Cognitive Fit: An Empirical Study of Information Acquisition

Iris Vessey

Department of Accounting and MIS
College of Business Administration
Pennsylvania State University
University Park, PA 16802

Dennis Galletta

Katz Graduate School of Business
University of Pittsburgh
Pittsburgh, PA 15260

From a broad perspective, our research can be viewed as investigating the fit of technology to task, the user's view of the fit between technology and task, and the relative importance of each to problem-solving or decision-making performance.

The technology investigated in this research is the mode of information presentation. Although there has been a considerable amount of research into problem solving using graphs and tables, until recently the circumstances in which each is more effective have been largely unresolved. Recent research has suggested that performance benefits accrue when cognitive fit occurs, i.e., when factors such as the problem representation and problem solving tools match the characteristics of the task. In this paper, we investigate the effects of the basic paradigm of cognitive fit and extensions to the paradigm in a laboratory experiment that examined the nature of subjects' mental representations as well as problem-solving performance. The experiment, using 128 MBA students in two identical, repeated measures designs, produced the following results:

- Performance improved markedly for symbolic tasks when the problem representation matched the task.
- Performance effects also resulted from matching specific problem-solving skills to the problem representation and the task, and to a lesser extent when the skills matched the task alone.
- The incremental effects of matching skills to the problem representation and/or the task were small compared with the primary effects of cognitive fit–that of matching problem representation to task.
- A large proportion of problem solvers have insight into the concept of supporting tasks with certain types of problem representation and vice versa.
- Participants preferred to use tables rather than graphs; they also preferred to solve symbolic rather than spatial problems.
- Finally, the problem representation more significantly influenced the mental representation than did task conceptualization.

1047-7047/91/0201/0063/$01.25

This research suggests that providing decision support systems to satisfy individual managers' desires will not have a large effect on either the efficiency or the effectiveness of problem solving. Designers should, instead, concentrate on determining the characteristics of the tasks that problem solvers must address, and on supporting those tasks with the appropriate problem representations and support tools. Sufficient evidence now exists to suggest that the notion of cognitive fit may be one aspect of a general theory of problem solving. Suggestions are made for extending the notion of fit to more complex problem-solving environments.

Cognitive fit—Information acquisition—Spatial tasks—Symbolic tasks—Spatial skills—Numeric skills

1. Introduction

For more than sixty years, since Washburne's pioneering study in 1927, researchers from disciplines as apparently diverse as journalism and agriculture, as well as information systems, have devoted considerable attention to the contribution of graphs and tables to problem-solving performance. Specifically, researchers have sought to substantiate their beliefs that graphs should lead to superior problem solving, compared with tables. With the more recent and very rapid increases in the availability of computer software capable of producing a range of graphical displays, it is important that researchers provide theory-based guidelines to aid decision makers using such decision support systems to choose the appropriate data displays to solve their problems.

Despite the volume of research conducted, clear guidelines for the use of graphs or tables do not exist. The studies conducted have produced inconsistent results. DeSanctis (1984), for example, identified 29 studies that compared graphs to tables. Seven of the 29 studies examined found graphs to be better than tables, while 12 found tables to be better than graphs. Ten studies found no significant difference between the two modes of presentation.

Previous studies have been largely atheoretical. Neither have researchers ex post facto been able to suggest those problem-solving contexts in which one problem representation outperforms the other. Furthermore, research has focused on the outcomes of problem solving such as decision quality (accuracy), and confidence and/or satisfaction with the results. The mechanisms by which problem solving takes place remain largely uninvestigated (see, for example, Benbasat and Dexter 1985, DeSanctis and Jarvenpaa 1985, Dickson, DeSanctis and McBride 1986, Lucas 1981, Remus 1984). If we are to fully understand how different problem representations support problem solving, we need to be concerned with problem solving processes.

The aim of this paper is to present and test a model that describes the relationship between graphs and tables and task type on information acquisition tasks. The model is based on the paradigm of cognitive fit (see, for example, Bettman and Zins 1979, Boehm-Davis, Holt, Koll, Yastrop, and Peters 1989, Vessey and Weber 1986). *Cognitive fit* is a cost-benefit characteristic that suggests that, *for most effective and efficient problem solving to occur, the problem representation and any tools or aids employed should all support the strategies (methods or processes) required to perform that task* (Vessey 1991). This means that the problem representation a problem solver uses must be considered in the context of the task to be solved. This paper reports the results of a study that empirically evaluates the basic paradigm of cognitive fit. It also extends the basic notion of cognitive fit as matching problem representation to task, to include the fit of individual problem-solving skills to both the problem representation and the task. Further, this research investigates factors influencing the formulation of problem solvers' mental representations.

From a broader perspective, our research can be viewed as investigating the fit of technology (in this case, mode of information presentation) to task, the user's view of the fit between technology and task, and the relative importance of each to problem-solving or decision-making performance. Note, however, that the theory presented here differs from the popular notion of task/technology fit in that it suggests that simply matching technology to task is insufficient to achieve the desired effects, and that the user must also use appropriate processes, and thus develop appropriate mental representations, for performance effects to occur.

The paper proceeds as follows. Section 2 presents the theoretical foundations on which the paradigm of cognitive fit is based, and applies the paradigm to problem solving using graphs and tables. Section 3 examines factors that influence the formulation of the mental representation. Section 4 describes the empirical research methodology. Section 5 presents the data analysis, while §6 discusses the findings and the implications of the findings for both researchers and practitioners.

2. Theoretical Approach

According to information processing theory on which this analysis is based, human problem solvers will seek ways to reduce their problem solving effort, since they are limited information processors (Newell and Simon 1972). One of the ways to reduce processing effort is to facilitate the problem-solving processes that human problem solvers use in completing the task. This can be achieved by matching the problem representation to the task, an approach that is known as cognitive fit (Vessey 1991).

For two reasons, we view the problem representation and the problem-solving task as independent in this research. First, the data and the task may be presented independently, unlike certain other types of problems, such as problem isomorphs (Kotovsky, Hayes and Simon 1985). Second, problem solvers *can* reach solutions for the types of problems examined when the data is presented in either graphical or tabular format; cognitive fit simply has performance advantages.

2.1. *The Paradigm of Cognitive Fit*

Figure 1 presents the model of problem solving on which the cognitive fit argument presented in this study is based. Note that cognitive fit is an emergent property of the model. Although there may be many factors that may "fit" the problem solving, we view the problem representation as perhaps the most important (see Simon 1981, p. 153), followed by other task-related factors such as problem-solving tools. We first discuss cognitive fit as resulting from matching the characteristics of the problem representation to those of the task (known as the basic model). In §2.2.2., we introduce the notion of matching problem-solving skills to the task and/or the problem representation (the extended model).

The basic model views problem solving as the outcome of the relationship between the problem (or external) representation and the problem-solving task, which are characterized for the purposes of this analysis by the type of information emphasized. Processes are represented by the directed flows linking pairs of elements in the model; for example, processes act on information in (1) the problem representation and (2) the problem-solving task, to produce the mental representation; and (3) the mental representation, to produce the problem solution. The mental (or internal) representation is the way the problem solver represents the problem in human working memory (Gentner and Stevens 1983). In this context, it is a subset of the total problem space (Newell and Simon 1972). The mental representation is formulated using the characteristics of both the problem representation and the task. Specifically, it is derived from the interaction of processes that act on the information in the problem representation and the problem-solving task.

When the types of information emphasized in the problem-solving elements (problem representation and task) match, the problem solver can use processes (and formulate a mental representation) that also emphasize the same type of information. Consequently, the processes the problem solver uses to both act on the problem representation and the task will match. The resultant consistent mental representation will facilitate the problem-solving process. Hence, cognitive fit leads to an effective and efficient problem solution.

When a mismatch occurs between problem representation and task, cognitive fit will not result, since similar processes cannot be used to both act on the problem representation and solve the problem. Because problem solvers induce their mental representations from materials presented to them (Perrig and Kintsch 1985), they will either formulate a mental representation based on the problem representation (in which case they will need to transform it to derive a solution to the problem), or they will formulate a mental representation based on the task (in which case they will need to transform the data derived from the problem representation into a mental representation suitable for task solution). In either case, performance will be worse than if the problem solver had been supplied a problem representation emphasizing the type of information that best supported task solution.

Theoretical support for the relationships in the general problem solving model comes from a variety of sources. The literature provides substantial support for problem solvers' use of processes that match the problem representation: (1) problem isomorphs (see, for example, Kotovsky, Hayes and Simon 1985); (2) behavioral decision theory (Tversky and Kahneman 1971, 1973, 1974); and (3) the behavioral decision-making literature together with the closely associated consumer behavior literature (see, for example, Bettman and Kakkar 1977, Russo 1977).

There is also substantial evidence that problem solvers use different processes in different types of tasks. Einhorn and Hogarth (1981), Slovic and Lichtenstein (1983), and Tversky, Sattath and Slovic (1988), for example, address the differences in processing strategies employed in judgment and choice tasks. Support for the notion that more effective and efficient problem solving occurs when the processes used match the type of task to be accomplished is also found in the systems development literature. Vessey and Weber (1986) have shown that different psychological processes are involved in the design and coding tasks of systems development, and that significant performance effects result when problem solvers use problem representations and problem-solving tools that encourage the use of processes that match those required for task solution.

There is also evidence that matching the problem representation directly to the task has significant effects on problem-solving performance. The majority of studies conducted comes from the consumer behavior literature. Bettman and Zins (1979) tested the effect of alternative, attribute, and mixed alternative and attribute representations on choice tasks facilitated by either alternative or attribute processing approaches. The methodology adopted is due to Wright (1975), who devised tasks incorporating the solution approach. Bettman and Zins found a difference in the

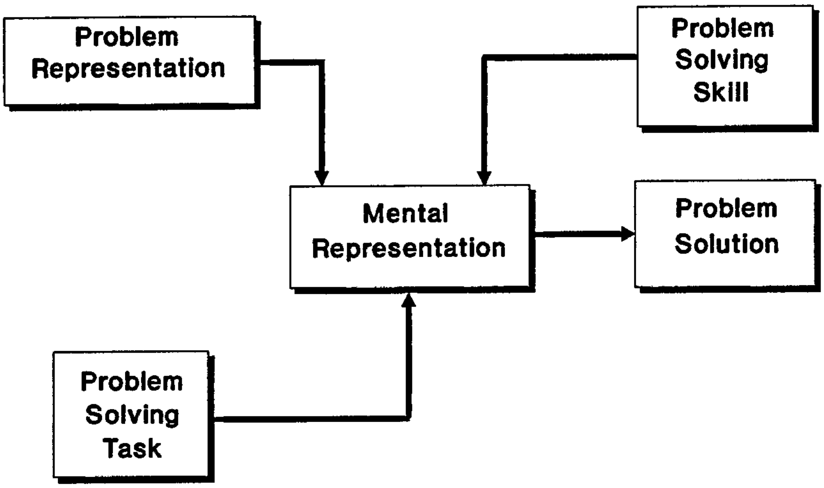

FIGURE 1. Problem-Solving Model.

time but not in the accuracy of performance, suggesting that problem solvers adapt the time to complete a task while keeping accuracy constant. Further, Simkin and Hastie (1987) propose a similar interaction between certain types of graphs and judgment tasks.

Hence, there is substantial theoretical support for matching problem-solving processes to both problem representation and task, and for the direct match of problem representation to task.

2.2. *Cognitive Fit in Graph/Table Problem Solving*

The separation of problem representation and task permits us to apply the notion of cognitive fit by identifying the distinguishing features of graphs and tables and the types of tasks for which they are useful. The distinguishing features of importance are the types of information that each emphasizes. Cognitive fit results when the problem representation and the task both emphasize the same type of information. The use of processes appropriate to the problem representation and the task is inferred. The problem-solving model presented in Figure 1 applies to problem solving using graphs and tables.

2.2.1. *Characteristics of Cognitive Fit.* Let us assume we are considering graphs and tables derived from equivalent data, so that all the information in one is also inferable from the other (Simon 1978). The same data is, then, represented in different ways in graphs and tables, so that a different type of information predominates in each. Our intuition quickly allows us to see a meaningful distinction between graphs and tables. This distinction is usually characterized in terms of images and words in the psychology literature (see, for example, Paivio 1971, 1978). Bertin (1981) makes a similar distinction in the graphics literature. Since the information conveyed in graphs and tables does not quite match that conveyed by "images" and "words" (for example, tables are usually numeric whereas "words" are not; images may be pictorial in nature, while graphs are not), we use the terms *spatial* and *symbolic* representation to characterize the differences between graphs and tables.

According to this classification, graphs are spatial problem representations since they present spatially-related information. According to Larkin and Simon (1987), a diagram (and therefore a graph) "preserves explicitly information about the topological and geometric relations among the components of the problem," i.e., they *emphasize information about relationships in the data.* Graphs do not directly present information on discrete data values. Tables are symbolic problem representations in that the information represented in them is symbolic in nature. Tables *emphasize information on discrete data values.* Discrete data values are the only type of information directly represented in tables. Tables represent information about relationships only indirectly.

We now need to identify the types of tasks that graphs and tables might support. Although we do not have a comprehensive theory of tasks (see, for example, Campbell 1988, Fleishman 1982, Wood 1986), we can examine specific tasks used in graph/table problem solving to determine abstract characteristics of tasks that might be facilitated by each problem representation. The abstract task characteristic we must identify is the type of information that needs to be emphasized to best accomplish the task.

Several researchers have identified two basic types of information acquisition tasks used in graphs versus tables studies (Washburne 1927, Umanath and Scamell 1988, Umanath, Scamell and Das 1990). Umanath and colleagues (1988, 1990) have empirically validated the two types of tasks from the viewpoint of recall. Examination of these two types of tasks shows that the first type (those said to be facilitated by graphs) assess the problem area as a whole rather than as discrete data values. Thus they are tasks that require making associations or perceiving relationships in the data; for the purposes of this analysis we refer to such tasks as *spatial.* The following is an example of a spatial task (Washburne 1927, p. 375):

> "Between the years 1100 and 1438 whose earnings increased most rapidly, those of the wool, silk, or Calimala merchants?" (This is a comparison of trends and is spatial in nature.)

The second type of tasks (those said to be facilitated by tables) involve extracting discrete, and therefore precise, data values (Washburne 1927, Umanath and Scamell 1988, Umanath et al. 1990). They are known as *symbolic* tasks. The following is an example of a symbolic task (Washburne 1927, p. 375):

> "How much did the wool merchants earn in the year 1100?" (This question requires a specific amount as the response. It is, therefore, symbolic in nature.)

Hence, we can readily see that spatial tasks are best supported by spatial representations, while symbolic tasks are best supported by symbolic representations.

Cognitive fit results in more effective and efficient problem solving. This statement is confirmed by an analysis of relevant studies in the literature, which successfully explained the results of 12 out of 13 experiments that produced significant effects for problem representation (Vessey 1991). Lack of a significant effect in the thirteenth study may have been due to the operationalization of the study. Although the results of these experiments have generally been considered inconsistent, there is, in fact, little inconsistency when they are viewed via the notion of cognitive fit.

Accordingly, we state the following proposition.

PROPOSITION 1: *More effective and efficient problem solving results when the problem representation matches the task to be accomplished.*

As stated earlier, a spatial representation does not have to be used to solve a spatial task; nor does a symbolic representation have to be used to solve a symbolic task. For example, a problem solver might determine a trend from a table or extract a specific numeric value from a graph. When the information in the problem representation and the task do not match, however, similar processes cannot be used to both act on the problem representation and solve the problem, and the mental representation will have to be transformed. The overall effect, then, will be increased variability in the time and accuracy of performance, and therefore less effective and efficient problem solving. Seven of the eight studies in the literature that had either the task type or the representation type confounded showed no effect for either graphs or tables (Vessey 1991).

2.2.2. *Cognitive Fit and Problem-Solving Skills.* The notion of cognitive fit can be extended to include, as for problem representation, other problem-solving elements that potentially may have an effect on task solution (see also Figure 1). Information systems researchers have long been fascinated with the notion that individual problem solver characteristics have a substantial impact on problem-solving performance. Perhaps the most researched of these aspects is cognitive style (see, for example, Benbasat and Taylor 1982, Dickson, Senn and Chervany 1977, Keen and Scott Morton 1978, Mason and Mitroff 1973). The results of the majority of cognitive style studies have, however, been inconsistent (Huber 1983), and when effects are found they are usually extremely small. Rather than seeking measures of cognitive style in an attempt to explain the incremental effects of individual differences on performance, we suggest seeking *information processing skills that support a particular task,* where skill is defined as "procedures for dealing with situations as they arise" (Simon 1981). Note that, according to this definition, a skill exists only in the context of some objective or task; it is not an individual difference characteristic that is manifested across all tasks.

Analogous to our basic cognitive fit arguments, we expect that a specific skill will have its greatest effect on performance when it emphasizes the same type of information as in the associated problem-solving elements (i.e., problem representation and task). In this case, the mental representation formulated will be consistent with each of the problem-solving elements (problem representation, task, and skills) and performance will be further enhanced. Further, problem-solving skills that match either the problem representation or the task may also influence performance, irrespective of the nature of the other problem solving element. We expect the effect to be less than that for matching skill to both problem representation and task. Hence, we state the following proposition.

PROPOSITION 2: *Problem-solving performance is improved when problem-solving skills match both problem representation and task, or either the problem representation or the task. Problem-solving performance is improved more if the skills match both the problem representation and the task, rather than matching only the problem representation or the task.*

3. Factors Influencing the Formulation of the Mental Representation

Recall that problem representation and task can be considered as distinct elements of graph/table problem solving. We can therefore decouple the problem representation from the problem, thereby gaining insights into the nature of the mental representation formulated. We can first present problem solvers with either the problem representation or the task and then request them to generate the task type or the problem representation they would choose to use with the problem-solving element first presented. This approach permits us to examine a number of aspects related to the formulation of the mental representation.

3.1. *Problem Solver Insight*

Given the opportunity to choose a problem solving element that either matches or does not match the element they have already viewed, we can examine whether problem solvers choose the matching element that the theory suggests will lead to performance advantages. Perrig and Kintsch (1985) show that different mental representations can be induced in problem solvers by "having subjects read appropriate texts." Since problem solvers have only one element on which to base their decision, it appears likely, therefore, that they will choose a problem-solving element that has similar characteristics to the one they have already experienced. In other words, we expect they will choose a second problem-solving element that matches the first. We state the following exploratory proposition.

PROPOSITION 3: *Problem solvers formulate a mental representation of the problem consistent with the type of information in the first problem-solving element examined.*

3.2. *Relative Importance of Problem Representation and Task Type*

We can also examine whether the problem representation or the task has a greater effect on the mental representation formulated; i.e., will problem solvers have better insights into the matching process when presented first with the problem representation or with the task? The literature provides substantial support for the fact that problem solvers use processes–and therefore formulate mental representations–that match the problem representation. See, for example, the literature on isomorphs (Kotovsky, Hayes and Simon 1985), on vividness and availability (Nisbett and Ross 1980, Slovic 1972, Taylor and Thompson 1982, Tversky and Kahneman 1971, 1973, 1974), and on behavioral decision making and consumer behavior (Bettman and Kakkar 1977, Russo 1977). Jarvenpaa (1989), using a methodology due to Wright (1975) in the consumer behavior literature, reports that information acquisition from bar charts in matrix format is based principally on the representation rather than the task. Much less evidence exists for the notion that problem-solving processes and therefore the mental representation formulated match the task (see Russo and Dosher 1983). Hence, we state the following proposition.

PROPOSITION 4: *The problem representation has a greater effect than task type on the mental representation formulated.*

3.3. *Relative Importance of Spatial and Symbolic Problem-Solving Elements*

One of the reasons frequently advanced for the lack of empirical support for the superiority of graphs over tables in research studies is that individuals have a greater exposure to tables than to graphs in their everyday lives or in their working lives (see, for example, Bariff and Lusk 1977, DeSanctis and Jarvenpaa 1985, Ghani 1981, Lucas 1981, Watson and Driver 1983). If this is so, the performance of such problem solvers will be biased in favor of tables. Lusk, for example, found that people prefer to use the reports they have been used to receiving (Bariff and Lusk 1977). Lusk and Kersnick (1979) use the term "operant conditioning" to describe the phenomenon:

Spatial Task
In which month is the difference between deposits and withdrawals greatest?

Symbolic Task
Please provide the following amounts:
withdrawals in April
deposits in February
deposits in January
deposits in November

FIGURE 2. Examples of Tasks Used.

> The report format which individuals have used in the past is the one for which they probably developed a strong conditioning bond. Therefore, one would expect these individuals to prefer reports which are approximately similar to the report for which they have developed operationally valid heuristics.

The notion that problem solvers have a bias toward using a particular problem representation might be extended to suggest that they are also biased toward solving the corresponding type of task, since similar types of information and similar processes are involved. Hence, as well as preferring to use symbolic representations, problem solvers might also prefer to solve symbolic problems. We therefore state the following exploratory proposition.

PROPOSITION 5: *Symbolic problem-solving elements (problem representation and task) have a greater effect on the mental representation formulated than spatial problem-solving elements.*

4. Method

To test these propositions on information acquisition, a laboratory experiment was conducted in which the performance of participants using spatial and symbolic representations was assessed on both spatial and symbolic tasks. The experiment tested the propositions presented in sections 2 and 3 relating to the extended paradigm of cognitive fit and factors influencing the formulation of the mental representation. As anticipated in §3, the study presented the problem representation and the task separately to provide data on factors influencing the formulation of the mental representation.

4.1. *Tasks*

The task setting required the participants to respond to the problems of a bookkeeper who had a number of bank accounts under his control. Participants responded to problems regarding deposits and withdrawals on five of the bank accounts over a 12-month period. Spatial and symbolic tasks were constructed for each account. Figure 2 presents examples of the spatial and symbolic tasks used. The months for which participants were required to extract data in the symbolic tasks were determined using random numbers.

4.2. *Problem Representations*

The performance of line graphs vis-a-vis two-dimensional tables was investigated in this study. Figures 3(a) and (b) present examples of the spatial and symbolic representations used in the experiment.

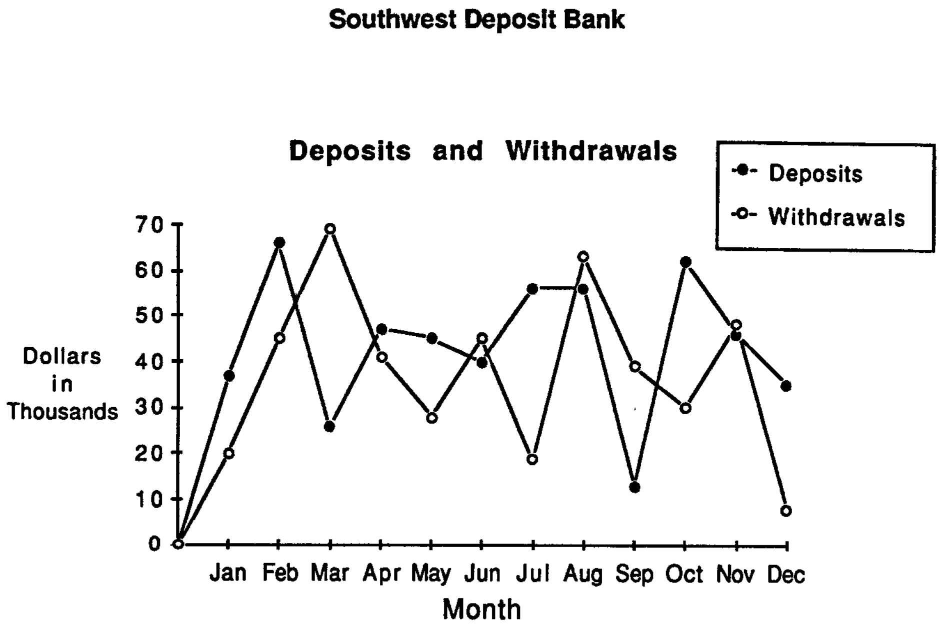

FIGURE 3(a). Spatial Problem Representation.

4.3. *Design*

Each subject completed five exercises. Two balanced 2 × 2 × 5 designs were used, one for each type of task, and each having 16 participants per cell. The two between-subjects factors were type of problem representation (graph and table) and the order of presentation of the problem representation and the task (problem representation-task sequence, *rt*, and task-problem representation sequence, *tr*); the within-subjects factor was task with five repetitions. All factors were counterbalanced.

All participants completed the same first problem; the order of presentation of the four remaining problems was fully randomized based on a Latin square design. All participants were presented with just one problem first, since we were concerned that a number of trials with similar problems might interfere with the type of mental representation formulated, particularly in mismatched contexts. This, however, proved not to be the case (i.e., there were no significant differences in the choices subjects made between the first problem presented and the remaining four problems). Similarly, there were no substantive differences in performance results between the first and the remaining four problems; neither were there any learning effects. Hence, the results from all five trials are presented in §5.

4.4. *Performance Measures*

Two performance measures were used: the time taken and the accuracy (or precision) with which the task was completed. Time was measured in fractions of a second. Participants' responses to spatial tasks, in general, were either correct or incorrect. There was one exception where the response to the bookkeeper's problem required categorization of each month in the 12-month period. In this instance, accuracy was recorded as a decimal fraction of the number of months correctly categorized.

Performance on symbolic tasks when using a spatial representation leads to

Southwest Deposit Bank

Dollars in Thousands

Month	Deposits	Withdrawals
Jan	37	20
Feb	66	45
Mar	26	69
Apr	47	41
May	45	28
Jun	40	45
Jul	56	19
Aug	56	63
Sep	13	39
Oct	62	30
Nov	46	48
Dec	35	8

FIGURE 3(b). Symbolic Problem Representation.

imprecise values. The Y-axis was presented in tens (representing thousands of dollars), starting at the origin (see Figure 3a). 17 of the 20 values extracted in the symbolic problems (four values in each of five problems) did not fall at a tick mark on the axis. The results were coded by subtracting 0.1 from the correct accuracy score of 1 for each unit difference from the correct value. Hence, if the correct response were 52, a subject response of 50 would score 0.8.

4.5. *Participants*

128 volunteer MBA students participated in the experiment. To motivate participants to perform to the best of their abilities, each was paid $5 for the 30–35 minute, individual session. Further, the highest performing participants in each of the eight treatments received prizes of $30, $20 and $10. Prizes were awarded based on the sum of the participants' normalized scores for time and accuracy in completing the task.

4.6. *Procedure*

Prior to the experiment proper, a pilot test using two replications of the experimental materials was conducted to identify any deficiencies in the experimental materials and to provide practice for the research assistants in administering the experiment. The experiment proper was conducted in two parts: an individual session and a class session. Each participant was run singly through the experimental tasks to avoid effects of peer pressure on performance. The individual session comprised instruction in the experimental procedure, completion of two practice exercises of the same type as the experimental task, the administration of five sets of experimental tasks, and the completion of a debriefing questionnaire.

The class session involved participant response to standard questionnaires of spatial and symbolic abilities. The Witkin's Group Embedded Figures Test (Witkin et al. 1971) was used to assess subjects' spatial skills, i.e., the ability of an individual to distinguish a simple spatial figure from within the context of a more complex spatial figure. The number comparison section of the Minnesota Clerical Test (Andrew, Paterson and Longstaff 1979), which requires extracting and comparing information from numbers, was used to assess the symbolic skills of interest in this study.

As noted earlier, two experimental procedures were required to obtain information on factors influencing the nature of the mental representation formulated: the *rt* and *tr* conditions. Following the presentation of the first problem-solving element (i.e., problem representation or task), participants responded to a question to gain insight into the nature of the mental representation they had formulated (see, for example, Perrig and Kintsch 1985, Rumelhart 1977). The question required participants to choose whether they would like to work with (1) a spatial or symbolic task in the *rt* condition, or (2) a spatial or a symbolic representation in the *tr* condition. Participants were then given the remaining problem-solving element and were requested to respond to the bookkeeper's problem. The time taken to complete the second phase of the experiment was recorded. Five repetitions were conducted.

5. Results

The results that test the paradigm of cognitive fit are presented first, followed by those that address factors influencing the formulation of the mental representation.

5.1. *Performance Effects*

Table 1 presents descriptive statistics of the data. Table 2 summarizes the propositions tested and the results obtained in the performance analysis.

The data analysis involved fitting repeated measures multivariate analysis of variance and covariance models (MANOVA and MANCOVA) to the data for spatial and symbolic tasks, since Pearson product moment correlation coefficients indicated that the dependent variables were moderately correlated. Skewness in the dependent variables resulted in violation of an important assumption of MANOVA, homogeneity of the variance-covariance matrices (Box's M statistic). Square root transformation of the dependent variable, time, and arcsine transformation of accuracy improved Box's M statistic, though it still remained significant. Keppel (1982) states that ANOVA is robust with respect to violations of the homogeneity of variance assumption for examining between-subject effects. However, as a further check on the data, we used Conover and Iman's (1976) rank transform procedure, which replaces the data with their ranks and uses the ranks as input to the appropriate parametric analyses. Box's M statistic was satisfied with the transformed data ($p = 0.121$). Conover and Iman state: "If the results are nearly identical, the rank transform has merely confirmed that the original analysis is likely to be accurate." The results of our analyses were identical with the data and with the ranks. We therefore used MANOVA with the transformed data in the ensuing analyses. Univariate statistics are also presented where appropriate.

The data were also examined for the presence of experimenter effects since the data were collected by two research assistants (MANCOVA). Since there were no experimenter effects for spatial tasks or for symbolic tasks ($p > 0.10$), this covariate was not used in further analyses.

5.1.1. *Effects of Matching Problem Representation and Task Type.* A MANOVA model was fitted to the data to test for problem representation and order of presentation effects on performance. For spatial tasks, problem representation significantly affected performance ($F(2, 59) = 17.78$; $p = 0.000$). Users with graphs solved the

TABLE 1

*Means and Standard Deviations for Time Taken and Response Score for Five Trials**

	Time in seconds	Score (out of 5)
rt Condition		
Spatial Task		
Graph	77.46	3.93
	(21.25)	(0.76)
Table	109.72	4.56
	(29.08)	(0.63)
Symbolic Task		
Graph	127.41	3.89
	(36.45)	(0.50)
Table	71.92	4.95
	(26.78)	(0.14)
tr Condition		
Spatial Task		
Graph	80.93	3.31
	(44.26)	(1.15)
Table	105.40	4.48
	(31.96)	(0.84)
Symbolic Task		
Graph	138.13	4.01
	(35.99)	(0.35)
Table	71.67	4.97
	(22.97)	(0.08)

* 16 participants per cell.

problems faster than users with tables ($F(1, 60) = 16.37$; $p = 0.000$). Users with tables, however, were more accurate than users with graphs ($F(1, 60) = 17.67$; $p = 0.000$). Neither the order main effect nor the problem representation × order interaction was significant. Proposition 1 is partially supported for spatial tasks.

For symbolic tasks, problem representation significantly affected performance ($F(2, 59) = 308.24$; $p = 0.000$). Tables resulted in both faster ($F(1, 60) = 70.66$; $p = 0.000$) and more accurate ($F(1, 60) = 515.20$; $p = 0.000$) performance on symbolic tasks than graphs. Neither the order main effect nor the problem representation × order interaction was significant. Proposition 1 is fully supported for symbolic tasks.

5.1.2. *Effects of Problem-Solving Skills.* To test the notion that specific skills are important when the characteristics of both the problem representation and the task are similar, we analyzed performance on spatial and symbolic representations with Witkin's Group Embedded Figures Test (GEFT) and the Minnesota Clerical Test (MCT) as the respective covariates. The results are presented in Table 2. The skill covariate is significant in both instances when the problem representation and the task match. For spatial representations and spatial tasks, spatial skill is significant at $p = 0.062$ ($F(2, 28) = 3.08$). The effect was in accuracy ($p = 0.019$). For symbolic representations and symbolic tasks, numeric skill was significant at $p = 0.000$ ($F(1, 29) = 13.02$). (High accuracy scores led to the use of time alone in this calculation.) These results provide substantial support for the concept that problem-solving skills

TABLE 2

Propositions and Results of Testing for the Effects of Cognitive Fit on Problem Solving Performance

Stimulus	Expected Outcome	Result	Significance
Propositon 1: Effect of Matching Problem Representation and Task			
spatial task	Graph > Table	Supported for time	p = 0.000
		Not supported for accuracy	p = 0.000
symbolic task	Task > Graph	Supported for both time and accuracy	p = 0.000 p = 0.000
Proposition 2: Effect of Matching Skill to Problem Representation and/or Task			
Matching Skill to Problem Representation and Task			
graph on spatial task	GEFT significant	Supported for accuracy	p = 0.019
table on symbolic task	MCT significant	Supported for time	p = 0.000
Matching Skill to Problem Representation			
graph on symbolic task	GEFT significant	Not supported	N.S.
table on spatial task	MCT significant	Not supported	N.S.
Matching Skill to Task			
spatial task	GEFT significant	Supported for accuracy	p = 0.017
symbolic task	MCT significant	Supported for time	p = 0.000
table on spatial task	GEFT significant	Not Supported	N.S.
graph on symbolic task	MCT significant	Supported for time	p = 0.023

have an impact on performance when the characteristics of the skills match those of both the problem representation and the task. None of the comparisons made in which the skill matched the problem representation but not the task was significant at the 0.10 level. We also tested the effect of skill on performance when the type of skill matched the task type. Spatial skill was significant at $p = 0.060$ ($F(2, 58) = 2.96$). The effect was in accuracy ($p = 0.017$). Numeric skill had a significant effect on performance on symbolic tasks ($F(2, 58) = 10.83$; $p = 0.000$). The effect was in time ($p = 0.000$).

We further tested the effect of matching skill to task by disaggregating tasks into groups based on non-matching problem representations. The additional analysis was conducted, since the results are directly comparable to those of the other skill analyses, i.e., comparisons of two cells only. Spatial skill had no effect on performance for spatial tasks using symbolic representations. Numeric skill had a significant effect on performance for symbolic tasks using spatial representations ($F(2, 28) = 4.46$; $p = 0.021$). The effect was in time ($p = 0.023$). Hence, three out of four results for matching skill to task were significant or marginally significant.

Overall, these results provide substantial support for Proposition 2, that matching problem-solving skills to both the problem representation and the task has a greater effect on performance than matching only problem representation or task. Further, the effects of matching skills to task are significant, while those of matching skills to problem representation are not significant. Interestingly, spatial skills have an effect on accuracy, while numeric skills have an effect on time.

5.2. *Effects of Factors Influencing the Formulation of the Mental Representation*

Since it is possible that participants' responses may be biased by repeated trials, we first compared results for the first and for all five trials. Table 3 shows the proportions of participant choices that match the nature of the first element presented for both the first trial and for all five trials. For example, over five trials when a spatial representation was presented first, subjects chose to respond to a spatial problem on 125 out of 160 occasions. The proportion of mismatches was therefore 35 out of 160. Comparison of the proportions of matches for the first and all five trials shows that there is no bias toward choosing a matching problem-solving element. Hence, we used the aggregated results to analyze the data. Table 4 summarizes the propositions and the results of factors influencing the formulation of the mental representation.

5.2.1. *Problem Solver Matching Capabilities.* The data first enabled us to determine whether subjects formulated mental representations based on the first problem-solving element presented (Proposition 3). Inspection of the data for five trials in Table 3 shows that, in each of the four cells, a majority of subjects would choose to use the problem representation or the task in which the information emphasized matched that in the problem-solving element they viewed initially. Given random assignment of subjects to treatments, it seems likely that our methodology yields a non-random choice of the second problem-solving element.

Each of the four treatments shown in Table 3 was tested using the binomial theorem to determine whether the observations could have been randomly generated. Three observations were significant at $p = 0.000$, while the fourth (spatial element in the *tr* condition) was significant at $p = 0.026$. These results demonstrate that subjects' choice of spatial or symbolic as the nature of the second problem-solving element was not random. Hence it appears that the characteristics of the intermediate mental representation were related to the first problem-solving element subjects received, i.e., subjects chose the problem representation that matched the nature of the task and vice versa. These results support Proposition 3. (Further, note that when

TABLE 3

Proportion of Responses for Matching Decision Element

Nature of First Element Presented	First Element Presented: First Trial — Reprn (rt)	First Trial — Task (tr)	Five Trials — Reprn (rt)	Five Trials — Task (tr)
spatial	25/32 (0.78)	21/32 (0.66)	125/160 (0.78)	94/160 (0.59)
symbolic	30/32 (0.94)	27/32 (0.84)	140/160 (0.88)	130/160 (0.81)

TABLE 4

Propostions and Results of Testing for the Effects of Factors Influencing the Formulation of the Mental Representation

Stimulus	Expected Outcome	Values Tested	Results	Signif.
Proposition 3: Decision Maker Insight				
spatial representation	spatial mental representation	125 vs 80	Supported	p = 0.000
spatial task	spatial mental representation	94 vs 80	Supported	p = 0.026
symbolic representation	symbolic mental representation	140 vs 80	Supported	p = 0.000
symbolic task	symbolic mental representation	130 vs 80	Supported	p = 0.000
Proposition 4: Problem Representation versus Task				
graph vs. spatial task	graph > spatial task	125/160 94/160	Supported	p = .000
table vs. symbolic task	table > symbolic task	140/160 130/160	Not supported	N.S.
Proposition 5: Spatial versus Symbolic Decision Making Elements				
spatial task or symbolic task	table > graph	130/160 94/160	Supported	p = 0.000
graph or table	symbolic task > spatial task	140/160 125/160	Supported	p = 0.026

we take into account participants' individual biases (§5.4.3.), all comparisons are significant at p = 0.000.)

5.2.2. *Relative Effects of Problem Representation and Task.* To determine whether the problem representation or the task had a greater effect in determining the characteristics of the mental representation (Proposition 4), we examined the information on mental representations to determine whether there was a bias toward one of the problem-solving elements. We first examined spatial representations and spatial tasks. When first presented with a spatial representation, participants chose to respond to a spatial task on 125 of 160 occasions. On the other hand, when first presented with a spatial task, participants chose data presented in spatial format on 94 of 160 occasions. These results show that the characteristics of the mental representations participants formulated were more frequently based on the problem representation than on the task. Testing the proposition that the proportions of subjects adhering to the task and the problem representation were equal lead to rejection of the proposition. The differences were significant at p = 0.000, supporting Proposition 4.

We next examined symbolic representations and symbolic tasks. The corresponding responses to symbolic representations and symbolic tasks were 140 out of 160 and 130 out of 160, respectively. Again, the effect for problem representation was stronger than that for task, though the difference in proportions was not significant (p = 0.128). The lack of significance may have been due to a ceiling effect on the desire to use tables within the particular context, i.e., certain subjects may have preferred to use graphs no matter what the circumstances. These results represent partial support for Proposition 4.

5.2.3. *Relative Effects of Spatial and Symbolic Problem-Solving Elements.* The data on mental representations was next used to assess whether problem solvers are biased toward using symbolic rather than spatial problem-solving elements (Proposition 5). First, problem solver bias toward using a particular representation was assessed. This was achieved by examining matched tasks and problem representations when participants were first presented with the task (*tr* condition). When the task was spatial, subjects chose to have data presented spatially on 94 out of 160 occasions. When the task was symbolic, however, subjects chose tables on 130 out of 160 occasions. The difference between the two proportions was significant at $p = 0.000$. This result supports the widely reported notion that problem solvers are biased in choosing to use tables rather than graphs.

Second, the information on mental representations was used to assess the extent to which participants have a concept of the types of tasks that the two problem representations support. This was achieved by examining matched tasks and problem representations when participants were first presented with the representation (*rt* condition). When the representation was spatial, subjects chose to solve spatial problems on 125 of 160 occasions. When the representation was symbolic, subjects chose to solve symbolic problems on 140 out of 160 occasions. The difference between the two proportions was significant at $p = 0.026$. These results suggest that subjects have a stronger concept of the types of tasks supported by tables than of those supported by graphs, or, in other words, problem solvers chose to respond to symbolic tasks rather than to spatial tasks. Proposition 5 is fully supported.

6. Discussion

Our research investigated the relationship between problem representation and task type in information acquisition. This section discusses the experimental findings, the limitations of the study, and the implications of those findings for both researchers and practitioners.

6.1. *Discussion of Findings*

Our results partially support the notion that the effectiveness of a problem representation must be considered in the context of the task to be solved. Tables enabled users to make faster and more accurate decisions on symbolic problems than graphs. However, users with graphs, though faster than those with tables on spatial tasks, were also less accurate. It is possible that the spatial tasks used may have been too simple for spatial representations to have an advantage over tables. However, Umanath and Scamell (1988) report that simple comparison was facilitated by graphs in their study (see §2.2.1.).

This study also investigated the influence of problem-solving skills that matched the tasks to be accomplished. Performance increased significantly with skills that supported either the task or both the problem representation and the task. Interestingly, there were no performance effects when the problem-solving skills supported the problem representation alone. Hence skill appears to influence task solution rather than information acquisition. Spatial skills impact accuracy, while numeric skills impact time. The size of the skill effects were not large, however, compared with the effect of supporting the task with the appropriate problem representation (see also Washburne 1927).

Examining factors influencing the formulation of the mental representation permitted us to investigate whether problem solvers have insights into the concept of adapting the information display to the type of task under investigation, and vice versa. We found that, in all instances, a significant proportion of problem solvers chose a matching element to support either the problem representation or the task they initially received. The fact that this study found effects for matching, while that of Bettman and Zins (1979), for example, did not, suggests that some prior experience with alternative formats is essential to develop matching capabilities.

Further examination of the factors influencing the formulation of the mental representation also revealed differences among the four conditions. First, there is some support for the notion that the problem representation has a greater effect on the formulation of the mental representation than the task. Second, the results of this study confirm what has long been suspected, but not substantiated empirically: problem solvers prefer to work with tables rather than graphs. However, this study also shows there may be little justification for their preferences: either representation may be more effective depending on the task to be performed. Similar arguments can be made regarding problem solvers' preference for solving symbolic problems.

6.2. *Limitations*

The limitations of the study center on the type of spatial task examined, the use of pre-test instruments, the use of line graph representations, and the use of student subjects. First, the paradigm of cognitive fit was supported for time to solve spatial problems with spatial representations, but not for the accuracy of the solution. In retrospect, we could have used tasks that embodied stronger spatial characteristics, such as determining a trend or determining other types of patterns in the data. The experiment could therefore be replicated using these types of spatial tasks.

Second, we used standard test instruments to assess spatial and symbolic problem solving skills in class prior to the experiment in 90% of our subjects; the problem solving skills of the other 10% were assessed individually following the experiment. Class time was available only prior to the individual experimental sessions. Given random assignment of subjects to treatments, this type of data is best collected after the experiment to overcome the possibility of biasing the experimental results. Alternatively, a control group could have been used to assess any bias.

Third, this study investigated only line graphs from the variety of spatial representations that could have been investigated. Line graphs were chosen since they are one of the most commonly used spatial formats. Future studies could empirically test the paradigm of cognitive fit using, for example, bar graphs as the spatial representation.

Fourth, this study used student subjects. Therefore the generalizability of the results to the population of "real-world" problem solvers should be assessed. Note, however, that the study is based on theory that does not depend on experience or expertise for its explanatory power.

6.3. *Implications of the Results*

What, then, are the implications of our findings for researchers and practitioners?

From the viewpoint of *researchers,* we have presented and empirically tested a paradigm that seeks to explain the performance of users of graphs and tables on simple information acquisition tasks. The fact that only partial support is provided for cognitive fit on spatial tasks suggests a more detailed investigation into the characteristics of this type of task.

The paradigm of cognitive fit is based on the use of consistent decision-making processes to both act on the problem representation and to solve the problem. This study addressed the outcome of applying those processes, i.e., the nature of the mental representation, rather than the way in which it is formulated. The use of processes appropriate to the problem representation and the task were inferred from the fact that both decision-making elements emphasized the same type of information. A further test of the paradigm could be provided by using a process tracing methodology such as protocol analysis (see, for example, Ericsson and Simon 1984, Russo, Johnson and Stephens 1989).

This research has shown that the concept of cognitive fit can be extended to include skills used in problem solving. Other research indicates that it can be further extended to include problem-solving tools (see Vessey and Weber 1986). It appears likely, therefore, that the notion of supporting problem solving by matching information characteristics may be one aspect of a general theory of problem solving.

The current research on cognitive fit applies to information acquisition and simple information evaluation tasks. The research should now be extended to encompass more complex problem-solving tasks. Examination of the literature shows two possible avenues. First, the paradigm of cognitive fit is a special case of the application of cost/benefit principles to problem solving (see Beach and Mitchell 1978, Payne 1982). Supporting the task to be accomplished with the display format leads to minimization of both effort and error. Cost/benefit theory, in general, however, views problem solving as a trade-off between effort and accuracy as a result of strategy shifts. Research into behavioral decision making, for example, has shown that the strategies used vary widely based on small changes in the task or task environment. In particular, decision makers have been shown to trade off small losses in accuracy for large savings in effort (Russo and Dosher 1983). Future research might apply the concepts of cognitive cost/benefit theory to problem solving using graphs and tables in more complex tasks and in problem-solving environments that constrain the amount of time and therefore the extent of processing required for task solution.

Second, the management literature has long investigated the notion of fit, known variously as contingency, congruency, coalignment, consistency, etc. (see, for example, Drazin and Van de Ven 1985, Van de Ven and Drazin 1985). This approach is useful since the notion of fit spans micro to macro perspectives, rather than simply the micro perspectives outlined in this paper for simple graph/table problem solving. Venkatraman (1989), for example, presents the theoretical and statistical implications associated with each of six types of fit characterized on the basis of the degree of specificity of the fit relationship (micro to macro) and on the presence or absence of a criterion for fit. Some of the macro concepts of fit offer a way of viewing support for problem solving in more complex tasks.

From the viewpoint of *practitioners,* our results suggest that we are now compiling sufficient information to help problem solvers choose an appropriate problem representation to support information acquisition tasks. Although significant numbers of problem solvers chose matching problem-solving elements, one out of four (23.6%) did not (see Table 3). It is these problem solvers that our research can aid. This problem can be approached either by training problem solvers to choose the data display that is appropriate to the type of task they wish to solve or by designing systems so that they provide data in an optimal format for solving certain types of problems.

The advice to limit the availability of options goes against the current trend in software development. New packages and new releases contain increased numbers of display features, thereby increasing flexibility rather than facilitating an informed choice of display format. For example, spreadsheets, perhaps the best known example of packaged software, now make available to problem solvers many kinds of spatial as well as symbolic formats. We have shown that this type of flexibility may be harmful rather than helpful to the problem solver (see, also Dos Santos and Bariff 1988, Silver 1990).

Further, although we found that specific skills had an effect on performance, the effect was small compared with that produced by supporting the task with the appropriate problem representation. This research suggests, therefore, that providing decision support systems to satisfy individual managers' desires will not necessarily have a large effect on either the efficiency or the effectiveness of problem solving. We should, instead, concentrate on determining the characteristics of the tasks that problem solvers must address, and supporting those tasks with the appropriate problem representations and support tools.*

Acknowledgments. The authors are indebted to Izak Benbasat and Sirkka Jarvenpaa for their comments on an earlier version of this paper, and to the three reviewers and Associate Editor for their insightful comments. The authors also thank Premkumar Gopalaswamy and Carol Pollard for their research assistance.

This research was supported by a grant from the Central Research Development Fund of the University of Pittsburgh, and a Faculty Research Grant to the first author from the Katz Graduate School of Business, University of Pittsburgh.

* Gerardine DeSanctis, Associate Editor. This paper was received on September 19, 1989, and has been with the authors 4 months for 3 revisions.

References

Andrew, D. M., D. G. Paterson, and H. P. Longstaff, *Minnesota Clerical Test,* The Psychological Corporation, 1979.

Bariff, M. J. and E. J. Lusk, "Cognitive and Personality Tests for the Design of Management Information Systems," *Management Sci.,* 23 (April 1977), 820–829.

Beach, L. R. and T. R. Mitchell, "A Contingency Model for the Selection of Decision Strategies," *Acad. Management Rev.,* 3 (1978), 439–449.

Benbasat, I. and A. S. Dexter, "An Experimental Evaluation of Graphical and Color-Enhanced Information Presentation," *Management Sci.,* 31, 11 (1985), 1348–1364.

——— and R. N. Taylor, "Behavioral Aspects of Information Processing in the Design of Management Information Systems," *IEEE Transactions on Systems, Man, and Cybernetics,* SMC-12, 4 (July/August 1982), 439–450.

Bertin, J., *Semiology of Graphs.* University of Wisconsin Press, Madison, WI, 1981.

Bettman, J. R. and P. Kakkar, "Effects of Information Presentation Format on Consumer Information Acquisition Strategies," *Journal of Consumer Research,* 3 (March 1977), 233–240.

——— and M. Zins, "Information Format and Choice Task in Decision Making," *Journal of Consumer Research,* 6 (Sept. 1979), 141–153.

Boehm-Davis, D. A., R. W. Holt, M. Koll, G. Yastrop, and R. Peters, "Effects of Different Data Base Formats on Information Retrieval," *Human Factors,* 31, 5 (1989), 579–592.

Campbell, D. J., "Task Complexity: A Review and Analysis," *Academy of Management Journal,* 13, 1 (1988), 40–52.

Conover, W. J. and R. L. Iman, "On Some Alternative Procedures Using Ranks for the Analysis of Experimental Designs," *Communication in Statistics—Theory and Methods,* A5, 14 (1976), 1349–1368.

DeSanctis, G., "Graphs as Decision Aids," *Decision Science,* 15, 4 (Fall 1984), 463–487.

———— and S. Jarvenpaa, "An Investigation of the 'Tables versus Graphs' Controversy in a Learning Environment," *Proceedings of the Sixth International Conference on Information Systems,* 1985, 134–144.

Dickson, G. W., G. DeSanctis, and D. J. McBride, "Understanding the Effectiveness of Computer Graphics for Decision Support: A Cumulative Experimental Approach," *Comm. ACM,* 29, 1 (1986), 40–47.

————, J. A. Senn, and N. L. Chervany, "Research in Management Information Systems: The Minnesota Experiments," *Management Sci.,* 23, 9 (1977), 913–923.

Dos Santos, B. and M. Bariff, "A Study of User Interface Aids for Model-Oriented Decision Support Systems," *Management Sci.,* 34, 4 (April 1988), 461–468.

Drazin, R. and A. H. Van de Ven, "An Examination of Alternative Forms of Fit in Contingency Theory," *Admin. Sci. Q.,* 30 (1985), 514–539.

Einhorn, H. J. and R. M. Hogarth, "Behavioral Decision Theory: Processes of Judgment and Choice," *Annual Review of Psychology,* 32 (1981), 52–88.

Ericsson, K. A. and H. A. Simon, *Protocol Analysis: Verbal Reports as Data.* The M.I.T. Press, Cambridge, Mass., 1984.

Fleishman, E. A., "Systems for Describing Human Tasks," *American Psychologist,* 37, 7 (1982), 821–834.

Gentner, D. and A. L. Stevens, *Mental Models.* Lawrence Erlbaum and Associates, Hillsdale, N.J., 1983.

Ghani, J. A., "The Effects of Information Representation and Modification on Decision Performance," Unpublished Doctoral Dissertation, University of Pennsylvania, 1981.

Huber, G. P., "Cognitive Style as a Basis for MIS and DSS: Much Ado About Nothing?" *Management Sci.,* 29, 5 (May 1983), 567–579.

Jarvenpaa, S., "The Effect of Task and Graphical Format on Information Processing Strategies," *Management Sci.,* 35, 3 (March 1989), 285–303.

———— and Dickson, G. W., "Graphics and Managerial Decision Making: Research Based Guidelines," *Comm. ACM,* 31, 6 (June 1988), 764–774.

Keen, P. W. G. and M. Scott Morton, *Decision Support Systems: An Organizational Perspective.* Addison-Wesley Publishing Company, Reading, Mass., 1978.

Keppel, G., *Design and Analysis.* Prentice-Hall, Englewood Cliffs, N.J., 1982.

Kotovsky, K., J. R. Hayes, and H. A. Simon, "Why Are Some Problems Hard? Evidence from Tower of Hanoi," *Cognitive Psychology,* 17 (1985), 248–294.

Larkin, J. and H. A. Simon, "Why a Diagram is (Sometimes) Worth Ten Thousand Words," *Cognitive Science,* 11 (1987), 65–99.

Lucas, H. C., "An Experimental Investigation of the Use of Computer-Based Graphics on Decision Making," *Management Sci.,* 27, 7 (July 1981), 757–768.

Lusk, E. and M. Kersnick, "The Effect of Cognitive Style and Report Format on Task Performance: The MIS Design Consequences," *Management Sci.,* 25, 8 (August 1979), 787–798.

Mason, R. O. and I. I. Mitroff, "A Program for Research on Management Information Systems," *Management Sci.,* 19, 5 (January 1973), 475–487.

Newell, A. and H. A. Simon, *Human Problem Solving.* Prentice-Hall, Englewood Cliffs, N.J., 1972.

Nisbett, R. E. and L. Ross, *Human Inferences: Strategies and Shortcomings of Social Judgment.* Prentice-Hall, Englewood Cliffs, N.J., 1980.

Paivio, A., *Imagery and Verbal Processes.* Holt, Rinehart, and Winston, New York, 1971.

————, "Dual Coding: Theoretical Issues and Empirical Evidence," in Scandura, J. M. and C. J. Brainerd (Eds.), *Structural Process Models of Complex Human Behavior,* Sijthoff and Noordhoff, Alpen aan den Rijn, The Netherlands, 1978, 527–550.

Payne, J., "Contingent Decision Behavior," *Psychological Bulletin,* 92, 2 (1982), 382–402.

Perrig, W. and W. Kintsch, "Propositional and Situational Representations of Text," *Journal of Memory and Language,* 24 (1985), 503–518.

Remus, W. E., "An Empirical Investigation of the Impact of Graphical and Tabular Data Presentations on Decision Making," *Management Sci.,* 30, 5 (May 1984), 533–542.

Rosen, L. D. and P. Rosenkoetter, "An Eye Fixation Analysis of Choice and Judgment with Multiattribute Stimuli," *Memory and Cognition,* 4 (1976), 747–752.

Rumelhart, D., "Understanding and Summarizing Brief Stories," In D. and S. J. Samuels, (Eds.), *Basic Processes in Reading: Perceptions and Comprehension.* Erlbaum Associates, Hillsdale, N.J., 1977.

Russo, J. E., "The Value of Unit Price Information," *Journal of Marketing Research,* 14 (1977), 193–201.

———— and B. A. Dosher, "Strategies for Multiattribute Binary Choice," *Journal of Experimental Psychology: Learning, Memory, and Cognition,* 9, 4 (1983), 676–696.

Russo, J. E., E. J. Johnson, and D. L. Stephens, "The Validity of Verbal Protocols," *Cognitive Psychology*, 17 (6) (1989), 759–769.

Silver, M., "Decision Support Systems: Directed and Nondirected Change," *Information Systems Research*, 1, 1 (1990), 904–916.

Simkin, D. and R. Hastie, "An Information-Processing Analysis of Graph Perception," *Journal of the American Statistical Association*, 82, 398 (1987), 454–465.

Simon, H. A., *The Sciences of the Artificial*, 2d ed., The MIT Press, Cambridge, Mass., 1981.

———, "On the Forms of Mental Representation," in C. W. Savage (Ed.), *Minnesota Studies in the Philosophy of Science*, Vol. 9, *Perception and Cognition: Issues in the Foundations of Psychology*. University of Minnesota Press, Minneapolis, 1978.

Slovic, P., *From Shakespeare to Simon: Speculations and Some Evidence—about Man's Ability to Process Information*. Oregon Research Institute Monograph 12, 1972.

——— and S. Lichtenstein, "Preference Reversals: A Broader Perspective," *American Economic Review*, 73 (1983), 596–605.

SPSS Inc., *SPSS-X User's Guide*, 3d ed., Chicago, IL, 1988.

Taylor, S. E. and S. C. Thompson, "Stalking the Elusiveness Effect," *Psychological Review*, 89 (1982), 155–182.

Tversky, A. and D. Kahneman, "Belief in the Law of Small Numbers," *Psychological Bulletin*, 76 (1971), 105–110.

——— and ———, "Availability: A Heuristic for Judging Frequency and Probability," *Cognitive Psychology*, 5 (1973), 207–232.

——— and ———, "Judgment Under Uncertainty: Heuristic and Biases," *Science*, 185 (1974), 1124–1131.

———, S. Sattath, and P. Slovic, "Contingent Weighting in Judgment and Choice," *Psychological Review*, 95 (1988), 371–384.

Umanath, N. S., R. W. Scammell, and S. R. Das, "An Examination of Two Screen/Report Design Variables in an Information Recall Context," *Decision Sciences*, 21, 1 (1990), 216–240.

——— and ———, "An Experimental Evaluation of the Impact of Data Display Format on Recall Performance," *Comm. ACM*, 31, 5 (May 1988), 562–570.

Van de Ven, A. H. and R. Drazin, "The Concept of Fit in Contingency Theory," In L. L. Cummings and B. M. Staw (Eds.), *Research in Organizational Behavior*, 7. JAI Press, N.Y., 1985, 333–365.

Venkatraman, N., "The Concept of Fit in Strategy Research: Towards Verbal and Statistical Correspondence," *Academy of Management Review*, 14, 3 (1989), 423–444.

Vessey, I., "Cognitive Fit: A Theory-Based Analysis of the Graphs versus Tables Literature," *Decision Sciences*, 22 (Spring 1991), 219–241.

——— and R. Weber, "Structured Tools and Conditional Logic: An Empirical Investigation," *Comm. ACM*, 29, 1 (January 1986), 48–57.

Washburne, J. N., "An Experimental Study of Various Graphic, Tabular and Textural Methods of Presenting Quantitative Material," *Journal of Educational Psychology*, 18, 6 (1927), 361–376.

Watson, C. J. and R. W. Driver, "The Influence of Computer Graphics on the Recall of Information," *MIS Quart.*, 7, 1 (March 1983), 45–53.

Witkin, H. A., P. K. Oltman, E. Raskin, and S. A. Karp, *A Manual for the Embedded Figures Test*, Consulting Psychologists Press, Palo Alto, California, 1971.

Wood, R. E., "Task Complexity: Definition of the Construct," *Organizational Behavior and Human Decision Processes*, 37 (1986), 60–82.

Wright, P. L., "Consumer Choice Strategies: Simplifying vs. Optimizing," *Journal of Marketing Research*, 11 (1975), 60–67.