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A MODEL OF THE EFFECTS OF AUDIT TASK COMPLEXITY*

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Abstract

A model is proposed for examining the effects of audit task complexity on audit judgment performance. The model is developed from a review of literatures in accounting, management, and psychology. Seven testable propositions are derived. Using the model, previous audit judgment research on ratio analysis and going-concern evaluations is reanalyzed to examine the relation between task complexity and judgment performance, while controlling for the possible interactive effects of skill. For these tasks, increases in (task complexity/skill) are related to decreases in judgment performance. However, for the ratio analysis task, this relation is driven primarily by skill.

Understanding audit task complexity and its effects on judgment performance is important for several reasons. First, previous research has shown that seemingly minor task characteristics, such as wording of instructions, can affect judgments (Libby, 1981). A critical task characteristic like complexity could have a major impact on audit judgments, especially since many audit tasks are highly complex (Libby, 1985). Second, some research has suggested that tasks of differing complexity require different types of decision aids or training (Abdolmohammadi, 1987; Fleishman, 1975; Keen & Scott-Morton, 1978); understanding levels of complexity of various audit tasks assists researchers in understanding current uses of decision aids and training as well as recommending changes for tasks where current judgment performance might be hindered. Also, if skill (knowledge and abilities) is more important in complex tasks, the identification of complex tasks could be important in explaining or recommending job assignments (Abdolmohammadi, 1987; Libby, 1992). Thus, task complexity deserves more attention as it could affect the interpretability of research results as well as auditors' actual performance of audit judgment tasks. The purpose of this paper is to develop a model that auditing researchers may employ in pursuing research on the effects of audit task complexity on auditors' judgment.

A large body of literature in psychology, management, and other social sciences has demonstrated wide-ranging effects of task complexity on judgments. Even though this literature is fairly extensive, it remains disjointed, partially due to the lack of a comprehensive definition or theory of task complexity and its effects. In general, increases in task complexity are thought to decrease judgment quality, but our understanding of why and how this occurs is still in the developmental stages. These shortcomings in the literature may explain the paucity of work on the effects of task complexity in auditing.

Research which directly examines the effects of audit task complexity on auditors' judgments has been minimal; instead, task complexity has played a subsidiary role in the audit judgments research. First, task complexity has been used

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as a *post hoc* explanation for the mixed results across studies of auditor judgment, particularly those on the effects of skill (as proxied for by years of experience). Many authors have posited that the tasks in these studies have varied substantially on the dimension of complexity and that the mixed results have occurred because the effects of experience increase as complexity increases (e.g. Colbert, 1989; Wright, 1988). However, tasks in these studies have varied on dimensions other than complexity, and subject characteristics other than experience have varied as well, so that it is unclear to what extent task complexity accounts for the variation in results. Task complexity also has been used in the selection of tasks for testing specific hypotheses; in these studies, task complexity was not manipulated. For example, Trotman (1985) chose a task perceived to be complex because of research showing that complexity increases systematic bias in judgments (Einhorn *et al.*, 1977); the goal was to have a task where subjects would exhibit bias to determine if group and review processes would reduce the bias. Although these tasks have face validity regarding their levels of complexity, no measurements of task complexity were made.

This paper is organized as follows. The next section reviews the literature on task complexity and develops a definition of task complexity. The following section develops a model of the effects of task complexity on audit judgments. Similar to the approach used by Gibbins (1984), this section includes testable propositions which arise from the model. Finally, guided by the model, previous audit judgment research is reanalyzed and possibilities for future research on the effects of task complexity in auditing are discussed.

DEFINITION OF TASK COMPLEXITY

Generally, ***task complexity*** is thought to be synonymous with either ***task difficulty*** (i.e. amount of attentional capacity or mental processing required; Kahneman, 1973) or ***task structure*** (i.e. level of specification of what is to be done in the task; Simon, 1973). Both of these aspects of task complexity are considered in this paper. Many task characteristics other than task complexity have been shown to affect the judgment performance of auditors and others. These include order of information, elicitation mode, response mode, and processing mode[1] (for reviews, see, e.g. Einhorn & Hogarth, 1981; Pitz & Sachs, 1984). These task characteristics are not included as elements of task complexity because no clear arguments exist regarding why, for example, one order of evidence would be more complex than another. Thus, in discussing the effects of task complexity on judgments, this paper only includes as elements of task complexity those variables for which clear arguments can be or have been made about which levels of those variables create more complexity than others.

The literature proposing definitions of task complexity is quite extensive and diverse. Unfortunately, this literature consists mostly of opinions and reviews focused on a single domain, e.g. management (Campbell, 1988; Wood, 1986). One debate which occurs in various domains, however, is whether task complexity is a function of the task *per se*, or relative to the task and the person doing the task (Campbell, 1988; Fleishman, 1975; Hackman, 1969; Wood, 1986). Note that those who think of task complexity as a function of only the task generally acknowledge that attributes of the person doing the task (such as skill

[1] Arguments can be posited about the relative complexity of various levels of these characteristics; however, they do not hold universally. For example, one could argue that simultaneous processing requires more attention than sequential processing and is, therefore, more complex. However, since persons can hold five to seven items of information in memory simultaneously (Miller, 1956), simultaneous processing might only be more complex when there are more than seven items of information to process.

and motivation) can interact with task complexity in determining judgment performance. As a result, the crux of the debate appears to be related to where in the information processing sequence task complexity and personal attributes can interact. Those who believe task complexity is a function of the task *per se* would appear to believe that the complexity of a task is perceived equivalently by all persons at the input stage, irrespective of differences in skill or motivation, and that these personal attributes affect judgment performance differentially during processing tasks of varying complexity. Those who believe task complexity is relative to the task and the person probably would posit that an interaction occurs in the initial perception of task complexity (i.e. at input), then carries on throughout information processing. Since these views would produce equivalent predictions about the effects of task complexity on judgment performance (output), distinguishing between the two ideas seems unnecessary at this stage of model development. Without resolving this issue, then, this paper attempts to bring together the diverse literatures and provide a comprehensive definition which can be used to study systematically the effcts of task complexity in auditing.[2]

The definition of task complexity in this paper classifies elements of task complexity into the three components of general information processing models: input, processing, and output. This classification scheme has been used in previous reviews of the audit judgment literature (e.g. Libby & Lewis, 1977). Within these three components, task characteristics that are elements of task complexity are classified as relating to either the amount of information or clarity of information. This scheme is used because amount and clarity of information, respectively, correspond fairly well to the two aspects of task complexity used in previous research: task difficulty and task structure. The elements of task complexity related to the input, processing, and output stages of a task are presented in Fig. 1. The relation of these elements of task complexity to judgment performance will be discussed in later sections.

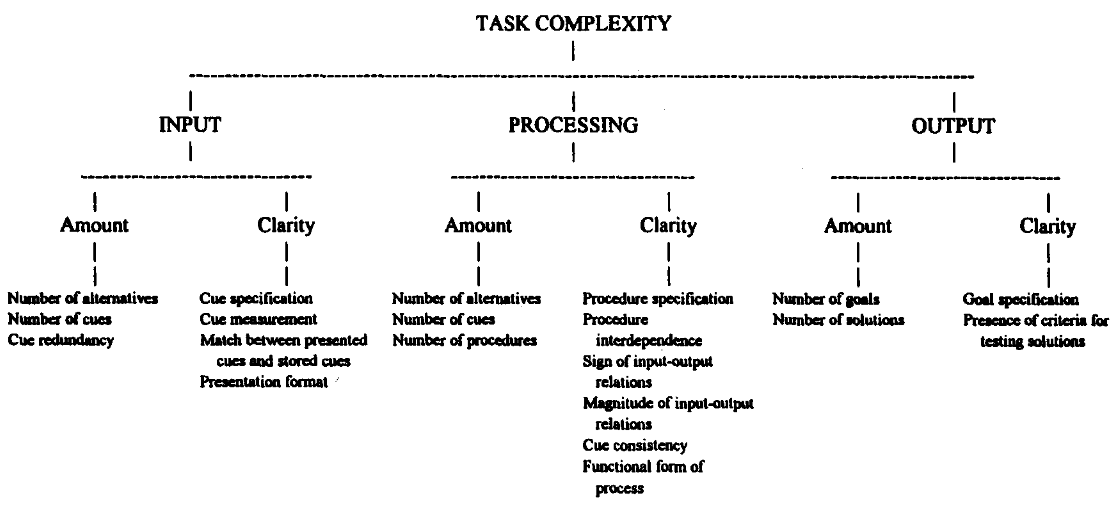

Fig. 1. Elements of task complexity.

[2] Later studies might pursue this issue as it may have implications for the development of decision aids or training designed to alleviate the effects of task complexity, e.g. whether input or processing should be targeted. This is discussed further in the last section of the paper.

Input complexity

Amount of input. Elements of input complexity related to amount of information include the number of alternatives a judge must evaluate and the number of cues or attributes per alternative (Beach & Mitchell, 1978; Hammond, 1986; Kahneman, 1973; Payne, 1976, 1982; Payne *et al.*, 1990; Wood, 1986). For example, studies by Payne and his colleagues presented subjects with "apartment choice" tasks, in which the number of apartments to consider (number of alternatives) varied, as well as the number of attributes of the apartments, e.g. price, location. These aspects of input complexity may be thought of simply as creating information load, so the hypothesis is that the greater the amount of information, the more complex the task because of the greater demands placed on memory.[3] Another element of the amount of input is the redundancy among cues. Because redundancy effectively reduces the number of cues one must consider, it is thought to reduce load and, thus, complexity, assuming the judge perceives the redundancy among the cues (Hammond, 1986; Naylor & Schenck, 1968).

Clarity of input. Variations in the clarity of input also can create variations in task complexity. Lack of clarity can be caused by cues not being clearly specified (Greeno, 1976) or by cues not being measured, i.e. not having a label attached to the situation-specific value of the attribute (Kerlinger, 1986); having to determine cues and measure them adds to memory demands. Although many experimental tasks, such as those employed in the apartment choice studies (e.g. Payne *et al.*, 1990), do not require specification or measurement of cues or alternatives, many "real-world" tasks may be difficult because of unclear input. For example, specifying cues in X-rays is thought to be one of the most difficult parts of radiological diagnosis (Myles-Worsley *et al.*, 1988). Other studies of medical diagnosis have found that, even when cues are specified, cue measurement makes radiological diagnosis a very complex task (Elstein *et al.*, 1978; Johnson *et al.*, 1981; Lesgold *et al.*, 1988). In auditing, for example, internal control cues must be measured based on descriptions of control systems and procedures (Bonner, 1991). Some have suggested that complexity in the clarity of input is that which experts are most equipped to handle, because of their superior knowledge about cue specification and measurement (e.g. Einhorn, 1972; Shanteau, 1984; Voss & Post, 1988), so that this aspect of complexity may be the primary determinant of overall task complexity.

Another aspect of input clarity relates to the match between the manner in which information cues are presented and the manner in which they are stored in memory, with mismatches creating more complexity because the mismatches must be reconciled or memory must be reformatted. As an example, Frederick's (1991) study shows the effects of categorical versus sequential presentation of internal control cues on the recall of auditors with categorical or sequential memory structures. Finally, clarity of input can be affected by the presentation format of information cues (tabular, graphical, etc.). In accounting, Moriarity (1979) defined and manipulated task complexity on the basis of clarity of input. He presented subjects with either financial statements, financial ratios, or graphical faces with the argument that graphical data would be more clear than tabular data for making bankruptcy judgments, making the faces presentation the least complex.[4]

[3] Note that complexity may only increase after the information load reaches a certain threshold (e.g. Payne *et al.*, 1992; Schroder *et al.*, 1967).

[4] Bankruptcy prediction tasks are similar to other audit tasks in the sense that they require the combination of several types of information, the consideration of trends, and so forth. For these types of judgments, graphs make the task less complex than tables (Vessey, 1991). Tabular presentations may be less complex than graphical presentations for extremely simplified tasks which require a response in the form of a single number. Very few auditing tasks appear to meet these criteria.

Processing complexity

Amount of processing. Amount of processing varies with the amount of input (alternatives and cues per alternative) and the number of steps or procedures that have to be executed, either sequentially or simultaneously, to make a judgment or solve a problem (Campbell & Ilgen, 1976; Earley, 1985; Hammond, 1986; Huber, 1987; Payne *et al.*, 1990; Smith *et al.*, 1982; Wood, 1986; Wright, 1989). For example, Huber varied the amount of processing by varying both the size of mazes subjects had to examine (number of cues) as well as the number of moves required to escape from a maze (number of steps). Again, the larger the number of steps or procedures or the amount of information they must be applied to, the more complex the task is considered to be because of the additional demands placed on memory.

Clarity of processing. The clarity of processing is also part of task complexity, with various factors making processing more or less clear. Processing can be unclear because the procedures to use are not specified (Greeno, 1976; Simon, 1973; Smith, 1988). In accounting, Heiman (1990) varied complexity by providing one of two groups of subjects with explicit processing instructions for ratio analysis. Clarity of processing also decreases when procedures are highly dependent on each other (Campbell, 1988; Campbell & Gingrich, 1986). Campbell and Gingrich manipulated this element of task complexity by using programming tasks with either few or large dependencies among commands.

The clarity of processing also depends on the nature of the individual input–output relations (or the overall relation between all input cues and the output, i.e. environmental predictability). Lens model research has examined four aspects of these input–output relations: (1) magnitude, (2) sign, (3) consistency among cues as to their relations with output, and (4) functional form (Brehmer, 1972, 1973; Brehmer *et al.*, 1974; Campbell, 1988; Deane *et al.*, 1972; Hammond, 1986; Naylor & Clark, 1968; Summers & Hammond, 1966; Wood, 1986). Greater magnitude is thought to lower complexity because of lower noise. For example, in accounting, Simnett & Trotman (1989) operationalized task complexity by whether auditors predicted the probability that a company would go bankrupt within either one or two years (the cues had lower overall predictability for the two-year group). Positive signs of functions are thought to lower complexity because people normally think in terms of positive linear functions (Brehmer, 1972, 1973). Cues which are inconsistent with each other make processing more complex (Brehmer, 1972). Finally, linear functions are similar to positive signs in that people tend to think in terms of linear functions, making them more clear to process than other functional forms.

Output complexity

Amount of output. The output stage of judgments can vary as to complexity as well. Amount of output would refer to the number of goals or solutions per alternative, where larger numbers create more complexity (Campbell, 1988; Hackman, 1969; Smith, 1988). Examples of these tasks include open-ended tasks like "compose an overture" or "conduct original research". Generally, auditing tasks require the output of one (or a few) judgments, so that amount of output does not vary substantially in auditing.

Clarity of output. Lack of clarity in output can refer to an indefinite or unspecified goal, which can be created by the environment (e.g. no clear goal exists) or by the judge's lack of familiarity with the goal (Greeno, 1976; Hackman, 1969; Smith, 1988). For example, an architect can have a goal of building a house that is more contemporary than her last. Lack of clarity about output also can be created by the lack of objective criteria for testing a proposed solution (Simon, 1973; Smith, 1988). Auditing tasks generally have a definite goal and standards by which to judge output, so that clarity of output in auditing varies little as well. As a result, output complexity does not seem to be as important in auditing as in other domains.

Overall task complexity

The amount of information and clarity of information at the input, processing, and output stages of a task have been proposed to be elements of task complexity. Input can vary as to the number of alternatives, the number of cues per alternative, and the redundancy of the cues. Input can also be unclear due to lack of specification or measurement of the relevant cues, mismatch between presented cues and stored cues, or form of presentation of information. Task processing can be complex because it requires a large amount of input or a large number of procedures. Processing also can be complex because procedures are not well-specified or dependent on each other. Further, if the function is nonlinear in form, cues are internally inconsistent, or cue validities (or overall environmental predictability) are low or negative, clarity of processing decreases and task complexity increases. Finally, amount and clarity of output are elements of overall task complexity. The presence of multiple or unspecified goals increases output complexity.

In this definition, no specification is made for how each element of task complexity relates to overall task complexity beyond the idea that, as the complexity of one element increases, overall complexity increases. It is not known whether different elements should be given different weights in determining overall complexity. Further, it is not necessarily the case that the function relating individual elements to overall task complexity is additive. Individual elements of task complexity may affect each other in determining overall task complexity. For example, an auditor who is estimating the dollar error in inventory could break the task down into multiple procedures by first estimating dollar error in various types of inventory, then aggregating the errors. While this increase in the number of procedures would generally increase task complexity, the breakdown into separate procedures might also decrease task complexity by decreasing the amount of information to process in each step, eliminating procedure interdependence, and so forth. Thus, overall task complexity might be increased or decreased, depending on the relative effects of the individual components. Again, the model presented here does not seek to explicate such intricacies.

The definition posited above regarding the elements of task complexity cannot be tested empirically other than through the use of manipulation checks to verify that people's perceptions of task complexity correspond to the definitions. As a result, no testable propositions are presented for the elements of task complexity.

EFFECTS OF TASK COMPLEXITY ON JUDGMENT PERFORMANCE

This section introduces the proposed model of the effects of task complexity on audit judgment performance and discusses each component of the model. The model is as follows:

$$\text{Judgment performance} = -f\left\{\frac{\text{Task complexity}}{(\text{Skill, Motivation})}\right\}$$

where Maximum threshold of task complexity > Task complexity > Minimum threshold of task complexity; Skill > 0; Motivation > 0.

The model first proposes that judgment performance is negatively related to task complexity. In general, as task complexity increases, performance is thought to decrease, *ceteris paribus*. Second, the model recognizes that there can be some interactive effects of task complexity and a person's skill and/or motivation on judgment performance.[5] The forms of these interactions are not well-specified currently, owing to lack of research. However, the bulk of the existing literature seems to suggest that the interaction of task complexity and skill occurs because the effects of skill on judgment performance increase as the level of task complexity increases (e.g. Campbell, 1988;

[5] Throughout the remainder of the paper, "skill" and "motivation" refer to skill and motivation relevant to a specific task rather than some "general" factors (Bonner & Lewis, 1990).

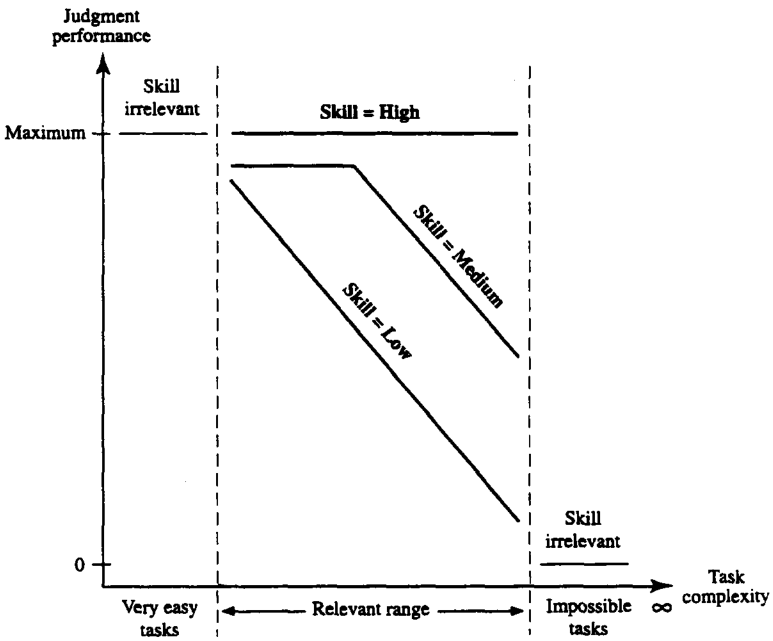

Fig. 2. Model of the effects of task complexity and skill on judgment performance.

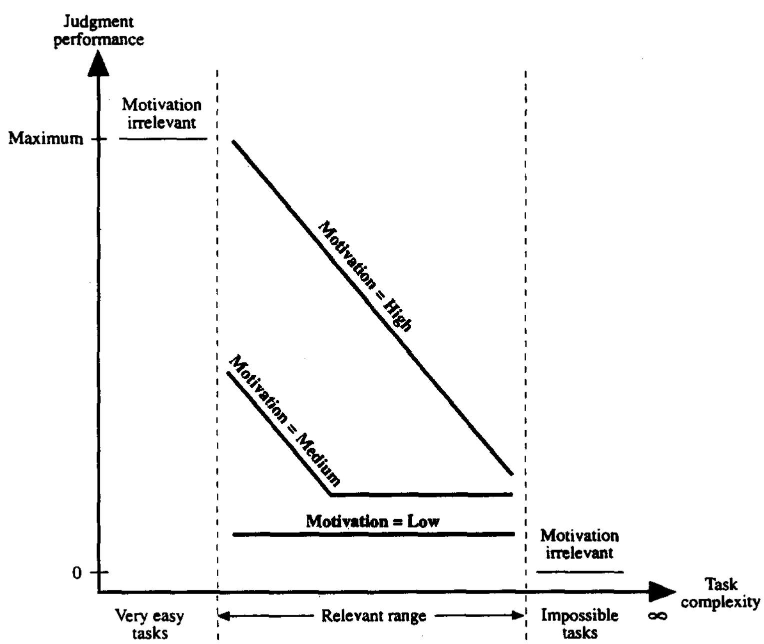

Fig. 3. Model of the effects of task complexity and motivation on judgment performance.

Earley, 1985; Wright, 1988).[6] An example of this interaction is portrayed in Fig. 2. The interaction of task complexity and motivation is less clear because studies have examined both effort-intensive and skill-intensive tasks. However, because this model is specifically developed for auditing tasks (which are proposed to be skill-intensive), the model presented here proposes that the relative effect of motivation on judgment performance decreases as the level of task complexity increases. This would occur because of the effect of skill hypothesized above, i.e. skill becomes more important to performance as complexity increases. Increases in motivation might result in increases in effort, but effort increases would not, in most cases, increase performance in skill-intensive tasks unless auditors already possessed adequate skills prior to performing the tasks. An example of this interaction is shown in Fig. 3. As shown in Figs 2 and 3, these interactions are posited to occur within a restricted range of task complexity.

Consistent with this, Figs 2 and 3 indicate that when task complexity is very low — tasks are very simple — variance in skill or motivation does not affect performance because performance will be uniformly high. In contrast, as task complexity exceeds some maximum threshold beyond which tasks become impossible, variance in skill or motivation is not relevant because performance is uniformly poor, ultimately approaching zero. Finally, note that the model assumes skill and motivation are greater than zero, because judgment performance would be zero under these circumstances.[7] The following sections are organized around the components of the model.

Effects of task complexity on components of performance

In this section, the negative effects of task complexity *per se* on judgment performance are discussed. These effects are divided into three components of judgment performance: (1) proper use of knowledge, (2) consistent use of knowledge, and (3) direct or unspecified effects. The first two classifications are similar to those used by the lens model (i.e. matching and consistency); they capture key aspects of judgment performance. Since much of the research on task complexity has used the lens model paradigm, these classifications of performance effects seem appropriate.

Proper use of knowledge. Both input complexity and processing complexity have been shown to affect the proper use of knowledge and, thus, judgment performance (no studies of output complexity showing these effects were found). As task complexity increases, use of knowledge becomes less optimal and judgment performance decreases. These performance effects manifest themselves in two ways: use of proper strategies and use of the appropriate amount of information. Using proper strategies encompasses using relevant cues, not using irrelevant cues, combining cues appropriately, and so forth.

Several studies have demonstrated the effects of input complexity on proper use of knowledge. Note that these studies are limited to elements of the amount of input; no studies were found showing the effects of clarity of input on proper use of knowledge. Work by Payne and his colleagues (Bettman *et al.*, 1990; Payne, 1976, 1982; Payne *et al.*, 1990) has shown that the number of alternatives in choice tasks affects the strategies chosen by subjects and the amount of information used. As the number of alternatives increases, subjects use easier, non-compensatory strategies which cause them to search different amounts of information on each alternative. These strategies and differential information use lead to lower quality, highly

[6] This hypothesis assumes that tasks are skill-intensive rather than effort-intensive. Skill-intensive tasks are those in which performance is affected more by skill than by effort. Performance in effort-intensive tasks is affected more by effort than skill, so that performance would benefit very little from increases in skill at any level of task complexity. Most auditing tasks are skill-intensive.

[7] The assumptions of the model clearly are not unreasonable in the auditing setting where professionals possess skill and motivation and do not perform excessively simple or impossible tasks.

variable judgments and decisions. When the number of alternatives is small, subjects are able to use fully compensatory strategies and search for the same amount of information on each alternative (Payne, 1976, 1982).[8] In accounting, Kida *et al.*'s (1990) subjects used smaller percentages of the available information as the number of bonds from which to choose increased. Work by Payne and his colleagues also has shown effects of the number of cues on proper use of knowledge and performance (Payne, 1976; Payne *et al.*, 1990). In those studies, as the number of cues increased, although subjects did not change strategies, they used increasingly smaller percentages of the available information and performance quality decreased. Huber (1987) found that increases in the number of cues (size of a maze) negatively affected strategies and performance. The final aspect of amount of input mentioned previously was cue redundancy. Naylor & Schenck (1968) showed that, as the redundancy of cues in a multiple-cue-probability-learning (MCPL) task increased, strategies became better and performance increased.

Work on process complexity also has shown that task complexity can affect use of knowledge and performance; these effects have been demonstrated with both the amount of processing and the clarity of processing. With regard to the amount of processing, as mentioned above, a great deal of research has shown that the number of alternatives affects both strategies chosen and amount of information used, and the number of cues affects the amount of information used. Another element of the amount of processing is the number of procedures or steps required in a task. Huber (1987) also varied the number of moves to escape from a maze and found that, as this number increased, the quality of strategies and performance decreased.

Variances in the clarity of processing also affect proper use of knowledge. The specification of the procedures to follow assisted subjects in Ashton's (1990) study in using the appropriate cues and, thus, improving performance. High levels of procedure interdependence created less optimal use of cues in Naylor & Dickinson's (1969) MCPL task. With regard to sign and magnitude of input–output relations, several studies have demonstrated that positive signs and higher magnitudes lead to use of more optimal strategies and more information (Brehmer, 1973; Brehmer *et al.*, 1974; Hirst *et al.*, 1992; Naylor & Clark, 1968; Naylor & Dickinson, 1969). Finally, linear functional forms allow subjects to use more optimal strategies (Brehmer, 1973; Brehmer *et al.*, 1974; Deane *et al.*, 1972) and greater amounts of information (Summers & Hammond, 1966). Thus, in both accounting and psychology studies, input and processing complexity have been found to affect the proper use of knowledge, with increases in complexity leading to decreases in appropriate use of knowledge and judgment performance.

Consistent use of knowledge. Several studies have shown that consistency of use of strategies and information is affected by task complexity. Again, these effects have been demonstrated with variations in input and processing complexity, but not output complexity. With regard to the amount of input, the work of Payne and his colleagues discussed above also suggests that the number of alternatives affects the consistency of strategy and information use. As the number of alternatives increased, subjects changed their strategies, which caused them to change the amount of information they used. This work also demonstrated that, as the number of cues increased, there was inconsistency in the amount of information used. Naylor & Schenck's (1968) results indicated that a decrease in the amount of input resulting from cue redundancy allowed subjects to be more consistent in their use of cues; the consistency effect

[8] Note that these effects concerning information search only occur when multiple alternatives, e.g. several different cars, are presented to subjects who then choose one of the alternatives. This is not common in auditing studies because most auditing tasks involve judgments, not choices among alternatives.

was much stronger than the knowledge effect. Again, there are no studies showing the effects of clarity of input on the consistency of knowledge use.

With regard to processing complexity, the results described above for the work by Payne *et al.* apply to the amount of processing required by the task as well. When the amount of processing required increases, subjects have difficulty determining the correct strategy, so they constantly change strategies. Subjects with low amounts of processing can find the correct strategy quickly and apply it consistently. Similar findings have been demonstrated with some manipulations of clarity of processing. When procedures are well specified, subjects can be more consistent in applying their knowledge (Ashton, 1990). Positive signs of input–output relations and higher levels of predictability lead to more consistent use of information (Hirst *et al.*, 1992; Naylor & Clark, 1968; Naylor & Dickinson, 1969; Naylor & Schenck, 1968; Summers & Hammond, 1966). Linear functional forms also promote consistent use of strategies (Brehmer, 1973; Brehmer *et al.*, 1974; Naylor & Dickinson, 1969). In summary, in both accounting and other areas, input and processing complexity appear to be negatively related to consistency of knowledge use and consequent judgment performance.

Direct or unspecified effects. Finally, other studies have shown effects of input and processing complexity on performance without specifying the affected performance components or after partialling out the effects of knowledge and consistency. With regard to amount of input, Paquette & Kida (1988) showed that, as the number of companies (alternatives) presented to accountants increased, accuracy with respect to choosing the company with the highest bond rating decreased; this effect was not due to changes in strategies used. Huber's (1987) results showed that the larger the number of cues, the worse performance was, after partialling out the effects of strategies. Studies of the effects of number of accounting cues have produced mixed results, with some studies finding better performance with increased information (e.g. Casey, 1980), others finding similar performance (Shields, 1980; Snowball, 1980), and others finding poorer performance (e.g. Chewning & Harrell, 1990). However, these studies have been criticized because they have confounded information load with information content and other variables or have not been successful in manipulating information load. More recent studies which have addressed these criticisms (Iselin, 1988; Simnett, 1993) have found decreases in the accuracy of accounting and auditing judgments with increases in the number of cues.

As to clarity of input, Fleishman (1975) found that perceptual clarity (encompassing a variety of factors) of tasks affected performance. Medical studies have shown that novice physicians have difficulty in making correct diagnoses because cues in X-rays and other sources of data are unmeasured (Johnson *et al.*, 1981; Lesgold *et al.*, 1988; Myles-Worsley *et al.*, 1988). In accounting, Moriarity (1979) found that CPAs were better able to predict bankruptcy with graphical faces (the most clear input) than with financial data (less clear input), although Stock & Watson (1984) only found similar results in one of two experiments. Two studies obtained similar results with business forecasting tasks using graphs versus tables of numbers (DeSanctis & Jarvenpaa, 1989; Dickson *et al.*, 1986). Wright (1992) showed that auditors making a complex loan collectibility judgment performed better when input was made more clear with graphs and tables versus just tables. Finally, Butler (1985) found that providing auditors with attention-directing questions to help them specify the appropriate cues for sample size decisions somewhat increased the accuracy of those decisions.

For process complexity, Huber's (1987) results also indicated that the required number of moves to get through the maze (amount of processing) affected performance, with more moves degrading performance, even after partialling out strategies. Earley (1985) manipulated process complexity based on the number of rules that subjects had to follow in making up class schedules; the larger the number of rules, the worse performance was. Shapira's (1989) subjects' performance decreased as the number of steps required to solve a puzzle increased. Finally, as mentioned previously, several studies have found direct effects of the number of alternatives and cues on the quality of performance.

Several studies have manipulated the clarity of processing and found performance differences that are consistent with the model proposed here. Auditors provided with formulas and tables (explicit procedures) provided better sample size estimates than those without in a study done by Kachelmeier & Messier (1990). Heiman's (1990) auditor subjects made better estimates of the likelihood of hypothesized financial statement errors when explicit processing instructions were given. Simnett & Trotman (1989) found that auditors were less able to predict bankruptcy two years in advance than one year in advance because of lower environmental predictability; this was a direct effect (not due to proper or consistent use of knowledge). The results of Ashton & Ashton (1988) and Tubbs *et al.* (1990) showed that auditors performed worse at internal control evaluations when cues were internally inconsistent (evidence was mixed) than when they were consistent. Again, then, input and processing complexity increases have been shown to negatively affect performance in both auditing and other types of tasks, in many cases after controlling for the effects of knowledge and consistency.

The discussion above regarding the effects of task complexity on components of performance leads to the following testable propositions:

P1. As task complexity increases, proper use of knowledge diminishes (i.e. strategies change from high quality to low quality and smaller percentages of available information are used).

P2. As task complexity increases, consistency of knowledge use diminishes.

P3. As task complexity increases, judgment performance decreases.

Interactive effects of task complexity and skill on performance

Skill (knowledge and abilities) can interact with task complexity to affect judgment performance. The general idea is that, the more complex the task, the greater the importance of skill to good performance (see Fig. 2). Recall that this proposition is predicated on the assumption that the tasks being studied are skill-intensive. Studies in accounting and other areas using skill-intensive tasks have demonstrated this result. Earley (1985) showed that giving subjects the knowledge needed for his class scheduling task compensated for increases in task complexity (i.e. performance differences existed between high complexity and low complexity tasks when subjects lacked knowledge; when given knowledge, there were no longer performance differences). Campbell & Gingrich (1986) found that programmers who participated in setting the number of hours to write a program gained knowledge which aided their performance (over non-participators) in a complex programming task, but not in a simple task. Bonner (1991) found that auditors performed equally as well in a complex task (either control risk or analytical risk evaluation with unmeasured cues) as they did in a simpler task (either control risk evaluation or analytical risk evaluation with measured cues) because they possessed the necessary knowledge. Interpreting Ashton's (1990) tasks under the model proposed here, knowledge gained through feedback helped auditors more in the complex task (bond-rating task without a rule) than in the simple task (one with a rule). Finally, Simnett (1993) found that experienced auditors (those presumably possessing greater knowledge) performed better than inexperienced auditors in the high information load (high complexity) condition of his bankruptcy prediction task, but not in the low load condition. This discussion leads to the following testable proposition:

P4. As task complexity increases, the effect of skill on judgment performance increases (in skill-intensive tasks).

Interactive effects of task complexity and motivation on performance

Task complexity also can interact with motivation to affect task performance. Motivation can be intrinsic or extrinsically induced by financial incentives, goals, or other techniques (e.g. accountability). Although the literature contains two divergent views about this interaction, this paper proposes that the interaction is such that the relative effect of motivation decreases as task complexity increases (see Fig. 3). This occurs because, in simple tasks, additional effort induced by motivation can have direct effects on performance (because the skills needed are minimal and, therefore, most people will possess them). In complex tasks, effort does not have as direct or strong an impact on performance because the effect of skills on performance increases as complexity increases (see Proposition 4). Studies finding the opposite effect, i.e. that motivation is more important (for improving performance) in complex tasks than in simple tasks, have some limitations. First, the "complex" tasks and "simple" tasks sometimes differ on dimensions other than complexity. For example, Jackson & Zedeck (1982) found that goals affected performance in the more complex task, but not in the less complex task. The more complex task in their study was a cognitive task which was not skill-intensive and the less complex task was a manual task in which performance could be affected largely by physical and spatial skills. Given that performance in the cognitive task could be improved through additional effort, it is not surprising that goals might improve performance there; however, subjects lacking skills for the manual task probably were not able to improve their performance through extra effort. Other studies (e.g. Ashton, 1990; Shapira, 1989) finding that motivation affected performance in the complex task more than in the simple task may have used "simple" and "complex" tasks that were very close in levels of complexity. For example, in Ashton's study, the rule provided in the "simple" task only classified 8 of 16 bond rating cases correctly.

The view adopted here is supported by other research using a variety of skill-intensive tasks. Huber's (1987) results showed that goals harmed performance in a complex problem-solving task and facilitated performance in a simple task. These results are similar to those found by Wood *et al.* (1987) in a meta-analysis of several goal-setting studies, i.e. that the effects of goals on performance were weaker for complex tasks. Earley *et al.* (1989) found that, in doing a complex stock market prediction task, subjects who received do-your-best goals did better than subjects with specific goals; this is generally not the case. Their argument was that specific goals may harm performance in complex tasks because those goals induce people to change strategies constantly in tasks where strategies (skills) are crucial to good performance. Given that most audit judgment tasks are skill-intensive, the following proposition is proposed:

P5. As task complexity increases, the relative effect of motivation on judgment performance decreases (in skill-intensive tasks).

Effects of task complexity on learning

Finally, task complexity can affect one's ability to learn, i.e. improve judgment performance over time. Two types of learning are ***immediate*** (or ***short-term***) learning and ***sustained*** (or ***long-term***) learning. Short-term learning refers to improvement in judgment performance within the initial experimental task, while long-term learning is reflected by performance improvements exhibited some time after the initial learning trials. Lens model studies have shown that ***short-term*** learning is facilitated when tasks are *less* complex, i.e. they have linear forms, internally consistent cues, and large and positive cue validities (Brehmer, 1973; Brehmer *et al.*, 1974; Naylor & Clark, 1968; Naylor & Schenck, 1968; Summers & Hammond, 1966). As noted previously, short-term learning occurs through increases both to proper use of knowledge and consistency. In contrast, ***long-term*** learning is facilitated when tasks are *more* complex initially. Campbell & Ilgen (1976) showed that practice on complex chess problems (as opposed to practice on simple problems) led to better performance on later problems and claimed that this occurred because the practice with complex problems created more knowledge.

Creyer *et al.* (1990) examined the impact of feedback on subsequent performance of either a simple or complex choice task. Feedback increased later performance on the complex task (due to better acquisition of knowledge), but not on the simple task. Studies of category learning show that, while immediate category learning is hampered by highly variable instances (a more complex setting), long-term category learning is facilitated (e.g. Fried & Holyoak, 1984). Thus, it appears that immediate learning is facilitated by simple tasks,[9] whereas knowledge that persists and can be used later (long-term learning) may best be gained by originally doing and receiving feedback on complex tasks. The following propositions reflect these ideas:

P6. As task complexity increases, short-term (immediate) learning decreases.
P7. As task complexity increases, long-term (sustained) learning increases.

REVIEW AND ANALYSIS OF PREVIOUS AUDIT JUDGMENT STUDIES

In order to examine the possible effects of task complexity (as proposed here), this section reviews audit judgment studies on three common tasks which have varied on task complexity in experimental settings. These three tasks are internal control evaluation, hypothesizing financial statement errors on the basis of ratio analysis, and going-concern evaluations.[10]

No specific analysis is presented for studies of internal control evaluation because Trotman & Wood's (1991) meta-analysis suggests that task complexity does not explain differences in performance results across studies of internal control evaluation. Trotman & Wood found that 89% of the variance in judgment performance (consensus) across studies was accounted for by sampling error. They examined the effect of the number of cues (an element of task complexity as defined here) and found that it did not account for variance in the results. This analysis was done for fourteen studies (see Trotman & Wood for the list of studies included).

Although these results are fairly strong, *existing* studies of internal control evaluation may not provide the best arena for examining the potential effects of task complexity. Both task complexity and performance varied very little in these studies. Most of them provided approximately five to seven cues which were measured for subjects (a medium amount of clear input). These cues were linearly and positively related to the criterion and could be evaluated independently because of factorial designs, then combined (a small amount of clear processing). Single-judgment responses were given on clearly marked, limited scales (a small amount of clear output). Finally, in all studies, subjects had the knowledge needed to do the task, so that skill varied very little as well. Thus, most tasks used in internal control studies have been quite simple, subjects have had adequate skills, and, not surprisingly, performance has been quite good.

For the other two groups of studies (ratio analysis and going-concern evaluations), an analysis of the effects of task complexity and skill on judgment performance is presented. For each study, the six elements of overall task complexity (amount and clarity of input, processing, and output) were rated on a three-point scale, where a "1" indicates a small amount of

[9] Note that this idea also is consistent with experimental studies which find relatively little short-term learning in complex market settings (e.g. Sunder, 1992).

[10] Based on Bonner & Pennington (1991), there were only four audit judgment tasks for which there were a sufficient number of studies with variation in task complexity to address this issue. The fourth task, not examined here, is evaluating the results of tests performed on a sample basis. This task is not examined because performance is uniformly poor, probably because of hardwiring limitations most people have with regard to statistical reasoning. As such, skill is likely to approach zero in these studies, so that variations in task complexity would probably not have an effect on performance.

or highly clear input, processing, or output, and a "3" indicates either a large amount of or very unclear input, processing, or output.[11] The scores for the six elements then were averaged for an overall task complexity score.[12] Next, subjects were rated as to whether they had the skills needed to perform the task, since skill has varied across studies as well; these ratings were on a three-point scale, where a "3" represents having most of the skills, on average across subjects, and a "1" represents lacking many of the skills.[13] Skill ratings are based on the level of experience of the subjects and information from Abdolmohammadi (1992) about when auditors begin to perform the task and Bonner & Pennington (1991) about the extent of training auditors receive for various auditing tasks, as well as information from the studies themselves if they directly measured skills (e.g. Bonner & Lewis, 1990; Libby, 1985). Since performance is hypothesized to be negatively related to (task complexity/skill), the indepen-

TABLE 1. Analysis of the effects of task complexity and skill on auditors' performance in ratio analysis judgments

Panel A: Ratings of task complexity, skill, and performance

Study	Input comp.		Proc. comp.		Output comp.		TC	Skill	TC/ skill	Perf.
	Amt	Clar.	Amt	Clar.	Amt	Clar.				
Bedard & Biggs (1991)	2	2	3	3	1	2	2.17	2	1.09	1
Bonner & Lewis (1990)	2	2	3	2	2	2	2.17	2	1.09	1
Heiman (1990)										
Experimenter provided	1	2	2	3	1	1	1.67	3	0.56	3
Self-generated	1	2	3	3	2	1	2.0	3	0.67	2
Libby (1985)	1	2	1	3	2	1	1.67	3	0.56	3
Libby & Frederick (1990)										
Experienced	1	2	1	3	2	1	1.67	3	0.56	3
Inexperienced	1	2	1	3	2	1	1.67	2	0.83	2
Marchant (1989)										
Experienced, high frequency	2	1	1	3	1	1	1.5	3	0.5	2
Experienced, medium frequency	2	1	2	3	1	1	1.67	2	0.83	1
Inexperienced, high frequency	2	1	1	3	1	1	1.5	2	0.75	1
Inexperienced, medium frequency	2	1	2	3	1	1	1.67	2	0.83	2

Input comp. = input complexity; Proc. comp. = process complexity; Output comp. = output complexity; Amt = amount; Clar. = clarity; TC = task complexity; Perf. = performance.

Panel B: Regression of performance on task complexity/skill

Variable	Beta	*t*-Statistic	Significance
Constant	4.257	6.499	0.000
Task complexity/skill	−3.130	−3.706	0.005

Adjusted R^2 = 0.604.

[11] Detail about tasks was insufficient to use a finer rating scale. Ratings were done by the author based on previous literature indicating which levels of these factors would be considered to be high, medium, and low.

[12] As noted before, equal weights were given to individual elements.

[13] None of these studies used subjects who had zero skill.

dent variable for analysis is obtained by dividing the overall task complexity score by the skill rating.[14] Finally, the performance of auditors in each study was rated on a three-point scale, where a "3" represents good performance and a "1" represents poor performance. These ratings were based on a review of the performance results and similar performance ratings made by Bonner & Pennington (1991). Tables 1 and 2 present these ratings for, respectively, ratio analysis and going-concern studies.

A regression analysis of the relation of (task complexity/skill) to performance was done for each group of studies. For both tasks, this variable is highly negatively related to performance, as predicted. Further explanation of the ratings and results follows.[15]

As shown in Table 1, Panel A, the ratio analysis studies included were Bedard & Biggs (1991), Bonner & Lewis (1990), Heiman (1990, Experiment 1),[16] Libby (1985), Libby & Frederick (1990),[17] and Marchant (1989).[18] Other studies of ratio analysis were not included because subjects chose the ratios they used, so that each subject did a different task (e.g. Biggs *et al.*, 1988). Ratings were done as follows. Amount of input was rated "1" if three or fewer ratios were provided, a "2" if four to six ratios were provided, and a "3" if greater than six were provided. Clarity of input was rated a "1" if the ratios indicated very large deviations from expectations, a "2" if the deviations were less extreme, and a "3" if there were no deviations. Amount of processing received a "1" if the pattern of ratios could be explained by a high frequency error, since these errors are generated by simple pattern matching, i.e. little processing, a "2" if the error was of medium frequency, and a "3" if the error was quite rare. Clarity of processing was given a "1" if rules for doing the ratio analysis were well-specified in the study, a "2" if some rules or hints were provided, and a "3" if no information about processing was given. Amount of output was rated in the same way as input: a "1" for one to three pieces of output, a "2" for four to six pieces, and a "3" for seven or greater pieces. Clarity of output was rated a "1" if instructions were entirely clear as to what the auditors were to do, a "2" if they were less clear, and a "3" if they were not at all clear. The skills needed for the task depended on the frequency of the error. For high frequency errors, subjects mainly need frequency knowledge and studies have shown that frequency knowledge increases with experience (e.g. Libby & Frederick), so that these ratings were done based on experience level. For lower frequency errors, subjects also need reasoning

[14] No measures of motivation were made since the studies on which the analysis is based did not measure or provide information about motivation. Motivation is expected to be positive since the studies used practicing auditors. Further, motivation is not expected to vary substantially because the studies did not provide monetary incentives or use any other procedure to increase or decrease motivation.

[15] In an experiment designed to examine the effects of task complexity on judgment performance, a better approach to data analysis would be to use ANOVA to examine the interaction of skill and task complexity. Here, since a fully crossed design is not available, the effects of task complexity and skill must be analyzed using a regression approach. If the interaction between task complexity and skill is similar to that depicted in Fig. 2, a regression of performance on (task complexity/skill) with a small number of data points will likely only detect a negative linear relation.

[16] Experiment 2 was not included because multiple task characteristics varied, some of which are associated with task complexity and some of which are not. Since task complexity was manipulated in Experiment 1, the analysis separates the results into the two task complexity conditions.

[17] Experienced and inexperienced auditors were used in this study. Since they have differing levels of skill, the analysis separates the results by subject group.

[18] This study included two subject groups and two types of error — high frequency and medium frequency. Since skill differs for the subject groups and task complexity differs for the errors, four separate sets of results are provided.

TABLE 2. Analysis of the effects of task complexity and skill on auditors' performance in going-concern judgments

Panel A: Ratings of task complexity, skill, and performance

	Input comp.		Proc. comp.		Output comp.					
Study	Amt	Clar.	Amt	Clar.	Amt	Clar.	TC	Skill	TC/ skill	Perf.
Asare (1990)	2	2	3	2	2	1	2.0	3	0.67	2
Choo & Trotman (1991)										
Experienced	3	2	3	2	1	1	2.0	3	0.67	2
Inexperienced	3	2	3	2	1	1	2.0	1	2.0	1
Kida (1980)	2	2	2	1	1	1	1.5	3	0.5	3
Kida (1984a)	2	2	3	3	1	1	2.0	1	2.0	1
Kida (1984b)	3	2	3	2	3	1	2.33	3	0.78	1
Simnett & Trotman (1989)										
One-year	2	2	2	1	1	1	1.5	2	0.75	3
Two-year	2	2	2	2	1	1	1.67	2	0.83	2

Input comp. = input complexity; Proc. comp. = process complexity; Output comp. = output complexity; Amt = amount; Clar. = clarity; TC = task complexity; Perf. = performance.

Panel B: Regression of performance on task complexity/skill

Variable	Beta	t-Statistic	Significance
Constant	2.859	6.133	0.001
Task complexity/skill	−0.960	−2.416	0.052

Adjusted R^2 = 0.493.

ability and other types of knowledge about errors. Bonner and Lewis directly measured these skills and found medium levels, thus the "2" rating. Ratings for Marchant, and Bedard and Biggs are based on Bonner and Lewis' measurements, since the subject groups were similar. Finally, performance ratings are based on the average level of accuracy of errors generated or the appropriateness of answers to questions about hypothesized errors, with a "3" being good, a "2" being moderate, and a "1" being poor.

The relation between (task complexity/skill) and performance was analyzed using regression. Panel B of Table 1 shows that (task complexity/skill) is significantly negatively related to performance ($t = -3.706$, $p < 0.005$). In a regression of performance on task complexity and skill, results revealed that this significant relation is primarily driven by skill ($t = 3.600$, $p < 0.007$), although task complexity is negatively related to performance ($t = -0.960, p < 0.365$).[19]

The going-concern studies were evaluated in a similar manner (see Table 2, Panel A). The studies examined were Asare (1992), Choo & Trotman (1991),[20] Kida (1980), Kida (1984a,b), and Simnett & Trotman (1989).[21] Other studies (e.g. Chewning & Harrell, 1990; Trotman & Sng, 1989) were not included because of insufficient information about skill or performance or

[19] Nonparametric tests (see Siegel & Castellan, 1988) showed similar results. A Spearman rank-order test showed that (task complexity/skill) was significantly related to performance ($p < 0.001$) and Kendall partial correlation coefficients showed that skill was significantly related to performance ($0.01 < p < 0.025$) and that task complexity was not ($p > 0.90$).

[20] Again, experienced and inexperienced auditor results are shown separately because of differences in skill.

[21] Task complexity varied in this study, so the conditions are shown separately.

because subjects were persons other than auditors (e.g. Moriarity, 1979). Amount of input was rated the same as above; the cues in these studies were ratios, probabilities, or descriptive statements. Clarity of input was rated based on the extent to which the cues were clear as to their meaning. In all the studies, cues were not entirely clear, so that each study received a "2". Amount of processing mainly depended on the amount of information that had to be combined and whether statistical reasoning was involved, so that these ratings were the same as for amount of information, with the exception of the Kida (1984a) study, where amount of processing was more than amount of information because Bayesian revision processes were required. Clarity of processing depended on whether the cues were internally consistent, whether the function was linear, additive, and positive, and the level of environmental predictability. A "1" rating was for simple linear additive functions with consistent cues;[22] a "2" rating was given when cues were mixed, i.e. internally inconsistent, and a "3" was given when the processing was very difficult (Bayesian revision). The amount and clarity of output were rated as above. Skill ratings were made based on level of experience and whether statistical reasoning was required (see Bonner & Pennington, 1991). Performance ratings reflect either the level of accuracy or the level of agreement about the probability of failure.

A regression of performance on (task complexity/skill) (Panel B, Table 2) revealed that performance on going-concern evaluations has a significant relation to (task complexity/skill) ($t = -2.416$, $p < 0.052$). Separate regressions of performance on skill and task complexity indicated that both skill ($t = 5.025$, $p < 0.004$) and task complexity ($t = -9.276$, $p < 0.000$) were significantly related to performance.[23]

The results support the idea that variation in task complexity may explain some of the variation in performance results across studies of auditor judgments, at least studies of going-concern evaluations. Variations in task complexity occurred in these studies because of differences in the way experimental tasks were constructed. These differences were normally substantive, e.g. structuring a task as a probabilistic judgment task versus one not requiring probabilities; however, it is possible that more minor differences could account for some of the variation as well. Also, skill levels varied, either increasing or diminishing the effects of task complexity. The next section more fully discusses the implications of the results.

DISCUSSION AND DIRECTIONS FOR FUTURE RESEARCH

Previous research in auditing and other fields has discussed and shown effects of task complexity on the quality of judgments. This paper develops a definition of task complexity and a model for examining its effects on judgments. In general, the model proposes that the amount and clarity of input, processing, and output affect (are part of) overall task complexity. The model then proposes that increases in task complexity lead to decreases in judgment performance, *ceteris paribus*. However, skill and motivation may interact with task complexity to affect judgment performance. Finally, the model proposes that task complexity may have negative effects on immediate learning and positive effects on long-term learning.

[22] Although many of the studies framed the judgment as the probability that the company would continue (rather than fail), thus making the judgments negatively related to the cues indicating failure, multiple studies have shown that auditors reframe these judgments to think about failure no matter how the experimental instrument frames them (Asare, 1992; Kida, 1984b; Trotman & Sng, 1989). Thus, the function effectively becomes a positive one.

[23] Again, nonparametric results were similar. (Task complexity/skill) was significantly negatively related to performance in a Spearman rank-order test ($0.02 < p < 0.05$). Kendall partial correlation coefficients showed significant relations to performance of both skill ($0.05 < p < 0.10$) and task complexity ($0.001 < p < 0.005$).

To consider whether task complexity could have an effect on audit judgments, an analysis of previous audit judgment research was made. This analysis entailed rating two groups of studies as to task complexity, skill level of subjects, and judgment performance quality, then relating (task complexity/skill) to performance. As noted above, this analysis revealed a negative relation between (task complexity/skill) and performance quality for both tasks. This relation was driven primarily by skill in one of the two tasks, however.

Since these results suggest that increases in task complexity may have a detrimental effect on the quality of auditors' judgments, further research on audit task complexity should be pursued as part of the broader goal of understanding and improving auditors' judgments. This research should examine the *conditions* under which task complexity may have negative performance consequences. For example, perhaps high levels of task complexity have the greatest negative impact at low levels of skill. This would suggest that reallocating tasks to more highly skilled persons may be very important to firm performance, despite the additional costs. It is also possible that benefits of high levels of task complexity such as better long-term learning may outweigh costs like diminished short-term performance; these questions should be investigated as well, since remedies for certain problems might create other problems, such as diminished learning.

Results of research on the effects of audit task complexity on auditors' judgments ultimately could improve audit practice in the following ways. If tasks are currently highly complex and, thus, judgment performance is not as good as it could be, performance could be improved by restructuring the task with a decision aid or other appropriate device. Performance also could be improved through changes to training programs. An understanding of the level of complexity in a task would provide necessary guidance on the appropriate form of aid or changes to training. Finally, an understanding of how various audit tasks differ as to complexity might provide some information on the types of auditors to whom those tasks should be assigned.

Final notes are cautionary. In pursuing this research, two issues should be given careful consideration. First, researchers should consider that the effects of task complexity should be studied for only certain types of audit tasks. One type of task which warrants study is one that currently varies as to task complexity across auditors, audits, or firms, e.g. ratio analysis. Studies of the effects of task complexity also would be warranted if the task is currently highly complex, e.g. estimating dollar error (Trotman, 1985) and could be made less complex in some way, e.g. via a decision aid or automization. Studies of the effects of task complexity in highly structured tasks, e.g. internal control evaluation, probably are not warranted because they vary little across auditors, audits, or even firms. Further, performance in many of these tasks is already quite good (Bonner & Pennington, 1991).

A second area deserving careful attention in studies of the effects of task complexity is experimental design and variable measurement. Previous studies in accounting either have not systematically manipulated task complexity (while controlling for the effects of other variables) or have failed to measure task complexity to validate their manipulations (i.e. their definitions). To be able to provide interpretable results, future research should consider the following. Studies should begin by manipulating task complexity within one task rather than across tasks. If tasks are varied, multiple aspects of the task besides task complexity also vary. Manipulation checks should be made to validate definitions and ensure that task complexity variations have been perceived. Finally, variables that can interact with task complexity (skills and motivation) should be either measured or controlled for in some way in the design, e.g. held constant. Measurement of perceived task complexity, skills, and motivation can also be useful in resolving the debate about whether task complexity and personal attributes interact at input or during processing. If measurements of perceived task complexity vary only with changes in the task and not across people of varying skills and motivation, then the interaction likely occurs during processing. However, if measurements of perceived task complexity vary with both task and people, then the effect probably occurs at input (note that these ratings should reflect the same interactions between task complexity and skill or motivation as performance measures do if the effect occurs at input). Currently, in both accounting and psychology, there is limited evidence supporting each of these views. For example, Abdolmohammadi & Read's (1992) auditors' ratings of task complexity were not affected by experience level (a proxy for skill). In Shapira's (1989) study, ratings of task complexity were affected by task characteristics, but not by goals (which supposedly influenced motivation). In contrast, Huber's (1987) study found ratings of task complexity that were related to the interaction of task difficulty and goal level (motivation).

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