Problem Solving for Effective Systems Analysis: An Experimental Exploration

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1. INTRODUCTION

In 1976, there were approximately 160,000 persons employed as business systems analysts with projected employment figures reaching 210,000 in the U.S. by 1985. Moreover, with earnings on the average of $21,000 per year, the job of the systems analyst is forecast to be one of the four "sunniest occupations of the 1980s" [44,54].

Despite the present widespread use of systems analysts by U.S. organizations, and the forecasts that indicate even greater demands will exist in the future, a substantial concern is growing about systems analysts' abilities and their ultimate performance. A practitioner commented on this problem, noting:

"In today’s business environment, a systems analyst needs to be much more than a computer specialist. The skills required to design and implement an effective system are not fully recognized by business nor by the analyst himself. Those analysts that have been successful have learned their skills more by trial and error than by any other means. Unfortunately, trial and error learning requires years of on-the-job training. With today’s demand for qualified analysts, industry cannot afford to rely on experience as the only teacher [60]."

This dilemma of a growing occupation coupled with the shortcomings in personnel selection, training, and performance stems primarily from two conditions. Historically, unlike the occupation of programming, the discipline of systems analysis has not developed well-accepted job performance criteria. Second, and most important, although we can enumerate the types of skills that analysts need [34,36], we lack an

ABSTRACT: The results of an empirical study comparing the thought processes of high- and low-rated systems analysts is presented. The report discusses the types of problem solving behaviors exhibited by the two groups of systems analysts and draws conclusions about the relationship of those behaviors to successful performance. The results suggest that qualitative differences exist in the problem solving methods of the two groups, and that the skills associated with high-rated problem solving may lead to better job performance and may be transferred to other practitioners. The article concludes with a set of recommendations for practitioners, managers, and researchers concerned with problem solving and systems analysis.
understanding of the underlying basis for these skills and their relationship to successful job performance [8,24].

Perhaps the most problematic and least understood area of analyst skill is in the information requirements determination task (IRD). Much has been written recently about the information requirements determination task [6,7,11,15–17,22,23,25,45–47,51,52,57]. However, the work to date has focused primarily upon the types of activities in the IRD phase or methodologies for requirements determination. Furthermore, most of this work has not been put to any scientific test. In fact, to our knowledge, the studies of Bell and Thayer [7], Boland [11], Munro and Davis [45], and Munro and Wand [46] represent the only empirical examinations of the IRD phase.

The purpose of this paper is to present the results of an experimental field study that investigates the problem-solving behavior of high-rated and low-rated systems analysts while performing an IRD task. Our search for the bases of analyst skill led us to hypothesize that the main differentiating feature among analysts is their problem-solving behavior. In other words, we suggest that successful systems analysts behave differently in solving analysis problems than those that are less successful.

To set the scene for the emphasis on problem solving, the following section of this paper develops the contention that systems analysis is largely an activity of this type. The third section of the paper describes, in detail, the research method employed in doing the study. The fourth section presents our results and discusses the relationship of those results to successful analyst performance. The fifth section concludes the paper with prescriptions for the practice of systems analysis and for future research of the type reported on here.

2. SYSTEMS ANALYSIS AND PROBLEM-SOLVING BEHAVIOR

The emphasis on problem-solving behavior is based on the work of cognitive psychologists who have studied problem solving behavior in a wide variety of areas. Most of this research has focused on well-defined tasks such as games (i.e., chess, cryptarithmetic, the tower of Hanoi problem), or real world problems that have well-defined objective functions (i.e., a working program, a successful investment portfolio, or a solution to a thermodynamics problem). This research benefits from this tradition by using its research methods and conceptualizations about the human information processing system.

The term problem solving refers here to the reasoning process that the analyst uses to analyze an information requirements determination problem and to synthesize a solution that meets the needs of the user and the organization. Specifically, the focus is on the frequency, ordering, and association with analyst performance of the clues, goals, strategies, heuristics, hypotheses, information, and knowledge manifested in the thought process of the analyst.

In addition, the characteristics of the analysis task domain itself led us to adopt a problem-solving perspective. The characteristics of the analysis task domain are:

1. Analysis problems, at their inception, have ill-defined boundaries, structure, and a sufficient degree of uncertainty about the nature and make-up of the solution.
2. The solutions to analysis problems are artificial, that is, they are designed and hence many potential solutions exist for any one problem.
3. Analysis problems are dynamic, that is, they change while they are being solved because of their organizational context and the multiple participants involved in the definition and specification process.
4. Solutions to analysis problems require interdisciplinary knowledge and skill.
5. The knowledge base of the systems analyst is continually evolving and the analyst must be ready to incorporate changes in the technology (e.g., upgrades in operating equipment, new techniques in developing systems) and to participate with users in different ways.
6. The process of analysis, itself, is primarily cognitive in nature, requiring the analyst to structure an abstract problem, process diverse information, and develop a logical and internally consistent functional set of specifications.

Because of these fundamental characteristics of the task domain, the analyst must work to set goals and develop strategies to solve each problem. Furthermore, as the analyst gains experience he or she develops well-rehearsed problem-solving behavior that becomes part of their skill repertoire. Similarly, each new analysis problem brings unique characteristics that require new solution strategies. Thus, given the nature of the task domain and the human problem solver we believe that the focus on the problem-solving process provides insight into the nature of the skill required to solve analysis problems competently.

A final reason for focusing upon the problem-solving process is that many traditional studies have searched for a link between successful job performance and the traits of individual analysts or identified skill clusters based upon management opinion or retrospective self-reports by the analysts [1,3,14,18,32,34,35,62]. Although these studies have provided valuable information, their major limitation is that they provide little understanding of the underlying behaviors that comprise the skills required for effective performance. While these studies can be helpful in the process of selecting analysts (if validated in a particular organization), the guidelines are not particularly helpful in transferring expertise for educational and training programs or in the evaluation of systems analysis techniques.

3. RESEARCH METHOD

3.1 Method of Sample Selection

The objective of the sampling strategy was to select two experienced analysts from each of the nine participating corporations for a total of 18 analysts. Analysts were selected for the study via a two-stage process. First, managers of systems analysts were contacted to explain the nature of the study, the criteria for analyst participation, and selection procedures.

In the second stage each manager was interviewed and was asked to evaluate the performance of four analysts using a behaviorally anchored rating instrument developed by Arvey and Hoyle [2]. The instrument has been successfully used in industrial settings and shown to have good convergent and
discriminant validity (see [2]). This instrument provided a standard measure across subjects and raters in different organizations.

In addition, each manager was also asked to provide a second overall rating, on a ten-point scale, indicating whether the analyst was average, above average, or below average in performance. The second measure provided a means to cross-check the evaluation given by the instrument.

Each of the ratings were placed in a sealed envelope and given to a research assistant for tabulation. Two analysts were chosen on the basis of the managers’ ratings as candidates for the study, the highest- and lowest-rated analyst from the group of four analysts in each company. All analysts chosen for the study agreed to participate.

The resultant sample included 18 systems analysts with a minimum of three years of experience in systems analysis from nine participating corporations located in a large midwest city. The corporations represented a cross-section of industries including food-processing, banking, publishing, insurance, retailing, medical technology, and wholesale distribution. Annual revenues for the sample corporations ranged from $500 million to over $5 billion. The sample included two female analysts, 16 male analysts, experience levels ranging from 3–14 years, and ages ranging from 26 to 52 years.

3.2 Data Collection

The experiment consisted of presenting the analyst with a problem of determining the information requirements for a new accounts receivable system for a large consumer retail company. Each analyst was required to define the purpose of the proposed system, to provide a rough outline of the proposed information requirements, and a plan of action for subsequent stages of systems development.

Data was collected via a protocol analysis technique wherein the analysts were instructed to verbalize their thought processes as they solved the problem. Protocol analysis has been employed in many previous studies and has proven useful in gathering a detailed set of data on the subject’s solution process. (See, for example, Clarkson [21], Newell and Simon [48], Brooks [12,13], Larkin et al. [41], and Johnson et al. [37].) The protocols were collected in accordance with generally accepted guidelines to protect the veridicality of the verbal reports [28,29].

The experiments took place in a private conference facility at the subject’s place of employment and both analysts from each site completed the experiment the same day. The experimental session lasted an average of two hours including administration of a background questionnaire that gathered demographic information and education history and a post-experimental debriefing.

3.3 Encoding of the Verbal Protocols

The protocols were transcribed by a trained secretary and parsed into numbered phrases for reference purposes in the coding process. The protocols were encoded by two independent coders via a predesigned coding schematic based upon structured interviews with practicing systems analysts and previous literature on systems analysis. The coding schematic and procedures were pretested for validity by running a test subject through the experiment and coding that analyst’s data. As a result, several categories were added to the schematic and several coding procedures were modified.

The coding schematic used in the study is a model of the expected components of analyst problem-solving behavior. Two areas were represented:

1. Mental Behaviors. These categories represent the types of cognitive behaviors employed by the analyst to solve the problem, such as searching for clues, generating hypotheses, setting goals, developing strategies to achieve goals, applying heuristics, requesting information, and drawing conclusions (24 categories in total).

2. Problem-Solving Modes. These categories represent five different modes of behavior during the course of the solution process. The categories include problem finding, problem reformulation, problem integration (integrating the solution into the current environment), problem facilitation (facilitating quality interaction with the user), and requirements determination (determining and specifying the information system requirements) (6 categories in total).

Each category in the coding schematic has a unique code and category definition. The encoding process consisted of assigning codes to each phrase in the subject’s protocol according to the definitions. The encoded data was statistically analyzed and compared for inter-coder agreement using the Wilcoxon Matched Pairs Test. The Wilcoxon test indicated that both sets of data came from the same distribution and that the encoding procedures were reliable between the two coders at the 0.01 level. The encoded data of the more experienced coder was chosen for analysis.

3.4 Hypotheses

Six major hypotheses about behaviors associated with highly rated performance were developed for this study. We based our hypotheses on a series of pre-study interviews with systems analysts (see Vitalari [59]) and previous literature and research in the MIS Field and Cognitive Psychology. The hypotheses are stated in general terms due to the exploratory nature of the study and the lack of previous research in the area.

3.4.1 Hypotheses in the Mental Behavior Categories

We expected that the high-rated analyst would employ more triggers, more hypotheses, more strategies, and more heuristics to solve the problem.

Trigger behavior refers to the analyst looking for or finding clues (triggers) in the problem statement. Trigger behavior was expected to be associated with highly rated performance because we felt that one source of expertise was a well-developed knowledge organization that included an organized set of clues related to the analysis problem domain. This would enable the successful analyst to use clues to determine the nature of the problem.

Hypothesis behavior refers to the analyst developing hypothetical constructs about the problem or speculating about some facet of the problem. It was expected that the high-rated analyst would make a greater use of hypotheses in the problem-solving process. First, in developing fields like systems analysis, where the total knowledge base is incomplete and fragmented, the hypothetical deductive method is often used. Second, the use of hypotheses in ill-defined problems can save time and effort because certain courses of action can be evaluated prior to development.

Strategic behavior refers to the analyst developing plans and strategies to achieve goals. Strategic behavior was expected to be associated with highly rated performance because the analyst works in a dynamic organizational environment with many uncontrollable variables, and must rapidly adapt to changing conditions. Adaptive strategies permit flexi-
bility because each strategy is a different approach to a goal given different conditions. In this way, the analyst reduces the need for information because he or she does not need to predict changes but rather adapt to the change with different strategies.

Heuristic behavior refers to the use of rules of thumb or other episodic knowledge that analysts employ to solve the problem. Heuristic behavior was expected because previous research in cognitive psychology (Newell and Simon [48]; Johnson et al. [37]) suggests that heuristics are related to successful problem solving. It was thought that the highly rated analyst uses more heuristics to reduce solution time and streamline the solution process, resulting in better performance.

3.4.2 Hypotheses in the Problem Solving Mode Categories
We used the concept of problem solving modes to investigate how the total analysis process was divided among the problem finding, problem reformulation, problem facilitation, problem integration, and requirements determination tasks. We expected that the highly rated analyst would devote more effort to the problem facilitation and problem integration modes. These hypotheses were inspired by the rather large number of research studies on MIS implementation and organization change. (See Feeny and Sladek [30]; Churchman and Schainblatt [30]; Boland [11]; Keen and Scott Morton [38]; and Ginzberg [33].) Basically, this research indicates the importance of quality dialogue between the analyst and the user (problem facilitation) and the importance of properly integrating the problem solution to the current operation of the organization (problem integration).

3.5 Analysis of the Data
For each subject's protocol, frequency distributions of each of the codes in the coding schematic were computed in SPSS (see [49]), to provide a measure of the incidence of that category in the subject's problem-solving process. The frequency counts in a given category as a percent of the total frequency over all categories were employed to permit useful comparisons across subjects. The frequency counts provided the means to compare the problem-solving behavior of the high-rated and low-rated groups.

The data was statistically analyzed for differences between the high- and low-rated groups of analysts using the two sample Median test. The Median test was chosen because of the small sample size, indeterminate nature of the underlying distribution, and the high degree of skewness in the frequency counts. A Mann-Whitney U tested was also performed as a cross-check and it produced the same results as the Median test. For a detailed discussion of the Median test and its appropriateness for this study, (see [49,55,59]). Because of the exploratory nature of the study, significance levels are shown as p values in the tables reporting the results and p values of up to 0.10 are examined.

4. RESULTS
4.1 Mental Behaviors Associated with High-Rated Performance
Table I summarizes differences found in the Mental Behavior categories. Significant differences in the Discard Hypotheses and Modify Strategy categories provided some support for our hypotheses. Due to the exploratory nature of the study, other less significant differences that appeared in the Search For Trigger, Set Goal, Verbalize Strategy, and Apply Heuristic categories are discussed.

### Table I: A Comparison of Differences in the Median Percent Frequencies in the Mental Behavior Categories

<table>
<thead>
<tr>
<th>Mental Behavior</th>
<th>Median Percent Frequency</th>
<th>Number of High-Rated Subjects Above/Median</th>
<th>Number of Low-Rated Subjects Above/Median</th>
<th>Significance (single-tail)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceives a Trigger</td>
<td>0.3</td>
<td>2/7</td>
<td>4/5</td>
<td>0.845</td>
</tr>
<tr>
<td>Searches for Trigger</td>
<td>0.2</td>
<td>6/3</td>
<td>3/9</td>
<td>0.086</td>
</tr>
<tr>
<td>Discards Hypotheses</td>
<td>0</td>
<td>7/2</td>
<td>0/9</td>
<td>0.000</td>
</tr>
<tr>
<td>Sets Goal</td>
<td>0.2</td>
<td>6/3</td>
<td>3/6</td>
<td>0.068</td>
</tr>
<tr>
<td>Satisfies a Goal</td>
<td>0.8</td>
<td>2/7</td>
<td>7/2</td>
<td>0.866</td>
</tr>
<tr>
<td>Verbalizes Strategy</td>
<td>9.2</td>
<td>6/3</td>
<td>3/6</td>
<td>0.085</td>
</tr>
<tr>
<td>Modifies Strategy</td>
<td>0.3</td>
<td>7/2</td>
<td>2/7</td>
<td>0.010</td>
</tr>
<tr>
<td>Applies Heuristic</td>
<td>0</td>
<td>5/4</td>
<td>2/7</td>
<td>0.083</td>
</tr>
</tbody>
</table>

1. Median for all subjects of the category frequency/total frequencies all categories × 100.
2. n1 = 9 high-rated subjects
3. n2 = 9 low-rated subjects
4. Computed according to the Two-Sample Median Test, see Siegel [55].

4.1.1 Rejection of Hypotheses
The results indicate that high-rated analysts reject more hypotheses than the low-rated analysts. For example, one high-rated analyst initially hypothesized that point-of-sale terminals would be a good solution for the problem. However, that hypothesis was rejected when the analyst compared that hypothesis to the realities of the project budget:

> 0156 So I guess that's one idea I have in the back of my mind as I start.
> 0157 I think we need some point of sale equipment
> 0158 and I have no idea at this point
> 0159 how that fits into my $300,000 budget.
> 0160 I have no idea of what an individual machine would be . . .
> 0161 and if we're talking about 53 stores
> 0162 with an average of 5 or 6 cash registers . . .
> 0163 I'm already talking about 300 point of sale machines
> 0164 which may—my first gut feel is way out of line with $300,000.

Other researchers have noted that experts discard hypotheses because active hypotheses, those not rejected, are expensive in terms of cognitive resources, such as memory and retrieval time, and can become confusing adding to the complexity of the problem.

4.1.2 Modification of Strategies
The modification of a strategy is typically motivated by a change in information gained from the environment, such as from a user, system documentation, or unanticipated changes in the environment that in turn requires a change in the analyst's working assumptions.

One explanation may be found in previous research on problem solving. For example Johnson et al. [37] discovered that expert pediatric cardiologists could gracefully recover from mistakes in their diagnoses more readily than medical students and medical residents. Recovery from failure was achieved because the experts could back track, find the reason for the failure, and modify their course of action. Others such as Simon [56], Schank and Abelson [53], and Barbara...
and Frederick Hayes-Roth [35] have noted that for machines and humans to act intelligently, they must adapt to changes in the environment and respond with relevant behavior.

4.1.3 Other Behaviors Associated with High-Rated Performance. Other categories of behavior associated with the high-rated group are:

1. Search for Triggers
2. Set Goal
3. Verbalize Strategies
4. Apply Heuristics

4.1.4 Searching for Triggers. Trigger Search Behavior suggests that the solver has a set of prior expectations about the problem and tries to find analogies between the present problem and previous problems. As the solver reads the problem description, he or she looks for clues. If certain clues are not evident, an expectation failure occurs and this triggers a question in the solver's mind about the problem. The absence of clues that favor their expectations may motivate the solvers to search for additional information from external sources. As seen in the following abstract from a verbal protocol, the absence of expected triggers is itself information about the problem that helps structure and direct subsequent information searches by the analyst:

0015 This write-up gives me pretty good indication
0016 of the direct kinds of data we need available to these individuals.
0017 their responsibilities.
0018 What I'm not sure from this
0019 is the extent to which the system is to interface
0020 with any other functional activities within the company.
0021 And so, the purpose of the scope discussion
0022 would be to get that defined, nailed down
0023 so I know how big this thing has to be
0024 and particularly what it has to interface with
0025 because that determines to a great degree
0026 some of the technical problems I have to solve... 

These initial efforts to constrain the size of the search space and may influence the goals and plans of the solution process, reduce search time, and identify areas where the analyst must gather external information. The approach involves risk, however, because it introduces a significant historical bias into the problem-solving process and thus is prone to failure in novel or unorthodox situations.

4.1.5 Setting Goals. The high-rated analyst group exhibited a higher frequency of Set Goal Behavior than the low-rated analyst group. The set goal category represents behavior wherein the analyst explicitly decides upon a specific goal to accomplish.

4.1.6 Verbalizing Strategies. The high-rated group exhibited a greater incidence of Verbalize Strategy Behavior than the low-rated group. The result provides additional evidence that the high-rated group was more likely to think in strategic terms than the low-rated group. Previous research on strategy development [5, 19, 40, 42, 58] has found a link between strategy development, the use of specific goals, and task performance.

4.1.7 Applying Heuristics. The highly rated group exhibited a greater incidence of applying heuristics in their solution processes. An Apply-Heuristic Code was assigned when a previously stated heuristic was actually used to solve a particular subproblem. For example, to simply state that "garbage in is garbage out" only illustrates that the analyst has this rule of thumb in memory. However, it is another level of skill to state that heuristic and then notice where it is relevant and use it to guide the solution of a particular subproblem [50].

The relatively small use of heuristics by either analyst group was surprising. This is contrary to previous research on problem-solving behavior. We expected to see a significant use of heuristics in the problem-solving behavior of analysts due to the embryonic nature of the field and the absence of a well-defined body of knowledge. Further research is needed to determine whether the limited use of heuristics is a function of the research design or indeed a facet of analyst behavior.

4.2 Problem-Solving Modes Associated with High-Rated Performance. Of the five problem-solving modes examined in the study, two were associated with the high-rated group. Table II shows the results for all five modes. The highly rated group exhibited more behavior in the Problem Facilitation and Requirements Determination Modes.

In the case of the Requirements Determination Mode, the high-rated group simply specified more requirements than the low-rated group.

The result in the Problem Facilitation Mode supports our hypothesis and reinforces the findings of other researchers that an analyst who explicitly facilitates and maintains a pro-

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4 For an excellent review of current literature on goal setting and strategy development, see Locke et al. [43].

<table>
<thead>
<tr>
<th>Problem Solving Mode Categories</th>
<th>Median Percent Frequency</th>
<th>Number of High-Rated Subjects Above/Median</th>
<th>Number of Low-Rated Subjects Above/Median</th>
<th>Significance (single-tail)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem Finding Mode</td>
<td>18.2</td>
<td>4/5</td>
<td>5/4</td>
<td>0.250</td>
</tr>
<tr>
<td>Problem Reformulation Mode</td>
<td>50.8</td>
<td>4/5</td>
<td>5/4</td>
<td>0.250</td>
</tr>
<tr>
<td>Problem Integration Mode</td>
<td>2.9</td>
<td>4/5</td>
<td>5/4</td>
<td>0.250</td>
</tr>
<tr>
<td>Problem Facilitation Mode</td>
<td>0.6</td>
<td>7/2</td>
<td>2/7</td>
<td>0.014</td>
</tr>
<tr>
<td>Requirements Determination Mode</td>
<td>22.8</td>
<td>6/3</td>
<td>3/6</td>
<td>0.086</td>
</tr>
</tbody>
</table>

1 Median for all subjects of the category frequency/total frequencies all categories × 100
2 N = 9 high-rated subjects
3 t2 = 9 low-rated subjects
4 Computed according to the Two Sample Median Test (see Siegel [55]).
ductive relationship with the user is in a better position to develop quality information requirements [11, 20, 39].

4.3 Behaviors Associated with Low-Rated Performance

The low-rated group exhibited a higher frequency of behavior in two categories. Neither result was hypothesized nor indicated in the literature. As a result, conclusions drawn from these results must be interpreted cautiously and viewed as speculative.

4.3.1 Perceiving Triggers

The Perceive Trigger Code was assigned each time analysts explicitly indicated that they found what they thought was a clue in the problem description. The result suggests that the low-rated group uses clues in a different manner than the high-rated group. One possible interpretation is that the low-rated analyst simply perceived existing clues in the problem description but could not go to the next level and use the absence of information as a clue.

4.3.2 Satisfying Goals

The satisfy goal category was assigned when the analyst explicitly indicated that a desired end-state had been achieved. This is interesting because, as seen in Table III, both groups had similar frequencies of behavior in all the other goal related categories, except for the set goal category in which the high-rated group had a higher frequency.

To develop an interpretation of this result, we examined those parts of the analyst protocols related to Satisfy Goal

| TABLE III: A Comparison of Similarities in the Median Percent Frequencies in the Mental Behavior Categories |

<table>
<thead>
<tr>
<th>Mental Behavior</th>
<th>Median Percent Frequency¹</th>
<th>Number of High-Rated Subjects Above/Median¹</th>
<th>Number of Low-Rated Subjects Above/Median¹</th>
<th>Significance (single-tail)¹</th>
</tr>
</thead>
<tbody>
<tr>
<td>Request Informa-</td>
<td>12.7</td>
<td>5/4</td>
<td>4/5</td>
<td>0.250</td>
</tr>
<tr>
<td>Clarify Informa-</td>
<td>4.7</td>
<td>4/5</td>
<td>5/4</td>
<td>0.250</td>
</tr>
<tr>
<td>Restate Informa-</td>
<td>5.4</td>
<td>4/5</td>
<td>5/4</td>
<td>0.250</td>
</tr>
<tr>
<td>Recall Knowledge</td>
<td>6.4</td>
<td>4/5</td>
<td>5/4</td>
<td>0.250</td>
</tr>
<tr>
<td>Search for Knowl-</td>
<td>0</td>
<td>2/7</td>
<td>1/8</td>
<td>0.250</td>
</tr>
<tr>
<td>State Hypothesis</td>
<td>11.1</td>
<td>4/5</td>
<td>5/4</td>
<td>0.250</td>
</tr>
<tr>
<td>Tests Hypothesis</td>
<td>1.2</td>
<td>5/4</td>
<td>4/5</td>
<td>0.250</td>
</tr>
<tr>
<td>Confirm Hypoth-</td>
<td>0</td>
<td>0/9</td>
<td>1/8</td>
<td>0.250</td>
</tr>
<tr>
<td>esis</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Verbalize a Goal</td>
<td>13.8</td>
<td>5/4</td>
<td>4/5</td>
<td>0.250</td>
</tr>
<tr>
<td>Discards a Goal</td>
<td>0</td>
<td>2/7</td>
<td>2/7</td>
<td>0.356</td>
</tr>
<tr>
<td>Choose a Strategy</td>
<td>0</td>
<td>3/6</td>
<td>2/7</td>
<td>0.250</td>
</tr>
<tr>
<td>Discard a Strategy</td>
<td>0</td>
<td>2/7</td>
<td>0/6</td>
<td>0.110</td>
</tr>
<tr>
<td>Verbalize a Heu-</td>
<td>1.8</td>
<td>5/4</td>
<td>4/5</td>
<td>0.250</td>
</tr>
<tr>
<td>nistic</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Test a Heuristic</td>
<td>0</td>
<td>5/4</td>
<td>2/7</td>
<td>0.500</td>
</tr>
<tr>
<td>Explain a Heuristic</td>
<td>0</td>
<td>0/9</td>
<td>0/6</td>
<td>0.250</td>
</tr>
<tr>
<td>State a Conclu-</td>
<td>15.9</td>
<td>5/4</td>
<td>4/5</td>
<td>0.250</td>
</tr>
<tr>
<td>Subject A (low-rated)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subject B (high-rated)</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Subject C (low-rated)</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Subject D (low-rated)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subject E (high-rated)</td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

FIGURE 1. Examples of Satisfy Goal Behavior

behavior. Figure 1 provides a sample of Satisfy Goal behavior extracted from the protocols.

The protocol abstracts show that both groups used the Satisfy Goal Behavior in similar ways, that is, to keep track of progress made in the solution process. However, the high incidence of Satisfy Goal behavior in the low-rated group leads us to speculate that the low-rated group uses a different method to monitor their progress in the problem-solving process. That is, since the low-rated group sets fewer specific goals, they may have to explicitly monitor their progress during the solution process. On the other hand, the lack of Satisfy Goal Behavior in the high-rated group may indicate more confidence in the solution process and a reliance on automatic, unconscious checking of goal attainment in the solution process. However, based on the data in this study, it is questionable to argue for Satisfy Goal Behavior as a deterrent to, or basis for, expertise. More research is required to investigate the reasons for this finding.
4.4 Similarities Between High-Rated and Low-Rated Analysts

The results indicate that there are more similarities in the problem-solving behavior of analysts than differences. The similarities are also instructive because they indicate basic areas of skills. Table 3 shows that 16 similarities were found in the mental behavior categories between high-rated and low-rated analysts.

Seven of the categories are similar simply because the frequency of behavior in those categories is low in both groups. This reflects either a problem in the coding scheme or indicates that most analysts do not employ these types of behavior in the problem-solving process. More research is required to determine the reason.

However, the other nine categories are instructive. If we take all percentages, including the percentages in Table 1, we find that approximately 25 percent of the behavior is spent on information acquisition and 75 percent of the behavior is spent structuring the problem. The similarities indicate that while information gathering is important to systems analysis, other activities such as goal formulation, hypothesis generation, and developing conclusions are probably more important.

Table II shows the similarities in the problem-solving mode categories. Both groups exhibited similar behavior in the problem-finding, problem-reformulation, and problem-integration modes. The relatively high frequencies in these categories suggest that each of these activities is important to the systems analysis process.

It is also interesting to note that only three categories related to the six hypotheses advanced in this study were significant at the 0.05 level. We feel this may have occurred for several reasons. First, this was an exploratory study that derived many of the hypotheses from research in other domains which could not provide us with direct information about problem solving in systems analysis. Second, it is possible that the behavior of the two groups is more similar than different. Third, the limited validation of our hypotheses may be a result of the limited sample size, and further study of larger and more diverse groups may uncover stronger relationships. As is the case with exploratory research, the study raises additional questions, but we now can recommend that additional study be directed toward trigger, hypotheses, and planning and strategy development behavior.

5. A PROGNOSIS FOR EFFECTIVE ANALYST PERFORMANCE

The results of this study suggest several bases of expertise in the systems analysis task domain, and in particular, the task of information requirements determination. At the most abstract level, expertise in information requirements determination appears to be related to the manner in which the analyst structures the problem. The expert analyst can structure the problem, remain flexible in the solution process, and employ previous knowledge and experience to a new problem.

5.1 Implications of the Results

Based upon the results of this study, we propose that there are at least four major types of behaviors that permit high-rated analysts to outperform their colleagues.

5.1.1 Analogical Reasoning. The Search for Trigger behavior suggests an underlying process of analogical reasoning wherein the analyst uses information from the environment to classify problems and relate them to previous experience. If a match is found, the analyst draws upon that previous problem experience to partially structure the current problem, search for additional information and, in some cases, employ previous solutions. If a match is not found or an expected clue is missing, this signals the analyst to search for additional information.

5.1.2 Planning, Goal Setting, and Strategy Formulation. We hypothesize that the effective analyst sets high level but measurable goals to map out the relevant subproblems and structure the overall task. It is conceivable that analysts deal with a hierarchy of goals that allow them to deal at different levels of detail. Atwood [4] found initial evidence of this in a study of systems designers. From this goal hierarchy, the analyst develops various strategies and modifies those strategies as necessary. Thus, the analyst has direction in the solution process and also maintains flexibility to deal with unanticipated events.

5.1.3 Hypothesis Management. While both the high- and low-rated analysts develop hypotheses, highly rated analysts are adept at managing those hypotheses in the problem solving process. As a result another area of expertise stems from the way that the analyst manages the hypothetical deductive process discarding low probability hypotheses and retaining hypotheses that are valid.

5.1.4 Operative Knowledge for the Application of Heuristic Knowledge. Despite the low incidence of heuristic behavior among the analysts in this study, we believe that it is an important aspect of expertise. Heuristics are used extensively in other disciplines and more study is needed to understand how the decision is made to apply a heuristic in a given situation.

5.1.5 Problem Facilitation. The highly rated analysts exhibited some understanding of the importance of the character and quality of the interpersonal relationship between the analyst and the user. This relationship becomes the interface between the cognitive behavior of the analyst and the external environment. In a sense, the entire problem-solving process depends on the character and quality of the behavior at this interface. The high-rated analyst knows this and consequently allocates time to that task.

5.2 Suggestions for Practice and Research

This research has implications for practitioners and researchers alike.

For systems analysts the results suggest the following. First, the study has reaffirmed the complexity and dynamic nature of the systems analysis task domain. The trigger and hypothesis behavior that we observed indicates that analysts should anticipate potential subproblems and use the lack of clues as information in problem diagnosis.

Second, analysts should strive to develop a flexible strategic approach in their problem-solving behavior. We encourage analysts to keep a "diary" of strategies that they have used in the past and create new strategies as situations develop. The development of a repertoire of strategies will give the analyst a degree of flexibility in order to cope with unanticipated events and new information.

Third, we recommend that analysts employ specific, measurable goals in developing a solution strategy. Analysts should begin the solution process by defining the most critical goals, that is, goals that must be achieved for a successful solution and then proceed to identify secondary goals. In this way, the
The analyst can map out the problem at a high level, maintain a global perspective on the problem, and avoid an excessive preoccupation with low-level detailed issues in the early stages of the problem-solving process.

Finally, the analyst should work at developing a positive relationship with the user and work to maintain that relationship throughout the development process with continual follow-up.

The results point to several issues for managers of data processing departments. First, as most managers realize, training in interpersonal dynamics is important. Second, we are optimistic, given additional research, about the ability to train analysts in the areas of expertise identified in this study, and develop selection criteria for recruitment. Third, the results of the study corroborate the conventional wisdom that success in systems analysis is a combination of technical and behavior skills. It is also clear that the recent wave of structured analysis techniques provide only a partial solution. Many of these techniques focus on a systematic process for structuring and documenting the information requirements. However, as suggested in this study, the analyst must also develop skills to properly approach the problem, and develop the solution as a prerequisite to defining the information requirements.

For researchers the study has indicated that protocol analysis is a useful method for studying problem-solving behavior in ill-defined task domains like systems analysis. The research approach also yields valuable information about systems analyst skill and indicates additional areas for further research. A particular area of interest is to examine in more detail the role of analogical reasoning, hypothesis management, planning, goal setting, and strategy formulation in the solution process. Research studies are also needed to determine if other cognitive models of systems analysis exist and what role they play in different analysis problem settings.

In addition to protocol-based research, other research is required to take the results of the protocol studies and using other research methods investigate the problems of recruitment and selection, training and development, and the evaluation of systems analysis tools.

Acknowledgments. We wish to thank Paul E. Johnson and Gordon B. Davis for their helpful comments on earlier versions of this paper and the two referees who were particularly helpful in their review. We also wish to thank Herb Schwartz for his comments.

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Additional Key Words and Phrases: Problem Solving, Cognitive Models of Systems Analysis, protocol analysis, systems analyst skills

Received 9/82; revised 8/83; accepted 8/83

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