DOCUMENT RESUME

ED 089 671 IR 000 382

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TITLE	An Investigation of Self-Study Computer-Based Instruction in Engineering.
PUB DATE	Apr 74
NOTE	33p.; Paper presented at the American Educational Research Association Annual Meeting (Chicago, Illinois, April 15 through 19, 1974)
EDRS PRICE	MF-$0.75 HC-$1.85 PLUS POSTAGE
DESCRIPTORS	*Academic Achievement; *Computer Assisted Instruction; Conventional Instruction; Educational Research; *Engineering Education; Higher Education; *Independent Study; Models; Multiple Regression Analysis; *Prediction; Predictor Variables; Student Characteristics; Teaching Methods; Undergraduate Study
IDENTIFIERS	Curvilinear Regression Analysis

ABSTRACT

Research investigated: 1) the effect of instructional mode on student achievement; 2) the relationship between a) the student factors of aptitude, sex, previous achievement, educational level, and academic major and b) achievement; and 3) the possibility of a homogeneity of regression equations for achievement of students in varying instructional modes with respect to student traits. Students in an engineering course received either conventional or computer-assisted instruction (CAI), and curvilinear regression procedures were used to construct models of achievement. Findings showed the CAI students achieved better in the course, although their overall grade point averages for the semester were not significantly better. Significant relations were found between instructional modes and student factors in terms of achievement, but homogeneity of regression equations was not manifested. It was concluded that: 1) CAI was an effective instructional mode; 2) models of the student could be developed to predict achievement with a particular instructional mode, but their predictive value was limited; and 3) it was not possible to construct a predictive model of achievement which did not take into account the instructional mode. Additional research was recommended on curvilinear analysis and other student variables. (LB)

An Investigation of Self-Study
Computer-Based Instruction in Engineering

A Paper To Present To
the
American Educational Research Association

April, 1974

by

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INTRODUCTION

In the preceding decade the rapid advances in computer technology have influenced growth and development of computer based instructional systems. The use of computers in education as instructional devices has been considered by only a handful of educators. However, the computer is recognized as being a major force in producing accelerated change in society.

Current applications of computers and related information processing techniques run the gamut in society from automatic control of factories to the scrutiny of tax forms (16). Bright (1) points out that all professions will be radically affected by the computer and all students will have to learn how it works and what it can do by using computers as data solving tools in such subjects as mathematics, physics, and economics.

The use of computers in these applications is extensive as compared to the applications in education, particularly as an instructional tool. A partial reason is that most educators are not familiar with the diverse uses of computers, their rapid operational speed, and their ability to handle large numbers of pupils.

The growth of computer based instruction is in part due to the development of programmed instruction, particularly by Crowder and Skinner, during the 1950's. Although programmed materials failed to meet the expectations of some educators, the attempt to individualize instruction using science and technology has carried over into the field of computer based instruction.

The advances in computer research and development and software design have been rapid. Program language development have been more important for educational purposes than have machine innovations. Many school systems, universities, and manufacturers are promoting languages for education. Over 30 languages and dialects have been produced especially for programming conversational instruction. Atkinson (1) points out:

> . . . computer-assisted instruction has grown to a point where several thousand students ranging from elementary school to university level receive a significant portion of their instruction in at least one subject under computer control.

Serious applications of computer based instruction are now in progress in many universities throughout the United States. A list of these institutions which have had major programs under way includes Stanford University, University of California at Irvine, University of Texas, Florida State University, Pennsylvania State University, University of Illinois, and Harvard. The University of California at Irvine, which is a relatively new university, has made a serious attempt from its earliest planning stages to integrate computer based instruction into its total instructional program (1).

Patrick Suppes (16) makes these comments, which clarify and strengthen the educational value of computer instruction:

> Just as books freed serious students from the tyranny of overly simple methods of oral recitation, computers can free students from the drudgery of doing exactly similar tasks unadjusted and untailored to their individual needs. Our new and wonderous technology is there for beneficial use. It is our problem to learn how to use it well.

I. STATEMENT OF THE PROBLEM

Most school teachers and college instructors will agree that there is a great need to individualize instruction to meet the needs of every student. Students can learn more, perhaps at an increased pace over a long period, when instruction is tailored to their level and rate of instruction.

At the university level students do not now receive a great deal of individual attention from instructors. Self-study computer based instructional lessons designed to accommodate to the individual student's rate of progress will provide greater attention. At the same time, instructors released from lecture sessions and preparation can provide tutorial sessions for students, and, thus, personalize instruction to an even greater degree.

The primary purpose of the present study was to investigate and evaluate the relationship between self-study computer based instruction and achievement in a university engineering course.

For this study Engineering 205: Mechanics of Solids was the particular course under consideration. This is a second year engineering course in the School of Engineering and Applied Science at the University of Virginia.

The relationship between self-study computer based instruction and the grade point average during the semester in which Engineering 205: Mechanics of Solids was taken has also been considered in this investigation.

Another purpose of the study was to determine certain student related factors which may be used to predict achievement in the specific course under consideration and overall achievement in total course work. In a sense this was an attempt to isolate some factors which would help to optimize the instructional process. The factors, which were obtained from student files maintained by the Dean of the School of Engineering and Applied Science, include mathematics and verbal aptitude, sex, previous grade point average, college major, school year, rank in high school class, size of high school class, and the percentile rank in the high school class.

Regression equations were constructed using the final examination score and grade point average during the semester under the self-study program as the criterion variables. The predictor variables were the student related factors. Suppes (16) has called for exploring alternatives to strictly linear regression models. Thus, this study attempted to determine a "best" model of the student, using curvilinearity of regression wherever indicated.

II. SPECIFIC OBJECTIVES

The following specific questions were considered in this study:

(1) What relationship, if any, exists between the mode of instruction and student achievement in Engineering 205: Mechanics of Solids?

(2) What relationship, if any, exists between the mode of instruction and student grade point average during the semester of Engineering 205: Mechanics of Solids?

(3) What relationship, if any, exists between student achievement in the self-study computer based section and each of the following student related factors:

A. Mathematics aptitude

B. Verbal aptitude

C. Sex

D. Previous grade point average

E. School year

F. College major

G. Percentile rank in high school class

H. Performance level in mathematics

(4) What relationship, if any, exists between student grade point average during the semester under the self-study computer based instruction and each of the following student related factors:

A. Mathematics aptitude

B. Verbal aptitude

C. Sex

D. Previous grade point average

E. School year

F. College major

G. Percentile rank in high school class

H. Performance level in mathematics

(5) What relationship, if any, exists between student achievement in conventionally taught sections of Engineering 205: Mechanics of Solids and each of the following student related factors:

A. Mathematics aptitude

B. Verbal aptitude

C. Sex

D. Previous grade point average

E. School year

F. College major

G. Percentile rank in high school class

H. Performance level in mathematics

(6) What relationship, if any, exists between student grade point average during the semester in conventionally taught sections of Engineering 205: Mechanics of Solids and each of the following student related factors:

A. Mathematics aptitude

B. Verbal aptitude

C. Sex

D. Previous grade point average

E. School year

F. College major

G. Percentile rank in high school class

H. Performance level in mathematics

(7) Is there homogeneity of regression equations for the self-study computer based instruction section and the conventionally taught sections of Engineering 205: Mechanics of Solids with respect to student achievement and the following student related factors:

A. Mathematics aptitude

B. Verbal aptitude

C. Sex

D. Previous grade point average

E. School year

F. College major

G. Percentile rank in high school class

H. Performance level in mathematics

(8) Is there homogeneity of regression equations for the self-study computer based instruction section and the conventionally taught sections of Engineering 205: Mechanics of Solids with respect to student grade point average during the semester and the following student related factors:

A. Mathematics aptitude

B. Verbal aptitude

C. Sex

D. Previous grade point average

E. School year

F. College major

G. Percentile rank in high school class

H. Performance level in mathematics

III. JUSTIFICATION

Computer assisted and programmed instructional materials have been used primarily to teach concepts on the lowest level of the learning continuum. That is, the major emphasis has been upon the teaching of skill and/or knowledge type tasks. Spelling drills (1), remedial reading and arithmetic programs (4), simple programming (10), and games (8) have been the subject of research since the earliest uses of computer assisted and programmed instruction.

A lesser amount of research has involved the higher levels in the cognitive domain of learning. The treatment of proofs in mathematics (9), algebra and symbolic logic (13), computer programming (14), solid-state electronics (19), and physics (6) are some of the areas of recent development. Engineering 205: Mechanics of Solids contains material of a high conceptual level. In addition, there is a definite void in research in the area of computer based materials used in engineering. The study was an investigation in this area.

Computer assisted and programmed instructional systems have been used by researchers such as Suppes (17) and Gagne' (5) to explore and establish models of how students learn. These studies fail to analyze the student related factors which influence achievement. The study reported here attempted to use curvilinear regression procedures to construct a predictive model of the student in self-study computer based instruction.

The author found only a relatively small number of research reports concerning computer based instruction in engineering readily available in the literature. Hansen (7) noted the reason for this in the statement:

> The vast majority of CAI projects have expended tremendous energy in the development of curriculum materials; consequently, this developmental phase has limited the availability of research findings.

The investigation reported here was inspired because of the need to evaluate computer based instruction at the University of Virginia. There was considerable concern voiced by both students and faculty over the extra time spent in the self-study computer based lessons. This may or may not be a valid concern at the university level. However, if this increase in time used for obtaining proficiency in the computer based lessons measurably effected student performance in the other course work taken during that semester, then it was certainly an important consideration. Thus, this aspect of the study was important for the total evaluation of the use of self-study computer based instruction.

The present study was not only an attempt to evaluate and determine the feasibility of using computer based instruction at the University of Virginia. The development of a model of the student, using the factors obtained from files maintained by the Dean of the School of Engineering and Applied Science, for prediction of success was also an important aspect of the study.

The problem of using students characteristics to predict success in engineering at the University of Virginia was considered by William C. Lowry and Harold S. Spraker in 1959 (12). The author hopes that the present study updates those results and extends research in this area.

IV. DEFINITIONS

For the purposes of this study, the following terms were operationally defined:

1. Self-study Computer Based Instruction

The following were the instructional materials and methods unique to the self-study computer based instructional treatment of Engineering 205: Mechanics of Solids.

A. A self-study programmed text entitled Statics, An Individualized Approach by Muhlbaner was used for the statics portion of the course.

B. Notes on deformable solids were provided by the instructor.

C. Computer programs which presented analysis of beams and trusses were used in a problem solving mode of instruction.

D. All testing was done by the computer, and the student could use the tests and examples of previous units in a drill and practice mode of instruction.

2. Traditional Instruction. The several sections of Engineering 205: Mechanics of Solids not under the self-study computer based instruction were taught by conventional methods. Instruction in these sections was typically classroom lecture and discussion.

3. Student Related Factors. The student related factors were those pieces of information which are obtained by the Dean of the School of Engineering and Applied Science of the University of Virginia, and which are contained in student files. These factors were:

A. College Board Scholastic Aptitude Test-Mathematics score (SAT-M)

B. College Board Scholastic Aptitude Test-Verbal score (SAT-V)

C. College Board Achievement Test-Mathematics score

D. Sex (S)

E. Previous grade point average (PGPA)

F. School year (SY)

G. College major (CM)

H. Percentile rank in high school class (% Rank)

4. Student Achievement (Y1). Student achievement was the score obtained by the student on the common final examination given to all sections of Engineering 205: Mechanics of Solids.

5. Student Grade Point Average (Y2). Student grade point average was the grade point average of the student on all courses other than Engineering 205: Mechanics of Solids during the semester of the investigation.

6. Mathematics Aptitude (SAT-M). Mathematics aptitude was student's score on the College Board Scholastic Aptitude Test - Mathematics.

7. Verbal Aptitude (SAT-V). The verbal aptitude was the score of the College Board Scholastic Aptitude Test - Verbal.

8. Performance Level in Mathematics (PL). The performance level in mathematics was determined by the student's score of the College Board Scholastic Achievement Test - Mathematics. The scores of the subjects in the sample were collected and divided into three equal groups. The division occurred at the thirty-third and sixty-seventh percentiles. The three groups were:

A. High Performance Group (HPG). The high performance group consisted of those students scoring at or above the sixty-seventh percentile.

B. Middle Performance Group (MPG). The middle performance group consisted of these students scoring at or above the thirty-third and below the sixty-seventh percentiles.

C. Low Performance Group (LPG). The low performance group consisted of those students scoring below the thirty-third percentile.

9. Treatment (T1)- Treatment T1 was the self-study computer based instruction.

10. Treatment (T2)- Treatment T2 was the traditional instruction.

V. HYPOTHESES

The following hypotheses were tested:

1. There is a difference in the means of achievement in Engineering 205: Mechanics of Solids for the treatments T1 and T2.

2. There is a difference in the means of student grade point average during the semester in Engineering 205: Mechanics of Solids for the treatments T1 and T2.

3. For treatment T1 there is a relationship between achievement and the student related factors.

4. For treatment T1 there is a relationship between student grade point average and the student related factors.

5. For treatment T2 there is a relationship between achievement and the student related factors.

6. For treatment T2 there is a relationship between student grade point average and the student related factors.

7. There is homegenity of regression equations for achievement of the treatments T1 and T2 with respect to the student related factors.

8. There is homogenity of regression equations for student grade point average of the treatments T1 and T2 with respect to the student related factors.

VI. LIMITATIONS OF THE STUDY

1. Generalizations of the results of the study are limited to the population from which the sample was taken.

2. For the purposes of the student, it was assumed that each of the instructors had a constant and equal effect on the students in each section.

3. A major limitation of the study may be that there are other student related factors which influence student achievement and which have not been considered in the study. The characteristics would be attitudes, motivation, background, etc.

4. The results of the study are limited by measurement errors and errors inherent in the instruments used.

VII. PROCEDURES

During the fall semester of 1972 several courses in the School of Engineering and Applied Science were taught under computer based methods. Generally, these courses involved only the testing of students in a computer managed mode of instruction. However, one section of Engineering 205: Mechanics of Solids was taught in a completely self-study computer based mode of instruction.

The experimental group used materials which were divided into sixteen instructional units. The course was self-study. Tests were administered at the end of each unit to determine whether or not the student had accomplished the objectives for that unit. For successful completion of a unit, a minimum score of 90 per cent was required. If this minimum was not achieved, the student was given further study and tried the test again. The student was allowed to proceed through the course at his own pace.

Certain instructional materials and methods were unique to the computer based treatment.

1. A self-study programmed textbook entitled Statics An Individualized Approach was used for the statics portion of the course.

2. Notes on deformable solids were provided by the instructor.

3. Computer programs which presented analysis of beams and trusses could be used by the student in a problem solving mode of instruction.

4. All testing was done by the computer. The student could use the tests and examples of previous units in a drill and practice mode of instruction.

The computer-based instructional materials were placed on a system developed by the School of Engineering and Applied Science of the University of Virginia especially for the Hewlett-Packard 2000-F computer. Students accessed the computer based materials in a time-sharing mode from terminals located at various points on the grounds of the University of Virginia.

The instructor monitored student progress on a daily basis. The student falling too far behind or having difficulty meeting the minimum requirements for successful completion of a unit was contacted by computer messages to have an individual conference with the instructor. The instructor was available for individual help sessions during the scheduled classroom hours. He was also available all day on Monday, Wednesday, and Friday to assist students having difficulty.

VIII. PROCEDURES FOR REGRESSION ANALYSIS

The evaluation of the self-study computer based instruction was carried out using multiple linear regression analysis of the data. Multiple regression is a technique for predicting one variable by means of one or more other variables. The details of the theory underlying multiple regression are too detailed to present here. A full account of the theory and computational aspects may be found in works by Bottenberg and Ward (3), (18).

The computer program, ITERREG2, provided the linear regression analysis of the data. The program, developed by the University of Virginia Bureau of Educational Research, is FORTRAN based and has been adapted to the Control Data Corporation 6400 series computer. This program considers both categorical and continuous data which are analyzed simultaneously. ITERREG2 does not assume that the data have normal distributions for each of the variables. For this study, each variable was read into or transformed by the computer. Calculations and print outs of the following statistics were also performed: means, standard deviations, zero order correlations, squared multiple correlation coefficients for both the full and restricted models generated, and the F-ratios and probabilities for all hypotheses tested.

For multiple linear regression analysis the variables are related by the general model:

$$Y = a_1X_1 + a_2X_2 + \ldots + a_nX_n + e.$$

where

Y is the vector of observed or estimated values of some random variable and is referred to as the dependent or criterion variable.

X_i is a vector of the known values of the independent or predicter variable.

a_i is a parameter of the system which is to be estimated from the data if possible.

e is the residual vector which has as elements differences or discrepancies between corresponding observed and estimated values in the dependent variable, Y.

The predictor equation is referred to as the full model. Each hypothesis concerning the relationship between the predictor variables and the criterion variable places restrictions upon the full model. Thus, a new predictor equation is formed which takes these restrictions into account; this equation is called the restricted model.

The F statistic was used to establish the regions of acceptance or rejection of the considered hypotheses. The equation:

$$F = \frac{(RSQ_1 - RSQ_2) / df_1}{(1 - RSQ_1) / df_2}$$

defines F, where

RSQ_1 is the squared multiple correlation coefficient obtained from the full model.

RSQ_2 is the squared multiple correlation coefficient obtained from the restricted model.

df_1 is the degrees of freedom of the numerator obtained by subtracting the number of linearly independent vectors of the restricted model from the number of linearly independent vectors of the full model.

df_2 is the degrees of freedom of the denominator obtained by subtracting the number of linearly independent vectors of the full model from the number of observations of the dependent variable.

The calculated probability given with each F-ratio for each restricted model was compared with the .05 probability accepted as the level of confidence in this study. If that calculated probability was greater than

.05, the null hypothesis was accepted. If that probability was less than or equal to .05, the null hypothesis was rejected.

The prediction models of the student were constructed using stepwise regression analysis of curvilinear variables. The predictor variables were certain student related factors, obtained from the Office of the Dean of the School of Engineering and Applied Science, and curvilinear transformations of those factors. The criterion variables were achievement in Engineering 205: Mechanics of Solids and grade point average in all courses other than Engineering 205 during the semester.

Suppes (15) put forth the following argument for curvilinear regression:

> . . . it is almost as easy to deal with simple nonlinear models as linear ones. Exploring alternatives to linearity provides excellent insight into the nature of the relations between the variables . . . .
>
> If we think the effects of increase in x or y proceeding at a faster than linear model, we can estimate the number of parameters in a quadratic model. On the other hand, if we think the nonlinear increase in y with increases in x as less than linear, we can easily test the logarithmic model.
>
> It is fantasy that we must always test for linear relations.

Thus, a general model in the form

$$Y = AX + E$$

may become

$$X = AX^2 + E$$

or

$$Y = ALCC\ X + E$$

or even some combination of these equations.

Thus, the most general form of curvilinear predictor equation may be written as the linear combination.

$$Y = a_1 f_1(X_1) + a_2 f_2(X_2) + \ldots + a_n f_n(X_n) + e$$

where

Y is the vector of observed or estimated values of some random variable.

X_i is a vector of the known values of the independent or predictor variable.

f_i is the function which provides a curvilinear transformation of the independent variable x_i.

a_i is a parametor of the system which is to be estimated from the data.

e is the residual vector which has as elements differences or discrepancies between corresponding observed and estimated values in the dependent variable, Y.

It is possible for some i and j that $f_i = f_j$ or $X_i = X_j$.

The use of curvilinear predictor models is appropriate in situations in which the simple linear forms of variables are inadequate for the purpose of expressing the criterion variable as a linear combination of the independent variables. Given a set of empirical data for which a curvilinear relationship exists between variables, the general equation is first generated. This process is at best haphazard. Lewis (11) noted the following:

> It is apparent that curve fitting is largely a trial-and-error process. In a sense, it is an art; it cannot be reduced to a set of inflexible rules. There is always room for disagreement and for judicious decisions.

In the present study, the author adapted certain subroutines of the program ITERPEG2 to transform linear variables using the FORTRAN functions defined by the system. These functions included:

1. Applying a power function to variables: square and cube.

2. Applying trigonometric functions to variables: sine, cosine, and tangent.

3. Applying the exponential function with base e to variables.

4. Applying the natural logarithmic and base 10 logarithmic functions to variables.

A number of vectors were developed in this study. The study investigated two criterion variables: achievement in Engineering 205: Mechanics of Solids and grade point average in all courses other than Engineering 205 during the semester. Six independent continuous vectors were produced from certain student related factors. These continuous vectors were: mathematics aptitude, verbal aptitude, previous grade point average, school year, rank in high school class, and size of high school class. The continuous independent vector percentile rank in high school class was generated from the latter two vectors. The categorical vectors were: sex, college major, and performance level in mathematics.

Additional vectors were generated to investigate any relationship between the treatments and the independent variables. These vectors were formed as the direct product of treatment vectors and independent vectors.

The curvilinear transformations generated a large set of functional vectors. The transformations were a result of applying the functions described above to significant continuous and categorical independent variables where they applied.

Stepwise regression using the computer program of the Statistical Package for the Social Sciences, developed by the International Business Machine Corporation, was done on a combination of linear and curvilinear variables in order to achieve a "best" model of the student with certain student related factors. Stepwise regression is a powerful variation of multiple regression which provides a means of choosing independent variables that will provide the best prediction model possible with the smallest number of independent variables. In this way, a best fitting curve is obtained from a set of empirical data. Thus, stepwise regression analysis gives a quick and efficient method to establish a near optimum solution.

The method is best described by relating its use to this study. It recursively constructed a prediction model one independent variable at a time. The first step was to choose the single variable which gave the best prediction. The next variable added to the model was that which provided the best prediction in conjunction with the first variable. The method proceeded in this recursive fashion adding variables step by step until either the desired number of independent variables was obtained from the model or until no other variable made a significant contribution to the model. For the specific model obtained for the data of this study, a precision model for each criterion was produced by specifying that variables be added to the model as long as there was an increase in the squared multiple correlation coefficient of at least .001. A more general model for each criterion was formed by limiting the model to the first 7 variables or as long as there was an increased in the squared multiple correlation coefficient of .03. This was essentially an arbitrary decision. However, Bormuth (2) has discussed the balance which must be achieved among precision, predictive validity, and economy of effort of determination and use of curvilinear regression equations. It appears that he is of the opinion that there are no general rules for determining the appropriate number of variables in the regression equation.

At each step of the procedure, the program selected the optimum variable, given the other variables of the predictor model. The program also provided the following information: multiple correlation coefficient squared, increase in multiple correlation coefficient squared, beta weights, and the F-ratio and degrees of freedom of the model.

When an equation is obtained from a set of empirical data, how well does the equation represent that data? If the squared multiple correlation coefficient is quite high, it may be concluded that a major portion of the variance of the dependent variable is attributable to changes in the independent variables and that only a small portion is due to other factors (11). However, the results of work by Bormuth (2) case doubt on whether it is possible for a regression equation to simultaneously exhibit high precision and predictive accuracy. For an equation to have high precision, it must contain a relatively large number of variables. But if many variables are included within the equation, the equation would almost certainly lack accuracy of prediction. Adding variables to a regression equation also adds to the error normally associated with the estimation of the beta coefficients. At some fairly early point, the error added by each new variable begins to exceed whatever predictive validity the variable may have added. Bormuth (2) made the following statement concerning this difficulty:

> Adding enough variables to obtain a formula having high precision will result in a formula having low predictive validity. Obviously, some sort of compromise has to be reached in a way which is not entirely clear.

Hence, the high squared multiple correlation coefficients obtained for several models in this study reflect only the data obtained in the study. That is, these models have high precision and provide a close fit of the data, but according to Bormuth they probably have a very low predictive validity. These models should not be generalized to other samples. More generalizable models were constructed by limiting the number of variables of the regression equations. In view of Bormuth's work, these models had higher predictive validity than the precision models, but in actuality replication on further samples of the population probably would determine their validity. Thus, a distinction was made in analyzing the results between precision equations of the data with many variables and more general models with a somewhat smaller number of variables in the regression equation.

IX. FINDINGS

The following are the important results of the study:

1. There was a significant difference at the .05 level of confidence in mean student achievement on the final examination of Engineering 205: Mechanics of Solids in favor of the self-study computer based treatment group over the traditionally taught group (F-Ratio = 3.5511, $df_1 = 2$, $df_2 = 178$).

A comparison of the mean achievement showed the experimental group having an average mean difference of 13.3094 over the traditional group. Table 1 shows these results.

TABLE 1

MEANS OF CRITERION SCORES BY TREATMENTS

Treatments	Achievement	Grade Point Average
T_1	89.5525	2.7282
T_2	76.2431	2.3413

TABLE 2

CURVILINEAR REGRESSION EQUATION OF STUDENT ACHIEVEMENT FOR COMPUTER BASED TREATMENT

Dependent Variable	Function (Variable)	Beta
Student Achievement	Sin (PGPA)	-1.63625
	(App. Math)	-.40517
	Exp (Nuclear)	-.22051
RSQ=.84298	Cos (Size Class)	-.29923
	Tan (PGPA)	-.81588
	Cube (% rank)	.27138
	Cube (Sat-M)	.20953
	Constant	76.57948
	F-Ratio	13.03853*

*Significant

TABLE 3

CURVILINEAR REGRESSION EQUATION OF STUDENT GRADE POINT AVERAGE FOR COMPUTER BASED TREATMENT

Dependent Variable	Function (Variable)	Beta
Grade Point Average	Sin (PGPA)	-.78932
	Exp (SY)	.42355
	Sin (SAT-V)	.26152
	Tan (% rank)	-.31215
RSQ=.87329	Exp (Civil)	.27694
	Exp (Nuclear)	.19674
	Exp (Chemical)	.15084
	Constant	1.72114
	F-Ratio	16.73818*

*Significant

TABLE 4

CURVILINEAR REGRESSION EQUATION OF STUDENT ACHIEVEMENT FOR TRADITIONAL TREATMENT

Dependent Variable	Function (Variable)	Beta
Student Achievement	Sin (PGPA)	-.57931
	Sin (Size Class)	.20690
	Sin (% Rank)	.15347
	Sgrt (% Rank)	.12580
RSQ=.69696	Sin (SAT-M)	-.13023
	Cos (Size Class)	-.13516
	Exp (Chemical)	.11047
	Constant	45.37738
	F-Ratio	18.76180*

*Significant

TABLE 5

CURVILINEAR REGRESSION EQUATION OF STUDENT

GRADE POINT AVERAGE FOR TRADITIONAL TREATMENT

Dependent Variable	Function (Variable)	Beta
Grade Point Average	(PGPA)	.66659
	Cos (Size Class)	.21278
	Tan (SAT-U)	-.11145
	Sqr (SAT-M)	.11272
RSQ = .79661	Tan (SAT-M)	.10969
	Cos (SAT-M)	.08699
	Sin (Size Class)	.07241
	Constant	-.12307
	F-Ratio	35.34901*

*Significant

2. There was no significant difference at the .05 level of confidence in student grade point average during the semester of the course between the treatment groups. However, the student grade point average during the semester of the course was higher for the self-study computer based treatment group than for the traditionally taught treatment group (F - Ratio = 2.1942, $df_1 = 2$, $df_2 = 178$).

3. Statistically, there was a significant relationship between the self-study computer based instruction and certain student related factors in terms of student achievement on the final examination in Engineering 205: Mechanics of Solids and student grade point average during the semester of the course. Thus, models of the student were produced which met the statistical criterion for predicting student achievement and student grade point average for the self-study computer based treatment. However, the validity of these models is open to question and can be determined by replication on similar samples. See Tables 2 and 3 for these results.

4. Statistically, there was a relationship between traditional instruction and certain student related factors in terms of student achievement on the final examination in Engineering 205: Mechanics of Solids and student grade point average during the semester of the course. Thus, models of the student were produced which met the statistical criterion predicting student achievement for the particular course and overall achievement for courses during the semester for the traditionally taught treatment. However, the validity of these models is open to question and can be determined by replication on similar samples. See Tables 4 and 5 for these results.

5. There was not homogeneity of regression equations with respect to student achievement on the final examination in Engineering 205: Mechanics of Solids for treatment at the .05 level of confidence. Therefore, no model of the student was determined which could predict student achievement on the final examination regardless of the type of instruction (F - Ratio = 15.8164, $df_1 = 1$, $df_2 = 169$).

6. There was not homogeneity of regression equations with respect to student grade point average during the semester of the course for treatments at the .05 level of confidence. Therefore, no model of the student was determined which could predict student grade point average during the semester of the course regardless of the type of instruction (F - Ratio = 17.7123, $df_1 = 1$, $df_2 = 169$).

7. There was not homogeneity of regression equations with respect to both criterion variables for treatments at the .05 level of confidence. Therefore, no "best" model of the student was determined which could be a predictor of either student achievement or student grade point average regardless of the type of instruction (F - Ratio = 37.4271, $df_1 = 3$, $df_2 = 173$).

X. CONCLUSIONS

As a result of the findings of this study, the following conclusions are drawn:

1. The self-study computer based instruction is an effective mode of instruction in a university engineering course. Students who receive this type of instruction perform significantly better than students in traditionally taught classes.

2. Students in self-study computer based instruction do not appear to have significantly lower student grade point average during the semester of the course than do conventionally taught students. On the contrary, the results seem to suggest that students in a self-study computer based instructional course have as high or higher grade point averages during the semester of the course as compared to the grade point averages of students in traditionally taught classes. One can conclude, then, that the additional time, if any, spent in obtaining proficiency in the self-study computer based instruction was not accompanied by a reduction in grade point average in all courses other than Engineering 205 taken during the semester.

3. Models of the student were constructed using certain student related factors in an attempt to predict achievement in a self-study computer based instructional course in engineering and grade point average during the semester. It is possible to develop a model. This is very good in terms of variance accounted for by using curvilinear analysis. However, because of the large number of variables involved, the predictive value of such a model is probably low.

4. Models of the student were constructed using certain student related factors to attempt to predict achievement in a traditionally taught engineering course and student grade point average during the semester of the course. It is possible to develop a model which can account for much of the variance by using curvilinear analysis. However, because of the large number of variables involved, the predictive value of such a model is probably low.

5. There does not appear to be a model of the student which could be constructed and which could predict student achievement regardless of the instructional method using the student related factors of this study.

6. There does not appear to be a model of the student which can be constructed and which could predict student grade point average regardless of the instructional method using the student related factors of this study.

Since the study was restricted to students in similar curricula and since the student related factors were limited in scope, the conclusions are not broadly generalized, but should be confined to the scope of this study.

The findings indicate that more research should be conducted in the area of the efficiency of curvilinear regression analysis. There are broad gaps in the research literature, and the difficulties involved are extensive.

The findings of this study indicate that no "best" model of the student could be determined using the student related factors defined in the study. However, these factors did not include important characteristics such as attitudes, motivation, and background factors. This is a wide area of research.

BIBLIOGRAPHY

1. Atkinson, R.C. and Wilson, (editors), Computer-Assisted Instruction. New York: Basic Books, Inc., 1965.

2. Bormuth, John R., Development of Readability Analyses. Chicago: University of Chicago Press, 1969.

3. Bottenberg, P.A. and Ward, Applied Multiple Linear Regression. Texas: U.S. Air Force, 1963.

4. Dorn, William S., "Computer-Extended Instruction", Mathematics Teacher. February, 1970.

5. Gange', Robert M., "The Learning of Principles", Analysis of Concept Learning. New York: Academic Press, 1966.

6. Hansen, D.N. Learning Outcomes of a Computer Based Multimedia Introductory Physics Course. Tallahassee, Florida: CAI Center, Florida State University, 1968.

7. Hansen, D.N., "An Investigation of Computer Based Science Testing", Progress Report. CAI Center, Florida State University, 1967.

8. Hughes, Helen S., "Gauss, Computer-Assisted", Mathematics Teacher. February, 1971.

9. Keats, John B. and Hannenm, "Definitions and Examples as Feedback in a CAI Stimulus-Centered Mathematics Program", Journal For Research in Mathematics Education. March, 1972.

10. Ledet, Nancy, et. al., Computer-assisted Instruction Program: Tennessee State University. Stanford: Institute for Mathematical Studies, 1973.

11. Lewis, Don, Quantitative Methods in Psychology. New York: McGraw-Hill, 1960.

12. Lowry, William C. and Spraker, Predicting Success in First Year of Engineering Study. Charlottesville: Division of Educational Research of the University of Virginia, 1959.

13. Suppes, Patrick, et. al., "Teacher's Handbook for CAI Courses," Technical Report No. 178. Stanford: Institute for Mathematical Studies, September, 1971.

14. Suppes, Patrick, "Computer-Assisted Instruction at Stanford," Technical Report N. 174. Stanford: Institute for Mathematical Studies, May, 1971.

15. Suppes, Patrick, "Facts and Fantasies of Education," Technical Report No. 193. Stanford: Institute for Mathematical Studies, October, 1973.

16. Suppes, Patrick, "Computer Technology and the Future of Education," Phi Delta Kappan. April, 1968.

17. Suppes, Patrick, "Modern Learning Theory", American Educational Research Journal. Volume 1, No. 2, 1962.

18. Ward, J.M., "Multiple Linear Regression Models," Computer Applications in the Behavioral Sciences. New Jersey: Prentice Hall, 1962.

19. Whitted, J.M., et. al., Development and Evaluation of an Automated Multi-media Course on Transistors. Wright-Patterson AFB, Ohio: Air Force Systems Command, 1966.