



## **Impacts of decision task, data and display on strategies for extracting information**

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Decision tasks often require the extraction of information from displays of quantitative data. This paper investigates how people extract information from any one of several common displays by analysing the match between display, decision task and data. We posit two kinds of activity: first, the formulation of an appropriate extraction strategy and second, the execution of that strategy. We then develop a model of *strategy formulation*. We hypothesize that with matched designs a higher proportion of subjects use common strategies characterized by less time to formulate, less time to execute and more accurate decisions. A laboratory experiment using a new technique of graphical protocol analysis supported these hypotheses. Moreover, the experiment demonstrated how changes in display, decision task and data alter the way people select decision strategies. This suggests new opportunities for designing more effective human-computer interfaces.

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### **1. Introduction**

Task-based rules for the selection of optimal displays have been proposed by a number of authors (e.g. Jarvenpaa & Dickson, 1988). These suggestions, however, have generally been based on practice and empirical findings rather than theories of the underlying behavior. This paper develops a model of how decision makers extract quantitative data from any one of several common displays to solve common decision tasks. This is the basis for defining an optimal display that leads to the most efficient behavior, for the very notion of an optimal display presupposes uniform and predictable behavior.

We restrict our discussion to the extraction of information for a given problem from quantitative displays (e.g. bar chart, line graph or table). This is a relatively structured task in comparison with more unstructured activities such as judgment (Einhorn & Hogarth, 1978) or comprehending free-form text (Daft & Lengel, 1984). It is important to understand how design affects behavior in structured tasks, which constitute a significant part of office work (Eason, 1988). We also believe that it is a necessary first step towards understanding behavior in more complex tasks that are often made up of many simpler sub-tasks.

A focus of research on quantitative displays has been the comparison of human performance using graphs vs. tables. Our model is not intended to resolve this specific question but rather to address the more general and more robust issue of designing the best display for a particular combination of tasks and data. The model rests on previous work related to task-based designs by Iris Vessey (1991) about cognitive fit and by Donald Norman (1991) about “naturalness”. Vessey argued that “for most effective and efficient problem solving to occur, the problem representation and any tools or aids employed should all support the strategies required to perform that task” (Vessey, 1991). Vessey and Galletta (1991) tested this notion with structured tasks of information acquisition. Their basic views problem solving in terms of its representation (e.g. tables vs. graphs) and the problem. Both representation and problem can be characterized as spatial or symbolic. Cognitive fit is the result of a match between these characteristics, e.g. a spatial representation for a spatial problem. Norman (1991) suggests that fit (naturalness) is related to directness, which “can be measured by the complexity of the relationship between representation and value, measured by the length of the description of that mapping” (Norman, 1991, p. 28).

In the next section we integrate the concepts of cognitive fit and naturalness by describing the interaction with a given design and measuring the “length of the description”. Designs can, therefore, be classified as matched (when the length of the description is minimal) or mismatched. This approach lets us develop a model whose granularity is likely to be successful in developing optimal displays for decision tasks. Some previously proposed models have been too coarse-grained [e.g. models that discriminate only between gross task characteristics such as retail site selection (Jarvenpaa, 1989)]. Others have been too fine-grained to be practically applicable (e.g. Simkin & Hastie, 1987). Having developed our model, we describe an experiment that tests the model. In the final section we describe briefly the program of additional research needed for the full application of our findings.

## 2. A research model for data extraction

### 2.1. THE FRAMEWORK

Recent research on display formats in decision making has taken two forms: (1) experiments that consider task-related moderators, particularly task requirements (Te'eni, 1989), task complexity (Remus, 1987) and data complexity (Lauer, 1986); and (2) meta-analyses of previous studies (Montazemi & Wang, 1988; Hwang & Wu, 1990; Schaubroeck & Muralidhar, 1991). The research has identified several factors that appear to influence decision behavior: the problem requirements (including the decision task to be solved and the data set available) and the display format. Individual skills, once a dominant factor in studies involving displays and decision making, appear to have been ignored in recent MIS studies (e.g. Diamond & Lerch, 1992) or added only as secondary factors (e.g. Vessey & Galletta, 1991).

We follow this lead and investigate the joint effect of three factors on user behavior: decision task, data and display format. We will further assume that user behavior can be decomposed into two stages: strategy formulation and strategy execution (Newell & Simon, 1972; Payne, 1982). Strategy formulation is the process of determining what needs

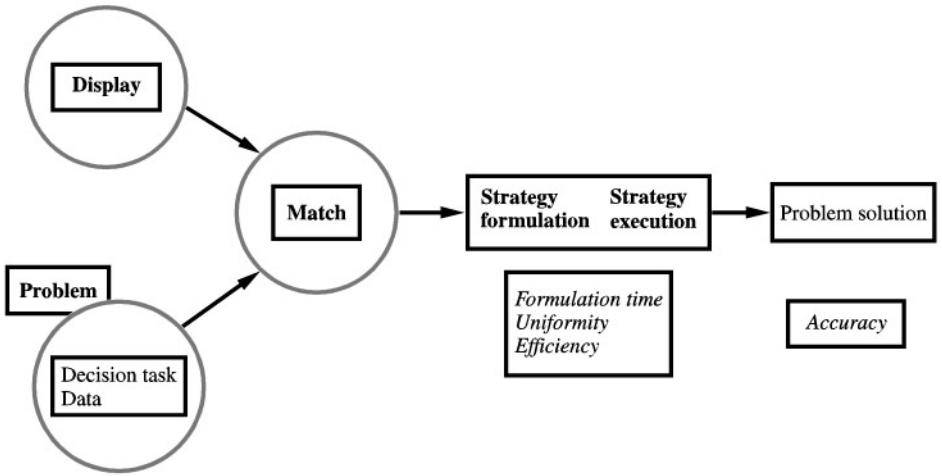


FIGURE 1. Research framework.

to be done and devising a sequence of steps to accomplish it. Strategy execution then carries out the chosen strategy. In reality these two interact, but separating them conceptually highlights the effects of strategy formulation on behavior. Figure 1 depicts the three factors affecting the two stages of decision behavior. The figure also shows (in italics) the characteristics of the decision-making process, which are explained later.

That these factors interactively affect strategy formulation is not new (Payne, 1982). For example, previous work noted the effects on strategy formulation of decision tasks and data (Huber, 1980) and of decision tasks and displays (Te’eni, 1990). The current study sets out to uncover the process by articulating the decision strategies employed and investigating the qualities of these strategies. To do this, we first define a method for describing information acquisition and then apply cognitive cost-benefit theory to predict strategy formulation.

2.2. STRATEGY AND ELEMENTARY INFORMATION PROCESSES (EIPs)

Following several recent streams of research on adaptive decision making (Huber, 1980; Payne, Bettman & Johnson, 1988), human–computer interaction (Newell & Simon, 1972; Olson & Nilsen, 1988) and graphical displays (Cleveland & McGill, 1984; Simkin & Hastie, 1987), we describe information acquisition behavior by using two components: an elementary information process (EIP) and a strategy. We define an EIP as a simple cognitive operation such as reading a value. A strategy is a set of EIPs that accomplishes a given retrieval task. This two-layered approach enables the behavior for a wide variety of data acquisition tasks to be specified with a relatively small set of EIPs (Chase, 1978). This has the advantage of providing a common basis for comparison across diverse studies.

Selecting the granularity of the EIPs depends on the purpose of the research. On the one hand, EIPs such as READ, COMPARE and MOVE (Bettman, Johnson & Payne,

TABLE 1  
*Classes of EIPs*

|    |         |
|----|---------|
| 1. | Scan to |
| 2. | Search  |
| 3. | Read    |
| 4. | Compare |
| 5. | Compute |

1990) focus on characteristics of the decision task and cannot directly relate to specific displays. On the other hand, several research projects have offered EIPs that focus on graph features without reference to the decision task. Cleveland and McGill (1984) proposed a list of 10 “elementary tasks” including POSITION ALONG A COMMON SCALE, DETERMINE LENGTH and DETERMINE ANGLE. Simkin and Hastie (1987) developed four “elementary mental processes” including ANCHORING, SCANNING, PROJECTION and SUPERIMPOSITION. Casner (1991) used a graphical procedural language that comprises 15 “perceptual operators” including HORIZONTAL and VERTICAL POSITION, HEIGHT and LABELS. Lohse (1993) developed a set of *ex post* “cognitive parameters” based on eye movements.

A testable formulation of the interactive effect of the decision task, data and display on strategy formulation requires that the specification of EIPs (by which we characterize the strategies) must be at a level that is detailed enough to take account of the physical differences in displays, but at the same time general enough to be applicable to a wide variety of data-related decision tasks. We, therefore, propose a set of EIPs built on a combination of those used in the decision-making and graphics literature. Our objective in selecting the set of EIPs was that they be at as aggregate a level as possible without losing sensitivity to the differences in data, display and decision task. Further, the list should be as short as possible but sufficient to describe all possible steps, and the EIPs should be observable. Table 1 lists five classes of EIPs. We use an example to introduce these EIPs and then demonstrate how strategy formulation is affected by changes in decision task, display and data.

The graph shown in Figure 2 plots the sales over time of two companies, A and B. If the decision maker is asked to retrieve Company B’s sales for 1985, the following strategy is likely to be used.

#### *Strategy I*

1. Scan to legend.
2. Search legend for Co. B.
3. Scan to *x*-axis.
4. Search for 1985 on *x*-axis.
5. Scan to line representing Co. B.
6. Scan to *y*-axis.
7. Read data.

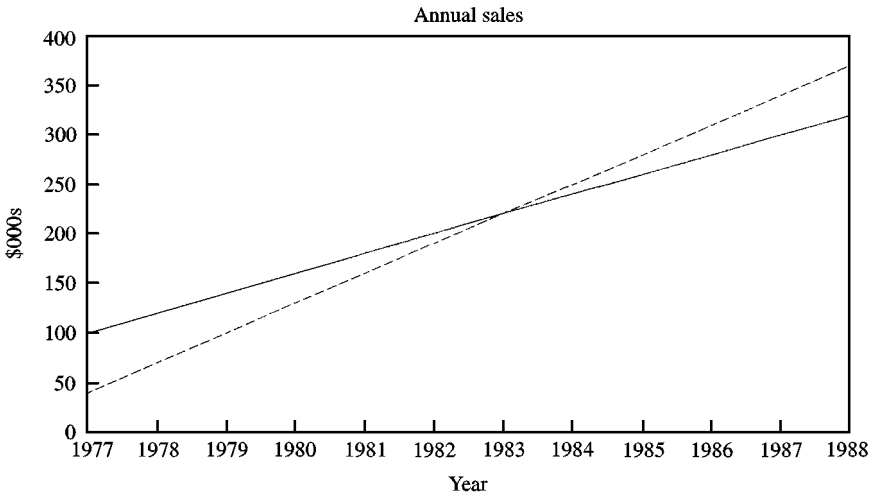


FIGURE 2. Example—regular data-line graph. Company A (---); company B (—).

*Scanning* involves moving the focus of attention to an appropriate area of the display such as a particular axis of a graph or legend block. *Searching* involves pinpointing the needed information within the area that scanning has selected. In the example above, first the user scans to the legend and searches Company B, then scans to the horizontal axis and locates (searches) the position of a particular year, viz. 1985, and finally scans to Company B's data line and from there to the vertical axis in order to read the appropriate data. *Reading* may be for textual labels or for data. For data, reading is essentially the inverse of searching. When searching, we answer questions such as "Where on the axis is the year 1990?"; when reading, we know the point of interest along the axis and answer the question "What point in time does this axis position stand for?"

Note the subtle interplay between the physical and symbolic nature of the activities represented by scan, search and read. Scan involves an eye movement to a physical area (which obviously has some meaning but nevertheless is referenced physically). Search focuses on symbols within some area (although every symbol is physically present, it is not referenced as such). Read interprets the symbol located at some physical point.

Decision tasks are usually more complicated, requiring two additional types of EIP: comparisons and computations. The precise nature of *comparisons* depends on the type of the display. Typical comparisons would include questions such as: "Which number (from a table) is the larger?" or "Which graph line is higher?" or "Which graph line has the steeper slope?" *Computations* are needed when the raw data (whatever its format) does not explicitly supply the data required to complete the task. Computations involve such operations as subtracting, adding, etc. In some cases it might be desirable to distinguish between various types of computations, but for the tasks we have studied this has not proven necessary.

| Years | Annual sales (000s) |           |
|-------|---------------------|-----------|
|       | Company A           | Company B |
| 1977  | 100                 | 40        |
| 1978  | 120                 | 70        |
| 1979  | 140                 | 100       |
| 1980  | 160                 | 130       |
| 1981  | 180                 | 160       |
| 1982  | 200                 | 190       |
| 1983  | 220                 | 220       |
| 1984  | 240                 | 250       |
| 1985  | 260                 | 280       |
| 1986  | 280                 | 310       |
| 1987  | 300                 | 340       |
| 1988  | 320                 | 370       |

FIGURE 3. Example—regular data table.

### 2.3. THE EFFECT OF DISPLAY, DATA AND DECISION TASK

#### 2.3.1. Display

If the decision maker is asked to complete the same task (retrieve sales for 1985) but is presented with the table in Figure 3, behavior may change to the following:

##### *Strategy II*

1. Scan to legend.
2. Search legend for Co. B (thereby identifying its column).
3. Scan to years column.
4. Search for 1985.
5. Scan to Co. B's column.
6. Read data.

In these two cases, the data and the task were constant but the display changed. *Strategy I* is no longer applicable and *Strategy II* is more suitable for the particular combination of display, decision task and data.

#### 2.3.2. Data

Different data sets may also affect the strategies selected. If the decision maker is asked to determine which company had the higher growth rate between 1984 and 1986, using Figure 2, the following is likely to be used.

##### *Strategy III*

1. Scan to  $x$ -axis.
2. Search for 1984 on  $x$ -axis
3. Search for 1986 on  $x$ -axis
4. Scan to lines representing sales from 1984 to 1986.

5. Compare slopes of the two lines.
6. Scan to legend (to identify the company with the steeper line).
7. Read text (to find its name).

Now look at Figure 4 to solve the same decision task. Clearly, the sales patterns in Figure 4 are more complex than in Figure 2 and preclude the simple strategy just described. Asked the same question with Figure 4, the decision maker may employ the following new strategy.

*Strategy IV*

1. Scan to x-axis.
2. Search for 1984 on x-axis.
3. Scan to lower (dashed) sales line.
4. Scan to upper sales line in 1984.
5. Search for 1986 on x-axis.
6. Scan to lower line in 1986.
7. Scan to upper line in 1986.
8. Compare gaps at 1984 and 1986.
9. Scan to legend.
10. Read text.

*2.3.3. Decision task*

Finally, different tasks obviously call for different strategies. Recall the differences between the strategy used to determine the value of sales in 1985 (Strategy I) and the strategy used to determine the fastest growth rate (Strategy III)—this despite the fact that each used the same data display (Figure 2).

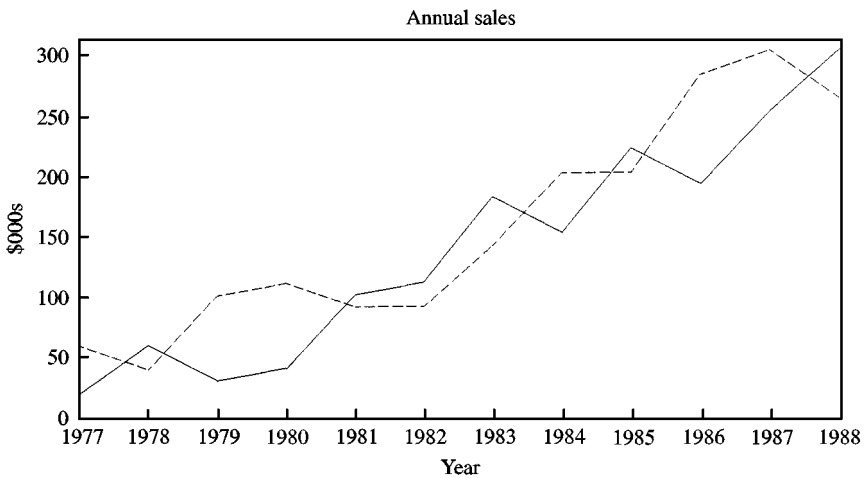


FIGURE 4. Example—irregular data. Company A (· · · ·); company B (—).

#### 2.4. A MODEL OF ADAPTIVE BEHAVIOR

The examples above demonstrate possible effects of data, decision tasks and displays on behavior, but do not explain the mechanism for strategy selection. Now we need to consider what makes a user more or less likely to select one strategy rather than another. Previous research has proposed two general explanations that, coincidentally, yield the same predictions (Payne, 1982). One view holds that strategy formulation is a deliberate process involving a cognitive cost/benefit analysis (Beach & Mitchell, 1978). Each strategy has cognitive costs (the effort put into the EIPs) and benefits which are a function of the decision's accuracy. Effort and accuracy are weighed to evaluate a strategy. The other view is habitual and sees behavior as a perceptual reaction based on experience (Kahneman & Tversky, 1979).

Habitual behavior, however, tends to invoke whichever strategy has been found from experience to be most cost-beneficial. Pinker (1981) articulated this idea with the concept of schema. A schema is a mental structure based on experience that guides the individual's organization and interpretation of incoming information (Schank & Abelson, 1977). Pinker's graph-related schemata are built around the display so that people will tend to use a predefined strategy for understanding the information presented in a particular display format. This notion that display format is the major determinant of mental representation of the problem has also been accepted by Russo and Doshier (1983), Jarvenpaa (1989) and Vessey and Galletta (1991).

Thus, whether by habit or by reckoning, it is commonly held that the strategy selected will tend to be cost-beneficial. Johnson and Payne (1985) point out, however, that effort is immediately felt, whereas feedback on accuracy will often be delayed and ambiguous. Our model thus predicts that individuals will concentrate on cost rather than accuracy. When the cheapest strategy is error-prone, one might expect accuracy considerations to become significant, so that the accuracy ordering of perceptual tasks proposed by Cleveland and McGill (1984) would need to be considered, but we maintain that in the simple tasks we are studying this refinement can be safely ignored.

The easiest way to measure cost is simply to count the number of EIPs that will be required, ignoring any differences between the effort and time they require (Newell & Simon, 1972). This is the approach most researchers take, though an argument can be made in favor of the slightly better fit that can be obtained when EIPs are weighted differentially (Betteman *et al.*, 1990). Some recent studies of human-computer interaction have revealed time differences between EIPs, but these differences are large only when EIPs that require motor activity (dragging a mouse, drawing a line, etc.) are contrasted with those that do not. Since the EIPs we are studying do not involve motor activity, it seems reasonable to adopt equal weights. With these observations in mind, we define three constructs and then formulate the hypotheses.

An *efficient strategy* for a specific DDD (combination of a Decision task, a Data set and a Display) is one that solves the problem with the fewest EIPs. This conforms to the notion proposed by Norman (1991) that the "natural" strategy has the shortest "length of description" (assuming, of course, that description length is measured in psychological rather than linguistic terms). When two strategies employ different EIPs it is possible—though rare—for them to be equally efficient (same EIP count).



A *common strategy*, if it exists, for a specific DDD is the strategy employed by the majority of problem solvers. Operationally we categorize a strategy by its EIPs regardless of their ordering. If a strategy consists of  $n$  EIPs there are  $n!$  possible orderings of those EIPs. Commonly, some orderings will accomplish the task correctly while others fly in the face of common-sense. For example, a comparison task may consist of three EIPs: (a) read fact a, (b) read fact b and (c) compare. Orderings **abc** or **bac** are equally valid but the other four orderings **cab**, **cba**, **acb** and **bca** imply performing a comparison activity when at least one of the values has not yet been ascertained. In our analysis we treat strategies that use the same set of EIPs as similar even if the EIPs used for one or more of the strategies may be differently (but legitimately) ordered. When two strategies have different orderings of the EIPs, it is possible that one might involve a little less eye movement than the other. But our model posits that such possible economies can be safely ignored because they are trivial in comparison with the effect of the total number of required EIPs.

Experience shows that most of these orderings make no sense at all—they will not produce the correct answer and are never used by subjects. Sometimes, however, there are a few orderings that are commonly employed and do, indeed, yield the correct result. In such cases we ignore ordering differences and consider these to be a single strategy. For instance, *Strategy IV*, as described above, involved comparing the lengths of two line segments, then searching the legend for the name of the company with the steeper line. We have chosen to consider the alternative strategy in which the legend was searched first, rather than last, to be operationally equivalent.

A *matched design* for a given combination of a decision task and data is the display that requires fewer EIPs than would be required with any other display. All other displays for the same task and data will be considered mismatched designs. Our definition of match is similar in principle to the notion of cognitive fit, but adds a quantitative function (number of EIPs) applicable to any decomposable task of the type we are investigating. In this sense, our attempt is closer to Norman's concept of naturalness, which builds on a rule-based characterization of human-computer interaction (Polson, 1987).

**Hypotheses:** The proposed model can predict how changes in decision task, data and displays will affect the decision strategies. Our experiment was designed to test these predictions. In addition, we formulate four general hypotheses that capture the underlying mechanisms of the model.

H1: Common strategies are efficient strategies.

H2: Common strategies are employed more frequently when the design is matched than when it is mismatched.

H3: Strategy formulation is faster with matched than with mismatched designs.

Adaptive decision making assumes people tend to choose the least costly strategies that accomplish the task. Common strategies should therefore be efficient. Recall the example of determining which company had the highest growth rate in Figure 2—*Strategy III*. A table of numbers instead of a graph requires a much longer sequence. This is a situation of mismatch. In situations of mismatch, we expect a longer process of strategy formulation as the more obvious strategies (schemata) will be ruled out. Furthermore,

since the mismatch will open up other strategies, a greater variety of strategies is likely to be employed. Hence, common strategies should be more frequent in matched designs.

H4: Errors are less frequent in matched than in mismatch designs.

Errors are more likely in mismatched designs because of the need to transform the representation in order to successfully solve the problem (Norman, 1991; Vessey, 1991).

### 3. Research method

We conducted a laboratory experiment to uncover the actual strategies used by subjects working with a variety of displays, decision tasks and data sets. From these observed strategies we extracted prototypes of the most commonly used strategies for each task/data set combination.

#### 3.1. EXPERIMENTAL DESIGN AND PROCEDURE

Thirty *subjects* each solved 36 unique *exercises* producing 1080 *cases* (30 × 36). An exercise is a combination of one of 3 **D**ecision tasks, 4 **D**ata sets, and 3 **D**isplays (3 × 4 × 3 = 36), i.e. each is a unique DDD combination. The exercises were administered in random order. Thus we have a within-subjects repeated-measures design with three independent factors. The 12 combinations of 3 tasks and 4 data sets are referred to as *problems*.

The subjects were given a notebook with 36 exercises, each on a separate page. Figure 5 shows the sample problem at the head of the notebook. The subjects were asked

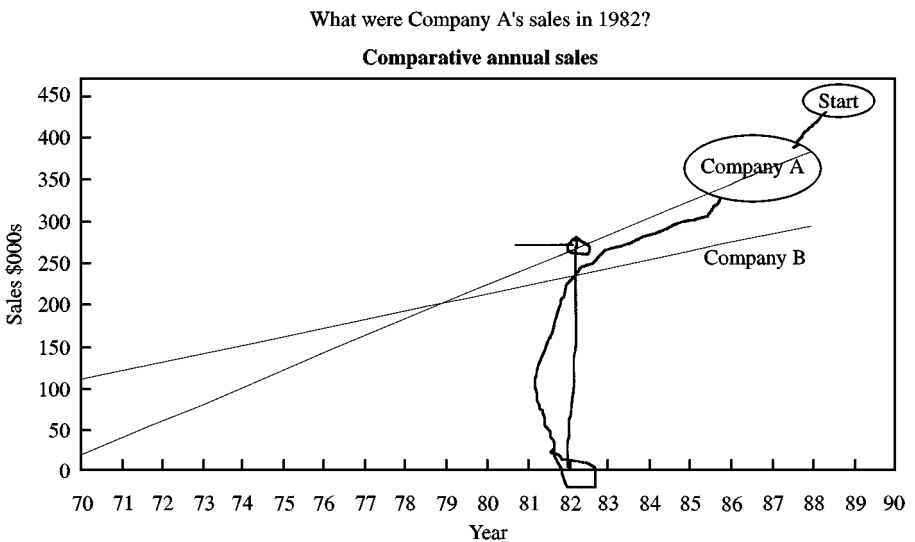


FIGURE 5. Sample display and trace.

to trace the areas of the display to which they referred as they progressed. They did so by using a pen to capture on paper the transitions between areas of interest, and were asked to keep the pen on the paper until they finished the task. Each of the 1080 cases was videotaped in order to help resolve any coding ambiguities.

One of the significant contributions of this study is the successful use of graphical protocol analysis in the study of detailed information acquisition (Benbasat, 1984; Ericsson & Simon, 1980). This study used a new form of graphical protocol which is relatively non-intrusive insofar as it lets users express themselves without having to change their mode of thinking. Furthermore, it identifies each EIP in the process and their order. Subjects were asked to first read the question which was at the top of each page. They were then asked to use a pen to circle the word “*start*” in the upper right-hand corner and then trace the path of interest, circling each area where information is retrieved. These traced protocols, combined with the video, provide a detailed record of the information acquisition process.

Requiring all subjects to begin their traces at the upper right location of the *Start* label seems, in a few cases, to have influenced the sequence in which EIPs were executed. However, we could find no cases where it influenced the set of EIPs selected or the viability of the selected sequence. We therefore believe that this constraint does not diminish the significance or validity of our findings.

We assume here that tracing with a pen does not change the selection of EIPs or the sequence that would have been followed without using a pen. A test supporting this assumption is reported in Treleaven (1990). Although it is possible that the relative timing of EIPs might be distorted by this method, it should be noted that relative timings do not affect our characterization of strategies. In a pilot study with six subjects, all six reported that they did not consider the technique to be intrusive.

A post-test with similar exercises was conducted using 55 subjects, most of whom were working business managers. Here, the subjects worked *on-line*, without pen and paper. Despite this difference, average task execution times (strategy selection plus strategy execution) for both the 1080 cases in this study and the post-test were about the same—approximately 21 s.

### 3.1.1. Subjects

The group of subjects (20 men and 10 women) were volunteers from the population on a university campus, but care was taken to include a mix of staff, faculty, full-time and part-time students so that there was a reasonable diversity in age, gender and level of education. All the subjects volunteered to participate primarily out of interest in the experiment.

### 3.1.2. Task and setting

Each subject was placed in a small private room equipped with a table, a chair and a video camera. A proctor directed the subject to follow the instruction contained in the notebook and pointed at a sample of the tracing technique required. The subjects then answered each of the 36 exercises. The entire session was videotaped. Each session took an average of 30 min.

### 3.2. OPERATIONAL DEFINITIONS

#### 3.2.1. Independent variables

The three variables are display, decision task and data. In combination, they determine the match, which is hypothesized to affect strategy formulation.

- (1) **Displays.** The three formats used were a table (Figure 3), a line graph (Figure 4) and a bar chart. These are the three most common formats found in the bulk of existing studies and in actual practice.
- (2) **Decision tasks.** One of the recurring difficulties in research on information acquisition from graphs and tables is the diversity of tasks. Simon and Newell (1973) and Fleishman (1982) note the importance of dealing with tasks at the appropriate level of aggregation. The more detailed the tasks, the less is the likelihood of confounding factors. However, tasks should also be sufficiently aggregate to have operational meaning in a real-world context. Tan and Benbast (1990) recommended three types of tasks.
  - (a) *Value extraction: What were Company <A>'s sales in <Year>?*  
Question #1 requires the subject to read the value either from the table or off the vertical axis. The subject must also locate the year on the horizontal axis.
  - (b) *Comparison: Which company reached <X> in annual sales first?*  
Question #2 requires the subject to locate the value of <X> on the vertical axis, scan rightwards into the graph and find which company's curve it encounters first.
  - (c) *Trend: Between <Y1> and <Y2>, which company increased sales the most?*  
Question #3 requires the subject to locate the period on the horizontal axis and the sales trends of both companies over the specified period.
- (3) **Data.** Researchers have generally used complexity as a means of differentiating data sets. The four data sets were specifically designed to add a different form of complexity relative to the base data set (Figure 2). In the second set the length of the ordinal variable (year) was varied from 12 to 19 years. In the third set the number of nominal variables (companies) was varied from two to four (Figure 6). These variations are expected to produce an increase in complexity (Lauer, 1986). Finally, the fourth set had more changes in the sign of the slope so the number of intersections of the two curves increased from one to seven (Figure 4). Irregularity in the data has traditionally been considered an important source of complexity (Berlyne, 1960).

#### 3.2.2. Dependent variables

For each of the actual 1080 cases, we measured four variables: the strategy's composition, its efficiency (number of EIPs), accuracy and formulation time. In addition, for the prototypical common strategies that were defined for each of the 36 unique DDD combinations, we measured three variables: the strategy composition and its efficiency (as above), and uniformity—the proportion of subjects who used the common strategy.

- (1) **Strategy composition**—the set of EIPs that were employed (see Section 2.4).
- (2) **Efficiency**—the number of EIPs used.

- (3) **Accuracy**—the accuracy of the result (a boolean variable) judged by whether the problem solution was correct or incorrect. An incorrect outcome, of course, could result from execution errors rather than inappropriate strategies.
- (4) **Strategy formulation time**—the time required to read the task and devise the requisite strategy. Each subject was timed from the moment she turned the page to begin reading a new task until she circled the first part of the display she used. The total strategy formulation time actually captures three activities: reading the problem, formulating a strategy and performing the first scanning EIP.

This measure was chosen for several reasons. It is impractical to distinguish between reading the question and planning the solution. Since the questions were all short and simple, the time required to read them can reasonably be assumed to be a constant. Card, Moran and Newell (1983) define task acquisition as both reading the task and determining the method for execution. For simple tasks, such as those in this study, they assert task acquisition is relatively fixed at between 2 and 3 s. Further, even though subjects were asked to circle the word start when ready to execute, the video often showed considerable thought taking place after circling *start*. As a result, the most consistent break point between formulation and execution was the first circled area of the display. This additional time (first scan) could reasonably be assumed to be roughly constant for each case at between 1.5 and 3.5 s (Treleavan, 1990). The significant source of variation in the total time is, therefore, assumed to be the variance in strategy formulation.

- (5) **Uniformity**. The proportion of subjects employing the common strategy. The statistic ranged from a low of 0.60 (18 out of 30) to a high of 1.0 (all subjects used the same strategy).

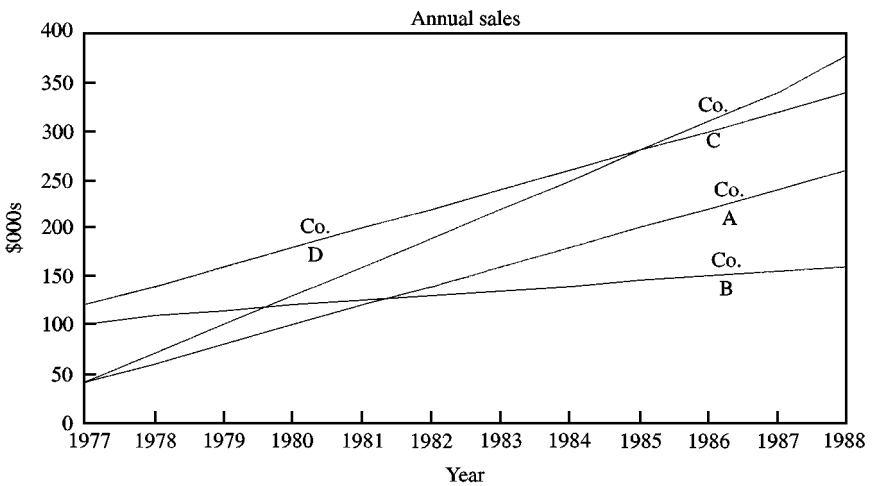


FIGURE 6. Experimental data set 4 (four companies).

TABLE 2

Summary of common strategies. For each DDD combination, two results are shown: uniformity—the fraction of subjects selecting the common strategy (range 60–1.0), and EIPs—the number of EIPs in the common strategy

|       |            | Question 1—Value |      |      |      | Question 2—Compare |      |      |      | Question 3—Trend |      |      |      |
|-------|------------|------------------|------|------|------|--------------------|------|------|------|------------------|------|------|------|
|       |            | 1                | 2    | 3    | 4    | 1                  | 2    | 3    | 4    | 1                | 2    | 3    | 4    |
| Table | Uniformity | 1.0              | 1.0  | 0.93 | 0.96 | 0.96               | 1.0  | 0.96 | 0.90 | 0.93             | 0.93 | 0.93 | 0.90 |
|       | EIPs       | 6                | 6    | 6    | 6    | 7                  | 7    | 7    | 11   | 16               | 16   | 16   | 28   |
| Line  | Uniformity | 0.86             | 0.96 | 1.0  | 1.0  | 1.0                | 0.96 | 1.0  | 0.96 | 0.90             | 0.83 | 0.86 | 0.76 |
|       | EIPs       | 7                | 7    | 7    | 7    | 5                  | 5    | 6    | 5    | 7                | 7    | 10   | 12   |
| Bar   | Uniformity | 0.93             | 0.96 | 0.96 | 0.96 | 1.0                | 0.96 | 1.0  | 0.83 | 0.63             | 0.60 | 0.86 | 0.66 |
|       | EIPs       | 7                | 7    | 7    | 7    | 6                  | 6    | 6    | 9    | 11               | 11   | 11   | 11   |

3.2.3. Analysis

All coding of the protocols was done by one researcher to produce consistent coding across all cases. Coding involved translating the progression from Start to End according to Table 1. To test for experimenter errors, a sample of 30 cases was coded by a second researcher, not one of the authors. Only two of the codings differed and the differences were so minor that the classification of the strategies in question was unaffected.

Each case was coded using both the hardcopy and the video. The first step was to examine the written protocol and then view the video in order to record the EIPs used. The video resolved issues such as missing steps (where the subject failed to trace clearly or at all) or ambiguous order (where the trace was not continuous). Each case was then timed twice using the video tape. The hypotheses regarding times and accuracy were tested using the standard ANOVA procedure within SPSS/PC + (Norusis, 1985). With large sample sizes and cells of approximately equal size, the ANOVA assumptions are satisfied. The hypotheses regarding the use of common strategies and matched and mismatched designs were tested using SPSS's chi-square procedure and by examining cross tabulations. We decided to exclude the first three cases from the analysis on the basis of a regression analysis in which behavior was found to stabilize after three trials (Treleaven, 1990).

In nine of the 30 cells it will be noted that all 30 subjects employed the same common strategy. The lowest uniformity was found for the Bar Graph used for Trend detection on data set 2, but even in this worst case the uniformity measure was 0.60 (18 of 30).

Turning to the EIP count in Table 2, it will be seen that this varied considerably from a low of 5 to a high of 28, indicating that the combination of task-type and data-type can increase required effort more than five-fold.

Comparisons of the Av columns across the Questions shows that Value-extraction and Comparison tasks require about the same amount of effort and that these EIP counts are much lower than those required for Trend detection.

Row-wise comparisons of EIP counts indicate that Tables are slightly better than either kind of graph for Value extraction, but are significantly inferior for Trend

detection. We can also see that Line graphs dominate Bar graphs. More specifically, however, we need to consider how our hypotheses fared in this test.

#### 4. Results

As hypothesized, each of the 36 combinations of data, display and decision task (DDD combinations) did produce a common strategy (these are listed in the appendix). For example, *Strategy I*, which we discussed in Section 2.2, is the common strategy used by 26 of our 30 subjects for the combination of the value extraction task on regular data using a line graph. (In the appendix, this strategy appears as entry #13.)

Table 2 summarizes the results of the protocols for the 36 DDDs. Each cell reports the proportion of subjects using the common strategy (uniformity) and the EIPs count. In nine of the 36 cells, it will be noted that the uniformity measure was 1.0 (all 30 subjects employed the same common strategy). The lowest uniformity was found for the bar graph used for trend detection on data set 2, but even in this worst case with uniformity of 0.60, there were 18 out of 30 subjects who followed the common strategy. The EIP count varied considerably from a low of 5 to a high of 28, indicating that the combination of task-type and data-type can increase required effort more than five-fold.

From Table 2 we can see that Value-extraction and Comparison tasks require about the same amount of effort and that these EIP counts are much lower than those required for trend detection. Comparisons of EIP counts indicate that tables are slightly better than either kind of graph for value extraction, but are significantly inferior for trend detection. We can also see that line graphs dominate bar graphs.

The impact of display type on the number of EIPs in the common strategy was largely as expected. For the value extraction question, tables proved to be slightly more efficient than graphs (six vs seven EIPs), regardless of the data set. For the comparison question, the line graph was most efficient for all data sets, followed closely by the bar chart and the table (mean EIPs of 5, 6 and 8, respectively). The trend question in the same order of efficiency across all data sets but with a much bigger spread (mean EIPs of 9, 11 and 19, respectively).

H1: Common strategies are efficient strategies. The few subjects who employed non-common strategies committed themselves to as much as double the effort (number of steps required to solve the task) of the common strategy. Of the 91 non-common strategies, only nine (0.8% of the 1080 cases) required fewer steps than the common strategies. Upon closer examination, eight of these nine cases resulted in errors and were incomplete or otherwise inaccurate. The ninth case was also incomplete but did fortuitously have a correct response.

The average number of EIPs employed in the common strategies (mean = 8.61 and S.D. = 4.36) was only 52% of the average for the non-common strategies (mean = 16.39 and S.D. = 10.03) and, using a *T*-test for non-equal groups, this difference is significant at the 99.9% confidence level. This result strongly supports H1, that the common strategies are more efficient than the non-common strategies.

An examination of the influence of the problem (task and data) produces some unexpected results. Chi-square results show significant effects for the problem, controlling for both line graphs ( $p = 0.0005$ ) and bar charts ( $p = 0.000$ ) but not for tables ( $p = 0.5$ ). Tables appear to elicit a significant use of the common strategy across all

TABLE 3  
*Frequency of non-common strategies by format and question*

| Task       | 1 (Value) | 2 (Compare) | 3 (Trend) | Total |
|------------|-----------|-------------|-----------|-------|
| Table      | 3*        | 5           | 9         | 17    |
| Line graph | 5         | 2*          | 19*       | 26    |
| Bar chart  | 5         | 6           | 37        | 48    |
| Total      | 13        | 13          | 65        | 91    |

\* indicates matched designs

problems. Data set differences, in the case of tables, have less impact, since they are not as readily apparent to, or exploitable by, the subjects. For line graphs, an unexpected result occurred for the trend question using the data set with four companies. In this case the use of the common strategy was somewhat lower than expected.

H2: Common strategies are more frequent in matched than in mismatched designs. As discussed in Section 2, the preferred display for a given task (and data set) would be the one which matches format to question and thereby minimizes cognitive effort as measured by the number of EIPs required. Following others (e.g. Vessey, 1991), we treat Tables as the matched design for value extraction (Question 1) and Line graphs for comparison and trend questions (Questions 2 and 3). Bar charts are not superior for any of these questions (Tan & Benbasat, 1990). Analysis of the data in Table 2 shows that mismatched designs caused fewer subjects to employ the common strategy.

Table 3 counts the non-common strategies according to display and task, indicating match by an asterisk. Of the 91 total cases which resulted in non-common strategies, 67 (72%) were in the mismatched combinations of format and task. In particular, 37 of them were found in the trend task when using bar charts. Subjects tended to convert the bar chart into a line graph by drawing lines connecting the tops of the bars or by calculating values for the end points, rather than the common strategy of comparing bar heights at the end points. Since bar charts have generally not been considered ideal for detecting trends, this result is not unexpected.

An unexpected result, however, did occur for detecting trends using the preferred line graph. Nineteen, or 20.8%, of the non-common strategies were accounted for here. The majority of these subjects calculated numeric growth rates. In these cases, as in most of the non-common instances, subjects appeared to be sacrificing efficiency for accuracy. Some people appear not to rely on the expected visual cues in line graphs even for the least complex data patterns. In total, 71.4% of the non-common strategies were used for trend detection tasks, where alternative strategies appear to be more prevalent. Recall, however, that the vast majority of subjects used the common strategy for this question also.

H3: Strategy formulation is faster in matched than in mismatched designs. For matched designs, strategy formulation was indeed faster (the means of matched designs and mismatched are 8.61 and 9.33 s, respectively, and their standard deviations are 3.35 and 3.17, respectively). Using ANOVA this result is significant at the 99% confidence level, strongly supporting the hypothesis. A significant conclusion is that, in addition to



having the most efficient strategy, the preferred display for a given task will also be easiest to select.

H4: Errors are less frequent in matched than in mismatched designs. This result is in the expected direction—accuracy for matched designs is higher than for mismatched designs—but is not confirmed statistically ( $p = 0.08$ ) with chi-square, probably because errors are so uncommon.

## 5. Limitations, implications and directions for future research

Our objective was to develop a framework for studying strategy formulation and execution for Decision tasks that involved the extraction of quantitative information under different combinations of Display and Data. We assume that decision makers adapt to different conditions by selecting the strategy that accomplishes the task with minimum cognitive costs. This tendency is clearest when the display presents the data in a form that is well matched to the needs of the decision task, making it easier for the decision maker to formulate and execute the most efficient strategy. We therefore hypothesized that common strategies are efficient and are likely to be used more frequently when the display is matched. We further hypothesized that with matched designs, strategies are formulated faster and executed more accurately. The results show that indeed different DDD combinations produced different common strategies and that these common strategies are significantly more efficient than non-common strategies. Secondly, in the mismatched designs, fewer subjects used the common strategy and it took them longer, on average, to formulate a strategy. Finally, there were fewer errors in the matched designs but this result was not statistically significant ( $p = 0.08$ ), probably because of the very low absolute number of errors overall.

In sum, the evidence from the experiment generally supported the model's predictions. The vast majority of subjects adapted their behavior according to the task and selected strategies that were easy to predict because they minimized effort while preserving accuracy. The concept of match between display and problem appears to be useful, as demonstrated previously by Vessey and Galletta (1991). It helps to show that behavior is predictable and tends to be more efficient when the display is well suited to the task. Moreover, the simplicity of the strategy descriptions makes it feasible to think of automated mechanisms for matching the display to the specific conditions.

The primary limitations of this study are methodological because of the need to measure “black box” processes. It was difficult to measure directly the strategy formulation time. The mean total strategy formulation time of 8 s appears to be plausible based on the expected values of the three components: reading, selecting and scanning. Reading the question should require approximately 2 s (Card *et al.*, 1983), selecting a strategy about 5 s (Treleaven, 1990) and scanning to the first point approximately 2 s, for a total of 9 s. This provides some comfort that, while the measured time included activities other than devising a strategy, the magnitude of the result and the sources of variance are reasonable. Nonetheless, it would be desirable to replicate this study using other measures.

It was infeasible to describe an information acquisition strategy and assess its complexity before the strategy was executed and observed. Moreover, both the strategy and the complexity are functions of three factors: data, decision task and display. As a result,

it was necessary to reconstruct the strategy using the details of the specific context. We did so by using the bi-level representation of EIPs and strategies. The five classes of EIPs (Table 1) were drawn from the decision making and graphics literature. They are used to describe human-computer interaction that bridges the gap between the task level and the physical level (Norman, 1991). This set was sufficient for the tasks in the experiment, but clearly may have to be expanded and refined to fit other tasks, e.g. tasks that include hand movements or more complex calculations and manipulations. We believe, however, that the basic approach can be extended.

We used the number of EIPs as a measure of the overall complexity that results from the combination of task, data and display. In some cases, however, the differences between the effort required for different EIPs might be significant enough to warrant the use of a weighted sum of EIPs as the complexity measure, rather than the simple count we used; this deserves further research. Particularly relevant would be cases in which there are different classes of processes (e.g. motoric processes) or different types of computations in decision making.

Furthermore, the emphasis on complexity (effort) as opposed to accuracy in the cost-benefit tradeoff, although common in empirical investigations, must be questioned in other cases. In fact, some of our anecdotal observations indicate that accuracy may act as a precondition to a comparison of costs. In other words, accuracy may be a yes/no feasibility test and effort a comparative test within the feasible set. This may be an interesting direction of augmenting the cost-benefit framework (cf. image theory—Beach & Mitchell, 1987).

The task domain of the study was relatively structured. Though these results may be generalized to other structured domains, it would be difficult to generalize the findings to unstructured decision-making activities. Indeed, Card *et al.* (1983) note that strategy formulation is less predictable in unstructured situations. It would seem important to test empirically the notion of common strategies in a less structured situation and what affects the level of commonality. Clearly, familiarity plays some role in the notion of match, but this is not to say that the notion of match is irrelevant to unfamiliar situations.

Finally, the study did not explicitly consider individual differences. The subjects were chosen to represent a heterogeneous sample, since commonality in strategy selection was a central focus of the study. As a result, the findings should exhibit external validity. Nevertheless, future studies might investigate individual differences, since these might cause certain EIPs to require extra effort which could lead to different strategy choices. Moreover, in line with the notion of trading accuracy for effort, individual differences that result in different tradeoffs might be relevant. For example, reflective individuals may prefer strategies that are more accurate even though they are less efficient (Messer, 1976). Future research should try to identify how such individual differences affect strategy formulation.

We believe our research has potential applications in a number of related fields. Our findings suggest that human behavior is reasonably efficient and predictable in information acquisition tasks such as the ones we studied. We used the bi-level representation of EIPs and strategies to relate the functional aspects of the task with the physical aspects of the form of data.

Both the approach and the findings are of importance to the designers of human-computer interfaces. Since task is the dominant factor, it might be desirable to

rework a number of human–computer dialogues. When a spreadsheet user wishes to present a subset of his data, for instance, he is currently offered a dialogue such as: Select (Line graph, Pie chart, Bar chart). A better alternative might be: Purpose of this display? (Detect trend, find turning-point, extract largest). The system would then automatically pick the display format that best matched the data-set and the selected purpose.

To fully exploit our findings and to evaluate their practical significance, further research is needed to relate individual fact acquisition tasks to the larger processes of which they are a part. Several such processes are relevant—we have stressed managerial decision making, but, education, training and advocacy are others requiring fact acquisition. Each of these will generally require the acquisition of multiple facts; research is needed to determine whether a single display format will be best for this collection of tasks. In the (likely) event that no one display is collectively optimal, there will need to be research on the presentation of multiple displays.

One must recognize that display format may influence the quality of outcomes of the process in subtle ways that go beyond the acquisition of individual facts. For instance, one needs to consider how the display may influence attention and recall. The use of information is often part of an ill-structured process that requires not only exploration of tentative hypotheses but also backtracking when dead ends are encountered. The overall utility of a display may thus depend, in part, on the extent to which it facilitates backtracking by improved recall of facts previously acquired. Clearly, much further research will be needed if we are to expand the present findings to the larger context of the overall processes involved in decision-making and information use.

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## Appendix: Common strategies

Table A1 lists the mnemonics used to describe the EIPs in the common strategies.

TABLE A1

| Class        | EIP               | Mnemonic |
|--------------|-------------------|----------|
| I. Scan to   | 1. Y-axis         | SCY      |
|              | 2. Bar/line       | SCB      |
|              | 3. X-axis         | SCX      |
|              | 4. Table column   | SCT      |
|              | 5. Legend         | SCL      |
| II. Search   | 6. X-axis (yr)    | SRX      |
|              | 7. Y-axis (value) | SRY      |
|              | 8. Table point    | SRT      |
|              | 9. Legend         | SRL      |
| III. Compare | 13. Slopes        | CRA      |
|              | 14. Length/gap    | CRL      |
|              | 15. Height        | CRH      |
|              | 16. Values        | CRV      |
| IV. Read     | 10. Data          | RED      |
|              | 11. Text          | RET      |
| V. Compute   | 12. Add/subtract  | CPT      |

Table A2 has 36 rows, one for each DDD combination—Display, Decision task and Data set. The numbers within each factor correspond to the numbers in the text describing the independent variables. The strategies are described by the sequence of EIP mnemonics defined below in the legend. The last column is the match/mismatch judgement—for each task and data set, only one display is matched.

Data set 1 = short, regular; 2 = long, regular; 3 = irregular; 4 = 4 nominal variables.

For example, Strategy I (Section 22) for regular data on a line graph with the value extraction task is equivalent to case #13 in Table A2 and Strategy II (Section 2.3.1) for regular data on a table is case #1, Strategy III (Section 2.3.2) for the trend task is case #21 and Strategy IV (Section 2.3.2) for irregular data is case #23.

TABLE A2

| Case no. | Display | Task | Data no. | Protocols Ordered EIPs  | Tot EIPs | Match Mismatch |
|----------|---------|------|----------|---|----------|----------------|
| 1        | TAB     | VAL  | 1        | SCL, SRL, SCT, SRT, SCT, RED  | 6        | MAT            |
| 2        | TAB     | VAL  | 2        | SCL, SRL, SCT, SRT, SCB, RED  | 6        | MAT            |
| 3        | TAB     | VAL  | 3        | SCL, SRL, SCT, SRT, SCT, RED  | 6        | MAT            |
| 4        | TAB     | VAL  | 4        | SCL, SRL, SCT, SRT, SCT, RED  | 6        | MAT            |
| 5        | TAB     | WHN  | 1        | SCL, SRT, SCT, RED, SRT, SCL, RET   | 7        | MIS            |
| 6        | TAB     | WHN  | 2        | SCT, SRT, SCT, SRT, CRH, SCL, RET   | 7        | MIS            |
| 7        | TAB     | WHN  | 3        | SCT, SRT, SCT, RED, SRT, SCL, RET   | 7        | MIS            |
| 8        | TAB     | WHN  | 4        | SCT, SRT, SCT, SRT, SCT, SRT, SCT, SRT, CRH, SCL, RET   | 11       | MIS            |
| 9        | TAB     | TRD  | 1        | SCT, SRT, SRT, SCT, RED, SCT, RED, SCT, RED, SCT, RED, CPT, CPT, CPV, SCL, RET  | 16       | MIS            |
| 10       | TAB     | TRD  | 2        | SCT, SRT, SRT, SCT, RED, SCT, RED, CPT, SCT, RED, SCT, RED, CPT, CRV, SCL, RET  | 16       | MIS            |
| 11       | TAB     | TRD  | 3        | SCT, SRT, SRT, SCT, RED, SCT, RED, CPT, SCT, RED, SCT, RED, CPT, CPV, SCL, RET  | 16       | MIS            |
| 12       | TAB     | TRD  | 4        | SCT, SRT, SRT, SCT, RED, SCT, RED, CPT, SCT, RED, SCT, RED, CPT, SCT, RED, SCT, RED, CPT, SCT, RED, SCT, RED, CPT, CPV, CPV, SCL, RET | 28       | MIS            |
| 13       | LIN     | VAL  | 1        | SCL, SRL, SCX, SRX, SCB, SCY, RED   | 7        | MIS            |
| 14       | LIN     | VAL  | 2        | SCL, SRL, SCX, SRX, SCB, SCX, RED   | 7        | MIS            |
| 15       | LIN     | VAL  | 3        | SCL, SRL, SCX, SRX, SCB, SCY, RED   | 7        | MIS            |
| 16       | LIN     | VAL  | 4        | SCL, SRL, SCX, SRX, SCB, SCY, RED   | 7        | MIS            |
| 17       | LIN     | WHN  | 1        | SCY, SRY, SCB, SCL, RET   | 5        | MAT            |
| 18       | LIN     | WHN  | 2        | SCX, SRX, SCB, SCL, RET   | 5        | MAT            |
| 19       | LIN     | WHN  | 3        | SCY, SRY, SCB, SCL, RET   | 6        | MAT            |
| 20       | LIN     | WHN  | 4        | SCY, SRY, SCB, SCL, RET   | 5        | MAT            |
| 21       | LIN     | TRD  | 1        | SCX, SRX, SRX, SCB, CRA, SCL, RET   | 7        | MAT            |
| 22       | LIN     | TRD  | 2        | SCX, SRX, SRX, SCB, CRA, SCL, RET   | 7        | MAT            |
| 23       | LIN     | TRD  | 3        | SCX, SRX, SRX, SCB, CRL, SCB, CRL, CRL, SCL, RET  | 10       | MAT            |
| 24       | LIN     | TRD  | 4        | SCX, SRX, SRX, SCB, SCB, CRA, SCB, CRA, SCB, CRA, SCL, RET  | 12       | MAT            |
| 25       | BAR     | VAL  | 1        | SCL, SRL, SCX, SRX, SCB, SCY, RED   | 7        | MIS            |
| 26       | BAR     | VAL  | 2        | SCL, SRL, SCX, SRX, SCB, SCX, RED   | 7        | MIS            |
| 27       | BAR     | VAL  | 3        | SCL, SRL, SCX, SRX, SCB, SCY, RED   | 7        | MIS            |
| 28       | BAR     | VAL  | 4        | SCL, SRL, SCX, SRX, SCB, SCY, RED   | 7        | MIS            |
| 29       | BAR     | WHN  | 1        | SCY, SRY, SCB, SCL, SRL, RET  | 6        | MIS            |
| 30       | BAR     | WHN  | 2        | SCX, SRX, SCB, SCL, SRL, RET  | 6        | MIS            |
| 31       | BAR     | WHN  | 3        | SCX, SRX, SCB, SCL, SRL, RET  | 6        | MIS            |
| 32       | BAR     | WHN  | 4        | SCY, SRY, SCB, SCB, SCB, SCB, SCL, SRL, RET   | 9        | MIS            |
| 33       | BAR     | TRD  | 1        | SCX, SRX, SRX, SCB, CRH, SCB, CRH, CRL, SCL, SRL, RET   | 11       | MIS            |
| 34       | BAR     | TRD  | 2        | SCX, SRX, SRX, SCB, CRH, SCB, CRH, CRH, SCL, SRL, RET   | 11       | MIS            |
| 35       | BAR     | TRD  | 3        | SCX, SRX, SRX, SCB, CRH, SCB, CRH, CRH, SCL, SRL, RET   | 11       | MIS            |
| 36       | BAR     | TRD  | 4        | SCX, SRX, SRX, SCB, CRH, SCB, CRH, CRH, SCL, SRL, RET   | 11       | MIS            |