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ABSTRACT

The roles of training, problem representation, and individual differences on performance of both automated (simple) and controlled (complex) process tasks were studied. The following hypotheses were tested: (1) training and cognitive style affect the representation developed; (2) training and cognitive style affect the development and performance of automated processing; (3) training and cognitive style affect controlled process task performance; (4) task representation affects development and performance of automated processes; and (5) task representation affects controlled process task performance. To test these hypotheses, 19 undergraduate students (9 males and 10 females) of varying cognitive abilities were trained in an alphabetic (n=9) or hierarchical (n=10) manner to use a word processor. After training, the subjects' task representation was assessed and they were required to perform both controlled and automatic process tasks. The first hypothesis was not supported; the second, fourth, and fifth hypotheses were supported; and the third hypothesis could not be confirmed. Performance on repetitive tasks associated with automatization was influenced by training style and the mental task representation held by individuals. Task representation was also a significant determinant of performance on complex cognitive-oriented (controlled process) tasks. No effect was found for individual differences. To maximize performance, training and task design should consider the mental representation of the task. Two figures and four tables present study data. (SLD)

The Role of Training, Individual Differences and Knowledge Represen ation in Cognitive-Oriented Task Performance

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This research examines the impact of training style, individual differences and task representation on automatized task performance and controlled task performance. Results indicate that performance on relatively straightforward repetitive tasks, usually associated with automatization, is influenced by training style and the mental task representation held by individuals. Also, task representation is a significant determinant of performance on complex cognitive-oriented tasks (i.e., controlled process tasks). Therefore, the task representation is suggested as a high level determinant for both simple and complex task performance. No effect for individual differences was found. It is concluded that training programs and task design for these type of activities must account for the representation in an effort to maximize individual performance.

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I. INTRODUCTION

As the United States begins to experience the effects of the "baby bust" and an increased emphasis on college training, rather than vocational, the labor pool from which to draw workers decreases. In addition, computer skill levels required for these jobs are increasing, thus further reducing the number of potentially qualified applicants. As more businesses become automated, persons with little computer experience are suddenly thrust into a virtual "computer world". Given this scenario, an effort must be made to determine those elements of training which will aide in the acquisition of skill on computer-based tasks.

In general, at least three primary factors exist, related particularly to the individual, which can impact productivity in cognitive-oriented work: previous learning (including training), present knowledge of the task and individual differences. While externally determined factors, such as work schedule and compensation are important, the present paper focuses on the internal factors.

It appears certain that the mental representation of the system one holds is a determining factor in the ability to solve complex problems. For example, Kieras and Bovair (1984) performed a study concerned with the importance of mental models in learning to operate an unfamiliar piece of equipment (a basic control panel). It was shown that the group trained with the mental model learned and executed the procedures more quickly, had superior retention and simplified inefficient procedures more often than the group trained without the model. In the realm of computer programming, Mayer (1989) suggests that the presentation of a concrete model early in a novice programmer's training program may have beneficial effects on his or her encoding and use of new technical information. Adelson (1981) demonstrated that expert programmers reorganize randomized computer code in a hierarchial structure, while novices group code according to its syntactic similarity. Likewise, McKeithen, Reitman, Reuter and Hirtle (1981) studied the memory strategies of novices and experts. In the reproduction of a computer program, novices used general mnemonic strategies, such as an alphabetic strategy, while experts used a more specific strategy of grouping the words according to their functions. While the results of Mayer's study would tend to favor the incorporation of a concrete model in training a novice programmer, the results of Adelson and McKeithen *et al.* would suggest the use of more hierarchial representations for attaining higher levels of skill.

Rather than focus on a single training style, recent research has suggested the need to tailor training programs to individual differences. Sein and Bostrom (1989), for example, have found that people with an "abstract" learning style will perform significantly better when provided a training program which emphasizes the abstract features of the domain, while those with a "concrete" learning style perform almost twice as well when given an analogical (concrete) training program compared to the abstract training program. Some researchers have attempted to train expert and novice programmers to form a particular mental representation. For example, Adelson (1984) showed that novices could be forced into a semantic representation (as opposed to their preferred syntactic representation), and experts could be forced into a syntactic representation (as opposed to their preferred semantic representation). However, these representations proved unstable, and both groups eventually switched back to their more "natural" representation. It would appear that, as implied by the results of Kolodner (1983), Murphy and Wright (1984), Novick (1988), and

Koubek and Salvendy (1989), this "change-over" from a concrete mental representation of the novice to an abstract representation of the expert will occur over time, only as the novice gains additional experience in a particular task domain.

Others have shown the importance of a breadth-first, compared to a depth-first training style for final performance on troubleshooting tasks. Zeit and Spoehr (1989) concluded that the degree of hierarchial structure within a learning tool is reflected in the structure of the learner's knowledge representation. In addition, a hierarchically organized knowledge base, along with applied practice, will lead to procedural representations, while subjects who lack a hierarchial knowledge base will not develop procedural representations. In support of the interplay of one's knowledge structure and the performance level of a given task, Lambert and Newsome (1989) studied the impact of question format and organization presented by an intelligent system on the problem-solving performance of experts (high-skill employees) and novices (low-skill employees). The results provide further evidence that experts and novices organize conceptual knowledge of a problem in different manners. When questions were posed by the system requiring concrete information organization, low-skill employees performed significantly faster than when the questions required abstract information organization. Additionally, high-skill employees performed faster in response to questions which required abstract information organization as compared to concrete information organization. These findings may have far reaching implications in the development of expert systems, as well as in training novices to program and debug efficiently.

Another emphasis in the literature suggests training to develop automatic processes (Fisk and Gallini, 1989). This is supported by Wiedenbeck (1985) who found that, even in simple, automated tasks, experts are significantly faster and more accurate than novices. Automaticity states that as practice accrues on consistent task components, then the processes associated with executing these consistent components become automated, and automated processes require no cognitive resources. Non-consistent task components, however, must be executed with controlled processes, which are resource intensive. Therefore, if one were able to be trained to automatically process certain cognitive information (i.e. computer code), thereby requiring less cognitive resources for the performance of that particular cognitive task, the speed and efficiency of task performance would increase.

Cognitive style may also be a determining factor of one's asymptotic skill level for computer-oriented tasks. For example, the cognitive style of field independence is "definable in terms of degree of dependence on the structure of the prevailing visual field, ranging from great dependence, at one extreme, to great ability to deal with the presented field analytically, or to separate an item from the configuration in which it occurs, at the other" (Witkin, Lewis, Hertzman, Machover, Meissner and Wapner, 1954). In a study which examined student and professional programmers' cognitive representations of software, Holt, Boehm-Davis and Schultz (1987) found that the mental models formed (which were examined while subjects performed either simple or complex modifications to a program) were affected by problem structure, problem type, and ease of program modification. Specifically, the mental models of the professionals were most affected by modification difficulty, while the mental models of the students were most affected by the structure and content of the programs. This suggests that the professionals may act in a "field independent" manner, since they were less influenced by the surface structure of the

program. Conversely, it is possible that the students, who were primarily affected by the surface structure and content of the programs, may be classified as "field dependent". While evidence supports each of the above stated factors as performance determinants, it is beginning to appear that a complex interaction exists between individual differences, training and the current knowledge representation of the task.

Derivation of Hypotheses

From the above review, several factors have been studied extensively as influential in producing cognitive-oriented task performance. The present research examines the role of training, problem representation and individual differences on performance of both automated (simple) and controlled (complex) process tasks. The following hypotheses are proposed.

Hypothesis One: Training and cognitive style affect the representation developed.

Hypothesis Two: Training and cognitive style affect the development and performance of automated processing.

Hypothesis Three: Training and cognitive style affect controlled process task performance.

Hypothesis Four: The task representation affects the development and performance of automated processes.

Hypothesis Five: The task representation affects controlled process task performance.

II. METHOD

In order to test the above hypotheses, subjects of varying cognitive styles were trained in either an Alphabetical or Hierarchial manner to use a word processor. Following training, their task representation was assessed and they were required to perform both controlled and automatic process tasks.

Task

Subjects were required to perform four tasks: cognitive style assessment, domain training, representation evaluation and stimulus task execution. The cognitive style of Field Independence (FI) - Field Dependence (FD) was used to categorize subjects with respect to their individual differences. Based on the cognitive style theory mentioned previously, one would predict that FI and FD subjects would tend to form conceptually different knowledge representations depending on the structure of their training.

Following the administration of the Hidden Figures Test (Ekstrom, French, Harman and Dermen, 1976) to assess cognitive style, subjects were trained to use a computer word processor (Microsoft Word version 4). Subjects received training on the word processor in

one of two ways. One group received the commands arranged alphabetically while the other group received training in which the commands were arranged in a hierarchial manner, based on their functional interrelationships. Each group was given the same commands and examples from which to learn. The only difference was presentation order.

The third task required subjects to complete a representation evaluation form. This form presented 17 learned word processing commands, paired with one another, to yield a total of 136 items. Subjects were asked to rate the degree of similarity on a 5-point Likert-type scale for each pair. This data was evaluated through clustering techniques to identify the subject's representation of the word processing domain.

The fourth experimental component required subjects to perform two text editing tasks using the word processing skills learned in the second phase. In the first editing task, subjects were presented a document and were asked to perform a centering task 30 times, once each on evenly spaced lines. This task was relatively straightforward and the cognitive process should have been easily automated. This is defined as the AP (automated process) task. The second task required subjects to place two paragraphs side-by-side in the document. The side-by-side procedure required a combination of several steps and was relatively complex. Subjects were allowed 15 minutes to complete this task. The side-by-side task is designated as the CP (controlled process) task.

Subjects

While 20 subjects volunteered for the experiment, one was eliminated due to her experience with the stimulus task. The remaining 19 (9 male and 10 female) were undergraduate university students, from a variety of academic majors with little or no general word processing experience and no prior experience with the present system. Based on their Hidden Figures Test score, subjects were classified as either FI or FD. The national average score on this test, 16, is used as the criterion for placement into groups. Ten subjects had scores below 16 (FD) while nine had scores of 16 or above (FI). These subjects were randomly divided into the training conditions, yielding nine trained alphabetically and ten hierarchically.

Variable Definition and Experimental Design

The independent variables for this study were cognitive style and training method. As described above, the representation was elicited through cluster analysis of similarity ratings. This analysis provided insight into the manner in which subjects group various commands and can suggest evidence regarding the accuracy and completeness of their mental representation. From the cluster analysis, the representation was characterized by the variables listed in Table 1.

TABLE 1. Description of Representation Variables.

VARIABLE	DESCRIPTION
Maximum Distance Between Clusters	Provides overall rating of the differentiation between clusters. Low values indicate little distinction between commands.
Total Number of Clusters	Calculated by counting the number of separate clusters that exceed one-half the maximum distance between clusters. Clusters which exceed this value can be considered prominent and significant.
Number of Horizontal Layout Commands Misclassified	Three conceptual clusters exist in the task: horizontal page layout commands, vertical page layout commands and font commands. This variable indicates the number of horizontal layout commands which were incorrectly classified into vertical layout or font clusters.
Number of Vertical Layout Commands Misclassified	See above.
Number of Font Commands Misclassified	See above.
Purity of Horizontal Layout Cluster	Binomial variable which indicates whether subjects had a single cluster which included all the horizontal layout commands and no others. Impure=0 and pure=1.
Purity of Vertical Layout Cluster	See above.
Purity of Font Cluster	See above.
Overall Cluster Purity	Composite value which is computed by summing the individual purity values.
Number of Commands Not Clustered	Provides an indication of domain representation completeness.

Three variables were derived to characterize automation: alpha, T_0 and T_{1000}. For the AP task, performance was described by the log-linear function $T_n=T_0n^{-alpha}$. In this equation, alpha represents the rate of learning and T_0 is the time for completion of the first trial. These parameters were derived directly from the data. Using these values, the time for the 1000th trial, T_{1000}, was calculated as an estimate of asymptotic performance. CP task performance was characterized by whether the subject completed the task in the allotted time. Therefore, the dependent variables are T0, T1000, alpha (for the AP task) and whether the CP task was completed. In addition, the representation oriented variables serve as either dependents or independents as a function of the analysis.

A 2x2 MANOVA design was used to test the first two hypotheses. The independent variables were cognitive style (FI versus FD) and training (Alphabetical versus Hierarchial). The dependent variables for each analysis were those derived from the representation and automated process tasks respectively. Due to sample size restrictions, the third hypothesis was tested with a Chi-Square procedure. The fourth hypothesis, designed to examine the relationship between task representation and automation, was performed with canonical correlation and multiple regression procedures, while the fifth hypothesis was tested with Chi-Square and discriminant analysis techniques.

Procedure

Prior to the training phase, subjects were administered the Hidden Figures test to determine their cognitive style and assigned to the appropriate training group. An attempt was made to evenly distribute FI and FD subjects into the training conditions. In the second phase, subjects received their respective training modules. During training, subjects read hard-copy descriptions of each command and were required to practice each command with the actual system before proceeding. Subjects were allowed as much time as necessary.

Upon completion of training, subjects were given the representation evaluation form and asked to bring the completed form back the next day, when they would perform the stimulus tasks. On the day following training, subjects were allowed to re-familiarize themselves with the system and then perform the AP and CP tasks in that order. The subjects were provided with a keyboard and a mouse as their computer interface for the two tasks. Their training manuals were also furnished for assistance. A concurrent verbal report was required of the subjects throughout the CP task. Each subject was allowed 15 minutes to complete the CP task. The testing session was video taped for later analysis. Following testing, a second representation evaluation form, identical to the first, was completed to identify any possible changes in knowledge representation.

III. RESULTS

Training and Individual Difference Effects

Representation Development. *Hypothesis 1: Training and cognitive style affects the representation developed.* The potentially complex interactions of various representation variables warrant multivariate analysis procedures, therefore, a 2X2 MANOVA was performed with cognitive style and training as the independent variables. (Vertical commands, horizontal commands and font purity were not included in this analysis due to their non-normality). The dependent variables were derived from the cluster analysis as described previously. No significant effects were found for training, cognitive style or the interaction. Therefore, Hypothesis One is not supported.

Automated Task Performance. *Hypothesis Two: Training and cognitive style affect the development and performance of automated processes.* As described above, the variables used to characterize automated task performance are alpha, T_0 and T_{1000}. As might be expected, these variables are all significantly correlated with each other at the $p<.02$ level. For the purposes of this experiment, each variable is examined independently through a 2x2 ANOVA procedure with training and cognitive style serving as the independent variables.

Regarding initial performance, T_0, while no main effects occur, a significant interaction between training and cognitive style is evident ($F(1,15)=7.04$; $p<.018$). See Table 2 for these results. With regard to learning rate (Table 3), once again, a significant interaction occurs ($F(1,15)=6.45$; $p<.023$). The highest values (or fastest learning rate) are found for FD subjects with Alphabetic training (significantly different from all other means at $p<.05$) while the lowest learning rate occurs for FD subjects with Hierarchial training. There appears only a slight trend for FI subjects to acquire automated processes more quickly with a hierarchial representation (see Figure 1).

From Figure 1, it appears that FD subjects perform better initially when presented with hierarchial training ($p<.05$ level; Newman-Keuls test). After practice, however, the computed T_{1000} value indicates that final performance for FD subjects is best served with the Alphabetic training rather than Hierarchial training ($p<.05$). Neither main effects nor the interaction were statistically significant for T_{1000}.

Apparently, the hierarchial representation training allows FD subjects to more quickly orient to the problem. As expected by the definition of Field Independence, performance of subjects classified into this group appear unaffected by the training style. Further research is needed to examine this issue more clearly.

TABLE 2. ANOVA results for the effect of training and cognitive style on the development and initial performance (T_0) of automated processes.

Source	df	Sum of Squares	Mean Square	F	p-value
Training	1	0.3709	0.3709	3.20	0.094
Cognitive Style	1	0.1929	0.1929	1.66	0.217
Interaction	1	0.8162	0.8162	7.04	0.018
Error	15	1.7393	0.1159		

TABLE 3. ANOVA results for the effect of training and cognitive style on the development of automated processes.

Source	df	Sum of Squares	Mean Square	F	p-value
Training	1	0.0381	0.0381	3.94	0.066
Cognitive Style	1	0.0091	0.0091	0.94	0.348
Interaction	1	0.0624	0.0624	6.45	0.023
Error	15	0.1453	0.0097		

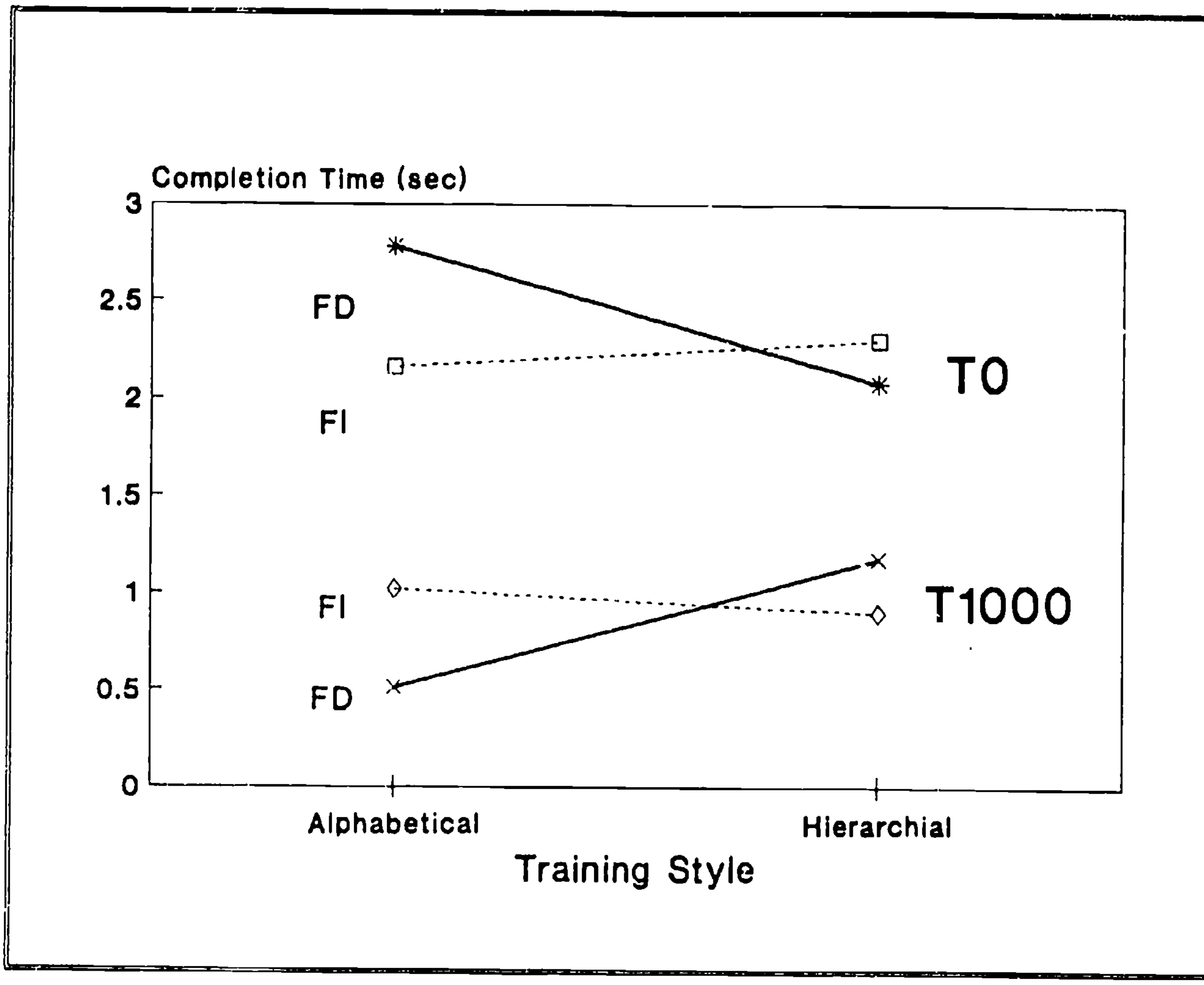

Figure 1. Automatized task performance: T_0 and T_{1000} completion times.

Controlled Task Performance. *Hypothesis Three: Training and cognitive style affect controlled process task performance.* On the CP task, six of the 19 subjects found the correct solution within the allotted time of 15 minutes. Due to the limited number of those completing the task, the effect of training and cognitive style on CP task completion were analyzed separately using Chi-Square procedures. The statistic was identical for both variables: $\chi^2=.693$; $p<.405$. Therefore, hypothesis three cannot be confirmed.

Representation Effects

Automated Process Task Performance. *Hypothesis Four: The task representation affects automated processes.* To evaluate hypothesis four, a canonical correlation was first performed on the representation variables (excluding overall cluster purity since it is a linear combination of existing variables) and the automation variables listed previously. This multivariate procedure determines the relationship between two sets of variables (SAS Institute, 1988). Results indicate a statistically significant correlation between the two groups. The Squared Canonical Correlation is 0.82, which is significant at the $p<.02$ level. It is therefore suggested that a relationship exists between the representation subjects possess and their performance on automated tasks, supporting hypothesis four.

In an effort to examine this relationship in more detail, three stepwise multiple regression analyses were performed on alpha, T_0 and T_{1000} respectively, using the representation variables as independent variables. From this analysis, the rate of learning (alpha) can be predicted by the Maximum Distance Between Clusters and the Purity of Font Cluster variables (using 0.15 as the entry and removal criterion). With these two independent variables, 31.55 percent of the variance in alpha can be predicted ($F(2,16)=3.69$; $p<.048$).

In addition to the above two independent variables, the regression equation to predict initial time to perform the AP task, T_0, includes the Number of Horizontal Commands Misclassified. This is logical since the AP task dealt primarily with horizontal page layout. With these three variables, the computed statistics are as follows: $R^2=.593$, $F(3,15)=7.28$; $p<.003$. No variables met the 0.15 significance level for entry into the model for predicting estimated final performance, T_{1000}. From the above results, hypothesis four is supported and it can be concluded that the knowledge representation impacts AP task performance, at least in the initial stages of developing automaticity.

Controlled Task Performance. *Hypothesis Five: The task representation affects controlled process performance.* For this analysis, subjects were divided into two groups based on whether they successfully completed the task in the allotted time. From this, a Chi-Square analysis was performed using the variables Overall Cluster Purity (grouped as 0-1 and 2-3) and successful or non-successful task completion (see Figure 2). This analysis reveals that there is a significant dependency between these variables ($\chi^2=6.094$; $p<.025$).

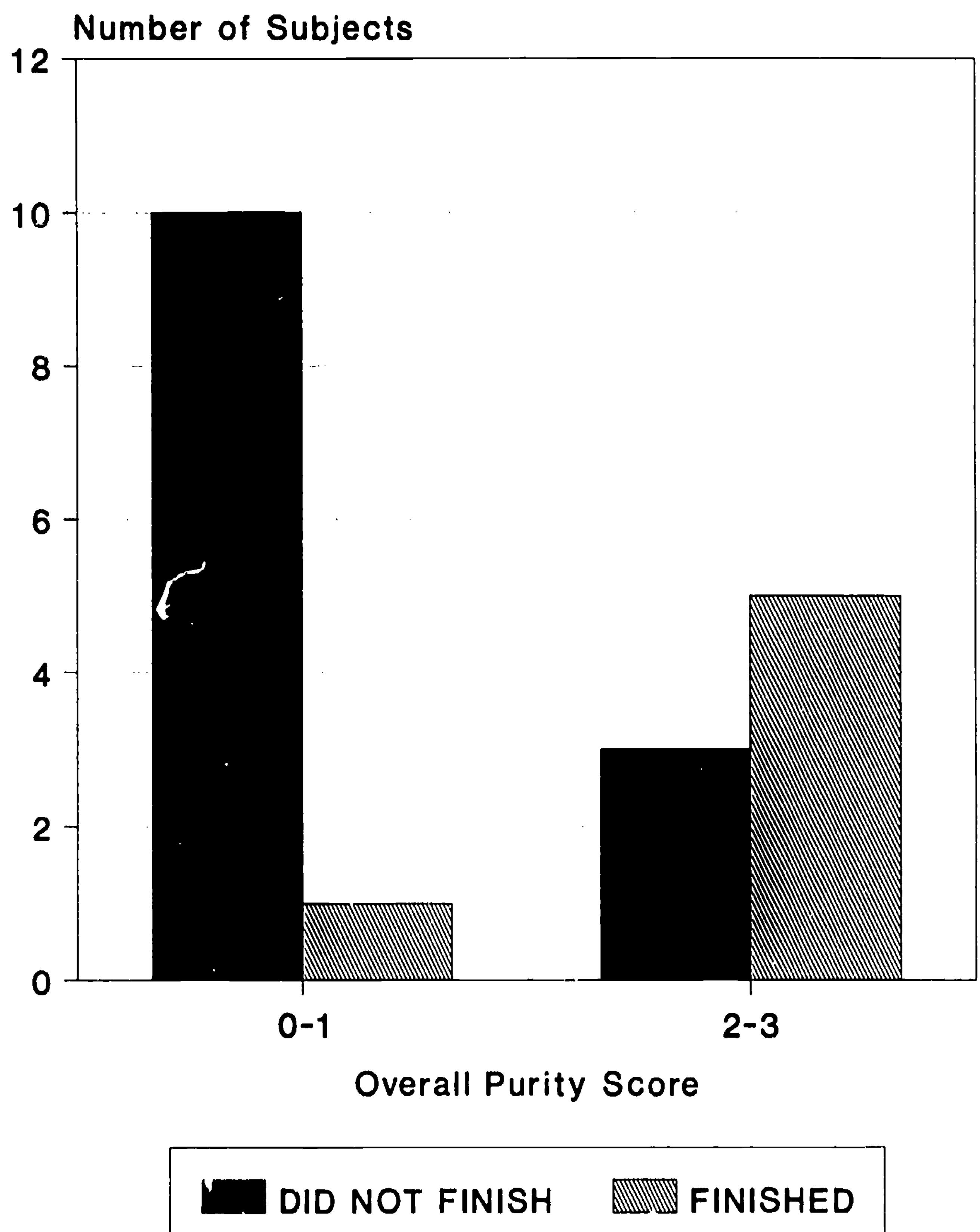

Figure 2. Overall purity score and controlled process task performance.

In order to determine the utility of this finding for predicting performance on CP tasks from knowing the knowledge representation features, a discriminant analysis was performed on the 19 subjects. Using the computed discriminant function with Overall Cluster Purity, 89.13 percent of the subjects were correctly classified as successful or unsuccessful. More specifically, one successful subject and three unsuccessful subjects were misclassified. With only one variable, the accuracy of this discriminant function supports hypothesis five, that representation significantly influences controlled task performance.

In order to determine the CP solution strategies of the subjects, a GOMS analysis was performed on the verbal protocol data (selection rules were not obtained in this analysis). A "master" GOMS solution containing a set of three goals and their coinciding methods and operators to accomplish those goals was developed upon which to compare subject solution strategies. From the analysis of the subjects' solutions, three strategies became evident: Direct, Single Branch and Multiple Branch.

Those subjects whose strategies contained no incorrect methods (that is, all methods utilized led the subject closer to the task goal) were classified as Direct (D). The only deviations of these subjects' solutions from the master GOMS solution were individual "operators" within the chosen methods. Four subjects were placed in this category, and of these, three successfully completed the task.

A second strategy classification is Single Branch (SB). These subjects tended to follow a single solution path, even when that particular path was not leading them closer to the task goal. The classification criterion for this category required the subject to have performed three successive methods (different by no more than one operator) that did not advance the subject closer to the ultimate goal. This pattern may have occurred at any point within the solution set. Five subjects were determined to be Single Branch, and none reached the solution of the CP task.

The final strategy is Multiple Branch (MB). The remaining ten subjects moved from method to method in search of the correct solution pattern (which three subjects located). To be placed in this category, subjects must have implemented 2 or less incorrect methods consecutively, while not following the Direct pattern. It should be noted that, in order to ensure the correct placement of subjects into their respective solution strategy groups, the classification process was performed independently by two raters.

Following the placement of subjects into their respective solution strategy groups, a Wilcoxon's Rank-Sum Test was performed, using Overall Cluster Purity as the ranked variable, in order to determine if representation differences existed between the groups. Purity scores were then tested for each solution strategy group against the purity scores of the other groups independently. The overall purity scores in the Direct group were found to be higher than those in the Single Branch group ($W_s(n_1=4,n_2=5)=11.5$; $p<.05$), and those in the Multiple Branch group ($W_s(n_1=4,n_2=10)=17$; $p<.05$). The overall purity scores appear to be slightly higher in the Single Branch group than in the Multiple Branch group, but the result was not significant. Figure 3 shows the relationship among the group means. From the previous results, it can be seen that subjects with high purity scores tend to utilize a Direct solution strategy when performing a controlled process task, while subjects with low overall purity scores follow a Multiple or Single Branch approach. It is noteworthy to mention that 75% of those subjects with Direct strategies completed the task compared to 30% and 0% of the Multiple Branch and Single Branch Groups respectively.

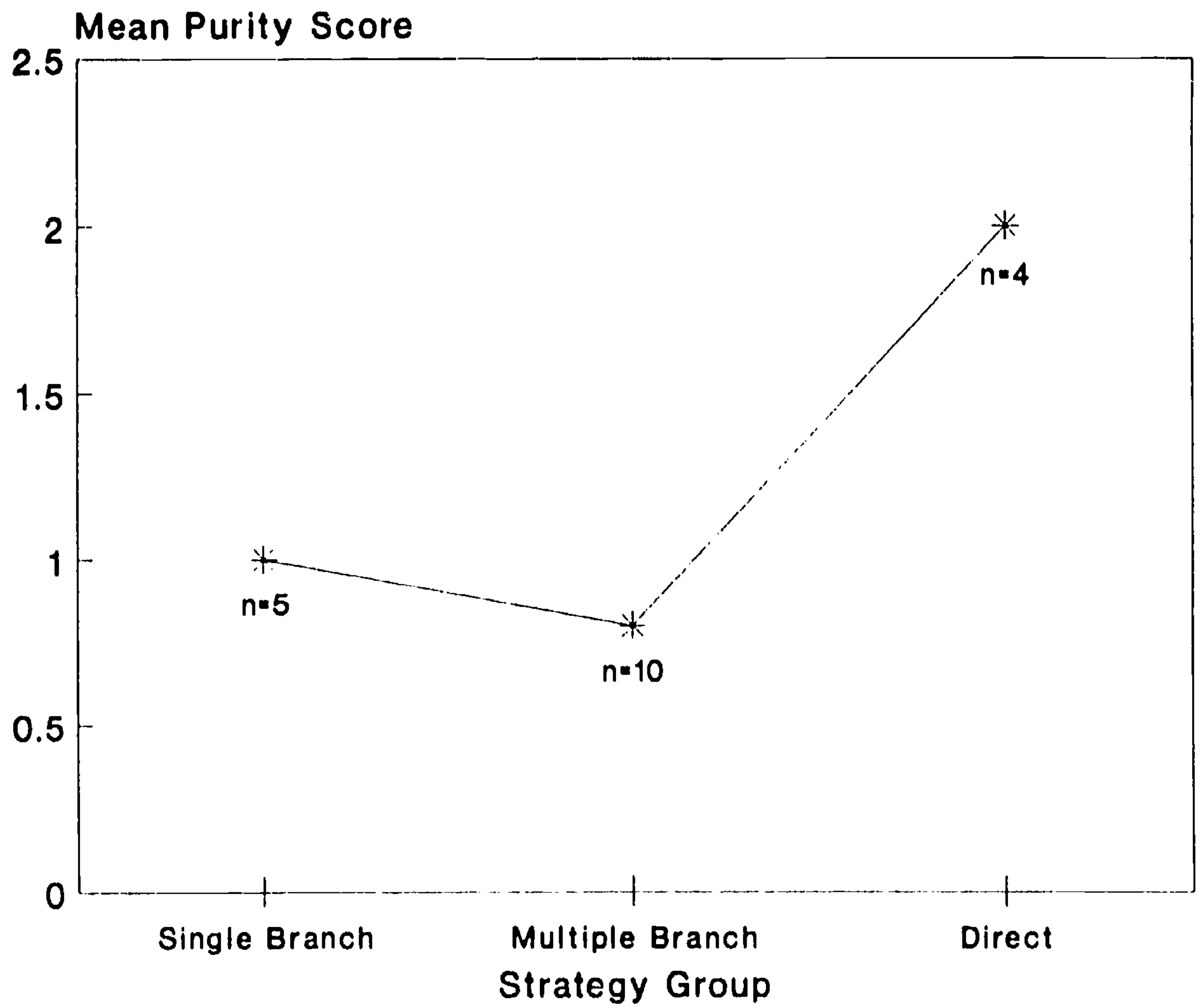

Figure 3. Mean overall purity scores of solution strategy groups.

In summary of this section, it appears that task representation affects the solution strategy employed in a complex cognitive task, which in turn is a determining factor of successful task completion. A complete summary of the statistical analyses performed in this study is given in Table 4.

IV. CONCLUSION

The first hypothesis of this study (training and cognitive style affects the representation developed) was not supported. Similar to the results of Adelson (1984), the particular training (Hierarchial versus Alphabetical) administered to the subjects, regardless of their cognitive style, did not affect their developed representation. Again, it appears that subjects will maintain their most natural representation.

Significant results were obtained for the effect of training and cognitive style on the development and performance of automated processes. The fastest learning rate was found for Field Dependent subjects with Alphabetic training, while the slowest learning rate occurred in Field Dependent subjects trained hierarchically. Initial AP task performance of FD subjects was actually aided by hierarchial training, but the final performance was best aided by alphabetic training. This result is related to previous findings which suggest a switch from a concrete to an abstract representation as one becomes experienced in a particular task domain. In particular, an individual is not necessarily an expert simply because a particular task has been automated.

No evidence was found to support the effect of training and cognitive style on controlled process task performance (that is, whether the subjects finished the CP task in the allotted time). Further research is needed in this area.

Automated processes were found to be affected by the task representation. More precisely, the rate of learning, alpha, was predicted by two independent variables: Maximum Distance Between Clusters and the Purity of Font Cluster. In addition, the initial time to perform the AP task, T_0, could be predicted with the inclusion of a third independent variable, the Number of Horizontal Commands Misclassified.

Controlled process task performance was also found to be affected by the task representation. Simply by knowing the subjects' task representations (based upon Overall Cluster Purity), approximately 89% of the subjects were correctly classified as to whether they finished the CP task. In addition, the particular strategy utilized to perform the CP task was affected by the task representation. Overall Purity scores were highest for those subjects who approached the task with a Direct strategy, and 75% of those subjects completed the CP task successfully.

TABLE 4. Summary of Results

HYPOTHESES	STATISTIC	SIGNIFICANCE
1. Training & Cognitive Style affect representation developed	2x2 MANOVA	N.S.[1]
2. Training & Cognitive Style affect development and performance of automated processes		
(a) Initial Performance (T_0)		
· Main Effects	2x2 ANOVA	N.S.
· Interaction	2x2 ANOVA	$p<0.018$
· Field Dependent subjects better with Hierarchial training than Alphabetical training	Newman-Keuls	$p<0.05$
(b) Final Performance (T_{1000})		
· Main Effects	2x2 ANOVA	N.S.
· Interaction	2x2 ANOVA	N.S.
· Field Dependent subjects better with Alphabetical training than Hierarchial training	Newman-Keuls	$p<0.05$
(c) Learning Rate (Alpha)		
· Main Effects	2x2 ANOVA	N.S.
· Interaction	2x2 ANOVA	$p<0.023$
· Highest for Field Dependent subjects with Alphabetical training	Newman-Keuls	$p<0.05$
3. Training & Cognitive Style affect controlled process task performance	Chi-Square	N.S.
4. Task representation affects automated processes	Squared Canonical Correlation	$p<0.02$
(a) Initial performance (T_0)	Multiple Regression	$p<0.003$
(b) Final performance (T_{1000})	Multiple Regression	N.S.
(c) Rate of learning (Alpha)	Multiple Regression	$p<0.048$
5. Task representation affects controlled process performance		
(a) Representation affects probability of success	Chi-Square	$p<0.025$
(b) Representation affects solution strategy		
· Higher overall purity scores in Direct group than in Single Branch	Wilcoxon's Rank-Sum	$p<0.05$
· Higher overall purity scores in Direct group than in Multiple Branch	Wilcoxon's Rank-Sum	$p<0.05$

[1]N.S. = Not significant at $p<0.05$ level.

The above results support the view that a high level determinant of operator performance on cognitive-oriented tasks exists: domain representation. Previously, it has been suggested that training to develop automaticity and high level performance simply requires repetitive practice. However, the present results appear to indicate that, depending on individual operator characteristics, a higher level factor can significantly influence initial performance and the rate of learning on mundane and straightforward tasks which are well suited for automaticity. In addition, the task representation influences performance on more complex tasks, including the strategy used to complete them. Since computer-oriented tasks may require both types of performance from operators (automatic and controlled processes), emphasis should be placed on selecting and reinforcing the correct representation for the particular task requirements and individual operator characteristics. However, further research is necessary to determine mechanisms for teaching and reinforcing these representations. The present study did not identify factors which lead to the particular representation developed. With this knowledge, training programs could be targeted to develop representations most suited to the task and operator, thereby decreasing training time and increasing task performance.

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