of knowledge at this level that directly determines the automaticity of an auditor's observed task behaviors.[11] The null hypothesis is that no global learning has occurred as a result of task experience:

$$H\,1_0 : L = 0$$

If global learning takes place then the measure of comprehensive learning will be sufficiently greater than zero as to reject this null at the level of risk chosen, and support the statement that the observed measure of global learning is a real effect of experience and not an artifact of experimental error. The implication of such a finding of support is that the expert potential of the auditor was increased by performance of the task.

Effects Across Knowledge Types

In performing a specific task, access to different types of knowledge occurs with different frequencies and degrees of accessibility, producing differential learning. Therefore, a diagnostic assessment of the effect of experience on expert-potential can be had if learning is examined by knowledge-type. These considerations suggest the following hypotheses:

Hypothesis 2: Knowledge-Type Learning

The null hypothesis for each knowledge type is that no learning has occurred:

$$H2a_o : L_1 = 0 \qquad H2b_o : L_2 = 0$$

Hypothesis 2a relates to strategic learning and hypothesis 2b to environmental learning. Rejection of either null is evidence that, at the level of risk chosen, the measure of comprehensive learning observed for the respective knowledge-type is not the result of experimental error but a real effect of experience. The implication of a finding of support for learning in a specific knowledge-type is that the auditor's expert potential was enhanced in a specific way by the task, although the time horizon for realization will depend, in part, on whether learning occurred in both knowledge types together. This matter is examined by hypothesis 3.

Hypothesis 3: Differential Learning

$$H3_o : L_1 - L_1 = 0$$

Although ultimately, all knowledge-type learning will produce increased automaticity, the drift toward that end may not occur in both knowledge types in a synchronous manner. Any presently unavailable knowledge that fails to evolve toward greater availability acts to limit the development of automaticity in task behavior. *Ceteris paribus*, to the extent that learning occurs synchronously in both knowledge types, the time horizon to expert realization is shortened. To test for synchrony, the null hypothesis is that the magnitude of learning, if it occurs, is the same for both types of knowledge.

Rejection of this null is evidence at the level of risk chosen that any observed difference in learning between knowledge types is not the result of observational error but a real difference in the effect of task experience on different types of knowledge. Because comprehensive learning is the measure of the effect of experience on an auditor's expert potential, rejection of this null is also evidence that the different kinds of knowledge responsible for expertise do not develop synchronously. By extension, a finding of asynchronous learning may provide valuable information related to such matters as auditor training and assignment, whose aims are to improve the efficiency and effectiveness of the expert development process.

Relationship Among Hypotheses

Examination of the effects of experience on an auditor's knowledge base must be carried out on two levels because metrics at each level convey different information. At the global level (hypothesis 1) change in knowledge properties, measured comprehensively by L, directly reflect the long-term effects of experience on assessments of an auditor's expert potential. At the knowledge-type level (hypotheses 2 and 3), L_T comprehensively measures the long-term effect of experience-induced changes on the properties of knowledge that determine the accessibility of each category of substantive knowledge. However, while long-term improvement in the accessibility of each knowledge type *contributes to* global knowledge accessibility and long-term improvement in an auditor's expertise, the relationship is not direct.

A complete exposition of the relationship between global and knowledge-type metrics is beyond the scope of this paper. In brief, its origin lies in how the knowledge base response vector, a 3-element vector reporting the level of response for each primary knowledge property, is affected by the change from a global to knowledge-type perspective. At the global level, response vectors are constructed without regard to the substance of the knowledge accessed (i.e., as if the entire knowledge base were composed of only a single knowledge type). In contrast, at the knowledge-type level, a separate response vector is constructed for *each* category of substantive knowledge. As a result, the global response vector is *not* always the sum of the response vectors at the knowledge-type level.[12]

IV. EXPERIMENTAL PROCEDURE

The details of the experiment performed and behavior observation methodology employed to obtain data on auditor behavior during performance of a field task are too lengthy and complex to be covered here. The following paragraphs present only a brief summary. For a more complete discussion, see Russo (1994, 1995).

Subjects, Task, and Procedure

Both inexperienced auditors and a non-financial-statement related audit task were chosen for this experiment in order to assure observation of a novice problem solving process and to increase the likelihood of capturing a learning process. The Subjects were four first-year auditors from the professional staff of a Big Six auditing firm. All Subjects were volunteers who had sat for and passed some, but not all, parts of the CPA examination and all had no prior exposure to the subject matter of the task.

The task in this experiment was a review of the Statement of Operating Expenses of a new office building in which the client is a tenant, rendered pursuant to the rent escalation provisions of the client's lease. To acquaint them with the terminology, administrative, and computational procedures associated with operating expense rent escalations, on the day before the experiment, each Subject was given background material and two samples of completed review reports to study. However, none of this material provided any information on examination or reporting procedures, the landlord's procedures, or the existence and nature of any documents used in the preparation of the statement rendered to the client. Therefore, such a task, to the extent that it differs from that of the usual financial audit, would be unfamiliar to the Subjects who participated in this experiment.

Each Subject performed the task on a different day. The task was performed in a simulated business office in which each Subject was presented with the equipment and supplies normally available in audit environments and the ability to communicate (via intercom) with and receive documents (via a mail slot) from other parties present in the task environment (e.g., client personnel, the audit partner, etc.). During performance of the task, each Subject was free to contact any party in the task environment and to request any documents or explanations required. Although the researcher played the roles of others in the task environment, no face-to-face or verbal contact took place between Subject and experimenter. Responses to requests for explanations were communicated to the Subject via a video display at the Subject's desk.

Behavior Observation Methodology

Synchronized videotaped and think-aloud verbal protocols were used to capture both the observable behaviors and cognition of the Subjects during their performance of the task. The experimental protocols were independently coded in terms of behaviors and cognition by the researcher and a first year doctoral student trained by the researcher. Kappa (Cohen, 1960), a widely used measure of the agreement between independent coders, ranged from .72 to .78 over a total of approximately 8 hours of behavior observation. These levels of kappa are significant at $p < .0000$.

Sources of Error and Tests of Significance

The sources of error of concern in tests of significance in this experiment are (1) non-systematic (i.e., random) coding error and (2) non-systematic over/under recognition of the cognitive and automatic components of mediating episodes. Each model metric is tested against the expected range of possible outcomes at the agreed upon level of risk under the null hypothesis. However, while the model's functional relationships provide expectations for mean outcomes, they do not provide any basis for forming expectations of the density of those outcomes, even if one were willing to accept that experimental error could be described by any of the commonly used probability distributions. Consequently, in order to test the model metrics for significance, the probability distributions associated with each model metric were generated by simulating each Subject's task behavior and knowledge base response 25,000 times. After each iteration, each response was accumulated by knowledge type, model effects computed, as described above, and the probability distributions updated.[13] The probability tables generated by this means are extensive. Selected critical values of the learning metrics are shown as Appendix A.

V. FINDINGS

Findings are reported in Table 1.

TABLE 1
THE EFFECT OF EXPERIENCE ON MEASURES OF COMPREHENSIVE LEARNING

Subject	Global Learning $H1_a$: $L > 0$	Strategic Knowledge $H2_a$: $L_1 > 0$	Environmental Knowledge $H2_b$: $L_2 > 0$	Differential Learning $H3_1$: $L_1 - L_2 \neq 0$
1	0.1500	**0.1439**	0.0443	**0.0996**
2	0.1420	0.0621	0.0540	0.0081
3	**0.2720**	0.0536	**0.2541**	**-0.2005**
4	**0.3690**	**0.1975**	**0.2172**	-0.0197

Notes: Column headings present hypotheses in alternative form of the related null. Bold entries are significant at $p \leq 10\%$. Findings show significant strategic learning for Subjects 1 and 4 and significant environmental learning for Subjects 3 and 4. Findings also show that there is a significant difference in learning produced by experience across knowledge types for subjects 1 and 3, while subjects 2 and 4 show no difference in the rate of learning across knowledge types. That is, the effect of experience on the expert potential of Subjects 2 and 4 was the same for both kinds of knowledge. However, in the case of Subject 4, the effect was to increase expert potential, while in the case Subject 2, experience has no significant effect on expert potential.

These findings are based on data extracted from Russo's database of task behaviors, compiled as described in Section IV, and summarized in Tables 2A and 2B at both the global and knowledge-type levels. Indications of significance are based on simulated knowledge base responses under the respective nulls.

TABLE 2A
OBSERVED BEHAVIOR AND KNOWLEDGE BASE RESPONSE FREQUENCIES
KNOWLEDGE-TYPE LEVEL

		Strategic Knowledge						Environmental Knowledge							Strategic Knowledge						Environmental Knowledge					
		Naive Group			Experienced Group			Naive Group			Experienced Group				Naive Group			Experienced Group			Naive Group			Experienced Group		
j	n_j	n_{sj}	n_{cj}	n_{vj}	n_{sj}	n_{cj}	n_{vj}	n_{sj}	n_{cj}	n_{vj}	n_{sj}	n_{cj}	n_{vj}	n_j	n_{sj}	n_{cj}	n_{vj}	n_{sj}	n_{cj}	n_{vj}	n_{sj}	n_{cj}	n_{vj}	n_{sj}	n_{cj}	n_{vj}
	SUBJECT 1													SUBJECT 3												
1	57	59	5 2	46	61	46	39	65	49	25	76	51	19	46	46	43	41	46	46	38	51	35	20	54	35	19
2	14	18	13	7	15	13	11	18	14	10	14	13	12	16	17	16	14	17	16	14	21	17	9	17	16	14
3	5	5	5	3	5	5	4	5	4	2	6	4	2	17	18	18	9	17	17	12	21	16	7	17	15	13
4	10	11	10	7	10	8	7	12	10	8	11	11	8	27	28	23	20	27	27	19	33	25	12	29	23	14
5	5	5	5	4	5	5	5	6	5	3	7	4	2	9	10	9	8	9	9	7	10	9	6	9	8	7
	SUBJECT 2													SUBJECT 4												
1	50	50	49	37	55	50	42	55	40	24	59	45	30	29	39	32	20	30	29	27	48	39	6	31	25	16
2	20	20	20	17	21	19	17	20	18	16	22	20	16	13	16	15	6	13	13	12	18	14	7	13	13	13
3	6	7	6	3	6	6	6	7	5	3	6	5	4	7	8	8	4	7	6	2	8	8	6	7	7	5
4	21	22	21	15	21	20	13	22	21	17	21	19	15	21	29	24	10	21	21	12	28	23	6	28	24	8
5	10	11	10	8	10	10	6	11	9	5	11	10	7	3	3	3	3	3	2	2	3	2	2	3	2	1

Note: Target behaviors (*j*) are: 1 = Reading, 2 = Inquiry, 3 = Calculating, 3 = Writing, 5 = Other. n_{sj} = Frequency of all responses, n_{cj} = Frequency of positive responses, n_{vj} = Frequency of available positive responses, n_j = Frequency of behavior *j*

TABLE 2B OBSERVED BEHAVIOR AND KNOWLEDGE BASE RESPONSES GLOBAL LEVEL														
		Naive Group			Experienced Group				Naive Group			Experienced Group		
j	n_j	n_{sj}	n_{cj}	n_{vj}	n_{sj}	n_{cj}	n_{vj}	n_j	n_{sj}	n_{cj}	n_{vj}	n_{sj}	n_{cj}	n_{vj}
	SUBJECT 1							SUBJECT 3						
1	57	74	51	21	91	51	12	46	56	37	20	59	40	16
2	14	25	16	6	16	13	10	16	24	19	9	19	17	13
3	5	6	5	1	7	5	2	17	27	22	4	18	16	9
4	10	14	11	6	12	10	6	27	39	26	10	31	25	8
5	5	7	6	3	7	4	2	9	11	9	5	9	8	5
	SUBJECT 2							SUBJECT 4						
1	50	60	44	16	68	49	26	29	67	51	6	34	27	16
2	20	21	19	14	24	20	14	13	26	21	5	13	13	12
3	6	10	7	2	6	5	4	7	10	10	4	8	7	1
4	21	24	22	12	22	19	8	21	44	34	3	34	30	5
5	10	13	10	4	11	10	3	3	3	2	2	4	2	1

Outcomes From Tests of Hypotheses

Hypothesis 1: Global Learning

Hypothesis 1, which holds that no global learning occurred as a result of task experience, is rejected for Subjects 3 (L = .2720, p <.03) and 4 (L = .3690, p<.06). We conclude that these two Subjects learned as a result of their experience in the experimental task, and as a consequence, performance of the experimental task increased their expert potential. Further, there is no evidence that either Subjects 1 or 2 learned from the task experience.

Hypothesis 2: Knowledge-Type Learning

The null hypothesis for each knowledge type is that no learning resulted from experience in performing the task. This hypothesis is rejected for strategic knowledge for Subjects 1 ($L_1 = .1429$, $p < .05$) and 4 ($L_1 = .1975$, $p < .03$), and for environmental knowledge for Subjects 3 ($L_2 = .2541$, $p < .00$) and 4 ($L_2 = .2172$, $p < .09$). Subject 4 is the only one for which the nulls are rejected for both knowledge types. None of the nulls is rejected for Subject 2.

It is interesting to note that the findings reported for Subject 1 for this hypothesis appear to be inconsistent with those reported for hypothesis 1: on the global level, no significant finding of learning is reported, while at the knowledge-type level there is a significant finding of learning. This matter is discussed later.

Hypothesis 3: Differential Learning

The null hypothesis holds that there is no difference in learning across knowledge types. The null is rejected for Subjects 1 (L_1 - L_2 = .0996, $p < .00$) and 3 (L_1 - L_2 = -.2005, $p << .05$). We conclude, therefore, that for these two Subjects, at least, the differences in learning between knowledge types is real at the level of risk chosen. Although Subject 4 showed significant learning for both knowledge types, the failure to reject hypothesis 3 indicates that for this subject, knowledge-type learning occurred synchronously. The finding of a significant negative difference for Subject 3 implies that the extent of environmental learning exceeded that of strategic learning. On the other hand, the significant positive finding for Subject 1 indicates that strategic knowledge was more strongly enhanced by task experience than was environmental knowledge.

Interpretation

The model provides insight into the learning effects of task experience at two levels. Comprehensive learning on the global level provides an overall measure of benefit from task experience while diagnostic and interpretive information is provided at the knowledge-type level. Findings with respect to Subjects 1 and 2 illustrate this important relationship. At the global level, both subjects fail to show any significant change in expert potential as a result of their performance of the experimental task. However, at the knowledge-type level, it can be seen that the two cases are not equivalent. In fact, Subject 1 did show a significant gain in potential due to strategic learning, while Subject 2 shows no significant indication of benefit at all. Further, the findings reported show that the difference between Subject 1's strategic and environmental learning is real while that for Subject 2 is most probably due to experimental error. The significant effect of diagnostic information can also be seen in the case of Subjects 3 and 4. While both Subjects show significant learning at the global level, Subject 4's experience is qualitatively different from that of Subject 3. Both Subjects experienced significant environmental learning, but Subject 4's experience involved significant gains in both types of knowledge while that of Subject 3 involved significant learning only with regard to environmental knowledge. Tests of Hypothesis 3 for these Subjects show that the difference in learning between knowledge types is real for Subject 3 while it is not significant for Subject 4. On the bases of this evidence, we can conclude that the expert potential of Subject 4 was changed to a greater extent by this task experience than was that of Subject 3.

VI. DISCUSSION

The research question posed in the Introduction asks what can be learned from observations of an auditor's behavior in a current task that can be used to anticipate performance in future tasks. Because behavior is knowledge-driven and task experience affects the properties of knowledge, the focus of this paper is on quantifying the effects of experience on the latter. The model proposes that experience changes knowledge along two dimensions: knowledge structure, which addresses the properties of the knowledge demanded by task performance, and substantive content, which addresses its purpose and intentionality. From an understanding of how the properties of knowledge along each of these dimensions is affected by an auditor's current task experience, one has a basis for anticipating changes in the level of that auditor's expertise in future tasks.

General Observations

Findings reported in Table 1 evoke two broad observations. First, comparison of the findings for Subjects 1 and 3 show that learning at the global level does not always reflect accurately learning at the substantive level, and *visa-versa*. The second observation rests on the relationship between global learning and changes in expert potential. Given any arbitrary task and behavior mix, changes in both realized and potential expertise are determined by global knowledge accessibility. Because of the imperfect relationship, described above, between learning at the global and knowledge-type levels, significant effects of experience on substantive knowledge are not always immediately evident in changes in either realized expertise or assessments of expert potential. Such is the case with Subject 1.

The Individuality of Expert Development

Findings reported here show effects that are both diverse and particular to each individual. At the global level, two auditors (Subjects 3 and 4) show significant learning effects and two (Subjects 1 and 2) do not. At the knowledge-type level, one auditor (Subject 2) shows no learning effect, two (Subjects 2 and 3) show learning in one knowledge type but not the other, and one auditor (Subject 4) shows significant learning for both knowledge types. Of the auditors showing differential effects across knowledge types, one (Subject 1) shows a significant effect for strategic knowledge but not environmental knowledge, and the other (Subject 3) shows just the opposite. Finally, the learning differentials by knowledge type are significant only for Subjects 1 and 3.

With such diversity and individuality, what, then, can be said for the process of expert development and, in particular, for the effect of experience on assessments of expert potential? On statistical grounds, findings from the four volunteer auditor's participating in this experiment do not justify their extension to the general population of auditors. However, on logical grounds, these findings contribute a basis for drawing certain conclusions about the process of expert development in individual auditors, anticipating the potential of particular auditors and, perhaps, hastening its realization. Let us consider each of these contributions.

The Process of Expert Development

Expert potential is defined earlier in this paper as the expected automaticity of an auditor's task behavior in the long-term. The attainment of expertise requires both structural and substantive changes in knowledge. In this paper, each of these requirements is hierarchically related; structural change involves changes in knowledge organization, accessible content, and availability, the properties of knowledge that determine its accessibility, while substantive change involves change in those properties as they relate to the accessibility of knowledge of categorically different intentionality.

Structural Changes

Globally and for each type of knowledge, realized expertise and, with some uncertainty, near-term expert-potential are positively related to specific directional changes in knowledge organization ($A_S < 1$), accessible content ($A_C < 1$), and availability ($A_V < 1$). Long-term, on the other hand, expert potential is related to *any* structural change (i.e., $A_S \neq 1, A_C \neq 1, A_V \neq 1$) as knowledge is reorganized, augmented, and discarded by task experience. This long-term relationship is captured by the measures of comprehensive learning, globally by L, and for each knowledge type by L_T.[14] A measure of comprehensive learning can have only positive values, and significant values are indicative of a positive effect of task experience on long-term expert potential.

Substantive Changes

Substantive change refers to the long-term effect of experience on the accessibility of intentionally categorized knowledge (knowledge-types). The model presented in this paper considers two such categorizations: strategic knowledge and environmental knowledge. The realization of a full measure of expertise requires maximum accessibility for both knowledge types. Consequently, learning in either or both knowledge types is consistent with increased potential for greater expertise in the long-term.

Anticipating the Effect for Particular Auditors

Given the preceding description of how changes in substantive knowledge affect expertise, further insight follows from differential learning across knowledge types. For novice auditors, the greatest effect on expert potential arises when learning is synchronous for both knowledge types. Where learning does not take place in this manner, there is a qualitatively different implication from the case in which it does. While asynchronous learning processes do contribute to increased expert potential, conditional on the initial states of the auditor's substantive knowledge, the expectations for such cases differ from those in which learning is synchronous. If both knowledge types are initially of relatively low accessibility, as is likely to be the case with novice auditors, realization of a full measure of expertise may be more distant if learning is asynchronous than if it is synchronous. On the other hand, if there is a significant initial difference in accessibility between knowledge types, the prognosis will depend on whether the learning effect is in the knowledge category having the lesser or greater accessibility. If the former is the case, realization will likely be observed earlier than if the case is the latter.

Hastening Expert Realization

Another implication of asynchronous learning is what such a finding may indicate about the nature of the auditor's initial expertise and possible strategies for further experiences that would accelerate expert development. The knowledge-type having the least accessibility is the limiting factor in the rate at which progress is made toward realization of an auditor's expert potential. This relationship suggests expert development strategies that tend to equalize levels of knowledge accessibility at that of the most accessible knowledge type. For example, if an auditor's responses show learning in one knowledge type but not the other, then additional training can be more efficiently employed if it is directed at enhancing the accessibility of the least accessible knowledge type. On the other hand, if in a particular task an auditor fails to show learning in either knowledge type, such a finding may not necessarily mean that the auditor lacks expert potential; the model only accesses *change* in expert potential. Therefore, the null finding simply means that the auditor's expert potential was not changed by the experience of performing that particular task. Assessment of such an auditor's current level of expertise, based on current task automaticity and the structural pattern of global learning, can be used to evaluate whether additional training or assignment rotation is appropriate.

VII. CONCLUSION

Summary

The model of task behavior presented in this paper utilizes task automaticity as an objective measure of expertise. It follows, then, that the process of expert development is a description of the experience-induced causes accounting for increasing task automaticity in the long-term. Russo (1999b) has demonstrated the relationship between experience-induced changes in the state of an auditor's knowledge (i.e., learning) and changes in realized expertise in a specific task. This paper extends that relationship to the anticipation of long-term performance in arbitrary future tasks by disengaging the link between knowledge and task strategy (i.e., behavior mix), and focusing on changes in the properties and intentionality of knowledge driving individual task behaviors. The model holds that an auditor's potential to develop expertise is limited by the properties of the knowledge driving that auditor's task behaviors at the global level. The effect of experience on those properties is measured by comprehensive learning. Beyond an assessment at the global level, an analysis of the relationship between learning at the global and knowledge-type levels permits one to develop informed expectations about both the effect of experience on the time horizon for realization of an auditor's expert potential and to develop informed strategies for hastening that realization.

Suggestions for Further Research

This paper presents basic research into the process by which expertise develops through experience. Bouwman & Bradley (1997: 110) point out that there is a lack of basic research in accounting, probably reflecting the applied orientation of the profession. They argue that this neglect is shortsighted; there is a great need for basic research in accounting because basic research fuels future applied research. They go on to say that accounting researchers must become constructors of theories rather than adopters of theories developed in other disciplines, where the institutional settings and complexities within which accountants operate are absent. It is in this context that the research presented in this paper and the suggestions discussed next are motivated.

Three suggestions for further exploration of expert behavior and the process by which expertise is acquired are discussed here. First, the implications of synchronous learning have not been fully explored. As a case in point, in the Discussion it is asserted that, conditional on the initial accessibility of an auditor's substantive knowledge, the greatest effect of experience on expertise and the most rapid realization of expert potential occur when knowledge-type learning is synchronous. Based on this assertion, one can anticipate that realizations of expert potential will be delayed by asynchronous learning compared with what will be the case when learning is synchronous. This is a prediction, which has practical application in training and assignment decisions, which can be empirically tested.

Another research opportunity exists in exploring in depth the effects of experience on the properties of knowledge. Although the structural dimension of learning is modeled and briefly discussed in this paper, the paper's primary empirical focus is on of the effects of experience along the substantive dimension of knowledge. While measures of comprehensive learning are sensitive to the magnitude of learning effects, they are not sensitive to its underlying structural pattern, i.e., the various combinations of knowledge properties effects at various hierarchical levels. Study of the effects of experience along the structural dimension provides an opportunity to learn about the modes of experiential learning. In this regard, the learning module of the model proposes that new knowledge acquisitions initially affect organization. Then, with successive accesses, that newly acquired knowledge progresses from accessible knowledge content to finally becoming available knowledge, at which state it has maximum impact on task automaticity. Russo (1999b) also discusses circumstances in which, conditional on an auditor's initial knowledge state, this sequence is altered. A research opportunity exists here in that progression of the properties of new knowledge with experience has not been empirically observed in a manner quantitatively consistent with Russo's model of task behavior.

Finally, it must be emphasized that strategy, defined as an observer's (one's own) characterization of another's (one's own) behaviors (Russo, 1999a), is itself an expression of knowledge. In this paper, only the changing properties of strategic knowledge are examined, not changes in strategy, *per se*. The study of strategy is made difficult by the interaction of learning effects with those of the evolving task environment as it reacts to the auditor's own actions. Because of this interaction, a significant research opportunity exists in modeling and interpreting the dynamics of behavior mix as a means of gaining a deeper understanding of expertise and its development than that which is possible solely from the structural-dynamical perspective presented here.

ENDNOTES

1. In using observed behavior as a criterion of expertise, the appropriateness of behaviors and the quality of task outcomes are not considered. Therefore, the behavior studied can only be described as being relatively expert-*like*.

2. In this research, the term "knowledge base" is used to represent the totality of the knowledge that an auditor called upon during performance of a task. While it is common usage to refer to the collection of that which drives an auditor's behavior as a "knowledge base," this usage has several serious shortcomings. Knowledge is information in action. The "content" of an auditor's knowledge base can only be ascertained by observing the auditor's response to situations making knowledge demands (Russo 1997a: 411). What is commonly referred to as "knowledge" is actually an action potential that is latent until called upon to initiate and guide behavior. This latent capacity is better referred to as "information" or perhaps "data" rather than "knowledge." Although not explicit in the putative usage of the terms "knowledge base" and "knowledge," I believe this distinction is on some level generally understood. Hence, in deference to common usage, I will continue to use these terms in contexts in which neglect of the precise distinctions mentioned are not troublesome.

3. Both purposefulness and intentionality are attributions to another made by observers of the other's actions. Russo's model of auditor behavior during empirically intense audit tasks holds that auditors are purposeful and intentional in their choice of task behaviors. Purposeful means that the behavior observed is consistent with the auditor's perception of the objective of that behavior. Intentional means that the behavior and its targets are consistent with the auditor's beliefs and opinions at the moment the behavior is performed. A concept of intrinsic purposefulness and intentionality is, in the context of this research, not useful. To illustrate, while a flathead screwdriver, as opposed to a Philips-head screwdriver (both common household tools), may be attributed intrinsic purpose and intentionality, neither would be correct attributions to make when it is observed that an individual is using it to pry open the lid of a paint can. The ostensible purpose here is to gain leverage, not to join two pieces of wood, and the intentional target of the behavior is the lid of the can, not a screw. For additional discussion of these assumptions, see Russo (1997b: note 26).

4. At the global level, we are concerned only with the nature of response, not its content. Consequently, the complexity of global episodes will differ from the sum of the complexities at the knowledge-type level. This difference, which relates to the efficiency of knowledge access and the learning effect, involves complex relationships that are beyond the capacity of a journal article to illuminate. In any event, these relationships are not immediately germane to the matters presented in this paper and will be explored in a future paper.

5. Knowledge type is indicated by the subscript T associated with any knowledge-specific variable. Therefore, variables having S, C, and V subscripts, and any measure of knowledge accessibility, are implicitly qualified by a knowledge type subscript, e.g., S_{jT}, n_{kT}, A_T, etc.

6. Knowledge accessibility (c_j) and task automaticity (a) in a *specific task performed* are related through a specific behavior mix as follows: $a^P = \sum^j c_j^P m_j^*$, where m_j^* is the mix of behavior j for the task. As will be discussed later in the paper, in an *arbitrary future task*, m_j is a constant for all behaviors.

7. Strategy is an observer's (one's own) characterization of the purposes and intentionality of another's (one's own) behavior. For an extensive discussion on this point, see Russo (1999a), esp. note 22.

8. Task automaticity is measured by $a = \sum^j c_j m_j$, where m_j the mix of behavior j and c_j is the accessibility of the knowledge supporting that behavior. The author is not aware of any research dealing with a

taxonomy of auditing tasks and their strategy implications that can serve as a basis for a more useful behavior mix assumption than the equiprobable assumption mentioned in the text. (This is a matter left for future research.) Consequently, given an arbitrary future task, the *ex ante* behavior mix is the same for each behavior, i.e., $1/b$, where b is the number of behaviors recognized by the behavior observation system. Therefore, the expected automaticity of any specific instance of an arbitrary future task is $1/b\sum^{j}\hat{c}_j = \hat{c}$, where the hat (^) over any variable indicates an instance of a specific possible realization of a variable in an arbitrary future task. Because of this relationship, from this point in the text forward, the terms "automaticity" and "accessibility" when used in the context of an arbitrary task are to be understood as being equivalent.

9. Although not quantified by the model presented in this paper, this probability is assumed to be positively related to changes in the properties of knowledge. Let the subscript n designate the ordinal number of a task performed in a sequence of tasks, {1,2,3, ..., n-1, n, n+1, ...}. Let $\bar{\xi}_n$ be the measure of an auditor's expert potential as ascertained at the completion of task n, where expert potential is operationally defined as the ratio of an auditor's expected knowledge accessibility in the next task to knowledge accessibility in the current task, i.e., $\bar{\xi}_n = \bar{c}_{n+1} - c_n$. Upon completion of task n, a set of knowledge properties effects, $\{A_k\}_n$, is obtained. From this set, two metrics can be determined: the effect of the current task experience on knowledge, measured by comprehensive learning, L_n, and the standard deviation of the density of expert potential, $\sigma_{\xi,n}$. For purposes of the current discussion, it is necessary only that $\bar{\xi}_n$ be considered as an unspecified positive function of comprehensive learning, i.e., $\bar{\xi}_n = L(L_n) + 1$, and $\sigma_{\xi,n}$ as an unspecified function of the *pattern* of changes in knowledge properties, i.e., $\sigma_{\xi,n} = \sigma(\{A_k - 1\}_n)$. Because L_n cannot have values less than zero, $\bar{\xi}_n - 1$ indicates the *expected* increase in knowledge accessibility of the *next* task, as ascertained at the completion of task n. As such, $\bar{\xi}_n$ represents a means of anticipating the expertise with which an auditor will perform task n +1, the nature of that task being unknown at the time that $\bar{\xi}_n$ is ascertained. In contrast, $\xi_{n+1} - 1$ indicates the *realized* increase in knowledge accessibility upon completion of task n+1.

Upon completion of task n, an observer expects an auditor to perform the next task with a level of expertise that can be expressed as a ratio, $\bar{\xi}_n$, of expected knowledge accessibility ($\bar{c}_{n+1}$) to the knowledge accessibility of the recently performed task (c_n). This expectation is, in turn, based on the properties set $\{A_k\}_n$, the effect of the experience on the state of that auditor's knowledge as ascertained at the conclusion of task n. Upon completion of the next task, a new set of knowledge properties, $\{A_k\}_{n+1}$, is ascertained. If $\{A_k\}_{n+1} = \{A_k\}_n$, then $L_{n+1} = 0$ and, therefore, $\bar{\xi}_{n+1} = \bar{\xi}_n$, implying that there has been no change in expert-potential as a result of experience in the task just completed. On the other hand, if $\{A_k\}_{n+1}, \neq \{A_k\}_n$, then $L_{n+1} > 0$ and $\bar{\xi}_{n+1} > \bar{\xi}_n$ implying that there has been a change in expert potential.
Regardless of any change in knowledge properties, it is possible that on completion of the next arbitrary task, the realized increase in knowledge accessibility ($\xi_{n+1} - 1$) can be greater or less than the expected increase ($\bar{\xi}_n - 1$). This fact makes it necessary to distinguish between long-term and near-term expert potential. The effect of current task experience on long-term expert potential, $\bar{\xi}_n$, is the change in knowledge accessibility to be expected in the fullness of experience, i.e., $\bar{\xi}_n = 1 + \int_{-\infty}^{\infty}(\xi_{n+1} - 1)p(\xi_{n+1} - 1 \mid L_n, \sigma_{\xi,n})d(\xi_{n+1} - 1)$, while its effect on near- term expert potential is measured by the probability relationship $P(\xi_{n+1} > 1 \mid L_n, \sigma_{\xi,n}) > P(\xi_n > 1 \mid L_{n-1}, \sigma_{\xi,n-1})$, i.e., an increase in near-term expert potential has occurred if the probability, *ex post* the current task, (*ex ante* the arbitrary next task), of observing an increase in knowledge accessibility in the next task is greater than it was *ex post* the previous task (*ex ante* the current task). It should be also noted that the relationships described are recursive, and that if there are no significant differences in knowledge properties from one task to the next, then $\{A_k\}_n = \{A_k\}_{n-1}$.

10. See Russo (2000) for an empirical examination of how use of the knowledge accessibility effect as a measure of assessing expert potential can result in significant distortions in assessments of expert potential.

11. The change in task automaticity with experience (l) is determined by two factors, knowledge accessibility (A) and knowledge utilization in a task (E_x), related by the equation $l = AE_x$, where $A = A_S A_C A_V$. Knowledge utilization is a function of the auditor's strategy in performing the task. For a given task, strategy is a constant, making the change in automaticity solely a function of the change in knowledge properties.

12. More specifically, a response vector is an ordered set of three elements, $\{r_1 r_2 r_3\}_{jn}$, with r_{ijn} being the response for element i of the response vector for the n th instance of behavior j. The vector elements represent the automatic response, the analysis and planning cognitive response, and the uncertainty cognitive response, respectively. Each element has a value of either 1 or 0, with 1 representing the presence of a response and 0 representing its absence. To illustrate one possible relationship between learning measures at the global and knowledge-type levels, assume that in the nth episode mediating the transition to target behavior j, knowledge-types $T = 1$ and $T = 2$ both respond cognitively as follows to the demand for knowledge: $\{010\}_{jn,T=1}$ and $\{010\}_{jn,T=2}$. At the global level, this mediating episode would be reported as a cognitive response with vector $\{020\}_{jn}$. On a subsequent demand for knowledge by the same target behavior, knowledge-type 1 responds automatically while knowledge-type 2 responds cognitively (i.e., $\{100\}_{j(n+1),T=1}$ and $\{010\}_{j(n+1),T=2}$, assuming the response for knowledge-type 2 was of the same nature as on the previous access). In this instance, at the knowledge-type level learning will have occurred for knowledge-type 1, but not for knowledge-type 2 At the global level, learning is also reported. However, the episode is reported as $\{010\}_{j(n+1)}$, being limited by knowledge-type 2's cognitive response. Additionally, while the global response indicates a decrease in complexity, there is no effect on either knowledge availability or task automaticity. Finally, on a third instance, both knowledge types respond automatically (i.e., $\{100\}_{j(n+2),T=1}$ and $\{100\}_{j(n+3),T=2}$. In this final instance, learning is reported both globally and, at the knowledge-type level, for knowledge-type 2 only. At the global level, while there is no change in episode complexity or accessible knowledge content, the entire episode is reported as automatic, $\{100\}_{j(n+2)}$ revealing increases in both availability and task automaticity. In this last instance, the response at the global level is no longer limited by the response of knowledge-type 2, which was, in the previous instance, the least-available knowledge-type.

13. Biddle, et al. (1990) discuss the use of computer intensive methods in auditing.

14. For findings at the structural level, see Russo, 2000.

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APPENDIX

APPENDIX
SELECTED CRITICAL VALUES OF LEARNING MEASURES

p	L	L_1	L_2	L_1-L_2	p	L	L_1	L_2	L_1-L_2
SUBJECT 1					SUBJECT 3				
0.050	0.0334	0.0048	0.0229	-0.2258	0.050	0.0134	0.0000	0.0085	-0.1428
0.900	0.3133	0.1146	0.2154	0.0238	0.900	0.1893	0.0726	0.1281	0.0137
0.950	0.3900	0.1407	0.2578	0.0509	0.950	0.2325	0.0882	0.1541	0.0304
0.975	0.4790	0.1658	0.3023	0.0748	0.975	0.2789	0.1037	0.1798	0.0470
SUBJECT 2					SUBJECT 4				
0.050	0.0191	0.0023	0.0075	-0.1249	0.050	0.0260	0.0100	0.0199	-0.1999
0.900	0.2105	0.1021	0.1220	0.0407	0.900	0.3084	0.1448	0.2005	0.0543
0.950	0.2534	0.1252	0.1464	0.2537	0.950	0.3915	0.1745	0.2441	0.0853
0.975	0.2993	0.1474	0.1693	0.0873	0.975	0.4903	0.2041	0.2932	0.1161

Note: Based on 25,000 iterations of simulated knowledge base responses. Probabilities reported in the text are based on linear interpolations from this table.