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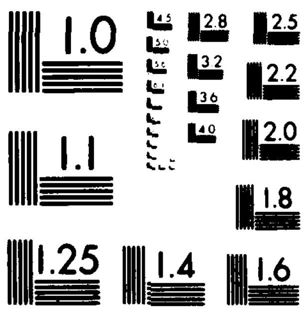

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MODELS OF STRATEGY AND STRATEGY-SHIFTING IN SPATIAL VISUALIZATION PERFORMANCE

PATRICK C. KYLLONEN
DAN J. WOLTZ
AND
DAVID F. LOHMAN

TECHNICAL REPORT NO. 17
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The relationship of aptitude, strategy, and cognitive task performance is explored through the use of mathematical models of performance time. Models of strategy and strategy-shifting on a spatial visualization task were tested individually for 30 male high school and college subjects. For each of three successive task steps (encoding, construction, and comparison), different models applied for different subjects suggesting that different subjects used different strategies for solving the same items. Some of the best fitting models specified that subjects

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SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered) frequently and flexibly switched strategies during the task in keeping with variations in item demands. This was considered a form of adaptive, within-task learning. Three alternative cases of aptitude-strategy relationship were examined. For the encoding and construction steps the most efficient strategy was restricted to subjects with a particular aptitude profile. For the comparison step, strategy selection appeared to be a more casual choice but aptitude differentially mediated performance depending on which strategy had been selected. The importance of strategy-shift models as a means for analyzing more precisely subjects' problem solving processes and for representing the adaptive, flexible quality of intelligent performance is discussed.

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We would like to thank Richard Snow for helpful comments on an earlier draft of this report.

OCTOBER 1981

PREFACE

The investigation reported herein is part of an ongoing research project aimed at understanding the nature and importance of individual differences in aptitude for learning. Information regarding this project and requests for copies of this or other technical reports should be addressed to:

Professor Richard E. Snow, Principal Investigator
Aptitude Research Project
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Abstract

The relationship of aptitude, strategy, and cognitive task performance is explored through the use of mathematical models of performance time. Models of strategy and strategy-shifting on a spatial visualization task were tested individually for 30 male high school and college subjects. For each of three successive task steps (encoding, construction, and comparison), different models applied for different subjects suggesting that different subjects used different strategies for solving the same items. Some of the best fitting models specified that subjects frequently and flexibly switched strategies during the task in keeping with variations in item demands. This was considered a form of adaptive, within-task learning. Three alternative cases of aptitude-strategy relationship were examined. For the encoding and construction steps the most efficient strategy was restricted to subjects with a particular aptitude profile. For the comparison step, strategy selection appeared to be a more casual choice but aptitude differentially mediated performance depending on which strategy had been selected. The importance of strategy-shift models as a means for analyzing more precisely subjects' problem solving processes and for representing the adaptive, flexible quality of intelligent performance is discussed.

Models of Strategy and Strategy-Shifting in Spatial Visualization Performance

Current research on aptitude uses information processing models to identify components of cognitive performance. Using such models, individuals have been found to differ parametrically, that is, in the efficiency with which particular performance components are executed (Chiang & Atkinson, 1976; Hunt, Frost, & Lunneborg, 1973; Snow, Marshalek, & Lohman, Note 1). It is also possible, however, that individuals differ in the sequence or type of components they employ. Snow (1978) proposed three sources of individual differences in task performance beyond simple parametric differences: sequence differences, where subjects differ in the order in which processing steps are executed; route differences, where subjects differ in the steps that are included; and summation or strategy differences, where the whole processing program adopted differs from subject to subject, or differs within a subject for different items within a task. Sternberg (1977) offered a similar hypothesis using other terminology. These sources have all been loosely referred to as strategy differences, and there is now some evidence that strategies affect performance and relate to aptitude differences (Cooper, 1980; MacLeod, Hunt, & Mathews, 1978; Sternberg & Weil, 1980; Kyllonen, Lohman & Snow, Note 2). It is important, however, for further research to distinguish among Snow's four source categories. In particular, if subjects regularly shift strategies within a task, then the prevailing theory that assumes a constant information processing model across items is wrong.

This investigation hypothesized two types of strategy-shifting within a task: *sequence-shifting*, where subjects vary the sequence in which different processing operations are applied across items; and *route-shifting*, where subjects apply qualitatively different processing operations for different items. Although potentially involved in all types of cognitive tasks, strategy-shifting may be particularly important in performance on spatial visualization tasks, which have long been thought subject to alternative solution strategies (French, 1965; Lohman, Note 3).

A further purpose here was to distinguish three possible types of aptitude-strategy relationships. In a *Case I* relationship, strategy selection is limited by aptitude; use of a strategy requires particular skills. Evidence for this possibility was obtained in a study of aptitude-strategy training interaction, where the training treatment appeared effective only if the subject's aptitude profile matched the strategy being trained (Kyllonen, Lohman, & Snow, Note 2). Case I relationships have also been suggested in syllogistic reasoning (Egan & Grimes, Note 4) and cube comparison tasks (Carpenter & Just, Note 5) in which the more efficient strategies have tended to be used by the more able subjects. A *Case II* relationship between aptitude and strategy specifies that strategy choice is unrelated to aptitude; once the decision is made to use a particular strategy, however, a person's effectiveness in the task is dependent on the aptitude called into play by the strategy. Sternberg and Weil (1980) found evidence for a Case II relationship. Those using a spatial strategy on linear syllogisms showed a relationship between spatial but not verbal ability and solution time, and those who spontaneously selected a linguistic strategy showed a relationship between verbal but not spatial ability and solution time. A similar Case II relationship was found in a sentence-picture verification task (MacLeod, Hunt, & Mathews, 1978). A *Case III* relationship between aptitude and strategy combines Cases I and II: Aptitude both restricts *strategy selection* and limits the effective use of the strategy selected. This possibility has not yet been demonstrated, but is explicitly tested here.

This study reanalyzed data collected by Lohman (Note 6) as part of a dissertation on spatial ability. Lohman's original analyses assessed the relationship between speed of problem solving and difficulty level of the problem solved, but specific information processing models were not tested. His task was ideally suited for examining the alternative processing models hypothesized here, however, since subjects were required to perform a variety of mental operations on visual forms. Further, extensive aptitude information was available for each subject.

Method

Subjects

Subjects were 30 male Palo Alto high school and Stanford undergraduate students selected to represent a wide range of ability. Subjects had previously been administered a large battery of reference aptitude tests including measures of general crystallized (Gc), general fluid (Gf), general visualization (Gv), closure speed (CS) perceptual speed (PS), visual memory (VM), and memory span (MS), abilities. (See Snow, Lohman, Marshalek, Yalow, & Webb, Note 7, for details regarding the administration and analysis of the reference battery.)

Composite aptitude scores were created for each subject by summing standardized (zero mean, unit variance) individual test scores. Thus, Gc was a composite of the WAIS subtests Vocabulary, Information, Comprehension, and Similarities (Wechsler, 1955); Gf was a composite of a concept analogy test (Terman, 1950), progressive matrices (Raven, 1962), Letter Series, (French, Ekstrom, & Price, 1963), and Necessary Arithmetic Operations (French, et al., 1963); Gv was a composite of Form Board, Paper Folding, Surface Development, and Hidden Figures (French, et al., 1963); CS was a composite of two figure gestalt tests (French, et al., 1963; Harshman, 1974); PS was a composite of Digit-Symbol (Wechsler, 1955), Number Comparison, and Finding A's (French, et al., 1963); VM was a composite of Memory for Designs (Graham & Kendall, 1948) and Visual-Number Span (Wechsler, 1955); and MS was a composite of forward and backward digit span (Wechsler, 1955).

Task

The task consisted of 216 items designed to measure spatial visualization ability. A typical item proceeded as follows. First, during an *encoding* step, subjects were presented with a three- to eight-sided figure, referred to as the *A* figure. Next, during a *construction* step, subjects were presented with one or two other figures, referred to as the *B* and *C* figures, which they were to combine mentally with the *A* figure. They did this by imagining the figure that would be formed if the *A* figure were adjoined either to the left or the right side of the *B* figure (depending on individual item instructions), and if the *AB* composite figure were similarly adjoined to the C figure. Finally, during a *comparison* step, subjects were presented with a test probe and required to indicate whether the image formed during the encoding and construction steps was the same as or different from the test probe. Figure 1 depicts this sequence of presented steps. (A fourth step, *rotation*, occurred between construction and comparison for two thirds of the items and required subjects to rotate their mental image 90 or 180 degrees. The rotation step is ignored in the present analysis, however.)

Insert Figure 1 about here

Subjects controlled presentation of item steps. Steps were performed in the same order for each item; turning back was not permitted. Response time for each step and correctness at the comparison step were recorded by the experimenter.

Design

There were three major item facets. First, three levels of the construction facet corresponded to the number of figures to be combined with the *A* figure: zero, one, or two. Second, there were two types of figure combination during construction: combination from the left side of the *B* and *C* figures and combination from the right side. (The side to be used was indicated by a plus sign appearing either to the left or the right of the *B* and *C* figures; Figure 1 shows an example of combination from the left.) Third, for half the items the test probe was the same as the constructed image and for half it was different. Figure complexity, defined by the number of sides, was balanced across these three facets, as was product image complexity (i.e. the number of sides in the figure formed by combining the *A*, *B*, and *C* figures).

Subjects were administered the 216 items in four blocks of 54 and paid $3.00 per hour for participating. They were allowed as much time as they needed to complete a step but were encouraged to work as quickly as possible. *Items were presented in random order.* For further details on the procedure, see Lohman (Note 6).

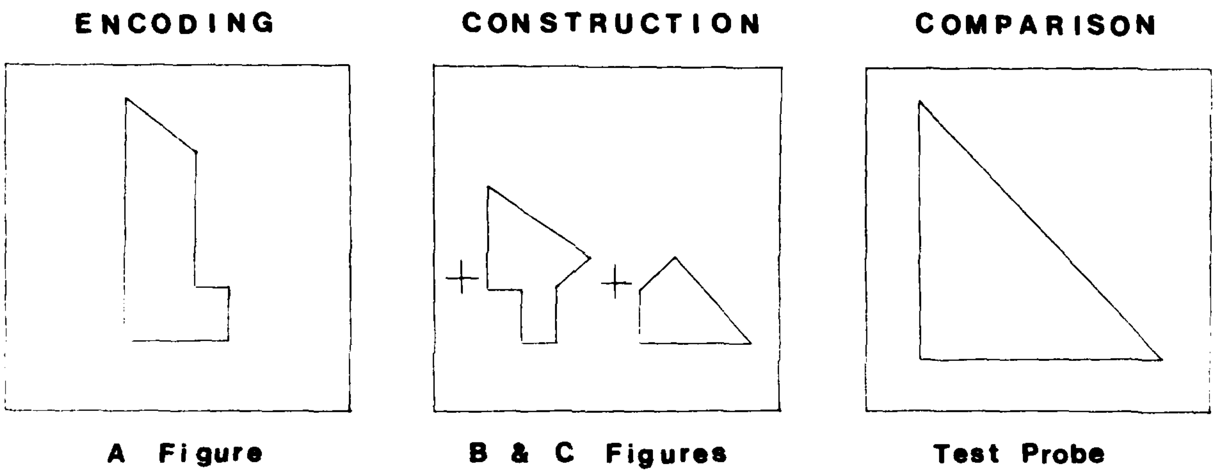

Figure 1. Depiction of sequence of task steps for typical item.

Model Testing

Various information processing models were tested separately for each subject and each step. For encoding all item times were fit, for construction only correct items were fit, and for comparison only correct items of the 72 that did not include a rotation step were fit. Modeling techniques were similar to the componential analysis procedures described by Sternberg (1977), with extensions to allow for strategy-shifting. In componential analysis, the investigator constructs flowcharts indicating possible sequences of mental events occurring in subjects performing a task. Each box in a flowchart represents a time consuming mental operation. A mathematical model of the flowchart sequence is expressed as a multiple regression equation in which performance time is the dependent variable, each term corresponding to a flowchart box is an independent variable, and either the number (for discrete variables) or the amount (for continuous variables) of operation executions is the value of the independent variable.

A sequence-shifting model specifies that the subject applies the same mental operations during all items in the task but varies either the sequence in which the elements within the item are operated upon (elements in this task were defined as the individual figures) or the sequence in which the operations themselves are applied. Route-shifting is a second type of strategy-shift model which specifies that subjects call upon one set of cognitive operations for some items and a partially or wholly different set for other items. (See Appendix A for details on strategy-shift models and the mechanics of testing them).

Results

Results are presented separately for each of the three task steps. In each case, we addressed two questions. First, do different strategies result in faster or more error free performances? Second, does aptitude affect strategy selection, or does it appear to mediate performance within a strategy group, or both?

Models for Encoding

Three consistent strategy models and a route-shifting model were tested for the encoding step. The models were similar in assuming that performance time during encoding is related to the form in which the *A* figure is represented for storage, but different in specifying how the figure is represented. Storage is assumed to be a process in which a mental representation of the *A* figure is constructed and stored in long-term memory so as to be resistant to interference from stimuli in subsequent steps. Though this assumption was not tested here, in a similar study involving spatial visualization (a figure analogy task), subjects did apparently commit figures to long-term memory as indicated, since they were highly accurate in figure recall on a delayed test even though they were not instructed to remember the figures (Bethell-Fox, Lohman, & Snow, Note 8).

Model E-I specified a *feature-analytic* strategy in which the figure is analyzed and stored as a set of basic features. This type of model of form memory has been used in previous research (Attneave, 1957) and accounts for the fact that more complex figures require longer study times. Complexity is usually defined as the number of sides in a randomly constructed figure. The figures used here were not randomly constructed, however, so variables in addition to number of sides were needed to account for figure complexity; these were the number of different side lengths, the number of different angle sizes, and the *number of irregular side orientations* (not counting horizontal and vertical orientations). Number of sides and the three additional variables together accounted for 87% of the variance in rated complexity of the encoding step figures. (Half the 216 figures were rated for complexity by six independent judges.) The regression equation that predicted the standardized ratings was:

$$
\begin{aligned}
C = {} & 1.83 \text{ (square root of number of sides)} \\
& + 0.08 \text{ (number of independent side lengths)} \\
& + 0.25 \text{ (number of independent angles)} \\
& + 0.64 \text{ (number of irregular orientations)} \\
& - 0.07 \text{ (number of irregular orientations X number of sides)} \\
& - 5.78,
\end{aligned}
$$

where C is the sum of the standardized (zero mean, unit variance) complexity ratings. In information processing terms, the additional variables account for the fact that during encoding subjects notice and take advantage of the redundancy in figures to reduce processing time.

In addition to the standard feature-analytic model two *complexity-reduction* models for remembering a figure were tested. Model E-II specified a *figure-decomposition* strategy in which a subject is assumed to imagine the figure broken into basic units such as triangles and rectangles. The figure is then represented internally as, for example, an image of a triangle on top of a square. This strategy requires that the subject overcome the natural figure gestalt and impose imaginary lines. That is, the subject "reads" something into the figure to reduce subsequent memory burden. The decomposition model predicts that encoding time is a function of the number of basic units making up the figure and the complexity of those units. It was necessary to retain the complexity variables in this model since not all figures could be decomposed into equally complex units. The inclusion of complexity variables allowed for the reasonable prediction that an image of an equilateral triangle on top of a square, for example, would take less time to encode than an image of an isosceles triangle on top of a rectangle. In both cases the figure breaks into two units, but the units are more complex in the latter case, and are thus predicted to take more time to process.

Model E-III was a second complexity-reduction model specifying a *verbal-labeling* strategy. Subjects using this strategy reduce memory burden by applying a verbal label that describes the figure as a whole, and then remembering the label. Encoding time is assumed to be a function of the difficulty of creating a label that adequately describes the figure. To determine a figure's "labelability," six independent judges rated how difficult it was to think of an adequate verbal label for each figure. (Although a figure's labelability is related to its complexity, the two characteristics are not identical. Only 65% of the variance in labelability was accounted for by the objective figure characteristics that accounted for 87% of the variance in rated complexity.)

Finally, a fourth model represented the strategy of shifting between the two complexity-reduction strategies, labeling some figures and decomposing others. To determine which figures were labeled and which decomposed, we compared subjective ratings of the ease of decomposition with ratings of the ease of labeling. A 50-50 shift model specified that figures for which labeling is easier than decomposition are remembered with a labeling strategy and the rest are remembered with a decomposition strategy. We also tested two 75-25 models in which a subject is assumed to be predisposed toward either labeling or decomposing. All the shift models for encoding were route-shifting models, since the variables that predicted encoding time were not the same for all items but depended on which strategic "route" was selected.

Results for Encoding

In general, the results supported the validity of the models and led to insights into the relationship between aptitude and strategy. No subject was fit perfectly by any model, but a comparison of model fits allowed reasonable judgments about which strategy each subject used. (See Appendix B, Table B1, for actual R^2 values for all models; and for a summary of model predictors, Table B4.)

Figure 2 shows overall errors and encoding times and identifies the best fitting model for each subject. There is an indication that speed-accuracy tradeoff was related to the strategy subjects used for encoding. Subjects best fit by the feature-analytic model committed few errors but spent a long time encoding. Apparently, the feature-analytic strategy led to good representations of the figure and therefore resulted in comparatively few errors. However, this strategy was costly, especially with complex figures; with no complexity-reduction scheme applied, the sheer number of features to remember led to long encoding times.

Insert Figure 2 about here

The two complexity-reduction strategies, labeling and decomposition, resulted in significantly shorter encoding times than the feature-analytic strategy. However, the two strategies differed with respect to error. Subjects best fit by the decomposition model appeared to engage in an optimal speed-accuracy tradeoff. They committed few errors and encoded quickly. Subjects best fit by a labeling model generally encoded quickly but made many errors. Applying a verbal label is apparently a quick way of remembering a figure, even a complex one. But use of the labeling strategy is perhaps likely to result in an inadequate representation of the *A* figure and therefore increases the

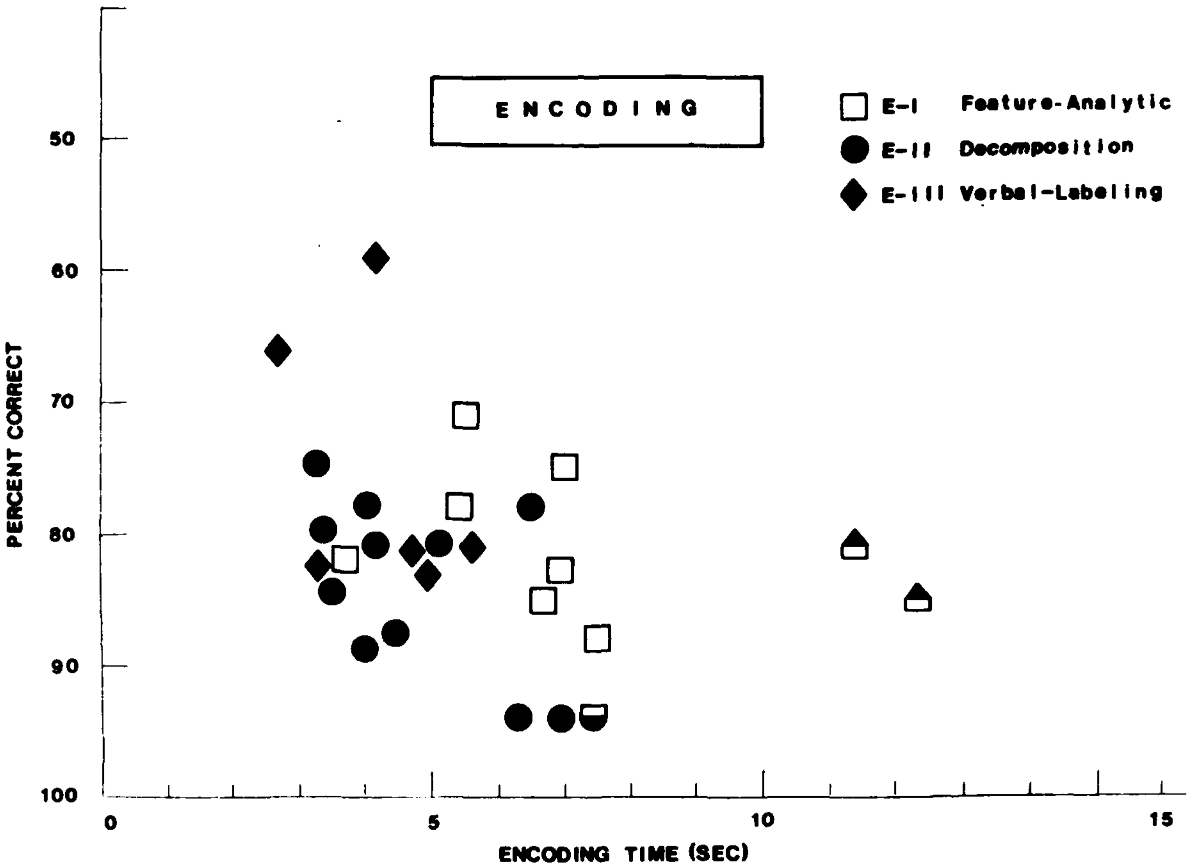

Figure 2. Encoding time vs. overall correctness (216 items; combined symbols indicate more than one best fitting model).

chances of error. No one was best fit by the 100% labeling model. Those so identified in Figure 2 labeled at least 50% of the time as determined by the strategy-shift models.

Thus, decomposition appears to be the most efficient strategy for encoding. Why then did most subjects fail to use it? We examined the hypothesis that aptitude restricts strategy choice (a Case I relationship) by comparing the aptitude profiles of members of the three strategy groups. We also examined the hypothesis that certain aptitudes affect performance within a strategy group (a Case II relationship) by correlating correctness scores and encoding times with the aptitude measures separately for members of each strategy group. The results indicated a Case III relationship between aptitude and strategy for encoding. Aptitude appeared both to restrict strategy choice and to determine performance success within a strategy group.

Figure 3 shows that subjects who used the decomposition strategy were generally higher in aptitude than those in the other two strategy groups, but the difference was greatest on closure speed (CS) and spatial visualization (Gv) aptitude measures. The superiority in spatial visualization ability is not surprising, but why were the decomposers so much higher than others on closure speed? Perhaps because closure speed represents the ability to impose a certain type of structure on forms--to "read in" parts of incomplete figures to make them whole. Similarly, decomposition is a strategy that requires one to impose a certain kind of stucture on the figure--to imagine lines that break the whole into parts. We might speculate that the feature-analyzers would have used the more efficient decomposition strategy had they been better equipped with the skills represented by CS, as well as those represented by Gv. In any event, the choice of the decomposition strategy appeared to be restricted by aptitude.

Insert Figure 3 about here

Table 1 shows that for each strategy group correctness was related most highly to spatial visualization (Gv) ability. More interestingly, for those who selected the feature-analytic strategy, performance depended also on memory span (MS), presumably because the feature-analytic strategy placed a severe burden on memory. The labeling strategy would presumably demand verbal ability more than spatial ability, but the results do not support this expectation. With relatively few subjects in the labeling strategy group, and the possibility that all were sufficiently skilled verbally to use this strategy, it is possible that the data are insufficient to test this hypothesis adequately.

Insert Table 1 about here

Finally, strategy-shifting occurred with experience on the task. The various encoding models were tested separately for the four blocks of 54 items. It appeared that subjects started out, in Block 1, by happening upon an encoding strategy; for 17 subjects this was the feature-analytic strategy. By Block 4, however, the feature-analytic

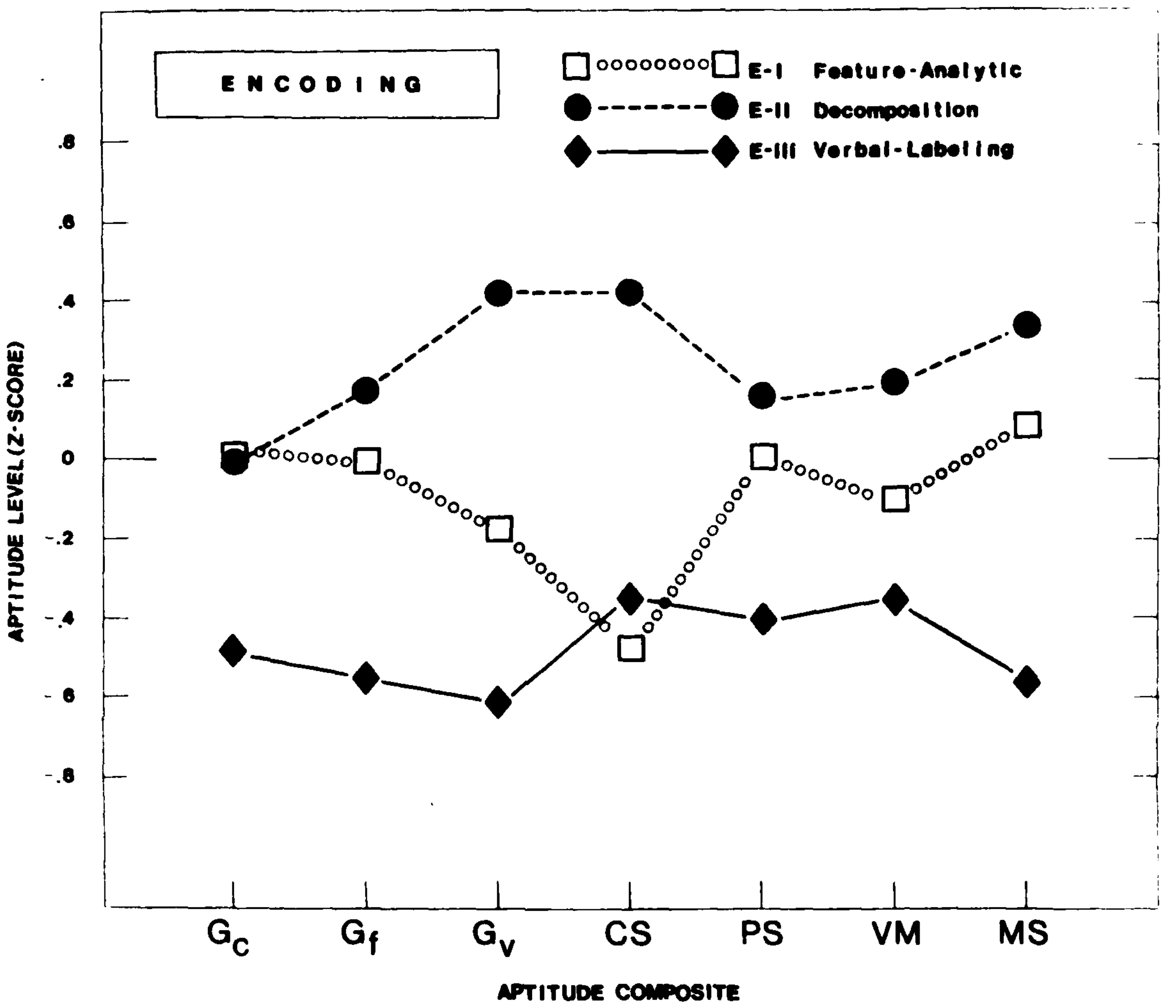

Figure 3. Aptitude profiles for subjects in various encoding strategy groups (see text for aptitude composite descriptions).

Table 1

Aptitude Performance Correlations Within Strategy Group for the Encoding Subtask

Model	Description	Gc	Gf	Gv	Cs	PS	VM	MS	M[b]	SD	N[c]
		Aptitude[a]									
		Item Correctness									
	overall	50*	58*	74*	13	37*	54*	51*	80.77	8.30	30
E-I	feature-analysis	70*	72*	76*	33	39	55*	65*	81.00	7.38	11
E-II	decomposition	62*	60*	87*	53*	54*	38	32	83.79	7.69	14
E-III	labeling	64*	93*	83*	-29	35	83*	50	76.56	9.38	9
		Encoding Time									
	overall	05	18	09	-19	12	23	05	5.45	2.25	30
E-I	feature-analysis	05	35	10	-05	09	53	-16	7.01	2.76	11
E-II	decomposition	26	21	53*	40	50	04	38	4.85	1.47	14
E-III	labeling	00	60	39	-14	17	56	-12	5.84	3.55	9

Note. Decimals in correlation coefficients omitted.

a Aptitudes are composite scores (see text).

b Item correctness is expressed as a percentage of 216 items; encoding times are expressed in seconds.

c Four subjects were fit equally well by two models. They are included in both groups for calculations.

* $p < .05$.

strategy had been abandoned by all but five subjects. Others had changed to complexity-reduction either by means of the labeling (total n for this group was thus 8) or the decomposition strategy (total n for this group was thus 17). Further, between Blocks 1 and 4 no one shifted away from either of the complexity-reduction strategies to the feature-analytic strategy. Thus, it appears that subjects discovered complexity-reduction with experience on the task. Because subjects apparently began the task by casually happening upon a strategy, there was no relationship between aptitude and encoding strategy during Block 1. By Block 4, however, the relationship between aptitude and strategy choice was consistent with the results for the overall fits. Thus, by Block 4, it appeared that subjects had assembled a strategy suited to their aptitude profile.

Models for Construction

Two groups of models were tested for the construction step. One group specified use of a consistent strategy and the other group specified sequence-shifting. All models assume that subjects perform the same cognitive operations for each item. These are: retrieving the *A* figure, synthesizing the construction step figures, and storing the resultant product image. The models differ from one another in specifying the sequence in which the synthesis and storage processes are applied to the figures and in specifying the form in which the figures are represented in memory; figures can be represented separately or in various combinations.

During the construction step, we assume that subjects use a feature-analytic strategy for storing images regardless of the way the figures are combined for storage. This assumption may appear curious given the earlier demonstration that a majority of subjects did not use the feature-analytic strategy for storage during encoding. Construction is unlike encoding in that what is stored is not directly available, but most undergo some transformation (the synthesis process) before it is in a form ready for storage. The temporary product of the synthesis process, which might be thought of as a tentative image, is stored only in short-term memory. In encoding, it is not necessary to hold a tentative image in short-term memory since the figure is available in front of the subject at all times during the step. Thus, for encoding, the subject has short-term memory capacity available for appling various transformations on the *A* figure, such as the transformations that are implicitly called for by the decomposition and labeling strategies. During construction, however, much short-term capacity is presumably usurped by the tentative image. Thus, strategies that require additional transformations, such as decomposition and labeling, are not available to subjects during the construction step, and only feature-analytic storage, which does not assume an additional transformation of the image, is possible during construction.

Model C-I specified a *consistent-synthesis* strategy in which the *A*, *B*, and *C* figures are always synthesized into a single unit and stored as a unit in memory. Construction and storage time for this model is predicted by the feature complexity of the adjoining sides (during synthesis, subjects "dissolve" the features of the adjoining surfaces of the to-be-synthesized figures sequentially) and the feature complexity of the product image.

Model C-II specified a *consistent-no-synthesis* strategy in which the figures presented in the construction step are never synthesized, but are instead stored as separate units in memory. For this model, construction time is predicted by the figure complexity of the separate units (i.e. the sum of the complexity values of the *A*, *B*, and *C* figures).

In addition to the consistent strategy models, four sequence-shift models were tested. Each specified that subjects combine the *A*, *B*, and *C* figures in different ways depending on the form and complexity of the item, and each consisted of two steps. The first step is an evaluation process in which the subject first imagines the figures combined in some way and then decides whether to store the figures in this combination or as separate units. For some of the models the evaluation step is performed once; for other models there are multiple evaluations. The second step is the storage process in which subjects construct a mental representation of the *A*, *B*, and *C* figures.

Model C-III represented a *forward-stepping* synthesis strategy. Subjects first attempt to synthesize the *A* and *B* figures into an *AB* product image. Next, subjects evaluate the complexity of the *AB* image. (In these models we arbitrarily defined images with five or fewer sides as simple and those with six or more sides as complex. Roughly half the images in the task were thus considered simple and half complex.) If, during this evaluation the subject determines that the *AB* image is too complex to store as a unit, then the *A*, *B*, and *C* figures of the item are stored separately, as they are in Model C-II. If, on the other hand, the *AB* image is determined to be simple enough, then the subject attempts to synthesize the *C* figure with the *AB* image into an *ABC* product image. In this case a second evaluation occurs in which the subject determines whether this *ABC* unit is simple or complex. If it is determined to be simple then the *ABC* image is stored as a single unit (as in Model C-I). If it is determined to be complex, then the *AB* image is stored separately from the *C* image. That is, two distinct units, an *AB* unit and a *C* unit, are represented in memory.

For Model C-III, processing time during the evaluation step(s) is predicted by the complexity of the adjoining surfaces of the synthesized figures (though we assume that any two figures are synthesized only once during an item) and the number of complexity evaluations for the item. Processing time during the storage step is predicted by the complexity of the final representation, determined by summing the complexity values for each unit stored.

Model C-IV represented a *backward-stepping* synthesis strategy similar to the forward-stepping strategy except that the subject is assumed to begin the construction procedure by first attempting to synthesize the *B* and *C* figures into a *BC* product image, rather than by synthesizing the *A* and *B* figures. In all other respects this model is parallel to the forward stepping model. Our hypothesis was that the backward-stepping strategy would be used only by those whose memory of the *A* figure was interfered with by the presentation of the *B* and *C* figures. Thus, the subject would be forced to try to synthesize the *B* and C figures and perhaps guess about the form of the *A* figure. Subjects were instructed to synthesize in *forward order*, so the *backward-stepping* strategy represents a deviation from instructions.

Model C-V represented a *simultaneous-synthesis* strategy. Subjects first synthesize the *A*, *B*, and *C* figures into an *ABC* product image, then evaluate this image for its complexity. If the image is simple, then it is stored as an *ABC* unit; if the image is considered too complex to store as a unit, then the individual figures are stored separately. The predictors are the same as for model C-I, but the complexity values are different, since for some items the figures are assumed to be stored as separate units and for others a single *ABC* product image unit is stored. A variation of this model specified that the simultaneous-synthesis strategy is applied only when figures are added from the left side. For items in which figures are added from the right side, a processing sequence identical to that for Model C-III (forward-stepping) is attempted. In the analysis, both these variants of Model C-V were considered together.

Finally, Model C-VI represented a strategy of *simultaneous-synthesis-with-recovery*. Subjects begin by synthesizing the *A*, *B*, and C figures into an *ABC* product image. If the image is considered simple it is stored as a single unit. If the image is considered too complex, then the subject evaluates the *AB* part of the image. This is the "recovery" aspect of the strategy. Before deciding to store the figures separately the subject first tries to determine if a section (in this case, the *AB* section) of the *ABC* image can be stored as a single unit rather than as two separate units. If the section is considered too complex, then the figures are stored separately, but if the section is considered simple, then two units are stored, an *AB* unit and a *C* unit. A variation of this model specified that if the *AB* unit is considered too complex during the second evaluation then the *BC* section of the *ABC* product image is evaluated and stored as usual. The predictors for both these models are the complexity of the adjoining surfaces, the number of complexity evaluations, and the complexity of the final representation. For the analysis, these two models were considered in the same category. The simultaneous-recovery strategy (C-VI) is the most demanding of the construction step strategies because the subject must combine and recombine figures and perform more complexity evaluations (on average) than are required by the other strategies. The subject is presumed to do this to ensure the most efficient representation of the item figures.

Results for Construction

As with encoding, no one was perfectly fit by any of the models. Judgments regarding best fit were clear except in one case where two models fit equally well. Some other subjects were fit equally well by essentially equivalent models (e.g., the two variants of C-V). (See Appendix B, Table B2, for R^2 values; Table B4 for a summary of predictors.)

Figure 4 shows the relationship between speed, accuracy, and strategy selected. As with encoding, a tradeoff between speed and accuracy appeared. Those who selected the simultaneous-recovery strategy generally committed the fewest errors but took the longest during the construction step. The two subjects most susceptible to the interference effect (as indicated by the fact that they used the backward-stepping strategy) were two of the poorest performers. Both the consistent-synthesis and the simultaneous-synthesis strategy groups performed reasonably quickly but committed a comparatively high percentage of errors.

Insert Figure 4 about here

The subjects who demonstrated the greatest facility for flexible adaptation to problem demands, as represented by model C-VI, showed the fewest errors, on average. Figure 5 shows that these subjects were higher than subjects in the other strategy groups on all aptitude measures. Thus, aptitude may have been a restricting factor in strategy selection for construction. Figure 5 also shows an interesting aptitude profile difference between the consistent-synthesis group and the simultaneous-no-recovery group. The latter group was higher in five of the seven aptitudes, but the former group was higher in spatial visualization (Gv) and visual memory (VM) abilities. The two groups performed equally well on average (see Figure 4) but apparently reached their performance level via different routes. Those with superior spatial visualization and visual memory aptitude were always able to synthesize all the figures in a problem, while those who were comparatively deficient in these visual skills had to employ a slightly more complicated shift strategy of synthesizing, evaluating, and deciding how to store the figures. Finally, Figure 5 shows that the two subjects fit by the backward-stepping strategy had extremely low spatial visualization and visual memory aptitude. This suggests that these subjects were forced to use the backward-stepping strategy because they did not have the visual skills needed to remember the *A* figure once it had disappeared from the screen.

Insert Figure 5 about here

Table 2 shows that within both the simultaneous strategy groups (with or without recovery), memory span (MS) and spatial visualization (Gv) aptitude were the best predictors of correctness. The other two strategy groups were too small to compute stable correlations.

Insert Table 2 about here

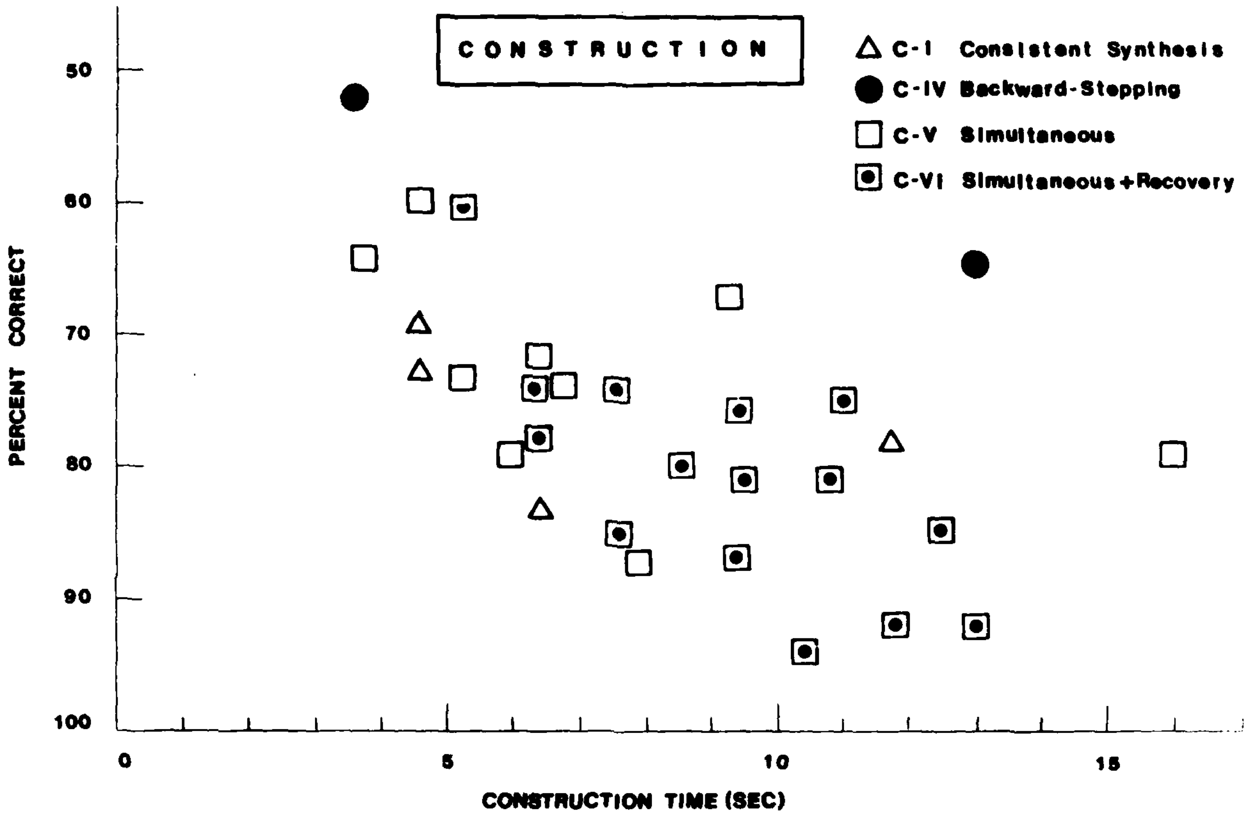

Figure 4. Construction time vs. correctness for items that included a construction step (144 items; combined symbols indicate more than one best fitting model).

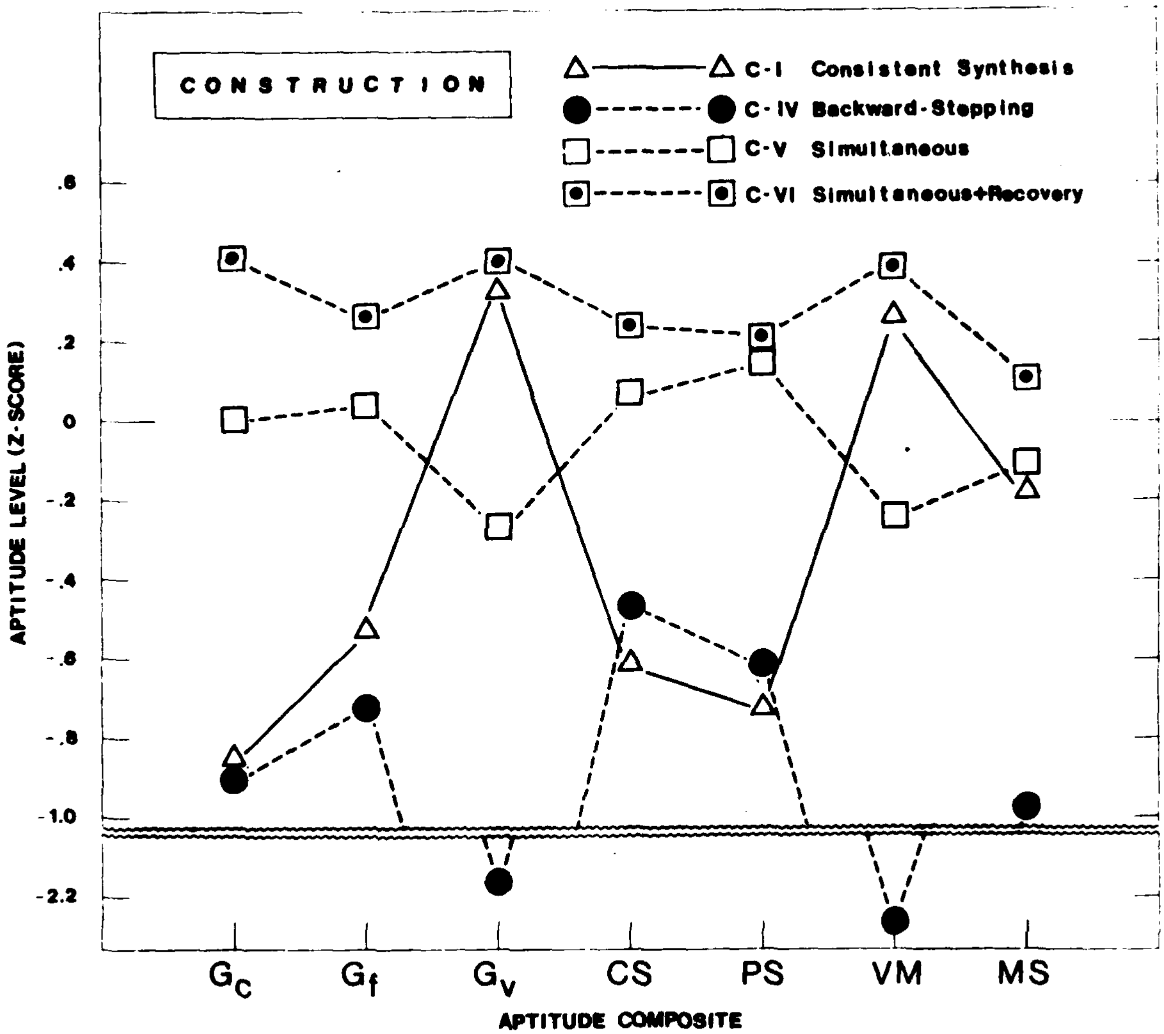

Figure 5. Aptitude profiles for subjects in various construction strategy groups (see text for aptitude composite descriptions).

Table 2

Aptitude Performance Correlations Within Strategy Group for the Construction Subtask

Model	Description	Aptitude[a] Gc	Gf	Gv	Cs	PS	VM	MS	*M*[b]	*SD*	*N*[c]
	Item Correctness										
	overall	49*	54*	76*	13*	39*	60*	53	76.20	9.87	30
C-I	consistent-synthesis	--	--	--	--	--	--	--	75.69	6.11	4
C-IVa	backward-stepping	--	--	--	--	--	--	--	58.68	9.33	2
C-V	simultaneous-no-recovery	35	51	54	01	32	34	64*	71.18	8.23	10
C-VI	simultaneous-recovery	07	29	53*	12	28	19	52*	81.02	8.58	15
	Construction Time										
	overall	38*	35*	14	-21	29	34	36*	8.28	3.21	30
C-I	consistent-synthesis	--	--	--	--	--	--	--	6.83	3.42	4
C-IVa	backward-stepping	--	--	--	--	--	--	--	8.35	6.58	2
C-V	simultaneous-no-recovery	33	08	-11	-38	-09	23	46	7.07	3.56	10
C-VI	simultaneous-recovery	-06	22	29	05	40	36	55*	9.27	2.37	15

Note. Decimals in correlation coefficients omitted; some coefficients are missing because group size was too small.

a Aptitudes are composite scores (see text).

b Item correctness is expressed as a percentage of 144 items; construction times are expressed in seconds.

c One subject was fit equally well by two models and was included in both groups for calculations.

* $p < .05$.

Models for Comparison

Three basic models for comparison were tested. All models assumed that subjects compare parts of the test probe with corresponding parts of their internal image. This comparison process is assumed to be sequential and exhaustive. That is, subjects compare all features or units, in sequence, regardless of any mismatches that occur during the comparison procedure. The models differ in specifying the size of the part that subjects compare sequentially.

Model M-I specified a *feature-comparison* strategy in which subjects compare, in sequence, each feature of the test probe with the corresponding feature of the mental image. Comparison time is predicted by the total number of features in the test probe (weighted as before to account for differences in the complexity of various features). A variant on this model includes a *quick-reject* option. Subjects using the quick-reject strategy first conduct a quick scan of the test probe to determine if it is radically different from their mental image. If it is, then the subject quickly responds with the "difference" response, otherwise the subject more carefully compares the features, in sequence, before responding. (We decided arbitrarily that figures were radically different if more than six corresponding sides of the figures and the image did not overlap.)

Model M-II specified a strategy in which subjects compare larger units than features. There were two types of *unit-comparison* strategies. One specified that subjects compare, in sequence, the *A*, *B*, and *C* images to the corresponding parts of the test probe (the features within the units are assumed to be compared in parallel). Note that this model assumes that regardless of how the image was represented for storage during the construction step, the subject retains a memory of the individual figures that were presented. The form of the representation from construction may be thought of as serving as a retrieval device for recalling the actual data, the individual *A*, *B*, and *C* figures which are then used in the comparison process. A variant of this model specified that the units are not the individual figures that were actually presented, but rather, the units as represented in memory from the previous task steps. That is, if the subject synthesized the *A*, *B*, and *C* figures into an *ABC* product image during construction, then the comparison test probe would be compared singly with the one *ABC* unit. If the subject represented the *A*, *B* and *C* figures as separate units during construction, then the three corresponding parts of the test probe would be compared, one-at-a-time, to the three stored units.

Finally, Model M-III specified a *feature-unit-shift* strategy. If, during construction, the figures were stored as a single product image, then the subject would employ a feature-comparison strategy identical to that specified by Model M-I, but if separate units were stored during construction, then the subject would compare those units as in Model M-II. The rationale for this model is that a completely synthesized figure allows for what we assume to be the more accurate comparison method--feature-comparison--whereas a not-synthesized figure makes the feature-comparison method more difficult, thus inviting the use of a unit-comparison method.

Results for Comparison

In general, the model fits for comparison were lower than those for the other two steps (see Appendix B, Table B3), probably because the comparison times were so much shorter than the times for the other steps. In further contrast to encoding and construction, there was no clear best strategy, since there were no significant differences between correctness scores for the three strategy groups. Table 3 suggests that those in the feature-comparison group committed more errors and performed more quickly than those in the other two groups, but these differences were not significant. The fast average response time for the feature-comparers was due primarily to those who used the quick-reject strategy, as Figure 6 shows.

Insert Figure 6 about here

Insert Table 3 about here

Figure 7 shows that aptitude profiles for the three strategy groups were similar, except that those who used the feature-unit-shift strategy were higher in closure speed (CS). Table 3 yields an interesting pattern of correlations within strategy groups. For those fit by the feature-comparison strategy, speed of comparison was highly related to closure speed (CS), spatial visualization (Gv), and visual memory (VM) aptitudes, while for those in the other two groups, comparison speed was not highly related to these aptitudes. Apparently, selection of the feature-comparison strategy brings in a greater dependence on visual and spatial skills, which is to say that high ability subjects are able to compare features more rapidly than low ability subjects, while selection of the unit-comparison strategies reduces this dependence and gives no advantage in speed for high ability subjects. This pattern suggests the Case II relationship between aptitude and strategy for comparison; selection of strategy is not strongly related to aptitude but performance speed in different strategies depends on different aptitudes.

Insert Figure 7 about here

Discussion

The three major findings from this study concern the relationship between aptitude and strategy, the importance of strategy-shifting by subjects, and the nature of aptitude for spatial visualization.

First, we found evidence for various types of relationships between aptitude and strategy for the different task steps. For encoding and construction, a Case III relationship was indicated; strategy selection appears to be restricted by aptitude and, in addition, performance efficiency within a strategy group depends on the aptitudes called into play by the particular strategy selected. For these task steps, the most efficient strategy was used only by those who brought to the task

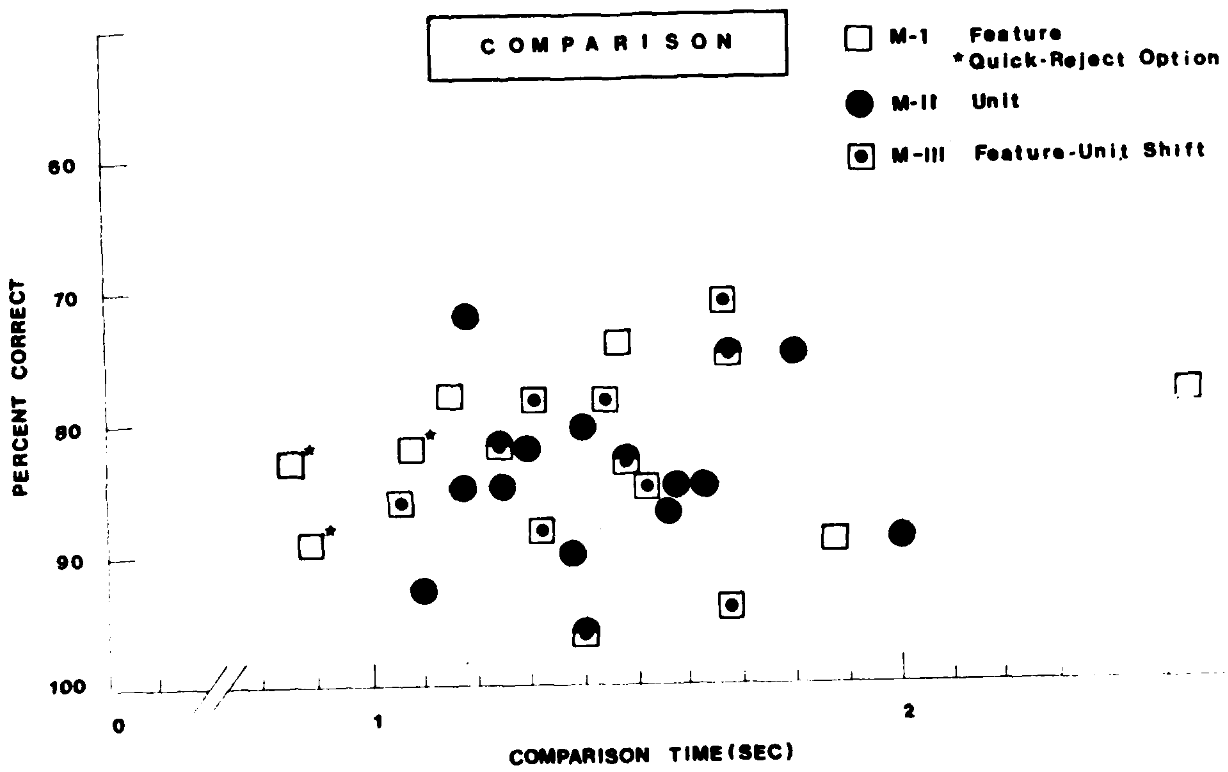

Figure 6. Comparison time vs. correctness for items that did not include a rotation step (72 items; combined symbols indicate more than one best fitting model).

Table 3

Aptitude Performance Correlations Within Strategy Group for the Comparison Subtask

Model	Description	Aptitude[a] Gc	Gf	Gv	Cs	PS	VM	MS	*M*[b]	*SD*	*N*[c]
	Item Correctness										
	overall	43*	54*	65*	26	36*	36*	40	83.10	6.43	30
M-I	feature-comparison	73*	18	54	43	-32	64	59	81.75	5.81	7
M-II	unit-comparison	48*	68*	70*	19	39	65	38*	83.85	6.37	16
M-III	feature-unit-comparison	40	45	78*	23	59*	07	52*	83.21	7.72	11
	Comparison Time										
	overall	-10	-03	-39*	-25	02	-35*	-10	1.44	.35	30
M-I	feature-comparison	-01	18	-65	-80*	14	-65	-02	1.41	.62	7
M-II	unit-comparison	-19	-20	-34	-07	-06	-37	-37	1.45	.25	16
M-III	feature-unit-comparison	-44	-37	-26	04	-33	-22	-06	1.44	.19	11

Note. Decimals in correlation coefficients omitted.

a Aptitudes are composite scores (see text).

b Item correctness is expressed as a percentage of 72 items; Comparison times are expressed in seconds.

c One subject was fit equally well by two models and was included in both groups for calculations.

* $p < .05$.

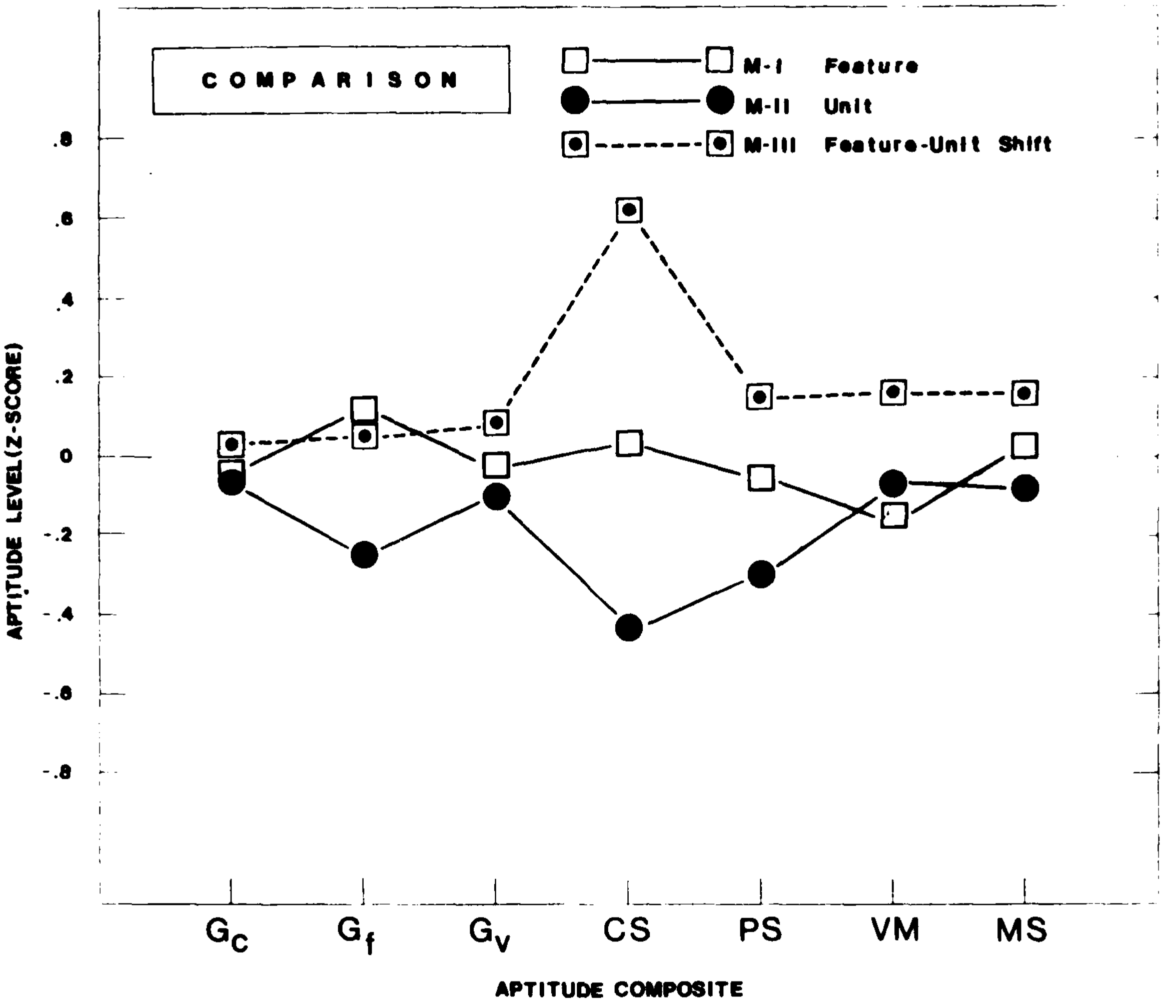

Figure 7. Aptitude profiles for subjects in various comparison strategy groups (see text for aptitude composite descriptions).

the aptitudes required to use the strategy. The most efficient approach to encoding was the figure-decomposition strategy, and it was used only by those who came equipped with the necessary closure speed and spatial visualization skills. The most efficient handling of construction was the simultaneous-synthesis-with-recovery strategy, which consisted of continually evaluating the complexity of various combinations of figures to construct the most efficient internal representation. This strategy, which calls for flexible adaptation to item demands, was used only by high ability subjects, especially those high in spatial visualization and visual memory.

In two of the task steps, it also appeared that aptitude played a role in determining performance efficiency within strategy groups. In encoding, performance within the decomposition and feature-analytic strategy groups depended most highly on the individual's level of general ability. Additionally, within the feature-analytic group, memory span and visual memory came into play, probably because this strategy demands that large numbers of features be stored in memory. In construction, performance within any of the strategy groups appeared to be highly dependent on spatial visualization ability and memory span.

A Case II relationship between aptitude and strategy was demonstrated for the comparison step. Strategy selection appears not to depend on aptitude, but the relationship between aptitude and performance is determined by which strategy is selected. For subjects who selected the feature-comparison strategy speed of comparison was related to level of closure speed and spatial visualization; that is, higher aptitude subjects were able to compare features more quickly. Among subjects who selected a strategy that involved comparing larger units, speed of comparison was not as dependent on these aptitudes.

The second major result of this study shows the importance of strategy-shifting models. We tested and found evidence for two types of strategy-shifting, route-shifting and sequence-shifting. These shift models proved to be useful for both methodological and substantive reasons. Such models help in explaining variance in problem solving processes at least on the task used in this study. Thus, strategy-shift models represent an important addition to the collection of modeling techniques for cognitive tasks, especially for tasks that may be susceptible to alternative solution strategies. Substantively, strategy-shift models indicate that aptitude constructs must include the ability to shift strategies. This may be an important aspect of intelligence, long included in definitions (see Snow, 1978) but not before demonstrated directly. Strategy-shifting may represent the process of flexibly adapting to problems to maximize performance. Some new and important differences between those who are able to adapt to problem demands and those who are not may be captured in such models.

Finally, the models developed and tested here include components that should be found also in performance on other spatial visualization tasks. A fairly small number of components--storage, retrieval, comparison, and transformation--may be involved in a large number of tasks that collectively have been called tests of spatial ability. We were able here to achieve a reasonably good accounting of subjects' visual problem solving behavior through various mixtures of this small set of basic components.

For simplicity, we have used terminology suggesting that causality runs from aptitudes to strategies. But the entire conceptual system can be reversed. To the extent that the task studied here can be regarded as a measure of spatial visualization and memory ability, then the flexible strategic phenomena illuminated here can be regarded as fundamental constituents, not only of the experimental task, but also of the reference aptitude constructs with which it is correlated. The aim of modeling such tasks and families of tasks, in the long run, is a comprehensive theory of aptitude for complex learning and problem-solving. Models that help to depict this complexity deserve more intensive investigation, and soon. As Snow (1981) saw it:

> Our work in this direction is progressing, but slowly. . . . models of particular tests are elaborated to include performance programs for other related tests. The . . . approach . . . outlined here is used to guide theory construction for families of related tests. We expect that task complexity, the degree to which a test shows *variance components* attributable to [general intelligence], can be interpreted in terms of the number and kinds of processing steps assembled into the performance program, and the degree to which these steps require flexible control and reassembly as the test or task proceeds. (p. 357.)

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Appendix A
Strategy-Shift Models

As an example of sequence-shifting, consider a case in which the task requires comparing two figures, an *A* and a *B* figure. Assume that the subject has two strategic possibilities. Strategy 1 requires encoding *A* and then comparing features of *A* to corresponding features of *B*. Strategy 2 works in the opposite sequence, encoding *B* and then comparing it to *A*. Assume further that encoding time is a linear function of the number of features in the to-be-encoded figure, and comparison time is a linear function of the number of matches between the corresponding features of the two figures. The regression model in this example would be:

$$RT = b1X1 + b2X2 + c, \tag{1}$$

where *RT* is the total item response time, *X1* is the number of features in the to-be-encoded figure, *X2* is the number of features in the to-be-compared figure that match corresponding features in the encoded figure, *b1* is the amount of time it takes to encode a single feature, *b2* is the amount of time it takes to compare a pair of features, and *c* is a constant decision or response time. The latter three terms, the *b* weights and the constant, are what must be solved for. It can seen that the values of *X1* and *X2* depend on which strategy is selected and therefore the two strategy models will usually make different predictions for *RT*.

A sequence-shift model in this example would specify that subjects work from *A* to *B* (i.e., use Strategy 1) for some items and from *B* to *A* (i.e., use Strategy 2) for the remaining items. Thus, in the sequence-shift model, the values for *X1* and *X2* would be identical to those in the model for Strategy 1 for some items and identical to those in the model for Strategy 2 for the remaining items. Of course, it is necessary before testing this type of sequence-shift model to determine for which items Strategy 1 might be favored and for which Strategy 2 might be favored. The investigator must determine beforehand what objective characteristics of the items might favor a particular strategy, or alternatively, collect subjective ratings from independent judges of the liklihood of a particular strategy being employed for a particular item. Having done this, it is a straight forward matter to compare the two possible no-shift models and the sequence-shift models for best fit since all models include the same predictors; only the values of the predictor variables differentiate the models.

As an example of route-shifting, consider again the previous example of the *A-B* comparison task. Assume that two qualitatively different comparison operations are possible, a feature comparison operation (as above) and a holistic comparison operation in which the subject compares the corresponding features of the two figures in parallel. A simple model of the holistic stategy would predict that comparison time is independent of the number of features to be compared.

A route-shift model, in this example, would specify that some figures are compared using the feature strategy and others using the holistic strategy. The regression equation to describe this would be

$$RT = b1X1 + b2X2 + b3X3 + c \qquad (2)$$

where all terms are defined as in Equation 1 except $b3$, which is the time it takes to make one holistic comparison, and $X3$, which is the number of holistic comparisons made on an item. The value of $X3$ would always be 1 if the subject always performed holistic comparisons (and thus the associated $b3X3$ term would drop into the constant). However, the route-shift model assumes that the subject sometimes does not perform the holistic comparison and instead performs the feature comparison. If the subject performs feature comparison on an item, then the value of $X3$ for that item is 0, and the value of $X2$ is the number of features compared; if the subject performs holistic comparison, then the value of $X3$ is 1 and of $X2$ is 0. It can be seen that comparing the fit of a no-shift and a route-shift model is not straight forward, because the route-shift model always has more predictors than the no-shift model; in this case it has three predictors whereas the no-shift model has only two (either the $X2$ or the $X3$ term, but not both). To make the comparison between the two models, it is necessary to adjust for differences in the number of predictors using the standard R^2 shrinkage formula (see, e.g., Kerlinger & Pedhazur, 1973).

Appendix B
Table B1

Model Fits for Encoding

subject	PE (7)	E-I (4)	E-II (5)	E-III 25% (6)	E-III 50% (6)	E-III 75% (6)	E-III 100% (1)
1	09	35	39*	37	31	32	27
2	36	42	46*	43	43	43	40
3	05	24	24	27*	27*	25	21
4	02	34	35*	33	29	34	28
5	10	45	48*	48*	42	43	34
6	23	38	41*	38	38	35	30
7	11	40*	38	34	33	37	39
8	08	36	36	34	32	37*	31
9	09	18*	14	13	12	12	12
10	17	51*	49	47	46	44	37
11	43	55	55	56*	52	52	47
12	12	23*	22	22	17	17	15
13	10	47	52*	51	47	42	33
14	26	65*	65*	61	56	52	46
15	32	49*	47	46	44	49*	47
16	17	51	53*	49	45	45	42
17	44	55*	52	52	51	53	50
18	13	17	16	18	17	18	16
19	29	45	47*	45	43	42	38
20	18	25	27*	27*	24	26	24
21	07	21	20	19	18	23*	16
22	15	34	36*	35	35	35	29
23	55	66*	64	63	61	60	59
24	36	63	64*	59	57	56	53
25	13	34*	31	28	27	28	26
26	11	31*	31	27	30	31	29
27	21	25	27	28	29*	28	24
28	05	24	22	28	32*	31	28
29	26	37*	33	33	33	31	30
30	05	31	35*	35	33	33	22

Note. Decimals in R^2 values omitted. Asterisks (*) indicate highest row value, after being adjusted for number of predictors (using shrinkage formula); ties occurred when adjusted R^2 values differed by less than .005. In parentheses are number of model predictors; each model also includes 7 predictors for practice effects (PE = practice effects).

Appendix B (cont.)

Table B2

Model Fits for Construction

subject	PE (7)	C-I (12)	C-II (8)	C-III (13)	C-IVa (13)	C-IVb (13)	C-Va (13)	C-Vb (13)	C-VIa (13)	C-VIb (13)
1	05	67	38	58	52	55	73	56	74*	74*
2	20	52	41	44	49	45	54*	44	54*	53
3	02	36	33	36	38	35	43	35	43	44*
4	07	50	36	41	47	45	62*	47	59	59
5	11	51	39	44	46	45	58	45	57	60*
6	04	48	32	45	42	41	51	45	54	55*
7	07	51	34	54	47	46	56*	53	56*	55
8	04	52	43	47	47	48	55*	49	55*	55*
9	21	52	41	53	53	52	54	52	55*	55*
10	25	66	52	58	64	57	68*	63	67	67
11	08	50	40	47	50	43	53*	48	53*	52
12	07	45	40	46*	46*	46*	44	44	44	44
13	11	65	43	66	58	60	72	61	72	73*
14	16	62	46	52	54	52	67*	52	67*	66
15	27	61*	52	58	59	56	60	60	60	58
16	11	57	40	46	50	47	59*	50	58	59*
17	31	56*	49	54	56*	56*	55	55	54	55
18	16	47	37	53	55*	55*	53	50	50	49
19	08	35	36	38	39	38	36	40*	35	35
20	12	51*	35	44	46	44	51*	46	51*	49
21	18	58	46	57	50	53	57	52	57	59*
22	12	53	40	49	47	48	56*	51	55	55
23	15	68	45	61	57	59	75*	63	74	73
24	23	67	60	65	61	66	69	66	71	73*
25	19	47*	29	42	40	43	47*	45	46	46
26	14	60	54	59	61	61	61	62*	61	61
27	05	54	42	55*	49	53	55*	54	55*	54
28	12	49	46	48	52	52	51	49	52	53*
29	20	59	49	61	62	62	64*	63	64*	63
30	06	68	46	61	59	59	70	59	72*	70

Note. Decimals in R^2 values omitted. Asterisks (*) indicate highest row value, after being adjusted for number of predictors (using shrinkage formula); ties occurred when adjusted R^2 values differed by less than .005. In parentheses are number of model predictors; each model also includes 7 predictors for practice effects (PE = practice effects).

Appendix B (cont.)
Table B3

Model Fits for Comparison

subject	PE (4)	M-Ia (4)	M-Ib (5)	M-IIa (1)	M-IIb (1)	M-IIIa (5)	M-IIIb (5)
1	07	22	21	28*	25	26	24
2	01	42	46	51*	51*	51*	49
3	07	08	08	07	10	15	17*
4	03	33	34	38	43	43	44*
5	05	28	30	35	33	44*	37
6	01	21	21	15	27	31	33*
7	17	22	25	41*	36	36	37
8	06	08	10	22	21	25*	22
9	08	27	32	44*	27	44*	31
10	03	07	06	15*	15*	15*	14
11	16	43	43	33	46	49*	48
12	35	45*	42	44	41	41	41
13	10	29	29	41*	29	39	32
14	16	40	38	44	53	54*	51
15	18	34	36	37*	29	34	36
16	01	15	15	28	38*	37	38*
17	14	28*	27	27	25	28*	27
18	12	24	22	33	30	34*	30
19	12	18	22	51	39*	39*	39*
20	12	53*	52	52	51	53*	52
21	01	35	43*	25	32	33	34
22	07	38	35	33	43*	43*	43*
23	28	45	47*	38	44	44	44
24	20	34	36	39	38	41*	39
25	05	26*	23	21	14	26*	23
26	22	33	35	38	39*	39*	39*
27	02	40	41	45	61*	60	60
28	30	38	37	42	42	43*	41
29	10	21	25	19	21	21	27*
30	01	16	18*	10	11	14	14

Note. Decimals in R^2 values omitted. Asterisks (*) indicate highest row value, after being adjusted for number of predictors (using shrinkage formula); ties occurred when adjusted R^2 values differed by less than .005. In parentheses are number of model predictors; each model also includes 4 predictors for practice effects (PE = practice effects).

Appendix B (cont.)
Table B4

Predictors for Task Step Models

Model		Predictors
		Encoding
E-I	feature-analysis	-complexity of *A* figure (4).
E-II	decomposition	-sum of complexity values for each decomposed unit (4). -number of units (1).
E-III	labeling	-rated labelability (1).
		Construction
all models		-complexity of retrieved (*A*) figure (4). -complexity of stored unit(s) (4). -complexity of dissolved sides (4) (not applicable to C-II). -number of evaluations (1) (not applicable to C-I, C-II).
		Comparison
M-I	feature-comparison	-complexity of test probe (4). -quick-reject (1) (M-Ib only).
M-II	unit-comparison	-number of units compared (1).
M-III	feature-unit-comparison	-complexity of test probe (4). -number of units compared (1).

Note. In parentheses are number of predictors associated with the entry; complexity actually consists of four predictors: number of sides, number of different side lengths, number of different angle sizes, and number of different orientations.

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