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The Effects of Expertise on Financial Problem Solving: Evidence for Goal-Directed, Problem-Solving Scripts

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The information-selection and problem-solving strategies of experts and novices presented with a complex, real-world retirement planning task were studied. Two extreme groups of financial planning expertise were created from a sample of 21 on the basis of their (1) occupational reputations, and (2) performance on a comprehensive financial knowledge questionnaire. Subjects were required to decide, in a two-phase experimental task, whether or not a hypothetical young couple should invest in an Individual Retirement Account. In the first phase, subjects listed the specific information they would need to make an informed decision. In the second phase, they were provided with the specific, detailed data they had requested and were asked to "think-aloud" as they worked toward a problem solution. A process-tracing technique was used to analyze the think-aloud protocols with the data revealing basic differences in a variety of problem-solving processes as a function of expertise. Experts solved the problem in less time using fewer overall steps to complete the task, appearing much more goal-directed than novices who engaged in complicated information search strategies which lacked both coherence and efficiency. Moreover, at the outset of the task, experts requested higher-level task information than novices, demonstrating a superior initial representation of the problem. The results are interpreted as support for a script-based model of expert performance. © 1990 Academic Press, Inc.

In the past decade, a growing body of research has explored the relationship between expertise and problem-solving abilities. The rationale for that work is that we can better understand (1) the nature and acquisition of expertise and (2) the role of expertise in problem solving by comparing the solution strategies of experts and novices. The goal of the present work is to examine how expertise affects problem-solving pro-

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cesses. We assume that expert skill comes from repeated experience within a particular problem domain. Specifically, it is proposed that enough encounters with the same problem will lead to the acquisition of a solution script: a well-practiced, generic sequence of procedural knowledge which experts can invoke when faced with the problem situation.

Historically, research in the area of expert problem solving has been guided by two different theoretical approaches that emphasize different research questions. *Outcome* models of expertise seek to describe the problem-solving behaviors that underlie high quality, accurate decision outcomes, for instance, trying to characterize the decision-making process of expert medical diagnosticians making accurate diagnoses. This work is often used to determine ways in which human information processing models can be used to design expert systems (c.f. Buchanan & Duda, 1983; Connelly & Johnson, 1980; Fox, 1984; Johnson, 1982). Thus, the emphasis tends to be on learning how to model accurate decisions and understanding the process is primarily a means to that end. Research examining *process* models, in contrast, aims to identify the nature of mental processes underlying individual performance, often focusing little attention on the quality of the solution (Haines, 1985; Johnson, 1985). The primary emphasis of the present study is on understanding the problem-solving process individuals use in real-world situations, rather than the study of strategies leading to correct decisions.

Expertise is a dimension along which interesting process distinctions occur. Although there is no single agreed upon definition of expertise, it is generally recognized that experts possess a good deal of both *procedural* and *declarative* knowledge (Anderson, 1985; Chi, Feltovich, & Glaser, 1981). In the problem-solving context, declarative knowledge consists of knowing *which* facts are relevant in a particular situation, while procedural knowledge connotes an understanding of *how* those facts can be combined to produce a solution.

With regard to declarative knowledge, experts have been found to possess a large body of domain-specific factual information (Chi, Glaser, & Rees, 1982; Gilovich, 1981; Larkin, McDermott, Simon, & Simon, 1980) which is usually stored in larger, and sometimes more abstract memory chunks (Charness, 1981a, 1981b, 1982; Chi *et al.*, 1982; de Groot, 1966), thus leading to a more integrated cohesive understanding of the problem domain (Chi, 1985; Gobbo & Chi, 1986). Furthermore, there is evidence to suggest that experts' schemas (knowledge structures) are arranged hierarchically (Bower, Clark, Lesgold, & Winzenz, 1969; Gobbo & Chi, 1986). That is, patterns or "chunks" of information are indexed in terms of their meaningful interrelations, allowing experts to scan their memory quickly and efficiently (Larkin *et al.*, 1980). Beyond these findings which imply that experts and novices differ in the quantity and organization of their declarative knowledge, there is other evidence to suggest that the processes they use to reach a solution are also different. Although novices may often be deficient in both of these types of knowledge, sometimes the primary deficit may be in procedural knowledge. For example, novices may understand the relationships among informational elements in a problem (declarative knowledge), but their lack of problem-solving procedures may leave them unable to generate a solution, or to be very inefficient at doing so.

One of the most notable differences between expert and novice problem solvers is the time it takes to arrive at a solution. Across a range of problem-solving domains, experts have been found to arrive at solutions faster than novices (Charness, 1979; Johnson, 1985; Simon & Simon, 1978; and Larkin *et al.*, 1980). Chi *et al.* (1981) hypothesize that this difference is the result of explicit procedural subroutines experts possess for generating solution strategies. Larkin *et al.* (1980), however, argue that it is the organization of experts' knowledge that allows them to identify important relationships and more quickly solve problems.

Experts and novices have also been found to differ in the quality of their initial representations of problems. Experts use the information in a problem statement to develop a more comprehensive representation of the problem than novices (Chi *et al.*, 1981). That is, experts perceive the "deep structure" of problems while novices are distracted by the superficial or "surface structure" (Chi *et al.*, 1981).

A third difference between the processes of experts and novices is in the sequence of steps used to obtain a solution. Simon and Simon (1978) found that experts use the information in a problem statement to "work-forward" through a problem. They quickly identify a plan and work forward form the starting point of the plan to the solution. Novices, in contrast, adopt a "working-backward" approach. Because they do not already possess a plan for the solution, they start at the goal and work backward toward the starting point, trying to develop a plan that will allow them to successfully move from the starting point to the solution. They must continually check to see whether each step they develop will reduce the difference between the starting point and the goal state. If it does not, they will have to try a different step. As a result, experts look much more systematic and directed than novices.

Experts and novices have also been found to differ in the number of informational cues to which they attend. Johnson (1985) found that experts attend to fewer pieces of information than novices in evaluating a problem, ostensibly because they have a stronger sense of which cues are important to generate a solution. Cues with little direct bearing on the outcome of the task are ignored, and relevant information is attended to in proportion to its importance. Thus, it seems that experts use their previous experience to develop a selective search strategy for evaluating task information. We believe that the empirical findings reviewed above suggest that with experience experts develop scripts for efficiently solving problems. We will briefly review the concept of scripts and then describe what role we believe they play in the performance of expert problem solvers.

Problem Solving Scripts

Since the late 1970s, the concept of scripts has been used to explain text comprehension (Thorndyke & Hayes-Roth, 1979), as the basis for designing artificial intelligence programs (Schank & Abelson, 1977), and as a way of understanding behavioral expectancies (Bower, Black, & Turner, 1979). Abelson (1981) defines a script as "a hypothesized cognitive structure that when activated organizes comprehension of event-based situations" (p. 717). He goes on to say that "In its weak sense, . . . [scripts are] a bundle of inferences about the potential occurrence of a set of events and may be structurally similar to other schemata than do not deal with events. In its strong sense, it involves *expectations about the order as well as the occurrence of events*" (p. 717; emphasis added). In the problem-solving context, we hypothesize that scripts provide a framework that organizes the set of operations leading to the solution.

We hypothesize that experts, through experience, develop problem-solving scripts: a set of rule-based mental operations into which relevant problem parameters can be imputed. It is further hypothesized that these scripts are stream-lined over time so that unimportant variables are dropped from the set of operations. The expert's first step then, is to select the proper script for a particular problem statement. Once this has been accomplished, proceeding to a solution is simply a matter of applying the algorithms called for by the script. It is important to emphasize that the script itself is a generic set of operations. The actual problem-solving process requires that parameters from the task be plugged into the problem-solving script. Novices, lacking prior experience, are hypothesized to lack generic operational steps to reach a solution. Thus, although their declarative knowledge may allow them to request relevant task information, their procedural efficiency in solving the problem should be low, due to the lack of a well-developed script. Specifically, their performance profiles should be less unidirectional or sequential than the performance profiles of experts.

If skilled problem-solving behavior is based on streamlined, scripted knowledge, as we hypothesize, then experts should be expected to have heuristics for evaluating task parameters. For example, consider the differences between an expert financial aid administrator and a novice parent trying to decide if a family of four can afford to send their children to a private university. The expert, upon learning that the family's annual income is $15,000, would immediately conclude they cannot. The parent, however, being unfamiliar with the costs of higher education, may want to consider a variety of details, such as the cost of tuition, books, living expenses, etc., before reaching a conclusion. Thus, experts are predicted to make fewer computations than novices, opting instead to draw a conclusion from heuristics applied to "script-defined," significant pieces of information.

Task Selection

Recent studies have demonstrated that task selection has a profound effect on the information search and selection strategies of problem solvers. The complexity, novelty, and structure of tasks have all been shown to impact information search. Complex cognitive tasks elicit procedural strategies that minimize search thereby emphasizing efficiency (Huber, 1980; Payne, 1976); novel tasks keep the subject's knowledge from playing a role in generating a solution (Charness, 1982); and well-structured tasks[1] leave little room for the subject to apply solution strategies they have designed on their own (Simon, 1973; Voss, Tyler, & Yengo, 1983). Since the goal of this study is to elicit individuals' unique solution scripts, we chose a task that is sufficiently complex to encourage search efficiency, sufficiently familiar that subjects' prior knowledge and experience contribute to the solution, and sufficiently ill-defined to allow subjects the opportunity to apply their own, personally acquired procedural knowledge.

METHOD

Our task required subjects to decide if an hypothetical couple should open an Individual Retirement Account (IRA). The IRA task was chosen because it meets the criteria described above, and because it can be logically analyzed into a prescriptive sequence of "proper" steps.

A task analysis was carried out to identify the conceptual elements required to reach a solution. A pilot study (N = 12) queried subjects about the variables they considered important in deciding whether to open an IRA account. Their reports were combined with guidance from retirement planning literature and used to design the IRA problem.

[1] Simon (1978) defines well-structured problems as those in which the initial state, the goal state, and the necessary task information are provided for the subject. Ill-structured problems characteristically: (1) have a relatively high degree of complexity and minimal definition; (2) fail to specify the necessary procedural information in the instructions to the subject; and (3) don't contain as part of the initial problem statement a set of prespecified rules (or moves) which could lead to the correct solution (p. 286).

The task analysis identified three higher-order issues which should be addressed when deciding whether or not to open an IRA account (see Fig. 1). One should first consider if there is a need for additional retirement funds (NEED). Second, if a need exists, one should determine if an IRA account is a suitable investment vehicle (ACCOUNT). Finally, the affordability of an IRA account should be considered (AFFORDABILITY). A complete consideration of any one of these factors requires the calculation of the interplay between a number of variables. A thorough analysis of the problem revealed 43 variables related to the problem solution. The variables for each factor (NEED, ACCOUNT, and AFFORDABILITY) were then arranged into the three hierarchical structures shown in Figs. 2, 3, and 4.

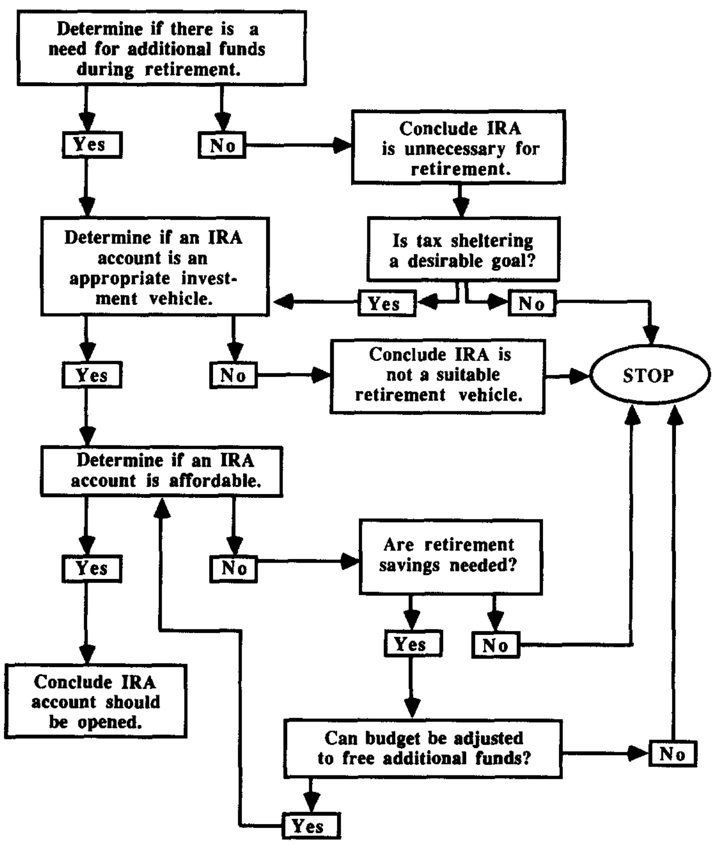

FIG. 1. Prescriptive sequence of major conceptual issues to be addressed while solving the IRA problem.

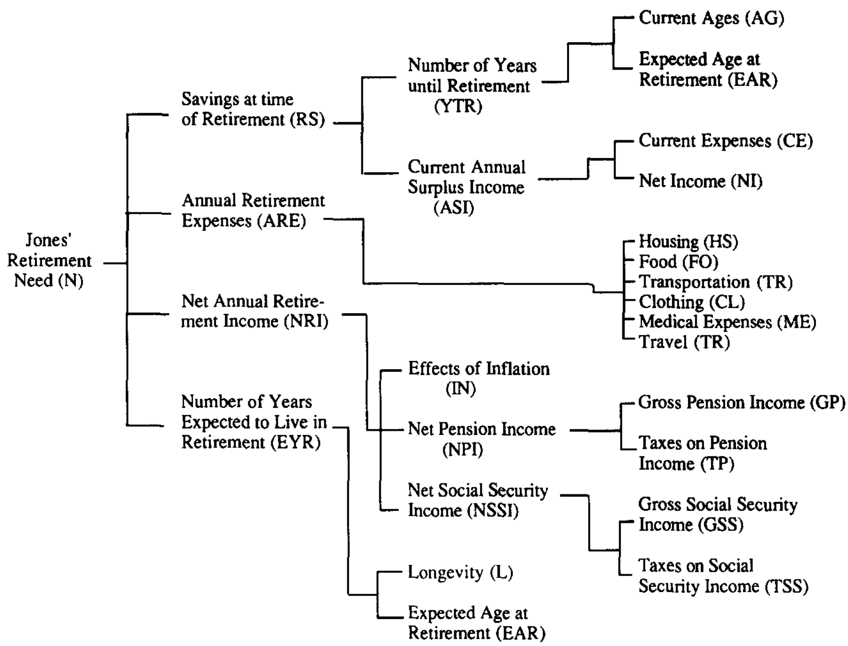

FIG. 2. Variables and concepts related to the issue of the Jones' additional financial need during retirement. Abbreviations (in parentheses) are used in the process-tracing maps of Figs. 5, 6, 7, and 8.

Subjects

Sixteen men and 5 women served as participants. Subjects were recruited in an effort to create two groups that were at opposite ends of the expertise dimension. Approximately half of the subjects were chosen because they were experienced financial planners. Subjects' expertise was further validated with an objective test created to sample their declarative knowledge of facts relating to the IRA problem. In order to avoid sensitizing subjects to the various IRA issues we administered the test after subjects completed the experimental task. Seven of the 21 subjects initially selected were eliminated from further analyses because their test results showed them to be either "sophisticated novices" or "naive experts." The resulting 14 subjects formed two apparently homogeneous groups composed of novices and experts; groups for which the two distributions of financial knowledge scores were nonoverlapping. The "novices" serving in the present study can be described as "typical American adults" who usually make their own personal financial decisions. They have not received formal training in financial planning nor do they know all of the "rules" of making "good" IRA decisions. In these

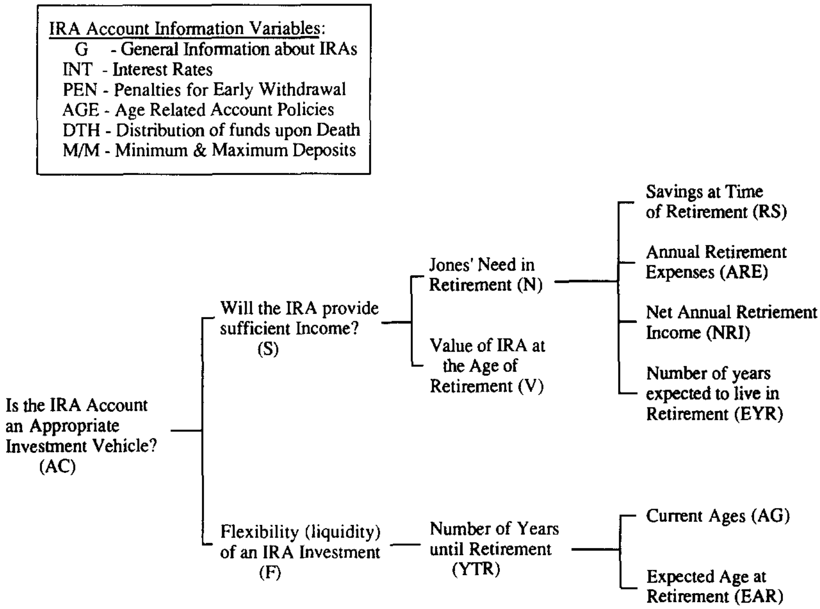

FIG. 3. Variables and concepts related to the adequacy of an IRA as an investment vehicle. Abbreviations (in parentheses) are used in the process-tracing maps of Figs. 5, 6, 7, and 8.

ways they are different from the novices used in studies of Physics who have completed one or two courses of formal training (e.g., Chi *et al.*, 1981; Larkin *et al.*, 1980; Simon & Simon, 1978) and the novices in studies of chess or bridge who clearly know all the rules (e.g., Charness, 1979, 1981a, 1981b, 1983).

Participation was strictly voluntary and no one was paid for their time. All subjects appeared to be highly motivated and interested in the task. Participants ranged in age from 19 to 70 years.

Documenting Expertise

After solving the IRA problem, participants completed a 10-page test we constructed to measure their knowledge of retirement planning and finance. The test sampled subjects' detailed knowledge about a variety of issues that our conceptual analysis of the IRA problem revealed as important to its solution. These issues include: Social Security benefits, marginal tax rates, IRA tax advantages, IRA characteristics and limitations, etc. Information about their own personal financial situation (e.g., annual income, whether or not they had an IRA account, etc.) was also collected. This measure served as our objective index of expertise. Based on this measure, seven subjects who were either "sophisticated novices"

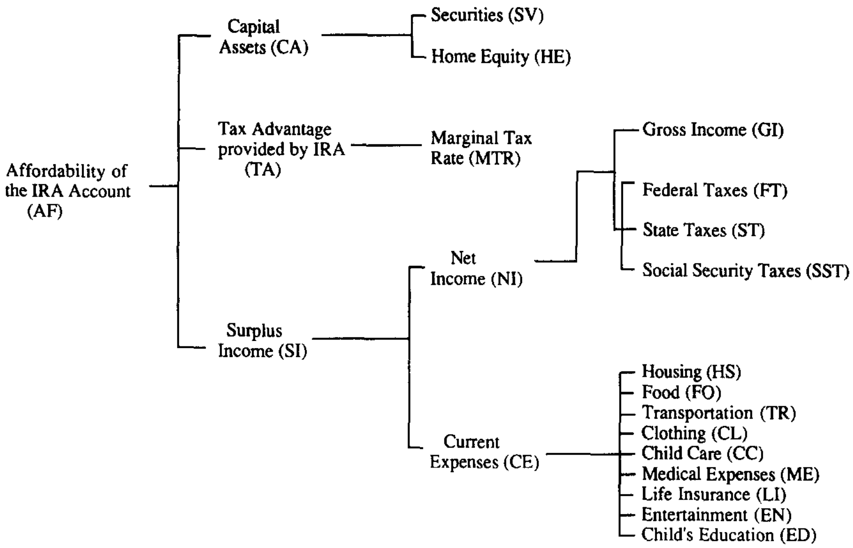

FIG. 4. Variables and concepts related to the affordability of an IRA account. Abbreviations (in parentheses) are used in the process-tracing maps of Figs. 5, 6, 7, and 8.

or "naive experts" were excluded from further analyses, thereby creating two extreme, nonoverlapping groups.[2] Experts (n = 7) had a mean score of 67% on the test (range = 62 to 74%), while novices (n = 7) averaged 34% (range = 20 to 45%). The groups did not differ on other characteristics that might be expected to affect their problem-solving abilities. Specifically, age and expertise were not significantly nor strongly related ($r[12]$ = .385, n.s.).

Six of the seven experts were, in fact, a subgroup of those selected on the basis of their occupation or reputation as financial planners. The one "expert" whose occupation was not finance-oriented (a) had a financial knowledge score clearly in the expert range [64%], and (b) had much personal experience with financial planning. None of the subjects whose occupation was in financial planning scored in the novice range.

Materials

A complete set of plausible values for all 43 variables identified in the

[2] The seven subjects eliminated from the overall analysis were a heterogeneous group that neither fit into the novice or expert groups, nor did they compose a homogeneous group of "intermediates." Although the mean performance of this group fell in between our expert and novice groups on all of the dependent variables, the standard deviation of this group was typically two or three times larger than those of the experts and novices. Not only would inclusion of this group be difficult to justify conceptually, its inclusion in the statistical analyses would have greatly reduced the statistical power of the inferential tests reported.

task analysis was constructed for the hypothetical couple. Both the name of the variable and the selected value were printed on 4 × 6 in. index cards; the name of the variable was typed on the backside of the card. Separate cards were printed for each of the variables shown at the terminal strings of the hierarchies in Figs. 2, 3, and 4 (e.g., "Current Housing Expenses," "Transportation Expenses During Retirement," etc.). Other cards containing all of the information relevant to higher order nodes were also prepared (e.g., "Current Expenses," "Capital Assets," etc.). Thus, subjects could request and receive information at any of the levels of the hierarchy. A large information board was used to hold the various number of cards a particular subject requested to solve the problem.

Procedure

Subjects were informed that the purpose of the study was to investigate the processes people use to make complex, real-world decisions. They were told their answers would not be scored as right or wrong, and that it was the process they used to solve the problem, not the outcome, that was of interest. Further, they were informed that the session would be conducted in two phases. In the first phase, they were to specify the information they thought was necessary to solve the IRA problem. In the second phase, they were to use that information to decide if the hypothetical couple should open the account. At the start of the first phase, subjects were asked to read the following instructions and scenario:

> Described below is a decision facing a young working couple. Please place yourself in their situation and describe what things you would consider and the detailed information you would need to know in order to solve the problem.
>
> Bill and Sally Jones met 10 years ago as college students and have been happily married for eight years. Bill is 32 years old and has been working for six years as an electrical engineer. Sally is 33 years old and works full-time as a university professor. They are both happy with their jobs which they hold at large and financially secure institutions. They have a good income, and earn equal annual salaries. Bill and Sally have one child, and live in a pleasant home they purchased two years ago. The whole family enjoys excellent health.
>
> Bill and Sally have recently seen a number of advertisements by banks and brokerage firms about their Individual Retirement Accounts (IRAs). They are wondering whether they should open such an account. If you were Bill or Sally, what factors would you consider in order to solve this problem? Please list the specific information you would want to know if you were going to help Bill and Sally make this decision.

Subjects were asked to list verbally and in writing the information they would need to solve the problem. If their request for a variable was ambiguous, they were further queried to clarify the information being requested. The extensive pilot work we carried out to produce our conceptual model of the task proved to be sufficiently exhaustive to anticipate virtually all of the variables subjects requested in an open-ended format. After they completed listing relevant variables, they were seated in an adjoining room. This concluded the first phase of the experimental session.

While the subject was out of the room, the experimenter placed the requested variable cards on the information board in a random arrangement. Only the back of the cards and the variable names were visible. A simple hand-held calculator, some paper, and a pencil were placed on the table. The subject was returned to the room and asked to read the following instructions:

> On the board in front of you are the variables you have named as being important in deciding whether or not Bill and Sally should open an IRA. On the other side of each card is a value to help you make that decision. You may only look at one card at a time, and cards must be replaced on the information board with only the title showing. If at any time you would like information about a variable that does not appear on the board, just tell the experimenter and he will provide you with an additional card(s). If you would like to use the calculator, pencil, or paper, please fell free to do so.

Subjects were told they could view cards as often and as long as they wished. There was no time limit on the decision process. Subjects were instructed to think "out loud" at every step in their effort to make a decision so that an audio recording of the problem solving process could be made. After questions were answered, the tape recorder was started and the subjects were asked to begin. Subjects were reminded to "think aloud" if they fell silent for more than a few seconds. The second phase of the session ended when the subject had determined whether or not the couple should open an IRA account. After completion of the task, the financial expertise questionnaire was administered. Subjects were seen individually through all phases of the experimental procedure. Finally, subjects were given the opportunity to ask questions about the study or their individual participation and then thanked for their cooperation.

RESULTS

The results will be presented in two sections. First, the processes underlying experts' and novices' problem solutions will be compared using a process-tracing technique. These comparisons will focus on the sequential nature of the problem-solving process and how it differs as a function of expertise. The second section examines differences in the ways in which experts and novices used task information. Table 1 summarizes the findings in both areas: it presents both the individual data of our seven experts and seven novices, as well as summary statistics for each group on all of our dependent measures.

TABLE 1
INDIVIDUAL AND GROUP DATA FOR EXPERT AND NOVICE PROBLEM SOLVERS

	Knowledge score (%)	Age	Sex	Total steps[a]	Recursions	Unique nodes	Time (min)	Hierarchy score	Secondary variables
	64	38	M	1	0	1	1.2	1.0	0
	62	42	M	2	0	2	2.3	1.5	0
	69	54	M	4	0	4	6.6	2.3	0
Experts	65	62	M	5	0	5	5.3	2.5	0
	65	45	M	6	0	6	7.9	4.0	0
	74	68	M	6	0	6	11.2	1.8	2
	69	54	M	16	1	15	27.2	2.7	2
Mean	66.9**	51.9	—	5.7*	.14**	5.6	8.8*	2.2*	.57
SD	4.1	10.9	—	4.9	.37	4.6	8.8	.97	.98
	45	30	M	26	7	19	22.6	2.9	10
	31	47	M	17	11	6	38.5	3.3	2
	26	64	M	17	4	13	17.9	3.1	3
Novices	36	24	M	16	4	12	42.3	2.6	2
	20	23	F	11	4	7	17.8	3.0	2
	43	46	M	5	0	5	4.3	3.3	0
	34	58	F	4	0	4	5.1	2.8	0
Mean	33.6**	41.7	—	13.7*	4.3**	9.4	21.2*	3.0*	2.7
SD	8.9	16.4	—	7.7	3.9	5.4	14.8	.25	3.4

Note. The individual data for a particular subject are presented across the rows. Asterisks on the group averages indicate that the groups differed at the level of statistical significance shown below.

[a] The unique nodes and recursions variables are "necessarily" correlated with the total steps variable, since the latter was computed by summing the two former variables. The total steps variable was correlated .92 with unique nodes and .79 with recursions. The unique nodes and recursions variables are not "necessarily" correlated, but their correlation was substantial ($r = .47$).

* $p < .05$;

** $p < .01$.

Process Models of Experts and Novices

The dynamic nature of subjects' problem-solving processes was represented with the use of Problem Solving Process Maps (PSPMs). A PSPM is a graphic presentation of the sequence of steps a subject took to arrive at a solution. PSPMs (see Fig. 5) were constructed by arranging, on a single page, abbreviations of the nodal elements contained within the problem hierarchies (NEED, ACCOUNT, and AFFORDABILITY; see Figs. 2, 3, and 4 for the abbreviation legend). In addition to the three hierarchies, information related to the IRA account was represented on the PSPM (the rectangular block of eight variables shown on Figs. 3, 5, 6, 7, and 8).

The actual step-by-step process an individual used to arrive at a decision was obtained from that person's think-aloud protocol. If a subject first considered the couple's *Gross Income* (as was the case for the subject represented in Fig. 5), that node was labeled as the "START," and an arrow was drawn to the subsequent node considered. We judged a node to be "activated" once the variable was removed from the infor-

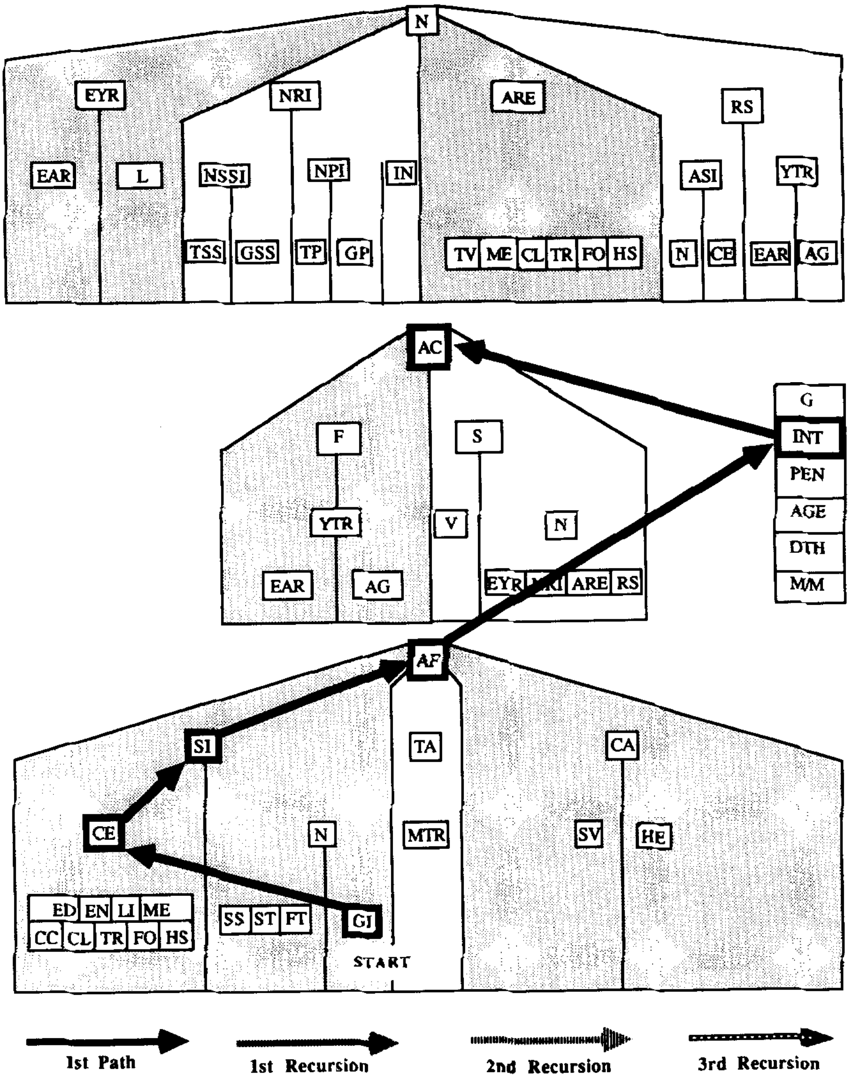

FIG. 5. The Problem Solving Process Map of an expert whose performance is representative of the average of the expert group. The three hierarchies (Need, Account, and Affordability, ordered from top to bottom of the page) are represented in the conceptual model of the problem found in Figs. 2, 3, and 4 (also, see these figures for the nodal abbreviations). Shaded areas within the hierarchies represent different information "branches" within the conceptual model. The beginning of the subjects' solution path is labeled "START" and the directional arrows show the successive sequence of variables they considered to arrive at a solution.

mation board and a calculation or qualitative assessment of the parameter was made. For example, accessing the *Current Expenses* card and subtracting this amount from the *Net Income* value was judged to be a computation—sufficient to activate the current expenses node. Likewise, if a subject viewed the *Gross Retirement Income* card and commented, "$8000 isn't going to be enough to live on during retirement," that node would be activated since a qualitative assessment had been made. Merely explaining how a problem step should be solved, or describing the importance of a particular piece of information without viewing the parameter, was not sufficient to activate a node.

If a node was activated more than once during the decision-making process, second and third arrows emanating from the node were distinguished from the original (first) path from the node. We refer to these reconsiderations of previously considered variables as recursions. No particular node was considered more than four times by a subject (i.e., three recursions).

The most striking difference between the PSPMs of experts and novices is that experts' solution paths are more goal-directed than those of novices. Figures 5 and 6 are actual PSPMs for an expert and a novice, respectively. These two PSPMs were selected for presentation because they are most similar to the average values shown for the various variables in Table 1. One way to quantify goal-directedness is to simply count the number of nodal recursions. Among the seven experts, only one recursion was found, while for the seven novices, 30 nodal recursions were recorded. This difference was statistically significant ($t[12] = 2.83$, $p < .01$; one-tail), supporting the hypothesis that experts are guided from the start of the problem space to the finish by a problem-solving script, while novices search about the problem space looking for a solution strategy.

Further support for this conclusion can be found in the individual data shown in Table 1 and the PSPM of the expert (see Fig. 7) who carried out the most thorough consideration of the problem space. Even though this individual considered 15 unique pieces of information in 16 total steps, his PSPM shows a systematic and directed sequence of processing steps with only one recursion. This subject's directed consideration of the problem is quite similar to the performance of the other experts who considered far fewer information nodes. We think the thoroughness of this expert in comparison to the other six experts, is best explained by his high-level administrative oversight of the human resources division of a large institution. Thus, he is knowledgeable about the complexities of the decision problem and has, apparently, a clear script to direct his solution, but he lacks the production efficiency which most of the other experts have acquired through day to day experience. Relative to his counterparts who completed the task in far fewer steps (a step being defined as the move-

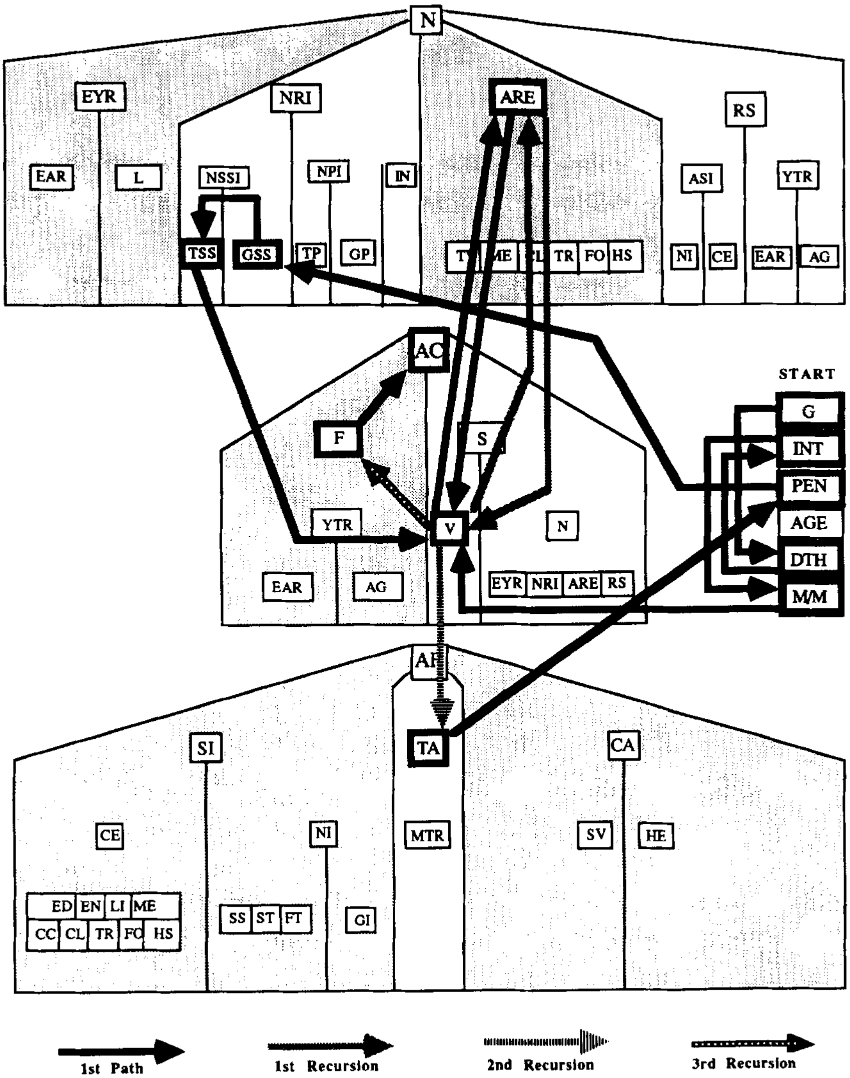

FIG. 6. The Problem Solving Process Map of a novice whose performance is representative of the average of the novice group. The three hierarchies (Need, Account, and Affordability, ordered from top to bottom of the page) are represented in the conceptual model of the problem found in Figs. 2, 3, and 4 (also, see these figures for the nodal abbreviations). Shaded areas within the hierarchies represent different information "branches" within the conceptual model. The beginning of the subjects' solution path is labeled "START" and the directional arrows show the successive sequence of variables they considered to arrive at a solution.

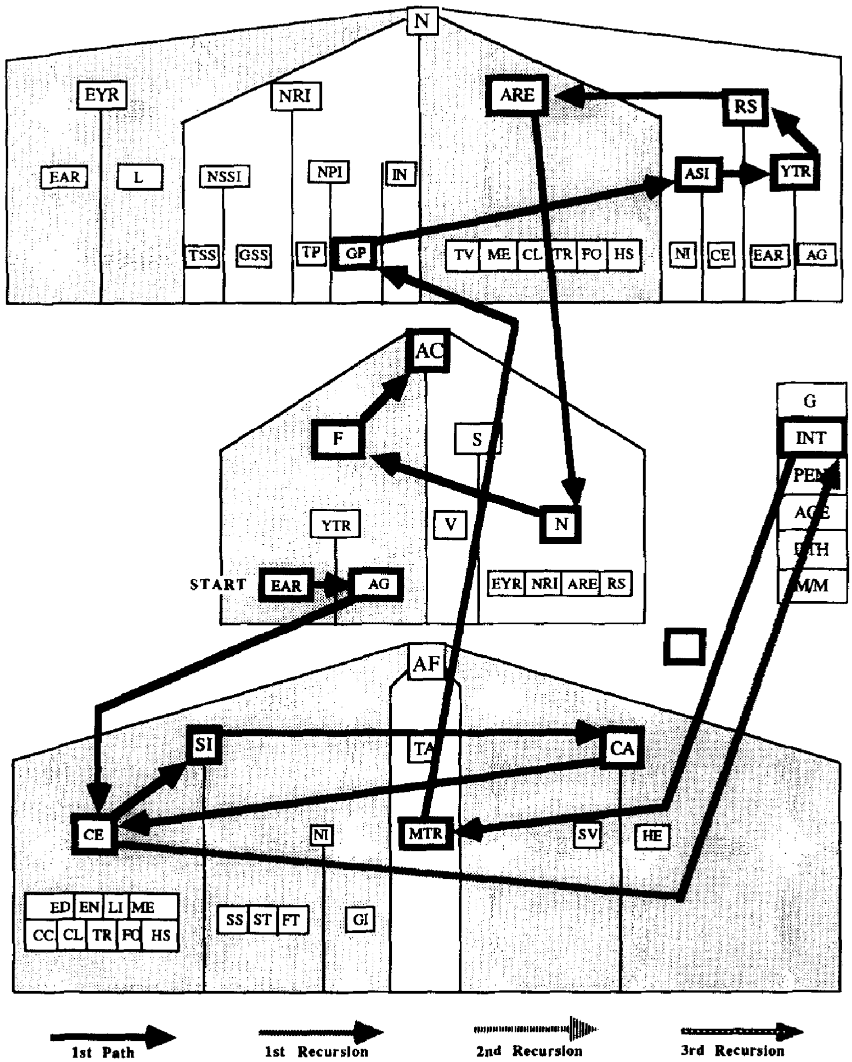

FIG. 7. The Problem Solving Process Map for the aberrant expert who considered the largest number of variables to reach a solution. The three hierarchies (Need, Account, and Affordability, ordered from top to bottom of the page) are represented in the conceptual model of the problem found in Figs. 2, 3, and 4 (also, see these figures for the nodal abbreviations). Shaded areas within the hierarchies represent different information "branches" within the conceptual model. The beginning of the subjects' solution path is labeled "START" and the directional arrows show the successive sequence of variables they considered to arrive at a solution. Note this expert's tendency to ignore lower-level information and sample variables from each of the three hierarchies while making only one recursion to a previously considered variable.

ment from one node to the next), he appears to be using an "unpruned" decision tree to direct his consideration of the problem.

The decision processes of experts and novices were also found to differ in the absolute number of steps used to move from the initial state to the goal state. On average, experts completed the task in significantly fewer steps than novices (5.7 versus 13.7 steps, respectively; $t[12] = 2.32$, $p < .05$; one-tail). In addition, novices required over twice as much time as experts to complete the sound phase of the task (averages of 21 and 9 min, respectively; $t[12] = 1.91$, $p < .05$; one-tail). We interpret this finding as support for the hypothesis that experts have better developed, and more streamlined scripts to guide their problem-solving solutions than do novices.

An additional comparison was conducted to determine if the total number of unique nodes activated was reliably different for the two groups. The unique nodes are the number of different pieces of information selected in the course of solving the problem (i.e., total steps minus recursions). The mean number of unique nodes activated for experts was 5.6, while the number for novices was 9.4—not significantly different although clearly in the direction of our predictions ($t[12] = 1.44$, n.s.). However, the data of Table 1 suggest that one subject may have washed out the inverse relationship between expertise and the number of unique nodes. Specifically, the aberrant expert shown in Fig. 7 (the seventh expert in Table 1) who considered three times as many unique nodes as the average of the other six experts. When this subject was eliminated from the analyses the difference between experts and novices on the unique nodes variable was found to be statistically significant ($t[11] = 2.3$, $p < .05$).[3]

Use of Task Information

Since each of the hierarchies in the problem space contain four levels, the average hierarchical level of information used by an individual can be calculated by summing the "level scores" of each node a subject considered and dividing by that number of nodes (a score of 1 indicating high-level information; a score of 4, low-level information). As predicted, the hierarchy score for experts ($\bar{X} = 2.26$, $s = 0.97$) was significantly lower than that of novices ($\bar{X} = 2.99$, $s = 0.25$), demonstrating that experts

[3] The more desirable strategy of carrying out a replication design (adding subjects to both groups) to obtain statistical support for the differences between novices and experts on the unique nodes and secondary variables measures was not possible. Data collection on the first 21 subjects was completed in November 1986 and the Tax Simplification Act became law in January 1987. The new tax law tremendously complicated the IRA decision question and invalidated the experimental task we had been using.

selected higher level variables in generating their solution to the problem ($t[12] = 1.93$, $p < .05$; one-tail).

Another finding was that novices requested more additional information during Phase 2 than experts (recall that subjects could request additional information, not requested in Phase 1, if they chose to do so in Phase 2). As a group, experts only requested four additional pieces of data ($\bar{X} = .57$, $s = .98$), while novices requested 19 additional pieces of data about the couple ($\bar{X} = 2.71$, $s = 3.40$). Although this difference was not statistically significant by conventional standards ($t[12] = 1.60$, $p < .06$), the pattern of results is consistent with the hypothesis of script-based problem solving. That is, if a script is guiding the selection of information, enumerating all the relevant variables prior to starting the task should be more likely. On the other hand, if a subject has to determine the correct solution process while engaged in solving the problem (as appears to be the case for novices), the number of variables that appear as "afterthoughts" should be increased).

DISCUSSION

Our results suggest that both information search and selection strategies vary markedly as a function of expertise. Moreover, the highly organized, goal-directed search patterns of experts provide empirical support for the hypothesis that skilled problem solvers use problem-solving scripts to guide them to the solution. The use of these scripts, we believe, leads to decreased solution times and more efficient patterns of information processing.[4]

A major finding, which echoes conclusions drawn by other researchers, is that the step-by-step problem-solving behavior of experts is more goal directed than that of novices (cf. Jeffries, Turner, Polson, & Atwood, 1981). This conclusion is supported by the relatively fewer number of nodal recursions and the fewer number of steps experts required to reach a decision. A similar finding, in a task requiring experts and novices to analyze a set of physics problems, led Chi *et al.* (1982) to conclude that

[4] An anonymous reviewer has pointed out that an explanation based on a memory capacity advantage for experts could account for their nonrecursive behavior. While we acknowledge that an expert's use of problem-solving scripts is not the only way to account for the present results, we think it is the most attractive alternative for the reasons spelled out in the text. Furthermore, we think memory-related hypotheses that focus on greater expert capacity must confront the striking fact that experts consider an average of 5.6 variables in reaching a problem solution while novices consider an average of 9.4. We think metamemory explanations of experts' performance may be more plausible than memory-capacity explanations—perhaps experts recognize their memory limitations and work within those constraints, avoiding memory failures and the need for recursions, while novices do not.

either (1) experts are able to mentally access the proper solution procedures before starting the task, *or* (2) novices were more data driven using their conceptually impoverished schemas to select information hierarchically lower than that of experts (p. 26). The present findings show that both interpretations are correct. For the IRA task, novices' choice of lower level variables *required* them to make more calculations, thus, by definition, creating a performance profile that was data driven. We also found that expert financial planners resemble expert physicists in that both use their prior knowledge to identify valid solution strategies. We believe this prior knowledge contributes to the experts' performance in two ways: (1) we think experts use this declarative knowledge to identify a small subset of variables that are most significant in reaching a valid conclusion and (2) they use their procedural knowledge to combine the variables to efficiently reach a decision.

Some support for the above analysis of experts' and novices' solution strategies can be seen in Figs. 5 through 8. Figures 5 and 6 show the expert and novice, respectively, whose PSPMs were most representative of the group averages. Figures 7 and 8 show the PSPMs of the expert and novice, respectively, who considered the largest number of variables (unique nodes) in arriving at a problem solution. The solution paths of the novices (Figs. 6 and 8) are both highly repetitive, with the subjects repeatedly considering variables they had already considered, usually after recognizing that the information was relevant to something they had just looked at: we would describe their pattern of search as "wandering about" trying to figure out what is relevant and how to use it to reach a solution. In contrast, the group-representative expert shown in Fig. 5 is clearly goal-directed and focused on a small subset of relevant variables: he knows what to consider and how to use it without any need to reconsider information already addressed. Likewise, the expert who considered a large number of variables (shown in Fig. 7) reconsiders only a single variable, Current Expenses. Thus, the experts are efficient, nonrecursive problem solvers whether they consider few or many variables; while the novices (in both exemplars) demonstrate highly recursive information search patterns.

Furthermore, it appears that experts' initial representation of the problem allowed them to select higher-order information that would be sufficient to reach a decision. This use of high-level information and their ability to specify virtually all of the parameters they would need, before hand, for phase two indicate that they knew, a priori, what the task would entail. We believe the experts' performance is best explained by a conceptualization that proposes that their initial problem representation contained the procedural steps necessary to reach a solution. Our findings are consistent with the hypothesis that experts were able to match attributes

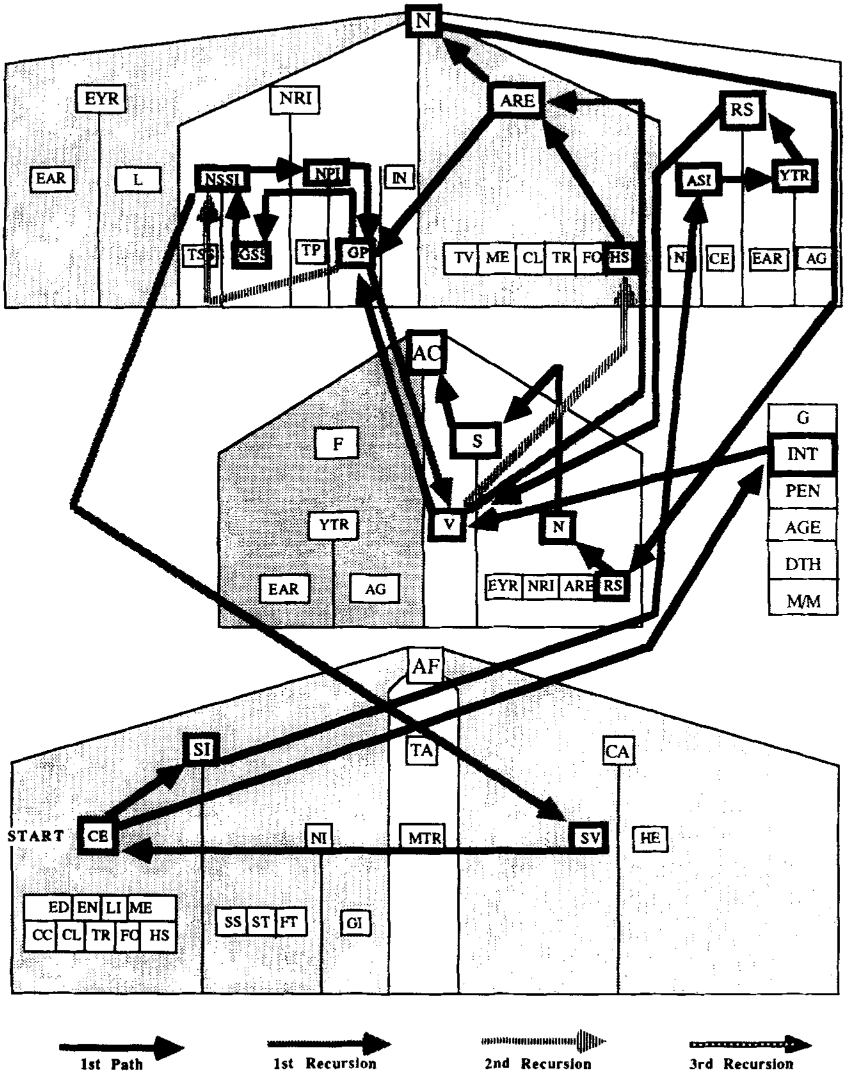

FIG. 8. The Problem Solving Process Map of the novice who considered the largest number of variables to reach a solution. The three hierarchies (Need, Account, and Affordability, ordered from top to bottom of the page) are represented in the conceptual model of the problem found in Figs. 2, 3, and 4 (also, see these figures for the nodal abbreviations). Shaded areas within the hierarchies represent different information "branches" within the conceptual model. The beginning of the subjects' solution path is labeled "START" and the directional arrows show the successive sequence of variables they considered to arrive at a solution. Note the tendency of this novice to reconsider many of the same variables repeatedly.

contained in the IRA problem statement to those encountered in previous problems, thus, quickly recognizing the type of problem they are dealing with.[5] This allowed them to know, before starting the task, what information would be needed. Novices, lacking a comprehensive representation, seem to have used their declarative knowledge of the task domain to select some relevant information, but not sufficient information to solve the problem. The inadequacy of their selection became apparent only after they were engaged in Phase 2 of the task. See Chi *et al.* (1982); Chi *et al.* (1981); Larkin *et al.* (1980); and Simon & Simon, (1978) for similar interpretations.

An interesting question is whether the problem-solving behavior of experts and novices in this study corresponds to the working forward/working backward strategies described by Simon and Simon (1978). Recall that working forward refers to a strategy in which a problem solver begins at the starting point and completes successive steps, executing steps in a procedure or plan with which they are already familiar or which can be easily constructed on the fly. Thus, they should have little need to reconsider problem parameters or retrace their steps. Working backward, in contrast, is used by people who do not already possess a plan or procedure for solving the problem and find it difficult to develop one. Problem solvers start at the goal state and attempt to develop a plan that allows them to move from the starting point to the goal state. At each point in the development of the plan, the problem solver must evaluate whether that step will reduce the difference between the starting point and the goal state. In the process of developing this plan, novices may have to retrace their steps or they may become confused as to where they are. In addition, novices, lacking a plan against which to compare the outcome of a given step, might return to previously viewed information (recur), to see how the new information corresponds to prior parameters and how both relate to the final goal.

[5] Five of the seven expert subjects were employed as financial consultants. It is our presupposition that their representation of the IRA problem in the form of what we refer to as a "goal-directed, problem-solving script" results from their work experience solving financial problems. It is of course possible that study and reading could produce a goal-directed, problem-solving script without the need for actual, repetitive encounters with a problem. However, we suspect that study alone is unlikely to produce "pruned decision trees" (i.e., a subset of only the most critical variables) as was the case for our expert subjects. On the contrary, we suspect that study alone might lead to complex, detailed problem solutions, even though these solutions may not be highly recursive as was true for the novices of this study. Also, the possibility should not be overlooked that individual differences may exist between expert problem solvers—some experts may not use scripts or the scripts they use may vary across types of problems. Research now under way in our laboratory is designed to address these questions.

On the basis of Johnson's (1985) work, we predicted experts would use fewer variables (unique nodes in the PSPMs) than novices. We did find a statistically significant difference in the number of unique nodes considered by experts and novices when we eliminated one outlier from the expert group. As argued above, the expert we eliminated from this analysis possessed a good deal of knowledge about the decision problem and the relevant considerations but lacked production experience in making specific, individual decisions. This individual used a relatively rich set of information to solve the IRA problem, an outcome that we attribute to lack of production experience which we believe motivates experts to "prune" their decision trees. With this one deviant subject eliminated from the analysis, our pattern of results was found to be consistent with that of Johnson (1985).

The discussion to this point has focused on the strengths of expert decision makers, emphasizing their goal-directed efficiency in solving the IRA problem. There are, we believe, some potential weaknesses to the problem-solving style that we see exhibited in these experts. They have limited the number of variables they consider to six or fewer, often ignoring variables that might counterindicate the solution they would choose in some cases. For example, many of the experts relied on information from the Affordability hierarchy, and ignored the Need hierarchy. While it was not the case that considering the Need hierarchy would have counterindicated the decision experts made in the IRA problem we created, we can imagine situations in which experts would make very poor decisions if they focused on the small subset of variables they used to solve this problem. The potential problem-solving weakness of experts is an important issue that should be addressed in future investigation. Unlike the present study that used a single, straightforward problem situation, work addressed to weaknesses in expert performance should employ a number of different problems with nonobvious, counterindicating information in various slots of the problem hierarchy. These conditions will be necessary to produce some reliable measures of decision quality that are not available from the present investigation.

The present study contributes to the expert–novice problem-solving literature in two additional important ways. First, a script-based conceptualization of problem-solving performance offers some general principles for thinking about the differences in the cognitive performance between experts and novices. In the past, it has been difficult to integrate findings across subject-domains because of the different tasks employed. Consider the physics expert. Behaviorally, he can be expected to be scrupulous in his calculations because he knows that physics problems have objectively correct solutions. In contrast, within the domain of retirement planning, experts are required to provide solutions to problems for which there are no such precise answers (interest rates fluctuate, tax and Social Security laws change, etc.). Therefore, comparing retirement planners to physicists strictly on the basis of concrete aspects of their performance may lead to the conclusion that expertise manifests itself in different ways in different domains. A more productive effort, we believe, is to focus on the way in which experts *know how* to solve the problem, as opposed to focusing on the detailed aspects of their problem-solving behavior. In this sense, considering expert performance profiles in terms of script competency (as opposed to manifest behaviors), will provide a better theoretical integration of research findings.

The second contribution of the present work is a practical one. PSPMs are a powerful and efficient way to represent the search strategies and solution procedures of subjects engaged in problem solving. This process-tracing technique can be used to represent the information search strategies of a problem solver for virtually *any* content domain that can be represented in a prescriptive or conceptual manner. Moreover, the graphing procedure is simple to apply, and can be used to effectively assess a rich and varied set of dependent variables related to information use and problem-solving processes.

The findings from the present study should have considerable generalizability to a large array of human problem-solving and decision-making situations. The IRA problem we used in this study shares much in common with a host of other personal and business related financial decisions. The important common characteristics include a large universe of potentially relevant information that has to be integrated into a single decision and the substantial latitude of acceptable but different "integration rules" that a decision maker can apply to the task. These are common characteristics of many other everyday problem-solving and decision-making situations including, but probably not limited to, such tasks as personnel selection, management decisions, medical diagnosis, and legal judgments.

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