A COMPARATIVE STUDY OF THE EFFECTIVENESS OF TWO BAYESIAN MODELS FOR PREDICTING THE ACADEMIC SUCCESSES OF SELECTED ALLIED HEALTH STUDENTS ENROLLED IN THE COMPREHENSIVE COMMUNITY COLLEGE

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TABLE OF CONTENTS

Chapter Page

LIST OF TABLES

Table		Page

Table		Page

Chapter 1

INTRODUCTION

Comprehensive community colleges were established in the mid-Twentieth Century to democratize higher education. These colleges proposed to make higher education available to all persons who could profit from their programs and curricula. Low tuition and easy accessibility were two predominate features of these commuter colleges. Teachers were to teach and not research. Testing for placement would replace entrance examinations that had previously been used to limit student accessibility.

New curricula leading to careers in the semi-professions were developed as enrollments soared dramatically. Five hundred new community colleges opened their doors during the 1950's and 1960's. By the 1970's approximately 1,200 community colleges were enrolling 3,000,000 students (Hall, 1974, p. 9).

As the community college movement grew, the needs for guidance and counseling became increasingly prominent because of the widely diversified course offerings and an open-door philosophy which admitted students with the widest ranges of abilities, characteristics, and interests (Koos, 1970, p. 549). Counselors and faculty members assumed roles as specialists in the placement of students in such widely diversified programs as developmental-remedial, occupaticnal-technical, or general education and liberal arts.

THE PROBLEM

The "Virginia approach" to democratizing higher education began in the Fall of 1966 with the opening of Virginia Western Community College and Northern Virginia Community College. Total enrollments for these two institutions were 3,578 students (Vaughan, 1971, p. 94). By the Fall of 1974, a total of 64,817 students was enrolled in the twenty-three colleges that comprised the Virginia Community College System (Virginia Department of Community Colleges, 1975, table 1A). From 1966 to 1974 widely diversified programs and curricula were added in order to meet the changing educational needs of Virginia. These diverse educational programs and curricula attracted new, non-traditional students whose personalities, interests, academic aptitudes, socioeconomic backgrounds, and other factors differ significantly with more traditional college students (Trufant, Kelly, and Snyder, 1975, p. 14). Because of these diverse student groups, the need for special programs of counseling and guidance appeared early as Virginia Community College educators moved to provide services that would assist each student to make sound decisions regarding his occupational, educational, and personal-social plans (Virginia Western Community College, 1974, p. 15). Therefore, in the typical community college, both quantitative and qualitative growths in programs and services were accomplished as the individual college moved to provide higher educational opportunities (Virginia Community College System, p. 4).

One area of major expansion in the Virginia Community College System (VCCS) in the early 1970's concerned the growth of the allied health fields of Dental Assisting, Nursing, Radiology, Mental Health, Dental Laboratory, Medical Records, Physical Therapy, Mortuary Science, and Respiratory Therapy. These programs were added to provide specialized training and experiences for paraprofessionals in the health fields. Because of a multiplicity of factors such as high enrollment demands, limited institutional spaces, and the high cost of programs, many community colleges were forced to place stringent admission requirements in the guidance and selection of students for several programs in these allied health areas. Although the "open door" policies of the individual colleges did not close, admissions to certain allied health programs were limited by the factors previously identified. Areas that limited student enrollments were typically Nursing, Radiology, Mental Health, Dental Assisting, and Dental Hygiene.

Present Status of the Problem

In this guidance-selection environment in which there were more candidates than vacancies, methods and/or procedures have been established that discern the "best" applicants. Two guidance-selection models which can be represented as two extremes on a continum have been traditionally used in these selection procedures. First, classical statistical predictive procedures employing multiple correlation, multiple regression, discriminant analyses, and/or other multivariate statistical techniques have been employed to "predict" the students who would have the highest grade point averages after their first quarter of study. In this model students were selected on the basis of their predicted criterion scores. However, in reality, most colleges do not employ this statistical method. Instead they employ a second type of guidance-placement model in which counselors and/or allied health faculties select the "best" candidates by examining previous academic records in conjunction with some type of student interview. Counselors typically object to the statistical selection model because of a multitude of reasons including in large measure a lack of understanding of the statistical methodologies. Other more valid objections to the use of classical statistical procedures have been expressed by several authors. Novick and Jackson (1969, p. 5) found that:

> When society adopts the formal classification model, it is satisfied because assignments, on the average, are then good. The student, however, is unconcerned with such average good. If he perceives that he belongs to some subgroup for which, on the average, poor assignment decisions are made, it will not comfort him to know that the system works well for almost everybody else.

Furthermore, these authors concluded that the impersonal classical statistical prediction models did not allow counselors and/or faculty advisors the advantage of bringing to bear their personal knowledge of those students with whom they have advised and counseled.

Another problem with the classical statistical prediction models was found to be in the sample size of the allied health programs. In general the lack of sufficient data and the heterogeneity of community college programs has meant that the common procedure of pooling information across all students that is customary in senior institutions was not valid for the small enrollments of allied health programs. In referring to the predictive research services of the American College Testing Program, Novick and others (1971) stated this problem as follows:

> A requirement for participation in the predictive research services has been the availability of a minimum sample of 100 students in a single year. This arbitrary number was set as a result of experience suggesting that smaller samples typically provide an unsatisfactory amount of sampling fluctuation (p. 3).

A more conservative approach has been recommended by Kerlinger and Pedhazur (1973, p. 442). In examining sample sizes in regression analyses, these authors proposed that even larger samples -- over 100 and preferably 200 or more -- were needed to protect against capitalization on chance. These larger sample sizes have not been available in most allied health programs of community colleges except by combining data over several years.

The counselor-selection model in which counselors and/or allied health faculties select the "best" qualified candidates by examining previous academic records with student interviews has traditionally been the most widely accepted selection procedure. This approach allowed the counselor and/or faculty advisor the advantage of bringing to bear all relevant information concerning the students and their educational goals. In this model the counselor/advisor was not limited to the usual predictors such as previous academic grades and/or standardized tests but the counselor's professional judgments concerning the students' motivations, study skills, and their desires to enter specific programs were added to the model. Diverse factors such as whether or not the student was financially secure, had just recovered from an illness, or even the fact that there was a recent death in the family were unquantified variables that were occasionally investigated and identified with the selection procedures. In summary, the professional skills of the advisor were the major criterion for selecting the "best" candidate.

The weaknesses of the classical statistical prediction models and the counselor-selection models were summarized as follows:

1. The classical statistical prediction models were impersonal, sometimes termed dehumanizing, and not fully understandable by the counselors. These models typically

allowed little or no imputs from professionally trained counselors and/or faculty advisors. Because the sample sizes of most allied health programs were small, there were major problems in pooling information across students from widely different curricula.

2. The counselor-selection models could not produce consistent, predictable, and dependable results regarding the selection conclusions for individual applicants. Selection decisions were typically made without discerning quantitative questions concerning what had been measured and why. For example, a student could be rejected for having a low high school chemistry grade when, in fact, no data had been discerned to verify the need for a high chemistry grade in order to successfully complete the program of study.

Statement of the Problem

Since neither the classical statistical model nor the counselor-selection model have typically utilized all the information about the student, a need for a more efficient and effective guidance-selection model was indicated. A model that would allow for both counselor inputs and statistical analyses would certainly be more appropriate for the guidance-selection procedures of selecting allied health students in the modern, comprehensive community college. This model should be sensitive not only to the traditional data but should take into account the unique characteristics of the individual students and programs. One type of models whose supporters believe can accomplish these objectives has been developed from the application of Bayesian statistical procedures in the guidance and counseling function. Novick (1970, p. i.) found that Bayesian methods are "uniquely capable of combining prior, collateral, and direct experimental information to provide probabilistic statements about parameters descriptive of students, educational programs and their relationships." Powers (1973, p. 12) found that the Bayesian model he proposed could incorporate individual characteristics as well as impersonal predictive measures to provide posterior probabilities of success. He concluded that Bayesian methods can be easily applied to a large number of counseling instruments and procedures in order to furnish students with valuable, personal information concerning their educational careers. These authors concluded that the Bayesian methods have great applicability to modern educational problems.

Purpose of the Study

The purpose of this study was to present and evaluate Bayesian-type methods for the guidance and selection of students for allied health programs of Nursing, Radiology, Mental Health, and Dental Assistant. These methods involved the construction of models which utilize all relevant information in establishing a guidance-selection procedure that would combine the strengths of the professional judgments of the counselors and faculty with the established methodological procedures of certain types of multivariate statistics. Such methods would provide a firmly based scientific procedure that could be more defensible to the public scrutiny for greater accountability of education programs, procedures, and expenditures.

Two Bayesian-type decision-making models were proposed and evaluated. Bayesian-Type Model 1 provided a probability estimate that the student would successfully complete the program of study. Bayesian-Type Model 2 provided a predicted first-quarter GPA for new students entering the allied health curricula for Fall 1975. In the present study the probability estimates of program completion were considered more important than the intermediate criteria of first-quarter GPA's because degree attainment in the allied health areas has typically been used to screen and/or restrict entry into these professions.

In order to effectively evaluate the Bayesian-type models, the study proposed to compare the predictive efficiencies of the Bayesian-type models to the predictive efficiencies of the counselor-selection models and the classical statistical models. These comparisons were examined in terms of actual student data of both successful program completion and first-quarter GPA's. Several statistical methods and tests such as average absolute and squared prediction errors, one-way analysis of variance, and the Friedman test were employed in evaluating the predictive efficiencies of the three models on the two predictive indices of first-quarter GPA's and probability estimates of program completion.

Specific Objectives of the Study

The study proposed to examine the following specific objectives:

1. To develop and implement a Bayesian-type model for predicting probability estimates of program completion in the allied health curricula of Radiology, Nursing, Mental Health, and Dental Assisting.
2. To develop and implement a Bayesian-type model for predicting first quarter GPA's in the allied health curricula of Radiology, Nursing, Mental Health, and Dental Assisting.
3. To evaluate the efficiency of the above Bayesian-type prediction models in comparison to the counselor guidance-selection models and the classical statistical models.

Justification of the Study

The cost of educating students in all allied health areas has been found to be extremely high in relation to other community college curricula. This cost can be further augmented by substantial number of failures and dropouts for whom expenditures will be totally lost. Therefore, a guidance-selection system that can reduce attrition in these allied health areas would substantially reduce overall cost per graduate while increasing the supply of qualified paraprofessionals.

Further justification for the study was based on the fact that, in most cases, all community colleges have received more applicants for these allied health curricula than there were available openings. For example, the American Dental Association reported that for Fall 1974 only 56 percent of all applicants were offered admission to dental assisting programs in the United States (American Dental Association, 1975, pp. 1-2). Preliminary investigations indicated that locally there was an approximate ratio of over two-to-one in terms of applicants to available openings with a higher ratio for Nursing. Therefore, the need to establish valid selection procedures was readily apparent in order to select the applicants that will most likely succeed in their program of study.

THEORETICAL FRAMEWORK

The design of the study required the construction of three prediction models in developing probability estimates of program completion and predicting first quarter college grade point averages. For classification convenience, the three prediction models used in developing probability estimates of program completion were named as follows:

1. Bayesian Model 1 -- Estimating Probabilities of Program-Completion -- A Bayesian-type procedure
2. Counselor Model 1 -- Estimating Probabilities of Program-Completion -- A counselor judgment model

3. Classical Statistical Model 1 -- Estimating Probabilities of Program-Completion -- A linear model built on traditional data use

The three prediction models used in predicting first quarter grade point averages were named as follows:

1. Bayesian Model 2 -- Predicting First-Quarter GPA's -- A Bayesian-type multiple regression model
2. Counselor Model 2 -- Predicting First-Quarter GPA's -- A counselor judgment model
3. Classical Statistical Model 2 -- Predicting First-Quarter GPA's -- A linear model built on traditional data use

Bayesian Model 1 -- Estimating Probabilities of Program-Completion

Bayesian Model 1 required the counselor and/or faculty advisor to assign an *a priori* probability that a particular student will succeed in a specific allied health program. In order to arrive at this probability, the counselor and/or faculty advisor must bring to bear all relevant information that was known about the student and his career objectives. The advisor was not limited to the usual predictors such as scores on achievement tests, high school grades, and/or high school rank but attention to the student's motivation, study habit, age, and other factors that influence college success were considered and quantified in the *a priori* probability. Thus the *a priori* probability represented a personal level of professional judgment by the advisor in considering data peculiar to a specific student.

After the assignment of *a priori* probabilities it was necessary to obtain likelihoods (conditional probabilities) that the student would graduate from a specific allied health program. The likelihood probabilities were developed by employing discriminant analysis to student characteristics and achievement scores using data of previous graduates and nongraduates. Likelihood assignments were made using the posterior probability of graduate group membership derived from discriminant analysis scores.

The posterior probability of successful program completion was obtained by combining the a priori probability and likelihood using a discrete form of Bayes' formula (Powers, 1973, p. 4). This formula was presented as follows:

$$P(S) = \frac{xy}{xy + (1 - x)(1 - y)} \qquad (1)$$

where P(S) represented posterior probability of successful program completion, x represented a priori probability assigned by the counselor and/or faculty advisor, and y was the likelihood obtained from the expectancy table of the posterior probabilities of graduate group membership derived from discriminate analysis scores. These calculations produced a Bayesian-type posterior probability of successful program completion.

<u>Counselor Model 1 -- Estimating Probabilities of Program-Completion</u>

Counselor Model 1 required the counselor and/or faculty advisor to assign an estimate of the probability that a particular student will succeed in a specific allied health program. This probability was the same probability that was used as the <u>a priori</u> probability in the Bayesian Model 1. It represented the advisor's professional opinions in considering data peculiar to a specific student. In assigning this probability the advisor considered all available student information including high school grades, achievement/aptitude scores, high school rank, etc. while adding and quantifying professional judgements concerning motivation, study habits, age, etc.

Classical Statistical Model 1 -- Estimating Probabilities of Program-Completion

Classical Statistical Model 1 utilized a discriminant analysis with the dependent variable being graduate and nongraduate group membership. Data from previous students were used to develop discriminate functions that would predict the probable future status of new students entering the allied health programs. The data base was limited to traditional measures of prior academic performance and represented current practices using classical statistics.

Bayesian Model 2 -- Predicting First-Quarter GPA

Bayesian Model 2 was developed as a special case of the Bayesian m-group regression analysis (Shigemasu, 1975) that was theoretically developed by D. V. Lindley (1969a, 1969b, 1970). This procedure resulted from an outgrowth of work by Truman Kelley. The Kelley method (1927) estimated a subject's true score by weighing the difference between the individual's observed score and the average value for all observed scores by test reliability. Kelley showed that unless the reliability of the test was high this procedure would provide estimates with substantially lower standard errors that the estimates based solely on the observed scores. Lindley (1970) demonstrated that the logic of Kelley's method could be used to improve predictions in individual groups by using information both from that group and from similar groups. Although the actual mechanics were complicated, they effectively involved the same kind of averaging as originally proposed by the Kelley method (Novick, Jackson, Thayer, and Cole, 1971,

p. 5). Jackson, Novick, and Thayer (1971) developed methods and procedures for obtaining Bayesian estimates of regression parameters by implementing Lindley's theory for the m-group regression. This procedure utilized the data of the group under study as prior information and the data from similar groups as collateral information. In applying this Bayesian procedure, it was proposed that the Bayesian estimates of the regression weights should yield very meaningful improvements over the classical least squares regression estimates.

Counselor Model 2 -- Predicting First-Quarter GPA's

Counselor Model 2 required the counselor and/or faculty advisor to predict the first quarter grade point average that a particular student might obtain. This estimate represented the professional opinions and judgments of the counselor/advisors as discerned from reviewing the student's academic records and by interviewing the student.

Classical Statistical Model 2 -- Predicting First-Quarter GPA's

Classical Statistical Model 2 employed multiple regression in the traditional sense in that only certain academic variables were used as independent variables with grade point averages as the dependent variable. The SPSS Statistical Package for Social Science (Nie and others, 1975) Regression computer program was used to develop the prediction equations for the allied health programs.

DEFINITION OF TERMS

For the purpose of the study, certain terms were defined as follows:

A Priori Probabilities are prior probabilities P(Aj) represented in Bayes' Theorem;

Allied Health Curricula are two-year or four-quarter community college occupational-technical programs in Dental Assisting, Mental Health, Nursing, and Radiology;

Bayes' Theorem is a general formula that gives the relationship among various conditional probabilities as follows:

$$P(Aj/B) = \frac{P(B/A_j)P(A_j)}{P(B/A_1)P(A_1) + P(B/A_2)P(A_2) + \ . \ . \ . + P(B/A_j)P(A_j)}$$

for any event Aj, where j is an integer between 1 and J, inclusive;

Posterior Probabilities are conditional probabilities P(Aj/B) defined in Bayes' Theorem;

Probabilities are values between 0 and 1, inclusive, that express uncertainty in quantitative terms;

SCOPE AND LIMIT OF THE STUDY

1. The study was limited in that certain restrictions were placed on the six prediction models. This fact was especially true for the Classical Statistical Model 1 which employed multiple regression in the traditional sense because counselors' evaluations of students first enrolled Fall 1972, 1973, and 1974 were unavailable to be used as independent variables in developing the GPA prediction equation; at the same time this model is an accurate representation of current use of regression.
2. The study was limited by certain time factors. This fact was especially true for the program-completion models in which third quarter enrollment was used as the graduate criterion for students first enrolled for Fall 1975. In this context students who were not enrolled for the third quarter were classified as nongraduates. This procedure was used in evaluating the prediction efficiencies of the three program-completion models.

3. The study was limited to examining a specific number of independent variables that were considered most relevant in the specific types of analysis.
4. The study was limited by the fact that missing data were found in the independent variables of high school rank and School and College Ability Tests (SCATS) scores especially for older students and those from out-of-state high schools.

SUMMARY

Because of high enrollment demands, limited instructional spaces, and the high cost of programs, many community colleges have been forced to place stringent admission requirements in the guidance and selection of students for certain allied health programs such as Nursing, Radiology, Dental Assisting, and Mental Health. Since recent research studies have reported withdrawal rates of 50 percent and higher for students entering these programs, a need for a more efficient and effective guidance-selection model was indicated. A model that accurately predicts first-quarter GPA's and efficiently estimates the probability of successful program completion would benefit both the college and the students that enroll in these programs. The purpose of the study was to present and evaluate two Bayesian models that have implications for the guidance and selection of students for certain allied health curricula of the comprehension community college. These two models were summarized as follows:

> Bayesian Model 1 -- Estimating Probabilities of Program Completion was developed from the discrete case of Bayes' formula (Powers, 1973, p. 4). Powers' methodology was extended by employing estimates of probable graduate status derived from discriminant analysis scores as likelihoods in Bayes' theorem. The efficiency of this model was compared to a counselor-selection model and a classical statistical prediction model.

Bayesian Model 2 -- Predicting First-Quarter GPA's utilized a computer program developed by Kazuo Shigemasu (1975). This model was developed as a special case of the Bayesian m-group regression analysis that was first theoretically developed by D. V. Lindley (1969a, 1969b, 1970). The efficiency of this model was compared to a counselor-selection model and a classical statistical model.

Chapter 2

REVIEW OF THE RELATED LITERATURE

Since Western societies have philosophically believed in a rough approximation of the equality of educational opportunities and instruction, studies that have identified creative and achievement potentialities of persons have been encouraged and developed in educational research. Some of the reasons for these studies were appropriately stated by Cattell and Butcher (1968, p. v.):

> The standard of living of a country is, in the end, not dependent on visible natural resources, or on monetary tricks of the economist, but is a function of the level of attainment and creativity prevailing among its citizens.

These authors concluded that it has not been enough to merely raise the achievement levels of people, but a more basic understanding of the processes of achievement and learning must be examined and developed in educational research. Therefore, the need for a greater understanding of factors that relate to and influence academic achievement has been well-established in educational research.

THE PREDICTION OF ACADEMIC SUCCESS

A review of the literature revealed a wealth of materials concerning the prognosis of college and university success. These studies have proposed to diagnose, select, and/or predict academic successes by examining certain academic and nonacademic variables and their relationship to criterion measures such as grades in individual courses, first quarter/cumulative GPA, and/or graduation from college.

Traditional Prediction Studies

Some of the earliest studies in modern educational research have attempted to explain the variability of academic success by studying the relationships of various correlates of college achievement. In many cases these studies proposed to establish standards that were used to limit college accessibility to certain students because their scores on the predictive test(s) fell below some predetermined cut-off score. Kerlinger and Pedhazur (1973, p. 4) have characterized these studies as "studying the relation between one independent variable and one dependent variable, and so on, and then trying to put the pieces together".

By the end of the 1930's however, the one-variable-at-a-time type of research was found inadequate in explaining the complexities of human learning and human behavior. While these procedures were not and cannot be considered as being invalid, they have been cited as being obsolescent, even obsolete (Campbell and Stanley, 1963, p. 2; Kerlinger and Pedhazur, 1973, p. 4).

Since many natural phenomena and constructs have several sources of variation, it became apparent that more than one independent variable was required to explain the variability of academic ability as measured by some dependent variable such as grade in classes, first quarter/cumulative GPA, and/or graduation from college. The analytic-statistical technique most widely accepted to accomplish the objective of analyzing the collective and separate contributions of two or more independent variables to the variation of one dependent variable was a method called multiple regression, a branch of multivariate analysis.

Although proponents of the multivariate methods have concluded that the unvariate methods are appropriate in certain classical experimental/control group experiments, there has been an overwhelming case made for adopting multivariate methods in the field of educational and behavioral research (Cattell and Butcher, 1968, p. 151; Cattell, 1966, p. 3). Therefore, the multivariate data analysts used the fitting of linear functions in order to find a relatively small set of variables which will suffice to "explain" all other variables because to achieve such a small set of "explainer" variables is the essence of scientific parsimony (Nunnally, 1967, p. 151).

Bayesian Prediction Studies

In recent years the application of Bayesian statistical procedures has received attention in the field of guidance and counseling (Powers, 1973, p. 1). Although Bayesian methods have not been accepted on the spot, proponents have found that these methods have wide applicability to many prediction problems, especially when sample sizes were small (Jones and Novick, 1972, p. 2). Phillips (1973, p. 5) stated the essence of Bayesian methods as follows:

> Opinions are expressed in probabilities, data are collected, and these data change the prior probabilities, through the operation of Bayes' theorem, to yield posterior probabilities.

Phillips (1973, pp. 9-10) concluded that

> Bayesians believe that a scientist should quantify his opinions as probabilities before performing an experiment, then do the experiment so as to collect data bearing on those opinions, and then use Bayes' theorem formally to revise those prior probabilities to yield

> new, posterior probabilities. These posterior probabilities are taken as the scientist's revised opinion in the light of the information provided by the data. That is the key idea behind all Bayesian methods.

In applying Bayesian methods to the prediction of educational performance, posterior probabilities must be obtained from the product of _a priori_ probabilities and likelihoods. Novick (1970, p. 2) stated that this straightforward application adds sample information to _a priori_ information about parameters descriptive of students, educational programs and their relationship. The key idea of this Bayesian viewpoint that differs with "classical" statistics concerned the use of _a priori_ probabilities. Novick (1970, p. 3) noted:

> The price one pays for the elegance of the Bayesian analysis is the need for specifying a prior Bayes distribution summarizing prior information or beliefs. There is controversy on this point because (a) some people do not wish to interpret probabilities as degrees of belief, but only as relative frequencies as in classical theory and, (b) even accepting a belief interpretation for probabilities there is still a very real problem of just how to quantify these beliefs. The latter problem is particularly acute because in any important study experts will disagree on the evaluation of prior information. Indeed the purpose of the study is typically to resolve such disagreements.

Classical statisticians have typically objected to _a priori_ probabilities as being personal and subjective which must be the antithesis of science. Novick and Jackson (1974, pp. 144-154) have classified and discussed many of the _a priori_ probability objections typically raised by classical statisticians:

> Objection 1. _A priori_ probabilities are like betting which is irrelevant to the process of scientific inference. It is also possibly immoral, and, therefore, cannot be contemplated.
>
> Counterpoint. This argument is rejected because a little reflection will reveal that we are inescapably involved in betting situations. To marry, to eat, or

to admit student A over student B are only three examples in which we gamble and examine costs against gains.

Objection 2. Subjective probabilities such as "my probability" and "your probability" are the antithesis of science whose aim is to always make "objective" statements.

Counterpoint. Scientifically controlled experiments are designed (1) to make the errors and their standard deviation as small as possible and (2) to repeat experiments until a firm conclusion is established; therefore, scientific results should not be classified as "objectivity" but as sample precision. Differences between "exact" and "nonexact" sciences lies chiefly in the extent in which observational errors can be controlled in terms of the precision of the experiment rather that between any fundamental differences between "objective" and "subjective" inferences.

Objection 3. Different persons will assign different a priori probabilities for the same event.

Counterpoint. Bayesian statisticians accept this fact and even agree; however, the wise scientist provides *a priori* probabilities that can be supported or presents strong evidences which can offset other opinions by his peers.

After assigning an *a priori* probability, the second step in applying Bayes' Theorem must be to collect data inserting values known as likelihoods. Since these values can be interpreted in terms of relative frequency, they have been readily acceptable to the classical statistician. *A priori* probabilities and likelihoods are then combined in Bayes' Theorem to yield posterior probabilities concerning the probability of group membership given certain academic scores.

Community College Prediction Studies

Although community colleges have typically shown little interest in prediction studies because of their "open door" policies, an investigation of previous studies indicated that there have been some concerns in counting, describing, and classifying students that drop out of community colleges. These studies (A. W. Astin, 1971, 1972a;

H. S. Astin, 1970; Astin and Panos, 1969; Cope, 1969; De Vecchio, 1972; Newman, 1965; Summerskill, 1962; Trent and Medsker, 1967) have suggested that a number of student background characteristics may be predictive of achievement and the proneness to drop-out of college. Academic ability, secondary school grades, socioeconomic status, and educational aspirations, as well as the students' own predictions about their chances of graduating were variables that were typically investigated and described in these research studies. Under most circumstances these studies were limited in scope and inadequate in design. Little or no attempts were made to collect longitudinal data from students attending several institutions or to predict students who will drop out of college (Astin, 1975, p. 3).

Astin (1975, p. ix) found that although dropping out of college has been a much-researched topic, there has been no research that clearly revealed which factors influence students to leave or how the factors might be controlled by those with vested interest in preventing students from dropping out. Therefore, his research focused primarily on predicting rather than describing personal characteristics of college entrants (Astin, 1975, p. 22). Astin provided techniques and procedures that are presently available in which a college can reduce the total number of college dropouts rather than simply tabulating dropout rates or describing their characteristics. The essence of this procedure was to compute an individual's probability for dropping out by multiplying selected demographic and academic variables times pre-established regression weights.

Predictive Studies in Allied Health Curricula

Most of the prediction studies in the allied health curricula have been completed in nursing education. In general, these studies have been most concerned with predicting grade point averages (GPA's) or graduate success on the State Board Examination (SBE). In fact, the predicting of SBE scores has been of major concern since satisfactory performance indicates that a nursing graduate meets the legal requirements for safe practice. Miller, Feldhusen, and Asher (1968, p. 555) stated that SBE results should be discerned because these scores can be used as a criterion for evaluating graduates and the specific nursing program itself. In most of these research studies, the procedures were to examine simple and/or multiple correlations between individual predictors and SBE performance (Taylor and others, 1963).

SUMMARY

Although a review of the literature dealing with the prediction of academic success revealed a wealth of materials concerning the prognosis of college and university success, there have been few studies that dealt with the problem in an experimental fashion. In general, prediction studies have been ex post facto research in which the independent variable or variables have already occurred and the researcher starts with the observation of a dependent variable or variables. In this methodology the researcher reported results concerning the success of predicting the academic achievements of students that had already completed the dependent criterion of the study whether this criterion was first quarter grade point average or graduate/nongraduate status. Little or no efforts have been directed toward cross validation studies which predict the academic success of the next class and/or evaluate the efficiency of the prediction model.

A literature review also noted that little effort has been made toward developing and examining multiple prediction procedures. That is, most researchers have been contented to employ a single methodology in developing and evaluating prediction models. In terms of early prediction studies most researchers studied the relationships of various correlates of college achievement. However, this new enthusiasm soon gave way because the one-variable-at-a-time type of research could not explain the complexities of human behavior. In terms of more recent studies, there have been major efforts directed toward discerning academic success using multivariate types of statistics. Only in very recent years has there been any concern that Bayesian methods have great applicability to educational problems.

Furthermore, the literature search has indicated that most correlation studies that report impressive coefficients shrink to unimpressive coefficients when subjected to cross validation. Novick (1973, p. 12) found it inexcusable that we fool ourselves or others with such psuedo-statistics. Therefore, Novick concluded that the need was to develop both least squares and Bayesian regressions in one year and use these weights for predictions in the second year.

In summary, there appeared to be a need to examine certain academic prediction models in a more quasi-experimental setting with a design that utilized several types of prediction models. Although this quasi-experimental setup cannot control and manipulate any of the independent variables such as high school rank and achievement, a model can be constructed that will predict, compare, and evaluate the efficiency of certain prediction models for new classes of students who have not obtained the criteria of the dependent variable. In this respect some control over the post hoc (after this, therefore caused by this) assumption can be made. These multiple comparative procedures should also promote greater understanding among community college staffs by relating statistical prediction procedures to counselors who have typically been highly suspicious of these techniques.

Chapter 3

DESIGN OF THE STUDY

The purpose of the study was to present and evaluate Bayesian models for estimating probabilities of program-completion and predicting GPA's for students enrolled in certain allied health curricula of the comprehensive community college. The Bayesian models were compared to classical statistical prediction models based on traditional data bases and counselor/advisor prediction models.

The Sample

The sample of the study consisted of allied health students enrolled at one of the comprehensive community colleges of the Virginia Community College System. Data concerning all students who were enrolled in Dental Assisting, Mental Health, Nursing, and Radiology were collected and used from the Fall of 1972 through the Fall of 1975. Table 1 presents the number of students by program and quarter first enrolled.

Data for students enrolled from Fall 1972, 1973, and 1974 were used in developing the six prediction models for students entering in the Fall 1975.

Predictor Variables

The predictor (independent) variables consisted of an examination of selected academic variables. The tendency to throw variables indiscriminately into the analytical models was avoided by examining both

Table 1

Number of Students by
Program and Quarter
First Enrolled

Curriculum	Fall 1972	Fall 1973	Fall 1974	Fall 1975	Total
Dental Assisting	17	12	21	15	65
Mental Health	16	21	22	19	78
Nursing	30	29	46	40	145
Radiology	21	25	21	19	86
Total	84	87	110	93	374

previous research results and present theories concerning academic achievement with recommendations from allied health counselors, faculty, and administrators. These academic variables were cited as follows:

1. School and College Ability Tests (SCATS) Total Score (11th Grade Test Scores)
2. High school rank (HSR)
3. High school senior English grade (ENG12)
4. High school junior English grade (ENG11)
5. High school Algebra I grade (ALG)
6. High school Geometry grade (GEO)
7. High school Biology grade (BIO)
8. High school Chemistry grade (CHEM)

Criterion Variables

The criterion (dependent) variables consisted of the following two measures:

1. First quarter grade point average
2. Graduate or nongraduate status

First-Quarter GPA. The first quarter grade point average (GPA) was determined by dividing the total number of grade points earned (A = 4 grade points per credit, B = 3 grade points per credit, C = 2 grade points per credit, D = 1 grade point per credit, F = 0 per credit) in courses by the total number of credits attempted.

Graduate or Nongraduate Status. Graduate and nongraduate status for students entering in Fall 1972 and 1973 was determined by examining graduation listings through Summer 1975. Graduate and nongraduate status for students entering in Fall 1974 was determined by examining the Fall 1975 enrollment status of the students. Students who had completed 45 quarter hours and were enrolled in Fall 1975 were assumed to graduate because a complete examination of student flow through the allied health programs indicated that approximately 95% of the students who attain second year status typically graduate from their programs. This assumption was also used in evaluating the prediction efficiency of the three graduate/nongraduate models for students first enrolled in Fall 1975.

Statistical Methods of the Study

Several statistical methods were employed in developing the six prediction models of the study. Other statistical methods were employed to compare the prediction models.

Statistical Methods in Building the Prediction Models. Table 2 presents the data requirements and the statistical methods for developing the six prediction models.

Bayesian Model 1 derived the posterior probability of successful program completion by combining the *a priori* probability and the likelihood using the discrete case of Bayes' formula as cited in Chapter 1. Counselor Model 1 required the counselor to quantify his professional judgment/belief that the student would complete the program of study. Classical Statistical Model 1 used the discriminant function to classify probable group membership for students enrolled in Fall 1972, 1973, and 1974. After an analysis of how well the function predicted graduate and nongraduate status of students enrolled in Fall 1972, 1973, and 1974, the function was used to predict the status of students first enrolled in the Fall 1975.

Table 2

Prediction Models with Statistical Methods

Model	Data Requirement(s) for Individual Students	Statistical Methods
Bayesian Model 1 - Estimating Probabilities of Program-Completion	1. *A priori* probability	Counselor's assignment of probability of successful program completion
	2. Likelihoods (conditional) probability	Discriminant analysis for graduate/nongraduate group membership using the discriminate score to estimate the students' success in completing the specific allied health program
	3. Program completion probability	Application of the Discrete Case of Bayes' formula
Counselor Model 1 - Estimating Probabilities of Program-Completion	1. Program completion probability	Counselor's assignment of probability of successful program completion
Classical Statistical Model 1 - Estimating Probabilities of Program-Completion	1. Program completion probability	Discriminant analysis for graduate/nongraduate group membership using the discriminate score to estimate the students' success in completing the specific allied health program
Bayesian Model 2 - Predicting First Quarter GPA's	1. GPA prediction	Bayesian M-group Regression Analysis with Identical Regression Coefficients

Table 2 (continued)

Model	Data Requirement(s) for Individual Students	Statistical Methods
Counselor Model 2 - Predicting First Quarter GPA's	1. GPA prediction	Counselor's assignment of first quarter GPA
Classical Statistical Method 2 - Predicting First Quarter GPA's	1. GPA predicting	Forward stepwise multiple regression using SPSS REGR

Bayesian Model 2 utilized the computer program entitled "Bayesian M-group Regression Analysis with Identical Regression" developed by Kazuo Shigemasu (1975). GPA's were used as the dependent variable with the M-groups being the four programs of Dental Assisting, Mental Health, Nursing, and Radiology. Independent variables were cited previously. Counselor Model 2 required the counselor to quantify his/her professional judgment/belief in estimating the student's first quarter GPA. Classical Statistical Method 2 used multiple regression from the SPSS Statistical Package for Social Science (Nie and others, 1970, pp. 320-360) in developing a regression equation that was used to predict the GPA's of students first enrolled in the Fall 1975.

Statistical Methods in Evaluating the Prediction Models. Several statistical methods were employed in comparing and evaluating the effectiveness of the three prediction models used in estimating the probabilities of program completion. The difference between the predicted probability and the actual observed criterion (0 - nongraduate and 1 - graduate) for each student was computed as one measure of the error of prediction. Comparisons of the mean absolute-errors and mean squared-errors of predictions provided descriptive evaluations of the program-completion models by individual curriculum and across all curricula.

The Friedman test was used to compare the three models by ranking the absolute-errors of the program-completion models (Table 3).

In the case that the null hypothesis of equally likely rankings within a block (student) was rejected, multiple comparisons were examined for ranked data (Anderson, 1959). These tests paralleled the parametric multiple comparison tests as proposed by Tukey, Scheffé, or Duncan.

Table 3

Absolute-Errors of the Program-Completion Models
(Sample Tabulation)

Curriculum	Bayesian Model 1	Counselor Model 1	Statistical Model 1	Actual Status**
Student 1	.12 (1)*	.20 (2)*	.35 (3)*	Graduate (1)
Student 2	.22 (3)*	.20 (2)*	.15 (1)*	Nongraduate (0)
'	'	'	'	'
'	'	'	'	'
'	'	'	'	'
Student n	.17 (2)*	.15 (1)*	.26 (3)*	Graduate (1)
ΣRj (totals):	____	____	____	

*Rank Assignment

**For use in the validation study, the students first enrolled for Fall 1975 were coded as graduate (1) if enrolled in the third quarter (Spring 1976) and nongraduate (0) if not enrolled for the third quarter (Spring 1976).

The three GPA prediction models were evaluated by examining the absolute-error-loss function (Novick and Jackson, 1975), squared-error-loss function, and using an analysis of variance having repeated measures on the same elements (Winer, 1962, pp. 105-124). This analysis compared and evaluated the efficiency of the models for the individual allied health programs as well as across all curricula.

Table 4 presents the methodology for comparing the three GPA prediction models.

The average absolute-error and average squared-error functions provided descriptive comparisons while a one-way analysis of variance tested the null hypothesis of no differences as being either true or false. In the case that the null hypothesis was rejected, Tukey's multiple comparison procedures were used to locate mean differences.

Missing Data

One of the greatest problems in studies of social behavior must be the concern for missing data. In almost all social science research the investigator must be concerned with incomplete data. This study was no exception in that SCATS scores and high school ranks (HSR) were missing for some students. Table 5 indicates the number and percent of missing data by program and year first enrolled.

The number of missing SCATS scores ranged from 22 (20% of total cases) for students first enrolled Fall 1974 to 9 (10% of total cases) for students first enrolled Fall 1975. Further investigations indicated that the following two groups typically had missing SCATS scores:

1. Older students who had graduated before SCATS testing was required by the Virginia Department of Education.

Table 4

Predicted GPA, Observed GPA, Absolute-
Error, and Squared-Error
(Sample Tabulation)

All Programs	Predicted GPA: Bayesian Model 2	Predicted GPA: Counselor Model 2	Predicted GPA: Classical Statistical Model 2	Observed GPA	Absolute Error			Squared Error		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(1)	(2)	(3)
Student 1	2.750	2.900	2.860	2.800	.050	.100	.040	.0025	.0100	.0016
Student 1	2.600	2.750	2.400	2.630	.030	.012	.230	.0009	.0144	.0529
'										
'										
'										
Student n										
				Average Absolute-Error*	____	____	____			
				Average Squared-Error**				____	____	____

$$*\text{Average Absolute-Error} = \frac{\Sigma\text{Absolute-Errors}}{N}$$

$$**\text{Average Squared-Error} = \frac{\Sigma\text{Squared-Errors}}{N}$$

Table 5

Number and Percent
of Missing Data*

Curriculum	Fall 1972				Fall 1973				Fall 1974				Fall 1975				Total			
	SCATS		HSR		SCATS		HSR		SCATS		HSR		SCATS		HSR		SCATS		HSR	
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Dental Assisting (N=65)	1	6	2	12	1	8	3	25	4	19	0	0	0	0	1	7	6	9	6	9
Mental Health (N=78)	4	25	1	6	5	24	2	10	4	18	0	0	3	16	1	5	16	21	4	5
Nursing (N=145)	10	33	6	20	6	21	1	3	11	24	4	9	5	13	2	5	32	22	13	9
Radiology (N=86)	2	10	2	10	2	8	2	8	3	14	3	14	1	5	1	5	8	9	8	9
Total (N=374)	17	20	11	13	14	16	8	9	22	20	7	6	9	10	5	5	62	17	31	8
	(N=84)				(N=87)				(N=110)				(N=93)				(N=374)			

*Percents based on enrollments by curriculum and year (Table 1).

2. Several students had graduated from high schools outside the State of Virginia that did not require them to take SCATS Tests.

The number of missing data for HSR rankings ranged from 11 (13% of total cases) for students first enrolled in Fall 1972 to 5 (5% of total cases) for students first enrolled in Fall 1975. Further investigations indicated that many students with missing HSR rankings came from the same high schools. Contacts with these high schools indicated that these schools did not compute and/or report the rankings of their students. This was the case for several private schools and one area high school.

Two procedures for providing missing values were employed in the study. In terms of missing SCATS scores it was noted that approximately 52% (32 cases) of the students with missing SCATS scores had available Scholastic Aptitudes Test (SAT) scores. These SAT scores were converted to SCATS scores by using estimated SAT-SCATS equivalents tables provided by Educational Testing Service (SCAT Series 11 - Handbook, 1973, p. 69-70). In providing for the other missing values, the SPSS default method was used by replacing each missing value with the variable's mean blocked by year first enrolled and graduate/nongraduate status. This default procedure was used in providing all missing values for the 31 cases of missing high school ranks.

SUMMARY

The purpose of the study was to present and evaluate Bayesian methods for estimating probabilities of program-completion and predicting

GPA's for students enrolled in allied health curricula. The sample of the study consisted of 374 allied health students enrolled in one Virginia community college from Fall 1972 through Fall 1975. The predictor (independent) variables consisted of selected academic variables. The criterion (dependent) variables were first-quarter GPA and graduate/nongraduate status. Several statistical methods employing discriminant analysis, multiple regression, Bayes' formula, Bayesian M-group regression, and counselor's probability assignments were utilized in building three program-completion models and three GPA prediction models. Other statistical methods such as the absolute-error-loss functions, the squared-error-loss functions, one-way analysis of variance, Friedman test, and Tukey's multiple comparisons procedures were employed in comparing and evaluating the models.

Chapter 4

RESULTS AND ANALYSES

The purpose of the study was to present and evaluate two Bayesian models that have implications for the guidance and selection of students for certain allied health curricula of the comprehensive community college. The effectiveness and the efficiency of the Bayesian models were compared and evaluated with two counselor-selection models and two classical statistical models.

The results and analyses of the study presented the methods and procedures for developing the three program-completion models and the three GPA prediction models. Analyses and comparisons of the effectiveness and the efficiency of the models were presented by individual allied health curriculum as well as across all curricula.

Program-Completion Prediction Models

The methodology for developing the program completion prediction models was reported in three sections entitled Bayesian Model 1 -- Probabilities of Program-Completion, Counselor Model 1 -- Probabilities of Program-Completion and Classical Statistical Model 1 -- Probabilities of Program-Completion. A fourth section reported and analyzed the efficiencies of the three models in terms of an actual predictive study for students first enrolled for Fall 1975. The criterion of this evaluation consisted of examining actual students status [enrolled coded graduate (1) or withdrawn coded nongraduate (0)] for Spring 1976. This criterion was appropriate as determined by previous research studies on the student flow of the 281 allied health students used in establishing the prediction models. These studies indicated that enrollment in the third quarter was highly predictive (approximately 95% of the students enrolled in the third quarter did graduate) of successful program completion.

Bayesian Model 1 -- Probabilities of Program-Completion. Bayesian Model 1 utilized the discrete case of Bayes' formula as presented in Chapter 1. This formula was used in computing the posterior probability of successful program completion by combining an *a priori* probability of program completion assigned by an allied health counselor with a likelihood probability obtained from a discriminant analysis function developed using data of previous graduates and nongraduates. These calculations produced the Bayesian posterior probability of successful program completion for all students first enrolled for Fall 1975. An example was cited as follows:

For student first enrolled for Fall 1975.

Let $x = .7$ (*a priori* probability of successful program completion assigned by counselor from Counselor Model 1) and $y = .63$ (likelihood probability of belonging to graduate group membership obtained from D-score of Classical Statistical Model 1)

Then

$$P(S) = \frac{xy}{xy + (1 - x)(1 - y)} = \frac{.7(.63)}{.7(.63) + (1 - .7)(1 - .63)} = 0.799$$

Therefore, the Bayesian posterior probability $[P(S)]$ of successful program completion was 0.799. This calculation was computed for each new allied health student first enrolled for Fall 1975.

Counselor Model 1 -- Probabilities of Program Completion. Counselor Model 1 represented the total professional judgments of the counselor in estimating the student's probability of successful program completion. These judgments were assigned after considering all relevant data peculiar to a specific student.

Classical Statistical Model 1 -- Probabilities of Program-Completion. Classical Statistical Model 1 utilized the discriminant analysis program from Statistical Package for Social Sciences (SPSS). Data from previous students enrolled from Fall 1972 to Fall 1974 were used to develop the discriminant function that was used to predict the probable future status of new students first entering in the Fall 1975. Table 6 presents the unstandardized discriminant function coefficients/ constant and the classification summary that correctly classified the largest number of cases.

The discriminant function was obtained using Rao's V stepwise criteria with Bayesian adjustment specification (graduate, .7 and nongraduate, .3). This procedure proposed to provide the greatest overall separation of graduate and nongraduate groups by selecting independent variables for entry into the analysis on the basis of their discriminating power. In this study the full set of independent variables contained excess information about group differences of graduate/nongraduate status. Therefore, a reduced set of variables using high school rank (HSR) and English 11 (ENG11) was found to provide the greatest overall separation of graduate/nongraduate groups.

Data for students first enrolled for Fall 1975 were used as inputs into this discriminant function in developing the Classical Statistical Model 1. An example was cited as follows:

Table 6

Discriminant Function Coefficients
and Classification Summary

D-score = -0.00438HSR + 0.3272ENG11 - 0.69422

Actual Group	No. of Cases	Predicted Group Membership Nongraduate	Graduate
Nongraduate	85.	16.	69.
		18.8	81.2
Graduate	196.	13.	183.
		6.6	93.4
Total	281.		

PERCENT OF CASES CORRECTLY CLASSIFIED 70.82

Summary Step Number	Table Variable Entered	F to Enter	Wilks' Lambda
1	ENG11	23.81926	0.92134
2	HSR	1.39381	0.91675

For students first enrolled Fall 1975:

Let HSR = 30 (this student ranked 30 in a high school class of 100)

ENG11 = 3.0 (junior English grade was B)

Then $D = -0.00438(30) + 0.3272(3) - 0.69422 = 0.157$

The D-score (0.157) was converted to the probability (.77) of graduate membership. Statistically, this conversion was accomplished through the aid of the classification equation for graduate group membership (Nie and others, 1975, p. 448). This calculation was computed for each new allied health student first enrolled for Fall 1975.

Analysis of the Program-Completion Models

An analysis of the three program-completion models was presented by individual curriculum. Descriptive analyses discerned absolute-errors, squared-errors, average absolute-errors, and average squared-errors by models. The Friedman (1937) test was used to analyze the three models in terms of a complete block design (Conover, 1971, pp. 264-270). In the case that the null hypothesis of equally likely rankings within a block (student) was rejected, multiple comparisons for ranked data were examined (Anderson, 1959).

Dental Assistant Curriculum. Table 7 presents the predicted probability of program completion, observed status for Spring 1976, absolute-errors, squared-errors, average-error, average squared-error, and ranking sums for the three program completion models for the Dental Assistant Curriculum.

An analysis of the data indicated that there were little differences in the prediction efficiencies of the three models in reducing both the average absolute-error and the average squared-error. A rank

Table 7

Predicted Probability of Program-Completion,
Observed Status, Absolute-Error, and Squared-Error
for Dental Assistant

Student No.	Predicted Probability: Bayesian Model 1	Predicted Probability: Counselor Model 1	Predicted Probability: Classical Statistical Model 1	Observed Status*	Absolute-Error |Observed-Predicted|			Squared-Error $\|Observed-Predicted\|^2$		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(1)	(2)	(3)
1	0.93	0.80	0.78	1	0.07 (1)**	0.20 (2)	0.22 (3)	0.00	0.00	0.05
2	0.92	0.80	0.74	0	0.92 (3)	0.80 (2)	0.74 (1)	0.85	0.64	0.55
3	0.92	0.80	0.75	1	0.08 (1)	0.20 (2)	0.25 (3)	0.01	0.04	0.06
4	0.94	0.85	0.75	0	0.94 (3)	0.85 (2)	0.75 (1)	0.88	0.72	0.56
5	0.88	0.85	0.56	1	0.12 (1)	0.15 (2)	0.44 (3)	0.01	0.02	0.19
6	0.97	0.90	0.76	1	0.03 (1)	0.10 (2)	0.24 (3)	0.00	0.01	0.06
7	0.74	0.70	0.55	1	0.26 (1)	0.30 (2)	0.45 (3)	0.07	0.09	0.20
8	0.95	0.85	0.78	1	0.05 (1)	0.15 (2)	0.22 (3)	0.00	0.02	0.05
9	0.94	0.80	0.80	1	0.06 (1)	0.20(2.5)	0.20(2.5)	0.00	0.04	0.04
10	0.96	0.85	0.81	0	0.96 (3)	0.85 (2)	0.81 (1)	0.92	0.73	0.66
11	0.92	0.80	0.74	1	0.08 (1)	0.20 (2)	0.26 (3)	0.01	0.04	0.07
12	0.95	0.85	0.78	1	0.05 (1)	0.15 (2)	0.22 (3)	0.00	0.02	0.05
13	0.97	0.85	0.87	0	0.97 (3)	0.85 (1)	0.87 (2)	0.94	0.72	0.76

Table 7 (continued)

Student No.	Predicted Probability: Bayesian Model 1	Predicted Probability: Counselor Model 1	Predicted Probability: Classical Statistical Model 1	Observed Status*	Absolute-Error |Observed-Predicted|			Squared-Error $\lvert\text{Observed-Predicted}\rvert^2$		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(1)	(2)	(3)
14	0.43	0.50	0.43	1	0.57(2.5)	0.50 (1)	0.57(2.5)	0.32	0.25	0.32
15	0.67	0.70	0.46	1	0.33 (2)	0.30 (1)	0.54 (3)	0.11	0.09	0.29
				Ranking Sum	(25.5)	(27.5)	(37.0)			
				Average Absolute-Error	0.37	0.37	0.45			
							Average Squared-Error	0.27	0.23	0.26

*0 - Nongraduate (Not enrolled Spring 1976)

1 - Graduate (Enrolled Spring 1976)

** Ranking of most efficient (1) to least efficient (3)

order of most efficient to least efficient for average absolute-errors was as follows: (1) Bayesian Model 1 and Counselor Model 1 (0.37) and (2) Classical Statistical Model 1 (0.45). A rank order of most efficient to least efficient for average squared-errors was as follows: (1) Counselor (0.23), (2) Classical Statistical Model 1 (0.26), and (3) Bayesian Model 1 (0.27).

The Friedman (1937) test was used to analyze the prediction efficiencies of the three models in terms of a complete block design (Conover, 1971, p. 264-270). The Friedman test statistic was computed using the following equation:

$$T = \frac{12}{b(k)(k+1)} \sum_{j=1}^{k} \left[Rj - \frac{b(k+1)}{2} \right]^2$$

where b is number of students

k is the three treatments and

Rj (totals) of ranking sums.

Since the Friedman test statistic (5.03) failed to exceed the .95 quantile of the chi-square random variable (5.991) with 2 degrees of freedom, the hypothesis of identical treatment effects was not rejected.

Mental Health Technology Curriculum. Table 8 presents the predicted probability of program completion, observed status for Spring 1976, absolute-errors, squared-errors, average absolute-error, average squared-error, and ranking sums for the three program-completion models for the Mental Health Technology Curriculum.

An analysis of the data indicated that there were little differences in the prediction efficiencies of the three models in reducing

Table 8

Predicted Probability of Program-Completion
Observed Status, Absolute-Error, and Squared-Error
for Mental Health Technology

Student No.	Predicted Probability: Bayesian Model 1	Predicted Probability: Counselor Model 1	Predicted Probability: Classical Statistical Model 1	Observed Status*	Absolute-Error |Observed-Predicted|			Squared-Error $\|Observed-Predicted\|^2$		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(1)	(2)	(3)
1	0.97	0.91	0.77	1	0.03 (1)**	0.08 (2)	0.23 (3)	0.00	0.01	0.05
2	0.93	0.81	0.77	0	0.93 (3)	0.81 (2)	0.77 (1)	0.86	0.66	0.59
3	0.97	0.90	0.80	1	0.03 (1)	0.10 (2)	0.20 (3)	0.00	0.01	0.04
4	0.72	0.70	0.52	1	0.28 (1)	0.30 (2)	0.48 (3)	0.08	0.09	0.23
5	0.97	0.95	0.64	1	0.03 (1)	0.05 (2)	0.36 (3)	0.00	0.00	0.13
6	0.91	0.63	0.85	1	0.09 (1)	0.37 (3)	0.15 (2)	0.01	0.14	0.02
7	0.93	0.79	0.77	1	0.07 (1)	0.21 (2)	0.23 (3)	0.00	0.04	0.05
8	0.74	0.63	0.62	0	0.74 (3)	0.63 (2)	0.62 (1)	0.55	0.40	0.38
9	0.98	0.94	0.77	0	0.98 (3)	0.94 (2)	0.23 (1)	0.96	0.88	0.05
10	1.00	0.98	0.89	1	0.00 (1)	0.02 (2)	0.11 (3)	0.00	0.00	0.01
11	0.97	0.95	0.60	1	0.03 (1)	0.05 (2)	0.40 (3)	0.00	0.00	0.16
12	0.81	0.70	0.65	1	0.19 (1)	0.30 (2)	0.35 (3)	0.04	0.09	0.12
13	0.62	0.71	0.40	0	0.62 (2)	0.71 (3)	0.40 (1)	0.38	0.50	0.16
14	0.67	0.75	0.40	1	0.33 (2)	0.25 (1)	0.60 (3)	0.11	0.06	0.36
15	0.84	0.90	0.38	1	0.16 (2)	0.10 (1)	0.62 (3)	0.03	0.01	0.38
16	0.96	0.90	0.75	0	0.96 (3)	0.90 (2)	0.75 (1)	0.92	0.81	0.56
17	0.83	0.90	0.36	1	0.17 (2)	0.10 (1)	0.64 (3)	0.03	0.01	0.41

Table 8 (continued)

Student No.	Predicted Probability: Bayesian Model 1	Counselor Model 1	Classical Statistical Model 1	Observed Status*	Absolute-Error |Observed-Predicted|			Squared-Error |Observed-Predicted|^2		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(1)	(2)	(3)
18	0.75	0.75	0.50	0	0.75(2.5)	0.75(2.5)	0.50 (1)	0.56	0.56	0.25
19	0.68	0.75	0.42	1	0.32 (2)	0.25 (1)	0.58 (3)	0.10	0.06	0.34
				Ranking Sum	(33.5)	(36.5)	(44.0)			
				Average Absolute-Error	0.35	0.36	0.43			
						Average Squared-Error		0.24	0.23	0.23

*0 - Nongraduate (Not enrolled Spring 1976)

1 - Graduate (Enrolled Spring 1976)

** Ranking of most efficient (1) to least efficient (3)

both the average absolute-error and the average squared-error. A rank order of most efficient to least efficient for average absolute-errors was as follows: (1) Bayesian Model 1 (0.35), (2) Counselor Model 1 (0.36), and (3) Classical Statistical Model 1 (0.43). A rank order of most efficient to least efficient for average squared-errors was as follows: (1) Counselor Model 1 and Classical Statistical Model 1 (0.23) and (2) Bayesian Model 1 (0.24).

The Friedman test was used to analyze the prediction efficiencies of the three models in terms of a complete block design (cited above). Since the Friedman test statistic (3.08) failed to exceed the .95 quantile of the chi-square random variable (5.991) with 2 degrees of freedom, the hypothesis of identical treatments was not rejected.

Nursing Curriculum. Table 9 presents the predicted probability of program completion, observed status for Spring 1976, absolute-errors, squared-errors, average error, average squared-error, and ranking sums for the three program-completion models for the Nursing Curriculum.

An analysis of the data indicated that there were little differences in the prediction efficiencies of the three models in reducing both the average absolute-error and the average squared-error. A rank order of most efficient to least efficient for average absolute-errors was as follows: (1) Bayesian Model 1 (0.41), (2) Counselor Model 1 (0.42), and (3) Classical Statistical Model 1 (0.45). A rank order of most efficient to least efficient for average squared-errors was as follows: (1) Classical Statistical Model 1 (0.26), (2) Counselor Model 1 (0.27), and (3) Bayesian Model 1 (0.32).

The Friedman test (cited above) was used to analyze the prediction efficiencies of the three models in terms of a complete block design.

Table 9

Predicted Probability of Program-Completion,
Observed Status, Absolute-Error, and Squared-Error
for Nursing

Student No.	Predicted Probability: Bayesian Model 1	Predicted Probability: Counselor Model 1	Predicted Probability: Classical Statistical Model 1	Observed Status*	Absolute-Error |Observed-Predicted|			Squared-Error |Observed-Predicted|^2		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(1)	(2)	(3)
1	0.83	0.80	0.55	0	0.83 (3)**	0.80 (2)	0.55 (1)	0.69	0.64	0.30
2	0.97	0.90	0.81	1	0.03 (1)	0.10 (2)	0.19 (3)	0.00	0.01	0.04
3	0.97	0.90	0.78	0	0.97 (3)	0.90 (2)	0.78 (1)	0.94	0.81	0.61
4	0.97	0.90	0.79	1	0.03 (1)	0.10 (2)	0.21 (3)	0.00	0.01	0.04
5	0.94	0.80	0.81	0	0.94 (3)	0.80 (1)	0.81 (2)	0.88	0.64	0.66
6	0.94	0.80	0.81	0	0.94 (3)	0.80 (1)	0.81 (2)	0.88	0.64	0.66
7	0.93	0.80	0.77	1	0.07 (1)	0.20 (2)	0.23 (3)	0.00	0.04	0.05
8	0.99	0.90	0.89	1	0.01 (1)	0.10 (2)	0.11 (3)	0.00	0.01	0.01
9	0.89	0.70	0.78	0	0.89 (3)	0.70 (1)	0.78 (2)	0.79	0.49	0.61
10	0.93	0.80	0.78	0	0.93 (3)	0.80 (2)	0.78 (1)	0.86	0.64	0.61
11	0.86	0.80	0.60	1	0.14 (1)	0.20 (2)	0.40 (3)	0.02	0.04	0.16
12	0.94	0.90	0.65	1	0.06 (1)	0.10 (2)	0.35 (3)	0.00	0.01	0.12
13	0.85	0.60	0.79	0	0.85 (3)	0.60 (1)	0.79 (2)	0.72	0.36	0.62
14	0.86	0.80	0.60	1	0.14 (1)	0.20 (2)	0.40 (3)	0.02	0.04	0.16
15	0.88	0.70	0.75	1	0.12 (1)	0.30 (3)	0.25 (2)	0.01	0.09	0.06
16	0.91	0.80	0.71	1	0.08 (1)	0.20 (2)	0.29 (3)	0.01	0.04	0.08
17	0.83	0.70	0.67	0	0.83 (3)	0.70 (2)	0.67 (1)	0.69	0.49	0.45
18	0.97	0.90	0.81	1	0.03 (1)	0.10 (2)	0.19 (3)	0.00	0.01	0.04
19	0.64	0.50	0.64	1	0.36(1.5)	0.50 (3)	0.36(1.5)	0.13	0.25	0.13
20	0.94	0.80	0.81	1	0.06 (1)	0.20 (3)	0.19 (2)	0.00	0.04	0.04

Table 9 (continued)

Student No.	Predicted Probability: Bayesian Model 1	Counselor Model 1	Classical Statistical Model 1	Observed Status*	Absolute-Error |Observed-Predicted|			Squared-Error $\|Observed-Predicted\|^2$		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(1)	(2)	(3)
21	0.98	0.90	0.87	0	0.98 (3)**	0.90 (2)	0.87 (1)	0.96	0.81	0.76
22	0.78	0.70	0.60	0	0.78 (3)	0.70 (2)	0.60 (1)	0.61	0.49	0.36
23	0.97	0.90	0.79	1	0.03 (1)	0.10 (2)	0.21 (3)	0.00	0.01	0.04
24	0.85	0.80	0.59	1	0.15 (1)	0.20 (2)	0.41 (3)	0.02	0.04	0.17
25	0.63	0.70	0.42	0	0.63 (2)	0.70 (3)	0.42 (1)	0.40	0.49	0.18
26	0.99	0.90	0.89	0	0.99 (3)	0.90 (2)	0.89 (1)	0.98	0.81	0.79
27	0.95	0.90	0.66	1	0.05 (1)	0.10 (2)	0.34 (3)	0.00	0.01	0.12
28	0.63	0.70	0.42	0	0.63 (2)	0.70 (3)	0.42 (1)	0.40	0.49	0.18
29	0.97	0.90	0.81	1	0.03 (1)	0.10 (2)	0.19 (3)	0.00	0.01	0.04
30	0.96	0.90	0.71	0	0.96 (3)	0.90 (2)	0.71 (1)	0.92	0.81	0.50
31	0.89	0.80	0.66	1	0.11 (1)	0.20 (2)	0.34 (3)	0.01	0.04	0.12
32	0.89	0.80	0.66	0	0.89 (3)	0.80 (2)	0.66 (1)	0.79	0.64	0.44
33	0.97	0.90	0.80	1	0.03 (1)	0.10 (2)	0.20 (3)	0.00	0.01	0.04
34	0.99	0.90	0.89	1	0.01 (1)	0.10 (2)	0.11 (3)	0.00	0.01	0.01
35	0.78	0.70	0.60	1	0.22 (1)	0.30 (2)	0.40 (3)	0.05	0.09	0.16
36	0.89	0.80	0.66	0	0.89 (3)	0.80 (2)	0.66 (1)	0.79	0.64	0.44
37	0.95	0.90	0.66	1	0.05 (1)	0.10 (2)	0.34 (3)	0.00	0.01	0.12
38	0.99	0.90	0.89	1	0.01 (1)	0.10 (2)	0.11 (3)	0.00	0.01	0.01

Table 9 (continued)

Student No.	Predicted Probability: Bayesian Model 1	Predicted Probability: Counselor Model 1	Predicted Probability: Classical Statistical Model 1	Observed Status*	Absolute-Error |Observed-Predicted|			Squared-Error $\lvert\text{Observed-Predicted}\rvert^2$		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(1)	(2)	(3)
39	0.59	0.70	0.37	1	0.41 (2)	0.30 (1)	0.63 (3)	0.17	0.09	0.40
40	0.88	0.70	0.75	1	0.12 (1)	0.30 (3)	0.25 (2)	0.01	0.09	0.06
				Ranking Sum	(71.5)	(81.0)	(87.5)			
				Average Absolute-Error	0.41	0.42	0.45			
				Average Square-Error				0.32	0.27	0.26

*0 - Nongraduate (not enrolled Spring 1976)

1 - Graduate (Enrolled Spring 1976)

** Ranking of most efficient (1) to least efficient (3)

Since the Friedman test statistic (3.24) failed to exceed the .95 quantile of the chi-square random variable (5.991) with 2 degrees of freedom, the hypothesis of identical treatment effects was not rejected.

Radiology Technology Curriculum. Table 10 presents the predicted probability of program completion, observed status for Spring 1976, absolute-errors, squared-errors, average-error, average squared-error, and ranking sums for the program-completion models for the Radiology Technology Curriculum.

An analysis of the data indicated that there were little differences in the prediction efficiencies of the three models in reducing both the average absolute-error and the average squared-error. A rank order of most efficient to least efficient for average absolute-errors was as follows: (1) Bayesian Model 1 (0.15), (2) Counselor Model 1 (0.20), and (3) Classical Statistical Model 1 (0.25). A rank order of most efficient to least efficient for average squared-errors was as follows: (1) Bayesian Model 1 (0.07) and (2) Counselor Model 1 and Classical Statistical Model 1 (0.08).

The Friedman test (cited above) was used to analyze the prediction efficiencies of the three models in terms of a complete block design. Since the Friedman test statistic (19.03) exceeded the .95 quantile of the chi-square random variable (5.991) with 2 degrees of freedom, the hypothesis of identical treatment effects was rejected. Further analyses using multiple comparisons aspects proposed by Anderson (1959) consisted of rearranging the data from Table 10 to form the 3 x 3 contingency ranking table cited in Table 11.

Table 10

Predicted Probability of Program-Completion,
Observed Status, Absolute-Error, and Squared-Error
for Radiology

Student No.	Predicted Probability: Bayesian Model 1	Predicted Probability: Counselor Model 1	Predicted Probability: Classical Statistical Model 1	Observed Status*	Absolute-Error |Observed-Predicted|			Squared-Error |Observed-Predicted|^2		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(1)	(2)	(3)
1	1.00	0.98	0.90	1	0.00 (1)**	0.02 (2)	0.10 (3)	0.00	0.00	0.01
2	0.93	0.80	0.76	1	0.07 (1)	0.20 (2)	0.24 (3)	0.00	0.04	0.06
3	0.97	0.83	0.85	1	0.03 (1)	0.17 (3)	0.15 (2)	0.00	0.03	0.02
4	0.90	0.85	0.62	1	0.10 (1)	0.15 (2)	0.38 (3)	0.01	0.02	0.14
5	0.99	0.97	0.79	1	0.01 (1)	0.03 (2)	0.21 (3)	0.00	0.00	0.04
6	0.72	0.85	0.32	0	0.72 (2)	0.85 (3)	0.32 (1)	0.52	0.72	0.10
7	0.98	0.85	0.88	1	0.02 (1)	0.15 (2)	0.22 (3)	0.00	0.02	0.05
8	1.00	0.98	0.87	1	0.00 (1)	0.02 (2)	0.13 (3)	0.00	0.00	0.02
9	0.95	0.85	0.77	1	0.05 (1)	0.15 (2)	0.23 (3)	0.00	0.02	0.05
10	0.65	0.60	0.55	1	0.35 (1)	0.40 (2)	0.45 (3)	0.12	0.16	0.20
11	0.88	0.70	0.76	1	0.12 (1)	0.30 (3)	0.24 (2)	0.01	0.09	0.06
12	0.97	0.85	0.87	1	0.03 (1)	0.15 (3)	0.13 (2)	0.00	0.02	0.02
13	0.98	0.95	0.74	1	0.02 (1)	0.05 (2)	0.26 (3)	0.00	0.00	0.07
14	0.92	0.89	0.60	1	0.08 (1)	0.11 (2)	0.40 (3)	0.01	0.01	0.16
15	0.76	0.70	0.57	0	0.76 (2)	0.70 (2)	0.57 (1)	0.58	0.09	0.18
16	1.00	0.99	0.87	1	0.00 (1)	0.01 (2)	0.13 (3)	0.00	0.00	0.02
17	0.60	0.50	0.60	1	0.40(1.5)	0.50 (3)	0.40(1.5)	0.16	0.25	0.16

Table 10 (continued)

Student No.	Predicted Probability: Bayesian Model 1	Predicted Probability: Counselor Model 1	Predicted Probability: Classical Statistical Model 1	Observed Status*	Absolute-Error |Observed-Predicted|			Squared-Error $\|Observed-Predicted\|^2$		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(1)	(2)	(3)
18	0.92	0.80	0.74	1	0.08 (1)	0.20 (2)	0.26 (3)	0.01	0.04	0.07
19	0.99	0.96	0.87	1	0.01 (1)	0.04 (2)	0.13 (3)	0.00	0.00	0.02
			Ranking Sum		(22.5)	(45.0)	(46.5)			
			Average Absolute-Error		0.15	0.20	0.25			
							Average Square-Error	0.32	0.27	0.26

*0 - Nongraduate (not enrolled Spring 1976)

1 - Graduate (Enrolled Spring 1976)

** Ranking of most efficient (1) to least efficient (3)

Table 11

Contingency Rankings for Radiology Technology*

Model	Rank 1	Rank 2	Rank 3	Total
Bayesian Model 1	16	2	1	19
Counselor Model 1	0	13	6	19
Classical Statistical Model 1	3	4	12	19
	19	19	19	

$$X^2_{c1} = \frac{r(n_{23} - n_{21})^2}{2n} = \frac{3(6 - 0)^2}{2(19)} = 2.84$$

$$X^2_{c2} = \frac{r(n_{11} - n_{31})^2}{2n} \quad \frac{3(16 - 3)^2}{2(19)} = 13.34$$

$$X^2_{c3} = \frac{(r - 1)(n_{11} - n_{13} + n_{33} - n_{31})^2}{4n} =$$

$$\frac{2(16 - 1 + 12 - 3)^2}{4(19)} = 15.16$$

*Tie assignment (Student No. 17) made in the direction least conducive to rejecting the null hypothesis.

Since the $X^2_{c_1}$ statistic (2.84) failed to exceed the critical value of $X^2_{.95}(1) = 3.8$, the data indicated no statistically significant difference between the rankings assigned to Counselor Model 1. Because $X^2_{c_2}$ (13.34) exceeded the chi-square statistic with one degree of freedom, it was concluded that there were linear comparison differences among models for rank 1. Further analyses indicated that the $X^2_{c_3}$ statistic (15.16) exceeded the chi-square critical value associated with a .05-level test which implied that there were statistically significant differences between linear ranking for Bayesian Model 1 and Classical Statistical Model 1. This analysis concluded that the Bayesian Model 1 was more efficient than the Classical Statistical Model 1 (Table 11).

Program-Completion Prediction Summary

Table 12 presents the mean absolute-errors by curricula and the weighted mean absolute-errors of all curricula for the three program-completion models.

An analysis of the data indicated that there were little differences in the prediction efficiencies of the Bayesian and Counselor Models in reducing the weighted average absolute-errors of the four allied health curricula. A rank order of most efficient to least efficient for the weighted average absolute-errors was as follows: (1) Bayesian Model 1 (0.34), (2) Counselor Model 1 (0.35), and (3) Classical Statistical Model 1 (0.40).

Table 13 presents the mean squared-errors by curricula and the weighted mean absolute-errors of all curricula for the three program-completion models.

Table 12

Mean Absolute-Errors
for the Three Program-Completion Models

Model	Dental Assistant (N=15)	Mental Health Technology (N=19)	Nursing (N=40)	Radiology Technology (N=19)	Weighted Average (N=93)
Bayesian Model 1	0.37	0.35	0.41	0.15	0.34
Counselor Model 1	0.37	0.36	0.42	0.20	0.35
Classical Statistical Model 1	0.45	0.43	0.45	0.25	0.40

Table 13

Mean Squared-Errors
for the Three Program-Completion Models

Model	Dental Assistant (N=15)	Mental Health Technology (N=19)	Nursing (N=40)	Radiology Technology (N=19)	Weighted Average (N=93)
Bayesian Model 1	0.27	0.24	0.32	0.07	0.24
Counselor Model 1	0.23	0.23	0.27	0.08	0.22
Classical Statistical Model 1	0.26	0.23	0.26	0.08	0.22

An analysis of the data indicated that there were little differences in the prediction efficiencies of the three models in reducing the weighted average squared-errors of the four allied health curricula. A rank order of most efficient to least efficient for the weighted average squared-errors was as follows: (1) Counselor Model 1 and Classical Statistical Model 1 (0.22) and (2) Bayesian Model 1 (0.24).

Table 14 presents the ranking sums by curriculum and by program-completion model.

The Friedman test (cited above) was used to analyze the prediction efficiencies of the three models in terms of a complete block design of the total ranking for the four allied health curricula. Since the Friedman test statistic (20.92) exceeded the .95 quantile of the chi-square random variable (5.991) with 2 degrees of freedom, the hypothesis of identical treatment effects was rejected. Further analyses using multiple comparisons aspects proposed by Anderson (1959) consisted of tabulating the rankings to form the 3 x 3 contingency ranking table cited in Table 15.

Since X^2_{c1} statistic (0.15) failed to exceed the critical value of $X^2_{.95}(1) = 3.8$, the data indicated no statistically significant difference between the ranking for Counselor Model 1. Because X^2_{c2} (15.50) exceeded the chi-square statistic with one degree of freedom, it was concluded that there were linear comparison differences among models for rank 1. Further analyses indicated that the X^2_{c3} statistic (18.72) exceeded the chi-square critical value associated with a .05-level test which implied that there were statistically significant differences between linear ranking for Bayesian Model 1 and Classical Statistical Model 1. In conclusion, inspection of Table 14 clearly supported the

Table 14

Ranking Sums by Curriculum
and by Program-Completion Model

Curriculum	Program-Completion Model: Bayesian Model 1	Counselor Model 1	Classical Statistical Model 1
Dental Assistant	25.5	27.5	37.0
Mental Health Technology	33.5	36.5	44.0
Nursing	71.5	81.0	87.5
Radiology	22.5	44.0	47.5
Total Rankings	153.0	189.0	216.0

Table 15

Contingency Rankings for Allied Health Curricula*

Model	Rank 1	Rank 2	Rank 3	Total
Bayesian Model 1	56	12	25	93
Counselor Model 1	12	66	15	93
Classical Statistical Model 1	25	15	53	93
	93	93	93	

$$\chi^2_{c_1} = \frac{r(n_{23} - n_{21})^2}{2n} = \frac{3(15 - 12)^2}{2(93)} = 0.15$$

$$\chi^2_{c_2} = \frac{r(n_{11} - n_{31})}{2n} = \frac{3(56 - 25)^2}{2(93)} = 15.50$$

$$\chi^2_{c_3} = \frac{(r - 1)(n_{11} - n_{13} + n_{33} - n_{31})^2}{4n} =$$

$$\frac{2(56 - 25 + 53 - 25)^2}{4(93)} = 18.72$$

*Tie assignments made in the direction least conducive to rejecting the null hypothesis

hypothesis that the Bayesian Model 1 was the most efficient model in selecting successful allied health students who will complete their programs of study.

Bayesian Model 2 -- Predicting First-Quarter GPA's. Bayesian Model 2 utilized a computer program developed by Kazur Shigemasu (1975). The model which was an application and specialization of the Bayesian linear model developed by Lindley and Smith (1972) involved the assumption of homogeneity of regression coefficients (but not intercepts) across groups (Shigemasu, 1975, p. ii). Dr. Shigemasu's methodology (first proposed by Novick, Jackson, Thayer, and Cole, 1971, p. 2) of comparing GPA predictions across different schools with similar programs was adjusted in terms of comparing similar programs within one college (i.e. the m-groups were now different programs instead of different schools). This procedure in which programs within an institution can be considered separately was proposed by Novick, Jones, and Cole (1973, p. 7) for institutions that are working on their own and do not have information from other colleges.

In developing the Bayesian m-group regression equation, the following procedures were applied:

1. Data for 281 students first enrolled for Fall 1972, 1973, and 1974 were processed in developing prediction equations by programs. These four equations were used to predict the first quarter GPA's for students first enrolled for Fall 1975.
2. Classical statistical B-coefficients were used as the starting values in developing the Bayesian B-coefficients as required by the computer program.

The four Bayesian m-group regression equations by allied health curriculum were computed as follows:

$$y = 0.0237\ \text{SCATS} - 0.0084\ \text{HSR} + 0.1069\ \text{ENG12} + 0.1305\ \text{ENG11} - 0.0283\ \text{ALG} + 0.0023\ \text{GEO} - 0.002\ \text{BIO} + 0.0159\ \text{CHEM} + \text{Intercept}$$

Intercept by Program:	Dental Assitant	- 8.7499
	Mental Health	- 8.3035
	Nursing	- 8.6796
	Radiology	- 8.1596

These four equations with different intercepts were used to predict the first-quarter GPA's for students first enrolled for Fall 1975. These predictions by curriculum were cited and evaluated in the section entitled Analyses of the GPA Prediction Models.

Counselor Model 2 -- Predicting First-Quarter GPA's. Counselor Model 2 required the allied health curriculum counselor to estimate the first quarter grade point average for students first enrolled in Fall 1975. These estimates reported in the section entitled Analyses of the GPA Prediction Models represented the professional opinions and judgments of the counselor as discerned by reviewing the students' academic records and/or by personal interviews of the students.

Classical Statistical Model 2 -- Predicting First-Quarter GPA's

Classical Statistical Model 2 utilized forward stepwise multiple regression (SPSS REGR) in developing the regression equation used to predict the GPA's of all allied health students first enrolled in the Fall 1975. Data for 281 students first enrolled for Fall 1972, 1973, and 1974 were processed in developing the prediction equation for all allied health

Table 16

SPSS Summary Table

Dependent Variable . . . GPA

Variable	Multiple R	R Square	RSQ Change	Simple R	B-i Coefficients
HSR	0.37503	0.14064	0.14064	-0.37503	-0.00771
SCAT	0.46127	0.21277	0.07213	0.37329	0.02316
ENG11	0.47439	0.22505	0.01228	0.31534	0.11650
ENG12	0.48063	0.23100	0.00596	0.31914	0.09672
ALG	0.48202	0.23235	0.00134	0.21257	-0.05479
GEO	0.48422	0.23447	0.00212	0.31217	0.03951
CHEM	0.48491	0.23513	0.00066	0.24187	0.02248
BIO	0.48507	0.23530	0.00016	0.22000	-0.01550
(Constant)					-8.16767

students first enrolled for Fall 1975. Table 16 cites the SPSS Summary Table for the 281 student cases.

The regression equation developed from the B-coefficients and constant cited in Table 16 was used to predict the GPA's for students first enrolled in Fall 1975. These predictions by curriculum were cited and evaluated in the next section entitled Analyses of the GPA Prediction Models.

Analyses of the GPA Prediction Models

An analysis of the three GPA prediction models was presented by individual curriculum. Descriptive analyses discerned absolute-errors, squared-errors, average absolute-errors, and average squared-errors by models. An analysis of variance of mean differences of absolute-errors and squared-errors was computed using a single-factor design having repeated measures on the same elements (Winer, 1962, pp. 105-124). In the case that the null hypothesis of equal treatment effects was rejected, Tukey's multiple comparison procedure was used to locate mean differences.

Dental Assistant Curriculum. Table 17 presents the predicted GPA's, observed GPA's, absolute-errors, squared-errors, average absolute-error, and average squared-error for the three GPA prediction models for the Dental Assistant Curriculum.

An analysis of the data indicated that the Bayesian Model 2 was the most efficient in minimizing the average absolute-error and the average squared-error for GPA predictions in the Dental Assistant Curriculum. The Classical Statistical Model 2 was the second most efficient model with the Counselor Model 2 being the least efficient.

Table 17

Predicted GPA, Observed GPA, Absolute-Error, and Squared-Error for Dental Assistant

Student No.	Predicted GPA: Bayesian Model 2	Predicted GPA: Counselor Model 2	Predicted GPA: Classical Statistical Model 2	Observed GPA	Absolute-Error |Predicted-Observed|			Squared-Error $\lvert \text{Predicted-Observed} \rvert^2$		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(1)	(2)	(3)
1	2.999	2.900	3.195	3.444	0.455	0.544	0.249	0.207	0.296	0.062
2	2.595	3.000	2.886	1.500	1.095	1.500	1.386	1.199	2.250	1.921
3	2.583	3.000	2.872	2.533	0.050	0.467	0.339	0.003	0.218	0.115
4	2.500	3.000	2.715	0.389	2.111	2.611	2.326	4.457	6.818	5.411
5	2.884	3.250	2.919	2.938	0.054	0.312	0.019	0.003	0.098	0.001
6	2.325	3.250	2.587	2.500	0.175	0.750	0.087	0.031	0.563	0.008
7	2.077	2.000	2.375	3.667	1.590	1.667	1.292	2.529	2.779	1.670
8	2.721	3.750	2.940	2.794	0.073	0.956	0.146	0.006	0.914	0.022
9	2.806	3.200	3.017	2.500	0.306	0.700	0.517	0.094	0.490	0.268
10	2.548	3.300	2.767	1.330	1.215	1.967	1.434	1.477	3.869	2.057
11	2.173	2.500	2.417	1.500	0.673	1.000	0.917	0.453	1.000	0.841
12	3.047	3.400	3.209	3.000	0.047	0.400	0.209	0.003	0.160	0.044
13	3.142	3.300	3.409	0.000	3.142	3.300	3.409	9.873	10.890	11.622
14	1.729	2.000	1.999	2.417	0.688	0.417	0.418	0.474	0.174	0.175
15	1.962	2.600	2.240	1.895	0.067	0.705	0.345	0.005	0.497	0.119
			Average Absolute-Error		0.783	1.153	0.873			
					Average Squared-Error			1.388	2.068	1.623

An analysis of variance of mean differences of absolute-error and squared-error was computed using a single-factor design having repeated measures on the same elements (Winer, 1962, pp. 105-124). Table 18 cites the analysis of variance summary for absolute-error differences of treatments for the Dental Assistant Curriculum.

The F ratio

$$F = \frac{MS_{treat}}{MS_{res}} = \frac{0.560}{0.032} = 17.500$$

was used in testing the hypothesis about the absolute-error differences for the three GPA prediction models. The experimental data contradicted the hypothesis that the three treatment effects were equal at the .01-level. Inspection of the average (Table 17) for the GPA prediction models indicated that the Bayesian Model 2 had the minimum average absolute-error. In order to test the difference between all possible pairs of means, Tukey's multiple comparison procedure was used. Table 19 reports Tukey's Test for differences between pairs of means. This analysis concluded all pairs of means differed.

Table 20 cites the analysis of variance summary for squared-error differences of treatments for the Dental Assistant Curriculum.

The F ratio

$$F = \frac{MS_{treat}}{MS_{res}} = \frac{1.790}{0.228} = 7.851$$

was used in testing the hypothesis about the squared-error differences for the three GPA prediction models. The experimental data contradicted the hypothesis that the three treatment effects were equal at the .01-level. Inspection of the averages (Table 17) for the GPA models

Table 18

Analysis of Variance for
Absolute-Error Differences
for Dental Assistant

Source of Variation	SS		df		MS	F
Between students		34.702		14		
Within students		2.006		30		
Treatments	1.119		2		0.560	17.500**
Residual	0.887		28		0.032	
Total		36.708		44		

$^{**}F_{.99}(2.28) = 5.45$

Table 19

Tukey's Test for Differences
of Absolute-Errors for Dental Assistant

GPA Model		Bayesian Model 2	Classical Statistical Model 2	Counselor Model 2
	Means	0.783	0.873	1.153
Bayesian Model 2	0.783	--	0.090*	0.3700*
Classical Statistical Model 2	0.873		--	0.2800*
Counselor Model 2	1.153			--

$$\sqrt{\frac{MSw}{n}}\ {}_{.95}q_{3,42} = (0.020)(3.438) = 0.069$$

*Significant at .05-level

Table 20

Analysis of Variance for
Squared-Error Differences
for Dental Assistant

Source of Variation	SS	df	MS	F
Between students	360.527	14		
Within students	9.970	30		
Treatments	3.580	2	1.790	7.851**
Residual	6.390	28	0.228	
Total	370.497	44		

$^{**}F_{.99}(2,28) = 5.45$

indicated that the Bayesian Model 2 had the minimum average squared-error. In order to test the difference between all possible pairs of means, Tukey's multiple comparison procedure was used. Table 21 reports Tukey's Test differences between pairs of means. This analysis concluded that - on the basis of the Tukey's Test - the mean of squared-errors of the Bayesian Model 2 differs from the mean of the Counselor Model 2 with no other mean pairs being different.

Mental Health Technology. Table 22 presents the predicted GPA's, observed GPA's, absolute-errors, squared-errors, average absolute-error, and average squared-error for the three GPA prediction models for Mental Health Technology.

An analysis of the data indicated that there were little differences in the prediction efficiencies of the three models in reducing both the average absolute-error and the average squared-error. A rank order of most efficient to least efficient was as follows: (1) Classical Statistical Model 2 (average absolute-error, 0.878; average squared-error, 1.341), (2) Counselor Model 2 (average absolute-error, 0.886; average squared-error, 1.623), and (3) Bayesian Model 2 (average absolute-error, 0.972; average squared-error, 1.643).

An analysis of variance of mean differences of absolute-error and squared-error was computed using a single-factor design having repeated measures on the same elements. Table 23 cites the analysis of variance summary for absolute-error differences of the Mental Health curriculum.

An analysis of variance failed to reject that the treatments were different at the .05-level.

Table 21

Tukey's Test for Differences
of Squared-Errors for Dental Assistant

GPA Model		Bayesian Model 2	Classical Statistical Model 2	Counselor Model 2
	Means	1.388	1.623	2.068
Bayesian Model 2	1.388	--	0.235	0.680*
Classical Statistical Model 2	1.623		--	0.445
Counselor Model 2	2.068			--

$$\sqrt{\frac{MSw}{n}}\ {}_{.95}q_{3,42} = (0.149)(3.438) = 0.512$$

*Significant at .05-level

Table 22

Predicted GPA, Observed GPA, Absolute-Error, and Squared-Error for Mental Health Technology

Student No.	Predicted GPA: Bayesian Model 2	Predicted GPA: Counselor Model 2	Predicted GPA: Classical Statistical Model 2	Observed GPA	Absolute-Error |Predicted-Observed|			Squared-Error $\lvert Predicted-Observed\rvert^2$		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(1)	(2)	(3)
1	3.186	3.000	2.962	2.793	0.393	0.207	0.169	0.154	0.043	0.029
2	2.893	2.900	2.684	2.320	0.573	0.580	0.364	0.328	0.336	0.132
3	3.426	2.900	3.199	2.471	0.955	0.429	0.728	0.912	0.184	0.530
4	3.185	3.100	3.016	3.067	0.118	0.033	0.051	0.014	0.001	0.003
5	3.034	3.200	2.859	0.615	2.419	2.585	2.244	5.852	6.682	5.036
6	2.672	2.400	2.439	1.462	1.210	0.938	0.977	1.464	0.880	0.955
7	3.104	2.800	2.856	3.846	0.742	1.046	0.990	0.551	1.094	0.981
8	3.141	3.500	2.954	1.500	1.641	2.000	1.454	2.693	4.000	2.115
9	2.924	2.900	2.710	1.692	1.232	1.208	1.018	1.518	1.459	1.037
10	3.835	3.200	3.599	2.706	1.129	0.494	0.893	1.275	0.244	0.798
11	2.584	2.700	2.382	2.765	0.181	0.065	0.383	0.033	0.004	0.147
12	3.197	2.600	3.035	2.824	0.373	0.224	0.211	0.139	0.050	0.045
13	2.228	2.100	2.114	2.294	0.066	0.194	0.180	0.004	0.038	0.033
14	2.398	2.200	2.227	2.235	0.163	0.035	0.008	0.027	0.001	0.000
15	2.059	2.400	1.916	2.414	0.355	0.014	0.498	0.126	0.000	0.248
16	3.034	2.700	2.601	0.000	3.034	2.700	2.601	9.205	7.290	6.766
17	1.986	2.600	1.958	3.067	1.684	1.070	1.712	2.836	1.145	2.931
18	2.013	2.700	1.894	0.000	2.013	2.700	1.894	4.052	7.290	3.588
19	2.507	3.000	2.380	2.692	0.185	0.308	0.312	0.034	0.095	0.098
			Average Absolute-Error		0.972	0.886	0.878			
						Average Squared-Error		1.643	1.623	1.341

Table 23

Analysis of Variance for
Absolute-Error Differences
for Mental Health Technology

Source of Variation	SS		df		MS	F
Between students		38.393		18		
Within students		1.714		38		
Treatments	0.103		2		0.052	1.155*
Residual	1.611		36		0.045	
Total		40.107		56		

*Nonsignificant at .05-level

Table 24 cites the analysis of variance summary for squared-error differences of treatments.

An analysis of variance failed to reject at the .05-level that the treatments were different.

Nursing Curriculum. Table 25 presents the predicted GPA's, observed GPA's, absolute-errors, squared-errors, average absolute-error, and average squared-error for the three GPA prediction models for Nursing.

An analysis of the data indicated that there were little differences in the prediction efficiencies of the three models in reducing both the average absolute-error and the average squared-error. A rank order of most efficient to least efficient for average absolute-error was as follows: (1) Bayesian Model 2 (0.706), (2) Classical Statistical Model 2 (0.726), and (3) Counselor Model 2 (0.806). A rank order of most efficient to least efficient for average squared-error was as follows: (1) Bayesian Model 2 (1.242), (2) Counselor Model 2 (1.349), and (3) Classical Statistical Model 2 (1.396).

An analysis of variance of mean differences of absolute-error and squared-errror was computed using a single-factor design having repeated measures on the same elements. Table 26 cites the analysis of variance summary for absolute-error differences of the Nursing Curriculum.

An analysis of variance failed to reject that the treatments were different at the .05-level.

Table 27 cites the analysis of variance summary for squared-error differences of treatments.

Table 24

Analysis of Variance for
Squared-Error Differences
for Mental Health Technology

Source of Variation	SS	df	MS	F
Between students	279.255	18		
Within students	18.060	38		
Treatments	1.090	2	0.545	1.157*
Residual	16.970	36	0.471	
Total	297.315	56		

*Nonsignificant at .05-level

Table 25

Predicted GPA, Observed GPA, Absolute-Error, and Squared-Error for Nursing

Student No.	Predicted GPA: Bayesian Model 2	Predicted GPA: Counselor Model 2	Predicted GPA: Classical Statistical Model 2	Observed GPA	Absolute-Error |Predicted-Observed|			Squared-Error $\lvert \text{Predicted-Observed} \rvert^2$		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(1)	(2)	(3)
1	2.037	2.400	2.201	3.018	0.981	0.618	0.817	0.962	0.382	0.667
2	3.295	3.200	3.485	3.167	0.128	0.033	0.318	0.016	0.001	0.101
3	3.065	2.700	3.271	2.972	0.273	0.092	0.479	0.075	0.008	0.229
4	3.157	2.400	3.307	2.966	0.191	0.566	0.341	0.036	0.320	0.116
5	2.800	2.900	2.956	2.188	0.612	0.712	0.768	0.375	0.507	0.590
6	3.257	3.000	3.479	3.182	0.075	0.182	0.297	0.006	0.033	0.088
7	1.981	2.500	2.128	2.714	0.733	0.214	0.586	0.537	0.046	0.343
8	3.421	3.800	3.563	3.688	0.267	0.112	0.125	0.071	0.013	0.016
9	2.708	2.800	2.863	0.000	2.708	2.800	2.863	7.333	7.840	8.197
10	2.856	2.100	3.040	3.176	0.320	1.076	0.136	0.102	1.158	0.018
11	2.406	1.800	2.610	3.244	0.838	1.444	0.634	0.702	2.085	0.402
12	2.612	2.800	2.823	3.077	0.465	0.277	0.254	0.216	0.077	0.065
13	2.937	1.900	3.108	0.300	2.637	1.600	2.808	6.954	2.560	7.885
14	2.109	2.200	2.342	2.923	0.814	0.723	0.581	0.613	0.523	0.338
15	2.485	1.800	2.657	2.328	0.157	0.528	0.329	0.025	0.279	0.108
16	2.534	2.100	2.748	2.642	0.108	0.542	0.106	0.012	0.294	0.011
17	2.673	2.900	2.931	0.000	2.673	2.900	2.931	7.145	8.410	8.591
18	3.265	3.400	3.467	3.786	0.521	0.386	0.319	0.271	0.149	0.102
19	2.662	2.000	2.880	2.766	0.104	0.766	0.114	0.011	0.587	0.013
20	3.286	3.000	3.479	3.000	0.286	0.000	0.479	0.082	0.000	0.229
21	3.133	2.900	3.218	3.000	0.133	0.100	0.218	0.018	0.010	0.048

Table 25 (continued)

Student No.	Predicted GPA: Bayesian Model 2	Predicted GPA: Counselor Model 2	Predicted GPA: Classical Statistical Model 2	Observed GPA	Absolute-Error |Predicted-Observed|			Squared-Error |Predicted-Observed|^2		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(1)	(2)	(3)
22	2.068	1.500	2.270	1.830	0.238	0.330	0.440	0.057	0.109	0.194
23	2.938	2.100	3.100	3.125	0.187	1.025	0.025	0.035	1.051	0.001
24	2.408	2.000	2.618	2.347	0.061	0.347	0.271	0.004	0.120	0.073
25	2.016	1.800	2.197	2.089	0.073	0.289	0.108	0.005	0.084	0.012
26	3.319	3.000	3.528	0.000	3.319	3.000	3.528	11.016	9.000	12.447
27	2.764	2.100	2.924	2.759	0.005	0.241	0.165	0.000	0.058	0.027
28	2.092	1.900	2.300	0.375	1.717	1.525	1.925	2.948	2.326	3.706
29	3.134	3.500	3.325	3.356	0.222	0.144	0.031	0.049	0.021	0.001
30	2.495	3.000	2.744	0.000	2.495	3.000	2.744	6.225	9.000	7.530
31	2.995	3.100	3.169	3.261	0.266	0.161	0.092	0.071	0.026	0.008
32	2.805	2.500	2.923	2.882	0.077	0.382	0.041	0.006	0.146	0.002
33	3.167	3.100	3.327	3.391	0.224	0.291	0.064	0.050	0.085	0.004
34	2.976	3.500	3.166	2.313	0.663	1.187	0.853	0.440	1.409	0.728
35	2.560	2.000	2.706	3.176	0.616	1.176	0.470	0.379	1.383	0.221
36	2.616	1.900	2.830	1.333	1.283	0.567	1.497	1.646	0.321	2.241
37	3.131	2.900	3.344	3.091	0.040	0.191	0.253	0.002	0.036	0.064
38	3.343	3.800	3.518	3.722	0.379	0.078	0.204	0.144	0.006	0.042
39	1.929	1.500	2.259	2.833	0.904	1.333	0.574	0.817	1.777	0.329
40	2.785	1.900	2.987	3.217	0.432	1.317	0.230	0.187	1.734	0.053
			Average Absolute-Error		0.706	0.806	0.726			
					Average Squared-Error			1.242	1.349	1.396

Table 26

Analysis of Variance for Absolute-Error Differences for Nursing

Source of Variation	SS		df		MS	F
Between students		86.767		39		
Within students		5.987		80		
Treatments	0.228		2		0.114	1.541*
Residual	5.759		78		0.074	
Total		92.754		119		

*Nonsignificant at .05-level

Table 27

Analysis of Variance for
Squared-Error Differences
for Nursing

Source of Variation	SS		df		MS	F
Between students		837.673		39		
Within students		38.653		80		
Treatments	0.497		2		1.790	0.509*
Residual	38.156		78		0.489	
Total		876.326		119		

*Nonsignificant at .05-level

An analysis of variance failed to reject that the treatments were different at the .05-level.

Radiology Technology Curriculum. Table 28 presents the predicted GPA's, observed GPA's, absolute-errors, squared-errors, average absolute-error, and average squared-error for the three GPA prediction models for Radiology Technology.

An analysis of the data indicated that there were little differences in the prediction efficiencies of the three models in reducing both the average absolute-error and the average squared-error. A rank order of most efficient to least efficient for average absolute-errors was as follows: (1) Bayesian Model 2 (0.445), (2) Classical Statistical Model 2 (0.446), and (3) Counselor Model 2 (0.562). A rank order of most efficient to least efficient for average squared-error was as follows: (1) Classical Statistical Model 2 (0.477), (2) Bayesian Model 2 (0.549), and (3) Counselor Model 2 (0.599).

An analysis of variance of mean differences of absolute-error and squared-error was computed using a single-factor design having repeated measures on the same elements. Table 29 cites the analysis of variance summary for absolute-error differences of the Radiology Curriculum.

An analysis of variance failed to reject that the treatments were different at the .05-level.

Table 30 cites the analysis of variance summary for squared-error differences of treatments.

An analysis of variance failed to reject that the treatments were different at the .05-level.

Table 28

Predicted GPA, Observed GPA, Aboslute-Error
and Squared-Error for
Radiology Technology

Student No.	Predicted GPA: Bayesian Model 2	Predicted GPA: Counselor Model 2	Predicted GPA: Classical Statistical Model 2	Observed GPA	Absolute-Error |Predicted-Observed|			Squared-Error $\|Predicted-Observed\|^2$		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(1)	(2)	(3)
1	4.000	3.500	4.000	4.000	0.000	0.500	0.000	0.000	0.250	0.000
2	3.195	2.500	2.792	3.200	0.005	0.700	0.408	0.000	0.490	0.166
3	3.292	3.100	2.907	3.182	0.110	0.082	0.275	0.012	0.007	0.076
4	2.891	2.600	2.618	3.400	0.509	0.800	0.782	0.259	0.640	0.612
5	3.675	3.200	3.349	3.667	0.008	0.467	0.318	0.000	0.218	0.101
6	3.119	2.900	2.831	2.684	0.435	0.216	0.147	0.189	0.047	0.022
7	3.895	2.500	3.577	3.400	0.495	0.900	0.177	0.245	0.810	0.031
8	3.630	3.300	3.331	3.067	0.563	0.233	0.264	0.317	0.054	0.070
9	3.336	2.500	3.053	3.200	0.136	0.700	0.330	0.018	0.490	0.109
10	2.589	2.300	2.404	2.733	0.144	0.430	0.329	0.021	0.185	0.108
11	2.886	2.400	2.592	2.316	0.570	0.084	0.276	0.325	0.007	0.076
12	3.465	2.600	3.108	3.200	0.265	0.600	0.092	0.070	0.360	0.008
13	3.191	3.300	2.915	2.889	0.302	0.411	0.026	0.091	0.169	0.001
14	2.783	2.500	2.464	3.263	0.480	0.763	0.799	0.230	0.582	0.638
15	2.744	2.500	2.487	0.000	2.744	2.500	2.487	7.530	6.250	6.185
16	3.903	3.000	3.515	3.000	0.903	0.000	0.515	0.815	0.000	0.265
17	2.934	2.200	2.631	3.000	0.066	0.800	0.369	0.004	0.640	0.136
18	3.374	2.800	3.153	2.866	0.508	0.066	0.287	0.258	0.004	0.082
19	3.508	3.300	3.130	3.727	0.219	0.427	0.597	0.048	0.182	0.356
			Average Absolute-Error		0.445	0.562	0.446			
					Average Squared-Error			0.549	0.599	0.477

Table 29

Analysis of Variance for
Absolute-Error Differences
for Radiology

Source of Variation	SS		df		MS	F
Between students		15.018		18		
Within students		2.462		38		
Treatments	0.171		2		0.086	1.344*
Residual	2.291		36		0.064	
Total		17.480		56		

*Nonsignificant at .05-level

Table 30

Analysis of Variance for
Squared-Error Differences
for Radiology

Source of Variation	SS		df		MS	F
Between students		119.351		18		
Within students		2.847		38		
Treatments	0.146		2		0.073	0.9733*
Residual	2.701		36		0.075	
Total		122.198		56		

*Nonsignificant at .05-level

GPA Prediction Summary

Table 31 presents the mean absolute-errors by curricula and the weighted mean absolute-errors of all curricula for the three GPA prediction models.

An analysis of the data indicated that there were little differences in the prediction efficiencies of the Bayesian and classical statistical models in reducing the weighted average absolute-errors of the four allied health curricula. A rank order of most efficient to least efficient for the weighted average absolute-errors was as follows: (1) Bayesian Model 2 (0.719), (2) Classical Statistical Model 2 (0.723), and (3) Counselor Model 2 (0.829).

An analysis of variance of mean differences of absolute-error using a single-factor design having repeated measures on the same elements was computed to locate treatment differences. Table 32 cites the analysis of variance summary table for the combined four allied health curricula.

The F ratio

$$F = \frac{MS_{treat}}{MS_{res}} = \frac{0.358}{0.062} = 5.774$$

was used in testing the hypothesis about absolute-error differences for the three GPA prediction models. The experimental data contradicted the hypothesis that the three treatment effects were equal at the .01-level. Inspection of the averages (Table 31) for the GPA prediction models indicated that the Bayesian Model 2 had the minimum average absolute-error. In order to test the differences between all possible pairs of means, Tukey's multiple comparison procedure was used. Table 33 reports Tukey's Test for differences between pairs of means.

Table 31

Mean Absolute-Errors for the Three GPA Prediction Models

Model	Dental Assistant (N=15)	Mental Health Technology (N=19)	Nursing (N=40)	Radiology Technology (N=19)	Weighted Average* (N=93)
Bayesian Model 2	0.783	0.972	0.706	0.445	0.719
Counselor Model 2	1.153	0.886	0.806	0.562	0.829
Classical Statistical Model 2	0.873	0.878	0.726	0.446	0.723

$$\text{*Weighted Average} = \sum_{i=1}^{4} \frac{\text{Curriculum Enrollment X Mean Absolute-Error}}{93}$$

Table 32

Analysis of Variance for
Absolute-Error Differences
for All Allied Health Curricula

Source of Variation	SS		df		MS	F
Between students		181.951		92		
Within students		12.168		186		
Treatments	0.715		2		0.358	5.774*
Residual	11.453		184		0.062	
Total		194.119		278		

*Significant at .01-level

Table 33

Tukey's Test for Differences
of Absolute-Error for
All Allied Health Curricula

GPA Model		Bayesian Model 2	Classical Statistical Model 2	Counselor Model 2
	Means	0.719	0.723	0.829
Bayesian Model 2	0.719	--	0.004	0.110*
Classical Statistical Model 2	0.723		--	0.106*
Counselor Model 2	0.829			--

$$\sqrt{\frac{MSw}{n}} \; .95q_{3,276} = (0.260)(3.356) = 0.087$$

*Significant at the .05-level

It was concluded - on the basis of Tukey's Test - that the Bayesian Model 2 and the Classical Statistical Model 2 do not differ, and the mean of the Counselor Model 2 differs from the means of both the Bayesian Model 2 and the Classical Statistical Model 2.

Table 34 presents the mean squared-errors by curricula and the weighted mean squared-errors of all curricula for the three GPA prediction models.

An analysis of the data provided a rank order of most efficient to least efficient for the weighted average squared-errors as follows: (1) Bayesian Model 2 (1.206), (2) Classical Statistical Model 2 (1.233), and (3) Counselor Model 2 (1.368).

An analysis of variance of mean differences of squared-error using a single-factor design having repeated measures on the same elements was computed to locate treatment differences. Table 35 cites the analysis of variance summary table for the combined four allied health curricula.

An analysis of variance failed to reject the hypothesis that the average squared-error differences were different at the .05-level for the three GPA models.

Table 34

Mean Squared-Errors
for the Three GPA
Prediction Models

Model	Dental Assistant (N=15)	Mental Health Technology (N=19)	Nursing (N=40)	Radiology Technology (N=19)	Weighted Average* (N=93)
Bayesian Model 2	1.388	1.643	1.242	0.549	1.206
Counselor Model 2	2.068	1.623	1.349	0.599	1.368
Classical Statistical Model 2	1.622	1.341	1.369	0.476	1.233

$$\text{*Weighted Average} = \sum_{i=1}^{4} \frac{\text{Curriculum Enrollment X Mean Squared-Errors}}{93}$$

Table 35

Analysis of Variance for
Squared-Error Differences
for All Allied Health Curricula

Source of Variation	SS		df		MS	F
Between studnets		1639.606		92		
Within students		69.516		186		
Treatments	1.404		2		0.702	1.897*
Residual	68.112		184		0.370	
Total		1709.122		278		

*Nonsignificant at .05-level

SUMMARY

The results and analyses of the study presented the methods and procedures for developing the three program-completion models. Analyses and comparisons of the effectiveness and the efficiency of the models were presented by individual allied health curriculum as well as across all curricula.

An analysis of the mean absolute-errors and mean squared-errors by individual curriculum and across all curricula indicated that there were little differences in the prediction efficiencies of the three program-completion models. The Friedman test was also used to analyze the prediction efficiencies of the three models in terms of a complete block design of the total rankings for the four allied health curricula. Since the Friedman test statistic (30.59) exceeded the .95 quantile of the chi-square random variable (5.991) with 2 degrees of freedom, the hypothesis of identical treatment effects was rejected. Further analyses using multiple comparisons procedures proposed by Anderson (1959) indicated that there were (1) no statistically significant differences between the rankings for Counselor Model 1, (2) linear comparison differences among models for rank 1, and (3) statistically significant differences between linear rankings for Bayesian Model 1 and Classical Statistical Model 1.

An analysis of the mean absolute-errors by individual curriculum and across all curricula indicated that there were little or no differences in the prediction efficiencies of the Bayesian and classical statistical models in reducing the average absolute-errors. Counselor Model 2 was found to be less efficient than either the Bayesian or classical statistical models. An analysis of variance of mean differences of absolute-errors using a single-factor design having repeated measures on the same elements contradicted the hypothesis that the three treatment effects were equal at the .01-level with Tukey's Test for differences for average absolute-errors confirming that the mean absolute-errors of the Counselor Model 2 differs from the means of both the Bayesian Model 2 and the Classical Statistical Model 2. An analysis of mean squared-errors by individual curriculum and across all curricula indicated that there were little or no differences in the prediction efficiencies of the three GPA-prediction models. An analysis of variance of mean differences of squared-errors using a single-factor design having repeated measures on the same elements failed to reject the hypothesis that the squared-error differences were different at the .05-level for the three GPA prediction models.

Chapter 5

SUMMARY

Because of high enrollment demands, limited instructional spaces, and the high cost of programs, many community colleges have been forced to place stringent admission requirements in the guidance and selection of students for certain allied health curricula such as Dental Assistant, Mental Health Technology, Nursing, and Radiology. Since recent research studies (A. W. Astin, 1975; H. S. Astin, 1970; Summerskill, 1962; Trent and Medsker, 1967) have reported withdrawal rates of 50 percent and higher for students entering community college programs, a need for more efficient and effective guidance-selection models was indicated. Models that accurately predicted first-quarter GPA's and efficiently estimates the probability of successful program completion would benefit both the college and the students that enroll in these curricula.

The purpose of the study was to present and evaluate Bayesian-type models for estimating probabilities of program completion and predicting first-quarter GPA's for students entering four allied health curricula of the comprehensive community college. Bayesian Model 1 -- Estimating Probabilities of Program-Completion was developed from the discrete case of Bayes' formula as presented by Powers (1973, p. 4). Powers' methodology which utilized counselor/faculty advisors' inputs as *a priori* probabilities was extended by using posterior probabilities of graduate status of the discriminant analysis function as likelihoods.

The *a priori* probabilities and likelihood probabilities were combined in Bayes' Theorem to produce posterior probabilities of successful program completion. Bayesian Model 2 -- Predicting First-Quarter GPA's utilized a computer program developed by Kazuo Shigemasu (1975). This model which was an application and specialization of the Bayesian linear model developed by Lindley and Smith (1972) involved the assumption of homogeneity of regression coefficients (but not intercepts) across groups. This methodology (first proposed by Novick, Jackson, Thayer, and Cole, 1971) comparing GPA predictions across different schools with similar programs was adjusted in terms of comparing similar programs within one college (i.e. the m-groups were now different programs instead of different schools). The efficiencies of the Bayesian-type models were compared and evaluated in terms of two counselor selection models and two classical statistical models.

Although a review of the literature dealing with the prediction of academic success revealed a wealth of materials concerning the prognosis of college and university success, there have been few studies that dealt with the problem in an experimental fashion. In general, prediction studies have been ex post facto research in which the independent variable or variables have already occurred and the researcher starts with the observation of a dependent variable or variables. Little or no efforts have been directed toward cross validation studies which predict the academic success of the next class and/or evaluate the efficiency of the prediction models in terms of the new class. The literature review also noted that little effort has been directed toward developing and evaluating multiple prediction procedures. Therefore, the purpose of the present study was to present and evaluate multiple prediction procedures in a quasi-experimental fashion by using data for new allied health classes first enrolled for Fall 1975.

The design of the study required that three program-completion models and three GPA prediction models be constructed from data discerned from previous students enrolled from the Fall of 1972 through the Fall of 1974. These models were used to predict first-quarter GPA and probabilities of program completion for students first enrolled for Fall 1975. The efficiencies of the models were compared by examining predicted GPA in terms of actual first-quarter GPA and estimates of probabilities of program completion in terms of actual graduate-nongraduate status (enrolled or withdrawn) for Spring 1976.

The total sample of the study consisted of 374 students who were enrolled in the curricula of Dental Assisting, Mental Health Technology, Nursing, and Radiology. Data for students enrolled from Fall 1972, 1973, and 1974 were used to develop statistical equations (discussed below) necessary for developing the six prediction models for students entering in the Fall 1975.

The predictor (independent) variables consisted of selected academic variables discerned by examining both previous research results and present theories concerning academic achievement with additional recommendations from allied health counselors, faculty, and administrators. The criterion (dependent) variables consisted of (1) first-quarter GPA and (2) graduate/nongraduate status.

Several statistical methods were employed in developing the six prediction models. These methods were summarized as follows:

Program-Completion Models	Statistical Methods
Bayesian Model 1 -- Estimating Probabilities of Program-Completion	Application of Bayes' formula using counselor's assignment of probability of successful programs completion as a priori probability and discriminate score of probability of graduate classification as likelihood.
Counselor Model 1 -- Estimating Probabilities of Program-Completion	Counselor's assignment of probability of successful program completion.
Classical Statistical Model 1 -- Estimating Probabilities of Program-Completion	Discriminant analysis for graduate/nongraduate group membership using the discriminate score to estimate the students' success in completing the specific allied health curriculum.

GPA Prediction Models	Statistical Methods
Bayesian Model 2 -- Predicting First Quarter GPA's	Bayesian M-group Regression Analysis with Identical Regression Coefficients
Counselor Model 2 -- Predicting First-Quarter GPA's	Counselor's assignment of first-quarter GPA
Classical Statistical Method 2 -- Predicting First-Quarter GPA's	Forward stepwise multiple regression using SPSS REGR

Several statistical methods were employed in comparing and evaluating the effectiveness of prediction models. The program completion models were evaluated by comparing the mean absolute-errors and the mean squared-errors by both individual curriculum and by combined curricula. The Friedman test was used to evaluate the three models by ranking the predicted probabilities in terms of actual status. In the case that the null hypothesis of equal likely rankings within a block (student) was rejected, multiple comparisons were examined in terms of tests presented by Anderson (1959) for rank data.

The three GPA prediction models were evaluated by examining the absolute-error-loss function, squared-error-loss function, and using the analysis of variance (F-test) of predicted and actual GPA differences for a single-factor experiment having repeated measures on the same element (Winer, 1962, pp. 105-124). The efficiencies of the models were compared and evaluated in terms of the average absolute-error-loss and average squared-error-loss by both individual curricula and combined curricula.

The study was limited in that certain restrictions were placed on the six prediction models. This fact was especially true for the Classical Statistical Model 1 which employed multiple regression in the traditional sense because counselors' evaluations of students first enrolled Fall 1972, 1973, and 1974 were unavailable to be used as independent variables in developing the GPA prediction equation. The study was also limited by certain time factors which required that the criterion of graduate/non-graduate status for students first enrolled Fall 1975 to be determined in terms of enrolled/not enrolled for Spring 1976. Other limitations concerned missing data of high school rank and School and College Ability Test (SCATS) scores.

CONCLUSIONS

The results of the study indicated that there were little differences in the prediction efficiencies of the three models in reducing the weighted average absolute-errors of the four allied health curricula. The analysis of rank order efficiencies of the three models indicated that the weighted average absolute-error differences between the actual status (1 - graduate and 0 - non graduate) and the predicted status for the 93 students in the four allied health curricula were as follows: (1) Bayesian Model 1 (0.34), (2) Counselor Model 1 (0.35), and (3) Classical Statistical Model 1 (0.40). Further descriptive analysis of the rank order efficiencies of the three models indicated that the weighted average squared-error differences between the actual status (1 - graduate and 0 - nongraduate) and the predicted status for the 93 students in the four allied health curricula were as follows: (1) Classical Statistical Model 1 and Counselor Model 1 tied (0.22) and (2) Bayesian Model 1 (0.24). Although inspection by curriculum and by individual students indicated that all three models were appropriate in specific cases, an analysis of ranking efficiencies of the three models using the Friedman (1937) test rejected the hypothesis of identical treatment effects at the .05-level. Further analyses using multiple comparisons aspects proposed by Anderson (1959) revealed the following:

1. There were no statistically significant differences between the rankings assigned to Counselor Model 1.

2. There were statistically significant linear comparison differences among models for rank 1. Inspection of the models receiving rank 1 clearly indicated that the Bayesian Model 1 (56 rank 1) exceeded the rank 1 of either the Classical Statistical Model 1 (25 rank 1) or the Counselor Model 1 (12 rank 1).

3. There were statistically significant differences between linear rankings for Bayesian Model and Classical Statistical Model 1. Inspection of the data clearly supported the hypothesis that the Bayesian Model 1 was the most efficient model in selecting successful allied health students who would complete their programs of study.

A descriptive analysis of the three GPA models indicated there were little differences in the prediction efficiencies of the Bayesian and classical statistical models in reducing the weighted average absolute-errors for the 93 students enrolled in the four allied health curricula. Counselor Model 2 was less efficient than either the Bayesian or classical statistical models. The rank order efficiencies of the three models indicated that the weighted average absolute-error differences between actual first-quarter GPA and predicted GPA were as follows: (1) Bayesian Model 2 (0.719), (2) Classical Statistical Model 2 (0.723), and (3) Counselor Model 2 (0.829). An analysis of variance of mean differences of absolute-errors using a single-factor design having repeated measures on the same elements [$F(2,184) = 5.774$] contradicted the hypothesis that the three treatment effects were equal at the .01-level with Tukey's Test for differences of average absolute-errors confirming that the mean absolute-errors of the Counselor Model 2 differs from the means of both the Bayesian Model 2 and the Classical Statistical Model 2. Further descriptive analysis of weighted mean averages of predicted and actual GPA differences of squared-error found little differences in the predicted efficiencies of the three models. A rank order of most efficient to least efficient for the weighted aveerage squared-errors was as follows: (1) Bayesian Model 2 (1.206), (2) Classical Statistical Model 2 (1.233), and (3) Counselor Model 2 (1.368). An analysis of variance of mean differences of squared-errors using a single-factor design having repeated measures on the same elements failed to reject the hypothesis that the squared-error differences were different at the .05-level for the three GPA prediction models.

Because several investigators (Nicholson, 1970; Heist, 1968; Savicki and others, 1970) have noted that dropouts were not different from successful persisters on predicted GPA, the study concluded that there was a greater need to learn more about the prediction of graduation from college as a criterion of college success rather than college GPA.

This fact was especially true for the allied health curricula because in most cases graduation itself was the key to entering the occupational fields. In order to provide the greatest information to counselors and students concerning an estimate of their predicted graduate/nongraduate status, the need for a multiple comparison selection system was established by the results of the present study. These results indicated that the counselor and possibly the student could benefit from examining the prediction estimates provided by the different program-completion models. Because graduation was partially a function of GPA, the study concluded that GPA's should be viewed as necessary but not sufficient conditions for future academic successes. Therefore, it was necessary to examine predicted GPA's in terms of predicted program-completion probabilities.

RECOMMENDATIONS

The results of the study supported several recommendations for further study. First and foremost, the Bayesian-type procedures produced results which indicated that they are deserving of further investigating. Since the major problem in Bayesian inference has been that of quantifying *a priori* information, further studies were recommended in terms of establishing methodologies that assist counselors and faculty advisors in quantifying and understanding the processes of estimating and assigning probabilities for program-completion and predicting first-quarter GPA's. Additional investigations should discern topics such as: How did these counselors actually make the decisions for assigning the program-completion estimates and the GPA predictions? Why were the models very accurate in the case of student 5 and totally inaccurate in the case of student 10? Were there characteristics that can be identified which would discriminate between students who were accurately classified and students who were inaccurately classified?

In terms of the GPA models, it was certainly obvious that additional variables should be added to the Classical Statistical Model 2 and the Bayesian Model 2. It was recommended that additional academic variables with biographical, demographical, and attitude/opinion variables be added to the study. The possibility of using certain types of factor analyses of the variables and using the factor scores as independent variables should be discerned. The use of additional academic and nonacademic variables for the program-completion models should also be investigated. In addition studies that jointly examine GPA and problem-completion prediction models and their relationship should be examined.

Although the three program-completion and GPA models represented extremes on a continuum, it was recommended that the following additional models be proposed and investigated in terms of multiple comparison studies:

1. Both the Classical Statistical Model 2 -- Predicting First-Quarter GPA and the Bayesian Model 2 -- Predicting First-Quarter GPA should be extended with the inputs of certain counselors' evaluations as independent variables.

2. The use of dummy independent variables in coding the four allied health programs for the Classical Statistical Model 2 -- Predicting First-Quarter GPA should be considered in future studies.

3. The use of certian nonlinear transformations should be considered in developing future GPA prediction models.

4. Novick's original M-group regression program should be considered in future studies.

5. Theoretical work should be extended to incorporate _a priori_ beliefs of counselors into the Bayesian M-group regression procedures.

In addition many cross validation studies should be examined in order to establish the validity of impressive correlation coefficients that have been developed by ex post facto research.

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A COMPARATIVE STUDY OF THE EFFECTIVENESS OF TWO BAYESIAN MODELS FOR PREDICTING THE ACADEMIC SUCCESSES OF SELECTED ALLIED HEALTH STUDENTS ENROLLED IN THE COMPREHENSIVE COMMUNITY COLLEGE

by

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(ABSTRACT)

Because of high enrollment demands, limited instructional spaces, and the high cost of programs, many community colleges have been forced to place stringent admission requirements in the guidance and selection of certain allied health curricula such as Dental Assistant, Mental Health, Nursing, and Radiology. In this guidance-selection environment in which there were more candidates than vacancies, methods and/or procedures must be established that discern the "best" applicants. Since neither the classical statistical models which utilize correlations, regression, discriminate analysis, etc. nor the counselor-selection models have typically utilized all the information regarding a student, the need for more efficient and effective guidance-selection models was indicated. In this context Bayesian-type models have been proposed that can utilize the strengths of both the classical statistical models and the counselor-selection models.

The purpose of the study was to present and evaluate Bayesian-type models for estimating probabilities of program completion and predicting first quarter grade point average (GPA). Bayesian Model 1 -- Estimating Probabilities of Program Completion was developed from the

discrete case of Bayes' formula with counselors' inputs as *a priori* probabilities and posterior probabilities of graduate status of the discriminant analysis function as likelihoods. The *a priori* probabilities and likelihood probabilities were combined in Bayes' Theorem to produce posterior probabilities of successful program completion. Bayesian Model 2 -- Predicting First-Quarter GPA's which was an application and specialization of the Bayesian linear model developed by Lindley and Smith (1972) involved the assumption of homogeneity of regression coefficients (but not intercepts) across groups. The efficiencies of the Bayesian-type models were compared and evaluated in terms of two counselor selection models and two classical statistical models.

Although inspection by curriculum and by individual students indicated that all three program completion models were appropriate in specific cases, an analysis of ranking efficiencies using the Friedman (1937) test rejected the hypothesis of identical treatments. Further analyses using multiple comparisons aspects proposed by Anderson (1959) indicated that there were statistically significant linear comparison differences among the models with the Bayesian Model 1 ranking as the most efficient model. An analysis of the three GPA models using an analysis of variance test contradicted the hypothesis that the three treatment effects were equal at the .01-level with Tukey's Test for differences of average absolute-errors confirming that the Bayesian Model 2 and the Classical Statistical Model 2 were more efficient than the Counselor Model 2. The results of the study supported several recommendations for further study.