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THE EFFECT OF AUDITOR KNOWLEDGE UTILIZATION IN A TASK ON OBSERVER ASSESSMENTS OF THE EFFECT OF TASK EXPERIENCE ON EXPERT POTENTIAL

By

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ABSTRACT

The study of expertise and expert-development has been and continues to be a major focus of auditing behavioral research. This paper furthers studies of the evolution of auditor expertise by augmenting Russo=s model of learning and expert-like behavior during performance of a field task (referred to herein as the Alearning model@) to include observer assessments of the effect of the current task experience on an auditor=s potential for expert development in the future.

The learning model assesses the effects of experience in a task on current task expertise. However, because learning model metrics are in part functions of task strategy, they do not generalize beyond the specific task from which they are derived. This paper takes up Russo=s suggestion that this functional dependence be addressed in future research by examining the effects of an auditor=s knowledge utilization while performing a task on the metrics upon which observers base their assessments of the effects of task experience on that auditor=s expert potential. For this purpose, *expert potential* is defined as an increased level of expertise at which an auditor is expected to perform in a future task. An augmented version of the learning model (the Aaugmented model@) is proposed that decomposes the learning model=s metrics into effects due to (1) experience on the properties of an auditor=s knowledge and (2) the manner in which knowledge is utilized within the particular strategy employed in performing a task. Based on the insights provided by the augmented model, new measures are introduced that better relate to assessments of an auditor=s potential for greater expert performance in the future than do those of the learning model. Russo=s data are then reevaluated using the augmented model and revised assessments of the effects of experience on the expert potential of the participating auditors are presented and compared.

Findings show that assessments of the effect of experience on an auditor=s expert potential that are made based upon the learning model are significantly affected by the way in which the auditor=s task strategy utilizes knowledge. Learning model evaluations of the effects of experience on expert potential for each of the auditor subjects who participated in Russo=s experiments are changed in some way by the more refined analysis presented here. The augmented model findings highlight a need to separate those effects that are relevant to realized changes in expertise in the specific task performed from the more fundamental effects on knowledge that carry over to future tasks and, ultimately, to the realization of expert potential in the long-term.

INTRODUCTION

Mangers, supervisors, and others in similar positions often must assess the potential for future growth in expertise of novices in their charge based on observations of those individuals' behavior while performing tasks in the field. A recent paper by Russo (1999b), provides an approach to objective discharge of that responsibility by proposing a model and analytical methodology (the Alearning model@) for measuring the effect of an auditor=s experience in performing a task on the knowledge properties that determine that auditor=s expert-like task behavior. The metrics so provided are then interpreted as indicators of potential near- and long-term expert development. However, because learning model metrics are in part functions of task strategy, they do not generalize beyond the specific task from which they are derived. Consequently, Russo suggests that future research should examine the extent to which this functional dependence can be overcome, thereby permitting more generalized assessments to be made.

This paper takes up Russo=s suggestion by examining the effects of an auditor=s knowledge utilization while performing a task on the metrics upon which observers base their assessments of the effects of task experience on that auditor=s expert potential. For this purpose, *expert potential* is defined as an increased level of expertise at which an auditor is expected to perform in a future task. Specifically, an augmented version of Russo=s learning model (the Aaugmented model@) is proposed that decomposes the learning model=s metrics into effects due to (1) experience on the properties of an auditor=s knowledge and (2) the manner in which knowledge is utilized within the particular strategy employed in performing a task. Based on the insights provided by the augmented model, new measures are introduced that better relate to assessments of an auditor=s potential for greater expert performance in the future than do those of the learning model. Russo=s data are then reevaluated using the augmented model and revised assessments of the effects of experience on the expert potential of the participating auditors are presented and compared.

Findings show that assessments of the effect of experience on an auditor=s expert potential that are made based upon the learning model are significantly affected by the way in which the auditor=s task strategy utilizes knowledge. Learning model evaluations of the effects of experience on expert potential for each of the auditor subjects who participated in Russo=s experiments are changed in some way by the more refined analysis presented here. The augmented model findings highlight a need to separate those effects that are relevant to realized changes in expertise in the specific task performed from the more fundamental effects on knowledge that carry over to future tasks and, ultimately, to the realization of expert potential in the long-term.

The remainder of this paper is organized as follows. Section I summarizes the learning model. Section II presents an augmented model of the effects of experience on the properties of knowledge and examines the rate of knowledge utilization in a task. Section III discusses the relationship between the two models and how model metrics are interpreted in terms of realized and potential expert development. Several research hypotheses are proposed in Section IV. Section V discusses the experimental data and analytical methodology. Findings are presented and discussed in Section VI. Finally, Section VII concludes the paper with several comments about model assumptions and limitations and the role of the augmented model in expertise research.

I. SUMMARY OF THE LEARNING MODEL

The learning model proposes examining the process by which an individual auditor progresses toward more expert-like task behavior by measuring the effect of experience during performance of a task on the properties of that auditor=s knowledge base. The properties examined are knowledge organization, content, and availability. It is shown that changes in these properties, measured by a set of serially dependent learning ratios, are directly related to changes in the automaticity of task behavior, a widely used indicator of task expertise (e.g., Alba & Hutchinson, 1987; Anderson, 1982, 1987; Mayer, 1992, p.305; Davis & Solomon, 1989; Bédard, 1989). This section presents a highly condensed summary of the learning model. Reference should be made to Russo (1999b) for further explanation.

Task Automaticity and Mediating Episodes

The learning model holds that the effect of experience on expert-like behavior[1] can be assessed by measuring the change in the automaticity with which knowledge to instantiate and perform task behaviors is accessed.[2] 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. Behavior automaticity is measured by the proportion of mediating episodes that are automatic. Measures of the properties of knowledge are based on analysis of the mental activity components of mediating episodes.

The Task Learning Ratio

Experience is operationalized as repetition in performing the various target behaviors. The analytical methodology for measuring learning 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 Anaive@ instances, and those in the above-median group are the experienced instances. The effect of experience on task automaticity is measured by the *task learning ratio*, the ratio of the automaticity of the experienced group to that of the inexperienced group, shown as equation (1). The superscripts N and X identify the naive and experienced frequencies of automatically mediated behavior transitions (n_v).

$$l \equiv \frac{n_v^X}{n_v^N} \qquad \textbf{(1)}$$

Properties Learning Ratios

The model proposes that changes in a knowledge base, and hence, learning, is manifest in automatic task behavior in various ways, depending on how knowledge organization, accessible content, and knowledge availability, the three properties of the knowledge forming a knowledge base, are affected by repeated accesses to knowledge required during performance of a particular task in a particular task environment. Data for measuring the level of each of the knowledge properties over any set of target behaviors is derived from an analysis of the knowledge base responses that form the episodes of mental activity mediating transitions to the target behaviors. Three forms of response are identified: subconscious transitions to target behaviors, cognitive responses indicating a positive search of the knowledge base, and cognitive responses indicating that sought knowledge is either not accessible or not present in the knowledge base. The first of these responses is referred to as being *automatic*. The two kinds of cognitive response mentioned are referred to as *analysis and planning* cognitions and *uncertainty* cognitions, respectively, 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.

To capture these manifestations in a way that permits a direct relationship to the measure of learning defined in (1), three additional learning ratios are defined:

> *Knowledge organization ratio* (l_s): measures the relative complexity of mediating episodes after experience using each target behavior in a task compared with complexity before experience.
>
> *Accessible knowledge ratio* (l_c): measures the relative proportion of knowledge responses indicating accessible knowledge content after experience using each target behavior in a task compared with the proportion before experience.
>
> *Available knowledge ratio* (l_v): measures the relative proportion of knowledge base responses indicating accessible knowledge content that were automatic after experience using each target behavior in a task compared with the proportion before experience.

Symbolically, these definitions are presented respectively as (2a), (2b), and (2c).

$$l_s \equiv \frac{n_s^X}{n_s^N}(a)\, l_c \equiv \frac{n_c^X\, n_s^N}{n_c^N\, n_s^X}(b)\, l_v \equiv \frac{n_v^X\, n_c^N}{n_v^N\, n_c^X}(c) \qquad \textbf{(2)}$$

The subscripts in (2) qualify the variables as follows: *s* indicates all responses, cognitive and automatic, *c* indicates accessible knowledge base responses, and *v* indicates only automatic responses. The relationship of the components of (2) to the overall task learning ratio is given by (3).

$$l = l_s l_c l_v \qquad \textbf{(3)}$$

Summary of Findings From the Learning Model

Table 1 summarizes Russo=s findings employing this model to analyze the task behavior of four first-year auditors. The probability distributions used to test the null hypotheses that each learning ratio has a value of unity (i.e., experience in performing the task has no effect on the auditor=s knowledge properties and task automaticity) were generated by simulating the knowledge base responses of each subject auditor=s task protocols 10,000 times. As discussed later in this paper, certain additional refinements made in the simulation methodology resulted in revised, and more precise, measures of risk. These revised levels are indicated in Table 1 with bold italics. These data will be discussed further in Section VI.

TABLE 1
LEARNING RATIOS

Effect on expert-like task behavior	**Subject 1**		**Subject 2**		**Subject 3**		**Subject 4**	
Increased Task Automaticity ($H1_a$: >1)	0.886	ns	1.192	***.08*** **.11**	1.114	ns	1.750	***.02*** **.03**
Effects on knowledge properties:								
Increase in Knowledge Organization ($H1_a$: l_s>1)	1.046	ns	1.023	ns	0.845	***.03*** **.05**	0.612	***.02*** **.05**
Increase in Accessible Knowledge Content ($H1_a$: l_c>1)	0.934	ns	0.997	ns	1.119	***.05*** **.03**	1.094	***.08*** **.10**
Increase in Available Knowledge Content ($H1_a$: l_v>1)	0.907	ns	1.169	ns	1.178	ns	2.614	***.00*** **.00**

Source: Russo, 1999b: 213 (except for amounts reported in italics).
Note: The hypotheses tested (stated in positive form) in each case is indicated in parentheses. Significance indications: ns = not significant; p<= value as originally reported in Russo (1999b) shown in **bold** typeface, ***italics*** indicate values adjusted as described in the text. Support for the hypothesis regarding task automaticity indicates that task experience has resulted in increased expertise in performing the current task. Support for hypotheses regarding knowledge properties are diagnostic as to effects of experience on behavior automaticity in the current task.

II. THE AUGMENTED MODEL

The augmented model presented in this section retains the conceptual foundations of the learning model except that the properties of a knowledge base are redefined in terms of their relationships to individual categories of target behaviors rather than to the pooled behaviors of the *N* and *X* groups. This change necessitates introduction of several new concepts as well as changes in and additions to notation.

Knowledge Base Properties

Let us define more precisely the properties of an individual auditor=s knowledge base. *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 4).

$$S_j^P \equiv n_{sj}^P / n_j^P \qquad \textbf{(4)}$$

In equation (4), *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 cognitions, 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 cognitions 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 (5), where n_{cj} is the frequency of positive knowledge base responses.

$$C_j^P \equiv n_{cj}^P / n_{sj}^P \qquad \textbf{(5)}$$

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 (6), where n_{vj} is the frequency of automatic responses.

$$V_j^P \equiv n_{vj}^P / n_{cj}^P \qquad \textbf{(6)}$$

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 7).

$$c^P \equiv (1/b)\sum^j S_j^P C_j^P V_j^P \qquad \textbf{(7)}$$

Effects of Experience on Knowledge Base Accessibility and Knowledge Properties

The effect of experience on the accessibility of a knowledge base is measured by the ratio of the mean knowledge accessibility of the experienced behaviors to that of the inexperienced behaviors. This effect is given by equation (8), where *A* is the *knowledge accessibility effect*.

$$A \equiv \frac{c^X}{c^N} \qquad \textbf{(8)}$$

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 (7), 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 (9a) through (9c) show the unconditional effects of experience on each knowledge property.

$$A_S = \frac{\sum^j S_j^X}{\sum^j S_j^N} (a) \quad A_C = \left(\frac{1}{A_S}\right)\frac{\sum^j S_j^X C_j^X}{\sum^j S_j^N C_j^N} (b) \quad A_V = \left(\frac{1}{A_S A_C}\right)\frac{\sum^j S_j^X C_j^X V_j^X}{\sum^j S_j^N C_j^N V_j^N} (c) \qquad \textbf{(9)}$$

A_S, A_C, and A_V are collectively the *knowledge properties effects*. In equation (9), 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 effect of experience on the mean knowledge accessibility of the knowledge base, as shown by equation (10).

$$A = A_S A_C A_V \qquad \textbf{(10)}$$

Equation (10) can easily be shown to be consistent with the change in mean knowledge accessibility given by equation (8). With regard to the interpretation of equation (10), 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.

Knowledge Utilization

Assessments of an auditor=s expertise are made by observers based on their perceptions of change in that auditor=s automaticity while performing a task. The demands made on an auditor=s knowledge are determined by the particular mix of behaviors employed as the task progresses toward a solution. This behavior mix is perceived and interpreted by observers as the auditor=s task strategy (Russo, 1999a: 8). Therefore, what an observer perceives is *effective* rather than inherent knowledge accessibility.[3] Effective knowledge accessibility is defined as the sum of the accessibility of the knowledge demanded by each type of behavior, weighted by the corresponding task behavior mix (i.e., $\sum^{j} c_j^P m_j^*$, where c_j is the accessibility of knowledge supporting behavior j (i.e., $c_j^P = S_j^P C_j^P V_j^P$), and m^* is the mix of that behavior (i.e., $m^*=n_j/n$) in the total instances of all behaviors, n).

An auditor=s *knowledge utilization rate* in a particular task is defined as the ratio of that auditor=s effective to mean knowledge accessibility.[4] The effect of an auditor=s experience in performing a task on that auditor=s knowledge utilization rate is the ratio of the auditor=s experienced to inexperienced rates of knowledge utilization, and is given by equation (11).

$$E_x \equiv \frac{c^N \sum^j c_j^X m_j^*}{c^X \sum^j c_j^N m_j^*} \tag{11}$$

The *knowledge utilization ratio* (E_x) provides an indication of the degree to which new knowledge acquired during performance of a task, which is initially latent, is permitted by the task strategy to be expressed in that auditor=s task automaticity (Russo 1997). When an auditor=s task strategy emphasizes behaviors whose knowledge accessibility has improved, then the knowledge utilization ratio will be greater than unity. On the other hand, if what an auditor has learned is not relied upon in performing the task, then that auditor=s knowledge utilization ratio will be less than unity.

Decomposition of the Knowledge Utilization Ratio

The knowledge utilization ratio is resolvable into effects due to changes with experience in the utilization of each of the knowledge base properties. Paralleling the concept of a knowledge utilization rate, the rate of utilization of a particular knowledge property is the ratio of its effective utilization in a specific task to its mean (unconditional) utilization. Applying this definition to each of the three knowledge base properties yields the *knowledge properties utilization ratios* given by equations (12a) through (12c).

$$E_{x(S)} = \frac{\sum^j S_j^X m_j^* \sum^j S_j^N}{\sum^j S_j^N m_j^* \sum_j S_j^X} (a) \quad E_{x(C)} = \frac{\sum^j S_j^X C_j^X m_j^* \sum^j S_j^N C_j^N}{E_{x(S)} \sum^j S_j^N C_j^N m_j^* \sum^j S_j^X C_j^X} (b) \quad E_{x(V)} = \frac{\sum^j c_j^N \sum^j c_j^X m_j^*}{E_{x(S)} E_{x(C)} \sum^j c_j^X \sum^j c_j^N m_j^*} (c) \tag{12}$$

In this equation, $E_{x(S)}$, $E_{x(C)}$, and $E_{x(V)}$ are, respectively, the effects of experience on the rates at which the organization, content, and availability properties of an auditor=s knowledge are utilized in the particular task the auditor performed. The product of these three property utilization ratios produces the knowledge utilization ratio (see equation 13.)

$$E_x = E_{x(S)} E_{x(C)} E_{x(V)} \tag{13}$$

III. RELATIONSHIP BETWEEN MODELS

The focus of this paper is on the effects of knowledge utilization in a current task on observer assessments of the potential for greater expert performance in the future. 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 greater task automaticity in the future.[5] Each measure of effect, be it on task automaticity, knowledge accessibility, or any knowledge property, provides useful information about the effects of experience on expertise. However, interpretation of these measures in terms of *realized* (i.e., currently displayed) and *potential* (i.e., future) expert development is a function of the model used to generate the metrics mentioned. Consequently, to properly frame and understand any hypotheses and interpret any finding regarding the effects of knowledge utilization, it is necessary to review the relationship between the models presented in Sections I and II. Consistent with the previously given operationalization of experience, in this discussion, the expression Along-term@ is to be understood in the sense of Athe fullness of experiences@ rather than Awith the passage of time,@ and Anear term@ in the sense of an auditor=s (arbitrary) next task.

Realized vs. Potential Expertise

Expert potential is realized in the form of greater expertise in the actual performance a specific task. Both models present information regarding the development of expertise. However, while the learning model provides direct information regarding *realized improvements in the current task*, it provides only indirect information regarding the potential for further development in the future. Assessments of developing task expertise during performance of the current task that are made using the learning model are based on changes in task automaticity with experience, indicated by a task learning ratio (l) greater than unity. The properties learning ratios (l_s, l_c, and l_v) are diagnostic as to the knowledge effects underlying that change; that is, realized progress in expert-development is indicated by decreasing episode complexity ($l_s < 1$), and increasing knowledge content ($l_c > 1$) and availability ($l_v > 1$).

The augmented model, like the learning model, indicates increased expertise in the current task by means of the same learning ratios. In this respect, the learning model is subsumed by the augmented model. However, while assessments of *realized* changes in expert-like behavior can be validly based on changes in the automaticity of current task performance, assessments of greater expert *potential* must be based on fundamental changes in the properties of knowledge that define the state of a 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 ultimate effect of experience is to increase the automaticity with which an auditor performs the next task. Task automaticity at that time will be a concurrent reflection of the state of the auditor=s knowledge base. 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. Therefore, all behaviors are equally likely.[6] While the learning ratios implicitly incorporate the effects of the current task=s behavior mix, the augmented model=s knowledge accessibility and knowledge properties effects are defined by an unconditional (equiprobable) behavior mix. Therefore, measures of change in an auditor=s knowledge accessibility and underlying knowledge properties, rather than the learning ratios, most directly capture the post-current-task state of the knowledge base that determines the automaticity of future task behaviors.

The augmented model=s superior ability to capture changes in fundamental knowledge properties arises from differences between the models in the function performed by behaviors employed in the current task. Behavior mix is an integral factor determining all learning ratios. In the augmented model, on the other hand, each instance of a behavior performed serves only to probe the auditor=s knowledge base. These probes produce the samples of responses that, in turn, are the basis for making inferences about the effects of experience on the properties of knowledge (Russo, 1997). Knowledge base responses are evaluated for each target behavior independently of all others, producing metrics that are free of behavior mix distortions.

Effects of Knowledge Utilization on Learning Ratios

The relationships between the learning ratios as defined in Section I and the augmented model=s metrics, defined in Section II, are revealed by restating equations (11) and (12) in the form shown as equations (14a) through (14d). These restatements show that the knowledge utilization rate, in total and for each knowledge property, reflects the manner and extent to which the learning ratios, when used as a basis for inferring the effects of experience on auditor knowledge, are distorted by the mix of behaviors an auditor employs in performing a task.

$$E_x = \frac{l}{A} (a) \quad E_{x(S)} = \frac{l_S}{A_S} (b) \quad E_{x(C)} = \frac{l_c}{A_C} (c) \quad E_{x(V)} = \frac{l_V}{A_V} (d) \qquad \textbf{(14)}$$

Knowledge utilization ratios greater than (less than) unity indicate that learning ratios overstate (understate) the effect of task experience on the underlying properties of an auditor=s knowledge base. Because evaluations of expert potential are most logically related to fundamental changes in the knowledge properties that determine knowledge accessibility, use of the learning ratios as a basis for assessing expert potential raises the possibility of serious misinterpretation.

IV. RESEARCH HYPOTHESES

The primary difference between the learning and augmented models lies in the way their respective measures of the effects of experience are affected by current task strategy, and by extension, knowledge utilization in the task. To address the implications of this difference, the four hypotheses discussed below are proposed. The first hypothesis relates to the possible effects of knowledge utilization in a task on the learning ratios and addresses the validity of learning ratios as measures upon which to base assessments of future expertise. The second and third hypotheses examine measures provided by the augmented model that parallel those of the learning model and that may be used for the same purpose. Findings related to these hypotheses will be used later in this paper to compare the learning and augmented models in terms of metric properties having implications for assessments of expert potential. Finally, the fourth hypothesis relates to a proposed metric for comprehensive assessment of the effect of task experience on expert potential. Findings related to the second, third, and fourth hypotheses will be used to make comparative assessments of the effect of task experience on the expert potential of the auditors who participated in Russo=s experiments. Following Russo (1997:419), these hypotheses are not intended as falsifiable statements in the traditional sense. Rather, they reflect the contingent nature of an iterative problem-solving process. Hence, they are employed in this research as ordinal measurement rules assist in elucidating underlying, evolving processes.

Hypothesis 1 - Effects of Knowledge Utilization

As discussed in Section III, the relationships between the learning ratios and the knowledge accessibility and properties effects provided by the augmented model are captured by the knowledge utilization ratios, summarized by equation (14), and described in detail by equations (11) and (12). If an auditor=s knowledge utilization in a task has an effect on an observer=s assessment of that auditor=s expert potential, then there must be a significant difference between the learning ratios and the augmented model=s knowledge accessibility and properties metrics. This suggests the following hypothesis, stated in positive form:

> H1: Given any pair of metrics forming a knowledge utilization ratio, the related learning ratio is distorted by an auditor=s task strategy when that ratio is used as a measure of the effects of experience on assessments of that auditor=s expert potential.

This hypothesis is tested by comparing each knowledge utilization ratio to unity, its expected value under the null. Given an auditor=s observed task behavior, support for this hypothesis for any of the four knowledge utilization ratios shown in equation (14) indicates that the learning ratios involved misrepresent the actual effect of task experience on that auditor=s knowledge base at the level of risk chosen. Therefore, any assessment of the effect of experience on that auditor=s expert-potential that is made on the basis of such a learning ratio may be seriously in error.

Hypothesis 2 - Knowledge Accessibility Effect

Greater knowledge accessibility, a measure that is not provided by the learning model, is the driver of greater task automaticity. The *a priori* expectation of the effects of experience is to increase knowledge accessibility and, *ceteris paribus*, automaticity in the current task. Paralleling the indications of the learning model, but relating to knowledge accessibility rather than to task automaticity, the following hypothesis, stated in positive form, is proposed:

H2: Knowledge accessibility increases with experience in performing a task.

Operationally, this hypothesis tests the relation $A > 1$. Subject to findings with respect to hypotheses 3 and 4, support for this hypothesis may be taken as *presumptive* evidence of greater expert potential.

Hypothesis 3 - Knowledge Properties Effects

Growth in expertise results from increases in knowledge accessibility with experience. While *ex-ante* it is expected that experience in a task will increase knowledge accessibility, because of the mediating effects of knowledge utilization and the possibility of differential effects of experience on each of the knowledge properties, *ex-post*, changes in both knowledge accessibility and task automaticity may not be positively related in currently observed task behavior (examined by hypothesis 4). Three knowledge properties effects are diagnostic as to the manner in which task experience affects an auditor=s knowledge base, and account for the change in knowledge accessibility. Therefore, the following multi-part hypothesis, in positive form, is proposed regarding the knowledge properties effects:

H3a: The complexity of knowledge search (knowledge organization) decreases (increases) with experience in performing a task.
H3b: Knowledge content increases with experience in performing a task.
H3c: Knowledge availability increases with experience in performing a task.

Operationally, these hypotheses test, respectively, the following relationships: $A_S < 1$, $A_C > 1$, and $A_V > 1$.

Hypothesis 3 provides the diagnostic information that allows assessments to be made of changes in knowledge that are likely carry over to future task behaviors and thereby affect the probability of observing greater task automaticity in the future. The measure of the effect of current task experience on this probability is discussed next.

Hypothesis 4 - Assessments of Changes in Expert Potential

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. These changes in the near-term, can manifest themselves as effects that are inimical to current 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 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 (15).

$$L \equiv \sqrt{\frac{\sum^{k}(A_k - 1)^2}{3}}, k \in \{S,C,V\} \qquad \textbf{(15)}$$

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 paragraph. Because expert potential is positively related to comprehensive learning, the following hypothesis, in positive form, is proposed:

> H4: The effect of experience performing the current task on expert potential is positively related to the measure of comprehensive learning.

By definition, L cannot take on negative values. Therefore, this hypothesis is rejected by finding a value of L that is so much larger than zero that the difference cannot be attributed to experimental error. Further, because L is at least an ordinal level measure, ranging from a minimum of zero to large positive values,[7] auditors can be ranked in the order of the effect of their experience in a task on their potential expert development.

V. DATA AND ANALYTICAL METHODOLOGY

The augmented model was applied to Russo=s data in order to evaluate the significance of any distortions present in the learning ratios as originally reported and to reassess the evaluations made based on those earlier findings. In addition to the use of a more refined model, two additional refinements are made in this paper in order to increase validity and improve the reliability of the procedure used to evaluate the significance of experimental error. First, a less aggregated data set is employed. Second, several modifications are made to the methodology used to generate the simulated probability distributions.

Data Set Modifications

The probability distributions originally used in testing the significance of the findings summarized in Table 1 were generated by a data set that employed only two levels of episode complexity, 1 and >1. This degree of aggregation was necessitated by the availability of time and equipment. To increase the validity of the simulations, the current data employs eight levels of complexity, the full range observed in the experimental protocols. Because of the volume of data involved, summarized data for only one subject is included with this paper (Table 2). The full data set can be obtained from the author upon request.

TABLE 2
SUMMARIZED EXPERIMENTAL DATA
Subject 1

A. OBSERVED FREQUENCY DATA

	Naive Subset				Experienced Subset				Total
j	n_j^N	n_{sj}^N	n_{cj}^N	n_{vj}	n_j^X	n_{sj}^X	n_{cj}^X	n_{vj}^X	n_j
1	58	75	49	20	58	94	52	11	116
2	14	25	15	5	14	16	13	10	28
3	5	6	5	1	5	7	5	2	10
4	10	5	11	6	10	12	10	6	20
5	5	9	6	3	5	7	4	2	10
Sum	92	130	86	35	92	136	84	31	184

B. KNOWLEDGE PROPERTIES

	Naive Subset			Experienced Subset		
j	S_j	C_j	V_j	S_j	C_j	V_j
1	1.293	0.653	0.408	1.621	0.553	0.190
2	1.786	0.600	0.333	1.143	0.813	0.769
3	1.200	0.833	0.200	1.400	0.714	0.400
4	1.500	0.733	0.545	1.200	0.833	0.600
5	1.800	0.667	0.500	1.400	0.571	0.500

Note: Target behaviors (j) are: 1=Reading, 2=Requesting, 3=Calculating, 4=Writing, 5=Other.

Analytical Methodology

Because the methodology for detecting learning and the model=s functional relationships do not lend themselves to application of any of the commonly used probability distributions, it is necessary to generate the distributions used to test model metrics for significance by means of Monte Carlo simulation.[8] Russo=s paper addresses experimental error (viz, nonsystematic coding error and nonsystematic over/under recognition of the cognitive and automatic components of mediating episodes) in testing the significance of findings. However, two additional sources of error, inherent in simulation methodology and affecting the reliability of findings, are not addressed in that paper. They are discussed next.

Simulation Error

For any given metric, simulated distributions are, in fact, random samples taken from the true distribution, generation of which would require an infinite number of iterations to produce. Consequently, their expected values and densities will vary with each instance of generation. Therefore, the use of simulations to approximate the sampling distributions of model metrics introduces two sources of error in addition to experimental error discussed by Russo: *translation error* and *density function error*. Together, the latter constitute *simulation error,* and contributes an element of unreliability to tests for findings that cannot be attributed to experimental error.

Correction for Translation Error

If two researchers simulate the probability distribution for a given metric based on the same set of data and using the same finite number of iterations, the expected value of the distribution produced by each will differ. Further, each distribution=s expected value will differ from the true mean. The amount of difference from the true mean is an instance of translation error, the shifting of a density function to the left or right by a constant amount. For any given simulated distribution, the magnitude of any instance of translation error is a random variable that is negatively related to the number of iterations used in generating that distribution.[9]

Where the expected value of the true distribution is known from theory, removing the effect of translation error is accomplished by increasing or decreasing, as appropriate, the raw values of all simulated outcomes, thereby creating distributions whose expected values equal that of the true distribution. Except for the values related to the distribution of comprehensive learning, for which the model provides no theoretical expectation, the critical values of all probability distributions used in this paper (see Table 3) have been adjusted in this way.[10]

TABLE 3
CRITICAL VALUES OF MODEL METRICS

	Knowledge Utilization				Knowledge Accessibility				Task Automaticity				Comprehensive Learning
	E_x	$E_{x(s)}$	$E_{x(c)}$	$E_{x(v)}$	A	A_s	A_c	A_v	l	l_s	l_c	l_v	L
Subject 1													
.025	0.649	0.791	0.769	0.613	0.564	0.738	0.721	0.520	0.654	0.801	0.814	0.608	0.022
.050	0.698	0.822	0.805	0.666	0.620	0.772	0.759	0.581	0.698	0.829	0.842	0.656	0.033
.100	0.755	0.856	0.846	0.726	0.687	0.813	0.807	0.652	0.754	0.861	0.872	0.716	0.051
.900	1.249	1.130	1.141	1.290	1.357	1.181	1.186	1.434	1.251	1.127	1.115	1.303	0.313
.950	1.349	1.177	1.197	1.404	1.502	1.243	1.257	1.606	1.345	1.170	1.155	1.421	0.390
.975	1.449	1.222	1.253	1.522	1.653	1.303	1.330	1.780	1.441	1.207	1.188	1.53	0.479
Subject 2													
.025	0.772	0.843	0.840	0.737	0.675	0.794	0.788	0.636	0.740	0.827	0.851	0.706	0.008
.050	0.806	0.868	0.868	0.775	0.718	0.822	0.818	0.682	0.773	0.851	0.871	0.745	0.019
.100	0.845	0.893	0.895	0.821	0.768	0.856	0.854	0.738	0.816	0.879	0.896	0.792	0.030
.900	1.143	1.090	1.089	1.170	1.227	1.131	1.130	1.270	1.173	1.107	1.088	1.203	0.211
.950	1.195	1.124	1.124	1.237	1.311	1.177	1.179	1.373	1.236	1.143	1.119	1.276	0.253
.975	1.247	1.156	1.161	1.299	1.395	1.216	1.224	1.467	1.293	1.174	1.144	1.35	0.299
Subject 3													
.025	0.810	0.916	0.905	0.885	0.685	0.819	0.843	0.648	0.717	0.846	0.850	0.685	0.005
.050	0.838	0.931	0.919	0.833	0.727	0.844	0.865	0.693	0.749	0.867	0.870	0.724	0.013
.100	0.870	0.943	0.935	0.867	0.778	0.874	0.891	0.748	0.795	0.891	0.895	0.775	0.025
.900	1.115	1.039	1.045	1.119	1.223	1.111	1.093	1.257	1.198	1.092	1.087	1.227	0.189
.950	1.159	1.053	1.063	1.163	1.312	1.152	1.125	1.355	1.273	1.124	1.119	1.308	0.233
.975	1.199	1.067	1.079	1.205	1.387	1.185	1.155	1.454	1.336	1.154	1.146	1.382	0.279
Subject 4													
.025	0.590	0.849	0.831	0.617	0.521	0.760	0.794	0.507	0.635	0.747	0.857	0.551	0.015
.050	0.645	0.871	0.856	0.671	0.578	0.792	0.823	0.567	0.684	0.780	0.877	0.606	0.026
.100	0.720	0.897	0.889	0.733	0.650	0.832	0.858	0.641	0.739	0.819	0.900	0.672	0.042
.900	1.295	1.086	1.095	1.277	1.430	1.160	1.128	1.459	1.270	1.173	1.082	1.372	0.308
.950	1.440	1.119	1.138	1.391	1.609	1.214	1.175	1.648	1.372	1.232	1.109	1.516	0.392
.975	1.569	1.146	1.171	1.513	1.791	1.265	1.219	1.828	1.466	1.287	1.135	1.675	0.490

Note: Based on 25,000 iterations. All values adjusted for translation bias except L. See discussion in text.

Minimization of Density Distribution Error

Continuing the preceding illustration, since each researcher=s simulated distribution is a random sample of the metric=s true probability distribution, the density of outcome values around the true mean will differ. For any given outcome or range of outcomes, this difference in magnitude is a random variable that is negatively related to the number of iterations used to generate the distributions. In this paper, density distribution error is minimized, within the limits of available resources, by increasing the number of iterations from the 10,000 used by Russo to 25,000.

VI. FINDINGS AND DISCUSSION

Findings

Findings from the augmented model with respect to the tests of hypotheses are presented first. These findings are then compared with those based on the learning model (see Table 1) in terms of the metric properties that have implications for assessments of expert potential. Finally, the effects of experience on the expert potential of the auditors who participated in Russo=s experiment are discussed in terms of the metrics from both the learning and augmented models.

Outcomes of Tests of Hypotheses

Hypothesis 1: Knowledge Utilization Effects

Hypothesis 1 tests for significant distortion in learning ratios due to knowledge utilization by comparing each knowledge utilization ratio to unity, its expected value if there were no effect. The hypothesis is tested for task automaticity and for each of the knowledge properties. Findings are presented in Table 4. With respect to task automaticity, only for Subject 4 is the effect of knowledge utilization sufficiently different from the null expectation that the measure observed cannot be attributed to experimental or simulation error at conventional levels of risk. Knowledge utilization has a significant effect on the measures of knowledge organization of subjects 2, 3, and 4, and a marginally significant effect for Subject 1. There is no finding of significant knowledge utilization effect for any subjects= knowledge content measures. Finally, only Subject 4 showed a very significant knowledge utilization effect for knowledge availability.

TABLE 4
KNOWLEDGE UTILIZATION RATIOS
(Hypothesis 1)

	Subject 1		Subject 2		Subject 3		Subject 4	
Task Automaticity ($E_x = 1$)	0.808	ns	1.063	ns	0.878	ns	1.577	**.05**
Knowledge Properties								
Organization ($E_{x(s)} = 1$)	1.172	**.11**	1.168	**.03**	1.064	**.06**	0.870	**.10**
Content ($E_{x(c)} = 1$)	0.940	ns	0.935	ns	0.981	ns	1.085	ns
Availability ($E_{x(v)} = 1$)	0.734	ns	0.973	ns	0.841	**.12**	1.670	**.00**

Note: The null hypothesis in every case is that the knowledge utilization ratio equals unity (i.e., task strategy has no effect on the indicated learning ratio). Significance indications: p<= value shown in **bold** typeface; ns = not significant. Significant values of a knowledge utilization ratio indicates that any assessment of the effect of task experience on an auditor=s expert potential that are made on the basis of that ratio may be seriously distorted by the auditor=s strategy in performing the current task.

Hypothesis 2: Knowledge Accessibility Effects

Hypothesis 2 addresses the *a priori* expectation that knowledge base accessibility increases with experience by comparing the mean knowledge accessibility effect with unity, its null expectation. Table 5 shows that experience had a significant effect on the mean knowledge accessibility of subjects 2 and 3.

TABLE 5 EFFECTS OF TASK EXPERIENCE ON KNOWLEDGE								
	Subject 1		Subject 2		Subject 3		Subject 4	
Hypothesis 2								
Knowledge Accessibility (H2: $A > 1$)	1.096	ns	1.121	**.05**	1.269	**.07**	1.110	ns
Hypothesis 3 - Knowledge Properties								
Organization (H3a: $A_S < 1$)	0.892	ns	0.875	ns	0.794	**.02**	0.703	**.00**
Content (H3b: $A_C > 1$)	0.994	ns	1.066	ns	1.141	**.04**	1.009	ns
Availability (H3c: $A_V > 1$)	1.236	ns	1.201	ns	1.401	**.04**	1.565	**.07**
Hypothesis 4								
Comprehensive Learning (H4: $L > 0$)	0.150	ns	0.142	ns	0.272	**.03**	0.369	**.06**

Note: The hypotheses tested (stated in positive form) in each case is indicated in parentheses. Significance indications: p<= value shown in **bold** typeface; ns = not significant. Support for hypothesis 2 regarding knowledge accessibility indicates that task experience has resulted in increased expertise in the current task and is *presumptive* evidence of increased expert potential. Support for hypotheses 3 regarding knowledge properties are diagnostic as to effects of experience in the current task in increasing knowledge accessibility and suggestive of the time horizon for realization of expert potential (see text). Significant values of comprehensive learning (hypothesis 4) indicate increased potential for greater expertise in the future.

Hypothesis 3: Knowledge Properties Effects

Hypothesis 3 is a multi-part hypothesis testing for the directional effects of experience that foster further expert development in the future. These directional indications are decreasing complexity of knowledge base searches ($A_S < 1$), increasing accessible knowledge base content ($A_C > 1$), and increasing knowledge availability ($A_V > 1$). Findings presented in Table 5 show increases in the expert potential of subjects 3 (in all three properties) and 4 (for two out of three properties). Findings are suggestive of increased expert potential for Subject 2 and mixed for Subject 1, but these outcomes are not sufficiently different from their hypothesized values under the null as to rule out experimental and simulation error as sources of these data.

Hypothesis 4: Comprehensive Learning

Hypothesis 4 is a comprehensive test for change in the knowledge base as a result of task experience. Findings, reported in Table 5, show that experience in performing the experimental task produced significant change in the knowledge bases of subjects 3 and 4, while the changes produced in subjects 1 and 2 are not significantly different from what would be expected solely from experimental and simulation error. Further, because comprehensive learning is at least an ordinal level measure, the findings show that Subject 4 (L = .369) benefited from the task experience to a greater extent that did Subject 3 (L = .272).

Comparison of Findings: Learning vs. Augmented Models

The effect of knowledge utilization on alternative metrics upon which assessments of expert potential are based can be gauged by comparing those metrics in terms of the properties that have interpretative implications. These properties are sense, degree of change, and statistical significance. *Sense* refers to interpretation of a metric as having a near-term positive or negative effect on expert potential.[11] *Degree* refers to the extent to which the sense changes when alternative metrics have the same sense. Finally, *statistical significance* refers to the risk assumed in incorrectly accepting as true the statement that a matrix is sufficiently different from its expected value under the null hypothesis that the difference cannot be attributed to experimental or simulation error. Table 6 presents a summary of the corresponding metrics produced by the learning and augmented models in terms of the properties just mentioned. Details of the meaning of the symbols used are provided in notes to the table.

TABLE 6
EFFECT OF KNOWLEDGE UTILIZATION ON ALTERNATIVE METRICS USED FOR ASSESSMENTS OF CHANGE IN EXPERT POTENTIAL

	Properties of finding	Subject 1	Subject 2	Subject 3	Subject 4
Metrics Interpreted as Indicators of Change in Expert-Potential					
Task learning (*l*) vs. Knowledge accessibility effect (*A*)	Sense	+	*na*	*na*	*na*
	Degree	*na*	!	+	!
	Significance[I]			+	!
Knowledge base accessibility (*A*) vs Comprehensive learning (*L*)	Sense				
	Degree[#]		-2	-1	+3
	Significance[II]		!		+
Metrics Interpreted as Diagnostic as to Why Expert Potential Changed					
Knowledge organization (l_s vs. A_S)	Sense[*]	+	+	*na*	*na*
	Degree	*na*	*na*	!	+
	Significance[I]				
Accessible knowledge content (l_c vs. A_C)	Sense	*na*	+	*na*	*na*
	Degree	+	*na*	+	!
	Significance[I]				!
Available knowledge content (l_v vs. A_V)	Sense	+	*na*	*na*	*na*
	Degree	*na*	+	+	+
	Significance[I]			+	

This table reports the effects of knowledge utilization in a task on the properties of alternative metrics when those metrics are used as the basis for making assessments of the change in expert potential resulting from experience in performing a current task. See Notes to Table 6[12]

The pervasiveness of model-induced changes is clearly evident from Table 6. The sense and degree properties, which bear directly on assessments of expert potential, are changed for every subject, and changes in the statistical significance of parallel metrics (*l* vs. *A*, l_s vs A_S, *lc* vs. A_C, and l_v vs. A_V) are found in four out of sixteen pairs. These findings establish the unsuitability and questionable validity of learning ratios as a bases for assessing the effects of experience on expert potential. In the next sections, I discuss the indications of increased expert potential as provided by the augmented model and illustrate the model=s application by comparing the *a priori* assessments based on the mean knowledge accessibility effect, *A*, with those based on a more sophisticated analysis of the knowledge properties and comprehensive learning effects.

Knowledge Accessibility as an Indicator of Increased Expert Potential

It is the state of an auditor=s knowledge upon completion of the most recent task that carries over to that auditor=s next task. A finding of $A > 1$ indicates that knowledge accessibility, the driver of expert-like task behavior, has increased as a result of performing the current task and as a consequence, we anticipate greater automaticity in the performance of future tasks compared with that of the most recently completed task. In fact, this interpretation of the value of *A* implies that some of the increased expertise has already been realized to a certain extent during performance of the current task but not made fully evident because of the methodological differences in the measurement of task automaticity, on the one hand, and learning, on the other.[13]

If $A > 1$, then we can say with a certain level of confidence that the automaticity of the next task the auditor performs will be greater than that of the last task performed. Conversely, if $A < 1$, then that statement cannot be made with the same level of confidence because the experiences of the current task that produced such a negative finding may actually have had positive but latent knowledge effects that may not become evident in behavior until given the opportunity for expression in future tasks, although not necessarily in the next task (Russo 1997: 411; 1999b: 207). However, analysis of the knowledge properties effects provides insight into what changes have taken place, and from this, the pre-current-task probability distribution of future automaticity outcomes can be revised and a better expectation formed.[14] Such considerations point to the knowledge accessibility effect, *A*, as an imperfect indicator of increased expert potential. The following sections apply these ideas to the findings reported in Table 5.

Comparative Assessments of Changes in Expert Potential

Rather than discuss all possible comparisons of the auditors participating in Russo=s experiment, I discuss specific pairs that illustrate rather clearly the discriminatory power of the augmented model.

Subject 1 vs. Subject 4

Both subjects 1 and 4 do not show a significant increase in knowledge accessibility. *A priori*, there is no change in our expectation of greater expert-like behavior for either auditor in the performance of a future task. However, a review of the knowledge properties effects in Table 5 shows significant improvement in Subject 4's knowledge organization and availability while no knowledge properties improvements are shown for Subject 1. Better knowledge organization and availability are both consistent with a higher probability of increased task automaticity in the future. Therefore, the initial assessment is changed with respect to Subject 4 but not with respect to Subject 1.

These findings show clearly the inadequacies of using the knowledge accessibility effect (*A*) to assess the effects of experience on assessed expert potential. Rather than basing such assessments on *A*, one needs a measure related more directly to changes in the underlying knowledge properties that determine *A*. Comprehensive learning, *L*, makes that discrimination. Table 5 shows that in contrast to *A*, *L* discriminates between subjects 1 and 4, showing a significant increase in expert potential for Subject 4, but not for Subject 1.

Subject 2 vs. Subject 3

Table 5 shows significant increases in knowledge accessibility for both subjects 2 and 3. Relying on this finding, one would form an *a priori* assessment of increased expert potential for both auditors as a result of their experience in performing the experimental task. However, from examination of the underlying knowledge properties effects, it can be seen that there are significant changes for Subject 3 but none for Subject 2.[15] Therefore, in terms of the effect of the experience in performing the experimental task on the potential for greater expert performance in the future, one=s confidence in making an assertion of benefit is greater for Subject 3 it is for Subject 2. Note that this differential assessment, which cannot be made based on the knowledge accessibility effect, is accurately reflected in the finding reported for comprehensive learning.

Subject 3 vs. Subject 4

Based on the knowledge accessibility effect, one would incorrectly conclude that Subject 3's expert potential increased while that of Subject 4 did not. However, the diagnostic properties effects and the measure of comprehensive learning all indicate that the expert potential of both auditors increased. Therefore, the question raised is: Of the two, in which do we have the greater confidence in asserting that experience in this task has brought the realization of greater expertise closer to the near-term?

Following Russo=s three-stage learning process (1999: Figure 2, 207-8), Subject 3 appears to have significant positive effects in all three stages (decreased complexity and increased accessible knowledge content and availability). Subject 4, in contrast, shows significant positive effects in the first and third stages (decreased complexity and increased knowledge availability) but no change in the second (accessible knowledge content). While Russo=s model proposes that learning progresses sequentially through all three stages (as displayed by Subject 3), auditors may already possess substantial knowledge that initially is in an inaccessible state, but when exposed to only a few cues while performing a task, is rapidly brought to an available state, bypassing the second learning stage. On this basis, it would not be unreasonable to conclude that as a result of performing the experimental task, the probability of observing greater expert-like task behavior in the near term has increased more for Subject 4 than it has for Subject 3. Again, findings regarding comprehensive learning are consistent with this differentiation (Subjects 3, L = .272; Subject 4, L = .369).

VII. CONCLUSION

Assumptions and Limitations

Both the learning model and the augmented model use task automaticity as an indicator of the level of an auditor=s expertise. Although widely accepted as a measure for this purpose, task automaticity is a process-oriented criterion, and, therefore, does not consider task outcome or the appropriateness of the behaviors observed. Hence, for certain purposes, the models presented here may not be the appropriate ones to use. The models also make certain assumptions regarding the purposefulness and intentionality of auditors= behaviors that rule out random automatic behavior as being indicative of expertise. The reader is referred to Russo (1999b) for further discussion on these matters.

The augmented model presented in this paper does not forecast the level of future expertise but deals only with whether and to what extent an observer=s expectation of an auditor=s future expert development has changed as a result of that auditor=s current task experience. Therefore, failure to find evidence of significant revision should not be taken as evidence of a lack of expert potential.

Finally, the revised expectation of expert potential is based on an analysis of both the magnitude and pattern of changes in individual knowledge properties. Any changes in these properties increases comprehensive learning (*L*) and is assumed to be consistent with increases in expertise in the long-term. However, while *L* is sensitive to the *magnitude* of change it is not sensitive to its *pattern*.[16] Therefore, it is still necessary to examine the pattern among the knowledge properties effects in order assess the quality of the effect of experience, as is illustrated by the comparative comments made in section VI, especially with respect to subjects 3 and 4.

The Role of the Augmented Model in Expertise Research

The study of expertise and expert-development has been and continues to be a major focus of auditing behavioral research (e.g., see reviews by Arnold & Sutton, 1997; Ashton & Ashton 1995). Interest in the effects of experience on changes in task automaticity, knowledge accessibility, and knowledge properties derives from the need, highlighted by Bowman & Bradley (1997: 120), for greater understanding of the process of expert development, an understanding that can lead to more effective auditor training, selection and assignment, and performance. Changes in task automaticity are of interest because they evidence current realizations of expert-like task behavior. Changes in knowledge base accessibility are of interest because it is an auditor=s accessible knowledge that is the driver of current expert-like task behavior and, subject to more diagnostic evidence, is suggestive of broader expert development in the future. Finally, changes in knowledge properties are of interest because they help to explain current changes in knowledge accessibility and are indicative of the potential for expert development in the future.

The learning model proposed by Russo assesses the effects of experience in a task on current task expertise. This paper demonstrates that it is not valid to infer expert potential by extending to the next task the change noted in the level of expertise displayed in a current task. The augmented model, on the other hand, provides appropriate metrics on which one can anticipate future increases in expert performance. Russo=s approach to issues in expertise research represents a departure from the current emphasis on judgment and decision making in auditing behavioral research in that it (1) emphasizes the ability of an auditor=s knowledge base to supply the information demanded by task behaviors over the substantive content of an auditor=s knowledge and thinking processes, and (2) focuses on aspects of an auditor=s knowledge that account for what an auditor does rather than on the substantive reasons for why it is done or whether what was done was the correct thing to do. This paper continues in that vein and, in its own right, contributes new concepts and metrics that can further focus the efforts of, and facilitate communication among, researchers interested in this alternative approach to studying the process by which expertise evolves out of experience.

ENDNOTES

1. In using a process-based criterion such as task automaticity as a criterion of expertise, neither the appropriateness of task behaviors nor the quality of task outcomes is considered. Therefore, the behavior studied can only be described as being relatively expert-*like*. In spite of this limitation, Russo has shown that automaticity of task behavior can serve as a productive focus for a comprehensive and internally consistent model for investigating and understanding several significant properties of task expertise.

2. Later in this paper, the capability of a knowledge base to instantiate and carry out a specific behavior will be referred to as the capacity of the knowledge base to Asupport@ that behavior.

3. Knowledge remains latent until it is used. When knowledge is used, what is observed are its *apparent* rather than actual properties. Knowledge utilization, how knowledge is actually employed in a task, depends on the mix of behaviors employed while performing the particular task. Knowledge base properties, *per se*, are not normally observable, but must be inferred by sampling the responses of the knowledge base to demands for information made by various kinds of behaviors. While the particular task an auditor performs provides that sample (Russo 1997, 411), the state of a knowledge base is inherent in its properties and is independent of the particular task performed.

4. The rate of knowledge utilization in a particular task is $k = \frac{\sum^{j} c_j^P m_j^*}{c^P}$.

5. Although not quantified by either model presented in this paper, this probability is assumed to be positively related to changes in the properties of knowledge.

6. Task automaticity in both the augmented and learning models 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 equi-probable 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 Aautomaticity@ and Aaccessibility@ when used in the context of an arbitrary task are to be understood as being equivalent.

7. A value of $L = 0$ indicates no *change* in expert potential as a result of current task experience; it does not indicate an absence of expert potential.

8. Each model metric can be considered to be composed of a true value plus error. Under the null hypothesis, the value of each model metric is unity. Therefore, the observed error term in each case is the difference between the measure of each model effect and unity. The error terms are as likely to be positive as they are to be negative, and to range in both directions over the realm of all real numbers. The error term, therefore, has a distribution with median zero. If we are willing to assume that these terms cluster about the median in such a way that they can be described by the standard normal distribution, then a strong argument has been made for using this distribution in testing the null hypothesis that the mean of the difference between an observed model effect and unity is zero. The difficulty in applying

this conclusion in the case of the model presented in this paper is the lack under the null hypothesis of an *a priori* measure of the standard deviation of the observed error terms. Hence, the need to resort to simulation.

9. The number of iterations used constitutes the size of the sample.

10. Assume that the expected value of the raw (initial) simulated distribution of a model metric is $\hat{X}$ and that the theoretical expected value is *X*. Then the translation-adjusted value of any specific outcome having a raw value of $\hat{X}_i$ is

$X_i = \hat{X}_i + (X - \hat{X})$, where $X - \hat{X}$ is the adjustment factor applied to the entire raw distribution. This adjustment cannot be made for the simulated distribution of comprehensive learning, *L*, because this metric is not symmetrically distributed about its mean of zero, and the model makes no assumptions about its mean or variance.

11. The long-term effect of all task experiences are to increase expert potential. However, near term, experiences can produce either an increase or decrease in automaticity (from which expertise is assessed).

12 **Notes to Table 6:**
* Decreasing complexity is interpreted as increased knowledge organization.
na Indicates that the comparison is not applicable. A change in sense concurrently with a change in degree is logically inconsistent, and *visa-versa*.
Change in rank (from lowest to highest) of subject based on *L* compared with rank based on *A*. As discussed in the text, *A* is not a measure that is at least of ordinal level. Therefore, it cannot be meaningfully ranked. However, since both *A* and *L* have such different expected values and density distributions, the ranking technique is a reasonable means of showing how comprehensive learning alters the impression upon which an assessment of expert-potential may be based.
Sense – the interpretation of a metric as indicating increasing or decreasing expert potential.
+ = the use of the augmented model changes the sense from decreasing to increasing.
! = the use of the augmented model changes the sense from increasing to decreasing.
Degree – the extent to which an assessment changes when both models produce a metric having the same sense.
+ = *A* has the same sense as *l*, but to a greater degree.
! = *A* has the same sense as *l*, but to a lesser degree.
Ι Significance – the metric is sufficiently different from the null value as to permit a statement that it is not due to experimental or simulation error at the levels of risk indicated in Tables 1 and 5.
+ = the augmented model metric is statistically significant while the parallel learning ratio is not statistically significant.
! = the augmented model metric is not statistically significant while the parallel learning ratio is statistically significant.
ΙΙ Significance – the metric is sufficiently different from the null value as to permit a statement that it is not due to experimental or simulation error at the levels of risk indicated in Table 5.
+ = Comprehensive learning is statistically significant while the knowledge accessibility effect is not statistically significant.
! = Comprehensive learning is not statistically significant while the knowledge accessibility effect is statistically significant.
Blank cells indicate no change in the properties of the findings.

13. Task automaticity is measured by the ratio of automatically mediated behavior transitions, n_v, to the total number of behavior transitions of all kinds, n_v, over a task. Learning, on the other hand, is based on the ratio of experienced transitions (n_v^X) to inexperienced transitions (n_v^N) to target behaviors during a task. The mean automaticity during the

current task is n_v/n. The expected automaticity in the next task, assuming identical tasks and strategy, is $2n_v^X/n$. If $A > 1$, then $2n_v^X/n > n_v/n$. If we now consider an arbitrary future task, then the mean knowledge accessibility of the most recent task, c, must be compared with the expected accessibility of the next task. The latter will be determined by c^X, the mean accessibility of the auditor=s knowledge at the conclusion of the current task. Therefore, the expected value of the automaticity of the next, arbitrary future task is c^X. If $A > 1$, then $c^X > c$.

14. 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 $\bar{x}_n$ 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., $\bar{x}_n = \bar{c}_{n+1} \_ c_n$. 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, $s_{x,n}$. For purposes of the current discussion, it is necessary only that $\bar{x}_n$ be considered as an unspecified positive function of comprehensive learning, i.e., $\bar{x}_n = L(L_n) + 1$, and $s_{x,n}$ as an unspecified function of the *pattern* of changes in knowledge properties, i.e., $s_{x,n} = s(\_ A_k - 1 \_{n})$. Because L_n cannot have values less than zero, $\bar{x}_n$ indicates the *expected* increase in knowledge accessibility of the *next* task, as ascertained at the completion of task n. As such, $\bar{x}_n$ 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 $\bar{x}_n$ is ascertained. In contrast, ξ_{n+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, $\bar{x}_n$, 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, $\bar{x}_{n+1} = \bar{x}_n$, 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 $\{A_k\}_{n+1}$, $\{A_k\}_n$, then $L_{n+1} > 0$ and $\bar{x}_{n+1} > \bar{x}_n$ 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, realized increase in knowledge accessibility (x_{n+1}) can be greater or less than expected increase ($\bar{x}_n$). 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, $\bar{x}_n$, is the change in knowledge accessability to be expected in the fullness of experience, i.e., $\bar{x}_n = 1 + \int_{-\infty}^{\infty} (x_{n+1} - 1) p(x_{n+1} - 1 \mid L_n, s_{x,n}) d(x_{n+1} - 1)$, while its effect on near-term expert potential is measured by the probability relationship $P(x_{n+1} > 1 \mid L_n, s_{x,n}) > P(x_n > 1 \mid L_{n-1}, s_{x,n-1})$, 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 $\{A_k\}_n = \{A_k\}_{n-1}$.

15. The increased knowledge accessibility of Subject 2 is due to the interaction among the knowledge properties effects which, individually, did not change significantly.

16. The magnitude of *L* determines if, and to what extent, there is a change in expert potential. The pattern of changes in knowledge properties, on the other hand, provides an indication of the time horizon (near-term, long-term) to probable realization of that change. Mathematically, one may equate the effect of the magnitude of *L* with translation of the density surrounding $\bar{x}_{n-1}$ to the right, and the effect of the pattern of knowledge properties effects with change in the variance of that density. Decreases in the variance can be interpreted as greater certainty regarding the realization of that potential in the next task, and increasing variances as decreasing that certainty with respect to the next task and requiring many future tasks before realization. These matters will be examined in greater detail in a future paper.