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ABSTRACT

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# COMPUTER-MANAGED INSTRUCTION: CRYSTALLIZED AND FLUID INTELLIGENCE

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Twenty-four measures crystallized intelligence ($G_c$) and fluid intelligence ($G_f$) were obtained for samples of graduates and failures of an innovative instructional situation in which computer-managed mastery learning was used to teach elementary electricity and electronics. Seven stepwise multiple discriminant analyses and associated statistics were computed to determine which linear combinations of $G_f$ and $G_c$ measures would optimally separate the two groups. Corresponding classification functions derived for the discriminant analyses were applied to the data to evaluate the effectiveness of differentiating failures and graduates. The results did not substantiate the hypothesis that $G_f$ measures would be associated more strongly with student success in a new instructional situation than would $G_c$ measures. Contrary to theory, the findings suggest that some unconventional educational environments are not necessarily dysfunctional for more able students. In these situations, they can just as easily exercise and exploit those skills developed and applied in more traditional instructional settings.

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## FOREWORD

This research was performed under exploratory development work unit RF63-522-801-013-03.04 (Testing Strategies for Operational Computer-based Training) under the sponsorship of the Chief of Naval Material (Office of Naval Technology). The general goal of this work unit is to evaluate the impact of different computer-based testing strategies for operational training.

The results of this study are primarily intended for the Department of Defense training and testing research and development community.

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## SUMMARY

### Background and Problem

Two types of intelligence have been defined: (1) crystallized intelligence ($G_c$), which consists of good predictors of conventional educational accomplishment or scholastic ability (e.g., verbal, quantitative, vocabulary, reading comprehension, information, mathematical, and prior scholastic achievement) and (2) fluid intelligence ($G_f$), which consists of assembly and control processes that adapt strategies for solving novel and immediate problems (e.g., abstract, spatial, figural, and nonverbal reasoning).

In unconventional instructional treatments, such as in computer-managed mastery learning, $G_c$ becomes less important to learning and an aptitude-treatment-interaction (ATI) will likely appear. The ATI approach to teaching emphasizes the use of aptitude measures for selecting instructional strategies or treatments to help individuals attain educational objectives. Consequently, Snow (1980) hypothesized that students who lack well-developed, conventional, academic aptitudes and abilities ($G_c$) will benefit from unconventional instructional situations, while those who possess these skills may not be able to apply them in these environments.

Computer-managed mastery learning is a form of computer-managed instruction (CMI). It is individualized instruction with carefully defined objectives, hierarchical content, modular presentation and assesment, diagnostic achievement tests, and immediate feedback to students. This instructional approach may structure, segment, and direct learning for students who cannot do so for themselves.

Snow also hypothesized that this unconventional instructional treatment probably makes learning more difficult for the students who can organize and process their own learning. Therefore, $G_c$ is probably of no particular advantage in unconventional instructional situations such as computer-managed mastery learning. He expected that $G_f$ would be associated with achievement in innovative instructional situations--that differ from those the students experienced in the past--and $G_c$ would be irrelevant.

### Objective

The purpose of this exploratory development was to test the hypothesis that measures of fluid intelligence ($G_f$) would be associated more with student success in unconventional or innovative instructional situations, such as computer-managed mastery learning, than would measures of crystallized intelligence ($G_c$).

### Approach

Twenty-four measures of crystallized and fluid intelligence were obtained for samples of graduates and failures of basic electricity and electronics school--an innovative instructional situation in which computer-managed mastery learning is used to teach elementary electricity and electronics. Seven stepwise multiple discriminant analyses and associated statistics were computed to determine which linear combinations of $G_c$ and $G_f$ measures would optimally separate the two groups. Corresponding classification functions derived for the discriminant analyses were applied to the data to evaluate the effectiveness of differentiating failures and graduates.

## Results

Measures of crystallized intelligence accounted for more of the discrimination between CMI failures and graduates than measures of fluid intelligence. Assuming either equal or adjusted probability of graduating or failing, crystallized intelligence measures correctly classified a greater number of actual failures and graduates than did fluid intellignece measures. Employing crystallized and fluid intelligence measures simultaneously, always classified a higher percentage of students correctly than did employing only measures of fluid intelligence. Assuming adjusted probability, actual failures were better classified using crystallized intelligence indices than crystallized and fluid intelligence indices combined. The data demonstrated that measures of crystallized intelligence are more important for predicting performance in a CMI environment, an instance of a new instructional situation, than measures of fluid intelligence.

## Discussion and Conclusions

Unlike Snow's speculations, the findings suggested that some unconventional educational environments are not necessarily dysfunctional for more able students. In these situations, they can just as easily exercise and capitalize upon those skills developed and applied in more traditional instructional settings.

If innovative instructional situations are used, then the relevancy of crystallized intelligence to learning is not lessened. Students who possess well-developed, conventional, academic aptitudes and abilities are able to apply them even in unorthodox, educational environments. Students who lack these accumulated skills will need to acquire them in order to benefit from nontraditional as well as traditional instruction.

Evidently, crystallized intelligence, representing prior assemblies of performance processes, can be retrieved and applied anew in an instructional situation unlike those experienced in the past. This implies that crystallized intelligence begins to take on some of the alleged attributes of fluid intelligence, especially considering adaptations to novel educational environments. The declared distinction between long-term assembly for transfer to familiar new situations, crystallized intelligence, and short-term assembly for transfer to unfamiliar new situations, fluid intelligence, tends to disappear. Alternatively, if this difference does not vanish, $G_c$ abilities and aptitudes are adaptive and advantageous in innovative instructional situations such as computer-managed mastery learning employed in this reported research.

Lastly, this computer-managed instruction may not have been innovative enough when compared to previously experienced educational environments. Consequently, it would not be expected to elicit accommodative $G_f$ strategies more than $G_c$ abilities and aptitudes used by students in traditional instructional settings.

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## INTRODUCTION

### Background

According to Snow (1980), Cattel's (1971) crystallized intelligence, $G_c$, represents a general dimension of measures that are good predictors of conventional educational achievement or scholastic ability (e.g., verbal, quantitative, vocabulary, reading comprehension, information, mathematical, and prior scholastic achievement). Cattel's (1971) fluid intelligence, $G_f$, represents another general dimension of measures that represents assembly and control processes necessary to structure adaptive strategies for solving novel and immediate problems (e.g., abstract, spatial, figural, and nonverbal reasoning).

In attempting to answer why $G_c$ measures are often better predictors of learning outcome than are $G_f$ measures, Snow (1980) speculated:

> One reason may be that $G_c$ represents the long-term accumulation of knowledge and skills, organized into functional cognitive systems by prior learning, that are in some sense crystallized as units for use in future learning. Because these are products of past education, and because education is in large part accumulative, transfer relations between past and future learning are assured. The transfer need not be primarily of specific knowledge but rather of organized academic learning skills. Thus $G_c$ may represent prior assemblies of performance processes retrieved as a system and applied anew in instructional situations not unlike those experienced in the past, whereas $G_f$ may represent new assemblies of performance processes needed in more extreme adaptations to novel situations. The distinction, then, is between <u>long-term</u> assembly for transfer to <u>familiar</u> new situations versus <u>short-term</u> assembly for transfer to <u>unfamiliar</u> new situations. (p. 37)

Computer-managed instruction (CMI) is employed to implement mastery learning of many complex curricula; for example, basic electricity and electronics (Baker, 1978; Kearsley, 1983; Kearsley, Hunter, & Seidel, 1983a, 1983b; Kulik, Kulik, & Cohen, 1980; Orlansky & String, 1980, 1981). This pedagogical implementation can probably be considered a "new" learning situation in Snow's (1980) scheme of things:

> What constitutes a "new" learning situation is not really clear. But one can predict that as an instructional situation involves combinations of new technology (e.g., computerized instruction or television), new symbol systems (e.g., computer graphics or artistic expressions), new content (e.g., topological mathematics or astrophysics), and/or new contexts (e.g., independent learning, collaborative teamwork in simulation games), $G_f$ should become more important and $G_c$ less important. (p. 59)

CMI can also be viewed as a relatively new instructional technology. The comprehension of many circuit schematics and the solution of numerous algebraic equations can be thought of as new symbol systems. The perception of several relationships among voltage, resistance, and current, as well as the reduction of complicated circuits to simpler ones, can be conceived as new content. Self-study, self-pacing, and mastery learning can be regarded as new contexts. According to Snow, the relationship of $G_c$ to achievement should be stronger in ordinary educational environments. This has been established in much of the aptitude-treatment-interaction (ATI) research (Cronbach & Snow, 1977).

If the typical instructional treatment is altered, as in computer-managed mastery learning, the association of $G_c$ to learning decreases and an ATI will likely appear. Consequently, according to Snow (1980), students who lack well-developed, conventional, academic aptitudes and abilities will benefit from the unorthodox, educational treatment; while those who possess these skills may not be able to apply them in unconventional instructional situations. Computer-managed mastery learning is individualized instruction with carefully defined objectives, hierarchical content, modular presentation and assessment, diagnostic achievement tests, and immediate feedback on student progress. This pedagogical approach structures, segments, and directs learning for less able students by doing for them what they cannot do for themselves. Snow maintained that this unconventional instructional treatment is probably dysfunctional for more able students, who can organize and control their own learning because of the nature of the cognitive processing required and acquired previously by conventional, educational experiences. Therefore, $G_c$ intelligence is probably of no particular advantage in novel instructional situations such as computer-managed mastery learning. Within this context, Snow expected that $G_f$ would be associated with achievement in innovative instructional situations--different from those students experienced in the past. In these novel educational environments, $G_c$ will likely be irrelevant; and $G_f$, relevant.

## Purpose

The purpose of this exploratory development was to test the hypothesis that measures of fluid intelligence ($G_f$) would be associated more with student success in unconventional or innovative instructional situations, such as computer-managed mastery learning, than would measures of crystallized intelligence ($G_c$).

# METHOD

## Subjects

The original sample of subjects consisted of 340 graduates from recruit training at the Naval Training Center, San Diego (NTC) who were scheduled for instruction at the Basic Electricity and Electronics (BE/E) School at NTC. Before beginning BE/E orientation, the subjects were administered tests of $G_c$ and $G_f$. Data for 20 subjects who failed to follow directions and/or to complete 9 of the 12 tests were discarded. Of the remaining 320 subjects, 40 failed to graduate from BE/E School--35 for academic reasons and 5 for nonacademic reasons. Thus, data were available for 315 BE/E trainees--280 graduates and 35 academic failures.

The subtests of the Armed Services Vocational Aptitude Battery (ASVAB) (MEPCOM Manual 601-1) provide some measures of $G_c$ for all Navy entrants. In this study, 108 BE/E graduates had incomplete or missing ASVAB scores or had been administered the Basic Test Battery (BTB) instead of the ASVAB. (Before the ASVAB was adopted, the BTB was used routinely for measuring aptitudes.) Thus, the final sample used in the study consisted of 207 BE/E trainees--172 graduates and 35 academic failures.

Measures of Crystallized and Fluid Intelligence

The 24 $G_f$ and $G_c$ measures used in this study (see Table 1) are in three categories: cognitive styles, abilities, and aptitudes. Cognitive styles are the dominant modes of information processing that individuals typically employ when perceiving, learning, problem solving, and decision making. Abilities are the general intellectual capabilities of individuals that are pervasive to the performance of many tasks. Aptitudes are indices used to select personnel to perform tasks that demand specific skills and to find the right person for a certain job or school.

Six measures of cognitive styles were selected as indices of $G_f$ because they are chiefly abstract, spatial, figural, and nonverbal reasoning tests as well as having implications for academic achievement and instruction (Kogan, 1971). Six ability and 12 aptitude measures were selected as indices of $G_c$ because they are chiefly verbal, quantitative, vocabulary, reading comprehension, information, and mathematical reasoning tests as well as representing various types of information-processing tasks (Carroll, 1975) and being relevant to the BE/E curriculum. The 12 aptitude indices of $G_c$ were chosen because they are ASVAB subtests that were thought to be readily available for Navy personnel and also because these scores are the basis of assigning individuals to different types of Navy schools. All of these measures are moderate to high in reliability, paper and pencil in nature, and fairly short in duration. Federico and Landis (1984) established the relative dependence of most cognitive style measures of $G_f$ with ability and aptitude measure $G_c$ inherent to general problem solving and the relative independence of some cognitive measures of $G_f$ from technical aptitude and verbal ability measures of $G_c$.

New Instructional Situation

The unconventional instructional treatment consisted of the first 11 modules of the BE/E school curriculum. This involved CMI to implement the mastery learning of the subject matter of the modules.

Computer-managed Instruction

In CMI, students self-study and self-pace themselves through off-line lesson modules; that is, they do not interact directly with the system while learning. (This is unlike computer-assisted instruction where course contents and tests are stored in the computer with which the student interacts in real time by means of on-line terminals.) Also, in CMI, the computer via its distributed terminals (1) scores criterion-referenced multiple-choice tests that the students take off-line, (2) interprets test results and provides feedback to each student regarding his/her performance, (3) advises the student to learn the next or alternative lesson or to repeat mastery modules, and (4) manages student records, instructional resources, and administrative data (Baker, 1978; Orlansky & String, 1980, 1981).

Table 1

Measures of Fluid ($G_f$) and Crystallized ($G_c$) Intelligence

| Factor | Abbreviation | Description | Measurement Instrument |
|---|---|---|---|
| | | **Fluid Intelligence, $G_f$** | |
| **Cognitive Styles** | | | |
| 1. Field-independence vs. Field-dependence | FILDINDP | Analytical vs. global orientation | Hidden Figures Test, Part I (Ekstrom, French, Harman, and Derman, 1976) |
| 2. Conceptualizing Style | CONCSTYL | Span of conceptual category | Clayton-Jackson Object Sorting Test (Clayton & Jackson, 1961) |
| 3. Reflectiveness-Impulsiveness | REFLIMPL | Deliberation vs. impulse | Impulsivity Subscale from Personality Research Test, Form E (Jackson, 1974). |
| 4. Tolerance of Ambiguity | TOLRAMBQ | Inclined to accept complex issues | Tolerance of Ambiguity Scale from Self-Other Test, Form C (Rydell & Rosen, 1966). |
| 5. Category Width | CATEWIDH | Consistency of cognitive range | Category Width Scale (Pettigrew, 1958). |
| 6. Cognitive Complexity | COGCOMPX | Multidimensional perceptions of environment | Group Version of Role Construct Repertory Test (Bieri, Atkins, Brier, Leaman, Miller, & Tripodi, 1966) |
| | | **Crystallized Intelligence, $G_c$** | |
| **Abilities** | | | |
| 7. Verbal Comprehension | VERBCOMP | Understanding the English language | Vocabulary Test, Part I (Ekstrom et al., 1976) |
| 8. General Reasoning | GENLREAS | Solving specific problem. | Arithmetic Aptitude Test, Part I (Ekstrom et al., 1976) |
| 9. Associational Fluency | ASSOFLUN | Producing similar words rapidly | Controlled Associations Test, Part I (Ekstrom et al., 1976) |
| 10. Logical Reasoning | LOGIREAS | Deducing from premise to conclusion | Nonsense Syllogisms Test, Part I (Ekstrom et al., 1976) |
| 11. Induction | INDUCTON | Forming hypotheses to fit certain facts | Figure Classification Test, Part I (Ekstrom et al., 1976) |
| 12. Ideational Fluency | IDEAFLUN | Generating ideas about a specific type | Topics Test, Part I (Ekstrom et al., 1976) |
| **Aptitudes** | | | |
| 13. General Information | GENLINFO | Recognizing factual information | General Information Subtest, ASVAB |
| 14. Numerical Operations | NUMROPER | Completing arithmetic operations | Numerical Operations Subtest, ASVAB |
| 15. Attention to Detail | ATTNDETL | Finding an important detail | Attention to Detail Subtest, ASVAB |
| 16. Word Knowledge | WORDKNOL | Comprehending written and spoken language | Word Knowledge Subtest, ASVAB |
| 17. Arithmetic Reasoning | ARTHREAS | Solving arithmetic word problems | Arithmetic Reasoning Subtest, ASVAB |
| 18. Space Perception | SPACPERC | Visualizing objects in space | Space Perception Subtest, ASVAB |
| 19. Mathematics Knowledge | MATHKNOL | Employing mathematical relationships | Mathematics Knowledge Subtest, ASVAB |
| 20. Electronics Information | ELECINFO | Using electronics relationships | Electronics Information Subtest, ASVAB |
| 21. Mechanical Comprehension | MECHCOMP | Reasoning with mechanical concepts | Mecnanical Comprehension Test, ASVAB |
| 22. General Science | GENLSCIE | Perceiving relationships between scientific concepts | General Science Subtest, ASVAB |
| 23. Shop Information | SHOPINFO | Knowing shop tools | Shop Information Subtest, ASVAB |
| 24. Automotive Information | AUTOINFO | Knowing automotive functions | Automotive Information Subtest, ASVAB |

## Mastery Learning

Mastery learning has many major features:

1. Mastery is measured relative to the specific instructional objectives every student is required to master.

2. The instruction itself is structured in clearly defined learning units or modules.

3. The student must master each module completely before proceeding to the next module.

4. A diagnostic objectives-referenced test is administered to every student at the end of each module to provide feedback on the adequacy of the student's learning.

5. Based upon the diagnostic information, the student's original instruction is repeated or supplemented so that he/she can successfully master the module.

6. Time to complete each module is used as the means of individualizing instruction and thus promoting mastery of the material (Block, 1974; Bloom, 1974, 1976).

## Learning Materials

The individualized learning materials were a set of 11 hierarchical learning modules that teach basic facts, concepts, principles, and rules regarding basic electricity and electronics. These modules were selected because students from all electronics-related Navy ratings must master them before proceeding to more specialized training. Each module was presented as a self-study booklet consisting of three to seven lessons. To learn a lesson within a booklet, students could choose, based upon their experience and preference, a narrative presentation, programmed instruction, and/or straightforward summary. The alternative training treatments for a lesson could be complemented by enrichment material or the instructor if the student desired. Learners were encouraged to use any or all of the instructional resources that they considered necessary to master the modular material. The descriptive prose in each booklet was supplemented by many schematics, circuit diagrams, photographs of meters, and algebraic expressions. Typically, the presentation of the many facts, concepts, principles, and rules was followed by appropriate examples.

Table 2 presents subject-matter content of the 11 modules.

## Statistical Analyses

Seven stepwise multiple discriminant analyses were computed to determine which linear combinations of $G_c$ and $G_f$ tests optimally differentiated between BE/E failures and graduates. These separate analyses were calculated using (1) cognitive style, ability, or aptitude indices of $G_c$ and $G_f$, (2) the three two-way interactions of these measures, and (3) the one three-way interaction. In these analyses, multivariate normality and homogeneity of group dispersions were assumed.

Table 2

Subject-matter Content of 11 (CMI) Modules of BE/E School

| Module Number | Subject-matter Content |
|---|---|
| 1 | Electrical current--electricity and the electron, electron movement, current flow, measurement of current, and the ammeter. |
| 2 | Voltage--electromotive force from chemical action, magnetism, electromagnetic induction, AC voltage, uses of AC and DC, and measuring voltage. |
| 3 | Resistance--characteristics of resistance, resistors, resistor values, and ohmmeters. |
| 4 | Measuring current and voltage in series circuits--measuring current in a series circuit, voltage in a series current, and using the multimeter as a voltmeter. |
| 5 | Relationships of current, voltage, and resistance--voltage, resistance, and current, Ohm's law formula, power, internal resistance, and troubleshooting series circuits. |
| 6 | Parallel circuits--rules for voltage and current, rules for resistance and power, variational analysis, and troubleshooting parallel circuits. |
| 7 | Combination circuits and voltage dividers--solving complex circuits, voltage reference, and voltage dividers. |
| 8 | Induction--electromagnetism, inductors and flux density, inducing voltage, and inductance and induction. |
| 9 | Relationships of current, counter electromotive force, and voltage in inductance-resistance circuits--rise and decay of current and voltage, inductance-resistance time constant, using the universal time constant chart, inductive reactance, relationships in inductive circuits, and phase relationships. |
| 10 | Transformers--transformer construction, transformer theory and operation, turns and voltage ratios, power and current, transformer efficiency, semiconductor rectifiers. |
| 11 | Capacitance--the capacitor, theory of capacitance, total capacitance, resistance-capacitance time constant, capacitive reactance, phase and power relationships, and capacity design considerations. |

Classification functions obtained for the derived discriminant functions were applied to the subjects' $G_c$ and $G_f$ measures. Two sets of analyses were conducted. In the first, it was assumed that students who entered BE/E school had an equal probability of failing or graduating. In the second, this probability was adjusted according to the a priori probabilities of failing and graduating from BE/E school (Cooley & Lohnes, 1962; Overall & Klett, 1972; Tatsuoka, 1971). Records showed that, during the period of interest, the base rates of failing and graduating--for all ratings requiring BE/E school--were 15 and 85 percent respectively. By classifying subjects initially used to produce the discriminant functions and comparing predicted and actual group memberships, it was possible to determine empirically the proportion of correct classifications and, thus, the adequacy of the discriminations.

## RESULTS

Table 3 presents the means, standard deviations, and univariate F-ratios for CMI failures and graduates on the 24 tests of $G_f$ and $G_c$. Failures scored significantly lower than did the graduates on 2 of the 6 cognitive style, $G_f$ measures, as well as on 4 of the 6 ability and 8 of 12 aptitude, $G_c$ measures. When these test scores were intercorrelated, as shown in Table 4, cognitive styles ($G_f$) seem to be generally independent of the others, except for field-independence. As expected, however, abilities and aptitudes appear to be related.

Table 5 provides the results of the seven stepwise multiple discriminant analyses computed to determine which linear combination of $G_c$ and $G_f$ measures optimally differentiate CMI failures from graduates, along with their associated statistics. As shown, for each analysis, one discriminant function (D) was derived. For example, for the analysis using $G_f$ measures, cognitive styles, the derived discriminant function is -.81 FILDINDP -.36 CONCSTYL +.26 COGCOMPX. Using this function, only three of the six cognitive styles were needed to discriminate significantly between the two groups. The absolute values of the coefficient in the function indicate how much each of the three $G_f$ measures contributes in discriminating between CMI failures and graduates.

According to this multivariate model, the maximum number of derived discriminant functions is either one less than the number of groups or equal to the number of discriminating variables, whichever is smaller. Since there were only two groups to be differentiated, each analysis yielded only one discriminant function and, consequently, only one eigenvalue ($\lambda$). An eigenvalue is a special measure computed in obtaining the discriminant function; it is an index of the relative importance of each differentiating function, and the sum of the eigenvalues indicates the total variance accounted for by the discriminating variables. In this case, having just two groups to be separated, the single eigenvalue reflects the amount of variance accounted for by $G_c$ and $G_f$ measures and their several interactions. A second index can be used as an additional aid in judging the importance of a discriminant function. This is its corresponding canonical correlation, $R_c$, which reflects the association between a single discriminant function and the set (g-1) dummy variables that define the g group memberships. It indicates how closely the function and the group variable are related and is another index of the function's ability to discriminate among the groups. Wilk's lambda ($\Lambda$) statistic and its associated chi-square test of significance indicate the discriminating power existing in the $G_f$ and $G_c$ test scores being used to separate the groups. The discriminating power in these variables decreases as the value of lambda increases. Rao's V, a generalized distance measure, is one criterion that can be used to select the order in which to enter variables into the

Table 3

Means, Standard Deviations, and Univariate F-ratios for CMI Failures and Graduates on Tests Measuring $G_f$ and $G_c$

| Test | Failure (N = 35) M | Failure (N = 35) SD | Graduates (N = 172) M | Graduates (N = 172) SD | Univariate F |
|---|---|---|---|---|---|
| | | | $G_f$ | | |
| **Cognitive Styles** | | | | | |
| 1. FILDINSP | 2.34 | 3.38 | 5.20 | 3.82 | 16.82*** |
| 2. CONCSTYL | 11.0 | 3.63 | 12.70 | 4.07 | 4.90* |
| 3. REFLIMPL | 4.06 | 2.79 | 3.33 | 3.13 | 1.62 |
| 4. TOLRAMBQ | 5.57 | 2.85 | 5.70 | 1.98 | 0.10 |
| 5. CATEWIDH | 32.34 | 12.61 | 31.70 | 9.59 | 0.12 |
| 6. COGCOMPX | 77.20 | 20.04 | 72.04 | 17.71 | 2.36 |
| | | | $G_c$ | | |
| **Abilities** | | | | | |
| 7. VERBCOMP | 7.40 | 3.49 | 8.95 | 3.23 | 6.54* |
| 8. GENLREAS | 5.00 | 3.05 | 8.17 | 2.95 | 32.36*** |
| 9. ASSOFLUN | 9.31 | 4.34 | 10.97 | 4.91 | 3.44 |
| 10. LOGIREAS | 1.97 | 4.06 | 2.76 | 4.51 | 0.92 |
| 11. INDUCTON | 50.17 | 15.21 | 59.72 | 16.95 | 9.53** |
| 12. IDEAFLUN | 10.00 | 3.50 | 11.59 | 4.34 | 4.12* |
| **Aptitudes** | | | | | |
| 13. GENLINFO | 55.29 | 5.44 | 58.78 | 6.97 | 7.81** |
| 14. NUMROPER | 48.60 | 6.71 | 53.92 | 7.45 | 15.29*** |
| 15. ATTNDETL | 49.20 | 7.49 | 51.16 | 9.57 | 1.30 |
| 16. WORDKNOL | 55.80 | 6.22 | 59.48 | 6.30 | 9.95** |
| 17. ARTHREAS | 53.00 | 8.37 | 60.20 | 8.36 | 21.54*** |
| 18. SPACPERC | 55.60 | 7.83 | 56.24 | 11.15 | 0.10 |
| 19. MATHKNOL | 53.09 | 5.87 | 60.44 | 8.13 | 25.84*** |
| 20. ELECINFO | 57.34 | 5.30 | 60.58 | 6.58 | 7.48** |
| 21. MECHCOMP | 56.02 | 6.81 | 59.62 | 6.74 | 8.21** |
| 22. GENLSCIE | 54.80 | 11.53 | 60.45 | 7.66 | 13.10*** |
| 23. SHOPINFO | 56.57 | 5.84 | 57.78 | 6.70 | 0.98 |
| 24. AUTOINFO | 55.97 | 6.06 | 57.55 | 8.02 | 1.21 |

*$p < .05$ ($F(1, 205) \geq 3.84$).
**$p < .01$ ($F(1, 205) \geq 6.64$).
***$p < .001$ ($F(1, 205) \geq 10.83$).

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Table 4

Intercorrelation Matrix of $G_f$ (Tests 1-6) and $G_c$ (Tests 7-24) Measures

| Test | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. FILDINDP | 1.00 | | | | | | | | | | | |
| 2. CONCSTYL | .14 | 1.00 | | | | | | | | | | |
| 3. REFLIMPL | -.12 | -.14 | 1.00 | | | | | | | | | |
| 4. TOLRAMBQ | .01 | .03 | -.00 | 1.00 | | | | | | | | |
| 5. CATEWIDH | .11 | -.05 | .16 | -.06 | 1.00 | | | | | | | |
| 6. COGCOMPX | -.08 | .03 | -.13 | -.02 | -.19 | 1.00 | | | | | | |
| 7. VERBCOMP | .13 | .08 | -.06 | .06 | .20 | -.14 | 1.00 | | | | | |
| 8. GENLREAS | .23* | .11 | -.02 | .15 | .15 | -.06 | .41* | 1.00 | | | | |
| 9. ASSOFLUN | .16 | .09 | -.09 | .01 | .08 | .02 | .39* | .17 | 1.00 | | | |
| 10. LOGIREAS | .12 | .05 | -.12 | .03 | .16 | .03 | .18* | .35* | .11 | 1.00 | | |
| 11. INDUCTON | .15 | .09 | -.11 | -.10 | .19* | .01 | .15 | .15 | .15 | -.00 | 1.00 | |
| 12. IDEAFLUN | .01 | .04 | -.02 | -.00 | .05 | .03 | .20 | .14 | .38* | .08 | .12 | 1.00 |
| 13. GENLINFO | .04 | .01 | .07 | .03 | .06 | -.10 | .33 | .18 | .20 | .15 | .01 | .18* |
| 14. NUMROPER | .07 | .06 | -.11 | -.02 | .11 | .07 | .18* | .37* | .07 | .10 | .08 | .21* |
| 15. ATTNDETL | -.00 | .03 | -.04 | -.11 | .08 | -.03 | .04 | .02 | -.04 | .09 | .12 | .11 |
| 16. WORDKNOL | -.02 | .05 | .09 | .06 | .04 | -.06 | .52* | .16 | .28* | .11 | .07 | .22* |
| 17. ARTHREAS | .08 | .03 | -.05 | .06 | .05 | -.10 | .23* | .38* | .07 | .22* | .04 | .06 |
| 18. SPACPERC | .15 | -.05 | .08 | .08 | .02 | -.09 | -.03 | .09 | .10 | -.00 | .03 | .01 |
| 19. MATHKNOL | .27* | .14 | -.05 | .03 | .08 | -.03 | .29* | .41* | .16 | .23* | .12 | .11 |
| 20. ELECINFO | .24* | .03 | -.09 | .06 | .02 | .02 | .28* | .24* | .15 | .20* | .10 | .10 |
| 21. MECHCOMP | .20* | .05 | .04 | -.01 | .11 | -.00 | .19* | .24* | .15 | .18* | .18* | .15 |
| 22. GENLSCIE | .04 | .02 | -.03 | .06 | .12 | -.00 | .32* | .16 | .17 | .17 | .09 | .12 |
| 23. SHOPINFO | .00 | -.07 | -.11 | .04 | .05 | -.00 | .17 | .12 | .01 | .11 | -.13 | .06 |
| 24. AUTOINFO | .12 | .05 | -.13 | .06 | .14 | -.03 | .28* | .18* | .03 | .18* | .01 | .13 |

| Test | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 13. GENLINFO | 1.00 | | | | | | | | | | | |
| 14. NUMROPER | .13 | 1.00 | | | | | | | | | | |
| 15. ATTNDETL | -.02 | .28* | 1.00 | | | | | | | | | |
| 16. WORDKNOL | .41* | .15 | -.00 | 1.00 | | | | | | | | |
| 17. ARTHREAS | .22* | .39* | .08 | .35* | 1.00 | | | | | | | |
| 18. SPACPERC | .12 | .07 | -.02 | .11 | .20* | 1.00 | | | | | | |
| 19. MATHKNOL | .19* | .40* | .12 | .30* | .50* | .11 | 1.00 | | | | | |
| 20. ELECINFO | .32* | .11 | -.09 | .38* | .22* | .24* | .40* | 1.00 | | | | |
| 21. MECHCOMP | .31* | .12 | -.00 | .35* | .26* | .34* | .31* | .51* | 1.00 | | | |
| 22. GENLSCIE | .33* | .02 | -.07 | .60* | .30* | .17 | .33* | .42* | .40* | 1.00 | | |
| 23. SHOPINFO | .29* | .10 | -.08 | .26* | .22* | .17 | .14 | .35* | .45* | .50* | 1.00 | |
| 24. AUTOINFO | .34* | .12 | -.09 | .27* | .22* | .14 | .19* | .47* | .47* | .29* | .49* | 1.00 |

*$p < .05$, $r(205) \geq .13$.

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Table 5

Summary of Stepwise Discriminant Analyses using Measures of $G_f$ and $G_c$

| Step Number | Cognitive Characteristic Entered | Cognitive Characteristic Removed | F to Enter or Remove | Wilks Lambda (Λ) | p | Rao's V | Change in Rao's V | p of Change |
|---|---|---|---|---|---|---|---|---|
| | | | | Cognitive Styles Only ($G_f$) | | | | |
| 1 | FILDINDP | | 16.82 | .92 | .00 | 16.82 | 16.82 | .00 |
| 2 | CONCSTYL | | 2.51 | .91 | .00 | 19.55 | 2.73 | .10 |
| 3 | COGCOMPX | | 1.46 | .91 | .00 | 21.16 | 1.62 | .20 |

$\Lambda$ = .91; $\chi^2(3) = 19.99$; $p < .001$; $\lambda = .10$.

$CN_f$ = .68; $CN_g$ = -.14; $R_c$ = .31.

D = - .81 FILDINDP - .36 CONCSTYL + .26 COGCOMPX.

$C_f$ = .17 FILDINDP + .63 CONCSTYL + .23 COGCOMPX - 1.27.

$C_g$ = .35 FILDINDP + .71 CONCSTYL + .22 COGCOMPX - 13.39.

| Step Number | Entered | Removed | F to Enter or Remove | Wilks Lambda (Λ) | p | Rao's V | Change in Rao's V | p of Change |
|---|---|---|---|---|---|---|---|---|
| | | | | Abilities Only ($G_c$) | | | | |
| 1 | GENLREAS | | 33.36 | .86 | .00 | 33.36 | 33.36 | .00 |
| 2 | INDUCTON | | 4.40 | .84 | .00 | 38.50 | 5.14 | .02 |

$\Lambda$ = .84; $\chi^2(2) = 35.11$; $p < .001$; $\lambda = .19$.

$CN_f$ = - .88; $CN_g$ = .18; $R_c$ = .40.

D = .88 GENLREAS + .35 INDUCTON.

$C_f$ = .43 GENLREAS + .17 INDUCTON - .32.

$C_g$ = .77 GENLREAS + .19 INDUCTON - 8.96.

| Step Number | Entered | Removed | F to Enter or Remove | Wilks Lambda (Λ) | p | Rao's V | Change in Rao's V | p of Change |
|---|---|---|---|---|---|---|---|---|
| | | | | Aptitudes Only ($G_c$) | | | | |
| 1 | MATHKNOL | | 25.84 | .89 | .00 | 25.84 | 25.84 | .00 |
| 2 | ARTHREAS | | 5.11 | .87 | .00 | 31.62 | 5.79 | .01 |
| 3 | GENLSCIE | | 2.46 | .86 | .00 | 34.49 | 2.86 | .10 |
| 4 | NUMROPER | | 2.83 | .84 | .00 | 37.83 | 3.35 | .07 |

$\Lambda$ = .84; $\chi^2(4) = 34.38$; $p < .001$; $\lambda = .18$.

$CN_f$ = .87; $CN_g$ = - .18; $R_c$ = .40.

D = - .32 NUMROPER - .29 ARTHREAS - .41 MATHKNOL - .33 GENLSCIE.

$C_f$ = .67 NUMROPER + .20 ARTHREAS + .29 MATHKNOL + .61 GENLSCIE - 46.17.

$C_g$ = .72 NUMROPER + .24 ARTHREAS + .36 MATHKNOL + .65 GENLSCIE - 57.46.

| Step Number | Entered | Removed | F to Enter or Remove | Wilks Lambda (Λ) | p | Rao's V | Change in Rao's V | p of Change |
|---|---|---|---|---|---|---|---|---|
| | | | | Cognitive Styles and Abilities ($G_f + G_c$) | | | | |
| 1 | GENLREAS | | 33.36 | .86 | .00 | 33.36 | 33.36 | .00 |
| 2 | FILDINDP | | 6.90 | .83 | .00 | 41.42 | 8.06 | .00 |
| 3 | INDUCTON | | 3.06 | .82 | .00 | 45.13 | 3.71 | .05 |
| 4 | CATEWIDH | | 2.66 | .81 | .00 | 48.42 | 3.29 | .07 |
| 5 | COGCOMPX | | 1.59 | .80 | .00 | 50.43 | 2.01 | .16 |
| 6 | IDEAFLUN | | 1.15 | .80 | .00 | 51.90 | 1.47 | .22 |

$\Lambda$ = .80; $\chi^2(6) = 45.59$; $p < .001$; $\lambda = .25$.

$CN_f$ = .99; $CN_g$ = - .20; $R_c$ = .45.

D = - .09 FILDINDP + .03 CATEWIDH + .01 COGCOMPX - .20 GENLREAS - .02 INDUCTON - .04 IDEAFLUN + 1.78.

$C_f$ = .03 FILDINDP + .34 CATEWIDH + .27 COGCOMPX + .31 GENLREAS + .12 INDUCTON + .40 IDEAFLUN - 21.68.

$C_g$ = .17 FILDINDP + .30 CATEWIDH - .26 COGCOMPX + .61 GENLREAS + .14 INDUCTON + .45 IDEAFLUN - 23.75.

Notes.

1. $CN_f$ and $CN_g$ = Centroids for failure and graduate groups respectively.
2. $R_c$ = Canonical correlation between the derived discriminant function and the set of dummy variables defining membership in the two groups.
3. D = Derived discriminant function.
4. $C_f$ and $C_g$ = Classification functions for failure and graduate groups respectively.

Table 5 (Continued)

| Step Number | Cognitive Characteristic Entered | Removed | F to Enter or Remove | Wilks Lambda ($\Lambda$) | p | Rao's V | Change in Rao's V | p of Change |
|---|---|---|---|---|---|---|---|---|
| | **Cognitive Styles and Aptitudes ($G_f + G_c$)** | | | | | | | |
| 1 | MATHKNOL | | 25.84 | .89 | .00 | 25.84 | 25.84 | .00 |
| 2 | FILDINDP | | 7.02 | .86 | .00 | 33.78 | 7.94 | .00 |
| 3 | ARTHREAS | | 5.76 | .83 | .00 | 40.55 | 6.77 | .01 |
| 4 | GENLSCIE | | 2.73 | .82 | .00 | 43.87 | 3.32 | .07 |
| 5 | NUMROPER | | 3.05 | .81 | .00 | 47.65 | 3.78 | .05 |
| 6 | CATEWIDH | | 1.81 | .80 | .00 | 49.94 | 2.29 | .13 |
| 7 | COGCOMPX | | 1.78 | .80 | .00 | 52.27 | 2.28 | .13 |
| 8 | SPACPERC | | 1.64 | .79 | .00 | 54.35 | 2.13 | .14 |
| 9 | | MATHKNOL | .90 | .79 | .00 | 53.18 | -1.17 | 1.00 |
| 10 | CONCSTYL | | 1.20 | .79 | .00 | 54.75 | 1.57 | .21 |

$\Lambda$ = .79; $\chi^2(8) = 47.58$; $p < .001$; $\lambda = .28$.

$CN_f$ = - 1.02; $CN_g$ = .21; $R_c$ = 46.

D = .45 FILDINDP + .15 CONCSTYL - .22 CATEWIDH - .21 COGCOMPX + .37 NUMROPER + .30 ARTHREAS - .18 SPACPERC + .38 GENLSCIE.

$C_f$ = - .28 FILDINDP + .67 CONCSTYL + .31 CATEWIDH + .28 COGCOMPX + .59 NUMROPER + .33 ARTHREAS + .40 SPACPERC + .53 GENLSCIE - 68.14.

$C_g$ = - .10 FILDINDP + .73 CONCSTYL + .27 CATEWIDH + .26 COGCOMPX + .66 NUMROPER + .39 ARTHREAS + .38 SPACPERC + .60 GENLSCIE - 76.55.

| Step Number | Cognitive Characteristic Entered | Removed | F to Enter or Remove | Wilks Lambda ($\Lambda$) | p | Rao's V | Change in Rao's V | p of Change |
|---|---|---|---|---|---|---|---|---|
| | **Abilities and Aptitudes ($G_c$)** | | | | | | | |
| 1 | GENLREAS | | 33.36 | .86 | .00 | 33.36 | 33.36 | .00 |
| 2 | MATHKNOL | | 7.51 | .83 | .00 | 42.13 | 8.77 | .00 |
| 3 | INDUCTON | | 3.50 | .82 | .00 | 46.39 | 4.26 | .04 |
| 4 | GENLSCIE | | 2.76 | .80 | .00 | 49.82 | 3.43 | .06 |
| 5 | LOGIREAS | | 1.81 | .80 | .00 | 52.12 | 2.30 | .13 |
| 6 | ARTHREAS | | 1.62 | .79 | .00 | 54.20 | 2.09 | .15 |

$\Lambda$ = .79; $\chi^2(6) = 47.39$; $p < .001$; $\lambda = .26$.

$CN_f$ = 1.01; $CN_g$ = - .21; $R_c$ = .46.

D = - .56 GENLREAS + .21 LOGIREAS - .25 INDUCTON - .22 ARTHREAS - .25 MATHKNOL - .23 GENLSCIE.

$C_f$ = - .72 GENLREAS - .32 LOGIREAS + .13 INDUCTON + .46 ARTHREAS + .56 MATHKNOL + .51 GENLSCIE - 42.46.

$C_g$ = - .45 GENLREAS - .39 LOGIREAS + .16 INDUCTON + .50 ARTHREAS + .61 MATHKNOL + .55 GENLSCIE - 52.49.

| Step Number | Cognitive Characteristic Entered | Removed | F to Enter or Remove | Wilks Lambda ($\Lambda$) | p | Rao's V | Change in Rao's V | p of Change |
|---|---|---|---|---|---|---|---|---|
| | **Cognitive Styles, Abilities, and Aptitudes ($G_f + G_c$)** | | | | | | | |
| 1 | GENLREAS | | 33.36 | .86 | .00 | 33.36 | 33.36 | .00 |
| 2 | MATHKNOL | | 7.51 | .83 | .00 | 42.13 | 8.77 | .00 |
| 3 | FILDINDP | | 4.31 | .81 | .00 | 47.38 | 5.25 | .02 |
| 4 | GENLSCIE | | 3.48 | .80 | .00 | 51.72 | 4.34 | .04 |
| 5 | LOGIREAS | | 2.30 | .79 | .00 | 54.66 | 2.94 | .09 |
| 6 | CATEWIDH | | 2.02 | .78 | .00 | 57.28 | 2.63 | .10 |
| 7 | INDUCTON | | 2.69 | .77 | .00 | 60.83 | 3.54 | .06 |
| 8 | NUMROPER | | 1.98 | .76 | .00 | 63.49 | 2.66 | .10 |
| 9 | | MATHKNOL | .86 | .77 | .00 | 62.33 | -1.15 | 1.00 |
| 10 | COGCOMPX | | 2.00 | .76 | .00 | 65.02 | 2.69 | .10 |
| 11 | SPACPERC | | 1.39 | .75 | .00 | 66.93 | 1.90 | .17 |
| 12 | ARTHREAS | | 1.62 | .75 | .00 | 69.18 | 2.25 | .13 |

$\Lambda$ = .75; $\chi^2(10) = 58.15$; $p < .001$; $\lambda = .34$.

$CN_f$ = -1.10; $CN_g$ = .23; $R_c$ = .50.

D = .33 FILDINDP - .26 CATEWIDH - .17 COGCOMPX + .43 GENLREAS - .16 LOGIREAS + .22 INDUCTON + .21 NUMROPER + .20 ARTHREAS - .17 SPACPERC + .31 GENLSCIE.

$C_f$ = - .07 FILDINDP + .29 CATEWIDH + .28 COGCOMPX - .91 GENLREAS - .26 LOGIREAS + .10 INDUCTON + .29 NUMROPER + .45 ARTHREAS + .37 SPACPERC + .56 GENLSCIE - 69.82.

$C_g$ = .08 FILDINDP + .24 CATEWIDH + .26 COGCOMPX - .67 GENLREAS - .32 LOGIREAS + .13 INDUCTON + .74 NUMROPER + .49 ARTHREAS + .35 SPACPERC + .63 GENLSCIE - 77.41.

Notes.

1. $CN_f$ and $CN_g$ = Centroids for failure and graduate groups respectively.
2. $R_c$ = Canonical correlation between the derived discriminant fuction and the set of dummy variables defining membership in the two groups.
3. D = Derived discriminant fuction.
4. $C_f$ and $C_g$ = Classification functions for failure and graduate groups respectively.

stepwise discriminant analyses. The variable chosen is the one that contributes to the largest increment in V when added to those previously selected. This produces the greatest overall discrimination of the groups.

In Table 5, the eigenvalues increase from the first discriminant analysis using only cognitive styles as measures of $G_f$ to the second and third analysis using only abilities or aptitudes as measures of $G_c$. There were similar increases in eigenvalues from the analysis using cognitive styles and abilities through the following ones all the way to the last using cognitive styles, abilities, and aptitudes. The canonical correlations computed for each discriminant analysis increased from the first to the last (i.e., using cognitive styles only to using cognitive styles, abilities, and aptitudes as differentiating variables). The change in Rao's V indicated that:

1. For the analysis using cognitive styles and abilities, $G_f$ measures accounted for 25.74 percent of the increases in this index; and $G_c$ measures, 74.26 percent.

2. For the analysis using cognitive styles and aptitudes, $G_f$ measures accounted for 25.72 percent of the increases; and $G_c$ measures, 74.28 percent.

3. For the analysis using cognitive styles, abilities, and aptitudes, $G_f$ measures accounted for 15.28 percent of the increase; and $G_c$ measures 84.72 percent. Also, Wilk's lambda tended to decrease from the first analysis to the last. All of these statistics seem to imply that $G_c$ measures (abilities and aptitudes) accounted for more variance between CMI failures and graduates than did $G_f$ measures (cognitive styles).

Once the coefficients for each discriminant function were determined, a set of corresponding classif. ation functions ($C_f$ and $C_g$) were obtained that enable the categorization of CMI students into two groups, failures and graduates respectively. For example, the classification functions obtained from the discriminant function derived for cognitive styles, $G_f$ measures, are:

$$C_f = .17\ \text{FILDINDP} + .63\ \text{CONCSTYL} + .23\ \text{COGCOMPX} - 1.27$$

and

$$C_g = .35\ \text{FILDINDP} + .71\ \text{CONCSTYL} + .22\ \text{COGCOMPX} - 13.39.$$

Thus, by inserting the appropriate test scores for a subject into the derived classification equations, a student could be assigned to the group in which he/she has the highest probability of being a member.

To check the effectiveness of the seven discriminant functions, the classification functions that were obtained were applied to the $G_f$ and $G_c$ test scores of the students who participated in this study, since their actual group membership was known. As indicated previously, separate classification analyses were conducted. In the first, each student who entered the CMI curriculum was assumed to have an equal probability of failing and graduating. In the second, this probability was adjusted according to the a priori probabilities of failing and graduating this CMI course. These results are presented in Table 6.

Table 6

Prediction Results Based on Derived Classification Functions

| Classification Function | Actual Failures (%) Predicted Failures | Actual Failures (%) Predicted Graduates | Actual Graduates (%) Predicted Failures | Actual Graduates (%) Predicted Graduates | $\chi^2$ |
|---|---|---|---|---|---|
| Equal Probability | | | | | |
| Cognitive Styles | 68.60 | 31.40 | 38.40 | 61.60 | 10.79** |
| Abilities (A) | 74.30 | 25.70 | 26.20 | 73.80 | 29.89* |
| Aptitudes (P) | 77.10 | 22.90 | 23.30 | 76.70 | 38.58* |
| S x A | 71.40 | 28.60 | 23.80 | 76.20 | 30.33* |
| S x P | 80.00 | 20.00 | 22.70 | 77.30 | 43.66* |
| A x P | 80.00 | 20.00 | 20.90 | 79.10 | 47.51* |
| S x A x P | 80.00 | 20.00 | 20.90 | 79.10 | 47.51* |
| Adjusted Probability | | | | | |
| Cognitive Styles | 0.00 | 100.00 | 0.60 | 99.40 | 0.20 |
| Abilities (A) | 14.30 | 85.70 | 3.50 | 96.50 | 6.74** |
| Aptitudes (P) | 11.40 | 88.60 | 2.90 | 97.10 | 5.08*** |
| S x A | 22.90 | 77.10 | 3.50 | 96.50 | 17.30* |
| S x P | 25.70 | 74.30 | 4.10 | 95.90 | 19.10* |
| A x P | 28.60 | 71.40 | 5.20 | 94.80 | 19.00* |
| S x A x P | 34.30 | 65.70 | 3.50 | 96.50 | 34.74* |

Note. Cognitive styles (S) are measures of $G_f$; abilities (A) and aptitudes (P) are measures of $G_c$.

*$\chi^2(1) \geq 10.83$; $p < .001$.

**$\chi^2(1) \geq 6.64$; $p < .01$.

***$\chi^2(1) \geq 3.84$; $p < .05$.

As shown in the equal probability analysis, the percentage of correct classifications for actual failures ranged from 68.6 to 80.0 percent; and of actual graduates, from 61.6 to 79.1 percent. More actual failures and graduates were correctly classified by $G_c$ measures (abilities and aptitudes) than $G_f$ measures (cognitive styles). When $G_f$ measures were employed together with $G_c$ measures, the three two-way interactions, and the one three-way interaction, the percentage of those correctly classified was always higher than when only $G_f$ measures were used. For actual failures and graduates, using cognitive styles and abilities resulted in fewer being correctly classified than using either cognitive styles and aptitudes or abilities and aptitudes.

In the adjusted probability analysis, the percentage of correct classifications of actual failures ranged from 0 to 34.3 percent; and of actual graduates, from 94.8 to 99.4

percent. More actual failures and graduates were significantly and correctly classified using abilities and aptitudes, $G_c$ measures, than using cognitive styles, $G_f$ measures. When employing the three two-way interactions of these measures, abilities and aptitudes classified actual failures better than did cognitive styles and abilities or cognitive styles and aptitudes. Using these multivariate combinations classified actual graduates approximately equally well. Using the three-way interaction of these measures classified actual failures better than did the cognitive styles ($G_f$) measures.

## DISCUSSION AND CONCLUSIONS

The results established that $G_c$ measures (abilities or aptitudes), accounted for more of the discrimination between CMI failures and graduates than did $G_f$ measures (cognitive styles). Assuming either equal or adjusted probability, $G_c$ measures classified a greater number of actual failures and graduates correctly than did $G_f$ measures. Employing these measures ($G_c$) simultaneously always classified a higher percentage of students correctly than did employing only $G_f$ measures. Assuming adjusted probability, actual failures were classified better using abilities and aptitudes (all $G_c$ indices) than by cognitive styles and abilities or cognitive styles and aptitudes ($G_c$ and $G_f$ indices combined).

The data demonstrated that $G_c$ measures are more important for predicting performance in this CMI environment, an instance of a new instructional situation, than are $G_f$ measures. Unlike Snow's (1980) speculations, these findings suggest that the unconventional educational environment used in this investigation was not necessarily dysfunctional for the more able students. In this situation, these students seemed to exercise, and capitalize on, those skills developed and applied in more traditional instructional settings. This study established that, in this new instructional situation, $G_c$ was more important and $G_f$, less important--the opposite of Snow's assertions.

If the traditional instructional treatment is altered, as in the novel pedagogical situation used in this investigation, then the relevancy of $G_c$ to learning is not lessened. Students who possess well-developed, conventional, academic aptitudes and abilities can apply them even in unorthodox, educational environments. Students who lack these accumulated skills will need to acquire them in order to benefit from nontraditional as well as traditional instruction. Evidently, $G_c$ abilities and aptitudes, representing prior assemblies of performance processes, can be retrieved and applied anew in instructional situations unlike those experienced in the past. This implies that $G_c$ begins to take on some of the alleged attributes of $G_f$, especially considering more extreme adaptations to novel educational environments. The declared distinction between long-term assembly for transfer to familiar new situations ($G_c$) and short-term assembly for transfer to unfamiliar new situations ($G_f$) tends to disappear.

Alternatively, if this difference does not vanish, $G_c$ abilities and aptitudes appear to be adaptive and advantageous in innovative instructional situations such as the computer-managed mastery learning employed in this research. $G_f$ as well as $G_c$ are associated with achievement in novel educational environments (i.e., ones that differ from those students experienced in the past). Contrary to Snow's expectations, both $G_f$ and $G_c$ are relevant in these instructional situations. The unconventional pedagogical treatment used in this study was not dysfunctional for more able students--those who can control and structure their own learning because of $G_c$ acquired and required previously by conventional, educational experiences.

Since, within this context, $G_c$ confers pervasive learning skills--not specific knowledge--it transcends the particular technology, symbol systems, content, and context of instruction. Regardless of whether students previously experienced novel educational settings, $G_c$ seems to instill a general learning set to process and interpret this type of innovative instruction. Consequently, $G_c$ would be expected to be important throughout the computer-managed course, even if this produced pronounced changes in the customary method of instruction. This need not be so with $G_f$. Possibly, the processing reflected by $G_f$ was required periodically and differentially by the content, context, technology, and symbol systems of instruction (Federico, 1982, 1983). Because some or all of these usually change during a course, the relationship of $G_f$ to learning may be lessened throughout the complete curriculum as demonstrated by this research.

Finally, the nontraditional instructional treatment used in this investigation may not have been innovative enough when compared to previously experienced educational environments. Consequently, computer-managed instruction would not elicit more accommodative $G_f$ strategies than would conventional $G_c$ abilities and aptitudes employed by students in traditional instructional settings.

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