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DEVELOPMENT AND ASSESSMENT OF AN ADAPTIVE STRATEGY UTILIZING REGRESSION ANALYSIS TECHNIQUES FOR THE PRESENTATION OF INSTRUCTION VIA COMPUTER

Lee Rivers

Florida State University

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CAI CENTER

TECH REPORT

DEVELOPMENT AND ASSESSMENT OF AN ADAPTIVE STRATEGY UTILIZING REGRESSION ANALYSIS TECHNIQUES FOR THE PRESENTATION OF INSTRUCTION VIA COMPUTER

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Tech Report No. 27
August 30, 1972

Project NR 154-280
Sponsored by
Personnel & Training Research Programs
Psychological Sciences Division
Office of Naval Research
Arlington, Virginia
Contract No. N00014-68-A-0494

FLORIDA STATE UNIVERSITY

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TECH REPORT SERIES

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In terms of content, one can anticipate a detailed discussion of the rationale of the research project, its design, a complete report of all empirical results as well as appendices that describe in detail the CAI learning materials utilized. It is hoped that by providing this voluminous information other investigators in the CAI field will have an opportunity to carefully consider the outcomes as well as have sufficient information for research replication if desired. Any comments to the authors can be forwarded via the Florida State University CAI Center.

Duncan N. Hansen
Director

Computer Assisted Instruction Center

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13. ABSTRACT

The advent of the use of the computer in instruction generated much discussion about the development of models of the teaching process that would adapt to the individual differences among learners in order to optimize achievement. One of the major advantages of using a computer in instruction stems from its capability to adapt the instruction based on the individual's most recent performance as well as his accumulating past history (Dick, 1965; Hanse, 1966; Gentile, 1967; Zinn, 1967).

The objective of this investigation was to develop and assess a methodology for adapting self-instructional materials to individual differences among learners. In this two-phased empirical approach, on-going performance was monitored and used to predict final achievement. Adaptations were made in

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ABSTRACT-continued

the course content for each individual as the instruction proceeded in order to optimize his performance.

In the first phase, data on within course variables of proportion correct, latency and anxiety were monitored across nine basic concepts in a course on the diagnosis of heart disease which was presented via the IBM 1500 system. Regression analysis was used to determine significant predictors of final performance on each concept. Seven points were identified where significant predictions could be made. The regression equations were coded into the computer logic and remedial instructional loops were added at those points.

Four treatments were employed in the second phase in order to assess the effectiveness of adapting the on-going instruction on the basis of regression analysis techniques at the concept level. One version of the course was programmed such that a group of students (the regression model group) proceeded through the CAI program to which has been added (a) the coding in the program logic to monitor the appropriate within course variables; (b) the prediction models which would detect those students in need of additional instruction; and (c) the remedial loops which would maximize their final performance. A second group of students (the All-Remediation group) received all of the remedial loops regardless of what the predictive models indicated. A third group (the No-Remediation group) received none of the remedial loops. They simply proceeded through the mainline instruction. The final group (the Student Control group) was given the option at each possible remediation point identified in the predictive condition to either go through the remedial loops or to continue with the next concept.

In terms of total posttest performance, it was revealed that the Regression Model and All-Remediation groups each had significantly higher scores than either the student choice or No-Remediation groups. There were no significant differences within the two sets of groups.

The remediation was effective in improving final performance as evidenced by the significantly higher performance level of the All-Remediation group when compared with the No-Remediation group. The finding of superior performance for the Regression Model group over the No-Remediation group indicates that the decision logic was effective in identifying those students in need of additional instruction. The effectiveness of the decision logic was further supported by the fact that the Regression Model group also performed significantly higher on the posttest than the Student Choice group.

With respect to total instructional time, it was expected that the All-Remediation group would take significantly more time (instructional plus remedial) than the No-Remediation group, and indeed it did. The All-Remediation group also took significantly more time than the Student Choice group which took the least amount. Although the Regression Model

ABSTRACT-continued

group ranked second in total time, it did not take significantly more time than the Student Choice or the No-Remediation groups, nor did it take significantly less time than the All-Remediation group. However, in five of the seven decision points almost all of the subjects in the Regression Model group were given the remedial instruction which, in essence, left little room for time saving in comparison with the All-Remediation group.

In conclusion, the results of this study have revealed the potential of an adaptive strategy for the presentation of instruction which utilizes regression analysis techniques. However, it has been noted that in order for the full effectiveness of this approach to be assessed, further research in the area needs to be conducted. Specifically, the needed research pertains to the selection and use of predictor variables and to the most appropriate type and amount of remediation to be supplied when lack of mastery is detected. Finally, it has been noted that the use of this approach need not be confined to situations where instruction is presented via the computer. This empirical approach can be an excellent research tool as well as an effective instructional process.

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I. INTRODUCTION

It might be stated that any attempt to account for individual differences among learners in providing instruction is an attempt to optimize the achievement of students pursuing a particular educational objective. Although it is widely recognized that individual differences in learning do exist, little has been done to allow for this in providing instruction because of the lack of consistent findings derived from experimentation. This view was expressed by Eckstrand in 1962 and is still largely true today.

One form of instruction that has paid some attention to individual differences is that of programmed instruction. However, the early form of programmed instruction, the linear programming model of Skinner (1954), only provided for individual differences in the rate of learning. All students received the same small bits of instructional material. Theoretically this would maximize achievement but time would be allowed to vary. The brighter the student, the faster he would be able to complete the instruction. However, many students still had to spend time on instruction that they didn't really need.

A second basic form of programmed instruction is the intrinsic programming model posited by Crowder (1959). Large blocks of information are presented to the student followed by a multiple choice question. If the student selects the correct alternative, he proceeds to the next question. If he is incorrect, he is told why or given a hint to help remedy his misconception and then he is directed back to the question. Students receive varying amounts and kinds of instruction and the rate of progress is simultaneously varying. Time is minimized to a greater degree than it is with the linear programming model. Briggs (1968) has stated that one could reasonably expect that branching programs should be superior to linear programs because they appear to provide the information the student needs when he needs it without his being bothered by superfluous information. That they have not, may reflect the inadequate techniques employed in making the decisions to branch. It would appear that more information can be gathered on the student than simply his response to a single multiple choice question. Without unwieldy procedures, however, it is difficult to do much more than this with programmed instruction.

When computers first became available for utilization in instruction, programmed instruction was the typical model used for implementation. One of the advantages of using the computer in education is that it has the capability to adapt the instruction based on each individual's most recent performance as well as many facets of his past history (Dick, 1965; Hansen, 1966; Gentile, 1967; Zinn, 1967). With the use of the computer, more complex decisions can be made about learner performance. However, as of this date, most computer-assisted instruction (CAI) applications have individualized only the rate at which the student proceeds through the CAI program. Certainly one factor contributing to this state of affairs has been the lack of consistent findings about the many learner entry characteristics and their implications for the design of instruction.

The question then arises as to what techniques might be employed to optimize achievement. One of the most important aspects of programmed instruction, which also has been applied to computer controlled programs, has been the use of learner data to revise the programs to make them effective instructional instruments. Although this process does seem eminently sensible, it may take many revision cycles and even then one cannot reliably predict how any particular individual will perform on the final achievement measure. With computer-assisted instruction it is possible to record all student performance and to make decisions about a particular student on the basis of responses to individual items or any combination of items as well as latencies in responding to any number of items. The question then becomes: what additional variables might be measured during computer controlled learning and what methodology might be employed to use these variables to predict final achievement for each individual as he proceeds through the CAI presentation in order to maximize his achievement and minimize his instructional time?

II. STATEMENT OF THE PROBLEM

The objective of this investigation is to develop and assess a methodology utilizing the computer's unique real-time monitoring capability to maximize achievement while minimizing time on instruction presented via the computer. If ongoing performance can be monitored and used to predict final achievement, then adaptations can be made for each individual in the course content as the instruction proceeds in order to optimize his performance. This approach implies the use of empirical techniques. Data on within course variables generated by an initial group of students would be utilized in establishing the adaptation points in the program as well as the decision criteria to be employed at each point. The prediction models established would be embedded in the logic of the instructional program which is under the control of the computer. As subsequent students proceed through the instructional materials, the relevant within course performance variables would be monitored by the computer. Criteria embedded in the logic of the computer program would allow for predictions of each student's final achievement. If a student's predicted achievement is below a predetermined level, he would be branched to remedial instruction. If his predicted achievement is satisfactory he would continue through the mainline of instruction.

The development of the prediction models would involve the identification of variables to be monitored during learning and the establishment of decision criteria for providing remediation. The use of regression analysis techniques would be an appropriate basis for building such models because variables that are effective predictors of final performance would be identified, and the relative weighting factors produced could be used in the decision process. This empirical approach utilizing regression analysis techniques and within course performance data involves a two-step process. An initial group of students would proceed through the instructional materials. Their data would be analyzed by means of regression analysis, and on the basis of this analysis, the prediction models would be developed.

The initial problem involves the identification of potential predictor variables that can be measured during learning that might relate to final achievement. The most obvious variable to be measured during learning is the probability of correct responding. To the degree that the final assessment of achievement is a reliable measure, the greater the frequency of correct responding, the greater the probability will be that the students will also perform successfully on the final examination. A second variable to be considered is that of response latency. Osgood (1953) has stated that latencies have the advantage of being applicable in a wide variety of situations, of providing continuous trial-to-trial measures as opposed to the dichotomous measure of frequency, and of retaining sensitivity after frequency measures have reached asymptote. Latency is defined here as the interval between the presentation of an information-question unit to a student and his response to that unit. A third variable, a performance related variable that has potential for predicting final achievement, is that of anxiety. O'Neil, Spielberger, and Hansen (1969) have found that performance on learning tasks is an interactive function of level of state anxiety and task difficulty. High anxious students tend to make more errors than low anxious students on difficult materials, while performing as well as or better than low anxious students on easy materials. The variables of performance, latency, and anxiety can be measured with little or no intrusion in the learning sequence, and they have high potential for the development of effective prediction models for maximizing performance and minimizing time on computer-assisted instruction.

The second major problem area involves the determination of the unit of analysis. That is, would the most effective predictions be obtained by a frame by frame analysis of the learning data, by analyzing the data over a series of frames covering a specific concept, or by analysis over a series of related concepts covering a large number of frames. The establishment of the unit of analysis determines the point in the instructional program at which adaptation can be effected. The adaptation points are the points at which remedial instruction would be provided. The unit of analysis should be large enough to provide a stable indication of behavior but be responsive enough to provide for adaptive decisions while the learning is still proceeding. The unit of analysis that would appear to have the highest potential payoff in terms of meeting the criteria of behavioral stability and instructional flexibility would be at the concept level. Although the initial analyses will be conducted over a series of frames relating to a single concept, data may be combined over several concepts in order to find the most effective predictors.

The second phase of the investigation involves an assessment of the effectiveness of this methodology of employing regression analysis techniques to optimize achievement. A group of students would proceed through the instruction with the predictive models and the remedial loops. Their achievement and instructional time would be compared with a group that receives no predictions and no remediation, a group where every student receives the additional instruction, and a group where each student is allowed to determine whether he needs the additional instruction.

The regression model and student choice groups can be considered adaptive strategies as contrasted with the all-remediation and no-remediation groups. Comparisons of the performance and time statistics of the regression model group with these three control groups as well as within control group comparisons will allow for an effective assessment of the efficacy of the regression model adaptive strategy. The no-remediation group will provide a base-line of performance and when compared with the AR group will allow for a direct assessment of the effectiveness of the remediation.

In a survey of eight major school districts and seven universities servicing the public schools, it was indicated that, as a very conservative estimate, over 20,000 children in 1970 would have some portion of their instruction presented via the computer (Dick, Latta, and Rivers, 1970). Considering the initial high costs of computer-assisted instruction, it is imperative that the full potential of this method of instruction be explored and developed. The capabilities of the computer for providing the maximum benefit for each student are great, but we must learn how best to take advantage of these capabilities. The methodology discussed here has high potential for improving the efficiency and effectiveness of instruction for each learner.

As a research tool, this empirical approach using regression analysis techniques may help to identify, in general, those variables that can be measured during learning that will enhance student achievement. As our research knowledge grows, other variables, those measured to the learning situation as well as during it, might be added to the predictive models in the attempt to individualize instruction more fully and provide the maximum effectiveness for each learner.

III. LITERATURE REVIEW

The advent of the use of the computer in instruction generated much discussion about the development of models of the teaching process that would adapt to the individual differences among learners in order to optimize achievement. The two basic models of programmed instruction (Skinner, 1954; and Crowder, 1959) attempted to do this, but achieved it in only a limited way in that the instruction was adapted, at most, to the student's most recent response. One of the major advantages of using a computer in instruction stems from its capability to adapt the instruction based on the individual's most recent performance as well as his accumulating past history (Dick, 1965; Hansen, 1966; Gentile, 1967; Zinn, 1967).

Stolurow and Davis (1965) put forth a general model of the teaching process that would be accomplished by an adaptive teaching machine system. Under their system a student would be branched to specific materials based on parameters such as frame difficulty, error rate, response latency, scholastic aptitude, previous learning performance, and interests. Lewis and Pack (1965) postulated a similar type of cybernetic or adaptive model using ideas from artificial intelligence. Their theoretical model stresses the characteristics of the student, the structure of the subject matter and the student's problem-solving processes. These two models can be characterized as general, all-inclusive theories for computer adapted instruction.

Another approach for optimizing performance by modifying the instructional program to the individual characteristics of the student has utilized the techniques developed within mathematical learning theory. The investigators attempted to utilize formal mathematical models of the learning process as a basis for determining optimal sequencing of instruction. (Deer & Atkinson, 1962; Atkinson & Hansen, 1966; Groen & Atkinson, 1966; Karush & Deer, 1966). Deer and others (1965) concluded that ‘‘the improvement of teaching procedures by seeking an optimal way of presenting the stimulus materials may have important practical consequences only in specific situations, for example, where there is a considerable degree of interdependent relations among the stimulus materials.’’ Results indicate that this approach has achieved only limited success. Another quantitative approach can be identified in the research efforts of Smallwood, Weinstein, and Eckles (1967). These investigators proposed the use of response probability estimation models to optimize the instructional strategy. Under the probability estimation model, the particular instructional block that a trainee received was based on decision rules that were dynamic in the sense that the trainee's accumulating performance history affected the decision process. Thus far, progress has been difficult in using quantitative methods for adapting instruction to the individual differences of the learners.

A technique for optimizing performance by attending to differences in the basic entry characteristics of the learners has been posited by Cronbach (1967). The instruction is adapted to various facets of the trainee's aptitudes or traits. However, as Cronbach & Snow (1969) have reported, research in the area of aptitude-treatment interaction has produced inconsistent findings. In addition, adapting instruction on the basis of preconditions does not permit the flexibility to change the instructional program during the acquisition of the materials.

Another major approach in accounting for individual differences has involved the use of empirical techniques. Data on within course variables generated by an initial group of trainees are utilized in establishing the branching or adaptation points in the instructional program, as well as the decision criteria to be employed at each point. As subsequent students proceed through the instructional materials, data are collected on the relevant variables and the students are branched to specific content based on their individually generated within course performance. The use of this technique can be seen in the efforts of Silberman and others (1961).

Using a short course in logic, Silberman, et al. established branching procedures based on cumulative errors within a topic, but found no significant differences in criterion performance when compared with a linear (nonbranching) sequence. The investigators reported that "it may be conjectured that some measures such as response latency or subject's self-evaluation are more appropriate than error rate and that the computer should have considered these behavior measures for its branching decisions instead of, or in addition to, errors." Coulson and others (1962) used the logic materials as did Silberman, but their branching decisions were based on both the cumulative errors and the subject's evaluation of his own readiness to advance to new topics. They found a significant difference on criterion scores for the adaptive branching group when compared with a linear sequence group.

Using empirically developed branching rules, Melaragno (1967) compared the effectiveness of three adaption procedures. The first used previous students' performance as the basis for branching decisions. The second procedure was based on prior students' pretraining abilities, a prediction condition, and the third treatment, the linear sequence condition served as a control group. Multivariate analysis of posttest scores and training times indicated that the branching condition was superior to the linear condition, but no significant difference was found between the branching and prediction condition.

The use of empirical techniques involving within course performance variables does appear to have high payoffs for optimizing the efficiency and effectiveness of instruction presented via the computer. The question still remains within this empirical approach as to what is the most effective methodology for identifying the relevant variables and for designing the decision logic for adapting the instruction. An empirical approach developed by Dick, Rivers, King, and Hansen (1970) utilized regression analysis techniques for identifying the variables to be monitored and for assisting in the design of the decision logic. There were many methodological problems involved with this study that limit the conclusions and generalizations that can be made. However, the approach is promising in that through the use of regression analysis techniques, performance during the instruction is directly related to final achievement for each student.

The main variable used in most of the empirical models has been performance in terms of correctness over some subset of responses. It would appear that this would be a reliable variable for predicting final achievement. The problem is determining what subset of responses or unit of analysis should be used. An additional learning variable which has been of interest is that of response latency. Most of the studies investigating the relationship of response latencies and performance have been in relation to basic psychological phenomena such as response strength in paired-associate learning and to mathematical models of the associative learning processes. Brooks, Clark, and Park (1967) have found that those students who spend more time on difficult instructional items relative to their time on easy items, make fewer posttest errors. Given that response latencies reflect varying degrees of facility with the instructional materials, they should add to the reliability of the predictions of final achievement. A self-evaluation variable that is related to performance and which can be measured during learning with a minimum of disruption to the instructional sequence is that of anxiety. A series of experiments by Spielberger, et al. (1969), O'Neil, et al. (1969), and O'Neil (1970), have indicated that individuals high in trait anxiety tend to show higher increments in state anxiety from easy to difficult materials than do individuals low in trait anxiety, and that individuals with high state anxiety tend to make more errors on difficult materials than do individuals low in state anxiety.

The inclusion of the variables of performance, latency, and anxiety, all measured during learning, may have high potential for the development of prediction models for maximizing achievement and minimizing time on computer-assisted instruction.

IV. METHOD

Introduction

In this chapter the materials, equipment, and overall experimental design are discussed. This is followed by a discussion of the procedures employed in the empirical development of the predictive models and remedial instruction which were used in Phase II of the study. The chapter concludes with a discussion of the procedures followed in Phase II: the experimental validation.

Materials

The Instructional Program. The instructional program deals with the incidence and risk of contracting heart disease and the diagnosis of myocardial infarction. Nine basic concepts were identified within the course. The program consists of two sections. The first section deals with material widely reported in the mass media with which the subjects are expected to have previous familiarity. The basic concepts covered in this section include (a) the definition, prevalence, and incidence of heart disease; (b) the role of various risk factors such as age, smoking, and cholesterol in increasing the probability of contracting heart disease; and (c) the physical factors involved in heart disease. The second section is composed of technical subject matter (the diagnosis of myocardial infarction) with which the subjects are not expected to have had previous experience. This section contains both verbal and graphic material. The basic concepts presented here relate to: (d) the types of heart damage and their reversibility; (e) the recording of electrocardiograms (ECG's); (f) the normal electrocardiograph (ECG) tracing; (g) the relationships of the ECG tracings to the types of damage; (h) the healing process of heart damage and its relationship to the ECG tracings; and (i) the conditions for diagnosing myocardial infarction.

The program consists of a total of 143 frames, 54 familiar and 89 technical, which require a total of 274 responses. The first section of the program requires 66 constructed and five multiple choice responses. The second section (the technical section) requires 203 responses. Of the 203 technical responses, 33 are multiple choice responses that require interpretation of ECG tracings and heart damage drawings. The remaining 170 are constructed response.

The program follows a linear format. After the student responds, the correct answer is given and the next frame is presented. The average time to complete the paper version of the program is one hour and fifteen minutes. The program originally developed by Mechner (undated) was revised by Tobias (1968). Approximately 200 subjects have gone through three revisions of the program. Tobias (1968) reports an error rate of 5% on the familiar section and 15% on the technical section. Tobias also reports a blackout ratio for the familiar and technical sections of 13% and 15% respectively. Blackout ratio is a measure of the amount of material in a program that can be removed without affecting error rate. A high blackout ratio indicates poorly programmed material, because the correctness of a response is not contingent upon mastery of the material. The blackout ratio is expressed as the ratio of the number of words in the materials that can be obliterated (blacked out) to the total number of words in the material.

Pre/Posttests. The pre and posttests for the instructional program were developed by Tobias (1968). The tests were constructed by classifying the various categories of subject matter covered by the instructional program, determining the weights each of the categories had in the program, and then assigning a similar weight to these areas on the test. The pretest was a 30-point test covering the familiar section of the program and contained 17 items of constructed response format (see Appendix A). The posttest, with 126 points, covered the familiar and technical sections of the instructional program. The posttest had 32 items and required graphic responses as well as short constructed responses (see Appendix B). Tobias (1968) reported reliabilities of .68 for the pretest and .82 for the posttest. The reliability data was based on a total N of 114. The concept that each pre and posttest item was judged to have covered is indicated in Appendices A and B.

Anxiety Measures. The State-Trait Anxiety Inventory developed by Spielberger, Gorsuch, and Lushene (1969) consists of separate self-report scales for measuring two distinct types of anxiety: trait anxiety (A-Trait) and state anxiety (A-State). A-Trait refers to a relatively stable individual difference in anxiety proneness, i.e., to differences in the tendency to respond with elevations in A-State in situations that are perceived as threatening. This is a 20-item inventory in which the individuals respond to statements indicating how they generally feel. A-State is conceptualized as a transitory emotional state or condition of the individual that varies in intensity over time. The A-State inventory used in this study was a five-item scale developed by O'Neil, Spielberger, and Hansen (1969) from the original 20-item inventory reported by Spielberger, Gorsuch, and Lushene (1969). For the A-State inventory, individuals responded to statements indicating how they presently felt in a particular situation.

Internal consistency (alpha) reliabilities reported by Spielberger, Gorsuch, and Lushene (1969) indicate that both the A-Trait and A-State have substantial internal consistency coefficients which range from .86 to .92 for A-Trait and .83 to .92 for A-State. The A-Trait and A-State inventories are given in Appendix C. The A-Trait was administered once at the beginning of the program, and was followed by the 5-item A-State measure. The A-State measure was also inserted at the end of the familiar portion of the program and again at the end of the technical section.

Background Questionnaire. A general background questionnaire was developed to assess the student's attitudes towards the program, and to provide information on the prior knowledge of the students on the technical section of the instructional program. It was also intended to provide student comments about the program that might be useful in developing the remedial loops. A copy of the background questionnaire is given in Appendix D.

Equipment

The instructional materials were presented by means of the IBM 1500 system located at the Florida State University Computer-Assisted Instruction Center. Each instructional terminal consists of a cathode ray tube (CRT) display as output, and both keyboard and light pen response modes as student input devices. Performance and latency for each response in the program as well as for the anxiety measures for each student were recorded automatically by the computer.

Experimental Design

The study was conducted in two phases. During the first phase an initial group of students proceeded through the CAI program. The students' data on the within course variables were analyzed to determine their relationship to achievement in the course. By means of correlational and regression analysis the relevant predictor variables and the points of remediation were identified. Coding changes in the program logic were made to monitor the appropriate within course variables, and the prediction models and the remedial loops were inserted in the CAI program.

The second phase involved the validation of the multiple regression methodology for maximizing performance and minimizing time on CAI presentations. Four treatments were designed in order to assess the effectiveness of identifying students who need remediation and providing it to them. Therefore, one version of the course was programmed such that a group of students (the regression model group) proceeded through the CAI program to which had been added (a) the coding in the program logic to monitor the appropriate within course variables; (b) the prediction models which would detect those students in need of additional instruction; and (c) the remedial loops which would maximize their final performance. A second group of students (the All-Remediation group) received all of the remedial loops regardless of what the predictive models indicated. A third group (the No-Remediation group) received none of the remedial loops. They simply proceeded through the mainline instruction. The final group (the Student Control group) was given the option at each possible remediation point identified in the predictive condition to either go through the remedial loops or to continue with the next concept.

Phase I: Empirical Development

Subjects. Thirty-three female students enrolled in Health Education 319, a course required of all elementary education majors, participated in the first phase of the investigation.

Procedure. Upon arrival at the CAI Center, the students were administered the paper and pencil pretest. The students then signed on the CAI system and responded to the A-Trait and A-State inventories. After completing the familiar portion of the program, the A-State was administered again. The final administration of the A-State measure occurred after the students completed the technical section of the program. The students then signed off of the CAI system and took the posttest and the background questionnaire. Figure 1 shows the instructional and procedural sequence for each student in Phase I of the study.

Development of the Predictive Models. Data from the students in Phase I on the following basic predictor variables were used as the input for the multiple regression analyses: trait anxiety, state anxiety, percent correct answers during learning, and response latencies during learning. The criterion variable was the posttest. The unit of analysis was determined empirically with the initial analyses at the concept level. The establishment of the level of analysis determines the points at which remediation should

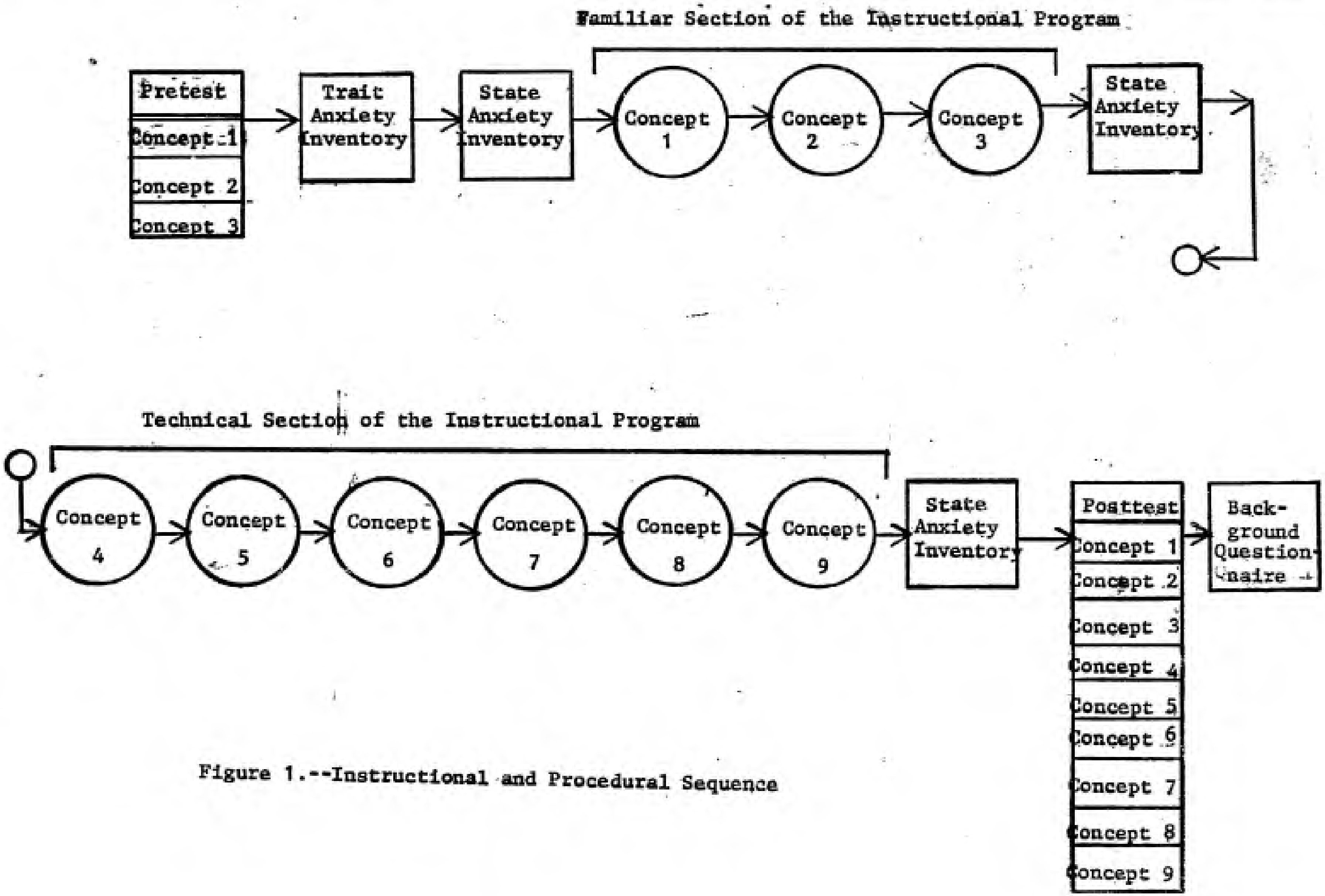

Figure 1.--Instructional and Procedural Sequence

take place. The optimal situation in this empirical approach to determining the unit of analysis would be to find significant equations for each of the concepts (the level of significance was set at .05). If significant regression equations are found for each concept, the remediation could be given at the end of instruction on each concept for those students whose predicted performance on the posttest for a particular concept is below the desired level. The initial information acquired by these students could be consolidated before they proceed to the next concept. Those students for whom the predicted performance covering a particular concept on the final test is acceptable would be branched to the next concept and thus would not be required to spend time on instruction they did not need. If significant equations are not found for each concept, then variables on adjacent concepts would be combined, and a new analysis would be conducted. It should be pointed out that although a particular regression equation may be significant at the .05 level or less, it may account for a small portion of the variance. For example, with 40 subjects and 4 predictor variables, a regression equation with a multiple R of .48 would be significant at the .05 level. This equation would be accounting for approximately 22 percent of the variance. In this study the objective was not only to find significant prediction equations over the smallest sample of behavior starting at the individual concept level, but also to account for approximately 25 percent of the variance.

Cumulative performance and latency as well as the most recent performance and latency were used as predictor variables for the concept analyses. For example, the predictor variables for concept one in section one were (a) performance on the trait anxiety scale; (b) performance on the first state anxiety scale; (c) percent correct responses on instruction on concept one; and (d) mean response latency on concept one. The predictor variables for concept two were the same as in concept one, plus (a) percent correct on concept two; and (b) mean response latency on concept two. The criterion variable was the score on the posttest questions relating to concept two. For the third concept in section one the predictor variables were (a) performance on the trait anxiety scale; (b) performance on the initial state anxiety scale; (c) performance on the second state anxiety scale; (d) percent correct on concepts one and two combined; (e) mean response latency on concepts one and two combined; (f) percent correct on concept three; and (g) mean response latency on concept three. The criterion variable for this analysis was the score on the posttest questions relating to concept three. Table 1 indicates the basic predictor variables that were used for each concept analysis. The criterion variable in each case was the score on the posttest questions relating to each concept.

When the prediction equations were determined they were coded into the program logic at the appropriate points. By monitoring the relevant variables at appropriate points in the instructional sequence, predictions were made of each student's final achievement. If a student's predicted achievement was at an acceptable level (as defined below), he proceeded to the next concept, but if it was not, he was branched to the remedial loop. With perfectly validated instruction an acceptable level of predicted final achievement could be set rather high (above 90%). However, in the initial stages of development it seemed more realistic to accept a slightly lower level. For this study the acceptable level of predicted achievement was set at 80 percent.

TABLE 1

Predictor Variables for the Regression Analyses by Concept

PRETEST $C_1 - C_3$	Instructional and Procedural Sequence									POSTTEST	BACKGROUND QUESTION-NAIRE
	FAMILIAR SECTION CONCEPTS				TECHNICAL SECTION CONCEPTS						
	$TA/SA_1/C_1$	C_2	C_3/SA_2	C_4	C_5	C_6	C_7	C_8	C_9/SA_3		
V A R I A B L E S	TA	TA	TA	TA	TA	TA	TA	TA	TA	C_1	
	SA_1	SA_1	SA_1	SA_1	SA_1	SA_1	SA_1	SA_1	SA_1	C_2	
	PC_{c1}	PC_{c1}	SA_2	SA_2	SA_2	SA_2	SA_2	SA_2	SA_2	C_3	
	ML_{c1}	ML_{c1}	$PC_{c1=2}$	PC_{c1-3}	PC_{c1-3}	PC_{c1-3}	PC_{c1-3}	PC_{c1-3}	SA_3	C_4	
		PC_{c2}	ML_{c1-2}	ML_{c1-3}	ML_{c1-3}	ML_{c1-3}	ML_{c1-3}	ML_{c1-3}	PC_{c1-3}	C_5	
		ML_{c1}	PC_{c3}	PC_{c4}	PC_{c4}	PC_{c4-5}	PC_{c4-6}	PC_{c4-7}	ML_{c1-3}	C_6	
			ML_{c3}	ML_{c4}	ML_{c4}	ML_{c4-5}	ML_{c4-6}	ML_{c4-7}	PC_{c4-8}	C_7	
					PC_{c5}	PC_{c6}	PC_{c7}	PC_{c8}	ML_{c4-8}	C_8	
					ML_{c5}	ML_{c6}	ML_{c7}	ML_{c8}	PC_{c9}	C_9	
									ML_{c9}		

Development of Remedial Loops. The placement of the remedial loops was determined by the points at which significant regression equations were found. The predictor variables and the direction of their beta weights were used as aids, in addition to the standard psychometric data, in developing the remedial loops. Dr. Ronald Byrd of the Physical Education Department at Florida State, who has taught courses on the interpretation of electrocardiogram tracings, acted as the content expert and assisted in the development of the remedial loops. A more complete description of the remedial loops appears in the Results chapter.

Phase II: Experimental Validation

Subjects. Eighty female students from Health Education 319 at Florida State University participated in the second phase of the study. They were randomly assigned to one of the four conditions. Twenty subjects were assigned to the linear regression group, 20 to the All-Remediation group, 20 to the No-Remediation group, and 20 to the Student Control group. Since the experimental materials were closely related to the regular course content, all students in the course were required by the instructor to participate in the study.

Procedure. The regression model group followed the same procedure as the Phase I group except that the program had the addition of (a) the coding in the program logic to monitor the appropriate within course variables; (b) the prediction models to detect those students in need of additional instruction; and (c) the remedial loops. The All-Remediation group received the basic instruction and all the remedial loops without the benefit of the predictive models. The No-Remediation group received only the basic instruction as had the initial group of students in Phase I. In the student control group, each student had the option of receiving the remedial loops or proceeding on to the next segment of instruction.

V. RESULTS

Introduction

In this chapter the results of the Phase I empirical development are discussed followed by the results of Phase II, the experimental validation. The efforts in Phase I include the development and implementation of the predictive models and the remedial loops which were employed in Phase II. The chapter concludes with a presentation of the comparative analyses of the four treatments administered in Phase II.

Phase I: Empirical Development

Within Course Performance and Latency Measures. Percent correct and mean latency for each concept within the instructional program was calculated from the data generated by the 33 students in Phase I. As was shown in Table 1, some of the predictor variables within each concept analysis involved the calculation of performance and latency measures across several concepts. Table 2 presents the mean percent correct, the mean latency per frame, the numbers of learning frames upon which each measure was calculated, the posttest means, and the total possible points on the posttest for each concept or combination of concepts.

Anxiety Measures. In addition to the predictor variables shown in Table 2, the trait anxiety measure was used in each of the analyses.

TABLE 2

Phase I: Predictor and Criterion Variable Means

Concept(s)	Mean Percent Correct	Mean Latency per frame (in seconds)	Number of Learning Frames	Mean Posttest Perform.	Total Possible on Posttest
1	93.44	22.77	30	4.06	6
2	95.96	18.90	33	9.33	15
3	97.73	15.12	8	3.00	6
2 & 3	96.31	18.16	41	12.33	21
1 thru 3	95.10	20.10	71	16.39	27
4	88.79	15.49	33	10.12	11
5	81.83	18.78	16	3.12	5
4 & 5	86.52	16.58	49	13.24	16
6	83.42	16.64	23	6.73	10
4 thru 6	85.53	16.59	72	15.28	28
7	81.52	12.44	112	19.58	39
6 & 7	81.84	13.16	135	26.30	49
4 thru 7	83.08	14.06	184	34.85	65
8	78.78	16.85	13	11.12	31
4 thru 8	82.80	14.24	197	45.98	96
9	65.16	23.53	6	1.33	3

The three state anxiety measures were administered at the beginning, middle, and end of the program. Table 1 (p.23) shows in which analyses these measures were used. Table 3 presents the means and standard deviations for the A-Trait and the three A-State measures.

TABLE 3

Phase I: Means and Standard Deviations for Anxiety Measures

Anxiety Measure	Mean	Standard Deviation
A-Trait	35.67	7.07
A-State 1	10.42	3.52
A-State 2	8.45	3.43
A-State 3	10.48	4.36

Regression Analyses by Concept. The regression analyses were conducted by means of the Biomedical computer program BMD02R, Stepwise Regression. A sequence of multiple linear regression equations are computed in a stepwise manner. At each step one variable is added to the regression equation. The variable added is the one which makes the greatest reduction in the error sum of squares. Table 1 indicated the variables that were used as input for the regression analyses for each of the concepts. For each of the nine analyses the input variables were regressed on final exam performance covering the corresponding concept. Table 4 presents the predictor variables, the multiple R and R^2 resulting from the original nine analyses. Since the regression equations for concepts 3 and 6 were not significant ($p. < .05$), the data from these concepts were combined with the data from adjacent concepts and these analyses were recalculated. The content of concept 2 was deemed to be more similar to that of concept 3 than concept 4. Therefore, the data from concept 2 was combined with that of concept 3. The predictor variables regressed on posttest performance covering concepts 2 and 3 were: percent correct on concept 1, mean latency per frame on concept 1, percent correct on concepts 2 and 3 combined, mean latency per frame on concepts 2 and 3 combined, state anxiety 1 and 2, and trait anxiety.

In a similar manner the data from concept 6 was combined with the data from concept 7. The predictor variables regressed on posttest performance covering concepts 6 and 7 were: percent correct and mean latency per frame on concepts 1 through 3 combined, percent correct and mean latency per frame on concepts 4 and 5 combined, percent correct and

TABLE 4

Predictor Variables, Multiple R, R^2, and Alpha Level for the Initial Nine Regression Analyses by Concept

Concept	Predictor Variables	Relationship to the Criterion	Multiple R	R^2	P
1	Percent Correct-Concept 1	+	.5352	.2865	.025
	State Anxiety 1	+			
	Trait Anxiety	+			
2	Percent Correct-Concept 1	+	.5343	.2855	.05
	Percent Correct-Concept 2	+			
	Mean Latency-Concept 2	+			
	Trait Anxiety	+			
3	Analysis not significant				
4	Percent Correct-Concepts 1-3	+	.5983	.3580	.025
	Mean Latency-Concepts 1-3	+			
	Percent Correct-Concept 4	+			
	State Anxiety 2	+			
5	Percent Correct-Concept 5	+	.5339	.2851	.05
	Mean Latency-Concept 5	+			
	State Anxiety 1	-			
	Trait Anxiety	+			
6	Analysis not significant				
7	Percent Correct-Concepts 1-3	+	.7315	.5351	.01
	Mean Latency-Concepts 1-3	-			
	Percent Correct-Concepts 4-6	-			
	Mean Latency-Concepts 4-6	+			
	Percent Correct-Concept 7	+			
	State Anxiety 2	+			

Table 4-continued

Concept	Predictor Variables	Relationship to the Criterion	Multiple R	R^2	P
8	Percent Correct-Concepts 4-7	+	.4861	.2361	.025
	State Anxiety 2	+			
9	Percent Correct-Concept 9	+	.5033	.2533	.05
	Mean Latency-Concepts 4-8	+			
	Mean Latency-Concepts 1-3	-			

mean latency per frame on concepts 6 and 7 combined, state anxiety 1 and 2, and trait anxiety. Table 5 shows the results of these two additional analyses. The complete data for each step in the final seven regression analyses conducted are given in Appendix E.

As can be derived from Tables 4 and 5, there were seven points then in the instructional program at which a prediction of an individual's posttest performance could be made and remediation provided if needed. In summary, these points were after instruction on: (a) concept one; (b) concept three (covering performance on concepts two and three combined); (c) concept four; (d) concept five; (e) concept seven (covering performance on concepts six and seven combined; (f) concept eight; and (g) concept nine.

Reliability of the Criterion Measures. An internal consistency reliability was used in calculating the reliabilities for the seven clusters of items of the posttest that served as the criterion measures for the seven regression analyses listed above. The coefficient of reliability was determined through the use of the analysis of variance. It is exactly equivalent to the Kuder-Richardson Formula 20 estimate (Guilford, 1954). In addition to the reliability of the overall test, the reliabilities of strata or clusters of items within the test can be computed. Table 6 presents the reliabilities for each of seven criterion measures as well as the overall posttest reliability.

Monitoring the Within Course Predictor Variables. The first step in implementing the predictive models involved coding of the coursewriter logic to monitor the appropriate predictor variables for each of the seven decision points. The trait and state anxiety measures were administered on

TABLE 5

Predictor Variables, Multiple R, R^2, and Alpha Level for the Regression Analyses for the Combined Concepts

Concept	Predictor Variables	Relationship to Criterion	Multiple R	R^2	p
2 & 3 combined	Percent Correct-Concepts 2-3	+	.5237	.2743	.01
	Trait Anxiety	+			
6 & 7 combined	Percent Correct-Concepts 1-3	-	.7582	.5749	.01
	Mean Latency-Concepts 1-3	-			
	Percent Correct-Concept 4	-			
	Percent Correct-Concepts 6-7	+			
	Mean Latency-Concepts 6-7	+			
	State Anxiety 1	+			
	Trait Anxiety	-			

TABLE 6

Criterion Measure Reliabilities

Concept	Reliability
1	.413
2 & 3	.459
4	.332
5	.391
6 & 7	.835
8	.892
9	.288

Total Posttest Reliability = .883

the CAI system and an individual's score was stored in a counter for future use at each of the decision points where appropriate.

Performance and latency measures were stored in counters in a cumulative fashion. Across instruction on concept one, for example, a student was required to respond to 30 frames. Each time he responded correctly the performance counter was incremented by one, and the amount of time taken to respond to each frame was accumulated in another counter. This general procedure was followed across each of the seven concept blocks of instruction identified by the regression analyses. At the end of instruction on each of the seven concepts or combination of concepts, data on all the predictor variables was available to make a prediction of each student's posttest performance covering the specific concept block.

Coursewriter Coding of the Regression Equations. The second step in implementing the predictive models involved coding the regression equations in the coursewriter logic so that an automatic, on-line prediction of each student's posttest performance could be made at each of the seven prediction points. If a student's predicted posttest performance for a particular concept block was less than 80 percent of the total possible, he would automatically be branched to remedial instruction covering that concept. If his predicted performance was 80 percent or better, the student would be branched past the remedial instruction to the next concept in the program.

In concept 1, for example, the predictor variables as shown in Table 4 were percent correct on concept one, trait anxiety, and the initial state anxiety measure. The complete regression equation for predicting posttest performance on concept one was:

$$\hat{y} = .04\ (\text{percent correct-concept one}) + .17\ (\text{state anxiety one}) + .03\ (\text{trait anxiety}) - 2.63.$$

The regression equation had been coded in coursewriter language after the last frame covering concept one. After each student responded to the last frame in concept one, his performance within concept one was calculated and multipled by .04. His scores on the state and trait anxiety inventories (which had previously been stored in counters) were multipled by .17 and .03 respectively. These three values were added by the computer and 2.63 was subtracted from the sum. The result was a prediction of his posttest performance covering concept one. This value was automatically compared with the preset criterion value of 80% of the total possible points. In the case of concept one, this was 80% of 6 or 4.8 (the total possible points on the posttest for each of the concepts is given in Table 2). At each of the seven decision points, the criterion value was rounded to the nearest integer. Thus, in concept one each student's predicted performance was compared with 5 rather than 4.8. If a student's predicted performance was below five, he would be branched to the remedial instruction, otherwise he would be branched to the next concept. This procedure was followed at each of the seven decision points in the instructional program. The actual coursewriter coding for the prediction after concept three is provided in Appendix F as an example.

Development of the Remedial Loops

It frequently happens that a student does not respond to a particular instructional presentation in a manner which allows him to reach a specific criterion level of performance. There are four basic approaches that might be taken to bring the student to the desired criterion level of performance. These approaches might be classified as repetition, multiform, multilevel, and error-diagnostic. With repetition the student would be recycled through the same presentation until he reaches criterion. A multiform approach would direct the student through a parallel but different form of presentation. With a multilevel approach, the student would be directed through a more expanded presentation of the content. The error-diagnostic approach would attempt to correct any error a student would make in responding to the instruction; in essence, an intrinsic programing approach.

The remedial loops developed at each of the seven prediction points basically followed the error-diagnostic and multiform approaches. The format of the mainline instruction was linear, requiring constructed responses with confirmation provided after each response. The format of the remedial loops was intrinsic with response sensitive feedback. Blocks of information were presented followed by a multiple choice question. If the student selected the correct answer, he was told why he was correct and then he was presented the next frame of instruction. If the student was incorrect, he was told why or given a hint to help remedy his misconception and then he was directed back to the question. The responses made by the students in the first phase were used as an aid in developing the alternatives and the feedback.

The following information was presented before each of the series of review frames: ''Before proceeding on to a discussion of ...let us take a few moments to review ....''. Thus, the students in the regression model group who had to proceed through this additional instruction were not sensitized to the fact that they were indeed receiving remedial instruction. This same point would apply to the group of students who received all of the remedial loops regardless of their predicted posttest performance.

The group of students who were allowed to select whether they wanted to go through the remedial loops (the Student Choice group) were presented with the following information before each of the seven remedial points in the program:

> ''A series of review frames has been developed covering the topic we have just discussed. You may select to proceed through this review, or if you feel you know the materials well enough, you may go directly to the next topic.''

Phase II: Experimental Validation

Overall Effects of the Instructional Treatments. Comparisons among the four instructional treatments were made in two separate one-way analyses of variance (ANOVA) involving the following dependent variables: (1) total raw score on the posttest, and (2) total time (instructional learning time plus remedial time). Table 7 presents the posttest means and standard deviations for the four treatment groups.

TABLE 7

Posttest Means and Standard Deviations for the Four Instructional Treatments

Instructional Treatment	Means	Standard Deviations
Regression Model	82.3	17.4
All-Remediation	77.7	15.9
Student Choice	65.5	22.3
No-Remediation	61.5	13.2

It can be noted that the posttest means vary widely among the groups. Indeed, Table 8 reveals a significant difference among the

TABLE 8

Analysis of Variance on Posttest Scores

Source	df	MS	F
Between Groups	3	1945.91	6.34*
Within Groups	76	306.88	
Total	79		

*p < .01

four instructional treatments. The Newman-Keuls sequential range test (Duncan, 1955) was conducted to determine the significance of the differences between each of the individual means (see Appendix G). These calculations indicated that the Regression Model and All-Remediation groups were significantly different from the student choice and No-Remediation groups ($p < .05$), but there were no significant differences within each of the two sets of groups.

Table 9 reports the means and standard deviations for the four instructional treatments on total time. As would be expected, the All-Remediation group took the longest time to complete the program. The analysis of variance on this data (see Table 10) revealed a significant difference among the four instructional treatments. The Newman-Keuls sequential range test indicated significantly greater time ($p < .05$) for the All-Remediation group than either the student choice or the

TABLE 9

Means and Standard Deviations for the Four Instructional Treatments on Total Time (in minutes)

Instructional Treatment	Means	Standard Deviations
Regression	86.1	19.9
All-Remediation	91.0	13.0
Student Choice	76.7	12.5
No-Remediation	78.2	13.6

TABLE 10

Analysis of Variance on Total Time

Source	df	MS	F
Between Groups	3	54,313.92	3.99*
Within Groups	76	13,621.88	
Total	79		

*p < .01

No-Remediation groups (see Appendix H). There were no significant differences between any of the other possible group comparisons.

Effects of the Instructional Treatments by Part. As discussed in Chapter IV, the instructional program consisted of two basic parts. The first part dealt with material with which the subjects were expected to have some prior knowledge, and it was composed of the first three concepts - approximately one-third of the course. The second part of the instructional program was composed of technical subject matter (the remaining six concepts) with which the subjects were not expected to have had previous experience. It was felt that differences in the degree of difficulty of the two parts might produce differential effects in the instructional treatments.

A two-way repeated measures analysis of variance was conducted on both posttest scores and mean time per frame (learning plus remedial). As indicated in Table 2 (page 27) there was an unequal number of frames in the instruction program and an unequal number of total possible points on the posttest covering the two parts. Therefore, the proportion correct on the posttest for each part and the mean time (learning plus remedial) per frame in each part were used as the dependent measures in these two analyses. The main effect of the parts and the interaction between instructional treatments and part were of primary interest. The main effect of instructional treatment was assessed in the overall analyses. Table 11 presents the mean proportion correct on the posttest by part for the four instructional treatments.

TABLE 11

Posttest Mean Proportion Correct by Part
for the Four Instructional Treatments

Instructional Treatment	Part One	Part Two
Regression Model	.8039	.6121
All-Remediation	.7021	.5929
Student Choice	.6336	.4383
No-Remediation	.4983	.4859
	.6595	.5446

Figure 2 reports this information graphically. The wide degree of difference found among the instructional treatments on the first part of the course is much lessened on the more difficult second part of the course. The analyses of variance on this data (see Table 12) indicated a significant difference between the two parts and a significant part by treatment interaction as well as the expected significant differences among the instructional treatments. The Newman-Keuls sequential range test on the group by part means revealed significant differences $(p < .05)$

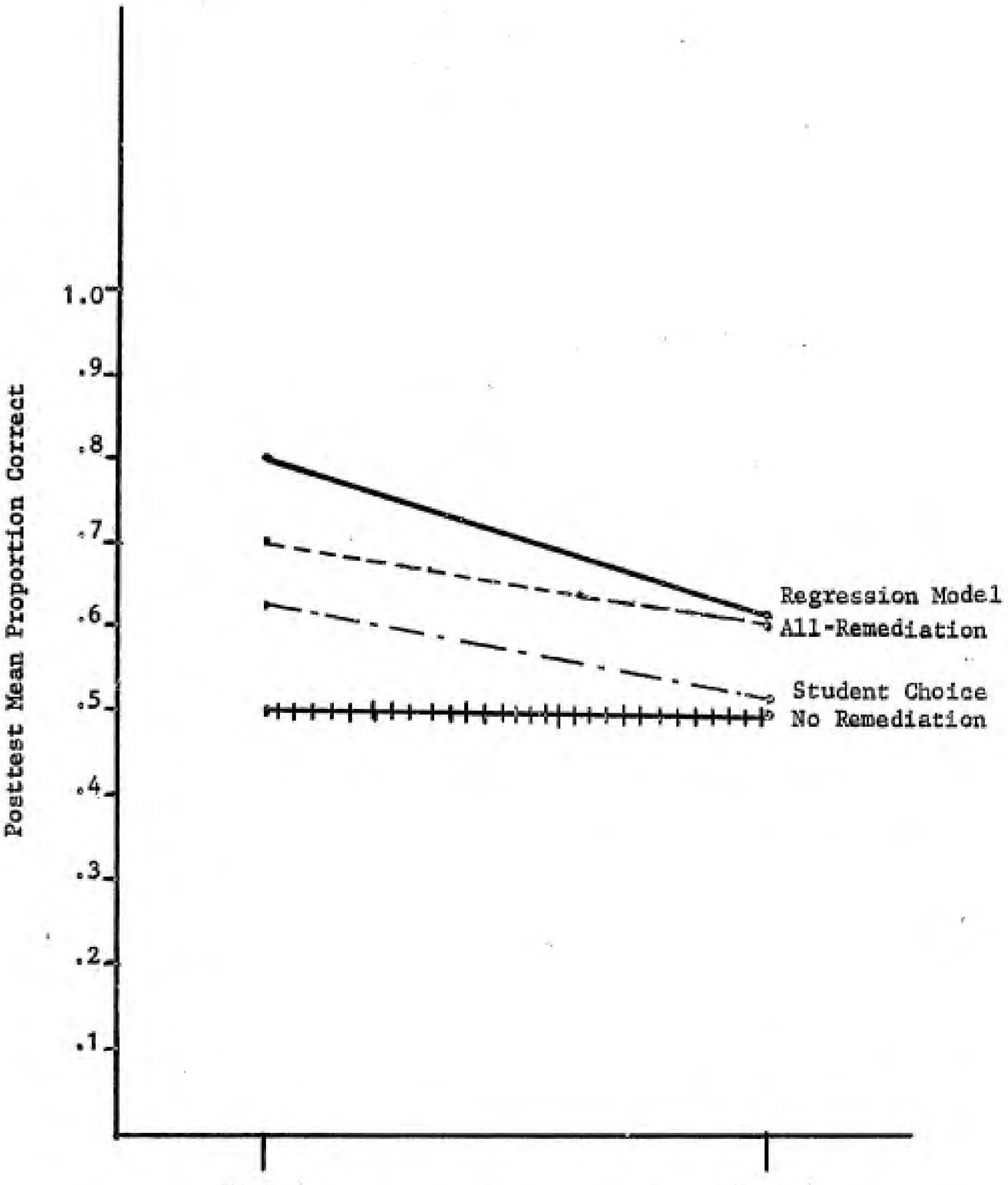

Figure 2.--Posttest mean proportion correct by part for the four instructional treatments.

TABLE 12

Analysis of Variance on Posttest Mean Proportion Correct by Part for the Four Instructional Treatments

Source	df	MS	F4
Group	3	.362292	12.91*
Subjects within Groups	76	.028021	
Part	1	.527850	47.49*
Group x Part	3	.057333	5.16*
Subjects x Part x Group	76	.011114	

*p < .01

between all possible group comparisons within Part 1 except for the Regression Model vs. the All-Remediation group and the All-Remediation vs. the Student Choice group. The regression model group showed the highest performance and the student choice group showing the lowest performance. Within Part 2 the Regression Model group and the All-Remediation group performed significantly better than the Student Choice and No-Remediation groups (p < .05), but there was no significant differences within the two sets of groups (see Appendix I).

Table 13 reports the mean times per frame (in seconds) by part for the four instructional treatments. This data is displayed graphically in Figure 3. The analysis of variance on this data (see Table 14) revealed that significantly more time per frame was taken on Part 1 and that there was a significant group by part interaction. The Newman-Keuls sequential range test on the group by part means indicated that the All-Remediation group took significantly (p < .05) more time per frame than either the

TABLE 13

Mean Time Per Frame in Seconds (Learning Plus Remedial) by Part for the Four Instructional Treatments

Instructional Treatment	Part One	Part Two
Regression Model	21.9	13.84
All-Remediation	22.7	14.2
Student Choice	20.2	14.0
No-Remediation	20.3	16.0
	21.3	14.5

TABLE 14

Analysis of Variance on Mean Time per Frame in Seconds (Learning plus remedial) by Part for the Four Instructional Treatments

Source	df	MS	F
Group	3	14.12	< 1
Subjects Within Group	76	24.11	
Part	1	1831.96	342.42*
Group x Part	3	38.85	7.26*
Subjects x Part x Group	76	5.35	

*p <.01

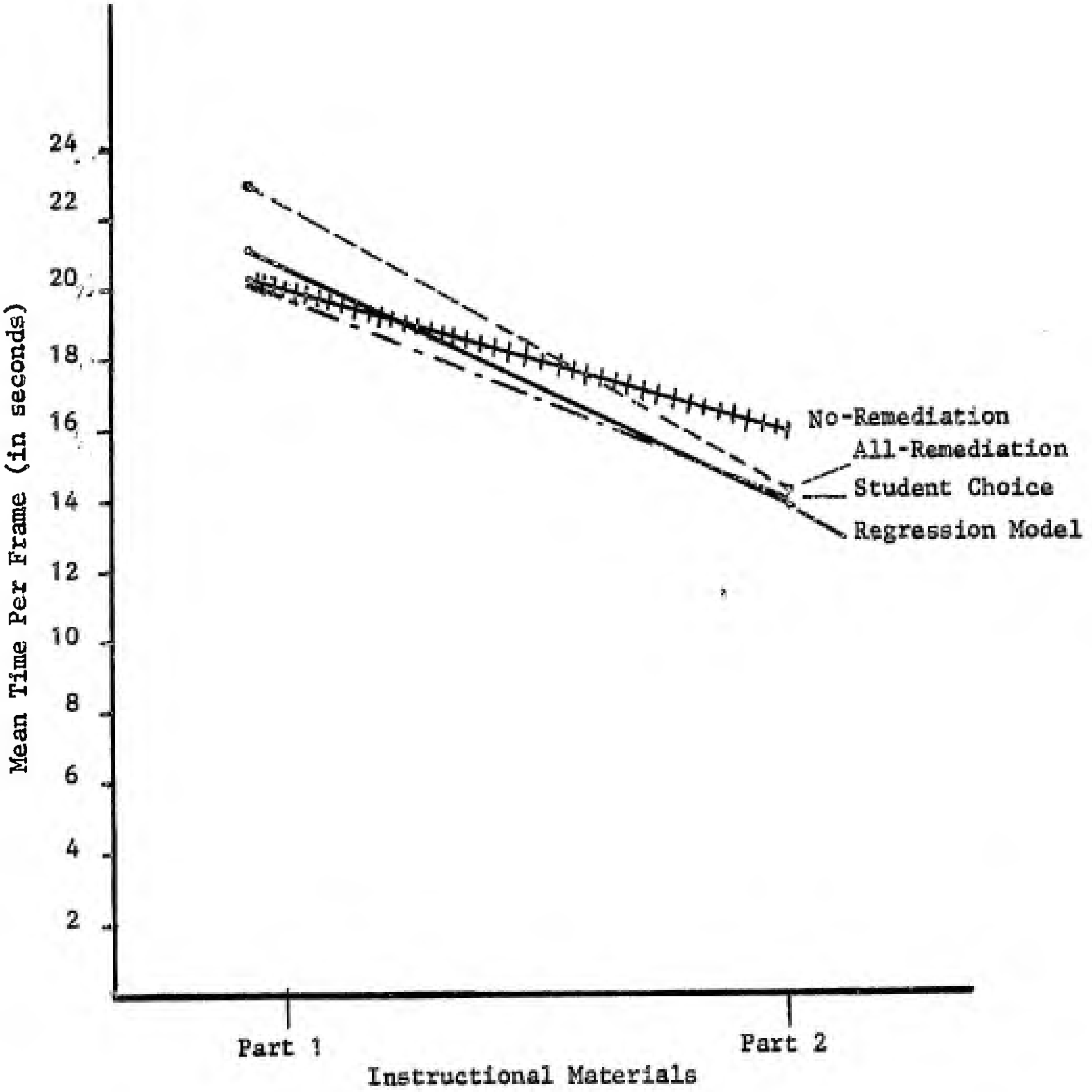

Figure 3.--Mean time per frame in seconds (learning plus remedial) by part for the four instructional treatments.

Student Choice or No-Remediation groups within Part 1. Within Part 2 the No-Remediation group took significantly more time per frame ($p < .05$) than any of the Student Choice or Regression Model groups. No other significant differences within parts were found (see Appendix J).

Effects of the Instructional Treatments by Concept. There were three concepts within Part 1 and six basic concepts within Part 2 of the instructional program. Several of these concepts were combined, leaving seven points at which adaptation could take place. In order to determine more precisely the locus of the differences that were noted within parts, two-way repeated measures analyses of variance were conducted at the concept level. The dependent measures were mean proportion correct on the posttest and the mean time (learning plus remedial) per frame for each of the seven adaptation or remediation points.

Table 15 presents the mean proportion correct on the posttest covering each concept or combination of concepts. There was considerable variation both within groups and across concepts as can be clearly seen in Figure 4. Table 16, the analysis of variance on this data, indicated a significant difference in performance across the concepts and a significant group by concept interaction as well as the expected group differences. The Newman-Keuls sequential range test on the concept means indicated that the only non-significant differences ($p < .05$) in performance among the seven concepts were between concepts 1 vs. 2-3, 1 vs. 5, 2-3 vs. 5, and 5 vs. 6-7 (see Appendix K).

The results of the post hoc test on the group by concept means are given within each concept (see Table 17), and the complete data are presented in Appendix L.

TABLE 15

Posttest Mean Proportion Correct by Concept for the Four Instructional Treatments

Instructional Treatment	CONCEPTS 1	2-3	4	5	6-7	8	9
Regression Model	.8332	.7953	.9318	.7500	.6337	.4502	.5335
All-Remediation	.6667	.7119	.9227	.5900	.6277	.4195	.6169
Student Choice	.6833	.6192	.8999	.6100	.5081	.3001	.3999
No-Remediation	.5584	.4808	.8954	.5700	.4765	.3484	.3834
	.6854	.6518	.9124	.6300	.5615	.3795	.4834

TABLE 16

Analysis of Variance on Posttest Mean Proportion Correct by Concept for the Four Instructional Treatments

Source	df	MS	F4
Group	3	.839884	7.33*
Subjects Within Group	76	.114534	
Concept	6	2.274883	735.43*
Group x Concept	18	.065132	2.10*
Subjects x Concept x Group	456	.030932	

*p < .01

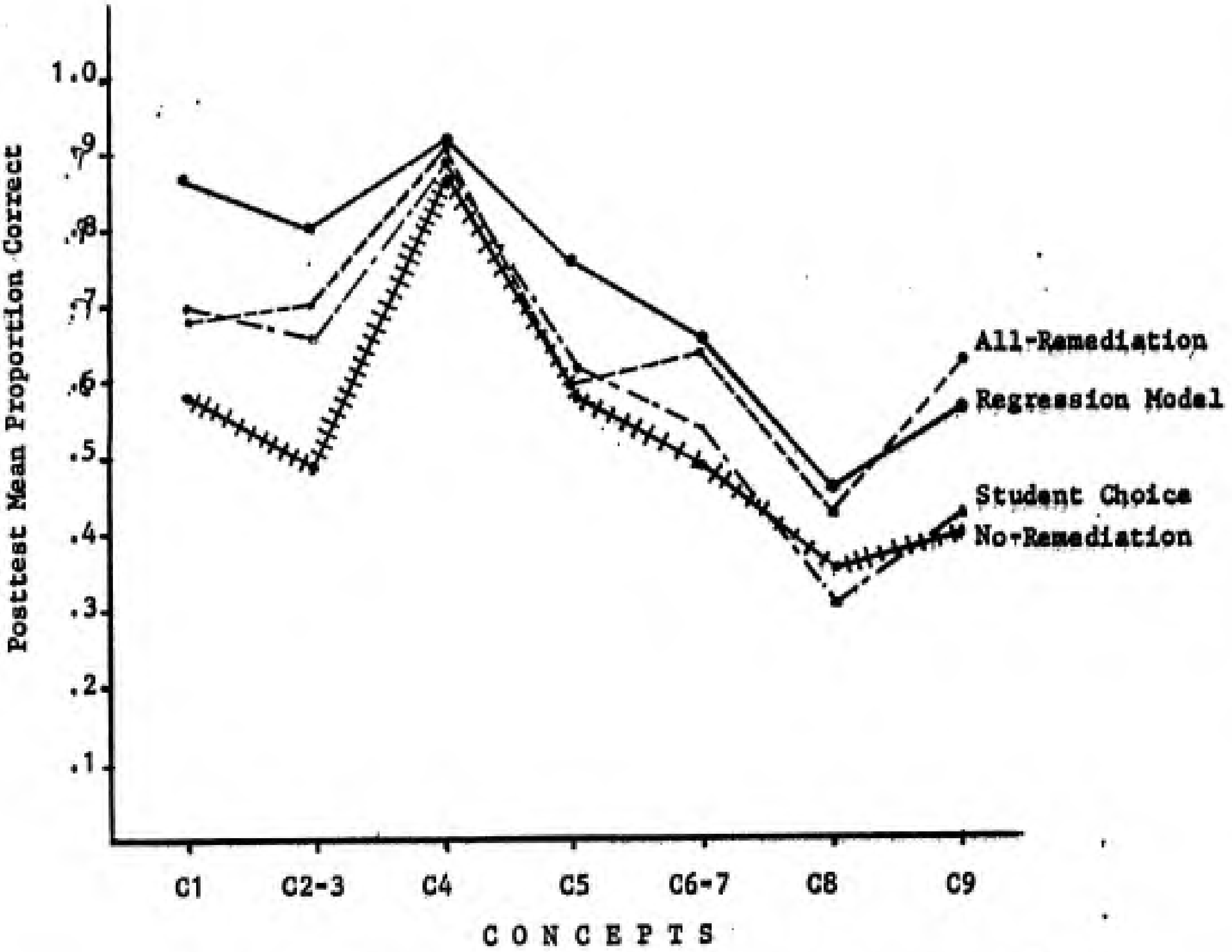

Figure 4.--Posttest mean proportion correct by concept for the four instructional treatments.

TABLE 17

Significant Differences ($p < .05$) Found Between Group Posttest Means Within Concepts

Concept	Significant ($p < .05$) Group Comparisons
1	Regression Model vs. All-Remediation and No-Remediation
2-3	Regression Model vs. Student Choice and No-Remediation and All-Remediation vs. No-Remediation
4	None
5	Regression Model vs. No-Remediation
6-7	None
8	None
9	All-Remediation vs. Student Choice and No-Remediation

*See Appendix L for the complete analysis.

Table 18 presents the mean time per frame in seconds by concept for the four instructional treatments. The data is displayed graphically in Figure 5. Wide differences in time taken across the concepts can be noted. The analysis of variance on this data shown in Table 19 revealed a significant difference in amount of time taken per frame across the concepts and a significant group by concept interaction. The Newman-Keuls sequential range test on the concept means indicated that the only <u>non</u>-significant differences ($p < .05$) in time among the seven concepts were between concepts 1 vs. 9, 2-3 vs. 5, and 2-3 vs. 9 (see Appendix M). The results of the group by concept analysis are given in Table 20 by concept. The complete data are given in Appendix N.

TABLE 18

Mean Time per Frame in Seconds (learning plus remedial) by Concept for the Four Instructional Treatments

Instructional Treatment	1	2-3	4	5	6-7	8	9
Regression Model	22.26	21.69	13.83	18.02	12.46	16.74	18.69
All-Remediation	23.43	22.27	14.22	19.00	13.18	15.52	18.58
Student Choice	21.75	18.90	14.41	19.02	12.59	15.89	23.67
No-Remediation	23.09	18.20	15.84	20.04	15.04	18.01	23.82
	22.63	20.26	14.57	19.02	13.32	16.54	21.[illegible]

TABLE 19

Analysis of Variance on Mean Time per Frame in Seconds (learning plus remedial) by Concept for the Four Instructional Treatments

Source	df	MS	F4
Group	3	57.76	< 1
Subjects Within Group	76	75.52	
Concept	6	977.24	97.23*
Group x Concept	18	48.49	4.82*
Subjects x Concept x Group	456	10.05	

*p < .01

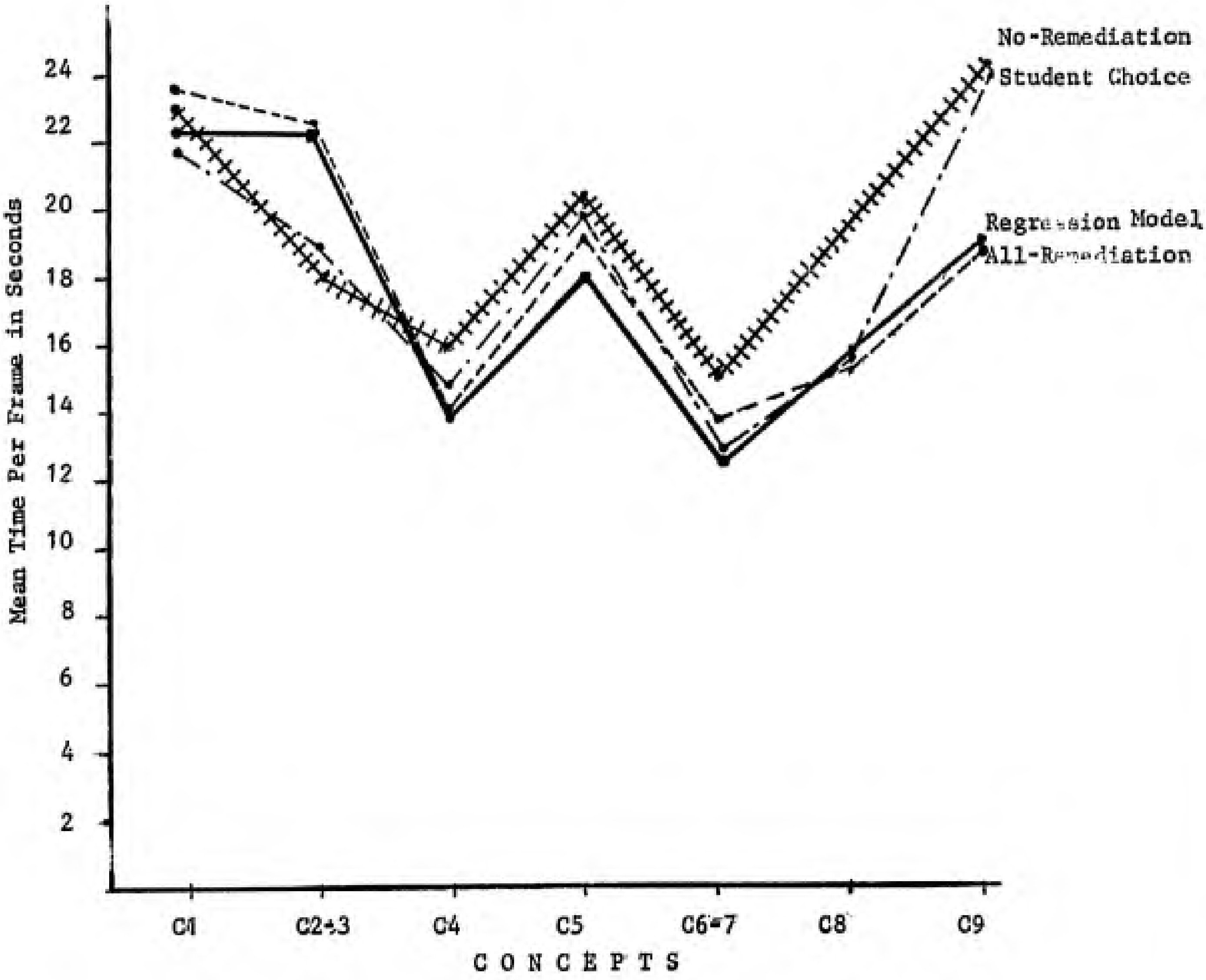

Figure 5.--Mean time per frame in seconds (learning plus remedial) by concept for the four instructional treatments.

TABLE 20

Significant Differences ($p < .05$) Found Between Group Mean Times per Frame Within Concept*

Concept	Significant ($p < .05$) Group Comparisons
1	None
2-3	All-Remediation vs. No-Remediation
4	None
5	None
6-7	None
8	None
9	Regression Model vs. Student Choice and No-Remediation; All-Remediation vs. Student Choice and No-Remediation

*See Appendix N for the complete analysis.

Remedial Predictions and Related Time by Concept. The variables used at each of the seven decision points were given in Tables 4 and 5, and the complete regression equations were presented in Appendix E. Table 21 reports the number of students in each group by concept for whom it was predicted that remediation was needed as opposed to the number who actually received it. Although the All-Remediation group received all of the remediation and the No-Remediation group received none, a record was kept by the computer as to the number who actually should have received it. Out of a total of 140 decision points (20 Ss in a group times seven decision points each) there were 123 cases where the need for remediation was predicted for the Regression Model group, 124 for the All-Remediation group,

TABLE 21

Number of Students Predicted (P) to Need Remediation
and Number Receiving (R) it by Group by Concept

GROUP	CONCEPT													
	1		2-3		4		5		6-7		8		9	
	P	R	P	R	P	R	P	R	P	R	P	R	P	R
Regression Model	19	19	20	20	13	13	18	18	13	13	20	20	20	20
All-Remediation	20	20	20	20	11	20	19	20	14	20	20	20	20	20
Student Choice	20	15	19	9	14	9	20	10	12	3	20	3	20	2
No-Remediation	19	0	20	0	10	0	18	0	13	0	20	0	18	0

125 for the Student Choice group, and 118 for the No-Remediation group. In the Student Choice group, although there were 125 cases where the need for remediation was predicted, only 51 times was it actually selected, and of these 51 times, there were five cases where it was predicted that remediation was not needed.

Appendix O indicates this data by individual student and, in addition, presents the individual and mean time taken on each review.

Table 22 presents the mean time per frame on main-line and remedial instruction by concept for the four instructional treatments. The total time spent on main-line and remedial instruction for the four groups, as calculated from Table 22, is presented in Table 23.

TABLE 22*

Mean Time per Frame (in sec.) on Main-Line (ML)
and Remedial (R) Instruction by Concept for
the Four Instructional Treatments

GROUP	CONCEPT													
	1		2-3		4		5		6-7		8		9	
	ML	R	ML	R	ML	R	ML	R	ML	R	ML	R	ML	R
Regression Model	21.1	28.5	16.5	35.8	13.2	14.8	16.9	24.5	12.3	19.5	15.0	20.6	20.1	13.4
All-Remediation	21.5	32.9	17.4	35.5	13.9	16.2	18.1	23.6	12.3	20.5	14.9	16.7	21.5	12.7
Student Choice	20.9	27.9	17.6	28.1	14.4	13.4	18.3	28.2	12.4	22.1	15.3	25.2	24.1	10.6
No-Remediation	23.1		18.2		15.8		20.1		15.1		18.0		23.8	

*The number of frames in each concept for the main-line instruction is given in Table 2, and the number of remedial frames by concept is presented in Appendix O.

TABLE 23

Mean Total, Main-Line and Remedial Time (in mins.) for the Four Instructional Treatments

Group	Total	Main-Line	Remedial
Regression Model	86.1	66.5	19.6
All-Remediation	91.0	68.2	22.8
Student Choice	76.7	68.9	7.8
No-Remediation	78.2	78.2	

VI. DISCUSSION

Introduction

This chapter presents a discussion of the results of the comparisons of the instructional treatments employed in assessing the effectiveness of the use of regression techniques in the development of an adaptive strategy for the presentation of instruction. The results are discussed with respect to the major parameters of performance and time. It should be recalled that the No-Remediation group was created in order to establish a base level of performance with the main-line instruction. The All-Remediation group when compared with the No-Remediation group allowed for an assessment of the overall effectiveness of the remedial instruction. One might have the most sophisticated decision logic to detect students in need of remedial instruction, but if the remedial instruction is not effective, then it is difficult to determine the efficacy of the decision logic. To the degree that the remedial instruction is effective, accurate assessments can be made of the regression model predictive approach to adapting instruction as compared with a procedure where the student makes the decision and a nonadaptive approach where all students receive all additional instruction.

Phase II: Instructional Treatment Comparisons

Performance. In terms of total posttest performance it was revealed that the Regression Model and All-Remediation groups each had significantly higher scores than either the student choice or No-Remediation groups. There were no significant differences within the two sets of groups. It was not expected that the Regression Model group would slow a significantly higher level of performance than the All-Remediation group, particularly over an instructional sequence of about an hour and a half's time.

The rank order from high to low posttest performance was: (a) Regression Model; (b) All-Remediation; (c) Student Choice; and (d) No-Remediation. The remediation was effective in improving final performance as evidenced by the significantly higher performance level of the All-Remediation group when compared with the No-Remediation group. The finding of superior performance for the Regression Model group over the No-Remediation group indicates that the decision logic was effective in identifying those students in need of additional instruction. The effectiveness of the decision logic was further supported by the fact that the Regression Model group also performed significantly higher on the posttest than the Student Choice group. It appears that subjects in the Student Choice group were not able to accurately determine for themselves whether they needed the review segments as indicated by the similar performance levels of the Student Choice and No-Remediation groups.

In order to investigate possible differential effects due to varying degrees of difficulty of the main-line instruction and varying degrees of effectiveness of the remedial instruction, the overall analysis was supplemented with an analysis by part. It should be recalled that the course consisted of two parts; a nontechnical section (concepts 1-3) and a technical section (concepts 4-9). It was felt that if the two parts of the course differed in degree of difficulty, differential effects in performance might be found across the groups. The analysis of posttest performance by part indicated a significantly lower level of performance in part 2 and a significant part by group interaction. There was significantly higher performance on the posttest covering part 1 for all groups except the No-Remediation group (see Table 11 and Appendix I). This finding indicates that although the main-line instruction was equally difficult, the remedial instruction was not as effective in part 2 as it was in part 1. Part 1 covered material with which the subjects were expected to have had some exposure, whereas part 2 dealt with technical subject matter of an unfamiliar nature. Although the review segments were significantly effective in both parts, it does appear additional practice beyond that provided, particularly with the ECB tracings, would be necessary to bring performance in part 2 to the level of part 1.

Although the rank order of the groups with respect to posttest proportion correct remained the same in both parts, the wide differences among the groups found in part 1 was much lessened in part 2 (see Figure 2). The Regression Model group still did perform significantly higher than the Student Choice and No-Remediation groups, and the All-Remediation group reached a significantly higher posttest performance level than the No-Remediation group on both parts of the course. On part 1, however, there was no significant difference between the All-Remediation and Student Choice groups, but the Student Choice group performed significantly higher than the No-Remediation group. The reverse was true in part 2. The All-Remediation group performed at a significantly higher level than the Student Choice group and there was no significant difference between the Student Choice and No-Remediation groups. The lower performance levels of the Student

Choice group points out the inability of these students to accurately determine their need for remediation, particularly on the more technical second part of the course. Although the degree of effectiveness of the remedial instruction obviously had some influence, Table 21 indicated that in part 1 where the need for remediation was predicted, over 50 percent of the time the student selected it, but in part 2 the percentage was only slightly over 25.

The analysis by concept which was conducted to determine more precisely the points of differences among the groups, and to determine the effectiveness of each adaptation point, showed a significant differen among concepts and a significant group by concept interaction (see Tables 15-17). Although the rank order of the groups in terms of posttest performance was remarkably consistent across concepts, Figure 4 clearly showed considerable variation among groups across the concepts. In identifying specific deficiencies, no significant differences were found among the groups for concepts 4, 6, 7, and 8. In concept 4, the No-Remediation group achieved a performance level of approximately 90 percent which left little room for improvement through additional instruction. In concepts 6-7 and 8 the performance level for the No-Remediation group was extremely low, and although the Regression Model and All-Remediation groups achieved much higher levels, the remediation was not effective enough to show any significant improvement. These concepts dealt with the drawing of normal, damaged, and healing ECG tracings, and it appears that additional practice recognizing and drawing the ECG tracings was needed, particularly since most students were predicted to be in need of remediation across these concepts.

The effectiveness of the Regression Model adaptive procedure might have been more apparent in part 2 with improved remediation at these points. It should be noted that the combined effect of the remediation in part 2 brought performance up 12 percent. In part 1, performance for the Regression Model group was raised 30 percent over the No-Remediation group (see Table 11).

Instructional Time vs. Performance. Of course, performance is only one aspect in the assessment of the efficacy of a procedure which attempts to adapt the instructional sequence to the individual needs of the students. Certainly a procedure that significantly improves performance but doubles the instructional time would not be too desirable unless a high level of performance were critical no matter what the times involved. Each individual must decide what an acceptable ratio would be in his own particular situation.

With respect to total instructional time, it was expected that the All-Remediation group would take significantly more time (instructional plus remedial) than the No-Remediation group, and indeed it did. The All-Remediation group also took significantly more time than the Student Choice group which took the least amount. Although the Regression Model group ranked second in total time, it did not take significantly more time than the Student Choice or the No-Remediation groups, nor did it, however, take significantly less time than the All-Remediation group.

In terms of overall course performance, the Regression Model group performed significantly higher on the posttest than either the Student Choice and No-Remediation groups, and in addition, there was no significant difference in the amount of time taken. The efficacy of the regression model approach would have been even more dramatically demonstrated had the Regression Model group taken significantly less time than the All-Remediation group. As Table 21 indicated, however, in five of the seven decision points almost all of the subjects in the Regression Model group were given the remedial instruction which, in essence, left little room for time saving in comparison with the All-Remediation group. It should be recalled that the criterion level for providing remediation at each adaptation point was set at 80 percent. With the base-level performance (the No-Remediation group) at approximately 50 percent (see Table 11), remediation was prescribed in most cases. This low level performance on the main line instruction made it difficult to show significant time savings over the All-Remediation group, since remediation was prescribed so often.

It is interesting to note that the group which received no remediation took the most amount of time per frame on the main-line instruction (see Table 23) followed by the Student Choice group which received the least amount of remediation of the remaining three groups. It would appear that the concepts were related, and that the remediation did enable the students to consolidate the information presented in each concept which resulted in the students spending less time on the following concept than if no remediation had been given.

For the analysis by part, the total time was broken down into mean time per frame which included any remedial frames and resultant time that might have been taken. The results in part 1 exactly paralleled the results found in the overall analysis. The results in part 2 presented quite a different picture. The rank order from high to low mean time per frame was: (a) No-Remediation; (b) All-Remediation; (c) Student Choice; and (d) Regression Model. The No-Remediation group took significantly more time per frame than either the Student Choice or Regression Model groups (see Table 13). The students did take significantly less time per frame on part 2, and proportionally less time per frame was taken on remediation by all groups in comparison to part 1. The time analyses by concept reflected the findings by part.

Directions for Future Research and Application

The results of this study have revealed the potential of an adaptive strategy for the presentation of instruction which utilizes regression analysis techniques. The prediction models employed were effective in detecting students who were in need of additional instruction. However, in order for the full effectiveness of this approach to be assessed, a number of questions must be answered by future research.

These questions can be grouped into three major areas: selection and use of predictor variables; determination of the type and amount of remediation to be employed; and other applications.

Selection and Use of Predictor Variables. It should be recalled that the variables dealt with in this study were (with the sole exception of trait anxiety) within-course variables; measures that were generated by the students as they proceeded through the instructional materials. Each of the major variables of proportion correct, latency, and anxiety were effective predictors of final performance. Both accumulated prior performance and immediate performance variables were represented at the seven decision points. However, the direction of the relationship of these variables with the criterion variable was occasionally reversed from one decision point to another. For example, mean latency across concepts 1-3 was positively related to final performance on concept 4, but negatively related to final performance on concepts 6-7. Further research needs to be conducted on the relationship of the variables of proportion correct, latency, and anxiety to each other as well as to criterion performance. A clearer picture of these relationships might provide insight for combining the variables in other ways which could produce more effective predictors. Guidelines might be established from these relationships for developing the most appropriate remediation.

Other variables, such as student confidence ratings, should be investigated as possibilities for inclusion in the model. Variables that can be measured prior to exposure to the material that might be posited to interact with the particular content should also be considered.

Type and Amount of Remediation. In this study, the students whose predicted final performance on a concept was below 80% were given a variation of the presentation that they received in the main-line instruction.

On some of the concepts the remediation was very effective and on others it was marginally effective. The question arose as to whether the format should have been different or whether more examples and practice exercises should have been provided.

More research needs to be conducted with the aim of determining the most appropriate amount as well as type of remediation needed when a lack of mastery is noted.

Other Applications. In this study the instruction was presented on the CAI 1500 system because it allowed for greater precision and for an application of the model as the students proceeded through the instruction without sensitizing them to the process. However, this strategy for adaptive instruction need not be tied to a CAI presentation. Instruction could be presented off-line and the appropriate data could be collected and submitted to the computer by the student or instructor. As our research knowledge grows we will be able to realize more fully our goal of improving the efficiency and effectiveness of instruction for each learner.

VII. SUMMARY

When computers first became available for utilization in instruction, programmed instruction was the typical model used for implementation. One of the advantages of using the computer in education is that it has the capability to adapt the instruction based on each individual's most recent performance as well as many facets of his past history (Dick, 1965; Hansen, 1966; Gentile, 1967; Zinn, 1967). With the use of the computer, more complex decisions can be made about learner performance. However, as of this date, most computer-assisted (CAI) applications have individualized only the rate at which the student proceeds through the CAI program. Certainly one factor contributing to this state of affairs has been the lack of consistent findings about the many learner entry characteristics and their implications for the design of instruction.

The objective of this investigation was to develop and assess a methodology utilizing the computer's unique real-time monitoring capability to maximize achievement while minimizing time on instruction presented via the computer. On-going performance was monitored and used to predict final achievement. Adaptations were made in the course content for each individual as the instruction proceeded in order to optimize his performance. In this empirical approach, data on within-course variables generated by an initial group of students were utilized in establishing the adaptation points in the program as well as the decision criteria to be employed at each point. The prediction models established by regression analyses were embedded in the logic of the instructional program which was under the control of the computer. As subsequent students proceeded through the instructional materials, the relevant within course performance variables were monitored by the computer. Criteria embedded in the logic of the computer program allowed for predictions of each student's final achievement. If a student's predicted achievement was below a predetermined level, he was branched to remedial instruction. If his predicted achievement was satisfactory, he continued through the mainline of instruction.

The initial problem involved the identification of potential predictor variables that could be measured during learning that might relate to final achievement. The most obvious variable to be measured during learning was the probability of correct responding. A second major variable used was that of response latency. The third variable, a performance related variable, was trait and state anxiety. The variables of proportion correct, latency, and anxiety were measured with little or no intrusion in the learning sequence.

The second major problem area involved the determination of the unit of analysis. The establishment of the unit of analysis determines the point in the instructional program at which adaptation can be effected. The adaptation points are the points at which remedial instruction was provided. It was established that the unit of analysis should be large enough to provide a stable indication of behavior but be responsibe enough to provide for adaptive decisions while the learning is still proceeding. The unit of analysis that appeared to have the highest potential payoff in terms of meeting the criteria of behavioral stability and instructional flexibility was at the concept level.

The instructional program deals with the incidence and risk of contracting heart disease and the diagnosis of myocardial infarction. Nine basic concepts were identified within the course. The program consists of two sections. The first section deals with material widely reported in the mass media with which the subjects are expected to have some previous familiarity. There are three basic concepts in this section. The second section is composed of technical subject matter (the diagnosis of myocardial infarction) with which the subjects are not expected to have had previous experience. This section contains both verbal and graphic material. There are six basic concepts in this section.

Cumulative performance and latency as well as the most recent performance and latency were used as predictor variables for the concept analyses. For example, the predictor variables for concept one in section one were (a) performance on the trait anxiety scale; (b) performance on the first state anxiety scales; (c) performance on the second state anxiety scale; (d) percent correct on concepts one and two combined; (e) mean response latency on concepts one and two combined; (f) percent correct on concept three; and (g) mean response latency on concept three. The criterion variable for this analysis was the score on the posttest questions relating to concept three. The instructional materials were presented by means of the IBM 1500 instructional system located at the Florida State University Computer-Assisted Instruction Center. Performance, and latency for each response in the program as well as for the anxiety measures for each student were recorded automatically by the computer.

Significant regression equations were found for all the concepts except 3 and 6. Data for these two concepts were combined with adjacent concepts and the result was significant prediction equations at seven points in the program: after concepts 1, 3, 4, 5, 7, 8, and 9. The regression equations were coded in the logic of the program and the remedial loops were inserted after each of these adaptation points.

Four treatments were designed in the validation phase in order to assess the effectiveness of adapting the on-going instruction on the basis of regression analysis techniques at the concept level. One version of the course was programmed such that a group of students (the regression model group) proceeded through the CAI program to which has been added (a) the coding in the program logic to monitor the appropriate within course variables; (b) the prediction models which would detect those students in need of additional instruction; and (c) the remedial loops which would maximize their final performance. A second group of students (the All-Remediation group) received all of the remedial loops regardless of what the predictive models indicated. A third group (the No-Remediation group) received none of the remedial loops. They simply proceeded through the mainline instruction. The final group (the Student Control group) was given the option at each possible remediation point identified in the predictive condition to either go through the remedial loops or to continue with the next concept.

In terms of total posttest performance, it was revealed that the Regression Model and All-Remediation groups each had significantly higher scores than either the student choice or No-Remediation groups. There were no significant differences within the two sets of groups. It was not expected, however, that the Regression Model group would show a significantly higher level of <u>performance</u> than the All-Remediation group, particularly over an instructional sequence of about an hour and a half's time.

The rank order from high to low posttest performance was: (a) Regression Model; (b) All-Remediation; (c) Student Choice; and (d) No-Remediation. The remediation was effective in improving final performance as evidence by the significantly higher performance level of the All-Remediation group when compared with the No-Remediation group. The finding of superior performance for the Regression Model group over the No-Remediation group indicates that the decision logic was effective in identifying those students in need of additional instruction. The effectiveness of the decision logic was further supported by the fact that the Regression Model group also performed significantly higher on the posttest than the Student Choice group. It appears that subjects in the Student Choice group were not able to accurately determine for themselves whether they needed the review segments as indicated by the similar performance levels of the Student Choice and No-Remediation groups.

With respect to total instructional time, it was expected that the All-Remediation group would take significantly more time (instructional plus remedial) than the No-Remediation group, and indeed it did. The All-Remediation group also took significantly more time than the Student Choice group which took the least amount. Although the Regression Model group ranked second in total time, it did not take significantly more time than the Student Choice or the No-Remediation groups, nor did it take significantly less time than the All-Remediation group. However, in five of the seven decision points almost all of the subjects in the Regression Model group were given the remedial instruction which, in essence, left little room for time saving in the comparison with the All-Remediation group.

In conclusion, the results of this study have revealed the potential of an adaptive strategy for the presentation of instruction which utilizes regression analysis techniques. However, it has been noted that in order for he full effectiveness of this approach to be assessed, further research in the area needs to be conducted. Specifically the needed research pertains to the selection and use of predictor variables, and to the most appropriate type and amount of remediation to be supplied when lack of mastery is detected. Finally, it has been noted that the use of this approach need not be confined to situations where instruction is presented via the computer. This empirical approach can be an excellent research tool as well as an effective instructional process.

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VITA

[redacted]

Business Address: Eclectic, Ltd.
Watergate 600, Suite 475
600 New Hampshire Avenue, N.W.
Washington, D.C. 20037
Phone: 202-965-4232

Academic History:

B.S.	Psychology, Pennsylvania State University, 1966
M.S.	Educational Research, Florida State Univ., 1969
Ph.D.	Instructional Systems and Educational Psychology, Florida State University, expected August 1972

Positions Held:

Eclectic, Ltd.--January 1972 to present. Director, Instructional Systems Division. Responsible for the management of all training and instructional development projects. Duties include the supervision of the project teams, development of the conceptual and detailed design approaches for the projects, establishment of criteria for the analysis of contract performance and the validation of learning materials, and the selection of staff necessary to meet the corporate requirements of each project.

U.S. Naval Academy, Educational Systems Center--July 1971 to January 1972. Consultant for the Educational Systems Center on the analysis of data and report writing for a four-year Education and Training Development project funded by the Bureau of Naval Personnel. The objective of the project was to test the feasibility of available new advances in instructional technology - specifically the use of computer-aided and other automated techniques in instructional procedures and content. Specific responsibilities involved analysis of revision, validation, and research data. Report writing involved the topics of management, facilities, data handling, and production requirements for the development and implementation of computer-aided instruction, as well as the feasibility and cost benefits.

Westinghouse Learning Corporation, Annapolis Division--June 1970 to June 1971. Research Director for the multimedia course development project conducted at the United States Naval Academy and sponsored by the Office of Education. The project was concerned with the preparation of an effective course in Naval Leadership and with the experimental study of instructional systems. Major responsibilities included designing the research, working with materials production and on-site personnel to insure proper implementation, analysis of data, and report writing. Media used included audiotape, videotape, programmed instruction, adjunct instruction, and computer-assisted instruction.

Florida State University, Graduate Fellow--July 1968 to May 1970. Investigation of individual difference variables important in the development of decision models for computer-assisted instruction. Assisted in the design and implementation of various research and development projects as well as learning and instructional studies via computer-assisted/managed instruction.

Florida State University, U.S. Office of Education Fellow in computer-assisted instruction from September 1967 to June 1968. Participant in year-long institute in Computer-Assisted Instruction (CAI). Obtained an in-depth understanding of CAI and the systems approach to the development of instructional materials. This included an operational understanding of the IBM 1500 instructional system, how to program it and how to obtain sophisticated data analysis.

HRB-Singer, Inc., Psychologist, form 1965 to 1967. On-site Director for the development, execution, and analysis of tests to evaluate photo-interpreter performance with various interpretation devices including closed-circuit television, light table and rear projection viewer. Responsible for construction of test items, and analysis and revision of programmed instructional texts for the interpretation of infrared imagery.

The Pennsylvania State University, Research Assistant in the Department of Planning Studies, Continuing Education, from 1962 to 1965. Task Director for automatic data processing and computer programming of state-wide surveys. Coordinator for compilation and submission of reports assessing the continuing educational needs of hospital personnel, engineers and industrial management personnel in Pennsylvania.

U.S. Army, Cryptographer and Communications Specialists from 1959 to 1962. Section supervisor of a security communications relay center.

Professional Affiliations:

American Psychological Association
American Educational Research Association
National Society for Programmed Instruction
Psi Chi (National Honor Society in Psychology)

Major Research Interests:

Individualized instruction, models for the design of instruction, the use of the computer in education, and the investigation of individual difference variables important in the development of decision models for computer-assisted/managed instruction.

Publications:

''Research and Implementation of Collegiate Instruction of Physi Computer-Assisted Instruction,'' Technical Report No. 3, Computer-Assisted Instruction Center, Florida State University, 1968. (With Hansen, et al).

''Computer-Assisted Instruction: A Glimpse of CAI Today,'' The BC Teacher, 49, No. 3, December 1969, 98-102 (With W. Dick and R. Latta).

''Computer-Assisted Instruction: Major Activities and Sources of Information,'' The BC Teacher, January 1970 (With W. Dick and R. Latta).

''Computer-Assisted Instruction: Interest in Canada Increasing,'' The BV Teacher, February 1970 (With W. Dick and R. Latta).

''Computer-Assisted Instruction: Planning for Implementation,'' The BC Teacher, March 1970 (With W. Dick and R. Latta).

''Public School Activities and Related Sources of Information Concerning Computer-Assisted Instruction,'' Educational Technology, March 1970 (With W. Dick and R. Latta).

Development of a Model for Adaptive Training via Computer-Assisted Instruction Utilizing Regression Analysis Techniques. Final Report. Contract N61339-68-C-0071, Naval Training Device Center, Orlando, Floda, 1970 (With W. Dick, A. King, & D. Hansen).

Annual Progress Report: January 1 through December 31, 1969. Technical Report 8, Computer-Assisted Instruction Center, Florida State University, Tallahassee, 1970 (With D. Hansen, et al.)

Publications: (continued)

Report of Phase II Research Findings: The Design and Methodology for Research on the Interaction of Media, Conditions of Instruction. and Student Characteristics for a Multimedia Course in Leadership, Psychology and Management, ''Part I: Conditions of Instruction,'' Contract No. N00600-69-C-1525, Westinghouse Learning Corporation, Annapolis Div., October 1970 (With D. Bessemer).

An Analysis and Evaluation of Instructional Methodology for a Multimedia Course in Leadership, Psychology, and Management, ''Phase II Evaluation Report,'' Contract No. N00600-68-C-1525, Westinghouse Learning Corporation, Annapolis Div., October, 1970 (With E. Hubert).

Report of Phase II Research Findings: The Design and Methodology for Research on the Interaction of Media, Conditions of Instruction, and Student Characteristics for a Multimedia Course in Leadership, Psychology and Management, ''Part II: Student Characteristics, Contract No. N00600-68-C-1525, Westinghouse Learning Corporation, Annapolis Div., December 1970 (With D. Bessemer).

An Analysis and Evaluation of Instructional Methodology for a Multimedia Course in Leadership, Psychology, and Management: Phase III Evaluation Report, Contract No. N00600-68-C-1525, Westinghouse Learning Corporation, Annapolis Div., December 1970 (With D. Bessemer).

Report of Phase III Research Findings for a Multimedia Course in Leadership, Psychology, and Management, Contract No. N00600-68-C-1525, Westinghouse Learning Corporation, Annapolis Div., May 1970 (With R. McEntee).

Final Report--Part I, Summary and Conclusions Relating to Research and Evaluation of a Multimedia Instructional System, Contract No. N00600-68-C-1525, Westinghouse Learning Corporation, Annapolis Div., May 1971.

Papers Presented at Professional Meetings:

''A Systems Approach to Photo-Interpretation Equipment Evaluation: Methodological Considerations.'' Society of Photo-Optical Interpretation Engineers, Los Angeles, 1967 (With D. Ventimiglia).

''Development of a Dynamic Decision Model for Computer-Assisted Instruction.'' American Educational Research Association, Minneapolis, 1970.

''Research and Evaluation in a Multimedia Psychology/Leadership/Management Course.'' American Educational Research Association, New York, 1971.

Teaching Interests:

Courses in Programmed Instruction, Computer-Assisted Instruction, instructional program design and development, the use of the computer in education, models for the design of instructional systems, and Educational Psychology.