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LEARNER CONTROL OF INSTRUCTIONAL SEQUENCING WITHIN AN ADAPTIVE TUTORIAL CAI ENVIRONMENT*

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ABSTRACT

The study described in this report was designed to test effects of learner control at the level of *instructional sequencing* within a self-contained tutorial course, administered by an adaptive computer program. Applicability to other levels is speculative and clearly requires further research.

The experimentation has as independent variables four features of our CAI system that afford the student a specified degree of control over the sequencing of instructional material. Three of the variables are student options that control remedial activity and acceleration. The fourth variable allows control over sequencing of topics at specified points in the course. The purpose is to assess the relative contributions and interactions of these variables with respect to instructional effectiveness and efficiency.

Following an entry test period, students were administered tutorial CAI instruction, a COBOL course (an average of 30 hours long), with four possible types of learner–control variables. These students were assigned at random to one of 2^4 factorial treatment conditions. Sessions were approximately three hours long per day with breaks left up to the individual. Following the instructional period, students were administered an "exit questionnaire" covering their opinions about course administration, content, and instructional environment.

During the conduct of the experiment, three types of measures were taken on each student: (a) entry characteristics, including information processing (Guilford's Structure of Intellect), affective, and biographical data; (b) learner strategies, including type and frequency of control usage and the circumstances of their use; and (c) achievement and other performance-related measures including quiz scores, transit times, programming errors, opinions of topics, and Level of Aspiration (LOA) prior to the quiz of each topic. Assessments were made of the relative contributions and interactions among the learner-control and entry characteristic variables with respect to instructional effectiveness and efficiency as represented by the dependent measures.

The result and implications can be described as follows. First, the study developed a well-tested instructional vehicle that meets the criterion of student mastery, a prerequisite for valid research in an instructional environment. Secondly, the study was performed in

* The study described in this report is part of an extensive program of research in the area of instructional strategies and decision models, sponsored by the U.S. Army and The National Science Foundation. The opinions expressed do not reflect official positions of any sponsors.

a rich instructional environment, preferred for generalizing results of Aptitude by Treatment Interaction (ATI) studies to a real instructional world. The third significant aspect of the current study has been the development of a very useful means to characterize high and low performers with an operationally defined set of criteria that has highlighted the value of discriminant function analyses in instructional research settings. Of great importance is the finding that the particular individuals designated high or low *performers* differed depending upon the particular instructional tasks. Yet, the phenomenon of high and low *performance* was consistent across two divisions of the course. High and low performers differed with respect to the usage of options, as well as their Level of Aspiration settings concerning their performance. Research is needed to identify more specifically the taxonomic characteristics of instructional tasks related to student profiles of high and low performers.

Another significant finding in our study was that self-assessment can make a significant contribution to instructional management, whether the latter be by students or by the learning system. The next step that should be taken is to use the instructional options based on expectations, as part of the decision-making process in an adaptive instructional environment. A proposed prescriptive use of LOA as an Expectancy Operator is described. Lastly, research requirements for systematic study of levels and types of self-managed learning paradigms are discussed.

Introduction

BACKGROUND

The study described in this report is part of an extensive program of research in the area of instructional strategies and decision models. This research program was accomplished over a five-year period in a computer-administered instructional (CAI) environment. The principal sponsor of HumRRO's CAI research and development efforts during that time was the Department of the Army. First, the U.S. Army Research Office was the technical monitor for an overall program entitled Project IMPACT. Then, the U.S. Army Institute for the Behavioral and Social Sciences was the monitor for Project CATALIST. A National Science Foundation (NSF) grant augmented the Army's sponsorship of this research [1].

RATIONALE

The problem of student-controlled learning has received a great deal of attention recently. It is obviously of prime importance in individualized instruction. Relevant to the study of student-controlled instructional strategies is the whole area of discovery learning (Gagné, 1970). Some learning studies have indicated a high degree of mastery by using discovery techniques (e.g. Gagné and Bassler, 1963).

But what are the psychological dimensions involved? Many assertions have been made (for example, Hartley, Sleeman, et al., 1969; O'Neal, 1973) that learner-controlled instruction can overcome the lack of predetermined, explicit models of instructional processes. But little systematic exploration of the nature and degree of desirable learner-generated control processes in an adaptive teaching system has occurred. Grubb (1967) has demonstrated the general feasibility of teaching statistics with learner control. Swets et al. (1964) found no difference between learner or program control in learning to identify complex auditory stimuli. Hartley (1966), using learning of logarithms as the problem-solving task, also found no differences (although his data are confounded by possible ceiling effects). Mager's research (1964), on the other hand, indicated significant learning value in having subjects determine sequencing of materials.

Carbonnell and Collins (1970) and Grignetti et al. (1974), constructed an innovative CAI system called SCHOLAR. Its prime instructional feature is a mixed-initiative mode of interaction with students. In this mode, the student can access information about a topic by typing questions and the system can direct the student's efforts by asking questions of its own. Unfortunately, no data except for sample protocols have as yet been published on student residence time in the various modes or on the effectiveness or efficiency of mixed-initiative versus conventional strategies.

In a carefully structured study by Olivier (1971), the student group having the capability for self-selection of instruction did significantly worse than system-controlled counterparts on criterion tests. Generalized interpretation, however, is difficult because of the rather short instructional period of 30–45 minutes, which could have had some kind of a warm-up effect. Similarly, Fry (1972) found suggestive hints that the value of learner control is affected by individual difference variables; however, the instruction was relatively brief (two one-hour sessions) and the data inconclusive.

When these findings are compared with those of Grubb (1967), Mager (1964), and Judd et al. (1970), hard and fast conclusions concerning the value of student versus system-controlled instruction are impossible. In these other studies, more than just learner-controlled sequencing is involved. Moreover, the individual student's profile by treatment interaction was considered in only three of the experiments (Fry, Olivier, and Judd et al.). Even in these cases the aptitude measures were of a general nature and not necessarily the best task-relatable content for the instruction given. Research is needed to clarify this issue (see Hickey, 1974).

The key to optimal allocation of learner controls in the instructional decision process would be for basic research in human learning to (a) identify those components of strategy selection and use of which students are capable, (b) relate these components to individual characteristics, and (c) determine where program control can or cannot handle the same components (Seidel, 1971). The premise is intended to imply that an all-or-none conclusion for locus of control is highly unlikely. We could then arrive at a cost-effective justification for optimally allocating components of instructional decision making to individual students *or* programs in an adaptive teaching system. Both Pask's cybernetic approach and that of the author and his associates (Seidel et al., 1969 a,b; Seidel, 1969; Seidel and Kopstein, 1968) are directed toward this end.

As an empirical example of this approach, the present experiment is unique in three respects:

(1) It employs a combined manipulative-correlational technique in order to further the understanding of the relationship between individual student characteristics and effectiveness of self-management or learner control.

(2) It is one of the few studies involving a rich, contingency-structured instructional environment.

(3) A battery of test instruments was administered to develop comprehensive profiles for individual students including cognitive, motivational, and specific performance indicators relevant to the instruction.

Method

OVERVIEW OF EXPERIMENTAL VARIATIONS

Before describing the experimental design detail, it is important to emphasize that student-centered decision making can take place on many levels in education. It may involve a choice of degree program, scheduling, objectives, strategy for studying, or use of resources. The present study was designed to test effects at the level of *instructional sequencing* within a self-contained tutorial course administered by an adaptive computer program. Applicability to other levels is speculative and requires further research.

Four features of the CAI system that afford the student a specified degree of control over the sequencing of instructional material serve as independent variables in the experiment. Three of the variables are student options that control remedial activity and acceleration. If the student types REVIEW, he returns to the beginning of the topic. If the student types RECAP, he is shown a list of topics that he has previously completed and is allowed to choose one for review. If the student types QUIZ, he is branched from his current location in a topic to the beginning of the "Quiz" Section of that topic.

The fourth variable, ROUTE, allows student control over sequencing of topics at specified points in the course. The system makes the options available, and the student uses them or not, as he wishes. In topic sequencing, the student must choose the next topic, if the choice is available.

Following a pretest period, students were administered tutorial CAI instruction with four possible types of learner-control variables. These students were randomly assigned to one of the 16 conditions in the (2^4) factorial design. Sessions were approximately three hours long per day with breaks left up to the individual. Following the instructional period, students were administered an "exit questionnaire" covering their opinions about course administration, content, and instructional environment.

During the conduct of the experiment, three types of measures were taken on each student: (a) entry characteristics, including aptitude, and biographical data; (b) learner strategies, including type and frequency of control usage and the circumstances of their use; and (c) achievement and other performance-related measures including quiz scores, transit times, programming errors, opinions of topics, and Level of Aspiration (LOA) prior to the quiz on each topic.

Thus, the purpose of the present experiment was to assess the relative contributions and interactions among the learner-control, entry characteristics, and dynamic motivational variables, with respect to instructional effectiveness and efficiency, as represented by the dependent measures.

DESCRIPTION OF ENTRY CHARACTERISTICS MEASURES

Student entry characteristics were measured in these four areas: Structure of Intellect Factors, Motivation, Computer Programming Aptitude, and Reading Comprehension.

The Entry Characteristics Test (ECT) battery consists of 27 instruments (26 are time tests) that yield 35 distinct scores. Their testing time ranges from 2 to 70 minutes, with a majority of the tests taking less than 20 minutes. In general, the tests are of the paper-and-pencil variety and designed for administration in group testing sessions.

Structure of Intellect Factor Tests

These tests measure 10 factors (Bunderson, 1967); there are 27 tests used for factor measurement. A description of the factors and the tests used to measure them follows:

(1) *General Reasoning* (Two tests). This factor has been described as "the ability to solve a broad range of reasoning problems, including those of a mathematical nature" (French et al., 1963). The tests selected to define this factor are the Ship Destination Test (Sheridan Psychological Services, Inc.) and Necessary Arithmetic Operations (Educational Testing Service).

(2) *Induction* (Three tests). This factor has been described as "associated abilities involved in the finding of general concepts that will fit

sets of data, the forming and trying out of hypotheses" (French et al., 1963). The Letter Sets Test (Educational Testing Service), Locations Test (Educational Testing Service), and Figure Classification Test (Educational Testing Service) define this factor.

(3) *Figural Adaptive Flexibility* (Five tests). French et al. describe this factor as "the ability to change set in order to meet new requirements imposed by figural problems." The following five tests define this factor:

(a) Match Problems IV–Parts 1 and 2 (Aptitudes Research Project, University of Southern California).
(b) Match Problems V (Educational Testing Service).
(c) Word Coding Test (designed by L. Sjoberg, J. Frederiksen, and V. Bunderson).
(d) Decoding Test (designed by L. Sjoberg, J. Frederiksen, and V. Bunderson).

(4) *Verbal Reasoning* (Three tests). This factor has been given a number of different names, including "Deduction" by Thurstone, "Logical Reasoning" by Guilford, and "Syllogistic Reasoning" by French et al. The last authors describe it as "ability to reason from stated premises to their necessary conclusions." The Nonsense Syllogisms Test (Educational Testing Service), Logical Reasoning Test (Sheridan Psychological Services, Inc.), and Inference Test (Educational Testing Service) were selected to define this factor.

(5) *Symbol Substitution* (One test). Guilford and Hoepfner (1966) classify this factor as convergent production and define it as "the ability to produce a completely determined, symbolic deduction from given symbolic information, where such an implication has not been practiced, as such." One test defines this factor: Sign Changes (Aptitudes Research Project, University of Southern California).

(6) *Chunking Memory* (One test). This is a new factor postulated by Bunderson, who has designed two tests. In the present study only one, the Binary Digit Span Test, measures this factor.

(7) *Memory Span* (Two tests). This factor has been described as "the ability to recall perfectly for immediate reproduction a series of items after only one presentation of the series" (French et al., 1963). The marker tests for this factor are the Auditory Number Span Test and the Auditory Letter Span Test (both from Educational Testing Service).

(8) *Associative Memory* (Three tests). This factor is defined as the ability to remember paired associates. The three tests that define this factor are: the Picture–Number Test, the Object-Number Test, and the First and Last Names Test (all from the Educational Testing Service).

(9) *Perceptual Speed* (One test). This factor is described as the ability to make comparisons and find figures fast and accurately. The test that defines this factor is the Number Comparison Test (Educational Testing Service).

(10) *Spatial Scanning* (One test). This factor is defined as "speed in visually exploring a wide or complicated spatial field" (French et al., 1963). The Maze Tracing Speed Test (Educational Testing Service) measures it.

Motivation

Included in the Entry Characteristics Test battery are those tests that were selected to measure anxiety and achievement motivation. The psychological literature is replete with studies showing relationships between anxiety and learning in laboratory situations (Spence and Spence, 1967). Recent studies (Hansen et al., 1969; Spielberger et al., 1972) have also shown some value in the study of anxiety as it relates to performance in CAI. The tests in the ECT battery are the IPAT Anxiety Scale Questionnaire (Institute for Personality and Ability Testing), the Sarason Task Anxiety Questionnaire (adapted from Mandler and Sarason, 1952), and the Sentence Completion Test of Achievement Values (Mukherjee, 1964).

Computer Programming Aptitude

A survey of the literature showed that the most widely used tests of aptitude for programming have been IBM's Programmer Aptitude Test (PAT) and Revised Programmer Aptitude Test (RPAT). A large body of reliability and validity data is associated with these tests. Recently, the PAT and RPAT have been replaced by the Aptitude Test for Programmer Personnel (ATPP), which is included in the battery. This test correlates highly with both PAT and RPAT.

A second test, Primary Mental Abilities (PMA), is used in the ECT battery to measure programmer aptitude. The Primary Mental Abilities Test has been used for years by the RAND and System Development Corporations as a programmer selection device (Perry and Cantley, 1965; Rowan, 1957).

The Army uses a programming aptitude test developed by a civilian company that is very similar to the ATPP. While the test is not included in our battery, the scores for military subjects were obtained for research purposes.

Reading Comprehension

The Entry Characteristics Test battery includes one test of reading comprehension, the Reading Comprehension Cooperative English Test (Cooperative Test Division of Educational Testing Service). This instrument provides four scores: vocabulary, level of reading comprehension, speed of comprehension, and total reading comprehension (level + speed/2).

EXPERIMENTAL COURSE

The experimental course consisted of the first two divisions of a four-division course designed to teach COBOL programming [2]. The first two divisions comprised 22 modules and about 30 hours of instruction.

Formative evaluation of the initial version of the course, COBOL1, was conducted with high school students and with Army students. Data were collected and analyzed on a total of 42 students. The evaluative data showed that subsets of instruction needed to be smaller for learning and research purposes. Thus arose the modular concept employed in COBOL2, the second iteration COBOL course developed by HumRRO. Also, more opportunities for program writing and training in debugging procedures (through gaming) were provided for the student in COBOL2.

The Instructional Decision Model (IDM) and associated support software also underwent changes at this point, with a major element being the separation of the logic of the IDM from the instruction. This development was extremely useful because it permitted the IDM to be modified unconstrained by the course content.

The COBOL2 course and associated logic were debugged and evaluated with 83 students of various civilian and military backgrounds. Following this, the 80 experimental subjects were administered COBOL2. A total of 205 students have taken the various versions of the COBOL materials.

The course structure (Fig.1) reflects the essential elements of a well-defined schema of objectives (i.e. single behavioral objectives are defined by single course objectives). The set of behavioral objectives for a division is

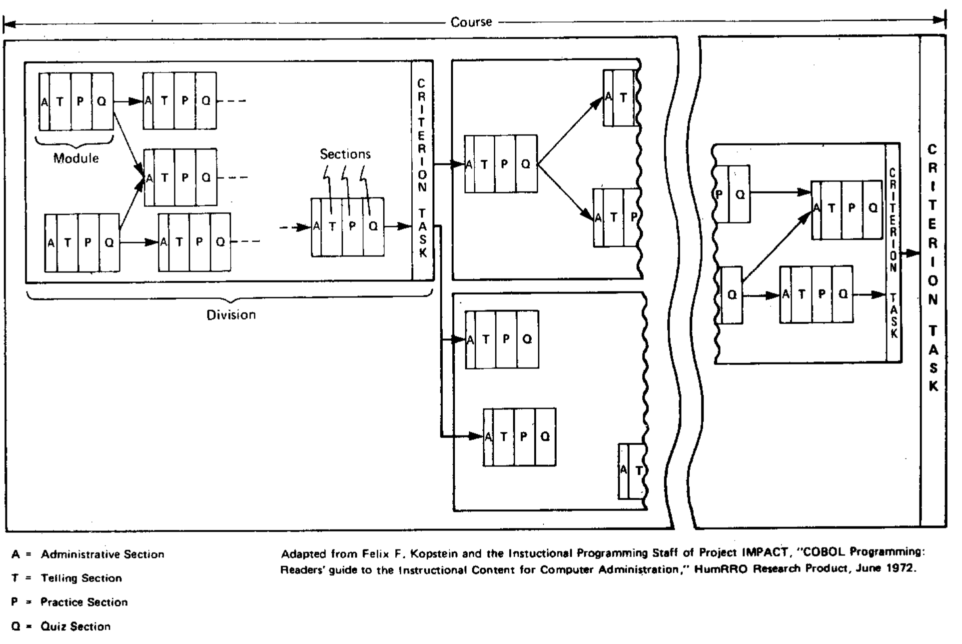


Fig. 1. Course structure – Divisions, Modules, and Sections.

sufficiently large and complex to require further partitioning into smaller subsets. This produces a Module Objective, operationally defined as the minimal observable subset of Terminal Achievement Objectives.

Modules are partitioned into sections. The first is the A (Administrative) Section, which contains a variety of administrative documentation that the student does not see, for the most part, but that is used to provide course management information. The second is the T (Telling) Section in which relevant subject-matter information is presented to the student. The third is the P (Practice) Section which permits the student to practice objective-related behavior. The P-Section is followed by the Q (Quiz) Section which tests for achievement of the behavioral objective(s). A module can have several versions of each section. The limitation is, of course, that each version cover the same basic material and, therefore, teach toward the same objective. The differences between versions are differences of form and/or thinking rather than content. For example: Version 1 of a T-Section (T_1) may require extensive reading, whereas Version 2 of the T-Section (T_2) for the same module may be highly pictorial or contain smaller chunks of information per display.

An author must write a module so that it instructs toward one objective as that objective is represented in the prerequisite structure (Fig.2). That is, if a module (objective) does not have a linearly prerequisite module, the module being written must be independent of other modules. For example, in Division A, as represented in Fig. 2, notice that Modules F, G, and H must

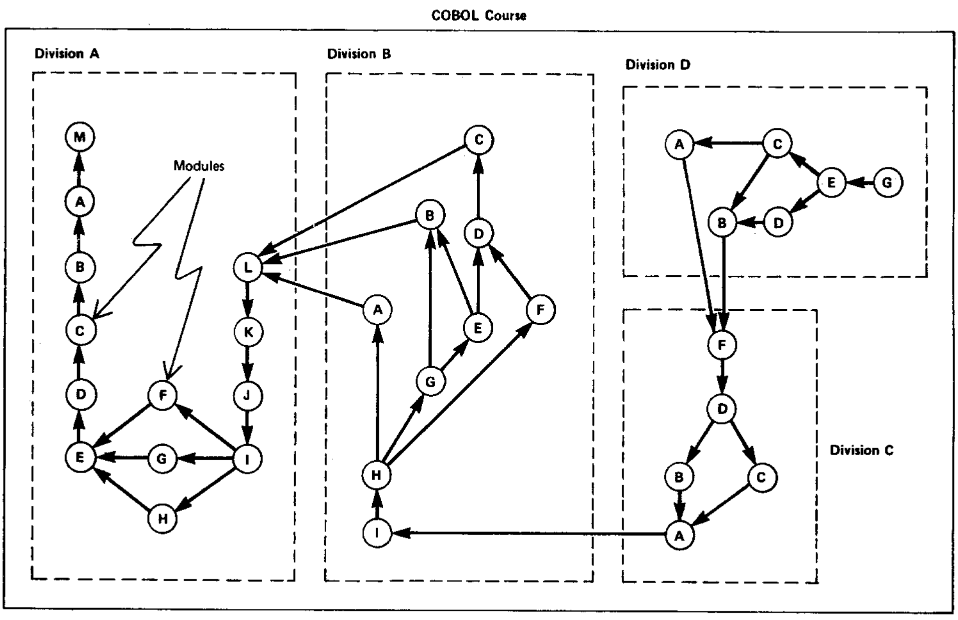


Fig. 2. COBOL2 prerequisite structure.

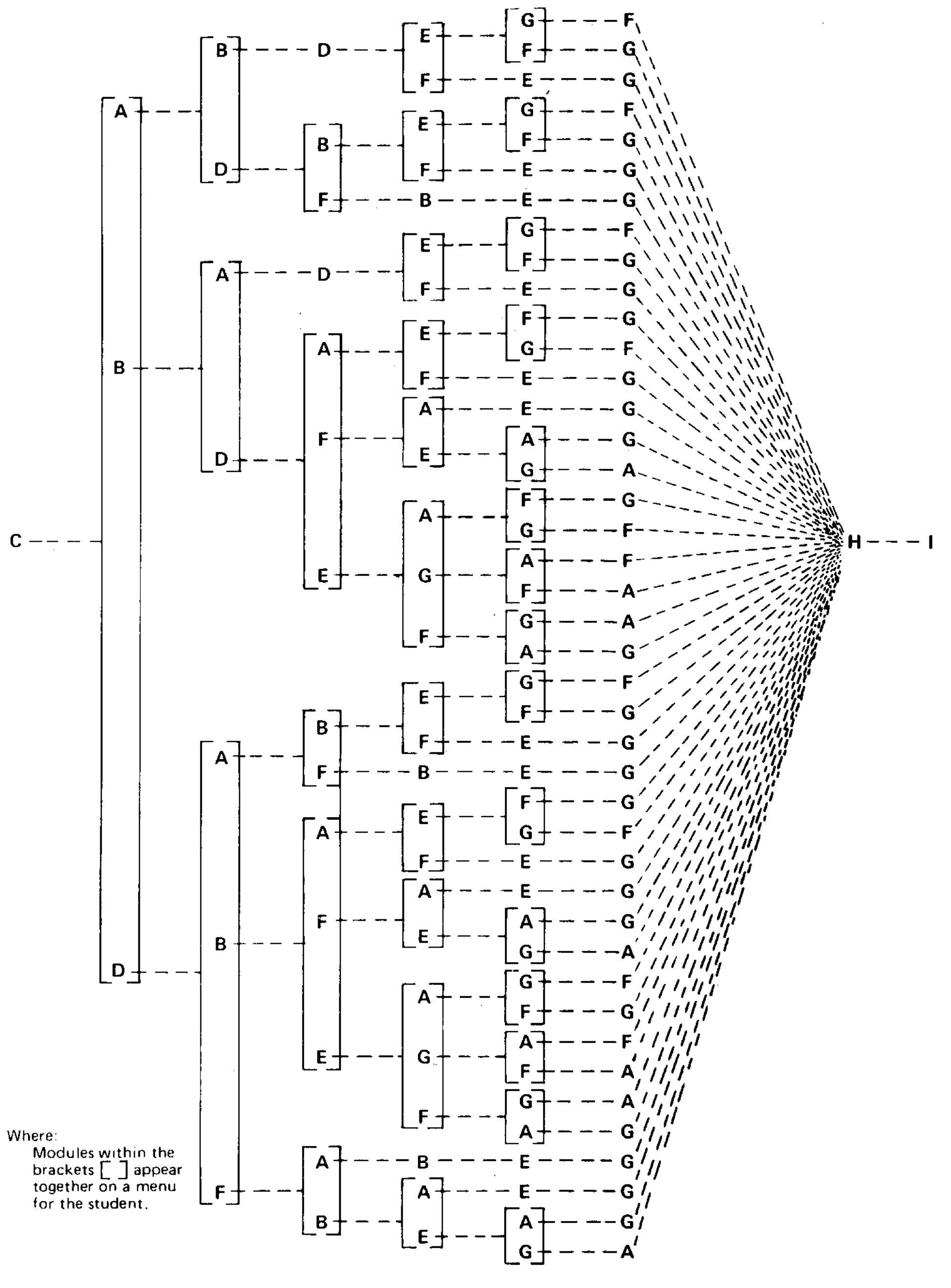


Fig. 3. Partial path diagram for Division B.

each be written so that the author of any of these modules assumes only mastery of the objective taught by Module E when the student is taking Modules F or G or H. The author of Module I, however, must assume that the student has mastery of the objectives taught in Modules F and G and H. The prerequisite structure shown was established for the COBOL2 course during its design phase and is based on an analysis of the relative nestings of behavioral objectives within others.

The implications of this design for the ways a student can learn the materials is evident in Fig. 3, a partial diagram of the path structure through Division B (if the student chooses Module C at his first choice point). Keeping in mind that the COBOL2 course is a self-contained tutorial (no nonsystem instructional support), the author must create the instruction so that all students, no matter what path they take to get to the module, can comprehend and thereby master any previously required module. For Module I this means all four modules in Division A, regardless of path chosen.

The design of the course and the total CAI system at HumRRO also included special features that permitted the student or the system to exercise instructional strategies in the form of options for RECAP, REVIEW, ROUTE, PRACTICE, QUIZ, and INFO. All but the last of these options served as branching mechanisms for individualizing instruction. The INFO option was designed for on-line glossary assistance with key terms and programming diagnostics. For purposes of ensuring the feasibility of the study, the PRACTICE option was not provided during the conduct of the research.

REVIEW, QUIZ, and RECAP Options

You may change the kind and amount of instruction you receive by using any of the options listed below. Remember that options are not available to you during quizzes.

To use an option, type it as an INFO—request.

Use your light pen to move the cursor to the dash after INFO. Move the cursor one more space to the right by hitting the SPACE key one time. Immediately after the dash next to INFO, type the name of the option you wish to use. Make sure there is no extra space between the dash after INFO and the word you type.

EXAMPLE. A request to RECAP should look like this: INFO—RECAP

REVIEW – Goes back to the beginning of the explanation section.

QUIZ – Skips all the remaining instruction before the quiz.

RECAP – Allows return to any topic previously taken.

Fig. 4. Example of directions provided experimental subjects.

Each student was told at the beginning of the course which options would be available to him. In the regular (nonexperimental) version of COBOL2, directions for exercising the options were included in the student reference manual. During the experiment, as a reminder, the particular options available were noted on a similar sheet placed over the cover of the student manual. An example of these directions is shown in Fig. 4.

STUDENT SUBJECTS

Ninety percent of the sample (N=80) were paid volunteers recruited through advertisements in the local newspapers; the remaining subjects were military personnel, also volunteers, supplied by the Army's Project Transition – an activity designed to assist separating soldiers in developing job-related skills for civilian life.

Our experience in the first COBOL course demonstrated that students who were severely deficient in programming aptitude were generally incapable of acquiring even the basic skills taught in the course as designed. Since such students provided little usable data while placing an additional strain on our already limited resources, we screened out any prospective student whose score on the IBM Programmer Aptitude Test fell below a raw score of 46 (a "low C") by more than one standard deviation.

To make our experimental findings relevant to real-world training, we intended that our subjects reflect the characteristics of programming trainees who are generally young, with a minimum of some high school, and naive with respect to programming. The data indicate that these requirements were met. Table I summarizes the relevant biographical characteristics of the sample.

Approximately 82% of the sample was 30 years old or younger; 62% was 25 or younger, and approximately 27% was under 21. Only three students had prior programming experience or training; two of these students were computer operators and one had some training in the rudiments of computer programming, but not in the COBOL language.

Nearly 99% of the sample had at least some high school education. Approximately 81% had completed high school, and 57% had at least some college, while 31% had a college degree or beyond.

While we consider the age spread of the sample to be appropriate, they were, if anything, somewhat overeducated for our purposes; the effect of their schooling on course performance will be shown in the results section of this report.

While over half the sample had vision difficulties (generally a need for glasses), in response to an "exit questionnaire" almost no one reported any problems reading the course materials from the display devices.

TABLE I

Personal Data for Experimental Subjects

Characteristic	Number of responses in category	Percent of total group
Sex		
Male	45	56.3
Female	35	43.7
Age		
Less than 21 years	22	27.5
21–25 years	28	35.0
26–30 years	16	20.0
31–35 years	3	3.8
36–40 years	4	5.0
More than 40 years	7	8.8
Vision Difficulties		
Yes	46	57.5
No	34	42.5
Typing Speed		
Nontypist	24	30.0
1–20 WPM	7	8.8
21–40 WPM	32	40.0
41–60 WPM	10	12.5
61–80 WPM	1	1.2
Greater than 80 WPM	2	2.5
No response	4	5.0
Educational Level		
Eighth grade (8 years)	1	1.2
Some high school (9–11 years)	14	17.5
Completed high school (12 years)	19	23.8
Some college (13–15 years)	21	26.2
Completed college (16 years)	14	17.5
Graduate (more than 16 years)	10	12.5
Other	1	1.2
Training and Experience		
No training or experience	77	96.2
Some training and/or experience	3	3.8
Current Occupational Status		
Student	27	33.8
Military	8	10.0
Employed–other	20	25.0
Unemployed	25	31.2

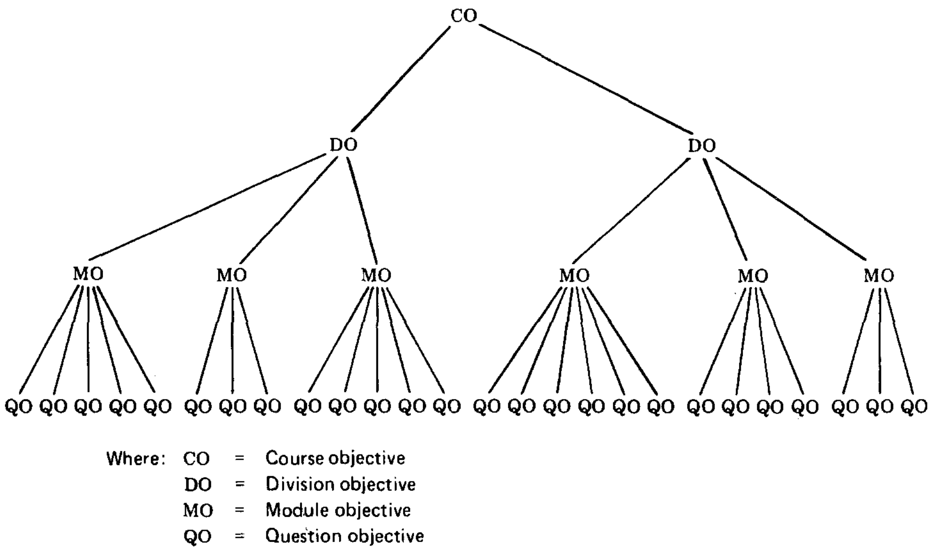


Fig. 5. Hierarchy of objectives.

EXPERIMENTAL DESIGN

As previously shown in Fig. 1, the COBOL course was designed with a hierarchy of parts. It is important to note that the nature of this hierarchy is a set of partially ordered input-output relationships. The approach to derive the total set was task analysis, and is based on information processing requirements (e.g., see Merrill, 1971, or Seidel, 1971). The course consisted of four divisions, comprising 33 modules or topics. Most of these modules were further subdivided into sections which included interactive questions requiring the student to make some kind of overt response. Figure 5 shows the relationship of course structure to course objectives.

The course structure was an outgrowth of an instructional design permitting a learner control over his path through the subject matter. T-Sections (See Fig. 1) were written so that general concepts were introduced first, and, as the student continued, the specifics were explained in detail. This technique enabled the student to discern, as early as possible, whether he thought he had sufficient mastery to skip to the Q-Section. It also enabled the student in REVIEW or RECAP mode to find the information he needed as early in the module as possible.

The Q-Section was designed as a discrete, self-contained section including explicit directions to the student on the mechanics of answering the question(s) that tested the module objective.

Authors found the course design and structure to be beneficial during the creation of materials, because it imposed enough constraints on the instruction to make different modules, written by different authors, com-

TABLE II

Instructional Treatments

Option combinations	Learner control options			
	ROUTE	RECAP	REVIEW	QUIZ
1	y	y	y	y
2	y	y	y	n
3	y	y	n	y
4	y	y	n	n
5	y	n	y	y
6	y	n	y	n
7	y	n	n	y
8	y	n	n	n
9	n	y	y	y
10	n	y	y	n
11	n	y	n	y
12	n	y	n	n
13	n	n	y	y
14	n	n	y	n
15	n	n	n	y
16	n	n	n	n

y = option available
n = option not available

patible in form and general order of content presentation. It allowed, however, much individual freedom to authors in the creation of within-module strategies. The modules that used gaming as an instructional method met the strategy and course structure requirements, as did the more conventional instructional techniques employed in some of the other modules.

The special features of the COBOL course were used as the experimental variables of this research. These four learner-control options were QUIZ, REVIEW, RECAP, and ROUTE. Prior to the start of the course, each student was randomly assigned to one of the 16 possible combinations of the learner-control options (see Table II). Thus, some students had all options available, some had access to none, some had only one of the four, while others had a combination of two or three control options.

Every student saw the same topics, although not always in the same order since those who had ROUTE were able to modify the sequence to some extent. Further, the particular option combination to which students were assigned and the extent to which they exercised those options would cause varied exposure to a given topic among students.

Students who failed the quiz for a given topic were branched back to the beginning of that topic to restudy the material and retake those quiz items previously missed. The amount of time spent in restudy depended on the student's own discretion and on his option combination (e.g. a student with the QUIZ option could jump to it immediately, whereas a student without QUIZ would perforce see all instruction in the topic before his second attempt at the quiz items). Should the student fail the quiz a second time, the same procedure would be followed except that a staff member would monitor his third attempt at the quiz and clear up any misconceptions evidenced by the answers.

At the end of each division of the course, the students were required to code, run, and debug a COBOL program to demonstrate mastery of the skills taught in the topics of that division. Successful completion of this task was a prerequisite to starting the topics of the next division.

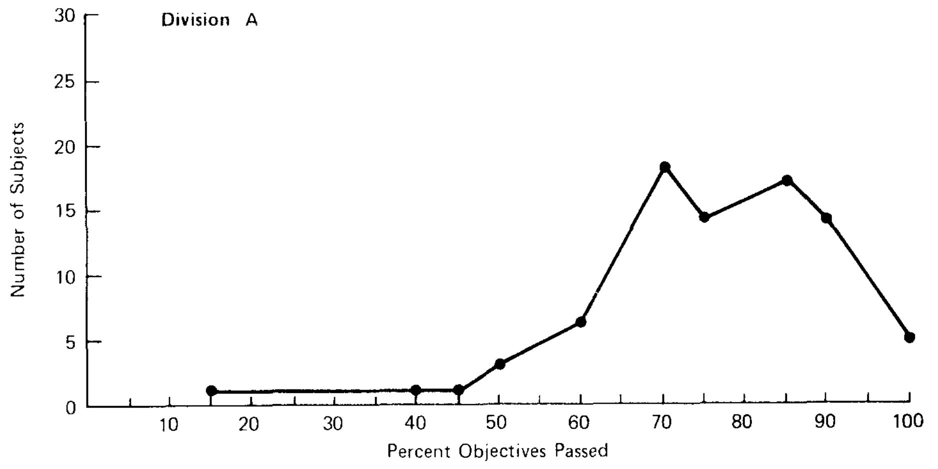
Results

As our study was designed to meet the dual goal of instructional adequacy and demonstration of instructionally relevant treatment effects, the data were analyzed for overall level of learning and, second, for experimental effects. The experimental analyses were accomplished on the total sample by means of analyses of variance (ANOVA) and on operationally defined subsamples of high and low performers by means of discriminant function analyses. The strength of effects was studied by multiple regression techniques.

EVIDENCE FOR LEARNING

Figure 6 indicates that the great majority of the students did quite well in the course. Notice that the frequency distributions of objectives passed on first try for both Divisions A and B are severely truncated with a marked positive skew. Seventy-five percent of the students achieved at least 70% of the objectives on the first try for Division A; fully half the students passed 75% of the objectives on the first try. The results for Division B are comparable. First quartile scores for Divisions A and B are 90% and 85%, respectively. Third quartile scores are identical – 70%.

These data strongly suggested that the limited variability of student performance, coupled with a restricted range and severely skewed distribution, would render a conventional technique such as the analysis of variance inappropriate as a means of analyzing the effects of the independent variables. Such an occurrence is not uncommon in educational research where the instructional material used as a vehicle for experimentation must also meet the requirement that it teach well. Nevertheless, in order to see whether other dependent variables such as time or expectancies (e.g. Level of



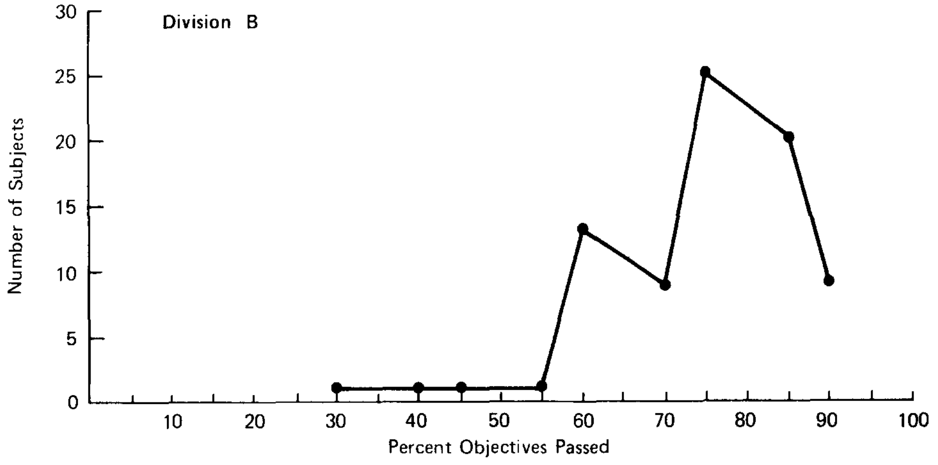


Fig. 6. Frequency distribution of subjects, by percentage of learning objectives passed on first try.

Aspiration, LOA) might show treatment effects, we initially performed an analysis of variance on the total sample.

TOTAL SAMPLE ANALYSES

The dependent measures gathered in the experiment were initally analyzed by means of the analysis of variance. The analyses were computed on quiz scores for the first try only and on transit times for the first and second tries. Beyond these limits, most of the cells of the design would be either empty or of unequal size because of the great number of students who achieved mastery on their first or second attempts.

TABLE III

Analysis of Variance Results

Dependent measure	Significant main effects & interactions	Ratio F	Degrees of freedom
Transit Time Telling/Practice Section (1st try)	Topics	105.88	20;1280
	Route X Quiz X Topics	1.86	20;1280
Transit Time Quiz Section (1st try)	Topics	254.40	20;1280
	Route X Topics	2.07	20;1280
	Review X Topics	1.60	20;1280
	Quiz X Topics	1.68	20;1280
	Route X Quiz X Topics	2.07	20;1280
Total Transit Time All Sections (1st & 2nd tries)	Topics	51.64	20;1280
	Recap X Review	4.01	1;64
	Review X Quiz	4.84	1;64
Transit Time Divisions	Divisions	41.41	1;64
	Recap X Review	4.01	1;64
	Review X Quiz	4.84	1;64
Quiz Score	Topics	1.75	25;1600
Compile Errors	Divisions	12.06	1;64
LOA	Objective	7.85	21;1008
	Route X Recap	5.41	1;48
	Route X Objective	2.48	21;1008
	Recap X Quiz	3.26	1;48
	Route X Review X Quiz	6.75	1;48
	Review X Quiz X Objective	1.55	21;1008

The results of the analyses are presented in Table III. Notice that the only statistically significant main effects ($p < 0.05$) occur for the units of instruction (divisions, topics). The very large F ratios obtained for all transit times, and the smaller but significant ones for quiz performance, compilation errors, and LOA indicate that the instructional units varied in their difficulty and length.

Therefore, criterion scores (quiz dependent measures and compilation errors) were affected by course location (topic and division). The few significant interactions that involve the learner-control options are due to the fact that the extent to which students make use of the options affects the amount of time spent on a topic. (See Experimental Design.)

HIGH AND LOW PERFORMERS

It was decided that, under the circumstances, a potentially productive way of investigating the effects of learner control would be through a comparison of the best and worst students in the sample for any treatment differences (e.g. in the use of the options). The "high/low" performer technique used in the development of psychological inventories was applied (Brennan, 1970). The individual items are analyzed for their capacity to discriminate between those whose overall test scores are high and those whose scores are low. In the present study we wanted to analyze the way learner-control options are used as discriminators of high and low performers in the COBOL course.

TABLE IV

Selection Criteria for High and Low Performers (Divisions A and B of the COBOL Course)

High Performers on Division A

Criterion 1:	Passed $\geq$ 84.6% of first-attempt objectives.
Criterion 2:	Of first-attempt passed objectives, 72.7% were $\geq$ 100 percentile.
Criterion 3:	Top 20 ranked according to score $\left(\text{score} = \Sigma \left(\frac{\text{obtained } S_i}{\text{max obtained } S_i}\right)\right)$

Low Performers on Division A

Criterion 1:	Failed $\geq$ 30.8% of first-attempt objectives.
Criterion 2:	Of failed first-attempt objectives, 75.0% were $\leq$ 23.75 percentile.
Criterion 3:	Bottom 20 ranked according to score $\left(\text{score} = \Sigma \left(\frac{\text{obtained } S_i}{\text{max obtained } S_i}\right)\right)$

High Performers on Division B

Criterion 1:	Passed $\geq$ 84.6% of first-attempt objectives.
Criterion 2:	Of first-attempt passed objectives, 66.6% were $\geq$ 98.75 percentile.
Criterion 3:	Top 20 ranked according to score $\left(\text{score} = \Sigma \left(\frac{\text{obtained } S_i}{\text{max obtained } S_i}\right)\right)$

Low Performers on Division B

Criterion 1:	Failed $\geq$ 23.1% of first-attempt objectives.
Criterion 2:	Of first-attempt failed objectives, $\geq$ 75.0% had scores $\leq$ 26.25 percentile.
Criterion 3:	Bottom 20 ranked according to score $\left(\text{score} = \Sigma \left(\frac{\text{obtained } S_i}{\text{max obtained } S_i}\right)\right)$

The following questions were posed for this aspect of the analysis:

(1) Who are the high performers in Division A of the course? Who are the low performers?
(2) Who are the high performers in Division B? Who are the low performers?
(3) Do they differ in the way or manner in which they make use of the options?
(4) Is there any difference in the attributes of the high and low performers that might help explain or predict differences in option use?

Selection

In order to have a sufficient number of observations for the analysis, it was decided that the 20 highest and lowest performers in each division would be identified for further study. A combination of absolute and relative performance criteria was used to select them. The specific criteria for high and low performers in each division are shown in Table IV.

High Versus Low Performance: A Task-Dependent Phenomenon

In an effort to identify the cognitive and affective characteristics on which high and low performers differ, the Entry Characteristics Test scores of these groups were subjected to multiple stepwise discriminant analysis. The results are summarized in Table V.

TABLE V

Summary of Stepwise Multiple Discriminant Analysis of High and Low Performers on 35 Entry Characteristics Test Scores

Division	Test selected	Standardized Discriminant weight
A	PMA–Verbal	7.738
	IPAT Anxiety–Score "B"	1.560
	Match Problems V	2.506
	Significance of overall discrimination: $F(3,36) = 10.154$; $p < 0.01$	
B	Cooperative English–Vocabulary	19.742
	ATPP	13.314
	PMA–Spatial Relations	−6.57
	Letter Sets	−2.693
	First and Last Names (Associative Memory)	3.007
	Significance of overall discrimination: $F(6.33) = 9.609$; $p < 0.01$	

The most striking set of findings is that there was no overlap in the ECTs discriminating high from low performers in Division A as opposed to Division B. (See Table V.) In addition, there was virtually no overlap in the high and low performers in Division A, and those who were high and low performers respectively in Division B. (Six students were high in both divisions; four students were low in both.) *The importance of these findings is that they emphasize the dependence of the phenomenon of high and low performance upon task-specific variables.* That is, we have a task-by-individual characteristic relationship. Just because individuals may be high performers in one set of tasks or in one level of an instructional course does not guarantee that they will continue to be high performers in another portion of the course. Therefore, it is extremely important to consider the dynamic nature of the situation in which individuals interact with the instructional tasks.

The overall discrimination for both divisions was highly significant (the overall F for Division A was 10.154; for Division B the F was 9.609; $p < 0.01$). In Division A, 3 of the 35 entry characteristics scores were selected by the analysis: the Primary Mental Abilities Test, a measure of general verbal aptitude; Match Problems, Test V, a measure of figural adaptive flexibility; and the IPAT Anxiety Test–Score B, a measure of the extent to which an individual reports anxiety-related feelings or behaviors. Examination of the standardized coefficients for these variables shows that the greater part of the discrimination is due to the verbal abilities test. The positive sign of the coefficients indicates that the high performers possess these attributes to a greater degree than the low performers.

For Division B, the analysis identified programming aptitude, the Aptitude Test for Programming Personnel, and vocabulary – measured by the Cooperative English Test – as the principal discriminators between the high and low performers. Two tests – the PMA Spatial Relations and the Letter Sets Test (a measure of inductive reasoning ability) – are not easily interpreted in the present context. In relation to the nature of the instructional requirements, these capacities (factors) were hindrances. The negative sign of the coefficients means the high performers possess fewer of these attributes than the low performers, although one would expect a positive relationship with success in the course. It is likely that the extremely small N, coupled with the particular statistical analysis, resulted in possible spurious results that masked valid relationships.

Manner of Option Use

The frequency with which the high and low performers used the options is presented in Table VI. The values have been adjusted to equate option availability across groups. This was necessary because, in some instances, the high and low performers did not come from treatment con-

TABLE VI

Frequency of First Attempt Option Usage (Adjusted)

	Options		
Performers	RECAP	REVIEW	QUIZ
Division A			
High	6.2	12.0	15.0
Low	35.0	65.0	25.0
Division B			
High	15.0	4.0	8.8
Low	20.0	52.5	11.1

TABLE VII

Use of the ROUTE Option by High and Low Performers

Performers	ACTIVE	PASSIVE	TOTAL
Division A			
High	14	5	19
Low	10	10	20
Division B			
High	21	11	32
Low	18	19	37

ditions having the same degree of access to options. (Because second attempts occurred with relatively low frequency, these data on option usage are not reported here.) Data on the ROUTE option usage are presented in Table VII.

Table VII shows that in both divisions the low performers consistently used the options more frequently than the high performers. This suggests that, if the options aid learning at all, the gain is due not to how often they are used but rather to where and when they are used.

Concerning the choice of ROUTE options, students who had the ROUTE option could, when presented with a "menu" of available topics, choose to pick their own or defer to the system to pick one at random. Table VII shows that the ROUTE option was made available by the IDM far more often in Division B than in Division A; this occurs because the prerequisite structure in Division B is less ordered (see figs. 2 and 3). In both divisions, the high and low performers saw "menus" about the same number of times. However, the proportion of occurrences in which subjects made an

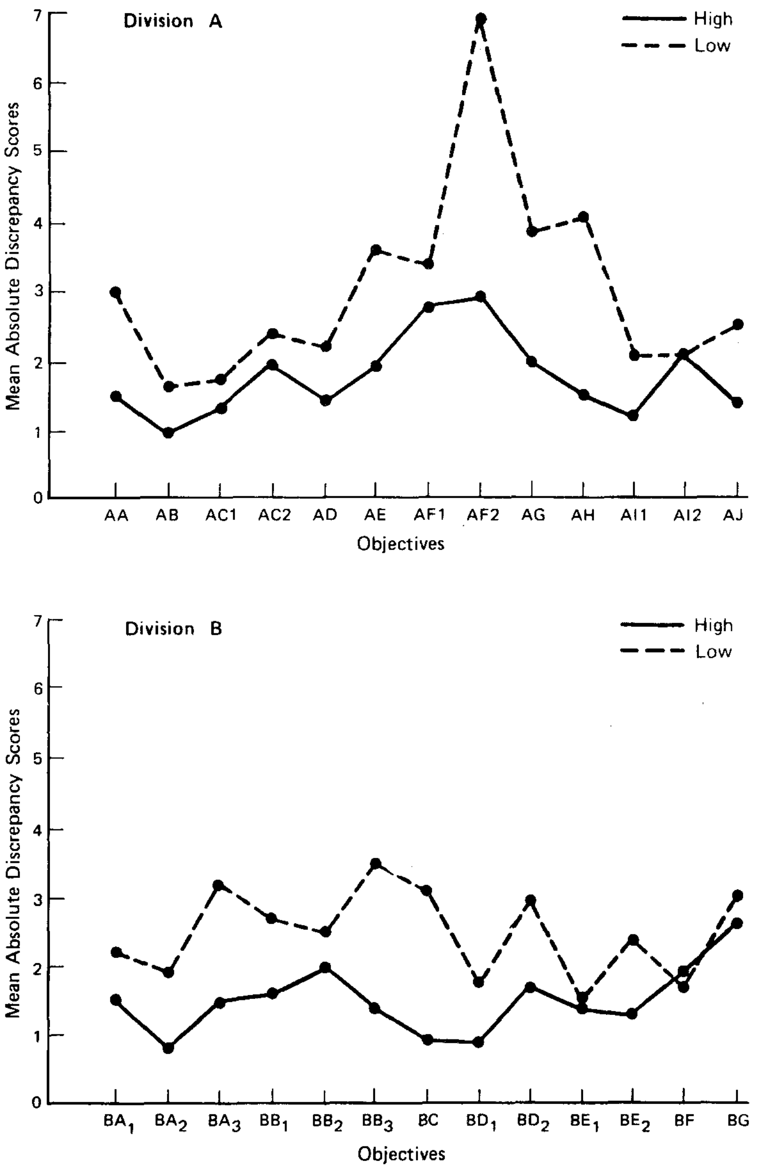


Fig. 7. Mean absolute discrepancy (LOA) for high and low performers, by specific objective.

active selection of the next topic differed markedly between the highs and lows. In Division A, the high performers made their own choice nearly three times more often than not; the low performers actively chose only half the time. In Division B, the high performers chose nearly twice as often as they deferred to the system; here, the low performers also chose about half the time.

Another interesting finding is that when given an option other than a linear path, most of the high and low performers chose a different path. For example, in Division A (refer to Fig.2 for the prerequisite structure) where the students were permitted an option of going through F, G, H, and I as opposed to other alternatives, 11 out of 14 of the high performers chose another alternative than the linear. Of the low performers, (a total of 10) only one chose the linear path, whereas the others chose five different unique paths (e.g. G, F, H; A, F, H). Thus, path choice, while freely exercised, did not differentiate between high and low performance.

Expectancy Measure

During the first IDM investigation in the current project, LOA (Level of Aspiration) was studied as a correlational variable. LOA correlated significantly with criterion performance in both levels of complexity in COBOL1. The correlations were + 0.42 and + 0.53 ($p < 0.01$), respectively. These findings were consistent with previous results in programmed instruction (see Seidel and Hunter, 1970).

Because of the modularization of COBOL2, it was possible to perform a finer-grain analysis than previously. The LOA data were analyzed at the level of specific objectives [3]. The basic hypothesis tested was that high performers would be more realistic than low performers. Operationally this would take the form of (a) a smaller positive discrepancy score for the high performers, and (b) a smaller absolute value of discrepancy between LOA and objective score for the high performers.

A ceiling effect because of the excellent performance by the high performers prevented an analysis of the *signed* differences. However, the test of absolute value differences as shown in Fig.7 clearly supported the hypothesis that high performers would be more realistic than the low performers. Coupled with the previous LOA findings these results substantiate the value of providing an Expectancy Operator for remediational purposes as part of an improved IDM. It is once again significant to note the consistency of the phenomenon across divisions. Generally, high performance was characterized by greater realism of expectancy than was low performance. Yet the specific individuals in whom the phenomenon was observed differed from Division A tasks to Division B tasks.

Time Criteria: Differences Between High and Low Performers

The first important finding, which had been expected, was that the high performers were significantly faster learners than the low performers. The means for completion time of Division A low and high performers are given in Table VIII.

Because of the significant differences between them, the high and low performers were analyzed separately by means of multiple-regression techniques. It may be assumed that they come from different populations.

TABLE VIII

Mean Completion Time (in Minutes) for High and Low Performers

Performers	Mean completion time (in minutes)	t ($df = 32$)	p (one-tailed)
Division A			
High	566.30 ($\sigma = 148$)	2.67	< 0.025
Low	743.31 ($\sigma = 257$)		
Division B			
High	494.94 ($\sigma = 119$)	1.69	0.05
Low	582.89 ($\sigma = 199$)		

TABLE IX

Results of Stepwise Multiple Regression Analysis:* Division A

Variable entered	$\hat{b}$	$se_{\hat{b}}$	$\hat{\beta}$	t	p	Proportion variance predicted
High Performers						
ATPP	− 8.660	2.851	−0.559	−3.038	< 0.005	0.580
Sign Changes	−10.658	5.990	−3.27	−1.779	< 0.05	0.006
Analysis of variance for regression: F (2.17) = 15.513 ($p < 0.01$) R = .8038						
Low Performers						
Sign Changes	−19.034	3.725	−0.6293	−5.110	< 0.005	0.728
ATPP	−18.947	5.293	−0.6061	−3.580	< 0.005	0.082
Ship Destination	13.880	6.273	0.3351	2.213	< 0.025	0.026
First and Last Names	11.758	4.190	0.3311	2.806	< 0.01	0.028
Analysis of Variance for Regression: F (5.14) = 21.802 ($p < 0.01$) R = 0.9414						

* Dependent Variable = Total Transit Time; Predictor Variables = 11 Entry Characteristic Tests.

Because of the exploratory nature of the study, the small number of subjects, and the high degree of error variance in this kind of research environment, we also attempted to look at correlations with time criteria in a slightly different way. Simple Pearson r's were calculated separately for ECT scores and for Divisions A and B completion time. The findings to be

TABLE X

Results of Stepwise Multiple Regression Analysis: * Division B

Variable entered	$\hat{b}$	$se_{\hat{b}}$	$\hat{\beta}$	t	p	Proportion variance predicted
High Performers						
Sentence Completion	17.326	3.257	0.7041	5.320	< 0.005	0.351
First and Last Names	− 7.543	2.315	−0.4398	−3.258	< 0.005	0.316
PMA Aptitude	− 1.735	0.741	−0.334	−2.341	< 0.025	0.085
Analysis of Variance for Regression: $F\,(3.16) = 16.188$ ($p < 0.01$)						
Low Performers						
Ship Destination	−16.093	4.978	−0.5391	−3.233	< 0.005	0.588
Sign Changes	− 9.022	3.858	−0.3899	−2.339	< 0.025	0.100
Analysis of Variance for Regression: $F\,(2.17) = 18.741$ ($p < 0.01$)						

* Dependent Variable = Total Transit Time; Predictor Variables = 11 Entry Characteristic Tests.

presented in this section should, therefore, be viewed as hypothesis-generating, rather than hypothesis-confirming or conclusive statements. The findings are to be used as indicating potential relationships that require additional studies using a greater number of students.

The results of the stepwise multiple-regression analyses for high and low performers in Division A are presented in Table IX. The high and low performers both showed as relationships between time to learn and convergent production of concepts, one of Guilford's SI factors, as well as programmer aptitude. The low performers also showed a relationship between general reasoning capability and associative memory with length of time to complete the course.

In Division B (see Table X) associative memory appears to be a desirable capacity as indicated by its inverse relationship with time of completion for high performers. Another finding was that high performers showed a relationship between sentence completion test scores and completion time. It is puzzling that this is a direct relationship indicating that the greater the achievement motivation, the more time the high performers seem to take to complete the instructional tasks in Division B. One could explain this if we assume that the high performers, given their high degree of motivation, were more careful and therefore took more time to ensure that they would achieve as much as possible. This is open to conjecture and requires further study. The low performers in Division B, as indicated in Table X, showed relatonships between learning time and general reasoning capability and convergent production of concepts.

TABLE XI

Unique and Common[a] Predictors of Division A Completion Time For High and Low Performers (Pearson r Correlations)

Predictor	Factor	Correlations With Time[b] High Performers	Low Performers
Common			
ATPP	––	–0.76**	–0.74**
Sign Changes	Convergent Production	–0.67**	–0.85**
PMA	––	–0.62**	–0.66**
Inference Test	Logical Reasoning	–0.48*	–0.51*
Unique			
Cooperative English	––	–0.39	–0.53*
Ship Destination	General Reasoning	–0.22	–0.47*
Logical Reasoning	Logical Reasoning (G)	–0.28	–0.49*
Sentence Completion	Achievement Motivation	0.10	0.52*
First and Last Names	Associative Memory	–0.52*	–0.29
Word Coding	Figural Adaptive Flexibility	–0.61**	–0.39
Figure Classification	Induction	–0.26	–0.33

[a] Common predictors show correlations with time for *both* high and low performers, whose significance is $p < 0.05$.
[b] *indicates statistical significance, $p < 0.05$; ** $p < 0.01$.

In addition to the stepwise multiple-regression analyses, we examined the individual correlations between specific ECT scores and the criteria for Divisions A and B separately, and for high and low performers separately.

In addition to programmer aptitude tests, the factors of logical reasoning and convergent production of concepts were significantly related to learning time in Division A for both high and low performers. The most important correlations unique to high performers were between the time criterion and the associative memory factor in Division A, and between the time criterion and the figural adaptive flexibility factor (word coding – capability of looking at materials in new ways). Table XI shows that the correlation for the associative memory factor with the time criterion was - 0.52 ($p < 0.05$); the correlation of time and the figural adaptive flexibility factor was -0.61 ($p < 0.01$).

As seen in Table XI, the low performers had a different set of significant unique correlations with the time criterion in Division A. Here, the factor of general reasoning showed up again. This factor significantly contributed to the multiple correlation discussed previously – its Pearson r correlation was -0.47. Also, the logical reasoning and achievement motiva-

TABLE XII

Unique and Common[a] Predictors of Division B Completion Time For High and Low Performers (Pearson *r* Correlations)

Predictor	Factor	Correlations With Time[b] High Performers	Low Performers
Common			
None			
Unique			
Sign Changes	Convergent Production	−0.38	−0.79**
Ship Destination	General Reasoning	−0.31	−0.77**
PMA	--	−0.27	−0.70**
ATPP	--	−0.25	−0.54*
Cooperative English	--	−0.35	−0.54*
Inference Test	Logical Reasoning	−0.16	−0.47*
Logical Reasoning	Logical Reasoning (G)	−0.002	−0.46*
Word Coding	Figural Adaptive Flexibility	−0.26	−0.53*
Sentence Completion	Achievement Motivation	−0.59**	0.15
First and Last Names	Associative Memory	−0.56**	−0.12
Figure Classification	Induction	0.04	−0.18

[a] Common predictors show correlations with time for *both* high and low performers whose significance is $p < 0.05$.
[b] * indicates statistical significance, $p < 0.05$; ** $p < 0.01$.

tion factors showed significant relationships with the time criterion for the low performers (-0.49 and + 0.52, respectively).

In Division B (see Table XII), the unique predictors for the high performers seemed to be achievement motivation as was indicated by the multiple-regression analysis and associative memory.

The low performers in Division B, contrary to the results of the stepwise multiple-regression analysis, had many factors related to the time criteria. The convergent production of concepts and general reasoning factors were significantly related to the criterion as the multiple-regression analyses had shown. However, marker tests used for logical reasoning were also significantly related to the criterion (- 0.47 for the inference test, and - 0.46 for the logical reasoning test, $p < 0.05$ for both). Also significantly related to the criterion were the general characteristics of English aptitude and programmer aptitude. These were indicated by the PMA, ATPP, and Coöperative English Test. The correlations with the criterion for these tests were - 0.70, - 0.54, and - 0.54, respectively.

In brief. the two different correlational analyses indicated that general programmer aptitude and the factor of convergent production of concepts are related to learning time in Division A of the course for both high and low performers. However, different sets of unique factors for high or low performers were found to be related to learning time in Division B. These findings provide further evidence of the importance of task variables, not only for the phenomenon of high versus low performance, but for learning time as well.

Discussion and Implications

This research on learner control and on structure of intellect has resulted in a number of significant findings and implications. First, the study clearly developed an instructional vehicle which meets one of the criteria set down by Seidel (1971) concerning valid research in an instructional environment. Specifically, the data presented clearly showed that the students learned the COBOL course, and learned it well.

Secondly, the study was performed in a rich instructional environment. Contrary to recent statements by Boutwell and Barton (1974), the complex treatment task, as opposed to the factorially simple task, is preferred in performing Aptitude by Treatment Interaction (ATI) studies in a real instructional world. Many past difficulties in obtaining generalizable and realistic results in instructional research have come from the fact that rather simplistic approaches in a paired-associate setting have yielded findings inconsistent with findings in instructionally rich settings.

The third significant aspect to the current study has been the development of a very useful way to characterize high and low performers with an operationally defined set of criteria. This has led us to an analytic approach different from the standard statistical inference techniques and has highlighted the value of discriminant function analyses in instructional research settings. Of great importance is the fact that the particular individuals designated high or low performers differ depending upon the particular instructional tasks involved (i.e. the phenomenon of high and low performance was identifiable across two divisions of the COBOL course). High and low performers differed with respect to the usage of options, as well as their level of aspiration settings concerning their performance. But the particular individuals identified as high or low performers in Divisions A and B were quite different. There were overlaps of only 20-25%. This suggests that future researchers need to identify the instructional task characteristics related to student profiles of high and low performers.

Another significant finding in our study was that self-assessment can make a significant contribution to instructional management, whether the latter is by students or by the learning system. The next step that should be taken is to use the instructional options based on expectations, as part of the decision-making process in an adaptive instructional environment. This approach is consistent with conclusions drawn in the recent literature (Rappaport and Rappaport, 1975; Boutwell and Barton, 1974). In a study to determine the effects of teacher and student expectations regarding the outcome of a learning task, the Rappaports found that posttest scores were influenced to a significantly greater degree by student expectations than by those of the teacher. Boutwell and Barton, discussing the inconsistency of ATI research findings, advocate a search for new variables as a basis for decision making in adaptive instructional settings. We agree with this and suggest an Expectancy Operator as one of these variables. It is clearly of a more dynamic nature than the standard aptitude tests which are designed to yield predictors within a relatively stable environment. We also suggest that the use of the Expectancy Operator is consistent with an approach to a process-oriented model of decision making in which the student develops his own heuristics toward making decisions, and applies the algorithm that he feels would be useful to solve problems.

PROPOSED PRESCRIPTIVE USE OF THE EXPECTANCY OPERATOR

The rationale behind the Expectancy Operator is based upon the relationship between a student's performance and the relative reality of his expectancies. If a student is judged to be unrealistic – with too great a discrepancy between LOA and performance – a Probe path analysis and remediation are advocated. Recommended instructional guidelines for initial use of the Expectancy Operator and Prope path follow.

It is suggested that implementation of the Expectancy Operator (LOA) take the form of providing for LOA measurement prior to a Q-Section or criterion test on specific subsets of objectives, and subsequent measurements of actual student performance for each subset of objectives. As part of a pilot implementation, there is the need to test – validate – the prescriptive value of LOA separately. Correlations do not ipso facto necessitate prescription, a causal interpretation of the relational outcome.

The proposed IDM would take specific action based on a comparison of the preceding measurements. The action to be taken by the IDM is based upon the outcome of a problem in *reality* estimation or conceptual understanding, or some combination of these. In essence, the discrepancy score relationship between the LOA score in combination with percent correct (and, when refined, confidence estimates) is to be used for determining whether or not a Probe path should be followed. A Probe path is initiated by the system in order to gain more information concerning the student's problem and to take appropriate remedial action.

For example, if, following the pretest, the alignment of expectation and percent correct represents "realistic" behavior, then the student is to follow the "normal" path for him. (Normality in this case is to be defined idiographically with a continually refined entry battery.) If discrepancies occur in the student's estimations of reality, then the Probe path will be followed for additional diagnosis and action (by noting the relationship between the measures of percent correct and the measures of the LOA).

The specific plan and guideline for an initial implementation of an Expectancy Operator in a tutorial environment follows:

1. Objective for using the Expectancy Operator: To lessen the relative distance between Level of Aspiration and performance by raising the level of the lower (LOA or performance) to meet the higher value.
2. Plan for measuring LOA and providing solutions:
   a. Measure LOA prior to entering the Quiz.
   b. Measure performance in the Quiz.
   c. Feedback to student on LOA versus performance, verbal plus numerical comparison.
   d. Provide solution.
      (1) Solution to raise performances to LOA: Follow-up alternate strategy with alternate quiz (check discrepancies).
      (2) Solution on subsequent modules to bring confidence level up to performance: Check discrepancy scores on subsequent modules.
3. STATE DIAGNOSES: Eighteen possible states are derivable from the three sets of characteristics that follow. For purposes of *initial* implementation it is suggested that A3a, A3b, C1a, C1b will be most useful as additions to an adaptive IDM.

LOA	PERFORMANCE	ABILITIES
A High	1 High	a. Above average
B Average	2 Average	b. Below average
C Low	3 Low	

4. Set of Alternative Instructional ACTIONS:
   a. Remedial modules geared to specific content failures concentrating on variation of practice exercises.
   b. Conference with proctor/instructor.
   c. Fun Option (on-line games).
   d. Skip ahead (practice).
   e. Leaving early.
   f. Alternate media module (CMI type, cassette, PI text).
   g. Compliment student.
   h. Do nothing.
5. Recommended ACTIONS for DIAGNOSES (A3a, A3b, C1a, C1b): c, d, e, g – Confidence Building (C1a, C1b) for Low Expectation and High Performance.

a, b, f – Performance Building (A3a, A3b) for High Expectation and Low Performance.

6. Actions to be implemented initially:
   STATE A3a: a
   STATE A3b: b and/or f
   STATE C1a: d, e, f, and/or g
   STATE C1b: g or h

Probe Path Using Pre- and Post-Quiz Estimates

General illustrations of how the Probe path would operate could also incorporate student estimates after his quiz performance. In previous research (e.g. Seidel and Hunter, 1970), we have generally found with successful students that such a post-performance expectancy estimate is closer to actual performance than the LOA measure. Such an approach might be used as follows. First, let E stand for the student's estimate of his performance after the fact; let L stand for his Level of Aspiration or expectancy before the fact; and let A stand for his actual performance. The definition of i is trial number of a referent for the particular measurement number of LOA or EST. Applied to COBOL2, it would reference the module number. Generally, the values for L, E, and A would be derived from the degree of criterion attainment determined for a particular application in a computer-based environment.

A. DIAGNOSIS: If $| L_i - A_i | > | E_i - A_i |$ & $(E_i \frac{\text{disk}}{i} = +)$

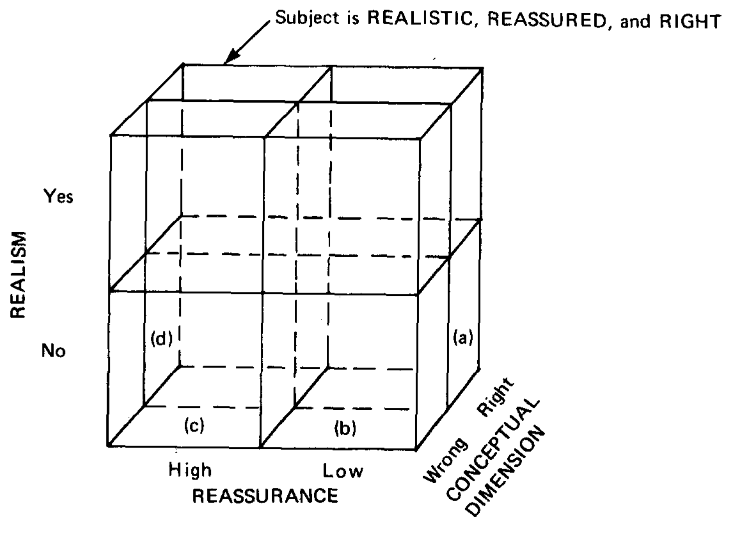


Fig. 8. Illustration of diagnostic states.

Then student state is defined as REALISTIC to the IDM.

ACTION: Diagnosis proceeds to next stage in IDM. Score on Test of Objectives, percent correct, defines CONCEPTUAL state and confidence value defines REASSURANCE state. Given A, and passage of criteria here, student continues on "normal" module path available (based on current options – eventually to be redefined by our improved Entry Battery and better within-course historical predictors). Subject possesses the three R's – Realistic, Reassured, and Right (see Fig. 8).

B. DIAGNOSIS: If $| L_i - A_i | < | E_i \dot{-} A_i |$ $(E_i^{disk} = -)$

ACTION: Go to PROBE path.

PROBE path: Here IDM can be thought of in the following way.

(1) It can query student directly to determine the nature of the problem as perceived by the student; that is, the student says, "No problem," or "I don't think I can hack it," or "I think I understand this stuff, but I'm not sure" (or some variation on this theme).

(2) Diagnosis of problem is defined as the intersection of three orthogonal binary dimensions. The resulting state is estimated as follows (verbally below and pictorially in Fig. 8):

(a) Given B above (diagnosis of UNREALISTIC) and Low Confidence and High Objectives score, then two dimensional motivational problems exist–REASSURANCE and REALISM.

(b) Given B, and Low Confidence and Low Objectives score, then problem is diagnosed as both overall motivational and CONCEPTUAL.

(c) Given B, High Confidence and High Objectives score, then problem is uniquely one of REALISM (e.g. the pessimist even though confident at time answering).

(d) Given B, High Confidence and Low Objectives score, then also REALISM, but probably of different type (e.g. delusions of grandeur).

(e), (f), and (g): Cases currently handled by the IDM where the Expectancy Operator would be in the zero condition.

Mathematically (and for IDM use) the state diagnosis can be described by ordered triples where 1=a problem condition, a remedial operator is called for, and 0=no problem. Thus, reading Realism, Reassurance, and Conceptual dimensions from left to right:

Case (a) is described as	<1,1,0>		
Case (b)	<1,1,1>		
Case (c)	<1,0,1>		
Case (d)	<1,0,0>		
Cases (e),(f),and (g)	<0,1,0>	<0,1,1> .	<0,0,1>

Use of Confidence Measure in Refined IDM

A second measure of assessment used in our IDM research effort was confidence responding by the students. In COBOL1, unlike the implementation of LOA measures, confidence responding was part of every student response. The student gave an answer to a question and immediately distributed his confidence with respect to the answer over a series of alternatives if the alternatives were available; or he attributed a degree of confidence to the correctness of the answer he provided in a completion type format.

The results indicated a lowering of the correlation between confidence measures and correct responding as the student progressed through the 18 modules of COBOL1. The implementation scheme apparently was not a useful one for the students, They were required to give a percentage value between 0 and 100% using two digits as appropriate (e.g. 45, 55) and eventually adopted a principle of least effort. That is, the students either used a 0 or 100% confidence choice eventually, and the result was a lessening of the value of the confidence measure as an indicator of a state of understanding on the part of the student.

The fact that the LOA measures indicated a high degree of value to self-assessment and the fact that other studies (e.g. Shuford et al., 1966; Shuford and Brown, 1975) support the value of confidence measures as an aid to learning led us to reevaluate the ways in which we would implement confidence measures in COBOL2 (rather than eliminating confidence as a sensitive index of state of understanding).

The goal in COBOL2 was (a) to make the implementation easier for the student to use, (b) make all input responses equivalent in effort and difficulty, (c) lessen the frequency with which the confidence measures were used to avoid interrupting and interfering with the learning process, and (d) to increase the value of providing confidence measures by making associative materials attached to the various states of understanding more meaningful and positive than they had been for the student in COBOL1.

The redesign was accomplished and initial off-line preliminary testing was achieved with staff members of the research project. However, because of the limited resources and other difficulties cited earlier, the reimplementation of confidence measures was not accomplished during this research project. We feel, nevertheless, that, in combination with the Expectancy Operator as discussed previously, the confidence measures should provide a very sensitive component to revised decision-making rules taking into account student motivation. The suggested implementation of confidence measures is provided as follows.

Confidence testing would be part of the Q-Sections of the course, and they would be handled in the following manner.

For the constructed response type of question, the student, after

TABLE XIII

Scoring System for Confidence Measure

Student Inputs for Correct Alternative	Payoff
0	0.000
1	0.500
2	0.650
3	0.739
4	0.801
5	0.850
6	0.889
7	0.923
8	0.952
9	0.977
T	1.000

making sure that his answer is the one he wishes to have recorded and checked, will input his response. His display (CRT, hard copy, etc.) will be cleared and a confidence question will be displayed. This confidence question will summarize the task asked of the student and ask him to place his confidence in a prescribed location on the display.

The student's confidence will be indicated by his selection of one of 11 characters from his keyboard. The characters are 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, and T-, where T stands for 10. A computer program computes the number of points the student receives by multiplying the number of points a question is worth (10–99), as determined by the author, by a three-place decimal associated with the student's confidence (see Table XIII). For a correct response, the student receives that number of points. If he is incorrect, he receives the number of points found by multiplying the three-place decimal associated with the ten's complement of the student's confidence by the author's point value for the question.

For example, if the student places a 7 in his confidence block, then the ten's complement is taken as his "no confidence" response, in this case, 3. Suppose the author states that the question is worth 60 points; then, if the student is correct he receives 60x0.923 = 55.3 rounded to 55 points, and if he is incorrect he receives 60x0.739 = 44.3 rounded to 44 points.

Each of the computer point values rolls onto the display in the proper location. If the student is dissatisfied with the number of points he will change his confidence. The computation will be done again. It can be done as many times as the student wishes until he is satisfied with his potential number of points. He will then signal his completion by proper key press, and the appropriate number of points will be credited to him.

The student will receive a feedback message on the display if his confidence is not one of the 11 characters just named.

For multiple-choice questions, the student will distribute his confidence over all alternatives (as in COBOL1). His confidence must add to T (ten) and he must strike a character for each alternative. Once again, the weight of the question supplied by the author will be multiplied by the three-place decimal associated with the student's response. These products will be rolled onto the display in payoff fields next to each alternative. If the student is satisfied, he just presses the appropriate key. If he is not satisfied, he will change his confidences until he is happy with the payoff involved. When it is found that the student has pressed his key without changing his confidence assignments, he will be awarded the number of points he has assigned next to the correct alternative.

For example, if a question is worth 50 points, and the student distributes his confidence as follows on a four-alternative question whose second alternative is the correct one, he will receive 33 points:

C		Payoff	
2	A.	33	Alternative
2	B.	33	Alternative
6	C.	44	Alternative
Ø	D.	Ø	Alternative

Here too, if the student types a character into his confidence that is not one of the 11 characters mentioned, or if his confidences do not add to 10, he will receive feedback requesting him to correct his error in assigning his confidence to each of the alternatives.

IMPLICATIONS OF EXPERIMENTAL FINDINGS FOR FUTURE RESEARCH

Based on the research findings it is recommended that a combination of reality testing, confidence measuring, and conceptual responding be performed, to provide a useful baseline for a next generation instructional strategy (IDM).

The results in earlier literature on learner control are generally conflicting, and the latest studies which the senior author reviewed (Jacobson and Thompson, 1975: McMullen, 1975; and Judd et al., 1975) are consistent with this confusion. The problems in conflicting or unclear results stem from a number of ambiguities in the concept of learner control and its application to experimentation. The following discussion is an attempt to explicate these dimensions and indicate directions for research in order to determine the viability of the area generally labeled "learner controlled instruction." The dimensions to be considered are: level and/or type of instructional process, individual learner characteristics, instructional task, previous training or sophistication of student in self-management, and type and availability of learning resources.

The first dimension is the level or type of instructional/educational process which is being studied. Significant effects may be revealed from the learner exercising a choice over what or how to study, depending upon whether we are speaking of a total curricular choice, a choice of some courses within a curriculum, objectives within a course, instructional options to reach prescribed objectives, time spent in all types of instruction, and so on. Obviously, there are different micro- or macro-levels of learner choice, and there are different complexities of the total educational/instructional process that are involved in such choices by students.

The recent studies just cited outline these differences in bold relief: Jacobson and Thompson – rich but highly structured IPI instruction in math with learner control specified by a student deciding whether or not to follow directions on a sheet of paper; Judd et al. – a short paired-associate task; McMullen – a concept identification task with learner control over instance-selection; Luskin – a college physics application where student option consisted of decision to use or not to use a problem-solving algorithm following PI on its merits. Conclusions concerning the value of self-management or "learner control" based upon one type or level of study may differ with evidence from another level or type. Unfortunately, there seems to be no literature that attempts to analyze differences in making comparisons across levels or type of study.

A second area for clarification is that of specific learner characteristics. Many (e.g. Atkinson, 1972) do not consider the *individual* characteristics of prior learning history on the part of the student. Thus, to introduce a student who is well trained in the authoritarian mode of instruction to a small paired-associate task in a learner-controlled mode may defeat accurate assessment of the value of learner control. Obviously, prior history of the learner must be taken into account and need for retraining must be considered.

Secondly, the most recent study by Judd and associates indicates a significant need for valid measuring instruments of learning capability. Judd attempted to relate the effects of learner control to the personality construct of independence. The construct of independence was defined operationally by two tests, one that showed a significant relationship with criterion and one that did not. Judd's conclusion was that because one of the tests yielded statistical significance, the independence construct *did* show a relationship to learner control. However, one out of the two tests *did not* show a significant relationship with learner control. The real question, then, is: is the construct validity or the measuring instruments suspect? It appears that before any conclusions can be drawn regarding the construct of independence and its relationship to learner control, more sensitive measuring instruments have to be studied. At the very least, a replication of Judd's study must be performed.

With respect to other within-course history variables, the current research and the senior author's earlier work (Seidel and Hunter, 1970) have shown the value of the dynamic properties of the student/task interaction for prediction of performance on criterion tests. The earlier study showed quite clearly that, with greater familiarity and skill in the instructional task, the student is able to be more realistic about his performance. Accordingly, a reasonable hypothesis would be that the student, given this greater familiarity, should also be better able to determine what piece of instruction he should receive next. So far, our data on this point have been descriptive in nature (correlational). The next step would be to test out such hypotheses in a prescriptive manner by introducing Level of Aspiration into the decision-making process for instructional choice (e.g. as just noted).

A third dimension requiring clarification is the kind of instructional task being studied under learner- versus system-control conditions. It is quite clear that a taxonomy is required. With the current state-of-the-art in instructional taxonomies, it does not make any difference what taxonomy is chosen, so long as it is consistent (Hunter and Seidel, Ch. 4 in Hunter et al., 1975). One can certainly observe that some instructional tasks readily lend themselves to browsing or open-ended kinds of instruction, whereas other kinds do not. Also, operationally paired-associate learning is not the same as concept identification which, in turn, is not the same as problem solving.

Thus, separate studies should be done to compare these various kinds of instructional tasks relative to the learner-control variable before drawing any conclusions across instructional tasks. Also, the specific content to be learned is a related area that needs clarification *vis-à-vis* its relationship to learner control. Such a taxonomy of instructional tasks and instructional content permits concentrated study at a microlevel. At another more macrolevel, one could study the effects of learner control over choice of instructional task and/or content itself. McMullen's study, for example, showed no particular advantage to learner control *within* a comparison of serial versus parallel paradigms in concept learning. However, learner control over *selection* of paradigm has already been shown effective in concept learning and problem solving by Pask.

A fourth dimension which must be clarified is the sophistication of the student in self-management, which is based upon previous, preferably long-term, training. This should be related to the first dimension discussed here – the type or level of the educational process being studied. Jacobson and Thompson's recent study (1975) is one of the few attempts to provide training in self-management within a highly structured IPI environment, but confounding experimental variables prevent any firm conclusions. The question of transfer effects *across* levels or types of the instructional/educational process is in need of careful experimental study.

Another dimension to consider is the type and availability of learner resources. It makes no sense to offer a student the option of controlling or managing his own learning process when the materials or resources are not available or amenable to browsing. For example, if we consider CAI, the entire TICCIT approach allowing a student to page back and forth through his materials is more amenable than a Coursewriter frame-oriented approach to CAI.

Research on refinement of decision rules using these dimensions should aid further development of useful computer-based instructional materials in meaningful tutorial environments.

Interpretation of the data in the current study can best be presented in terms of a provisional set of guidelines for prescribing instructional management.

With respect to option control by students, the data suggest that we:

(1) Establish high and low performer initial predictions for sets of similar instructional tasks.

(2) Provide maximal *student* control for the predicted high performers.

(3) Design maximal *system* control for predicted low performers.

(4) Track the performance of *all*.

(5) Adjust the degree of student control, based upon the changes in performance, according to an empirical model that maintains the maximum percent of high performers. This model would have to be derived for each subject-matter application since tasks and instructional materials would have unique complexities and forms.

The finding that high performers make more effective use of learner control options underlines the need and desirability for systematic study of the factors that may affect the utility of this feature for the student. If, for example, effective use of options depends on an accurate assessment by the student of his progress during instruction, then the appropriate research problem involves: (a) establishing the elements of information or data whose identification and evaluation underlie the decision to use or not use a given option at a given time; (b) identifying the cognitive and attitudinal characteristics of learners that affect the accuracy of information processing and decision making; and (c) developing instructional strategies, which through careful empirical evaluation of these parameters, provide an amount and kind of control appropriate to each individual student.

The ability to be able to discriminate, using an appropriate entry test battery, the high and low performers on an initial basis is related to the research problem. To the degree that this can be done, the designated student- or system-control options will be more or less appropriate.

As noted from the preceding ECT analyses in the current study with a primarily verbal course like COBOL2, the single best predictors were verbal entry tests such as the Primary Mental Abilities Test used for programmer aptitude selection, as well as the Cooperative English and, in another case, a uniquely suited Programmer Aptitude Test called the ATPP. The significance of the ATPP, as well the other structure of intellect test which showed up as significant in our discriminant analysis, emphasize that there will be other unique characteristics of any given instruction that will also aid in discriminating the predicted high from the low performers. These factors would have to be discerned from a structural analysis of the subject matter and its related tasks. (In the current instance, we are still doing analysis of this subject matter by factor structure using multiple raters to arrive at a reliable index, *vis-à-vis* the Guilford Structure of Intellect characteristics.)

Again, from the current study, supportive evidence for differential task transfer and the contribution of unique task and subject-matter characteristics comes from the comparison of Division A and Division B predictors from the ECT batteries. For example, in the introductory part of the course, Division A, the discriminant function was characterized by the most general and smallest number of predictor tests; however, in Division B, which was more heavily loaded with unique characteristics of COBOL programming and specific technological tasks, there were more variables present, and we found that the characteristics of these ECT predictors were more unique to the programming and specific tasks related to factor structure. Specifically, we refer to the fact that the ATPP, a uniquely oriented programmer aptitude test, was a heavily weighted factor under Division B prediction. Moreover, there was the appearance of Structure of Intellect factors involving associative memory and logical reasoning. In like manner, the anxiety test, IPAT B, was a predictor of performance in the introductory part of the course but dropped out as people became more familiar, comfortable, and sophisticated in the COBOL programming tasks.

For longitudinal study and longer-term transfer interpretation, it is necessary to test this hypothesis of specific task transfer with even more unique and specific, sophisticated COBOL course materials (like the other two divisions which were not available for our experimental subjects during the conduct of this research). It is predicted that more specific factors like logical reasoning and figural adaptive flexibility (the ability to change set with new materials) would take on even greater importance (relatively) to the specific nature of the task the individual would be encountering. This logic also applies equally to transfer across divisions within other hierarchically structured courses (e.g. electronics maintenance and other technical training).

Combining the preceding discussion of option availability and relevant

ECT for prediction of high or low performers with the previous description of the self-assessment result provides an indication of a workable instructional decision model to be tested in future research. It would take something like the following form.

Given that the high performer predicted by specific entry tests is more efficient in his use of options and is more realistic about his own performance, the self-assessment via the use of LOA could be used as a tracking device or technique for adjusting the degree of student control over the available remediational or accelerating options within the course of instruction. When a predicted low performer, for example, begins to fall within the realistic range of predicted high performers, that individual would then be allowed more control over the use of available options. Note that the previous findings are descriptive (correlational) and Expectancy now is to be verified as a prescriptive variable in an IDM.

However, when an individual falls outside the range of reality testing and is predicted to be a low performer, then the adjustment would take the form of eliminating student control over available options until such time as the individual performance begins to come more in line with reality and, indeed, until the predicted performance jumps back up to what a high performer would show. This model, however, does require continued research in order to verify its appropriateness to various applications of instructional tasks.

As an adjunct to this model, it would also be relevant to add other parameters which describe in a more sensitive way the high or low performer's state of understanding. This might be done by use of the revised confidence measures discussed earlier under self-assessment. It may well be that a previously designated high performer who yields some unrealistic estimates of performance in some novel material might be signaling that he is getting into deep water and can no longer handle the instructional tasks required of him. In this case, supplementing the probing of that individual's understanding by the use of confidence techniques might provide additional indices for the kind of specific remediation unique to his requirements. All of the above awaits further verification in a real-world instructional environment, similar to that used within the current study.

Clearly, more research is required to get a closer identification of relevant ATI relationships in varied computer-based learning environments.

Instructional management of resources (e.g. via the use of student-controlled options) must be considered relative to the student characteristics and still be relevant to the instructional tasks. While our results were not as definitive as we would have liked, differences in relevant ECT scores *were* found for high and low performers. Follow-up work should more carefully relate the entry tests to specific taxonomically labeled characteristics of the instructional tasks. It is challenging to consider within the same instructional environment, the differences in the sets of relationships revealed among ECT scores, high versus low performance, and learning time criteria. It is hoped that subsequent research will reveal the reasons for these findings and the ways in which they are related in a broader construct of learning.

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Notes

1 NSF Grant GJ 774 to Human Resources Research Organization, "Research on Instructional Decision Models," Robert J. Seidel, Principal Investigator. See *Research on Instructional Decision Models*, HumRRO Final Report FR–D1–73–6, December 1973.

2 The COBOL course contained four divisions with a total of 33 topics comprising about 60 hours of instruction. A reduction in resources, coupled with impending temporary loss of HumRRO's in-house computing facilities, necessitated shortening the course in order to guarantee a sufficient number of subjects for the experiment.

3 Because of the consistent descriptive findings, it had been decided to make LOA part of the decision-making strategy in the revised IDM for COBOL2. Extensive course revision coupled with curtailed resources prevented implementation of LOA as the newly developed Expectancy Operator (a decision-making rule using the discrepancy between actual performance and anticipated performance by the learner), but LOA was used again as a correlational variable. The results were consistent with the previous data indicating significance of student expectations as predictors of achievement.

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