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The identification of differentiating success factors for students in computer science and computer information systems programs of study

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THE IDENTIFICATION OF DIFFERENTIATING SUCCESS FACTORS FOR STUDENTS IN COMPUTER SCIENCE AND COMPUTER INFORMATION SYSTEMS PROGRAMS OF STUDY

A Dissertation Presented

by

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ABSTRACT

THE IDENTIFICATION OF DIFFERENTIATING SUCCESS FACTORS
FOR STUDENTS IN COMPUTER SCIENCE AND
COMPUTER INFORMATION SYSTEMS PROGRAMS OF STUDY

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Although both are computer-based, computer science and computer information systems programs of study are markedly different. Therefore, it is not unreasonable to speculate that success factor differences may exist between them, and to seek an objective means of making such a determination based on a student's traits.

The purpose of this study was therefore two-fold - to determine whether differences do in fact exist between successful computer science majors and successful computer information systems majors, and if such was affirmed, to determine a classification rule for such assignment.

Based on an aggregate of demographic, pre-college academic, and learning style factors, the groups were found to differ significantly on the following variables

(listed in decreasing likelihood of significance, for those with $p < .05$): sex, abstract conceptualization and concrete-abstract continuum measures, SAT - Mathematics, interest ranking for science, active experimentation measure, interest ranking for foreign language, and concrete experience measure. Computer science majors were found to consist of significantly more males than females, and to have significantly higher abstract conceptualization, concrete-abstract continuum, SAT - Mathematics, and interest ranking for science measures than computer information systems majors, while computer information systems majors were found to have significantly higher active experimentation, interest ranking for foreign language and concrete experience measures.

A classification rule, based on a subset of these factors, was derived and found to classify correctly at a 76.6% rate. These results have potential as a research-based component of an advising function for students interested in pursuing a computer science or computer information systems program of study.

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CHAPTER 1

INTRODUCTION

Background and Problem Statement

Recent years have brought about scientific and technological advances of tremendous scope. Mouly [1970] asserted that half of the scientific knowledge at the time had been the result of efforts made in the preceding 25 years. More recently, Sanders asserts that scientific information is doubling every 5 1/2 years. [1987] One most notable facet of this scientific and technological revolution has been the emergence of the electronic computer.

History is replete with efforts that have been directed at the problem of extending man's computational and information processing capabilities. The abacus, the earliest known mechanical computing device, has been traced to the 500 B.C. era, and is known to have been used by the Egyptians, Babylonians, Japanese, Arabs, Chinese and Romans. [Simpkin, 1987] Significant developments are again encountered beginning in the early 1600's, with the focus of the most noteworthy efforts being either the development of mechanical calculators or punched-card driven devices. Finally, in the late 1930's and throughout the 1940's, several prototype electronic computers were designed, built, and installed, setting the stage for the commercial availability of computers in the early 1950's. [Graham, 1986]

Since that time, a computer "explosion" has taken place, both in terms of capability and quantity. Early computers had instructional capabilities measured in hundreds of instructions per second; today's more powerful systems are measured in the millions or billions of instructions per second. Memory capacity has seen similar dramatic growth. The IBM 1401, a commercial data processing mainframe computer of the late 1950's, had a maximum capacity of approximately 16,000 characters; the current IBM PC, an affordable microcomputer often bought by individuals for home use, has a maximum capacity in excess of 2 million characters. [Brightman and Dimsdale, 1986]

Interestingly, these remarkable increases in capability have been accompanied by dramatic decreases in price. In 1950, the cost of performing 100,000 multiplications was $1.25; in 1986, the cost of performing the same operations was approximately five cents. [Brightman and Dimsdale, 1986] This combination of increased capability and downward price trend has been extrapolated onto the aircraft industry in the following manner:

> If the aircraft industry had evolved as spectacularly as the computer industry over the past 25 years, a Boeing 767 would cost $500 today, and it would circle the globe in 20 minutes on five gallons of fuel. [Toong and Gupta, 1982, p. 87]

This inverse relationship between price and performance is much more than a mere point of interest. It represents a constant movement toward affordability, and is probably the most significant factor in the computer's increasingly pervasive influence in our society. [Brightman and Dimsdale, 1986] In 1950, the number of computers in existence was in the single digits; by 1978, the number was approaching one million, and currently, the number is estimated to be near 50 million. [Goldstein, 1986] By 1990, it is anticipated that computers will be selling at the rate of 11 million per year, with 400 million machines in use in the United States alone. [Slotnick, et al., 1986]

This continually expanding base of installed computers has had a great impact on employment opportunities in the computer field. As of 1980, there were approximately 1.5 million people employed in the computer industry positions of computer scientist, systems analyst, programmer, operator, data entry clerk, and service technician; it is projected that this figure will reach 2 million by 1990. [Parker, 1987] In 1980, approximately 600,000, or 40% of the total, were in positions requiring four-year college degrees (computer scientists, programmers, and systems analysts); by 1990, it is anticipated that over 900,000, or over 50% of the total, will be in positions requiring at least the four-year college degree. [Goldstein, 1986]

Two distinct majors have evolved in four-year college curricula that provide students with skills requisite to these positions - the computer science and the computer information systems programs of study. The computer science program is the more technical of the two majors, with an emphasis on the design of system software. An extensive knowledge of the hardware (physical organization and design of the machine) along with a calculus-based study of the theoretical aspects of the discipline, are characteristics of the computer science program that generally distinguish it from the computer information systems program. [Burstein, 1986] Its graduates are usually sought for positions such as systems programmers, with responsibilities for designing compilers, operating systems and utility programs. [Parker, 1987]

The computer information systems program - often known by the essentially synonymous terms business data processing, management information systems, or information resource management - emphasizes the processing of data to produce information that will be used by a business or governmental employer at the operational, management information, or decision support level. Its purpose is to provide applications for the end-user, such as payrolls, billing systems and various management reports. [Burstein, 1986]

Although similar in some respects, such as in the generic concepts of programming, the majors differ substantially in two ways. In the early stages of the majors, fundamental programming principles are addressed with markedly different languages (COBOL is generally used with computer information systems majors, and Pascal is generally used with computer science majors). Later stages become even more disparate, in that differences are found not merely in implementation, but in concept and content entirely. [Parker, 1987] Thus, although both majors are "computer" majors, they are substantially different in content, and overlap, if any, is often found at only the most introductory level.

For these reasons, the choice between the computer science and computer information systems major (by a prospective student interested in studying "computers") is a decision to be weighed carefully. Obviously, there is no correct choice for all students considered collectively, but there certainly can be a more appropriate choice for any particular student. However, as illustrated by a 1984 survey of Westfield State College computer science majors, in which fully half of the respondents indicated a desire to be enrolled in a proposed computer information systems major at the college, often the choice of "computer" major has been less than optimal.

Numerous studies have addressed the issue of predicting the likelihood of student success in both the computer science and computer information systems majors. These studies have examined various factors in an attempt to determine whether they could be shown to be predictors or indicators of success by students in the major considered. The factors examined in these studies usually can be placed into one of two distinct categories.

The first category can be classified as pre-college academic predictors, which includes items such as high school grade point average or rank in class; number of courses and/or level of success in high school mathematics, science and computer courses; results of standardized tests, such as the Scholastic Aptitude Test or the American College Testing exams; and the results of tests independently designed and developed for the specific purpose of predicting success in future computer programming endeavor, such as the Programmer's Aptitude Test. [Butcher and Muth, 1985; Campbell and McCabe, 1984; Gathers, 1986; Ramberg, 1986] The second category includes measures of non-achievement oriented constructs, such as cognitive style, personality type, learning ability, and intellectual development stages. [Corman, 1986; Petersen and Howe, 1979; Werth, 1986]. Generally, these studies have been correlational in nature, attempting to determine whether one or more of the factors correlated significantly with success in a particular introductory level computer class or sequence of classes, although occasional attempts have been made at drawing conclusions beyond the introductory level. [Campbell and McCabe, 1984].

Regardless of whether pre-college academics or non-achievement oriented constructs are considered, most studies have attempted to identify correlations between any number of the above factors and a single, homogeneous group - such as "introductory programming class", "completion of computer science major", or "computer information systems studies". However, none have attempted to identify distinguishing factors between the two groups of students that graduate from the markedly different but often confused computer-related programs of study available to students in higher education - "successful computer science majors" and "successful computer information systems majors".

This study attempts to accomplish exactly that. Students having been adjudged to have attained success in either a computer science or computer information systems program of study will be contrasted with respect to selected demographics, pre-college academics, and non-achievement oriented constructs, in an attempt to identify those factors that significantly distinguish members of one group from those of the other. The utility of such research becomes apparent when one considers the advising function (both at the high shool level and in the early college years) which in this case is particularly difficult due to the significant differences that exist between the majors but perception by those outside of the discipline of a sameness with respect to these "computer" majors.

Purpose of the Study

The purpose of this study is to determine if differences exist between students having been adjudged to have attained success in computer science and those having been adjudged to have attained success in computer information systems with respect to various pre-college academics and non-achievement oriented constructs. The pre-college academics to be examined will be high school grade point average and rank in class, SAT - Mathematics and SAT - Verbal scores, and amount of high school coursework, and inclination for same, in each discipline. The non-achievement oriented constructs to be examined are dimensions of learning style, as measured by the Learning-Style Inventory [Kolb, 1985].

Since no previous studies attempting to identify discriminators between successful computer science and computer information systems students have been found by the researcher, the following null hypothesis will be tested: there is no significant difference between successful computer science and computer information systems students based on a multivariate analysis of factors considered in aggregation, nor on any of the factors considered individually.

In the event that statistical analyses shall form the basis for rejection of the null hypothesis identified above, a classification rule to predict group membership, based on a combination of those variables studied, will be advanced.

Definition of Terms

Several terms used in this study require operational definition; they are computer science major, computer information systems major, and success in a major.

Computer Science Major

A student is classified as being a computer science major if the program in which the student is enrolled is purported to be based on the Association for Computing Machinery's (ACM) recommendations for undergraduate programs in computer science. [Austing, et al., 1979] (These recommendations are outlined in Appendix A.) Generally a program such as this is offered by, or in conjunction with, a Computer Science and/or Mathematics Department in a School of Arts and Sciences environment.

Computer Information Systems Major

A student is classified as being a computer information systems major if the program in which the student is enrolled is purported to be based on either the ACM's recommendations for undergraduate programs in information systems [Nunamaker, et al., 1981], or the Data

Processing Management Association's (DPMA) model curriculum for computer information systems education. [Adams and Athey, 1981; CIS '86, 1986] (These recommendations are outlined in Appendices B and C respectively.) Generally a program such as this is offered by, or in conjunction with, a Computer Information Systems and/or Quantitative Methods Department in a School of Business environment.

Success in a Major

From a scholastic point of view, success in a major generally requires that three conditions be met - that the student 1) be enrolled in the program of study (ie. declare the major), 2) pass certain prescribed courses (often within a specified passing grade range - ie. C- or better) within the major department or from various disciplines closely-enough related to be considered a part of the major's coursework, and 3) complete the courses specified in part 2 above with at least a minimum (ie. C or better) grade point average. The non-technical implementation, however, tends to be simple longevity within the program of study; that is, seniors tend to succeed in their currently declared majors, whereas freshmen are much more likely than seniors to transfer and thus not succeed in their currently declared major.

For the purposes of this study, facets of both of the above views will be incorporated into the operational definition. This operational definition of success in a major will be any student who is of at least junior year standing, is enrolled in the major, and meets criteria 2 and 3 listed in the preceding paragraph (utilizing passing grades and a grade point average of at least 2.0) with respect to courses already taken.

Delimitations of the Study

The study assumes the following delimitations:

1. All subjects will be of junior or senior year standing, and be majoring in computer science or computer information systems at one of the following colleges: Keene State College, Siena College, Springfield College, Western New England College or Westfield State College.

2. The attributes comprising learning style will be those of concrete experience, reflective observation, abstract conceptualization, and active experimentation, and measures of placement on abstract/concrete and active/reflective continua as reported by the Learning-Style Inventory of Kolb as revised in 1985.

The voluntary nature of the participating students is recognized as a factor of negative impact on generalizability. However, the fact that they all attend institutions that profess to subscribe to the same curricular recommendations for the programs of study under consideration is mitigative in this regard.

Limitations of the Study

The study assumes the following limitations:

1. It is assumed that all subjects will respond completely, honestly, candidly and without reservation to the survey and Learning-Style Inventory utilized in the study, the instruments from which all data to be used in the study will be gathered.

2. It is assumed that an individual's learning style is not influenced by exposure to a computer science or computer information systems program of study.

The latter limitation is of particular interest to this study. Numerous factors have been utilized by other researchers in studies involving identification of success factors for computer science and computer information systems majors. Typically-employed instrumentation that fall into this category would include those of cognitive style, as with the Group Embedded Figures Test, of intellectual development level, as with the Kurtz-Karplus Formal Test, or of logical ability, as with the Watson-Glaser Critical Thinking Scale. [Conoley and Kramer, 1989] However, it can be judiciously postulated that they would be influenceable by the program of study itself, and thus would not be suitable for a study of this design. The choice of Learning-Style Inventory is therefore based, at least in part, on the premise of obviating such concern.

Significance of the Study

Only speculation can be made concerning the number of students who have left college without graduating, or never achieved their full potential in their college studies or subsequent careers due to their pursuit of a major that was not appropriate for them based on their aptitude or temperament. Clearly the issue of assisting the student in determining appropriate academic and career paths is central to any guidance function. The number of aptitude tests and vocational batteries utilized in education, industry and government, and by private academic and career counselors, stand in testimony to the attempts that are made to assist students in identifying academic and career paths that will be appropriate for them.

This study is significant in that it attempts to draw distinctions between groups of students considered to have been successful in two different computer majors - computer science and computer information systems - based on pre-existing factors that could be applied to students considering, but not yet enrolled in the majors. The results become significant when one recognizes that the majors are vastly different, as discussed previously, and that most people, outside of practicing professionals in the fields, do not have a full understanding of the distinctions between the disciplines under study. Results of this study would be extremely useful in the advising of students who are interested in pursuing a program of studies involving computers, but who are unsure as to which specific discipline they should pursue.

CHAPTER 2

LITERATURE REVIEW

Introduction

Numerous studies have addressed the issue of predicting the likelihood of success in some facet of computer studies. Generally, success in an introductory computing course, usually within a computer science major, has been studied, although some studies have attempted to draw conclusions beyond the introductory course level. Potential predictor factors used in these studies cover a wide range, but can generally be categorized as being either of the academic/aptitude variety, such as grade point average, rank in class, number of courses and/or measure of success in a particular area (such as mathematics), and scores on widely-used standardized tests (SAT, ACT), institutionally-sponsored placement tests, and specifically designed computer aptitude tests, or of the non-achievement oriented construct variety, focusing on such constructs as cognitive style, personality type, learning ability or intellectual development stages.

For discussion purposes, a division of the studies into groups based on similarity of dependent variables is employed. In dividing the studies in this manner, six categories were readily identified: 1) early (pre-1982) studies involving achievement in a first computer science programming language course, 2) recent (post-1982) studies involving achievement in a first computer science programming language course, 3) studies dealing with the completion of, or withdrawal from, a computer science program of study, 4) studies involving achievement in introductory courses of a computer information systems program of study, 5) studies involving several programming languages not necessarily associated with either a computer science or computer information systems program of study, and 6) miscellaneous studies not belonging in any of the first five categories. Recalling that the reason for examining these studies is to gain insight into factors that could be valuable in the advising of students enrolling in computer-related programs of studies, those studies in the first four categories would appear to be most cogent; however, studies from the last two groups will be seen to be valuable not only in terms of reinforcing some notions offered in the first four groups, but also in advancing several propositions not otherwise considered.

Review of Selected Studies

Five studies met the criteria of the first group - those being a study involving achievement in a first computer science course that was done prior to 1982. At the time, the introductory computer science course generally used FORTRAN as a high-level language, and often included a low-level symbolic language component. Alspaugh's 1972 study is the first in this group, and is generally recognized as being the earliest, widely recognized study attempting to identify "components of computer programming aptitude." [p. 89]

In this study, fifteen measures were correlated against proficiency in an introductory computer science course (BAL and FORTRAN IV). Included among these measures were critical thinking ability as measured by the Watson-Glaser Critical Thinking Appraisal, seven aspects of temperament (active, vigorous, impulsive, dominant, stable, sociable and reflective) as measured by the Thurstone Temperament Schedule, four measures of reasoning (number series, figure analysis, arithmetic reasoning and total score) as measured by the IBM Programmer Aptitude Test, verbal and mathematical reasoning ability as measured, respectively, by the SCAT - Verbal and Quantitative instruments, and a measure of mathematical background. Significant positive correlations were found for only two of the fifteen variables considered - mathematics background and the arithmetic reasoning component of the IBM Programmer Aptitude Test, although it is interesting to note that both the impulsive and sociable temperament constructs were of significant negative correlation. However, without a more detailed discussion of the course, it is difficult to determine if it was taught as a first computer science course is traditionally taught today, or as a mathematically-based, abstract approach to computer programming that was sometimes employed in the early years of computer science instruction.

Mazlack examined the grades of 1,350 students who had completed an introductory FORTRAN programming class in an attempt to "aid in answering questions about the competitiveness and compatibility of students of differing disciplines, gender, and academic experience." [1980, p. 15] Using a distinction of arts versus science, and academic experience as measured by the semester of college studies in which the course was taken, Mazlack found no significant correlations. However, nearly 700 students who either dropped out of the course or had an "adjusted grade" were not taken into consideration in arriving at these conclusions, thereby introducing the possibility of bias toward successful students into the study.

Kurtz [1980] administered a test designed to classify students by development of abstract reasoning - intellectual development - into one of three intellectual development levels: late concrete, early formal or late formal. The type of reasoning assessed in this intellectual development instrument included conservation of displaced volume, separation of variables, combinations, direct proportion, inverse proportion, probability, permutations, correlation, deductive logic, and propositional logic. Any students not successful in direct proportion or probabilistic reasoning were classified as being at the late concrete level, any students succeeding in three out of four of the most difficult reasoning tasks (permutations, correlation, deductive logic and propositional logic) were classified as being at the late formal stage, while all others were classified as being at the early formal stage. When course performance (grade) for the (FORTRAN IV) course that served as the item of interest was divided into three groups - low (C- and below), average (C+ to B), and high (A and A-) (the groupings were suggested by the absence of any B+ or C grades), a contingency table of these grade groupings with intellectual development level indicated a strong relationship, and one which was particularly striking with respect to late concrete - low achievement and late formal - high achievement pairings.

Konvalina, Stephens and Wileman, in two 1981 studies of students taking an introductory computer science course using a simulated assembler and the PL/C high-level language, created an aptitude exam consisting of five components: reading comprehension, sequences, logical reasoning, algorithmic execution and alphanumeric translation. In one study, the scores on the sequences, logical reasoning, and algorithmic execution portions of the aptitude test proved to be significantly correlated with achievement as evidenced by final exam grade [Stephens, Wileman and Konvalina, 1981]; in the other study, the same three portions plus reading comprehension were found to be significantly correlated with course achievement. [Wileman, Konvalina and Stephens, 1981]

While these early studies established little in the way of consensus, they did suggest that mathematical and abstract reasoning abilities were related to achievement in an introductory computer science programming class, and generally laid the foundation for future studies in the area. Within the second group, which includes post-1982 studies involving achievement in a first computer science programming language course, are studies which expanded upon "leads" uncovered in previous work, such as Werth's [1986] and Barker and Unger's [1983] studies involving intellectual development; others continued to pursue academic, aptitude or demographic factors.

Two such studies were those by Konvalina, Stephens and Wileman, which dealt with academic and demographic factors. [Konvalina, Stephens and Wileman, 1983; Konvalina, Wileman and Stephens, 1983] In these 1983 studies, eight independent variables were considered - high school performance, hours worked per week, previous computer science education, previous non-programming computer work, previous work experience, years of high school mathematics, semesters of college mathematics, and age. Of these, four, high school performance, previous computer science education, years of high school mathematics and semesters of college mathematics, were found to be significantly correlated with success in the course as measured by a final exam grade [Konvalina, Stephens and Wileman, 1983], while high school performance, semesters of college mathematics, previous computer science experience, and age were found to be significant factors in a separate, but similar study. [Konvalina, Wileman and Stephens, 1983].

Butcher and Muth [1985] and Gathers [1986] conducted similar studies; the former tested thirteen independent variables, including the ACT Mathematics, English, Natural Science, Social Science and Composite scores, and other academic and demographic factors to include high school class rank, high school class size, high school grade point average, number of high school computer science/data processing courses taken, number of high school physics/chemistry courses taken, number of high school mathematics courses taken, and number of high school mathematics/physics/chemistry/biology/computer courses taken. In this study, of 372 first semester freshmen enrolled in a first course in a computer science major, 269 completed the course and were used as subjects. Significant correlations with respect to final grade in the course were found for all factors but high school size and number of high school computer science/data processing courses taken. Additionally, they noted that the "best" three variable regression equation for predicting course grade was based on the variables ACT - Mathematics, ACT - Composite, and high school grade point average.

Gathers studied ten factors, including all the components and composite scores of the ACT, the Nelson Denny Reading scores (vocabulary, comprehension, and total) and the University of Tennessee at Martin Mathematics Placement Test score. When considered against achievement in the first computer science course in the major, where achievement is defined bilaterally as success (grade of A, B, or C) or lack of success (grade of D or F), only the university mathematics placement exam and the ACT - English score were found to be significant in achieving the desired bilateral discrimination.

Barker and Unger [1983] and Werth [1986] both studied intellectual development level in their research, expanding upon the earlier work of Kurtz [1980], although Werth also considered other factors. Barker and Unger reduced the number of questions in the Kurtz test from 15 to 11 by eliminating second questions in the direct proportion, probabilistic reasoning, inverse proportion and correlational reasoning categories. Using the same criteria as Kurtz for separating examinees into late concrete, early formal and late formal levels of intellectual development, significance was demonstrated in differentiating A and B students from the D and F group. In fact, 73% of those classified as late formal received a grade of A or B, while 66% of those classified as late concrete received a grade of C, D, or F.

Werth [1986] considered not only intellectual development level, as described previously and measured by Barker and Unger's modification of the Kurtz test, but also cognitive style as measured by the Group Embedded

Figures Test, personality type as reported by the Myers-Briggs Type Indicator, and the factors of sex, age, high school and college academic performance, number of high school mathematics courses, and work experience. When correlated with course grade for the Pascal-based first course in the computer science major, college grade point average, amount of high school mathematics, cognitive style (field independent), and intellectual development were all found to be of significance, although only the 58 students completing the course (of 115 originally enrolled) were considered in the study.

A third group to be used for considering studies was identified earlier as being the completion of, or withdrawal from, a computer science program of study. Although similar in the types of independent variables considered to the previously discussed studies, the studies in this group differ in that they are concerned with whether or not a student finished the program of study (graduates with the computer science major), not merely how successful one is in a single introductory course in the major. Two studies of this type were identified, those of Campbell and McCabe [1984] and Sorge and Wark [1984].

Campbell and McCabe [1984] considered ten factors - SAT Mathematics score, SAT Verbal score, high school rank in class, high school class size, semesters of high school mathematics, semesters of high school science, semesters of high school English, high school mathematics grades, high school science grades, and high school English grades. In this study, 256 freshman computer science majors were examined during their third semester in college and categorized as being in one of two groups - CS+, consisting of computer science, engineering, or other science major, or Other, which simply consisted of those not classified as being in the CS+ category. When differences of means were considered between students in the two groups, significant differences were found in SAT Mathematics and Verbal scores, high school class rank, semesters of high school mathematics and science, and grades in high school mathematics and science.

Sorge and Wark [1984] analyzed the records of 1323 computer sciences majors at Purdue University, considering completion of four computer science courses as success in the major. Based on regression analysis, they determined that students should have an SAT Mathematics score of at least 560, SAT Verbal score of at least 500, a score of 5 or higher on the trigonometry portion of a universtiy algebra/trigonometry placement test, at least six semesters of high school mathematics with a B- or higher average and a rank in the top third of one's high school class "to have a reasonable chance of making satisfactory progress in the [computer science] program." They further concluded that "it is unrealistic for a student to expect to succeed as a computer sciences major without significant mathematical and verbal skills," and that "the high attrition rate, even by capable students, suggests that there are factors other than academic ability involved." [Sorge and Wark, 1984, p. 44] Based on interviews with those leaving the major, they suggest that these other factors may include the time demands, attention to detail, systematic thinking, and impersonal interaction with machines that is required of those pursuing the major.

Although many different factors have been considered with respect to activity in computer science courses or programs of study, those that stand out most notably tend to be those reflective of mathematical competence. Number of mathematics classes, high school mathematics grades, the Arithmetic Reasoning component of the IBM Programmer's Aptitude Test, the Sequential, Logical and Algorithmic sections of the KSW Aptitude Test, the SAT Mathematics score and ACT Mathematics score have all been recognized in at least one study as being related to success in computer science coursework. And, as Werth points out, the promise of intellectual development (abstract reasoning) level as an indicator of potential success in computer science is not then surprising, since the test used to assess it contains problems that may be solved mathematically! [1986] Non-mathematical indicators have been of the general intelligence type, such as ACT Composite score, or high school class rank or grade point average, or in some cases a more specific non-mathematical attribute, such as the ACT English or SAT Verbal score, or amount of or grades in high shool science classes, which would be subsumable within the general intelligence attribute. However, from 1972 on, the key word with regard to predicting success in computer science seems to be a short and simple one - math!

In the next group of studies, the item of interest changes from computer science courses and programs of study to those that are a part of, or constitute a program in, computer information systems. Fowler and Glorfeld [1981] conducted one of the earliest studies dealing with this type of course, using an Introduction to Data Processing course that had an approximate 50% programming component. Factors considered included age, sex, college grade point average, number of college mathematics courses taken, and SAT Verbal and SAT Mathematics scores as possible predictor values for determining inclusion in the A or B grade category or C, D or F grade category for the course. Using a logistic classification model approach, college grade point average was found to be the most important determinant of any factor, with number of college mathematics classes and SAT Mathematics score as the next most significant contributors.

Corman, in a 1986 study, compared introductory COBOL students with marketing students with respect to personality type as measured by the Myers-Briggs Type Indicator and a Type A-B Questionnaire, cognitive style as measured by the Group Embedded Figures Test, learning ability as measured by the Learning Style Inventory, and various other factors such as age, college grade point average, major grade point average, and high school rank. Other than college grade point averages being significantly higher for the COBOL students than for the marketing students, there were no other significant differences found. The following conclusion was of interest:

> Based on this study, there appears to be little contribution to the predictability of a student's success in an introductory programming course [of a computer information systems nature] by the consideration of psychological and personality variables. It appears that high achievers are naturally drawn to computer science [actually computer information systems in this case] versus a "softer" discipline. [Corman, 1986, pp. 82-83]

Morecroft and Ameen [1986-87] compared students finishing a computer information systems major to those starting but not completing the major on the following factors: SAT Verbal score, SAT Quantitative score, SAT Total score, cummulative college grade point average - first four semesters in college, and grade in an information systems concepts course that is required of all business students as part of their 54 semester hour foundation program (in accord with American Assembly of Collegiate Schools of Business requirements). Significant differences between finishers and those not completing the program of study were found in all factors considered except the SAT Verbal score; however, the information systems concepts course grade was offered as being the "most prominent" factor. [Morecroft and Ameen, 1986-87, p. 47]

From the few studies done in this area (relating to computer information systems), it can be seen that no clear factor emerges (as did mathematics for computer science). Generally, it appears that overall intelligence, which reasonably would be expected to include mathematical ability, tends to separate the computer information systems major from other business majors, and finishers of the program from non-finishers. However, the relative dearth of research in the area, and the disparate approaches taken by the few studies done therein, make it difficult to draw firm conclusions.

In the fifth category, consisting of studies involving success in programming language courses not clearly identified as being associated with either a computer science or computer information systems program of study, three studies were identified. The first, by Oman [1986], found SAT Mathematics score, SAT Verbal score, number of programming languages previously used, and number of time-share systems previously used (but interestingly, not number of microcomputers previously used) to be significantly correlated with the final grade in introductory programming classes. Ramberg and Van Caster [1986, p. 37] compared finishers and non-finishers from four different introductory computer classes, and found that "the single most important key to success in computer science is a prior exposure to computers, whether that be a literacy/programming course in high school or college," and that "prior math background is a good predictor in many cases." Deh and Mand [1986, p. 148], in examining the grades of 467 students across three different introductory programming language courses with respect to mathematics preparation, concluded that "background skills in mathematics appear to be contributory to success in introductory computer science courses," noting that the relationship "appears to be stronger when the background is obtained in high school."

The final category consists of several interesting studies that did not fit into any of the previously identified groups. Petersen and Howe [1979] correlated numerous factors with grades in an introductory computer class and found significance with respect to high school rank and grade point average, number of high school mathematics and science courses, grade point average in both high school mathematics and science, and college grade point average; also the Thurstone Temperament Schedule components vigorous, impulsive, dominant and sociable were found to be of significant negative correlation. Stevens [1983], using the Group Embedded Figures Test, found cognitive style to be significantly correlated with achievement in an instructional computer course for education majors. Finally, Hannafin and Cole, from a perception inventory of high school students, found that high school students perceived computer science to be "an area for students of high math or science aptitude," but not necessarily the exclusive province of the intellectually gifted. [1983, p. 225]

Summary of the Literature

Comprehensive conclusions based on this research are, unfortunately, difficult to delineate. Certainly, mathematics appears to be the key with respect to computer science programs of study. However, the computer information systems program of study does not lend itself to any singular predictor attribute, or group of attributes, as readily as does the computer science program of study. Furthermore, none of the studies attempted to differentiate between the characteristics requisite to success in a computer science program of study, and those necessary for success in a computer information systems program of study.

The solution to the problem of effectively advising students interested in pursuing a computer-related major is one that must be addressed at two levels. At the first level, it becomes necessary for accurate, informational advising to occur, both at the pre-college and college levels. A clear distinction between the computer science and computer information systems programs of study must be presented to students interested in pursuing a career in a computer-based field. This includes the presentation of accurate descriptions of both the courses required of each major, and also of the occupations to which they lead.

However, to be truly effective, advising must be more than descriptive in nature. Every student is not capable of succeeding in every program of study; therefore, an important part of the advising process is to match students with programs of study in which they have a reasonable expectation of success. It is at this second, prescriptive, level that the need for insightful, research-based facts regarding appropriateness of a student for a particular program of study is evident. Within the framework of the computer-related programs of study, it is clear that mathematics relates highly to computer science; however, characteristics of the computer information systems major, or characteristics that distinguish one major from the other, have not been clearly identified. Therefore, the literature is supportive of the assertion in Chapter 1 that additional research must be undertaken to determine the factors that constitute "distinguishers" between the computer science and computer information systems programs of study, thereby providing the means for more effective advising of students interested in pursuing a program of study involving computers.

CHAPTER 3

METHODOLOGY

Introduction

The purpose of this chapter is to describe the procedures used in the investigation. Included are descriptions of the subjects, instrumentation and methods of collecting data, research design and data analysis techniques.

Subjects

All subjects were either computer science or computer information systems majors at Keene State College, Siena College, Springfield College, Westfield State College or Western New England College who met the criteria for success in a major as defined in Chapter 1. Therefore, they were of at least junior year standing as of May, 1990, were maintaining at least a 2.0 GPA (on a 4.0 scale) in their major courses, and had no outstanding failing grades in any of their major courses.

Since the number of students that met the criteria specified above was not large (106 students - 55 computer science majors and 51 computer information systems majors), sampling was not done. Rather, all subjects were used in the study. To provide further insight into the nature of the subjects, brief descriptions of the institutions that they attend are provided.

Keene State College is located in Keene, New Hampshire, and is a four-year, public, coeducational state college. It is one of four state colleges in the New Hampshire State College System, and enrolls approximately 3000 full-time undergraduate students, of whom nearly 35% are commuters. It is organized into 27 departments within three divisions. Keene State College supports both a mathematically-based technical computer science major and a business application-oriented computer systems major, both of which are housed in a Computer Science/Mathematics Department in a Sciences Division.

Siena College is located in Loudonville, New York, and is a four-year, independent, liberal arts, coeducational college founded and nurtured by the Franciscan Order. It enrolls approximately 2900 full-time undergraduate students of whom nearly 45% are commuters. The college is organized into 24 departments within three divisions. Siena College is primarily a teaching institution, and offers two computer science majors - one a science track and the other a business track; the former is analogous to computer science as defined in Chapter 1, while the latter is analogous to computer information systems as defined in Chapter 1.

Springfield College is located in Springfield, Massachusetts, and is a four-year, private, coeducational, tuition-based institution. It enrolls approximately 3300 full-time undergraduate students, of whom nearly 25% are commuters. The college is organized into 19 departments. It is primarily a teaching institution. Both the computer science and computer information systems majors are housed within the Department of Mathematics, Physics and Computer Science.

Westfield State College is located in Westfield, Massachusetts, and is a four-year, public, coeducational state college. It is one of nine state colleges in the Massachusetts State College System, and enrolls approximately 3000 full-time undergraduate students, of whom nearly 35% are commuters. The college is organized into 19 departments. Both the computer science major and the computer information systems major are housed within the Department of Computer and Information Science. Westfield State College is primarily a teaching institution.

Western New England College is located in Springfield, Massachusetts, and is a four-year, private, coeducational, tuition-based institution. It enrolls approximately 3500 full-time undergraduate students, of whom nearly 50% are commuters. The college is organized into 13 departments within three schools. It is primarily a teaching institution. The computer science major is housed within the Department of Mathematics and Computer Science within the School of Arts and Sciences, while the computer information systems major is housed within the Department of Quantitative Methods and Computer Information Systems within the School of Business.

Instrumentation

Three types of data were obtained - data concerning selected demographics, pre-college academics, and the learning style of the subjects. Data regarding the demographics and pre-college academics of the subjects were obtained from a questionnaire devised by the investigator for purpose of the study. (see Appendix D) Learning style was measured by the Learning-Style Inventory. [Kolb, 1985a]

Questionnaire

The questionnaire developed for the purpose of this investigation contains questions eliciting identifying, qualifying, and potentially predictive demographic and pre-college academic data. Questions 3, 5, 6, and 7 qualify a subject for inclusion in the study, requiring that major be either Computer Science or Computer Information Systems, that "junior or senior year standing" and "currently have at least a 2.0 grade point average in your major courses" be responded to positively, and that "any outstanding failing grades in any of your major courses" be responded to negatively. Of the total of 134 questionnaires administered, 28 were not included in the study for the following reasons: 6 were neither computer science nor computer information systems majors, 21 were not of junior or senior year status, and 1 did not have at least a 2.0 grade point average in major courses. Thus, 106 questionnaires were available for analysis.

Questions eliciting data not for the purpose of qualifying a subject for inclusion in the study included question 1, seeking date of birth, questions 4a and 4b, seeking historic information regarding a subject's participation in the major in previous college years, and questions 8a and 8b, seeking availability of and, if positive, type of computer available to a subject during high school. It should be noted that no form of personal identification was sought, and responses were therefore anonymous.

The remainder of the questions elicited responses that would be investigated as having the potential for being discriminatory, and therefore possibly predictive, factors. Included among these were question 2, seeking the sex of the subject, question 9, seeking the subject's class rank upon graduation from high school, question 10, seeking the subject's scores from the Verbal and Mathematical components of the Scholastic Aptitude Test (with highest scores requested if the subject has taken the test multiple times), question 11, seeking the number of years of coursework taken and passed by the subject in high school in each of English, mathematics, computer studies, science, social studies, and foreign language, and question 12, seeking the subject's relative interest preference during high school for each of computer studies, English, foreign language, mathematics, science, and social studies.

The potentially predictive factors included in the questionnaire were chosen based on two guiding parameters. Initially, based on a review of the literature, there was reason to believe that each could be significant in a discriminatory or predictive manner. Secondly, each is self-reporting, and collectively, the time required to respond to all items of the questionnaire is brief - in the 5 to 10 minute range. Thus, when taken in conjunction with the Learning-Style Inventory, the total subject administration time is generally 15 minutes or less. Additionally, the instrumentation is such that it may be administered in a group setting. Although not an important factor for this investigation, the brief nature of the instrumentation may be very important if and when it is used prescriptively in an advising situation.

<u>Learning-Style Inventory</u>

Learning style has been described by Keefe as the characteristic behaviors of learners that serve as relatively stable indicators of how they perceive, interact with, and respond to their learning environment. [1979] Thus, assessment of learning style involves identification of individual differences in ways or conditions of learning. Kolb [1984] has proposed a model for examining learning style based on experiential learning theory, that embodies four stages - concrete experience, reflective observation, abstract conceptualization and active experimentation.

Concrete experience emphasizes learning from feeling based on personal involvement in specific experiences; relating to people and relying more on feelings than on a systematic approach to problems and situations is characteristic of this stage. Reflective observation emphasizes learning by watching and listening; viewing things from different perspectives and looking for meanings of things, while exercising patience, objectivity and judgment are characteristic of this stage. Abstract conceptualization involves logic and ideas, rather than feelings, to formulate a systematic plan for dealing with problems and situations; action based on intellectual understanding is characteristic of this stage. Active experimentation emphasizes learning by doing, and brings an active, experimental and practical approach to situations; risk-taking and ingenuity are characteristic of this stage. [Kolb, 1984, 1985a] Taken as a cyclical mode, the stages suggest "concrete experiencing of a learning situation; reflective observation of relevant phenomena; abstract conceptualization about the meaning of what has been observed; and the active testing of hypotheses relative to what has been experienced, observed and conceptualized as pertinent to a learning situation." [Merritt and Marshall, 1984, p. 464]

Based on the strength of association a learner exhibits with each of the stages, Kolb defines four specific learning styles: converger, diverger, assimilator, and accomodator. [1984] The converger emphasizes abstract conceptualization and active experimentation, and is characteristic of those who apply ideas in the solution of specific problems; such a style is characterized by a focus on things rather than people, and often is utilized by those in narrow, specialized technical fields. The diverger emphasizes concrete experience and reflective observation and is characteristic of those who are capable of bringing many different points of view to concrete situations; such a style is often found with those in arts, entertainment or service careers. The assimilator emphasizes abstract conceptualization and reflective observation, and is characteristic of those who assimilate observations into an integrated framework by means of inductive logic; such a style is characterized by a greater appreciation for abstract ideas, concepts and logical soundness than practical value and people, and is often found to be the learning style of those in mathematics and basic science fields. The accomodator emphasizes concrete experiences and active experimentation and is characteristic of those who are adaptable and employ trial-and-error with regard to problems; such a style is often found with those who are at ease with people and involved with practical and/or action-oriented fields such as those in business.

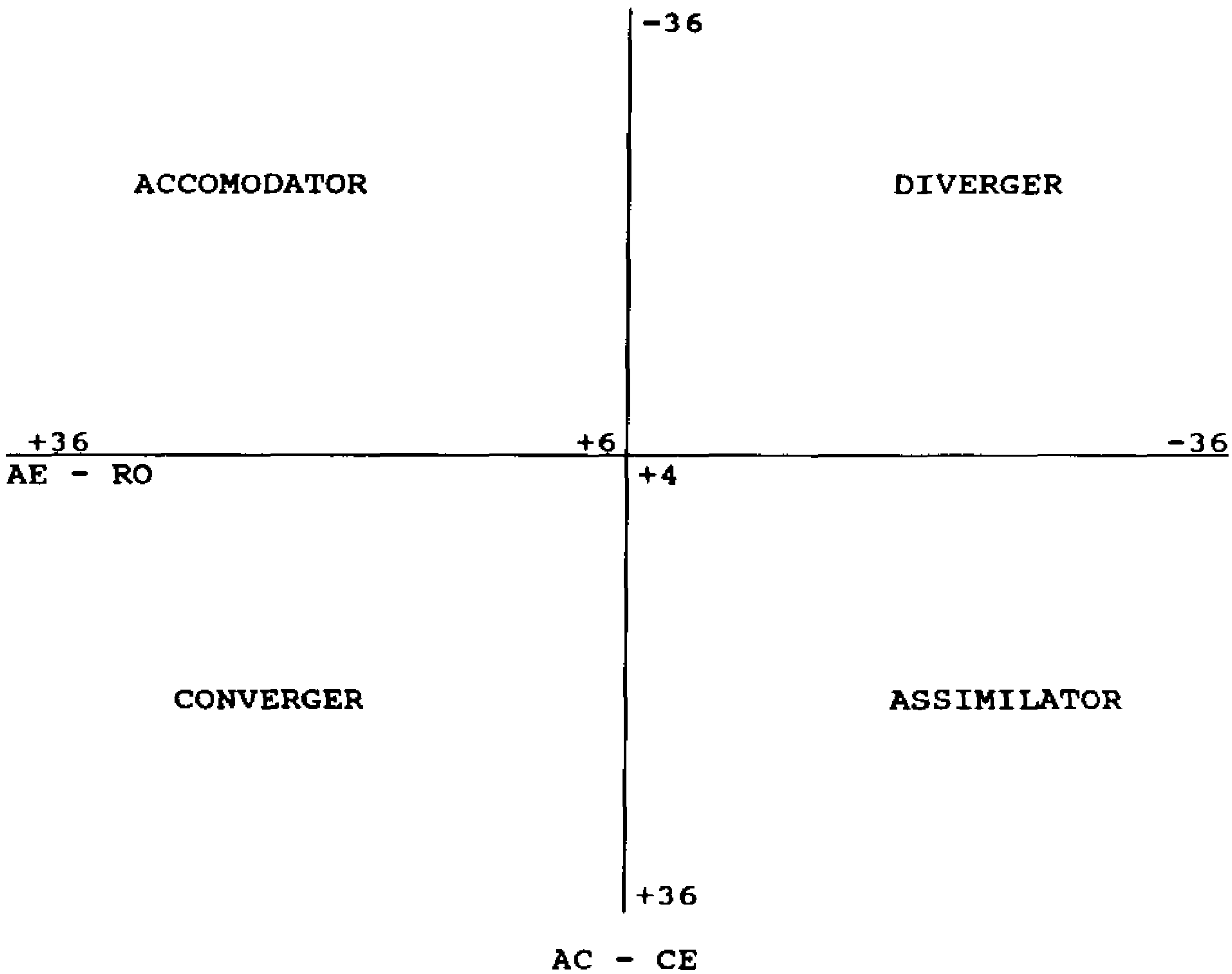
Moreover, the four stages represent two primary dimensions, in that concrete experience is the opposite of abstract conceptualization, and reflective observation is the opposite of active experimentation. Therefore, placements along concrete-abstract and active-reflective continua are possible. The former has significance in this study.

The Learning-Style Inventory was developed by Kolb in 1976, and was revised in 1985. The inventory is made up of 12 sentence completion items in which the respondent is required to rank order four self-descriptive sentence endings for each item with a value from 1 to 4, with 4 assigned to the ending that the respondent feels best describes him or her, down to 1 for the ending that the respondent feels is the least appropriate completion for him or her. A tally of the responses to the first sentence completion item for the twelve sentences yields the concrete experience measure; tallies for the responses to the second, third and fourth items yield, respectively, measures for the reflective observation, abstract conceptualization and active experimentation components. Each yields a raw score indicator of from 12 (lowest) to

48 (highest), since each response item must take on a value of 1, 2, 3 or 4 for the component.

An abstract-concrete continuum score is derived by subtracting the concrete experience measure from the abstract conceptualization measure, yielding a continuum score in the range from 36 (high abstract-low concrete) to -36 (low abstract-high concrete). Likewise, an active-reflective continuum score is derived by subtracting the reflective observation measure from the active experimentation measure, yielding a measure in the range from 36 (high active-low reflective) to -36 (low active-high reflective). [Kolb, 1985a]

Learning styles are associated with each of the four quadrants that are formed by using the active-reflective continuum scale as an x-axis and abstract-concrete continuum scale as a y-axis. Used as an origin is the intersection of the mean values for the scales, which are 5.42 for the active-reflective x-axis scale and 4.28 for the abstract-concrete y-axis scale. Thus, a diverger has an active-reflective continuum score less than 5.42 and abstract-concrete continuum score less than 4.28; an accomodator has an active-reflective continuum score greater than 5.42 and abstract-concrete continuum score less than 4.28; a converger has an active-reflective continuum score greater than 5.42 and abstract-concrete continuum score greater than 4.28; and finally, an assimilator has an active-reflective continuum score less than 5.42 and abstract-concrete continuum score greater than 4.28. These are illustrated in Figure 1 below.



AC - CE = Abstract Conceptualization - Concrete Experience
AE - RO = Active Experimentation - Reflective Observation

Figure 1

Continua Dimension Attributes of the Learning-Style Inventory and Their Relationship to Learning Style Type

Normative figures beyond those cited for the continua scores above are derived from a sample of 1,446 adults described as being "between the ages of 18 and 60 . . . 638 men and 801 women . . . ethnically diverse and representing a wide range of career fields . . . with average education of two years of college." [Kolb, 1985b, p. 5] Means and standard deviations are reported as 26.00 and 6.8 respectively for concrete experience, 29.94 and 6.5 for reflective observation, 30.28 and 6.7 for abstract conceptualization, 35.37 and 6.9 for active experimentation, 4.28 and 11.4 for the abstract-concrete continuum score and 5.42 and 11.0 for the active-reflective continuum score. Further, intercorrelations of raw score values, using Pearson correlation, indicate strongest negative relations between abstract conceptualization and concrete experience (-.42) and reflective observation and active experimentation (-.33), while maintaining no relation (statistical independence) between the abstract-concrete and active-reflective combined scores (-.09). Technical specifications for the Learning-Style Inventory show good internal reliability for the four basic scales and two combination scores as measured by Cronbach's Standardized Scale Alpha (.82 for concrete experience, .73 for reflective observation, .83 for abstract conceptualization, .78 for active experimentation, .88 for abstract-concrete continuum and .81 for active-reflective continuum, with n=268), and near-perfect additivity as measured by Tukey's Additivity test (.91 for concrete experience, 1.09 for reflective observation, 1.07 for abstract conceptualization, 1.03 for active experimentation, 1.00 for abstract-concrete continuum and .99 for active-reflective continuum, with n=268). [Kolb, 1985b] According to Gregg [1988, p. 442], "the LSI is a promising measurement...[and] a quick and reliable self-report instrument measuring learning style."

Administration of the Instruments

During the Spring, 1990 semester, the questionnaire and Learning-Style Inventory described in the Instrumentation section were administered to volunteering students thought to be computer science or computer information systems majors of junior or senior year standing at the participating colleges. Administrations for the questionnaire and inventory were conducted at each institution during the last several weeks of the semester. These took place either in regularly scheduled classes typically taken by junior or senior computer science or computer information systems majors, or in sessions conducted specifically for the purpose.

Research Design and Data Analysis Techniques

Causal-comparative methods are employed in this study to determine whether or not significant differences exist for the variables examined in the study. The design of the study is as illustrated in Figure 2 below.

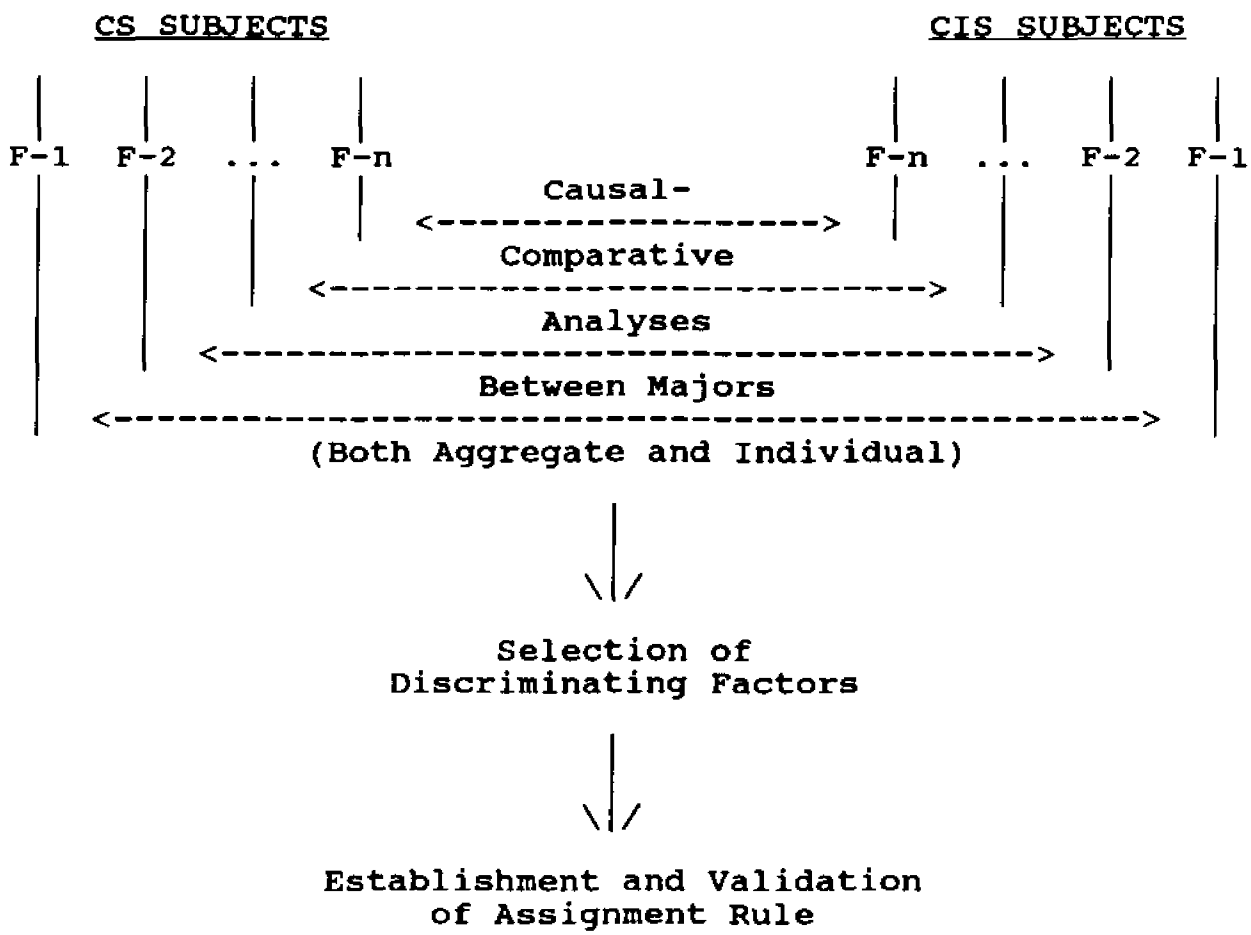


Figure 2

Design of the Research Procedures

The intent of this investigation is conditionally two-fold - to determine whether or not students who have been adjudged to be successful computer science majors are significantly different from students who have been adjudged to be successful computer information systems majors, and, if such a difference is affirmed, to derive predictive criteria for assignment of future students to the group for which he or she has the greatest compatibility.

Traditional multivariate analysis of variance techniques are well-suited to the former task. However, the latter has a greater range of potential procedures applicable thereto, and for that reason, bears further discussion.

Traditional techniques employed in predicting academic performance have been those of correlation and regression; however, as pointed out by Fowler and Glorfeld [1981, p. 100], "the appropriateness of a correlation- and regression-based approach is somewhat questionable and reported results are often not very satisfactory." The affinity of such approaches for predicting placement on a continuous linear dependent variable, rather than into mutually exclusive groups, likely explains the less than optimal performance of such traditional techniques.

Rather, a more satisfactory approach to the prediction problem is to view it as a classification problem, which has as its goal the development of a decision rule that can be used to classify a subject of unknown group origin in that group which he or she most closely resembles. [Hunt, 1977] Various discriminant analysis techniques are available to accomplish classification. Linear discriminant analysis requires that predictor variables have a multivariate normal distribution, thus suggesting use in the non-parametric circumstances of continuous data. [Norusis, 1985] However, logistic discrimination handles both continuous and discrete (to include both dichotomous and polychotomous) variables, and combinations thereof, with equal facility; it also operates throughout a much broader range of assumptions regarding the underlying distributions than does the linear discriminant function. [Fowler and Glorfeld, 1981]. Therefore, logistic discrimination has been recommended as a general classification procedure. [Anderson, 1973; McSweeny and Schmidt, 1977]

Thus, the analyses undertaken in this study proceed as follows. Initially, a multivariate analysis of variance for all potentially predictive independent variables is accomplished, yielding Hotelling's T^2

statistic and derived p-value, for the purpose of establishing group difference. This is followed by analysis of the individual variables, to identify which may contribute to any observed difference between groups. Since most such analyses will involve comparison of continuous variables, the independent-sample t test is used extensively; however, since dichotomous variables are amongst the potentially predictive independent variables, the non-parametric chi-square test is also employed. Thereafter, logistic discriminant analysis is utilized to derive the coefficients of a decision rule that may be used for predictivity purposes. Validation of the decision rule, by means of applying the derived decision rule to the subjects of the study, who are of known origin, and calculating the percent of those subjects correctly classified by the rule, is then accomplished.

CHAPTER 4

ANALYSIS OF THE DATA

Introduction

The purpose of this chapter is to identify the results of the data analyses and report the outcomes. To this end, a description of the data is provided, followed by analyses of the data, and a summary of the outcomes. Since the data analyses are undertaken to resolve the conditionally two-fold purposes of the investigation - those being to determine whether or not differences do exist between groups adjudged to be successful computer science and computer information systems majors, and to derive differentiating predictive classification criteria for assignment to the groups if differences are affirmed - the analyses are divided into two types, those testing difference and those identifying and substantiating discriminatory parameters.

Two statistical packages have been employed in the data analyses. The first is SPSS-X (the Statistical Package for the Social Sciences), a product of SPSS Inc. of Chicago, Illinois. The particular product utilized in this study was SPSS-X, version 2.1, a batch system installed on a Data General MV/10000 computer running under the AOS/VS version 7.67 operating system. Descriptive statistics, analyses of variances and discriminant analyses were run under $SPSS^X$.

The second statistical package used in the data analysis procedures was EGRET (Epidemiological GRaphics, Estimation, and Testing package). This package is a product of the Statistics and Epidemiology Research Corporation, located in Seattle, Washington. It is designed to be an interactive system operating in a DOS environment on IBM-PC compatible machinery. The analysis module of EGRET employed in this study was PECAN (Parameter Estimation through Conditional probability ANalysis), version 0.23.25; it was installed on a Leading Edge D2 microcomputer. Logistic regression analyses were run under EGRET.

Certain procedures were required to be performed outside of the two statistical packages. These included the selection of an optimal cutoff point and classification of cases in conjunction with the logistic regression model of EGRET, and were programmed by the researcher using AOS/VS BASIC, revision 03.22, as installed on a Data General MV/10000 computer system.

Description of the Data

Twenty-two independent variables were considered in the analyses. These were respondent sex, class rank in high school, SAT - Verbal and SAT - Mathematics scores, years of English, mathematics, computer studies, science, social studies and foreign language taken in high school, interest ranking for computer studies, English, foreign language, mathematics, science and social studies during high school, and the Learning-Style Inventory concrete experience, reflective observation, abstract conceptualization, active experimentation, concrete-abstract continuum and reflective-active continuum scores.

Respondent sex was coded dichotomously as male or female, and was reported by all subjects. Of the 106 respondents, 48 males and 7 females made up the group of 55 computer science majors included in the study, and 30 males and 21 females made up the group of 51 computer information systems majors included in the study.

Class rank was solicited from the responses "Top 5%", "Top 10%", "Top 25%", "Top 50%", and "Bottom 50%", with instruction to choose that response which was first true for the subject. These were coded 1, 2, 3, 4 and 5 respectively, and the item was reported by 101 of the 106 subjects. Table 1 identifies the distribution and frequencies of responses for both the computer science and computer information systems majors individually, and also collectively for all respondents.

Table 1

Respondents Classified by Class Rank

	Computer Science			Computer Information Systems			Aggregate		
	Count	Valid Pct	Cum Pct	Count	Valid Pct	Cum Pct	Count	Valid Pct	Cum Pct
Top 5%	8	14.8	14.8	4	8.5	8.5	12	11.9	11.9
Top 10%	18	33.3	48.1	9	19.1	27.7	27	26.7	38.6
Top 25%	18	33.3	81.5	21	44.7	72.3	39	38.6	77.2
Top 50%	8	14.8	96.3	12	25.5	97.9	20	19.8	97.0
Bottom 50%	2	3.7	100.0	1	2.1	100.0	3	3.0	100.0
No Response	1	n/a	n/a	4	n/a	n/a	5	n/a	n/a

A comparison worthy of note is that nearly half of the computer science majors came from the top 10% of their class, while less than 28% of the computer information systems majors were from the top 10% of their class.

SAT - Verbal and SAT - Mathematics scores were entered as the subject's response to a query of highest score on each of the components of the Scholastic Aptitude Test. Each test component has a possible score range of from 200 (minimum) to 800 (maximum), with a standardized mean score established as 500. Mean and range values for the 82 respondents reporting SAT - Verbal scores, and 84 reporting SAT - Mathematics scores, reported by major and in aggregate, are as indicated in Tables 2 and 3.

Table 2

Means, Medians and Ranges for SAT - Verbal Scores

	Computer Science	Computer Information Systems	Aggregate
Mean	496.2	463.9	481.6
Median	490	460	480
Minimum	240	300	240
Maximum	710	640	710

Table 3

Means, Medians and Ranges for SAT - Mathematics Scores

	Computer Science	Computer Information Systems	Aggregate
Mean	596.6	531.9	568.1
Median	600	550	575
Minimum	400	360	360
Maximum	780	670	780

Another interesting observation regarding the respondents' SAT scores involves the percentage of students above and below the normalized mean value of 500 for each test component. These are reported in Table 4.

Table 4

Percentages of Respondents Above and Below Score of 500 on SAT - Verbal and SAT - Mathematics Exams

	Computer Science		Computer Information Systems		Aggregate	
	SAT-V	SAT-M	SAT-V	SAT-M	SAT-V	SAT-M
Above 500	35.6	83.0	29.7	59.5	30.5	72.6
Below 500	57.8	10.6	64.9	32.4	61.0	20.2

(Columns do not add to 100% due to the exclusion of scores equal to 500.)

These figures portray the relative strength of the respondents, and particularly those of the computer science majors, with respect to mathematics, while indicating a general weakness by both groups, considered against national norms, with respect to verbal skills.

A series of responses was elicited from the subjects regarding the number of years of coursework taken during high school in each of the following subject areas: English, mathematics, computer studies, science, social studies and foreign language. Courses taken in eighth grade, but for which high school credit was granted, were required to be included in the responses. Ninety-eight subjects reported for all categories except computer studies, where only 90 subjects reported. The difference was attributable to a group of eight subjects reporting that computer studies were not available at their high school; these were treated as missing values for purposes of data analysis. A summary of these data are reported in Table 5.

Table 5

Mean Years of Coursework Taken During High School in Various Subject Areas

	Computer Science	Computer Information Systems	Aggregate
English	4.1	4.0	4.0
Mathematics	4.2	4.0	4.1
Computer Studies	1.8	1.5	1.6
Science	3.7	3.5	3.6
Social Studies	3.1	2.8	3.0
Foreign Languages	2.4	2.6	2.5

As can be seen, the values are very close with regard to years of coursework taken in high school in all subject areas investigated. The tightness of the data probably represents the perceived need on behalf of students to fulfill a typical college preparation prescription. Thus, any differences between the computer science and computer information systems groups of students that were studied are probably better explained by their performance level in their courses, or their taking of different courses within the same subject area, than by a simple count of courses taken in the various subject areas.

Another series of responses was elicited from the subjects that sought an interest ranking for computer studies, English, foreign languages, mathematics, science, and social studies, as they were perceived during high school. For each, a response of 6, 5, 4, 3, 2, or 1 was elicited, with 6 asserting greatest interest, 1 asserting least interest, and values in between representative of a continuum from greatest to least interest. However, no interest response was allowed to be used more than once, thus, a preference ordering of the subject areas was achieved. One subject did not respond to the English, mathematics, science and social studies queries, two did not respond to the foreign language query, and nine did not respond to the computer studies query. Again, the discrepancy with respect to the computer studies area was due to the non-availability of computing coursework in high school for the additional eight non-respondents.

Frequencies of response for each interest level, by subject area, are reported in Table 6 below:

Table 6

Frequencies of Interest Ranking by Subject Area

Subject Area	Interest Rankings 1	2	3	4	5	6	No Response
Computer Studies							
For CS Students:	5	2	1	7	8	29	3
For CIS Students:	4	4	5	1	6	25	6
Aggregate:	9	6	6	8	14	54	9
English							
For CS Students:	9	18	14	6	5	3	-
For CIS Students:	10	13	5	8	9	5	1
Aggregate:	19	31	19	14	14	18	1
Foreign Language							
For CS Students:	23	7	12	6	3	3	1
For CIS Students:	11	10	7	11	6	5	1
Aggregate:	34	17	19	17	9	8	2
Mathematics							
For CS Students:	2	5	7	12	21	8	-
For CIS Students:	7	3	6	13	14	7	1
Aggregate:	9	8	13	25	35	15	1
Science							
For CS Students:	1	1	12	15	17	9	-
For CIS Students:	4	6	15	13	8	4	1
Aggregate:	5	7	27	28	25	13	1
Social Studies							
For CS Students:	11	20	11	9	3	1	-
For CIS Students:	11	11	12	8	7	1	1
Aggregate:	22	31	23	17	10	2	1

The remaining data items were derived from the responses made on the Learning-Style Inventory. Values for concrete experience, reflective observation, abstract conceptualization, and active experimentation have potential ranges of from 12 to 48, with lower values indicating less of an association with the factor than higher values. Scores for concrete-abstract continuum (computed as abstract conceptualization minus concrete experience scores), and reflective-active continuum (computed as active experimentation minus reflective observation scores) have potential ranges between -36 and 36, with a larger (positive) value for either continuum associating more with the second-noted aspect of the continuum, and a lesser (negative) value associating more with the first-noted aspect of the continuum. Mean, median and range values for the 98 respondents completing the Learning-Style Inventory are reported in Table 7 on the following page.

While the means for the computer information systems majors appear to be fairly consistent with the instrument's normative figures, it is readily apparent that the means of concrete experience, abstract conceptualization and concrete-abstract continuum for computer science majors vary considerably from not only the norms, but indeed from those of the computer

Table 7

Means, Medians and Ranges for LSI Stage Component and Combined Continua Measures

	Computer Science	Computer Information Systems	Aggregate	LSI Norm
Concrete Experience:				
Mean	21.5	24.2	22.8	26.0
Median	21	22	22	
Minimum	12	14	12	
Maximum	36	45	45	
Reflective Observation:				
Mean	28.3	30.2	29.3	30.0
Median	28	31	29	
Minimum	16	13	13	
Maximum	42	45	45	
Abstract Conceptualization:				
Mean	36.5	29.5	33.0	30.3
Median	37	29	34	
Minimum	21	14	14	
Maximum	46	42	46	
Active Experimentation:				
Mean	33.4	36.5	35.0	35.4
Median	33	38	35	
Minimum	21	19	19	
Maximum	48	47	48	
Concrete-Abstract Continuum:				
Mean	15.1	5.3	10.2	4.3
Median	16	4	12.5	
Minimum	-9	-19	-19	
Maximum	31	25	31	
Reflective-Active Continuum:				
Mean	5.1	6.5	5.8	5.4
Median	5	8	7	
Minimum	-20	-15	-20	
Maximum	24	34	34	

information systems group. Certainly, scores for computer information systems majors can be seen to approximate the norms better that those of computer science majors, in that the computer information systems majors group means are closer to the normative values than the means of the computer science majors in five cases out of the six. These differences will be analyzed statistically in the next section.

Data Analyses

Data analyses in this study may be broadly classified as being of one of two types - those testing and establishing differences between the computer science and computer information systems groups, and those attempting to identify and validate discriminatory parameters for development of an optimal assignment rule.

Analyses of Differences

A multivariate analysis of variance was performed on the 22 potentially discriminatory independent variables of the study - sex, class rank, SAT - Verbal, SAT - Mathematics, years of English, mathematics, computer studies, science, social studies and foreign language, interest ranking for computer studies, English, foreign language, mathematics, science and social studies, and the Learning-Style Inventory concrete experience, reflective observation, abstract conceptualization, and active experimentation component scores and concrete-abstract and reflective-active continua combined scores - to determine whether or not the computer science and computer information systems groups differed significantly on the collective vector of independent variables. This difference between groups was affirmed by Hotellings T^2 test statistic of 1.36, which yields a probability value of .001 with respect to equality of the groups based on all factors taken collectively.

To gain insight into the factors that were responsible for the differences between the groups, independent sample t-tests and chi-square analyses were performed on the data. Table 8 reports the results of t-tests performed on all variables of interest except for the dichotomous and polychotomous variables sex and class rank, for which chi-square statistics are reported in Table 9. Both tables are on the following page.

Table 8

T-Test Analyses for Selected Variables

	Computer Science		Computer Information Systems		t	p-
	Mean	S.D.	Mean	S.D.	stat.	value
SAT-Verbal	496.2	92.7	463.9	75.1	1.74	.085
SAT-Mathematics	596.6	12.8	531.9	14.7	3.31	.001
Yrs-English	4.1	.4	4.0	.4	1.26	.212
Yrs-Mathematics	4.2	.9	4.0	.8	.89	.375
Yrs-Computer Studies	1.8	1.1	1.5	1.3	1.30	.197
Yrs-Science	3.7	1.0	3.5	1.0	.94	.348
Yrs-Social Studies	3.1	1.0	2.8	1.1	1.33	.188
Yrs-Foreign Language	2.4	1.4	2.6	1.4	-.55	.581
Int-Computer Studies	4.9	1.6	4.7	1.8	.56	.579
Int-English	2.8	1.4	3.2	1.7	-1.18	.240
Int-Foreign Language	2.4	1.5	3.1	1.6	-2.28	.025
Int-Mathematics	4.3	1.3	3.9	1.6	1.24	.218
Int-Science	4.3	1.2	3.5	1.3	3.20	.002
Int-Social Studies	2.6	1.2	2.8	1.4	-1.06	.293
LSI-Concrete Exper	21.5	5.8	24.2	7.2	-2.00	.049
LSI-Reflective Observ	28.3	6.4	30.2	6.5	-1.45	.151
LSI-Abstract Concept	36.5	6.2	29.5	5.9	5.65	<.001
LSI-Active Experiment	33.4	6.4	36.5	6.3	-2.40	.018
LSI-Concrete/Abstract	15.1	10.3	5.3	10.6	4.68	<.001
LSI-Reflective/Active	5.1	11.3	6.5	10.0	-.64	.527

Table 9

Chi-Square Analyses for Selected Variables

	Computer Science	Computer Information Systems	Chi-Square Statistic	P-Value
Sex				
Male	48	30		
Female	7	21	11.02	<.001
Class Rank (First Applicable)				
Top 5%	8	4		
Top 10%	18	9		
Top 25%	18	21		
Top 50%	8	12		
Bottom 50%	2	1	5.24	.264

From these analyses, the terms determined to be of greatest potential in attributing to differentiation between the two groups, identified by means of $p < .05$, in ascending order of p value, are: sex ($p < .001$), LSI - abstract conceptualization ($p < .001$), LSI - concrete-abstract continuum ($p < .001$), SAT - Mathematics ($p = .001$), interest ranking for science ($p = .002$), LSI - active experimentation ($p = .018$), interest ranking for foreign language ($p = .025$), and LSI - concrete experience ($p = .049$).

Pearson correlation coefficients for the variables identified as having p-values less than .05 are reported in Table 10 below.

Table 10

Correlation Coefficient Matrix for Variables with P-values less than .05 in Table 8

Variable	Sex	LSI-AC	LSI-C/A	SAT Math	Int-Sci	LSI-AE	Int-FrLg
Sex	1.00						
LSI-AC	-.23	1.00					
LSI-C/A	-.12	.84	1.00				
SAT-Math	.23	.46	.40	1.00			
Int-Science	-.29	.34	.35	.20	1.00		
LSI-AE	.23	-.31	-.04	-.10	-.14	1.00	
Int-For Lang	.24	-.25	-.29	-.05	-.44	.01	1.00

The high correlation (.84) indicated between the Learning-Style Inventory abstract conceptualization component and concrete-abstract continuum score is not unwarranted, since the latter is derived from a subtractive computation involving the former as the minuend. Since the Learning-Style Inventory concrete-abstract continuum measure is additionally based on concrete experience, with which it has a -.83 correlation coefficient, and since the abstract conceptualization and concrete experience correlate at a -.42 level, the abstract conceptualization component has been removed from further analyses, allowing the effects of both the abstract conceptualization and concrete experience to enter via the concrete-abstract continuum score. By doing this, the .46 correlation between SAT - Mathematics and the Learning-Style Inventory abstract conceptualization component is also removed.

Further examination reveals a -.44 correlation coefficient between the interest rankings for science and foreign language. Collinearity is suggested, since interest rankings among subjects are interrelated by the requirement that the ranking value given to any subject be different than that given to any other subjects, and that the differences between means for computer science and computer information systems majors are the greatest for science (4.33 and 3.54 respectively - for a difference of .79) and foreign language (2.41 and 3.12 - for a difference of -.71). Since means for all other subjects are relatively close, with the largest other difference between groups being -.36 for English, and other differences being .35 for mathematics, -.28 for social studies, and .19 for computer studies, it appears that the science and foreign language positionings are of greatest impact on one another. Thus, based on the above, and the more significant discriminatory measure associated with the interest ranking for science ($p = .002$) than that for foreign language ($p = .025$), the science factor is retained for primary consideration in further analyses, while the foreign language factor is retained secondarily.

Analyses of Discrimination

Regression analysis is concerned with the prediction of a dependent variable's value based on that of an independent variable or, in the multivariate case, those of multiple independent variables. Simple regression involves a single independent variable, whereas multiple regression involves more than one independent variable. In either case, both dependent and independent variables should be measured on at least an interval scale of measurement. [Norusis, 1985] The prediction of a Graduate Record Exam score based solely on undergraduate grade point average would be an example of simple regression; prediction of the same Graduate Record Examination score based on undergraduate grade point average, intelligence quotient, and number of years of college mathematics taken would be appropriate to multiple regression.

Often however, the dependent variable is not linear in nature, but rather is nominally scaled or ordinal in nature. Group discrimination is subsumed within this type of situation, as in the case of predicting success or failure in college study based on a number of pre-college factors. With normally distributed, linear independent variables, this type of predictive activity is the purview of discriminant analysis. [Hanke, Reitsch and Dickson, 1984]. The introduction of dichotomous or polychotomous variables to the independent variable list introduces a violation of the assumptions of discriminant analysis (regarding continuity of independent variables). Logistic discrimination is suggested for such situations, since it handles both continuous and discrete data with facility, and is optimal for a wider range of assumptions with respect to the underlying data distributions. [Fowler and Glorfeld, 1981] For these reasons, it has been recommended as a general classification procedure. [Anderson, 1973; McSweeny and Schmidt, 1977] Due to the facility of logistic regression in handling predictive problems such as assigning or not assigning a patient to a coronary care unit based on duration and location of chest pain, lab results, and family history, it has been implemented and widely used in statistical packages serving the medical field (BMDP - Biomedical Computer Programs and EGRET - Epidemiological Graphics, Estimation and Testing package, for example). In fact, logistic regression is the default model of EGRET.

Yet, the superiority of logistic regression over discriminant analysis, for purposes of this study, is not definitive. Although it is generally true that the linear discriminant function is less than optimal in cases involving dichotomous or polychotomous variables, much evidence suggests that the linear discriminant function performs well when dealing with dichotomous variables. [Gilbert, 1981; Moore, 1973] Based on this caution, and the fact that the analysis module of the EGRET package is beta stage (version 0.23.25), the analyses of discrimination utilized in this study will consist primarily of EGRET's logistic regression, and corroboratively of SPSS-X's discriminant analysis.

EGRET Logistic Regression Analyses. The default model for EGRET analysis is logistic regression with multiplicative risk type - which corresponds to the standard logistic regression model. In this model, regression coefficients are logarithms of odds ratios, and the binomial probability, p, of observing a positive response is:

$$p = (e^{zB}) \;/\; (1 + e^{zB})$$

where B is the vector of regression coefficients and z is the vector of covariates. (EGRET Reference, 1990).

The assertion previously made that interest ranking for science and interest ranking for foreign language were interrelated is supported by the first two EGRET analyses. In the first, the variables sex, SAT - Mathematics, interest in science, interest in foreign language, and Learning-Style Inventory active experimentation and concrete-abstract continuum scores are utilized; in the second, the same variables, less interest in foreign language, are utilized. Outputs of EGRET analyses report the variables used, their regression coefficients, standard errors and p-values. These are reported in Tables 11 and 12 on the following page. (Of particular interest is the p-value, which is derived from the Wald test statistic, and reports the statistical significance of adding the term with which it is associated to a model consisting of all the other terms.)

Table 11

EGRET Analysis for Variables Sex, SAT - Mathematics, Interest in Science, Interest in Foreign Language, LSI - Active Experimentation and LSI - Concrete-Abstract Continuum Measures

Term	Coefficient	Standard Error	p-value
Constant	1.627	2.98	.585
Sex	2.016	.724	.005
SAT-Math	-.005313	.00341	.119
Interest-Science	-.1394	.247	.572
Interest-Foreign Language	-.06068	.215	.778
LSI-Active Experimentation	-.5943	.0479	.215
LSI-Concrete-Abstract	-.07018	.0308	.023

Deviance on 71 D.F. = 77.712
Likelihood Ratio Statistic on 7 D.F. = 30.419, p < .001

Table 12

EGRET Analysis for Variables Sex, SAT - Mathematics, Interest in Science, LSI - Active Experimentation and LSI - Concrete-Abstract Continuum Measures

Term	Coefficient	Standard Error	p-value
Constant	1.287	2.71	.635
Sex	1.971	.702	.005
SAT-Math	-.005253	.00339	.121
Interest-Science	-.1171	.233	.615
LSI-Active Experimentation	.06130	.0475	.197
LSI-Concrete-Abstract	-.06933	.0306	.023

Deviance on 72 D.F. = 77.792
Likelihood Ratio Statistic on 6 D.F. = 30.339, p < .001

Using either of the preceding assignment rules results in likelihood ratio statistics with significances of $p < .001$, and correct classifications in 75.3% of the original cases of the study that had valid responses for the variables involved in the classification rules. This, along with the p-value of .778 associated with interest in foreign language in Table 11, reinforces the notion of non-consequentiality of interest in foreign language with respect to predictability of group membership.

Tables 13 and 14 provide two additional EGRET analyses, each with one factor removed from the analysis reported in Table 12. In Table 13, interest in science is removed, due to its relatively high p-value in the previous analysis; in Table 14, sex is removed, so as to provide a classification rule for situations in which gender is considered to be an inappropriate variable.

Table 13

EGRET Analysis for Variables Sex, SAT - Mathematics, LSI - Active Experimentation and LSI - Concrete-Abstract Continuum Measures

Term	Coefficient	Standard Error	p-value
Constant	.7696	2.51	.759
Sex	2.041	.687	.003
SAT-Math	-.005259	.00340	.122
LSI-Active Experimentation	.06306	.0473	.182
LSI-Concrete-Abstract	-.07346	.0293	.012

Deviance on 73 D.F. = 78.044
Likelihood Ratio Statistic on 5 D.F. = 30.087, $p < .001$

Table 14

EGRET Analysis for Variables SAT - Mathematics, Interest in Science, LSI - Active Experimentation and LSI - Concrete-Abstract Continuum Measures

Term	Coefficient	Standard Error	p-value
Constant	1.8506	2.52	.462
SAT-Math	-.00539	.00309	.073
Interest-Science	-.2549	.206	.217
LSI-Active Experimentation	.07592	.0456	.096
LSI-Concrete-Abstract	-.05800	.0290	.046

Deviance on 73 D.F. = 86.731
Likelihood Ratio Statistic on 5 D.F. = 21.399, $p < .001$

Interestingly, the assignment rule reported in Table 13, involving sex, SAT - Mathematics, Learning-Style Inventory active experimentation and concrete-abstract continuum measures, classifies 76.6% of the original cases correctly, which is slightly higher than the models including interest in science or both interest in science and interest in foreign language (both of which classified correctly at the 75.3% level). Again, worthy of note are the p-values (.003, .122, .182 and .012), in that all have very low values indicating the importance of each to the assignment rule.

The final analysis, which removes sex (a major factor in each of the three previous analyses with p-values of .005, .005 and .003) from the model, leaving SAT - Mathematics, interest in science, Learning-Style Inventory active experimentation and concrete-abstract continuum measures, classifies correctly at the 74.0% level. This spreads the influence much more uniformly over the variables, with p-values of .073, .096 and .046 for SAT - Mathematics, Learning-Style Inventory active experimentation and concrete-abstract continuum respectively, as contrasted with previous models that have been overwhelmingly influenced by sex and the Learning-Style Inventory concrete-abstract continuum measure. Furthermore, this provides a gender-neutral rule that performs within 3% of the optimal rule identified, for use in situations where gender may be deemed to be an inappropriate predictive factor.

SPSS-X Discriminant Analyses. Discriminant analysis operates under a more stringent set of assumptions than does logistic regression. However, the probability of the linear discriminant function misclassifying cases is lessened if the predictor variables are from multivariate normal distributions and the covariance matrices for the groups are equal. [Norusis, 1985] The former is of particular concern with regard to the dichotomous variable sex; however, when coded as "0" and "1" values, the means for such variables simply represent a percent of "1" responses and as such tend to be less problematic than other discrete polychotomous variables. Box's M test is available to address the matter of equality of covariance matrices; this yields a significance probability (based on an F transformation) that tests the null hypothesis regarding equality of the covariance matrices.

Discriminant analysis in SPSS-X may be driven either by a vector of independent variables, all of which are required to enter into the discriminant function, or by a stepwise selection procedure, in which the "best" variables are entered into the discriminant function from a specified set of independent variables. The method employed in this study combines the features of forward selection and backward elimination, based on the minimization of Wilks' lambda. Both the stepwise variable selection method and the exact specification of variables to be utilized in the analysis will be employed in the analyses that follow.

The first analysis employs stepwise variable selection, given the variables sex, SAT - Mathematics, interest in science, interest in foreign language, and the Learning-Style Inventory active experience and concrete-abstract continuum measures as available for inclusion in the derived discriminant function. This results in four of the six variables being chosen for inclusion in the model - sex, SAT - Mathematics, and

Learning-Style Inventory active experimentation and concrete-abstract continuum measures. Thus, interest in science and interest in foreign language have not entered the model. Box's M test statistic for the group covariance matrices evaluates to 14.384 and a significance value of .1944, which is not sufficient to reject the null hypothesis of group covariance matrix equality. Table 15, on the following page, notes the standardized canonical discriminant function coefficients (coefficients to be used when variable values have been standardized to a mean of 0 and standard deviation of 1), pooled within-groups correlations between the discriminating variables and the discriminant function coefficients (based on the Pearson correlation of each variable with the discriminant function's value, computed within each group and combined), the unstandardized canonical discriminant function coefficients (multipliers of variables when expressed in original unit magnitudes), and the group centroids (mean value of discriminant function scores for each group). This results in a 70.5% correct classification rate. From the pooled within-groups correlation values, it can be seen that sex, Learning-Style Inventory concrete-abstract continuum measure and SAT - Mathematics score contribute heavily to the resulting discriminant values.

Table 15

SPSS-X Discriminant Function Results
of Stepwise Variable Selection Procedure with
Sex, SAT - Mathematics, Interest in Science,
Interest in Foreign Language, LSI - Active Experimentation
and LSI - Concrete-Abstract Continuum Measures
Available to Analysis

Factor	Standardized Canonical Discriminant Function Coefficients	Pooled Within-Groups Correlation Value	Unstandardized Canonical Discriminant Function Coefficients
Sex	.65686	.66030	1.6319
SAT-Math	-.31959	-.55057	-.0035993
LSI-Active Experimentation	.25008	.28687	.39827
LSI-Concrete-Abstract	-.56760	-.56127	-.55119
Constant	n.a.	n.a.	.80402

Centroids: Group 0: -.61474 Group 1: .75525

Forcing all of the variables considered above to be a part of the discriminant function - that is, including both interest in science and interest in foreign language along with the four variables selected and included in the previous model - yields a discriminant function that results in a correct classification rate of 71.8% (only slightly higher than the 70.5% of the previous model) and group centroids of slightly greater difference (1.37577 compared to 1.36999). The results of the analysis are summarized in Table 16 on the following page.

Table 16

SPSS-X Discriminant Function Results with Sex, SAT - Mathematics, Interest in Science, Interest in Foreign Language, LSI - Active Experimentation and LSI - Concrete-Abstract Continuum Measures Included in Analysis

Factor	Standardized Canonical Discriminant Function Coefficients	Pooled Within-Groups Correlation Value	Unstandardized Canonical Discriminant Function Coefficients
Sex	-.63905	-.65752	-1.5876
SAT-Math	.31756	.54826	.0035764
Interest-Science	.10404	.43867	.080016
Interest-Foreign Language	.03992	-.24155	.026946
LSI-Active Experimentation	-.23458	-.28566	-.037358
LSI-Concrete-Abstract	.54158	.55891	.052593
Constant	n.a.	n.a.	-1.2568

Centroids: Group 0: .61733 Group 1: -.75844

Two other analyses were conducted. The first included the variables of the previous model less interest in foreign language, leaving sex, SAT - Mathematics, interest in science, and Learning-Style Inventory active experimentation and concrete-abstract continuum measures. The second retains all variables of the model just described, but excluding sex, thus providing a gender-neutral rule. These are reported in Tables 17 and 18 respectively, which are on the following page.

Table 17

SPSS-X Discriminant Function Results
with Sex, SAT - Mathematics,
Interest in Science, LSI - Active Experimentation
and LSI - Concrete-Abstract Continuum Measures
Included in Analysis

Factor	Standardized Canonical Discriminant Function Coefficients	Pooled Within-Groups Correlation Value	Unstandardized Canonical Discriminant Function Coefficients
Sex	-.63207	-.65795	-1.5703
SAT-Math	.31812	.54861	.0035828
Interest-Science	.09116	.43896	.070111
LSI-Active Experimentation	-.23927	-.28585	-.038104
LSI-Concrete-Abstract	.53854	.55928	.052297
Constant	n.a.	n.a.	-1.1276

Centroids: Group 0: .61693 Group 1: -.75794

Table 18

SPSS-X Discriminant Function Results
with SAT - Mathematics, Interest in Science,
LSI - Active Experimentation and
LSI - Concrete-Abstract Continuum Measures
Included in Analysis

Factor	Standardized Canonical Discriminant Function Coefficients	Pooled Within-Groups Correlation Value	Unstandardized Canonical Discriminant Function Coefficients
SAT-Math	.46906	.68482	.0052827
Interest-Science	.31767	.54794	.24432
LSI-Active Experimentation	-.38273	-.35681	-.060952
LSI-Concrete-Abstract	.52733	.69813	.051209
Constant	n.a.	n.a.	-2.3884

Centroids: Group 0: .49423 Group 1: -.60719

Box's M test for the analyses evaluate to 18.348 and 5.6229, yielding significance test values of .3172 and .8704 respectively, non-supportive of rejection of null hypotheses concerning equality of covariance matrices. In the former, 73.1% are correctly classified (sex included, interest in foreign language not), whereas in the latter, 68.0% are correctly classified (neither sex nor interest in foreign language included - other variables included in each instance being SAT - Mathematics, interest in science, and Learning-Style Inventory active experimentation and concrete-abstract continuum measures). The 73.1% correct classification rate of the former is the best performance of any of the discriminant models examined; thus, it is not surprising to note that the difference between centroids for the model is virtually the same as that for the model derived by SPSS-X's stepwise selection procedure, which had the same variables except for interest in science.

Summary of the Findings

Groups of students adjudged to be successful in computer science and computer information systems programs of study were surveyed with respect to 22 independent variables. These were sex, class rank, SAT - Verbal and

SAT - Mathematics scores, years of English, mathematics, computer studies, science, social studies and foreign language taken in high school, interest ranking for computer studies, English, foreign language, mathematics, science and social studies during high school, and the Learning-Style Inventory concrete experience, reflective observation, abstract conceptualization, active experimentation, concrete-abstract continuum and reflective-active continuum scores.

Multivariate analysis of variance confirmed that the groups differed on a collective vector of the 22 independent variables, based on a Hotelling's T^2 test statistic value of 1.36, which yielded a probability value of .001 with respect to equality of the groups. The attribution of the group difference to individual factors was explored by means of independent sample t-tests and chi-square analyses. Those factors identified as having significance of difference between the groups at the .05 level or better included, in ascending order of probability, sex, Learning-Style Inventory abstract conceptualization and concrete-abstract continuum measures (all with $p < .001$), SAT - Mathematics ($p = .001$), interest ranking for science ($p = .002$), Learning-Style Inventory active experimentation ($p = .018$), interest ranking for foreign language ($p = .025$) and Learning-Style

Inventory concrete experience (p = .049). However, interrelationships of correlation and/or collinearity were identified for the Learning-Style abstract conceptualization and concrete experience measures (both with the Learning-Style Inventory concrete-abstract continuum measure), and suggested for the interest ranking for foreign language (with the interest ranking for science). The former were removed from further consideration at that point, while the latter was retained as a factor of secondary consideration.

EGRET's logistic regression and SPSS-X's discriminant analysis were utilized to derive predictor functions. Underlying assumptions of data distribution were tested by means of covariance matrix equality utilizing Box's M test statistic, and revealed no severe violations of assumptions. The existence of the non-linear, dichotomous variable sex in the discriminant analyses was of concern, but it is generally accepted that the procedure is robust with respect to this particular type of assumption violation.

The optimal rule from logistic regression, which was found to classify 76.6% of the original cases (with values available for all predictor varaibles), was found to be:

$$G = .770 + 2.041(\text{Sex}) - .00526(\text{SAT-Math}) + .0631(\text{LSI-AE}) - .0735(\text{LSI-C/A})$$

with values above the .595 cutoff point identified as belonging to the group of computer information systems majors, and those below belonging to the group of computer science majors.

The optimal rule from discriminant analysis, which assigned 73.1% of the original cases correctly, was found to be:

$$G = -1.128 - 1.57(\text{Sex}) + .00358(\text{SAT-Math}) + .0701(\text{Int-Sci}) - .0381(\text{LSI-AE}) + .0523(\text{LSI-C/A})$$

with positive values indicating membership in the group of computer information systems majors, and negative values indicating membership in the group of computer science majors. Gender-neutral rules were also derived, which operated at the 74.0% and 68.0% correctness of assignment levels respectively for those generated through logistic regression and discriminant analysis. Both involved the variables SAT - Mathematics, interest for science, and Learning-Style Inventory active experimentation and concrete-abstract measures.

The analyses reveal that differences do exist between computer science and computer information systems majors, and that predictability with regard to a subject of unknown group affiliation can be determined in over 75% of the cases using rules involving various subsets of parameters taken from the variables sex, SAT - Mathematics, interest ranking for science, and the Learning-Style Inventory active experimentation and concrete-abstract continuum measures. They also tend to validate the performance of the logistic regression analyses of EGRET, and in fact tend to support, at least minimally, the performance of the logistic regression approach to classification over that of traditional discriminant analysis procedure.

CHAPTER 5

SUMMARY AND DISCUSSION

This final chapter is presented in four sections. The first presents a brief discussion of the study, to include problem statement, past research, methodology, and findings. The second presents implications of this research. The third cautions limitations of the study, while the final section suggests directions for future research.

Summary of the Study

The goals of this study were two-fold: to determine whether differences existed between students who had been adjudged to be successful computer science majors and those who had been adjudged to be successful computer information systems majors, and if such difference was affirmed, to determine an optimal classification rule for assignment to each. Such success was deemed to have occurred if the student was of junior or senior standing and declared in the major, had at least a 2.0 grade point average in courses required of the major, and had no failing grades within the major that had not been successfully retaken. A major was considered to be a computer science major if it was purported to be based on the Association for Computing Machinery's recommendations for undergraduate computer science curriculum, and was considered to be a computer information systems major if it was purported to be based on either the Association for Computing Machinery's recommendations for undergraduate information systems curriculum or the Data Processing Management Associations's recommendations for undergraduate computer information systems curriculum.

Although often confused due to their "computer-relatedness", the computer science and computer information systems programs of study are markedly different, and involve substantially different preparation, with overlap, if any, at only the most introductory level. Numerous studies have attempted to identify correlations (success predictors) between variables of a multitude of homogeneous groups (including computer science majors and computer information systems majors) predicated on their association with computers, to include a variety of demographic, pre-college academic, and non-achievement oriented construct factors; however, none have attempted to identify differentiators between the two groups (ie. successful computer science majors and successful computer information systems majors). That became the focus of this study.

A review of the literature provided leads for this study, in that successful computer science majors were generally associated with mathematical competence, or traits closely related thereto, such as logical thinking or abstract reasoning. On the other hand, studies dealing with success in a computer information systems major were few, and no factors emerged from those few studies that clearly differentiated that group from typical norms. Therefore, a cross section of demographic and pre-college academic factors were included in this study. The desire to include a short, easily and quickly completed and interpreted instrument that would measure an inclination toward abstract reasoning led to use of the Learning-Style Inventory.

Students from five colleges that support both majors (Keene State College, Siena College, Springfield College, Western New England College and Westfield State College) were included in the study. (The criterion that a school support both majors was important, since this would eliminate the possibility of a student being in the more inappropriate of the two majors simply because the other was not available at the institution that the student was attending.) Of the 134 students to whom questionnaires were administered, 106 met the criteria of the study and were included in the analyses; of these, 58 were computer science majors and 48 were computer information systems majors.

Twenty-two variables were explored in the study: sex, high school class rank, SAT - Verbal and Mathematics scores, years of English, mathematics, computer studies, science, social studies and foreign language taken in high school, interest ranking for computer studies, English, foreign language, mathematics, science and social studies, and the Learning-Style Inventory concrete experience, reflective observation, abstract conceptualization, active experimentation, concrete-abstract continuum and reflective-active continuum measures. A multivariate analysis of variance established that the two groups did in fact differ significantly (at the $p = .001$ level) on an aggregate of all factors. Further univariate analysis identified as significantly different between groups the following variables (listed in ascending order of p value, with $p < .05$ as constraint): sex, Learning-Style Inventory abstract conceptualization and concrete-abstract continuum, interest ranking for science, Learning-Style Inventory active experimentation, interest ranking for foreign language, and Learning-Style Inventory concrete experience. Due to a high degree of correlation, or suggestion of collinearity, with other variables, Learning-Style Inventory abstract conceptualization and concrete experience were removed from further analysis, and interest for foreign language was relegated to a secondary level of concern.

Both logistic regression through EGRET and classic discriminant analysis through SPSS-X were employed to develop various prediction equations - the best of which was accomplished through logistic regression and classified correctly in nearly 77% of the cases. And although sex was a major contributor to the model, a gender-neutral model was able to be derived that would classify correctly at just over a 73% rate; this could be of value in situations where sex may be deemed to be an inappropriate factor.

Implications of the Study

In the first chapter, it was noted that the utility of this research was apparent when the advising function was considered. At the high school level, students are advised with regard to their choice of major upon entering college, both by classroom teachers and by guidance counselors. At the college level, this function continues in the form of advising - particularly with regard to course selections, but more generally with regard to the suitability of a given major for a given advisee - by a major adviser. The consequences of "misplacement" with regard to a major are at the very least inconvenience and frustration, and possibly much worse. This, coupled with the fact that every student is not "right" for every major, should make any endeavor that attempts to assist the student in choosing a major that is right for him or her a priority. This study has implications in one of the finer areas of distinction that must be dealt with in this context.

During the last decade, an increasing pervasiveness of computers, arguably at an exponential rate of growth at times, has been witnessed. Students noted the career fields that grew out of this computer revolution, and responded most enthusiastically to academic programs that were preparatory to these career fields. However, the distinction between the computer science and computer information systems majors has not been well-known outside of the discipline, and certainly not by students at the high school level.

The answer to this problem is two-fold. At the first level, the simple understanding of the distinction between the majors is required. This is simply informational in nature, and as more and more high school teachers and guidance counselors become familiar with these fields of study, so will their students. However, beyond the recognition of the distinctiveness of the fields is the determination of suitability of a student for a particular discipline. It is at this level that the results of this study are significant. A short, simple instrument now exists, the results of which can align a subject with a computer science or computer information systems program of study, based on a comparison of their traits to those that are typical of successful majors in either of the disciplines, with an accuracy of over 75%. Thus, the guidance function with respect to differentiating between computing fields may now operate not only in a descriptive manner, but also in a research-based classification manner.

Limitations of the Research

The following research limitations are cautioned. Initially, the participants in the study are noted to be volunteers from five different institutions. The representativeness of the subjects within each institution is unsubstantiated. Furthermore, differences across institutions that may be inherent in the institutional compositions, if such should exist, are uncontrolled;

however, no conspicuous reasons for assuming such are evident, and a multivariate analysis of variance on all variables taken collectively across institutions showed no significant institutional difference.

The programs of study at the various institutions are not identical. In fact, they are offered under several different names, and in various academic settings. However, each school's professing to offer programs based on common curriculum recommendations of the Association for Computing Machinery and/or the Data Processing Management Association has been allowed to serve as a coalescing factor.

Finally, the relatively small size of the researched population is noted - 106 subjects, of which varying numbers had missing values for one or more items. The results, however, were buttressed by the confidence intervals employed (all with $p < .05$, most with $p < .01$ and some with $p <= .001$). This sparsity of data items did however, preclude the formation of a third group, one of "non-assigned's" (those in proximity to the model's cutoff point that would be anticipated to have a lower rate of correct classification that those more greatly differentiated from one another), the removal of which would improve the percentages of correct classification for those directed to an "assigned" group (those determined to be of computer science or computer information systems type).

Directions for Future Research

This study involves two groups that have been drawn from five colleges. In the previous section, it was noted that the necessity of drawing subjects from five different institutions introduced a potential for institutionally-based differences confounding the results (although simultaneously enhancing generalizability), and that the use of volunteers introduced the potential for bias. Thus, any studies of a replicative nature might attempt to perform the research within a single institution, and either include all, or select a random sample of, the majors adjudged to be successful.

Future research might also attempt to define additional groups. For example, the traditional computer information systems field, which was historically of mainframe computing orientation, has seen microcomputing, and the associated end-user computing support area, grow rapidly in recent years. Due to this, many institutions offer, or are considering offering, program tracks of both traditional mainframe-based activity and microcomputer-oriented development/support activity. Thus, future endeavors might choose to identify and attempt to discriminate between three groups - computer science, computer information systems/mainframe-based, and computer information systems/microcomputer-based (ie. end-user computing). Other "additional groups" to be considered might be those of non-computer-related majors, or of students having attempted but subsequently having withdrawn from a computer-related major, that would allow for comparison of those involved in computer-based majors, or end-user computing, with those not involved in, or ultimately completing, such studies.

In addition, the instrumentation might be changed based on the results of this study. Although the Learning-Style Inventory performed remarkably in differentiating between the groups in several aspects, other instruments involving abstract reasoning and logical or critical thinking might be utilized. Furthermore, certain items of the questionnaire could also be changed. For example, it was found that the number of years of coursework taken in any of the six subject areas considered in the study did not vary significantly for any area between the groups. Yet, the SAT - Mathematics scores did! Since the amount of coursework did not account for the difference, it is possible that the nature of the coursework, or grades in the coursework, did.

Therefore, modifications that include these factors should be incorporated into future research.

Finally, recalling that the purpose of the research was to determine differentiating characteristics between the groups for the purpose of providing guidance to those prospectively considering a "computer-related" major, follow-up studies dealing with subjects classified by means of this rule, to include not only those classified correctly but also those classified incorrectly, ought to be accomplished at various intervals after the subjects' graduation from college. In this way, the operational definition of success in a major could be defined in a manner that also includes professional orientation - certainly an attribute of interest to prospective students of these types of academic preparation.

APPENDIX A

ASSOCIATION FOR COMPUTING MACHINERY'S UNDERGRADUATE CURRICULUM RECOMMENDATIONS FOR COMPUTER SCIENCE

The report of the ACM Curriculum Committee on Computer Science entitled "Curriculum '78: Recommendations for the Undergraduate Program in Computer Science" [Austing, et al., 1979], recommended that the following be required courses of a computer studies component of undergraduate computer science programs of study.

CS 1. Computer Programming I

CS 2. Computer Programming II

CS 3. Introduction to Computer Systems

CS 4. Introduction to Computer Organization

CS 5. Introduction to File Processing

CS 6. Operating Systems and Computer Architecture I

CS 7. Data Structures and Algorithm Analysis

CS 8. Organization of Programming Languages

APPENDIX B

ASSOCIATION FOR COMPUTING MACHINERY'S UNDERGRADUATE CURRICULUM RECOMMENDATIONS FOR INFORMATION SYSTEMS

The report of the ACM Curriculum Committee on Information Systems entitled "Information Systems for the 80's: Undergraduate and Graduate Programs" [Nunamaker, Couger and Davis, 1983], recommended that the following be required courses of a computer studies component of undergraduate information systems programs of study.

IS 1. Computer Concepts and Software Systems

IS 2. Program, Data and File Structures

IS 3. Information Systems in Organizations

IS 4. Database Management Systems

IS 5. Information Analysis

IS 6. Data Communication Systems and Networks

IS 8. Systems Design Process

IS 10. Information Systems Projects

APPENDIX C

DATA PROCESSING MANAGEMENT ASSOCIATION'S UNDERGRADUATE CURRICULUM RECOMMENDATIONS FOR COMPUTER INFORMATION SYSTEMS

The report of the DPMA Education Foundation Curriculum Committee entitled "CIS '86: The DPMA Model Curriculum for Undergraduate Computer Information Systems" [CIS '86, 1986], recommended that the following be required courses of a computer studies component of undergraduate computer information systems programs of study.

CIS/86-1. Introduction to Computer Information Systems
CIS/86-2. Microcomputer Applications in Business
CIS/86-3. Introduction to Business Application Programming
CIS/86-4. Intermediate Business Application Programming
CIS/86-5. Systems Development Methodologies: A Survey
CIS/86-6. Data Files and Databases
CIS/86-7. Information Center Functions
CIS/86-8. Systems Development Project

APPENDIX D

QUESTIONNAIRE ADMINISTERED TO SUBJECTS

Appendix D contains the questionnaire that was administered to the subjects. The questionnaire was used to solicit demographic and pre-college academic data regarding the students. Instructions for completion of the questionnaire are contained within the instrument.

CS/CIS SURVEY

Spring, 1990

The purpose of this survey is to ascertain certain characteristics of computer science and computer information systems majors with respect to selected demographic and pre-college academic attributes. The results of this survey will be used in research being conducted with regard to the identification of differentiating success factors for the two majors.

Obviously, this is not a test, and there are no uniformly correct answers from one student to the next. Your honest and carefully considered responses are all that is asked of you. Your responses will be kept anonymous, so please do not put your name anywhere on the survey.

Throughout the survey, you will find various types of question formats used. Instructions are provided wherever necessary; however, should you have any questions regarding how to answer any item, please raise your hand and the survey administrator will assist you. The survey should take about 15 minutes to complete.

Thank you for your help with this research project.

---

1. What is your Date of Birth? _____ _____ _____
   mon day yr

2. What is your Sex? (Circle one)

   1. Male 2. Female

3. What is your major? (Circle one)

   1. Computer Science 2. Computer Information Systems

   3. Other (Please specify:____________________________)

SURVEY CONTINUES ON NEXT PAGE.

4a. Has this been your major since freshman year? (Circle one)

1. Yes 2. No

4b. If you answered <u>No</u> to question 4a, what was your previous major?

____

5. Are you of Junior or Senior Year standing at this time?

1. Yes 2. No

6. Do you currently have at least a 2.0 GPA in your major courses?

1. Yes 2. No

7. Do you currently have any outstanding failing grades in any of your major courses (that is, failed courses that you have not subsequently retaken and passed)?

1. Yes 2. No

8a. Did you have a computer available to you at home when you were in high school? (Circle one)

1. Yes 2. No

8b. If you answered "Yes" to Question 8a above, indicate the type of computer that you had (for example, Apple IIe, IBM PC XT):

____

SURVEY CONTINUES ON NEXT PAGE.

CS/CIS Survey (Spring, 1990), p. 3

9. Indicate your High School Class Rank (Circle the first that is true):

   1. Top 5%   2. Top 10%   3. Top 25%   4. Top 50%

   5. Bottom 50%

10. Indicate the score that you received on the Verbal and Mathematics sections of the SAT (if you've taken them more than once, record your highest score for each):

    SAT Verbal Score _______   SAT Math Score _______

11. Fill in the Grid below so as to indicate the number of Carnegie Units of coursework that you took and passed in each subject each year in high school (a Carnegie unit is a full year's coursework in a subject); for example, if you took a full year Calculus course and a half year Statistics course in your Senior Year, you would indicate 1 1/2 in the second (Math) column on the last (12th grade) row.

Gr.	English	Math	Computer Studies	Science	Social Studies	Foreign Language
9*						
10						
11						
12						

* Include any high school courses taken in the 8th grade, such as Algebra I, in with the 9th grade courses.

SURVEY CONTINUES ON NEXT PAGE.

12. Rank the following areas of study in the order of interest that they were to you during high school. There are six items; use responses "6", "5", "4", "3", "2" and "1", where "6" represents most interest to you, "1" represents least, and "5", "4", "3" and "2" represent in-between values from "most" to "least". Do not indicate any tie scores.

_______ Computer Studies

_______ English

_______ Foreign Language

_______ Mathematics

_______ Science

_______ Social Studies

THANK YOU FOR YOUR PARTICIPATION IN THIS SURVEY!

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