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FACTORS AFFECTING ACADEMIC SUCCESS IN INTRODUCTORY  
COMPUTER PROGRAMMING

*The University of Iowa*

PH.D. 1986

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**FACTORS AFFECTING ACADEMIC SUCCESS  
IN INTRODUCTORY COMPUTER PROGRAMMING**

by

Stephen C. Renk

A thesis submitted in partial fulfillment  
of the requirements for the degree of  
Doctor of Philosophy in Education  
in the Graduate College of  
The University of Iowa

December 1986

Thesis supervisor: Professor Alan B. Henkin

Graduate College  
The University of Iowa  
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CERTIFICATE OF APPROVAL

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PH.D. Thesis

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## ABSTRACT

The magnitude of student demand for computer science courses has resulted in resource allocation and student access problems at many institutions of higher education. These circumstances are likely to continue, as faculty resources remain stable, at best, assuming continued competition from the private high-tech sector for limited personnel. Denning (1980) reports that a significant proportion of the students enrolled in high demand computer science courses do not successfully complete these courses; especially those at the introductory programming level. The identification of factors that affect student success in introductory computer programming will assist administrators and faculty at colleges and universities to design and develop functional guidance systems and resource allocation schema that address concurrent needs for operational efficiency and responsive educational programming.

The purpose of this study was to explore potential relationships between the independent variables: abstract reasoning ability, math ACT score, high school grade point average, previous math background, previous computer use,

sex, age, academic major, academic class, expectation and perseverance level and the dependent variable, academic success, in introductory computer programming courses. To accomplish this purpose, the study included a population of 154 students enrolled in introductory computer science courses as subjects. The study subjects completed an abstract reasoning instrument and a student profile questionnaire at the beginning of the term. The collected data were then matched with course examination measures of academic success to test for statistically significant relationships between each of the independent variables and academic success in introductory computer science courses.

Of the eleven variables studied only ACT math scores, abstract reasoning scores, expectation, previous computer experience, grade point average, and math background showed significant relationship to academic success.

## TABLE OF CONTENTS

	Page
LIST OF TABLES .....	vii
LIST OF FIGURES .....	x
INTRODUCTION .....	1
Chapter	
I. THE PROBLEM .....	6
Problem Statement .....	7
Hypotheses .....	7
Delimitations .....	8
Definitions .....	9
Assumptions .....	10
II. REVIEW OF RELATED LITERATURE .....	11
Prediction and Psychological Testing .....	12
Prediction of Academic Success Potential in Higher Education .....	14
Prediction of Programming Success .....	16
Prediction of Computer Science Success ..	18
Abstract Reasoning as a Predictor .....	23
III. THE STUDY .....	27
Setting .....	28
Population .....	28
Research Methodology .....	29
Instrumentation .....	30
Data Collection .....	32
Treatment of the Data .....	34
Treatment by Hypothesis .....	37
IV. THE RESULTS .....	52
Overview of the data .....	53
Academic Success .....	55
Abstract Reasoning .....	56
Logical Reasoning .....	59
Reasoning Skills .....	61
ACT Math .....	64

	Page
High School Gade Point Average .....	66
Math Background .....	69
Math Self-preception .....	71
Previous Computer Experience .....	73
Microcomputer Ownership .....	77
Age .....	79
Sex .....	81
Perseverance .....	82
Academic Major .....	84
Academic Class .....	86
Expectation .....	88
 CONCLUSION .....	 91
Discussion .....	92
Implications .....	98
Future Research .....	100
 APPENDIX A. ABSTRACT REASONING INSTRUMENT .....	 103
APPENDIX B. STUDENT PROFILE QUESTIONNAIRES .....	110
APPENDIX C. ACT/SAT EQUIVALENTS TABLES .....	114
APPENDIX D. SCATTERPLOTS .....	116
 BIBLIOGRAPHY .....	 126

## LIST OF TABLES

Table	Page
1. Distribution of students by block .....	54
2. Distribution of academic success Z scores (STD) .....	55
3. Abstract Reasoning scores distribution ...	57
4. Crosstabulation ART By SUCCESS .....	58
5. Distribution of responses to the question: How would you characterize your logical reasoning skills? .....	59
6. Crosstabulation LOGIC By SUCCESS .....	60
7. Analysis of variance STD By LOGIC .....	61
8. Distribution of responses to the statement: I have well developed reasoning skills. ..	62
9. Crosstabulation REASON By SUCCESS .....	63
10. Analysis of variance STD By REASON .....	64
11. Distribution of ACT math scores .....	65
12. Crosstabulation MATH ACT By SUCCESS .....	66
13. Distribution of high school GPAs .....	67
14. Crosstabulation GPA By SUCCESS .....	68
15. Distribution of the number of high school and college math classes .....	69
16. Crosstabulation MATH By SUCCESS .....	70
17. Distribution of math self-perception values .....	71
18. Crosstabulation MATH2 By SUCCESS .....	72

	Page
19. Analysis of variance STD By MATH2 .....	73
20. Distribution of responses to the question: Previous computer experience? .....	74
21. Crosstabulation EXPER By SUCCESS .....	75
22. Analysis of variance STD By EXPER .....	76
23. Crosstabulation EXPR By SUCCESS .....	76
24. Analysis of variance STD By EXPR .....	77
25. Crosstabulation MICRO By SUCCESS .....	78
26. Analysis of variance STD By MICRO .....	78
27. Distribution of STUDENT AGE .....	79
28. Crosstabulation AGE By SUCCESS .....	80
29. Crosstabulation SEX By SUCCESS .....	81
30. Analysis of variance STD By SEX .....	82
31. Distribution of perseverance scores .....	83
32. Crosstabulation PERS By SUCCESS .....	84
33. Crosstabulation MAJOR By SUCCESS .....	85
34. Analysis of variance STD By MAJOR .....	86
35. Distribution of students by academic class .....	86
36. Crosstabulation CLASS By SUCCESS .....	87
37. Analysis of variance STD By CLASS .....	88
38. Distribution of responses to the question: What grade do you expect to receive in this class? .....	89
39. Crosstabulation EXPECT By SUCCESS .....	89
40. Analysis of variance STD By EXPECT .....	90
41. Findings by variable .....	93



	Page
42. Cross correlations of all variables in the study .....	95
43. ACT math equivalents for SAT scores .....	115

## LIST OF FIGURES

Figure		Page
1	PLOT OF ART WITH STD .....	117
2	PLOT OF ACT WITH STD .....	118
3	PLOT OF SEX WITH STD .....	119
4	PLOT OF CLASS WITH STD .....	119
5	PLOT OF MICRO WITH STD .....	119
6	PLOT OF AGE WITH STD .....	120
7	PLOT OF MATH WITH STD .....	121
8	PLOT OF LOGIC WITH STD .....	121
9	PLOT OF EXPECT WITH STD .....	122
10	PLOT OF EXPER WITH STD .....	122
11	PLOT OF MAJOR WITH STD .....	122
12	PLOT OF GPA WITH STD .....	123
13	PLOT OF MATH2 WITH STD .....	124
14	PLOT OF REASON WITH STD .....	124
15	PLOT OF EXPR WITH STD .....	124
16	PLOT OF PERS WITH STD .....	125

**INTRODUCTION**

American higher education is seeking to respond to the demands of an increasingly technological society. Societal demand for technologically skilled professionals has led many students of varying backgrounds and ability levels to consider the study of computer science. Computer science enrollments in some areas have increased ten fold in the last five years. Enrollments in entry level programming courses at the University of Iowa, for example, have increased from an average class size of forty-four in 1977 to over 600 in 1984. According to a special task force report (Johnson, 1982), University of Iowa computer capacity must grow at a rate of twenty-five percent per year in order to stay even with demand. The strain on university resources, given computer science enrollments, is being felt by the university community as a whole. Petersen and Howe (1979) noted this dramatic increase in demand for instructional computing. Some suggested reasons for the rise in demand have been advanced. Specifically: 1) computers are more accessible in schools and homes (Stevens, 1983); 2) alternative vocations in the computer market are enticing (Rothman and Mosman, 1972); and 3) computers are such a dominant force in society that computer literacy cannot be ignored by educated persons (Ralston, 1971). The sudden influx of computer science students has strained the resources of many institutions, and has required, at times, that limitations be placed on

enrollments.

A significant proportion of aspiring students, for one reason or another, are unsuccessful in their computer studies. An exemplary five year study conducted by Denning (1980) at Purdue University, the nation's oldest computer science program, found a sixty percent drop-out rate in the computer science department. Figures compiled in a University of Iowa computer science department self-study (Bresdal, 1985) of the entry level pre-computer science program suggest similar outcomes. Of the 600 students who registered for the entry level computer programming course, approximately 200 completed the course and received a final grade. Stephens, Wileman and Konvalina (1981) also recognized the problem facing computer science programs.

As demand for beginning computer science courses continues its phenomenal growth into the 1980's, the problems of identifying components of computer science aptitude and predicting academic success in computer science become increasingly important. Advisement and placement of prospective computer science students has become a necessary function for educators, especially those educators in computer-oriented disciplines (p.84).

Hunt (1977) pointed to the need to identify potentially successful students for such important reasons as early counseling into appropriate career paths, and the formation of honors sections. In addition, identification of factors related to success is important in the course of curriculum development (Ralston and Shaw, 1980).

Faced with these needs, computer science departments are searching for some valid criteria useful in the stratification of burgeoning enrollments. The objective here is to identify students with the most potential for success in order to make the best use of limited resources. There is, however, minimal research to guide decisional processes. Astin (1971) revealed that although he found considerable literature and data on the general problem of predicting academic success, only recently have related findings and techniques been applied, to any significant extent, to computer science. Little is known about those factors that influence student success or the high withdrawal rates common in computer science courses. The results of research on salient factors, noted Astin (1971), can be helpful in advising and placing prospective students as well as in planning for their future educational needs. Stephens, Wileman, and Konvalina (1981) similarly recognized that "very little research has been done in identifying the major components of computer science aptitude" (p.85).

The data related to the salient variables may provide administrators with substantive information requisite for more rational, timely and informed judgments. While a definitive response to questions regarding a given student's ability to gain maximum advantage from programs of study in computer science may depend upon variables and

contingencies that were not addressed in this study, the contribution of this research to the knowledge base focused on factors affecting academic success in computer science is axiomatic.

**CHAPTER I**  
**THE PROBLEM**



### Problem Statement

The purpose of this study was to examine the independent variables: abstract reasoning ability, high school grade point average (HSGPA), ACT math score (ACT-M), previous computer use, math background, sex, age, academic major, academic class and perseverance level, and the dependent variable of academic success in introductory computer science courses to determine if relationships exist between any or all of the independent variables and the dependent variable.

### Hypotheses

- H<sub>1</sub>: There is no significant relationship in the academic success rates between students with respect to abstract reasoning instrument scores.
- H<sub>2</sub>: There is no significant relationship in the academic success rates between students with respect to ACT-M scores.
- H<sub>3</sub>: There is no significant relationship in the academic success rates between students with respect to high school grade point average.
- H<sub>4</sub>: There is no significant relationship in the academic success rates between students with respect to math background.

- H<sub>5</sub>: There is no significant relationship in the academic success rates between students with respect to previous computer use.
- H<sub>6</sub>: There is no significant relationship in the academic success rates between students with respect to age.
- H<sub>7</sub>: There is no significant relationship in the academic success rates between students with respect to sex.
- H<sub>8</sub>: There is no significant relationship in the academic success rates between students with respect to the student perseverance level.
- H<sub>9</sub>: There is no significant relationship in the academic success rates between students with respect to academic major.
- H<sub>10</sub>: There is no significant relationship in the academic success rates between students with respect to academic class.
- H<sub>11</sub>: There is no significant relationship in the academic success rates between students with respect to student expectation.

#### Delimitations

This study did not attempt to directly investigate relationships between abstract reasoning levels and

computer programming skills. The study is, rather, an effort to explore potentially related dimensions of a student's abstract reasoning levels and other relevant variables, and performance on examinations in an introductory computer science course. Examinations are composed of approximately one-half program writing and evaluation, and one-half related materials. The research does not seek to determine if the study of computer programming increases an individual's level of abstract reasoning. The study was designed to inquire into the potential association of abstract reasoning ability and other variables and academic success in introductory programming courses.

#### Definitions

For the purposes of this research the following definitions apply:

Academic success - obtaining a combined midterm and final examination score in the upper fifty percent of the class.

ART scores - scores compiled from the Abstract Reasoning Test.

Perseverance - the persistence score derived from the perseverance measurement questions of the student profile.

Academic class - Freshmen, Sophomore, Junior, or Senior.

Academic major - general area of undergraduate major:  
undecided, science, humanities, or business.

Expectation - the student's self-perception of how well  
he/she will perform in the class.

#### Assumptions

A<sub>1</sub>: Computer Science enrollments will remain high.

A<sub>2</sub>: Faculty resources for instruction in computer courses  
will remain limited.

A<sub>3</sub>: Physical facilities for instruction in computer courses  
will remain limited.

**CHAPTER II**  
**REVIEW OF RELATED LITERATURE**

### Prediction and Psychological Testing

"Traditionally, the function of psychological testing has been to measure differences between individuals or between the reactions of the same individual on different occasions" (Anastasi, 1982, p.4). The educational sector has been a major beneficiary of the testing movement in the United States. Today, schools are among the largest test users. Tests are designed for classification of children with reference to ability so that they may profit from different types of school instruction; others are targeted to the identification of the intellectually retarded, on the one hand, and the gifted, on the other. Measures useful in the diagnosis of academic failures, educational and vocational counseling of high school and college students, and the selection of applicants for professional and other special schools constitute additional applications of tests in education. Increasingly, tests are being employed in counseling and guidance prior to the development of educational and vocational plans.

Government and private industry also make extensive use of psychological testing. Psychological tests have proven useful in evaluating personnel in nearly every phase of employment including hiring, job assignment, transfer, promotion, or termination.

The term 'mental test' was first introduced into the

psychological literature by James M<sup>C</sup>Keen Cattell in 1890 (Anastasi, 1982). Cattell developed a series of tests similar to a number of the instruments developed during the last decade of the nineteenth century. The validity and reliability of these tests, however, were soon questioned. Wissler (1901) and Sharp (1898) both concluded that an individual's performance showed little correspondence from one test to another, and exhibited little or no relation to independent teachers' estimates of intellectual level.

Among the most important tests to be developed during the early years were the Binet-Simon intelligence tests (Anastasi, 1982). The Binet tests were designed to cover a wide variety of functions, with special emphasis on the areas of judgment, comprehension, and reasoning. Binet considered the latter to be an essential component of intelligence. Subsequently, Terman revised the Binet test and coined the measure 'intelligence quotient' (IQ), a ratio between mental age and chronological age (Anastasi, 1982). Most early intelligence tests were primarily measures of verbal ability and, to a lesser extent, of the ability to handle numerical and other abstract and symbolic relations. Gradually, people came to realize that in many cases the term intelligence test was a misnomer. It became apparent that many of these tests actually measured that combination of abilities demanded by academic work.

The term scholastic aptitude test began to be used to

describe many of the tests developed during the 1920's. Among the most widely used were tests of mechanical, clerical, musical, and artistic aptitudes (Anastasi, 1982). The recognition that intelligence is actually a measure of many components rather than one, led to the development of multiple aptitude batteries. A plethora of multiple aptitude batteries have appeared since 1945. The popularity of aptitude tests may be largely the result of related military research conducted during World War II. The military's desire to make predictions about the abilities or aptitudes of its trainees, and to channel their efforts into the most productive fields, gave impetus to the new testing movement. The term "aptitude test" traditionally is used to refer to tests measuring relatively homogeneous and clearly defined segments of ability. In contrast, "intelligence test" customarily refers to more heterogeneous tests yielding a single global score.

Prediction of Academic Success Potential in  
Higher Education

Efforts to predict potential for success in academic endeavors have continued for decades in American higher education. Most colleges and universities in the United States require that applicants take either the Scholastic



Aptitude Test (SAT) or the American College Test (ACT) to assist them in evaluating the prospective students' potentials for academic success. Correct identification allows schools to best utilize their finite resources; especially where demand exceeds resources. Few institutions, however, make widespread use of predictive instruments for intra-institutional program entrance at the undergraduate level.

Graduate programs often require Graduate Record Examination (GRE) scores to evaluate applicants and some, where resources are particularly scarce -- for example, law, medicine -- require special aptitude tests such as the Law School Aptitude Test (LSAT) or the Medical College Aptitude Test (MCAT). Recently, some undergraduate programs -- for example, engineering and business -- have experienced increases in enrollments which, in turn, have strained institutional resources. In the absence of additional faculty and/or facilities, some programs have been forced to place limitations on enrollments. Enrollment limitations have made it even more important that programs identify students with the potential for success. Faculty are searching for valid and reliable criteria upon which to base entrance decisions. The problem is particularly acute in computer science where enrollments have burgeoned in recent years.

### Prediction of Programming Success

Measuring computer programming aptitude or potential is not a new area of research. The first initiative to identify computer programming aptitude came from the private sector. In the early 1960's, the demand for computer programmers motivated government and industry to begin the effort to identify measures related to computer programming potential. The purpose then was to identify the best candidates for computer programming training. Correct evaluation was important because the candidates chosen were given extensive and expensive company training. Nearly all large companies had their own internal educational systems designed to meet the demand for skilled computer professionals.

Most of the early efforts resulted in the use of, and dependence on mathematically oriented tests to predict programming success (Tillman, 1979). Several research efforts focused on mathematical ability and programming ability, and showed that significant relationships existed between the two. Bauer, Mehreus, and Vinsonhaler (1968) observed a strong correlation between mathematics aptitude and trainee performance.

Howell, Vincent and Gray (1967) revealed that in 1961, the U.S. Public Health Service (USPHS), anticipating a demand for programmers, experimentally administered several selection tests to potential programmer candidates with a

view toward later conducting training or job performance evaluations with the individuals who subsequently entered the programming field. Few of the selected individuals entered the field, however, and in 1966 USPHS deemed such follow-up evaluations inappropriate.

In the late 1950's, International Business Machines (IBM) developed and published a Programmers Aptitude Test (PAT) which was widely used in industry for the next ten years (Perry, 1962). Perry conducted a survey of 132 organizations and found that sixty-eight percent were using the PAT as one component in the programmer selection process at that time.

Similar tests were developed by other large organizations. The Rand corporation developed a test for inhouse use which was designed to identify candidates for programming positions and advancement (Reinstadt, Hammidi, Peres, and Ricard, 1965; Rowan, 1957). Another test, the Primary Mental Abilities Test (PMAT), was appraised by the Systems Development Corporation to ascertain its predictive value (Perry, 1964). The reasoning section of the PMAT showed the greatest weight in regression equations for predicting training and job criteria. In addition, age correlated with performance during programmer training; however, age was not predictive of supervisory rating of on-the-job performance as a programmer. Abilities tests

such as the Federal Service Entrance Examination (FSEE) have also been studied in order to ascertain their predictive value. Staubly (1963), in an unpublished report to the United States Department of Commerce, Bureau of the Census, maintained that the FSEE did not appear to be a valid predictor of supervisory ratings of programming performance. In a previous report to the same group, Staubly (1963) showed poor validity for the FSEE in predicting training criteria. However useful these tests may or may not have been in industry, it became increasingly clear that they were of minimal utility in academic contexts. Mazlack (1980) and Alspaugh (1972) demonstrated low predictive value for the IBM PAT instrument when it was applied to entry level computer science courses.

#### Prediction of Computer Science Success

Most early academic research to identify factors influencing computer science success, similar to those in industry, focused on efforts to correlate programming achievement with mathematical abilities and high school performance (Konvalina, Stephens, and Wileman, 1983; Alspaugh, 1971). Berger (1968) found a high correlation ( $r=.55$ ) between advanced mathematics' abilities and midterm examination scores in introductory computer science. In 1971, Alspaugh began to study the relationships between

math background and success in FORTRAN programming endeavors. He asserted that mathematics ability seemed to play an important role in college computer programming courses. Alspaugh (1972) concluded that math background was the major component influencing achievement in programming courses. The finding was supported later by studies by Wileman (1982) and Stephens, Wileman, and Konvalina (1981), which found that mathematical reasoning ability is an important factor.

Tillman (1979) studied several potential predictors of programming performance. The three predictors he chose to investigate were 1) the Biographical Information Blank -- a 163 item life history questionnaire developed specifically for use with computer programmer applicants; 2) the School and College Abilities Test -- a test with a verbal component, a math component, and a total score; and 3) the Strong Vocational Interest Blank -- a test that measures occupational interest, and provides an index of the similarity between an examinee's interest and those of successful people in a wide range of occupations. The only valid predictor of programming success was the math portion of the School and College Abilities Test. In a 1982 study, Wileman observed a relationship between math competencies and probable success in beginning computer science courses. Jacobs (1973) noted that in 1968 Manny reported that

several studies have shown positive correlations between the processes of solving algebraic equations and computer programming.

What is involved in the mathematical process that correlates with programming skills? Mathematics ability is only one characteristic that may be correlated with an individual's ability to program (Howell, Vincent, and Gray, 1967). Recent research has begun to examine other areas. Tillman (1979) questioned the use of mathematics based tests as predictors because candidates have been able to increase their scores through repetition of the same test. Petersen and Howe (1979) studied a set of background and aptitude variables. Their study included the background variables of sex, age, college academic class, hours worked, and previous college performance. Aptitude variables included reading comprehension, sequence completion, logical reasoning, algorithmic execution, and alpha-numeric translation. They came to the conclusion that only general intelligence and college grade point average contributed significantly to predicting success in introductory computer courses. The work done by Petersen and Howe (1979), coupled with the unmet demand for computer science courses, appears to have encouraged new research in the area of computer science aptitude. Konvalina, Stephens, and Wileman (1983) later suggested that high school grade point average is also a good predictor of both

computer science aptitude and achievement. Their study also demonstrated that achievement scores increased with age for students under thirty-five. This outcome supported the previous findings of Perry (1964), while contradicting those reported by Fowler and Glorfeld (1981) who found that as age increased academic success rates declined.

The role of cognitive style in computer studies became a focus of research in the early 1980s. Barkin (1974) posited that cognitive style is another factor that potentially could predict a person's programming ability. He believed that cognitive style is not biased in favor of those applicants with an educational advantage in mathematics. Cognitive style can be defined as the problem-solving methodology employed by an individual in a decision situation (Lusk and Kersnick, 1979; Huysmans, 1970). There are two types of cognitive style, analytic and heuristic. Cheney (1980) describes the two styles in the following manner.

Analytic problem solvers utilize a structured approach to decision-making. The analytic person attempts to reduce problem situations to a core set of underlying causal relationships. Analytic problem solvers emphasize common sense, intuition, and unqualified feelings of future developments when selecting alternatives.

The heuristic approach is characterized by a trial-and-

error method and the use of feedback to adjust the course of action chosen. The search is for analogies to familiar solved problems rather than for a system of underlying causal relationships.

Cheney (1980) studied high and low analytic ability students and concluded that cognitive style provides one new tool for selecting individuals for entry-level programmer positions. He demonstrated that the analytic person performed better on the programming exams, and has fewer conceptual problems with the programming exercises in general. Cheney felt that Tillman's (1979) research findings supported his conclusion. Analytic thinkers were more mathematically oriented than heuristic thinkers; hence, a potential correlation may exist between an analytic cognitive style and a student's ability to write computer programs. In his conclusion, Cheney hypothesized that students who have different cognitive styles might be taught to program using different techniques.

Prichard (1982) advanced the same concept and recommended that studies on student cognitive processes were needed to effectively teach with and about computers. Stevens (1983) subsequently studied cognitive style for its effect on student performance. She recognized that many educators are coming to believe that cognitive style is a potential variable affecting students' academic success. Stevens' study subjects were divided into two groups on the



basis of cognitive styles. Each group was defined: Group 1) - field dependent = members' perceptions are analytical and not dominated by the prevailing field; Group 2) - field independent = members' perceptions are global and tend to focus on the total environment. Stevens (1983) discovered that on the more technical aspects of computers and the programming portions of the achievement tests, field dependent subjects scored significantly higher than field independent subjects.

Cognitive styles have been shown to influence vocational preferences, continued academic development, how students learn, how teachers teach and how students and teachers interact in the classroom (Witkin, Ottman, Raskin and Karp, 1977). Brillhart (1982) contended that successful computer science students enjoyed working alone on computers. This notion appeared to be supported in a study by Hopmeier (1981) who found that Computer Assisted Instruction was more beneficial to introverted students than to extroverted ones; an introverted student was defined as one who has the ability to quietly concentrate and pay attention to details.

#### **Abstract Reasoning as a Predictor**

An underlying theme of the research into computer related aptitudes of the past thirty years may be

identified. Certainly, mathematical ability is a strongly supported and recurring element in computer programming aptitude research. Is knowledge of the mechanics of mathematics a critical issue in programming ability, or does mathematics ability only share a common subcomponent with computer science ability? Might that component be the ability to reason and sequence in a step-wise manner?

Perry (1964) demonstrated that the reasoning section of the Primary Mental Abilities test showed the greatest predictive value for estimation of a programmer's ability to complete training successfully and to meet job performance criteria. Cheney (1980) concluded that analytic persons perform better on computer programming examinations, and that they have fewer conceptual problems with the course materials. Wileman, Konvalina, and Stephens (1981) suggested that math reasoning ability was one of the most important components in predicting computer science success. A study by Stephens, Wileman, and Konvalina (1981) revealed that the sequencing and logic components of the aptitude instrument they studied were the most significant and clearly related to the mathematical reasoning ability of the students.

Howell, Vincent, and Gray (1967) pointed out that reasoning factors, particularly those measured by the IBM PAT, were major components of performance on the Robot Test. A study by Staubly (1963) found significant

correlations between the Robot Test and programmer aptitude; hence the link to the reasoning component may be supported. The contribution of reasoning skills was also supported by the General Aptitude Test Battery given to prospective employees by the United States Employment Service, one section of which was devoted to arithmetic reasoning (Staubly, 1963). In addition, a section of the FSEE examination for computer personnel was devoted to abstract reasoning.

The research cited suggests that reasoning skills may lie at the heart of the predictive equation for academic success in computer science classes. Many measures of reasoning ability are available. The abstract reasoning instrument used in this study combines both reasoning and sequencing, and potentially avoids biases introduced by language and verbal abilities via its total reliance on graphic symbols. Konvalina, Stephens, and Wileman (1983) found that computer science achievement scores increased with age, up to age thirty-five. Abstract reasoning scores, with this instrument, also have been shown to increase with age. The lack of adult norms, however, makes it impossible to say at what point the increase levels off or drops.

This study compared a direct measure of a specific reasoning skill with academic success in introductory

computer science courses. The knowledge gained from such a study may provide a unifying or binding element for previous research.

**CHAPTER III**

**THE STUDY**

### Setting.

A small liberal arts college of just over 1100 students was the study site. The college had a geographically diverse student body and an almost even distribution of males (49%) and females (51%). The average ACT composite score of the student body was 24 during the term of this study. The college is atypical in terms of its academic calendar. A block scheduling plan is utilized. Under the block plan the academic year is divided into nine, three and one half week blocks. Students take only one course per block. As a consequence, students in this study were not distracted by concurrent courses which might have diverted their attention and competed for available study time.

### Population

One hundred fifty-four students who registered for CS-131, Introduction to Structured Programming, in blocks 1,4,5,6,7,8,9 of the 1984-1985 school year were included in the study population. CS-131 is an entry level computer programming course using the BASIC programming language; typically the first college computer exposure for the student. The course attracts a wide variety of students from many disciplines other than computer science or mathematics. CS-131 is a required course for education majors and can be used to satisfy the college's minimum math requirement.

### Research Methodology

Every student enrolled in one of the specified CS-131 blocks was asked to participate. Participation was voluntary and students were advised that the study would have no affect on their final course grade. Under the block plan, students were allowed to drop or add courses in the first three days of a block. On the fourth day, course enrollments were finalized. On Friday of the third week, students were again given the option of dropping the course.

Full participation in the study consisted of completing the following tasks:

1. completing Bennett and Seashore's Abstract Reasoning: Differential Aptitude Test. (see Appendix A.)
2. filling out one of the student profile questionnaires (see appendix B.)
3. completing the midterm and final examination or dropping the course on the final Friday of the block.

Participants completed the two instruments on the fourth day of class. Five student failed to complete the abstract reasoning instrument and the student profile questionnaire.

At the end of class on the fourth day, students were given the abstract reasoning test and the student profile questionnaire. Students were instructed to fill out the student profile questionnaire first. When all students had

completed the questionnaire, the students were read a set of directions and allowed 25 minutes to complete the abstract reasoning instrument. Students were generally able to complete the instrument without difficulty.

At the end of each block, the results from the midterm and final examinations were totaled and used to assign a class rank for each student. All participants who dropped the course in the first three days, or who dropped the course for medical reasons, were excluded from the study. All participants who dropped the course at the end of the third week for other than medical reasons were retained in the study, and were considered as having failed to achieve academic success.

Students with incomplete data were retained in the study. Where information was incomplete or unavailable it was coded as missing for statistical analysis.

#### Instrumentation

The Abstract Reasoning: Differential Aptitude Test (Appendix A) was developed by Bennett, Seashore and Wesman as one part of an eight part battery of the Differential Aptitude Test (Bennett, 1974). The battery was last published by the Psychological Corporation in 1974. The authors intended this series of tests to be used in predicting areas of achievement. Extensive norms are available for the test with 8th thru 12th grade students,



but no norms were published for adults. This battery of tests, according to the authors, was used by several universities to make predictions about their students. The norms that were available show that abstract reasoning scores improve with age for 8th-12th graders. The mean for 12th grade males was 34.8 with a standard deviation of 9.3, while females scored about one point lower with one point greater standard deviation. Substantially higher scores were observed from this instrument when it was applied with this more select college population.

The test itself consisted of 50 multiple choice questions of 5 foils each. Each question was based upon a geometric series, and the student's ability to recognize a pattern and abstract what the next step in the sequence should be. Test takers were given 25 minutes to complete the test. The score for the test is equal to the number of items answered correctly.

Two different student profile questionnaires were used to elicit student demographic information. Student profile 1 (Appendix B) was administered to one hundred and two students in blocks 1,4,5, and 6. Student profile 2 (Appendix B) was administered to fifty-two students in blocks 7, 8, and 9. The student profile questionnaires contained items which elicit biographical and attitudinal information. These instruments provided study data including: student age, sex, academic major, high school

grade point average, mathematics background, previous computer background, and academic class. Items 9 and 10 relating to logic and academic expectation were added after block 1. Student profile questionnaire 2 provided the same information plus information on the level of perseverance of each student.

The perseverance measurement element of the profile consisted of the eight question perseverance section of Ory's (1974) instrument designed to measure achievement motivation. Ory defined perseverance as,

persistence or determination of a subject to finish or complete task, problems, challenges, etc. The factor attempts to show the pattern of behavior that subjects undergo after work or effort has been initiated on some task (p.14).

Previous studies by Atkinson and Litwin (1960) and Winterbottom (1958) demonstrated an apparent difference in behavior between subjects with high and low achievement motivation. It appeared that subjects with high achievement motivation, as opposed to those with low motivation, tended to work longer on problems or tasks but realized their limits sooner and, subsequently, gave up on fruitless efforts.

#### Data Collection

Data aggregates consisted of a raw score from the abstract reasoning instrument, the final course rank

calculated using midterm and final examination scores, and information from the student profile questionnaire. The data from the abstract reasoning test consisted of scores from 0 to 50 corresponding to the number of questions answered correctly. Final course rank or academic success was computed by using the scores from the midterm and final examinations for each student in the course.

American College Test (ACT) and/or Scholastic Aptitude Test (SAT) scores for each of the students were obtained from the registrar's office. Where ACT scores were not available, SAT scores were substituted. SAT scores were converted to equivalent ACT scores by means of a set of ACT/SAT conversion tables (Appendix C) published by Langston and Watkins (1981) at the University of Illinois. The equivalents tables were based on data from over 12,000 students who took both the ACT and SAT. The table values have a correlation of .849 for Math/Quantitative. Neither ACT nor SAT scores were available in the case of foreign students, transfer students and adult reentrant students; these entries were coded as missing for the Statistical Package for the Social Sciences (SPSS). One instructor did not furnish the names of the students in his class and therefore no ACT information was available on students in block 9.

Perseverance scores were gathered from the student profile questionnaire 2 (Appendix B) by assigning points to

each answer - one point to an answer of one, two points to an answer of two, three points to three and four points to four - and then adding them, for each of the eight questions (8, 9, 11, 12, 13, 14, 17, and 19) dealing with perseverance to produce a final score.

The demographic variables related to sex, age, academic major, math experience, computer experience, academic class, and high school grade point average were obtained from information the students supplied on the profile questionnaire.

#### Treatment of the Data.

Study data were encoded and processed using the SPSS package. SPSS was used to calculate frequencies, distribution statistics, scattergrams, crosstabulations, Pearson correlation coefficients and multiple regression correlations, and to perform student T analysis and one-way analysis of variance in an attempt to assess the degree of relationship between the independent variables and the dependent variable. In searching for prediction variables any number may be analyzed in the multiple correlation, but little accuracy is gained by adding more than three variables in a prediction equation.

Frequency tables and histograms were developed to help determine the distribution of each variable and to provide

mean and standard distribution statistics for each of the variables. The histograms allow visual representation of the distribution across evenly spaced units.

Crosstabulations between each of the independent variables and the dependent variable academic success were calculated to examine the degree of relationship between the two variables. These crosstabulation tables show the distribution of the variable when it is split into two groups, those who achieve academic success and those who do not. The tables begin to reveal whether or not a relationship exists between the dependent and independent variables. Continuous or non-discrete variables with many strata were restratified into a smaller number of layers for analysis.

In this research, the strength and nature of the dependence of variables is of central concern. No single measure adequately summarizes all possible types of associations. Measures vary in their interpretation and in the way they define perfect and intermediate factors such as marginals. For example, many measures are "margin sensitive" in that they are influenced by the marginal distributions of rows and columns. Such measures reflect information about the marginals along with information about associations. Thus, sometimes a particular measure may be low for a given table, not because the two variables are not related but because they are not related in a way

to which the measure is sensitive. No single measure is best for all situations.

Measures of linear association were calculated. First a scatterplot was graphed to form a visual image of each variable as it related to the raw Z score for academic success. Although a scatterplot is an essential first step in studying the association between variables, it generally is useful to qualify the strength of the association by calculating a summary index. The most commonly used measure for this is the Pearson correlation coefficient. The absolute value of the Pearson measurement indicates the strength of the linear relationship. The largest possible absolute value that can be achieved is 1, which occurs when all points fall exactly on a line. When the line has a positive slope, the value is positive, and when the slope of the line is negative, the value is negative. A value of zero indicates no linear relationship. Again Pearson correlation measures must not be taken alone. Two variables can have a strong association but a small correlation coefficient, if the relationship is not linear. It is important to examine correlation coefficients together with scatterplots, since the same coefficient can result from very different underlying relationships. A common mistake in interpreting the correlation coefficient is to assume that correlation automatically implies causation. No such

conclusion is automatic. A T score was calculated for the Pearson's correlation to assess the degree of significance.

The T value was derived by the following formula:

$$t = \frac{r (df - 2) \cdot .5}{(1 - r^2) \cdot .5}$$

where:  
r = Pearson's correlation  
df = degrees of freedom

For discrete variables such as academic class, a one-way analysis of variance (ANOVA) was used to determine if a statistical difference exists between groups. Significance was determined by the use of T and F statistic tables found in Croxton and Cowden (1940). The level of significance used to accept or reject hypotheses in this study was set at .01.

#### Treatment by Hypothesis

The data collected were grouped for analysis according to the hypothesis to which they pertained. Each hypothesis was then independently tested. The procedure for testing each hypothesis is outlined below. Since academic success was the dependent variable in each hypothesis, the first task of analysis was to create distributions for academic success that would allow analysis across individual block boundaries.

#### **Academic Success**

The determination of academic success was established via a process of standardizing the midterm and final

examination scores. The procedure allows for description of the relative position of an observation within a distribution. Knowing that a student achieved a score of 80 on the midterm examination conveys little information about performance. Judgment of performance would depend on whether 80 is the lowest, the median, or the highest score. One way of describing the location of a case in a distribution is to calculate its standard score (STD). This score, sometimes referred to as a Z score, indicates how many standard deviations above or below the mean an observation falls. It is calculated by first finding the means and standard deviations for each block and each test. Each test score was then subtracted from its respective mean and then divided by the standard deviation. The following formula is illustrative:

$$Z = \frac{S - M}{s}$$

where:

S = test score  
M = test mean  
s = test standard deviation  
Z = standard score

The standard score for midterm and final examinations were then added together and divided by two to achieve a final success score. The standardized final success scores reflect the true distribution of the original distribution of midterm and final exams giving them equal weight. It is known that the new distribution will have a mean of zero and a standard deviation of one. This process was necessary because each block had a different number of total possible



points for the examinations. Once standardized, scores could be used to analyse the data across all blocks since the new score now reflected the direction and deviation from the individual class means. Final standardized Z scores greater than zero reflect total midterm and final scores that were greater than the class mean. Students with these Z scores are considered to have achieved academic success (SUCCESS). Students with Z scores less than zero were considered not to have achieved academic success. Any scores equal to zero were not assigned to either group.

#### **Abstract Reasoning**

$H_1$ : There is no significant relationship in the academic success rates between students with respect to abstract reasoning instrument scores.

The data related to this hypothesis include the individual student scores from Bennett and Seashore's Abstract Reasoning test (ART) applied to all blocks of subjects. Student profile questionnaire 1 (item 9), "How would you characterize your logical reasoning skills?" - (LOGIC), and questionnaire 2 (item 15), "I have well developed reasoning skills." - (REASON), also elicited information on student self-perception of reasoning

ability. The abstract reasoning instruments were scored by assigning one point for each of the fifty questions correctly answered, and no points for each of the fifty questions answered incorrectly. A total abstract reasoning test score was calculated for each subject.

A histogram of the resulting reasoning data for all subjects in the study was produced. The histogram was used to reveal the nature of the distribution of the data observed. As previously noted, the distribution of ART scores was expected to be relatively dense in the upper portion of the distribution because of the age and rather select character of the population. A mean ART score was derived and the standard deviation of the distribution of ART scores was calculated.

To examine the hypothesis that no relationship exists between abstract reasoning and academic success in introductory computer science classes, a crosstabulation between these two variables was performed. For this analysis ART scores were divided into five groups: group 1 - scores from 21 to 29, group 2 - scores from 30 to 35, group 3 - scores from 36 to 40, group 4 - scores from 41 to 45, and group 5 - scores from 46 to 50.

A Pearson's correlation coefficient was calculated for the raw ungrouped academic success Z score STD and the ungrouped ART scores. This measure was taken to assess the degree of relationship between the two variables without

reference to grouping. A T value was calculated and used to determine the significance of the correlations obtained.

The support variables LOGIC and REASON are not continuous and, therefore, an analysis of variance was performed with STD to examine if there was a difference between the individual groups comprising each variable. The significance of the F statistic derived was determined by looking up its value in an F table.

#### Math ACT (ACT-M)

H<sub>2</sub>: There is no significant relationship in the academic success rates between students with respect to ACT-M scores.

The data related to this hypothesis are the ACT-M scores obtained from the registrars' office for subjects in all blocks of the study. A histogram of the resulting ACT-M scores for all subjects in the study was produced. The histogram was used to reveal the nature of the distribution of the scores observed. The distribution of ACT-M scores was expected to be normally distributed and average for a general college population. The mean ACT-M score and standard deviation was calculated for all students in the study.

To examine the hypothesis that no relationship exists

between ACT-M scores and academic success in introductory computer science classes a crosstabulation between these two variables was performed. For this analysis, ACT-M scores were grouped into four groups: group 1 - scores below 18, group 2 - scores from 19 to 23, group 3 - scores from 24 to 27, and group 4 - scores over 27.

A Pearson's correlation coefficient was calculated for the raw ungrouped academic success Z scores and the ungrouped ACT-M scores. This measure was taken to assess the degree of relationship between the ACT-M scores and academic success Z scores without reference to grouping. A T value was calculated and used to determine the significance of the correlations obtained.

#### High School Grade Point Average (GPA)

H<sub>3</sub>: There is no significant relationship in the academic success rates between students with respect to high school grade point average.

The data related to this hypothesis are the GPAs obtained from the registrars' office for subjects in all blocks of the study. A histogram of the resulting GPAs for all subjects in the study was produced. The histogram was used to reveal the nature of the distribution of the averages observed. The distribution of GPAs was expected to be normally distributed and average for a general college

population.

To examine the hypothesis about the non-existence of a relationship between GPAs and academic success in introductory computer science classes, a crosstabulation between these two variables was performed. Academic success was stratified into two groups, those with standard Z scores greater than zero (midterm and final scores above their class mean) were considered as having achieved academic success, and those with Z scores less than zero were considered as not having achieved academic success. For this analysis, GPAs were grouped into four groups: group 1 - scores 1.75 - 2.49, group 2 - scores from 2.50 to 3.00, group 3 - scores from 3.01 to 3.49, and group 4 - scores 3.50 - 4.00.

A Pearson's correlation coefficient was calculated for the raw ungrouped academic success Z score (STD) and the ungrouped GPA scores. This measure was taken to assess the degree of relationship between the two variables without reference to grouping. A T value was calculated and used to determine the significance of the correlations obtained.

#### **Math Background**

H<sub>4</sub>: There is no significant relationship in the academic success rates between students with respect to math background.

The data related to this hypothesis were the number of previous math courses obtained from the student profile questionnaires 1 and 2 (item 6), - "Number of high school & college math courses taken?" - (MATH), for subjects in all blocks of the study. Additionally (item 16) on questionnaire 2, - "I have a strong math background." - (MATH2), elicited information on the students' self-perceptions of their math ability. A histogram of the distribution of responses to the questions for all subjects in the study was produced. The histogram was used to reveal the nature of the distribution of the observation. The mean number of math classes taken and the standard deviation was calculated for all students in the study.

The hypothesis that no relationship exists between math background and academic success in introductory computer science classes is examined using a crosstabulation between these two variables. A Pearson's correlation coefficient was calculated for the raw ungrouped academic success Z scores and the number of math classes taken, and for academic success Z scores and math self-assessment measures. These measures were taken to assess the degree of relationship between math background and academic success Z scores. An analysis of variance was calculated to determine if differences exist between groups on the variable MATH2 with STD.

### Previous Computer Use

H<sub>5</sub>: There is no significant relationship in the academic success rates between students with respect to previous computer use.

The data related to this hypothesis are derivative of the inquiry into microcomputer ownership from (item 7) on questionnaires 1 and 2, - "Do you (or your family) own a microcomputer?" - (MICRO). Additionally, the students self-perception of the strength of their background was obtained from the student profile questionnaire 1 (item 8), - "Previous computer experience?" - (EXPER), and questionnaire 2 (item 18), - "I have worked with computers before." - (EXPR). A histogram of the distribution of responses for all subjects in the study was produced. The histogram was used to reveal the nature of the distribution of the responses observed.

To examine the hypothesis that no relationship exists between previous computer experience and academic success in introductory computer science classes, a crosstabulation between these variables was performed. Pearson's correlation coefficients were calculated for the raw ungrouped academic success Z scores and previous computer experience measures. These measures were undertaken to assess the degree of relationship between previous computer background and academic success Z scores without reference

to grouping. A T value was calculated and used to determine the significance of the correlations obtained. An analysis of variance was performed on the variables EXPER and EXPR to determine if a difference existed between grouping with the variable STD.

### Age

H<sub>6</sub>: There is no significant relationship in the academic success rates between students with respect to age.

The data related to this hypothesis are the ages reported on the student profile questionnaires 1 and 2 (item 2), - "Age?" - (AGE), for subjects in all blocks of the study. A histogram of the ages for all subjects in the study was produced. The histogram was used to reveal the nature of the distribution of the scores observed. The mean age and standard deviation were calculated for all students in the study.

To examine the hypothesis that no relationship exists between age and academic success in introductory computer science classes, a crosstabulation between these two variables was performed. For this analysis ages were grouped into three groups: group 1 - ages below 19, group 2 - ages from 20 to 23, and group 3 - ages over 24.

A Pearson's correlation coefficient was calculated for the raw ungrouped academic success Z scores and the



ungrouped ages. This measure was taken to assess the degree of relationship between age and academic success Z scores without reference to grouping. A T value was calculated and used to determine the significance of the correlations obtained.

### Sex

H<sub>7</sub>: There is no significant relationship in the academic success rates between students with respect to sex.

The data related to this hypothesis are the responses to the gender question on the student profile questionnaires 1 and 2 (item 3), - "Sex?" -. (SEX) for all blocks of the study.

To examine the hypothesis that no relationship exists between sex and academic success in introductory computer science classes, a crosstabulation between SEX and SUCCESS was performed.

A Pearson's correlation coefficient was calculated for the raw ungrouped academic success Z scores and sex. This measure was taken to assess the degree of relationship between sex and academic success Z scores without reference to grouping. A T value was calculated and used to determine the significance of the correlations obtained.

### Perseverance Level

H<sub>3</sub>: There is no significant relationship in the academic success rates between students with respect to the student perseverance level.

The data related to this hypothesis are the perseverance scores obtained from the student profile questionnaire 2 (PERS) for subjects in blocks 7,8 and 9 of the study. A histogram of the resulting scores for all subjects in the study was produced. The histogram was used to reveal the nature of the distribution of the scores observed. The mean perseverance score and standard deviation was calculated for students in the study.

To examine the hypothesis that no relationship exists between perseverance and academic success in introductory computer science classes, a crosstabulation between these two variables was performed. For this analysis, perseverance scores were divided into three groups: group 1 - scores below 24, group 2 - scores from 24 to 27, and group 3 - scores over 27.

A Pearson's correlation coefficient was calculated for the raw ungrouped academic success Z scores and the ungrouped perseverance scores. This measure was taken to assess the degree of relationship between the perseverance scores and academic success Z scores without reference to grouping. A T value was calculated and used to determine the significance of the correlations obtained.

**Academic Major**

$H_9$ : There is no significant relationship in the academic success rates between students with respect to academic major.

The data related to this hypothesis include responses to the academic major inquiry (item 1), - "Major?" - (MAJOR) of student profile questionnaires 1 and 2 for subjects in all blocks of the study. A histogram of the resulting majors for subjects in the study was produced. The histogram was used to reveal the nature of the distribution of the majors observed.

To examine the hypothesis that no relationship exists between major and academic success in introductory computer science classes, a crosstabulation between these two variables was performed. For this analysis, majors were divided into four groups: group 1 - undecided, group 2 - science, group 3 - humanities, and group 4 - business. An analysis of variance was performed to see if there was any statistical difference between the four majors with respect to STD.

**Academic Class**

$H_{10}$ : There is no significant relationship in the academic success rates between students with respect to academic class.

The data related to this hypothesis are the responses regarding academic class obtained from the student profile questionnaires 1 and 2 (item 4), - "Class" - (CLASS) for subjects in all blocks of the study. A histogram of the resulting classes for all subjects in the study was produced. The histogram was used to reveal the nature of the distribution of the classes observed.

To examine the hypothesis that no relationship exists between class and academic success in introductory computer science classes, a crosstabulation between these two variables was performed. For this analysis, academic class was divided into four groups: group 1 - freshmen, group 2 - sophomores, group 3 - juniors, and group 4 - seniors. An analysis of variance was performed to see if there was any statistical difference between the four classes with respect to STD.

### **Expectation**

H<sub>11</sub>: There is no significant relationship in the academic success rates between students with respect to academic expectation.

The data related to this hypothesis are the responses regarding academic expectation obtained from the student profile questionnaires 1 (item 10), - "What grade do you expect to receive in this class?" - (EXPECT). A histogram

of the resulting expectations for all subjects in the study was produced. The histogram was used to reveal the nature of the distribution of the observation.

To examine the hypothesis that no relationship exists between expectation and academic success in introductory computer science classes, a crosstabulation between these two variables was performed. For this analysis, EXPECT consisted of three groups: group 1 - A, group 2 - B, and group 3 - C. An analysis of variance was performed to see if there was any statistical difference between the expectations with respect to STD.

**CHAPTER IV**  
**THE RESULTS**

### Overview of the Data

Study findings pertaining to the dependent variable academic success, as measured by the final standardized Z scores, are presented first. Then, findings related to each independent variable are provided by individual hypothesis. Summary tables of cross correlations (Table 42) and findings (Table 41) are included in the discussion section. Scatterplots (Figures 1 - 16) of all variables plotted against STD are included in Appendix D.

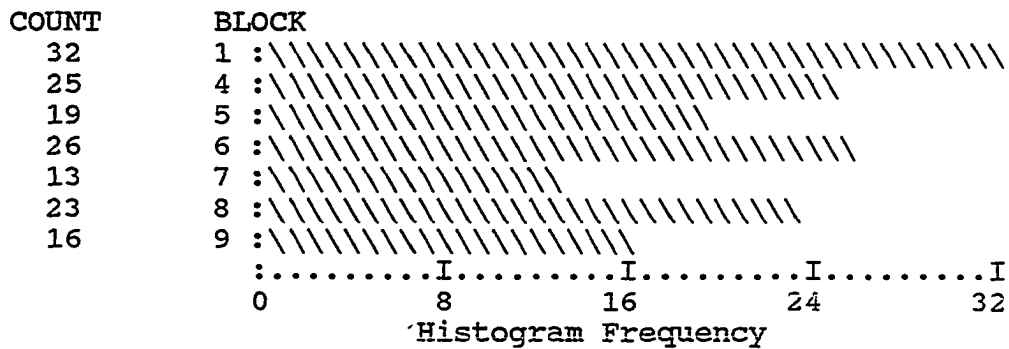
The distribution of the population by block is shown in Table 1. The table reveals that class sizes were largest in the early blocks of the year, and steadily decreased in size as the year progressed. CSC 131 is a popular class, and many students try to enroll early in the year. Registration for later blocks is generally high. Mid-year schedule adjustments, however, decrease late block enrollments substantially.

The high drop-out rate reported by Denning (1980) was not in evidence here. The actual percentage of students dropping the class was less than ten percent. This low attrition rate may be related, in part, to the academic regulations applicable to dropping a class under the block plan. Students are allowed to drop on the final Friday of each block only. At that point in the session, only two class sessions and a final examination remain. There is

little incentive to drop-out, unless the individual wishes to avoid receiving a low grade. Given this consideration as the primary motivation for a student dropping the class, the practice of assigning a final examination score of zero to all study subjects dropping appears reasonable.

Table 1  
Distribution of students by block

Block	Frequency	Percent	Valid Percent	Cum Percent
1	32	20.8	20.8	20.8
4	25	16.2	16.2	37.0
5	19	12.3	12.3	49.4
6	26	16.9	16.9	66.2
7	13	8.4	8.4	74.7
8	23	14.9	14.9	89.6
9	16	10.4	10.4	100.0
TOTAL	154	100.0	100.0	



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Valid Cases	154	Missing Cases	0
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Academic Success

Table 2 shows the distribution of the standardized academic success Z scores for all students in the study.

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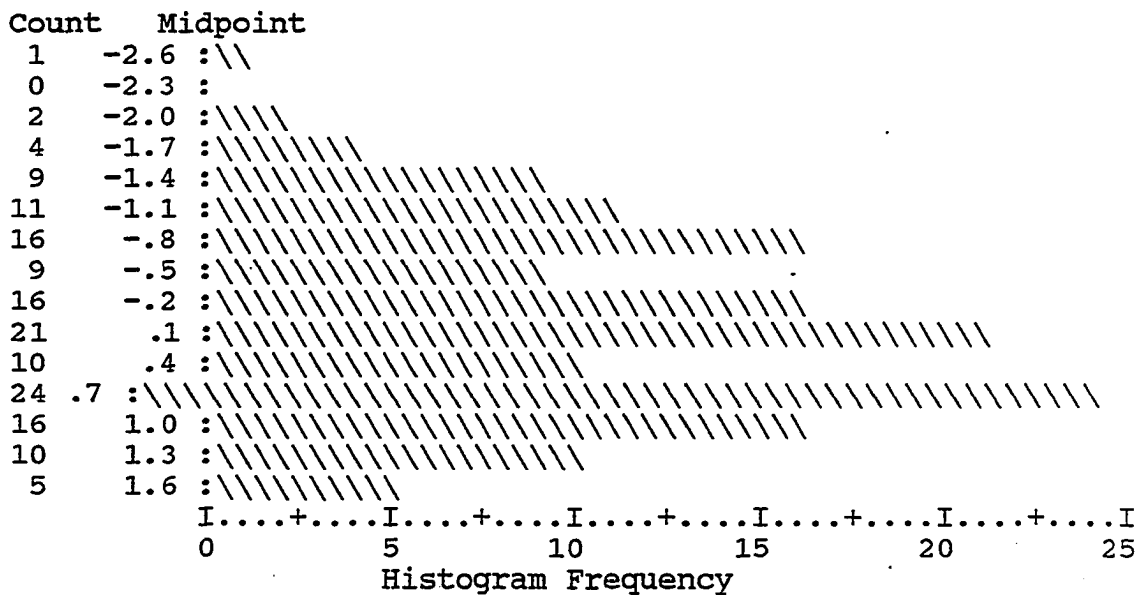
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Table 2  
Distribution of academic success Z scores (STD).

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Mean = .003	Std Dev = .919	Minimum = -2.685
	Maximum = 1.570	

Valid Cases	154	Missing Cases	0
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The table shows that the process of standardizing midterm and final examination scores was completed satisfactorily. The mean of the total distribution is .003, which closely approximates the expected mean of zero. The standard deviation of the Z scores is .919 which, similarly, is

close to the expected value of one.

The bulk of the scores fall within plus or minus 1.5 standard deviations of the mean. A few scores fall more than 1.5 standard deviations below the mean. These scores may be the result of the procedure for handling students who drop the class. As noted in the discussion of methodology, any student dropping the class on the third Friday of the block was given a final examination score of zero. The procedure will tend to lower these students' Z scores; a circumstance which would have been less pronounced had they taken the examination and received some points.

#### Abstract Reasoning

H<sub>1</sub>: There is no significant relationship in the academic success rates between students with respect to abstract reasoning instrument scores.

Table 3 shows the distribution of student ART scores. The scores are normally distributed, beyond the scores of those few students who scored below 37 on the test. Ninety percent of the scores fall between 39 and 50. The observed mean of 42.7 is substantially higher than the mean of 34.3 reported by Bennett and Seashore for high school seniors. The higher scores are probably attributable to the select nature of this college population, and not solely related



Students who scored in the 36 to 45 range had a 40 of 87, or 46 percent success rate. At the same time, students in the 46 to 50 range had a greater than 78 percent chance (40 of 51) of achieving academic success. The trend for students with high ART scores to out-perform students with low ART scores is clear. The Pearson's correlation coefficient for ART with STD is .27, significant at the 0.001 level. This strong correlation suggests that a relationship does exist between abstract reasoning test scores and academic success; therefore, hypothesis  $H_1$  is rejected.

Table 4: Crosstabulation ART  
By SUCCESS

SUCCESS->	Count	no	success	Row Total
ART	21 - 29	4	0	4
	30 - 35	5	2	7
	36 - 40	16	14	30
	41 - 45	31	26	57
	46 - 50	11	40	51
	Column Total	67	82	149
	Total	45.0	55.0	100.0

Correlations: STD with ART

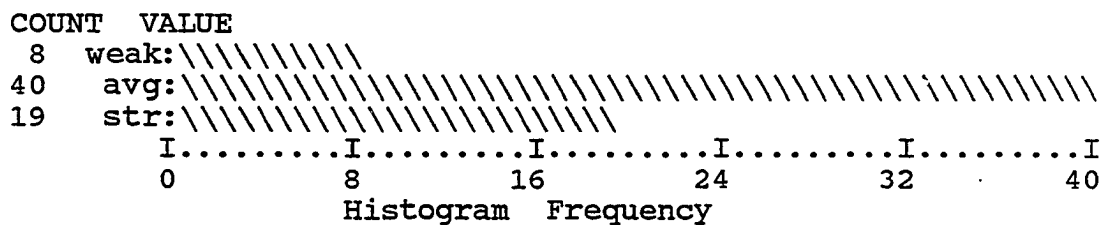
r = .2696\*\*      N of cases: 149  
T = 3.38      Significance: \*\* - .001

### Logical Reasoning

The distribution of responses to the logical reasoning question is shown in Table 5. The table reveals that over one-half of the students characterized themselves as average in logical reasoning skills. Twice as many students perceived themselves as strong in this area as felt that they were weak.

**Table 5**  
Distribution of responses to the question:  
How would you characterize your logical reasoning skills?

Value Label	Frequency	Percent	Valid Percent	Cum Percent
weak	8	11.4	11.9	11.9
average	40	57.1	59.7	71.6
strong	19	27.1	28.4	100.0
.	3	4.3	MISSING	
TOTAL	70	100.0	100.0	



The crosstabulation in Table 6 shows a finding similar to the ART crosstabulation. Only 25 percent of the students who characterized themselves as weak in reasoning skills achieved academic success. However, 55 percent of those who

characterized themselves as average were successful, and 79 percent of those who felt that their reasoning skills were strong experienced academic success. If the data are treated as a continuum, there is a correlation coefficient of .32 for LOGIC with STD, significant at the .01 level.

Table 6: Crosstabulation		LOGIC		
		By SUCCESS		
LOGIC	SUCCESS	no success	success	Row Total
weak		6	2	8
average		18	22	40
strong		4	15	19
	Column Total	28	39	67
		41.8	58.2	100.0

Correlations: STD with LOGIC		
r = .3220*	N of cases:	67
T = 2.742	Significance:	* - .01

An examination of LOGIC as a collection of discrete groups by a one-way analysis of variance is shown in Table 7. The table shows that the F ratio between the three groups is 3.7. This ratio is significant at the .05 level, and implies that there is a difference between the three groups with respect to STD. This finding lends support to

the assertion that logical reasoning skills are an important factor in a student's academic success, and provides an additional basis for the rejection of  $H_1$ .

Table 7: Analysis of variance		STD By LOGIC			
Source	D.F.	Sum of Squares	Mean Squares	F Ratio	F Prob.
Between Groups	2	5.9688	2.9844	3.7048	.0300
Within Groups	64	51.5545	.8055		
Total	66	57.5233			

### Reasoning Skills

Table 8 shows the distribution of student responses when asked about their reasoning skills. The results are similar to those observed for LOGIC. There were 74 percent of the respondents who agreed with the statement, while 13 percent of the respondents either disagreed or strongly agreed. Again, most respondents tended to place themselves in the middle range. It is noted that no student chose to strongly disagree with the statement.

The crosstabulation of the data presented in Table 9 shows that 33 percent of those students who disagreed with the statement were successful. This percentage is in sharp





is .16; considerably lower than the correlation observed for LOGIC. The difference may be the result of strictures in the response, in that no clear middle range response was allowed. How should a student who characterizes her/himself as average respond? Is well-developed average?

Table 9:		Crosstabulation		REASON
				By SUCCESS
SUCCESS	:	no	:	Row
	:	success:	success:	Total
REASON	-----:	-----:	-----:	
disagree	:	4	:	2
	:		:	6
agree	:	14	:	21
	:		:	35
strongly agree	:	2	:	4
	:		:	6
Column		20		27
Total		42.6		57.4
				100.0
-----				
Correlations: STD with REASON				
-----				
r = .1565		N of cases:		47
T = 1.062		Significance		< .05

The analysis of variance in Table 10 shows that even when the groups are treated as discrete, there is no statistically significant difference between the three groups. The trend of the data is supportive of the findings of ART and LOGIC, but the cell sizes are too small to establish significant support.

Table 10: Analysis of variance		STD By REASON			
Source	D.F.	Sum of Squares	Mean Squares	F Ratio	F Prob.
Between Groups	2	1.3293	.6646	.7690	.4696
Within Groups	44	38.0280	.8643		
Total	46	39.3573			

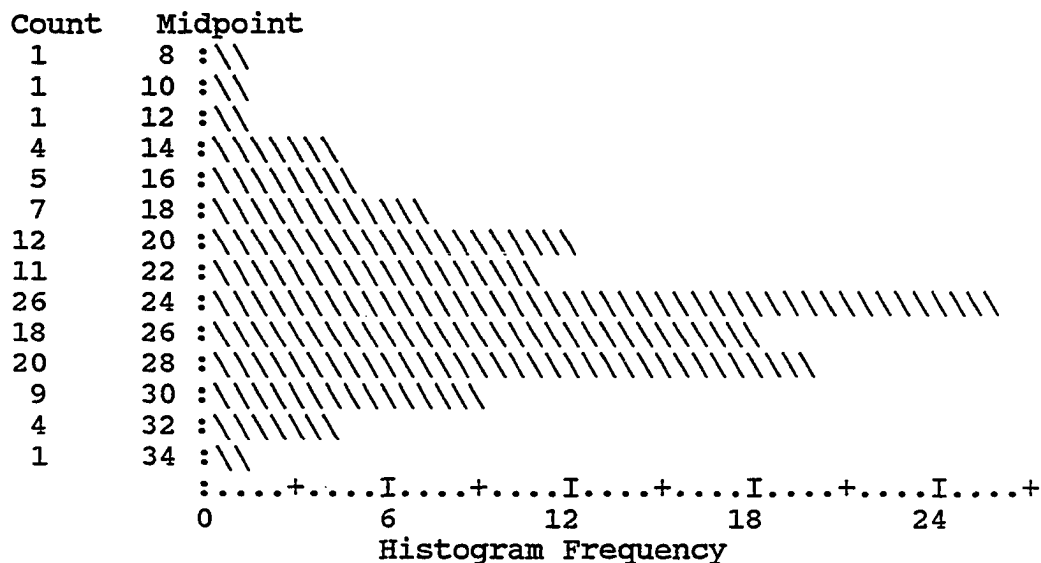
### Math ACT

H<sub>2</sub>: There is no significant relationship in the academic success rates between students with respect to ACT-M scores.

The ACT-M scores for the subjects in this study ranged from a low of 7 to a high of 36. The ACT-M scores were divided into 5 groups for analysis. Table 11 shows the distribution of subjects by ACT-M score across all blocks. The students' ACT-M scores are normally distributed. The mean ACT-M score for all students in the study was 23.3.

The crosstabulation in Table 12 reveals a progression in the percentage of academic success as the ACT-M scores increase. Only 11 percent of students with ACT-M scores below 19 achieved academic success. This percentage rises to 49 for those with scores of 19 to 23. The percentage increases again to 63, for those in the 24 to 27

Table 11  
Distribution of ACT math scores.



Mean = 23.275	Std Dev = 4.955	Minimum = 7.000
	Maximum = 34.000	
Valid Cases	120	Missing Cases     18

range. At the top of the scale, 94 percent of those students who scored above 27 went on to achieve academic success.

The Pearson's correlation coefficient between STD and ACT is .47, significant at the .001 level. This strong correlation points to a definite relationship between ACT-M scores and academic success; therefore,  $H_2$  is rejected.

Table 12: Crosstabulation: MATH ACT  
By SUCCESS

SUCCESS	no	success	Row Total
ACT score 7 - 18	17	2	19
19 - 23	18	17	35
24 - 27	18	31	49
28 - 34	1	16	17
Column Total	54	66	120
	45.0	55.0	100.0

Correlations: STD with ACT

r = .4682**	N of cases:	120
t = 5.76	Significance:	** - .001

High School Grade Point Average

H<sub>3</sub>: There is no significant relationship in the academic success rates between students with respect to high school grade point average.

Grade point averages ranged from a high of 4.0 to a low of 1.76, on a 4.0 scale, and averaged 3.27. This is slightly higher than the average GPA of the entire student body at the institution, as reported by the admissions office. Table 13 provides a summary of the distribution of GPAs. It is interesting to note that 77 percent of the subjects in the study had a high school grade point average



Table 14: Crosstabulation GPA  
By SUCCESS

GPA	SUCCESS	no	success	Row Total
	1.75 - 2.49	3	3	6
2.50 - 3.00	30	12	42	
3.01 - 3.49	19	21	40	
3.50 - 4.00	9	42	51	
Column	61	78	139	
Total	43.9	56.1	100.0	

Correlations: STD with GPA

r = .4063\*\*      N of cases: 139  
t = 5.70      Significance: \*\* - .001

success are only 31 percent, if the GPA is 3.0 or less. In contrast, students with a GPA greater than 3.0 have a 68 percent chance of success; a ratio of more than two to one. When only those students with GPAs from 3.5 to 4.0 are considered, the percentage of success rises to 82 percent.

The correlation between STD and GPA is .41, and is significant at the .001 level. Students with histories of academic success appear to possess attributes (intelligence and good study habits, among others) which enable them to perform well in an academic setting. The data point to a strong relationship between academic

success and GPA; therefore,  $H_3$  is rejected.

### Math Background

$H_4$ : There is no significant relationship in the academic success rates between students with respect to math background.

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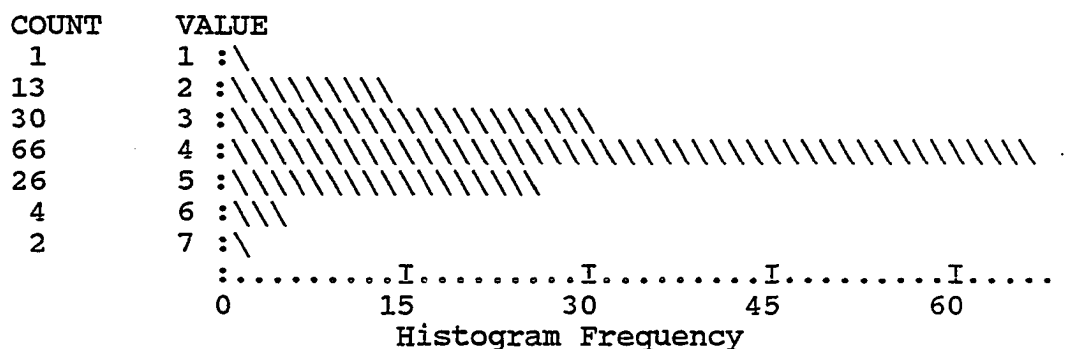
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Table 15  
Distribution of the number of high school and college math classes.

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#Classes	Frequency	Percent	Valid Percent	Cum Percent
1	1	.6	.7	.7
2	13	8.4	9.2	9.9
3	30	19.5	21.1	31.0
4	66	42.9	46.5	77.5
5	26	16.9	18.3	95.8
6	4	2.6	2.8	98.6
7	2	1.3	1.4	100.0
.	12	7.8	MISSING	
<b>Total</b>	<b>154</b>	<b>100.0</b>	<b>100.0</b>	



Mean = 3.866      Std Dev = 1.026      Minimum = 1.000  
Maximum = 7.000

Valid Cases      142      Missing Cases      12

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Table 15 shows the distribution of the number of mathematics classes that each subject had taken prior to entering the study. Almost half of the students completed four math classes. Sixty-nine percent had completed four or more math classes. The mean for all students in the study was 3.8 math classes.

Table 16: Crosstabulation MATH  
By SUCCESS

SUCCESS	no	success	Row Total
MATH 1	1	0	1
MATH 2	8	5	13
MATH 3	19	11	30
MATH 4	27	39	66
MATH 5	6	20	26
MATH 6	2	2	4
MATH 7	0	2	2
Column Total	63	79	142
	44.4	55.6	100.0

Correlations: STD with MATH

r = .2974\*\*      N of cases: 142  
T = 3.686      Significance: \*\* - .001

The crosstabulation presented in Table 16 reveals that



students with three or fewer math classes had a 36 percent success rate. Students with four math classes had a 59 percent success rate. It is interesting to note that students with four classes, slightly above the average, had a success rate of 59 percent, slightly higher than the 56 percent overall rate. Students with five or more classes had a 75 percent success rate; more than double the rate of those with three or fewer classes.

The steady increase in success rate as the number of math classes increases suggests a relationship between math background and success. The Pearson's correlation coefficient between MATH and STD is 0.30, and is significant at the .001 level; therefore,  $H_4$  is rejected.

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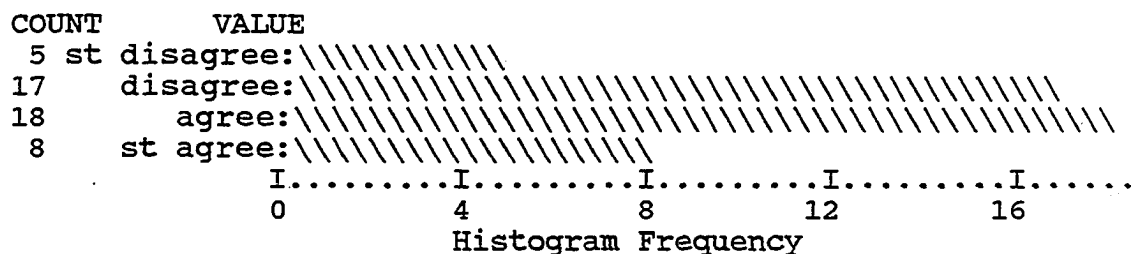
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Table 17  
Distribution of math self-perception values.

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Valid Cases	48	Missing Cases	4
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### Math Self-perception

Table 17 gives the distribution of students' responses

when questioned about their perception of their math background. The respondents were almost equally divided in their answers, with 22 seeing themselves as low and 26 seeing themselves as high in terms of math background.

Table 18: Crosstabulation MATH2  
By SUCCESS

SUCCESS->	Count	no	success	Row Total
MATH2				
st disagree	4	1	5	
disagree	12	5	17	
agree	4	14	18	
st agree	1	7	8	
Column Total	21	27	48	
	43.8	56.3	100.0	

Correlations: STD with MATH2

r = .4681\*\*                      N of cases: 48  
T = 3.593                        Significance: \*\* - .001

Table 18 shows that only 27 percent of respondents who characterized themselves as not having a good math background were successful, while 81 percent of those characterizing themselves as having a good background attained success; a ratio of three to one. The Pearson's

correlation coefficient of .47, significant at the .001 level, supports the finding of a relationship between math self-perception and academic success.

The analysis of variance in Table 19 lends further support to the contention that a relationship exists between math background and academic success. The F ratio of 5.7 is significant at the .01 level, and suggests that there is a statistical difference between the three groups.

Table 19: Analysis of variance		STD By MATH2			
Source	D.F.	Sum of Squares	Mean Squares	F Ratio	F Prob.
Between Groups	3	11.1654	3.7218	5.7133	.0022
Within Groups	44	28.6627	.6514		
Total	47	39.8281			

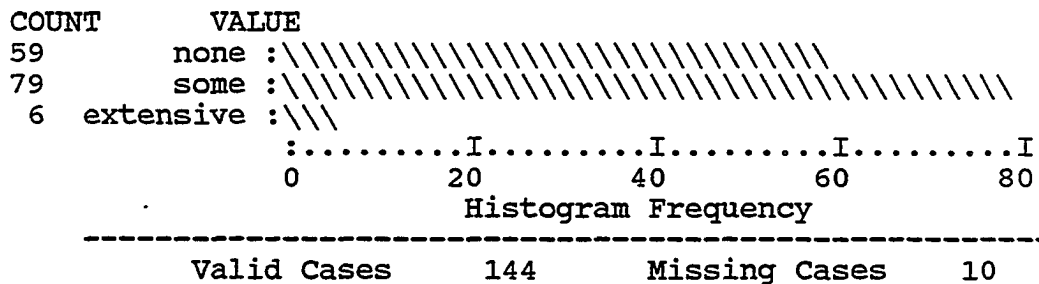
#### Previous Computer Experience

H<sub>5</sub>: There is no significant relationship in the academic success rates between students with respect to previous computer use.

Table 20 shows that over half of the students in this study had had some previous computer experience. Since CSC-131 is the entry level class, it is apparent that a

Table 20  
Distribution of responses to the question:  
Previous computer experience?

Value	Frequency	Percent	Valid Percent	Cum Percent
none	59	38.3	41.0	41.0
some	79	51.3	54.9	95.8
extensive	6	3.9	4.2	100.0
.	10	6.5	MISSING	
<b>TOTAL</b>	<b>154</b>	<b>100.0</b>	<b>100.0</b>	



significant number of the students are entering the institution after some computer experience.

Table 21 provides the crosstabulation of academic success for each of the three groups. The table shows a pattern of rising success rates as experience levels increase. Students with no previous experience are at a disadvantage in terms of competing academically with those who have had previous exposure. Only 39 percent of students with no previous experience achieved success, while students with some exposure had a 67 percent success rate. The success rate increases substantially to 83 percent, for

those who have had extensive experience. The Pearson's correlation coefficient of EXPER with STD, when EXPER is treated as a continuum, is .31; it is significant at the 0.001 level.

Table 21: Crosstabulation		EXPER				
		By SUCCESS				
SUCCESS-	:	no	:	Row		
EXPER	-----	success:	success:	Total		
none	:	36	:	23	:	59
some	:	26	:	53	:	79
extensive	:	1	:	5	:	6
Column		63		81		144
Total		43.8		56.3		100.0

Correlations: STD with EXPER		
r = .3062**	N of cases:	144
T = 3.833	Significance:	** - .001

Treating the three groups as discrete, the analysis of variance in Table 22 gives an F ratio of 8.05, significant at the .01 level. Given the Pearson's correlation and the F ratio, a relationship does exist between previous computer experience and academic success.

Table 23 was derived from responses gathered from questionnaire 2. The data show that 18 percent of the respondents disagreed or strongly disagreed that they had

Source	D.F.	Sum of Squares	STD		
			Mean Squares	F Ratio	F Prob.
Between Groups	2	12.7610	6.3805	8.0543	.0005
Within Groups	141	111.6975	.7922		
Total	143	124.4585			

EXPR	SUCCESS		Row Total
	no success	success	
str disagree	3	0	3
disagree	4	2	6
agree	9	10	19
str agree	5	15	20
Column Total	21	27	48
	43.8	56.3	100.0

Correlations: STD with EXPR

r = .4312\*      N of cases: 48  
T = 3.241      Significance: \* - .01

previous computer experience, while 81 percent agreed or strongly agreed. These findings do not differ significantly from those observed on questionnaire 1. The

table shows that 22 percent of respondents who disagreed or strongly disagreed with the statement achieved success, while those who agreed or strongly agreed had a success rate of 64 percent.

The Pearson's correlation coefficient for EXPR with STD is .43, significant at the .01 level. This result strongly supports the findings in EXPER. A relationship between previous computer experience and academic success has been established, and  $H_5$  is rejected.

Table 24: Analysis of variance			STD By EXPR		
Source	D.F.	Sum of Squares	Mean Squares	F Ratio	F Prob.
Between Groups	3	7.4993	2.4998	3.4022	.0258
Within Groups	44	32.3289	.7347		
Total	47	39.8281			

The analysis of variance in Table 24 also tends to support rejection. The table shows an F ratio of 3.4 which indicates a difference between groups significant at the 0.025 level.

#### Microcomputer Ownership

Table 25 shows the distribution of microcomputer ownership and the success rates for owners and non-owners.

Table 25: Crosstabulation:		MICRO		
		By SUCCESS		
SUCCESS	:	no	:	Row
	:	success:	success:	Total
MICRO	-----	-----	-----	
not own	:	51	:	57
	:		:	108
own	:	12	:	23
	:		:	35
Column		63		80
Total		44.1		55.9
				143
				100.0

-----  
Correlations: STD with MICRO  
-----

r = .0930      N of cases:      143  
T = 1.109      Significance: < .05

Table 26: Analysis of variance		STD			
		By MICRO			
Source	D.F.	Sum of Squares	Mean Squares	F Ratio	F Prob.
Between Groups	1	1.0746	1.0746	1.2292	.2694
Within Groups	141	123.2624	.8742		
Total	142	124.3370			

A significant number of students, 24 percent, responded affirmatively to the question of microcomputer ownership.

The table reveals that non-owners have a 52 percent success rate; about the overall average. Students who did



report ownership, however, have a 66 percent success rate. The finding tends to suggest some relationship. The analysis of variance in Table 26, nonetheless, fails to show that this trend is statistically significant. The evidence tends to be supportive of the previous rejection of  $H_5$ , but it is inconclusive.

Table 27  
Distribution of student AGE.

Age	Frequency	Percent	Valid Percent	Cum Percent
17	4	2.6	2.8	2.8
18	47	30.5	32.4	35.2
19	51	33.1	35.2	70.3
20	21	13.6	14.5	84.8
21	9	5.8	6.2	91.0
22	5	3.2	3.4	94.5
23	1	.6	.7	95.2
24	2	1.3	1.4	96.6
25	2	1.3	1.4	97.9
26	1	.6	.7	98.6
34	1	.6	.7	99.3
38	1	.6	.7	100.0
.	9	5.8	MISSING	
TOTAL	154	100.0	100.0	
-----				
Mean = 19.338	Std Dev = 2.940		Minimum = 1.000	
	Maximum = 38.000			
Valid Cases	145	Missing Cases	9	

### Age

$H_6$ : There is no significant relationship in the academic success rates between students with respect to age.

Table 27 reveals that most of the students in this study were in the traditional 17 to 24 age group. There were actually too few older students to adequately test the hypothesis.

Table 28:		Crosstabulation		AGE
				By SUCCESS
SUCCESS	:	no	:	Row
	:	success:	1.00:	Total
AGE	-----:	-----:	-----:	
17 - 19	:	41	:	61
	:		:	102
20 - 23	:	17	:	19
	:		:	36
24 - 38	:	6	:	1
	:		:	7
Column		64		81
Total		44.1		55.9
				145
				100.0

Correlations: STD with AGE		
r =	-.1428	N of cases: 145
T =	-1.725	Significance: < .05

Table 28 shows a negative relationship between age and success. In this study, younger students were more successful than their older counterparts. The Pearson's correlation coefficient is  $-.14$ . The negative correlation may be related to a tendency for well-qualified students to enroll in the class in their freshmen or sophomore years, while students who are less qualified may defer taking the

class until their junior or senior years. The low success rate for those over 24, 14 percent, may also be related to the increased likelihood that older students were not introduced to computers in high school. Indeed, both experience measures showed a negative correlation with age.

Although some relationship between age and success is indicated, it is not strong enough to be statistically significant; therefore,  $H_6$  is accepted.

### Sex

$H_7$ : There is no significant relationship in the academic success rates between students with respect to sex.

Table 29: Crosstabulation		SEX	
		By SUCCESS	
SEX	SUCCESS	no success	Row success: Total
	male	37	40 : 77
	female	31	42 : 73
	Column	68	82 150
	Total	45.3	54.7 100.0
-----			
Correlations: STD with SEX			
-----			
	r = .1302	N of cases:	150
	T = 1.598	Significance:	< .05

Table 29 shows the distribution of success by sex. The male to female ratio in the class was about even. The success rates for males was 51 percent, and the success rate for females was slightly higher at 57 percent. There seems to be minimal difference in the success rate between males and females as shown by the Pearson's correlation coefficient of .13, and the analysis of variance (Table 30) F ratio of 2.6; neither is significant. Therefore, the existence of a significant relationship between sex and academic success has not been established. Hypothesis H<sub>7</sub> is accepted.

Table 30: Analysis of variance		STD by SEX			
Source	D.F.	Sum of Squares	Mean Squares	F Ratio	F Prob.
Between Groups	1	2.1714	2.1714	2.5521	.1123
Within Groups	148	125.9182	.8508		
Total	149	128.0896			

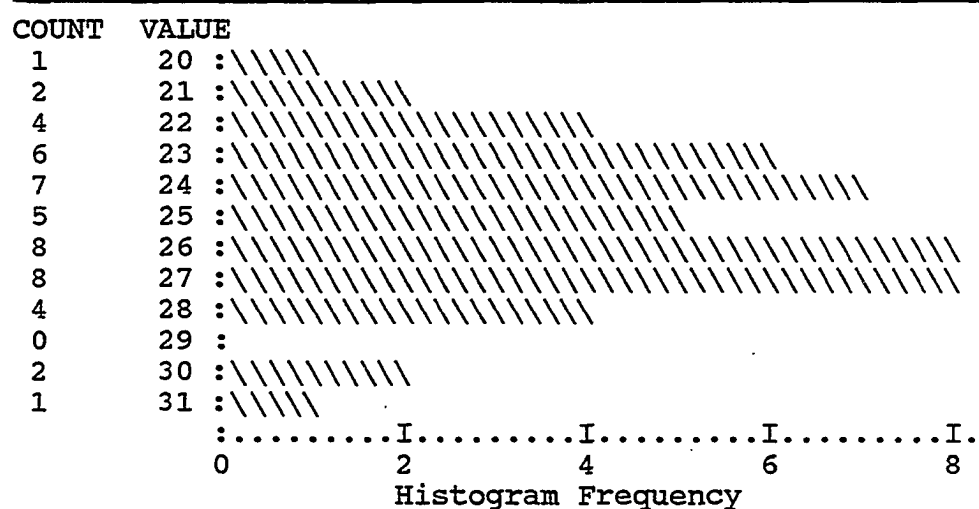
#### Perseverance

H<sub>8</sub>: There is no significant relationship in the academic success rates between students with respect to the student perseverance level.

Table 31 shows the distribution of perseverance scores

for all students in the study. The scores are normally distributed, and range from a high of 31 to a low of 20. The mean is 25.

Table 31  
Distribution of perseverance scores.



-----  
Mean = 25.167            Std Dev = 2.461            Minimum = 20.000  
Maximum = 31.000

Valid Cases            48            Missing Cases            4

Table 32 reveals no significant difference in the success rates with respect to perseverance scores. The Pearson's correlation coefficient was .25; however, this was not significant. There is no statistically significant relationship between perseverance scores and academic success; therefore, hypothesis  $H_8$  is accepted.

Table 32: Crosstabulation		PERS		
		By SUCCESS		
SUCCESS	no	success	Row Total	
PERS	20 - 23	7	6	13
	24 - 27	11	17	28
	27 - 31	3	4	7
	Column Total	21	27	48
		43.8	56.3	100.0

---

Correlations: STD with PERS

---

r = .2547	N of cases:	48
T = 1.670	Significance:	< .05

---

#### Academic Major

H<sub>0</sub>: There is no significant relationship in the academic success rates between students with respect to academic major.

Table 33 shows the distribution by academic major. Two-thirds of the students in this study were evenly distributed in terms of majors between the sciences and the humanities. The remainder were in the business or undecided categories. The substantial number of undecided students is explained by the heavy freshmen enrollment in the class.

Of all the groups, the lowest success rate was experienced by students from the humanities -- 43 percent.

Table 33: Crosstabulation  
By MAJOR SUCCESS

MAJOR	SUCCESS	no	success	Row Total
	undecided	5	17	22
sciences	21	32	53	
humanities	30	23	53	
business	4	8	12	
Column	60	80	140	
Total	42.9	57.1	100.0	

The undecided group had the highest success rate -- 77 percent. Sciences and business majors had success rates of 60 and 67 percent, respectively. The high scores observed among those undecided students may be a side-effect of the fact that they were, for the most part, freshmen. Freshmen scored highest as a class. The analysis of variance in Table 34 shows an F ratio of 3.8, significant at the .02 level. There is a tendency for the groups to differ with respect to academic success, but the trend is not clear; especially if the students without majors are removed. Therefore, hypothesis  $H_0$  is accepted.

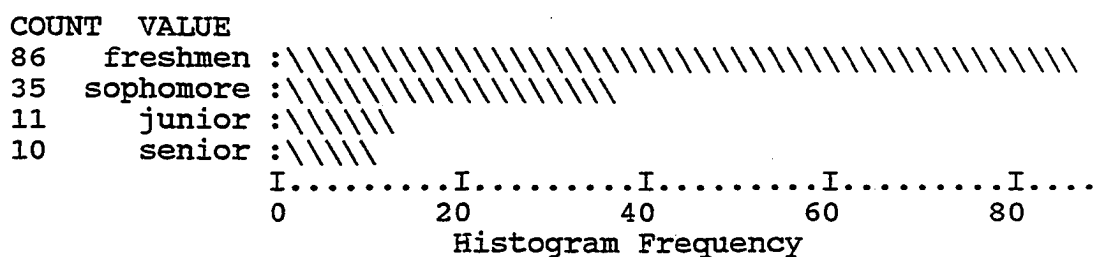
Table 34: Analysis of variance  
STD By MAJOR

Source	D.F.	Sum of Squares	Mean Squares	F Ratio	F Prob.
Between Groups	3	9.3436	3.1145	3.8388	.0112
Within Groups	136	110.3394	.8113		
Total	139	119.6830			

Academic Class

$H_{10}$ : There is no significant relationship in the academic success rates between students with respect to academic class.

Table 35  
Distribution of students by academic class.



-----  
Mean = 1.613            Std Dev = .906            Minimum = 1.000  
Maximum = 4.000

Valid Cases            142            Missing Cases            12

Table 35 reveals that freshmen enrollment exceeded that



of all other classes combined. The trend to take CSC-131 early in the college curriculum becomes apparent when one considers the steady enrollment decline for upper-classmen.

Table 36 provides the distribution of success by the four academic classes. Freshmen, as a class, had a 60 percent success rate. Sophomores' success rate declined to 48 percent. Upper classmen fared less well. Juniors and Seniors combined showed only a 38 percent success rate. This progression of diminishing success rates in the upper classes is supported by the Pearson's correlation coefficient of  $-.17$ .

Table 36: Crosstabulation		CLASS By SUCCESS		
SUCCESS	no	success	Row Total	
CLASS	freshmen	34	52	86
	sophomore	18	17	35
	junior	8	3	11
	senior	5	5	10
	Column Total	65	77	142
		45.8	54.2	100.0

Correlations: STD with CLASS		
r = $-.1711$	N of cases:	142
T = 2.055	Significance:	.05

Table 37: Analysis of variance		STD By CLASS			
Source	D.F.	Sum of Squares	Mean Squares	F Ratio	F Prob.
Between Groups	3	8.2049	2.7350	3.2593	.0235
Within Groups	138	115.8009	.8391		
Total	141	124.0058			

The analysis of variance in Table 37 shows an F ratio of 3.26, significant at the .03 level. The four groups tend to show a difference in success rates, supporting the existence of a relationship between class and academic success. However, the significance is not at the .01 level; therefore, hypothesis  $H_{10}$  is accepted.

### Expectation

$H_{11}$ : There is no significant relationship in the academic success rates between students with respect to academic expectation.

Table 38 shows the distribution of responses to the expectation question. Students generally showed high expectations. Over 50 percent of the students started the class with expectations of receiving an A. Some 34 percent reported expectations of a B, and 14 percent expected a C.

Table 38  
Distribution of responses to the question:  
What grade do you expect to receive in this class?

COUNT	VALUE
34	A : \\\\\\\
23	B : \\\\\\\
10	C : \\\\\\\
	I.....I.....I.....I.....I...
	0            8            16            24            32
	Histogram Frequency

-----

Mean = 1.642	Std Dev = .732	Minimum = 1.000
	Maximum = 3.000	

Valid Cases	67	Missing Cases	2
-------------	----	---------------	---

-----

Table 39: Crosstabulation                      EXPECT  
By SUCCESS

SUCCESS	no	success	success	Row Total
EXPECT				
A	4	30	34	34
B	16	7	23	23
C	8	2	10	10
Column Total	28	39	67	67
Total	41.8	58.2	100.0	100.0

-----  
Correlation EXPECT with STD  
-----

r = .3716*	N of cases:	64
T = 3.152	Significance:	* - .01

-----

No students reported expectations of a grade lower than C.

Table 39 shows the distribution of academic success among the three groups. There is a definite relationship exhibited by the data. The group expecting an A showed an 88 percent success rate, while the groups expecting a B or a C had dramatically lower success rates of 30 and 20 percent, respectively. The existence of a relationship is supported by the Pearson's correlation coefficient of .37, significant at the .01 level. Further evidence of a strong relationship is provided by the analysis of variance in Table 40, which shows an F ratio of 20.4, significant at the .001 level. The data point to the existence of a strong relationship between student expectation and academic success; therefore,  $H_{11}$  is rejected.

Table 40: Analysis of variance		STD By EXPECT			
Source	D.F.	Sum of Squares	Mean Squares	F Ratio	F Prob.
Between Groups	2	22.4230	11.2115	20.4425	.0000
Within Groups	64	35.1003	.5484		
Total	66	57.5233			

**CONCLUSION**

### Discussion

Table 41 provides a summary of the findings of this research. Of the eleven hypotheses studied, abstract reasoning, ACT-M scores, high school grade point average, academic expectation, previous computer experience, and math background have been shown to have statistically significant relationships with academic success in introductory computer science classes. The remaining five hypotheses -- sex, age, perseverance, class and major -- showed no statistically significant relationship. Academic class and major tended to show relationships, but were not significant at the .01 level.

The findings that math background and ACT-M scores had a significant relationship to academic success in introductory programming support the prior research by Konvalina, Wileman, and konvalina (1983), Wileman (1981), and Alspaugh (1972, 1971). The correlations observed also tend to affirm earlier studies by Bauer, Mehreus, and Vinsonhaler (1968), Perry (1965, 1964), and related inquiry focused on math abilities as a key component in selecting programmer trainees. The accumulation of past research, coupled with the present study, suggests that strong math abilities may be a necessary, but not entirely sufficient, condition for high-level performance in introductory computer science classes.

Table 41  
Findings by variable.

Variable	F/r	significance	accept/reject
Abstract reasoning	: r = .27 :	.001	: reject :
Act math	: r = .47 :	.001	: reject :
Grade point average	: r = .41 :	.001	: reject :
Math background	: r = .30 :	.001	: reject :
Computer background	: r = .31 :	.001	: reject :
Sex	: F = 2.26 :		: accept :
Age	: r = -.14 :		: accept :
Perseverance	: r = .25 :		: accept :
Class	: F = 3.26 :		: accept :
Major	: F = 3.80 :		: accept :
Expectation	: r = .62 :	.001	: reject :

The correlations observed in this study between high school grade point average and academic success are consistent with the findings of Peterson and Howe (1979). Although the Peterson and Howe study used college grade point average alone, the general tendency for students with high academic credentials to perform well in introductory programming classes is supported, similarly, by this study. The findings confirm the study by Konvalina, Stephens, and Wileman (1983) which concluded that high school grade point average is a good predictor of both computer science aptitude and achievement.

The study shows that previous computer experience seems to give students an advantage in introductory programming classes. The findings here, however, should not be

generalized to imply that students possessing such experience will continue to be highly successful in later computer science courses. The programming language used in this study, BASIC, is generally the first computer language encountered by students with high school experience. CSC-131 may function as a review or extension of existing skills among students reporting previous computer experience. Therefore, the academic success of students with previous experience may not be reflective of their abilities to comprehend new materials.

Expectation seems to be an important factor in the realization of academic success. The results of this study show that most students' expectations were realized. It is uncertain whether this is a result of an accurate self-appraisal of abilities, or of a self-fulfilling prophecy. Students with expectations lower than their actual capabilities would warrant may exhibit, subsequently, sufficing behaviors that lead to the realization of the lower grade. The expectation of a high grade, on the other hand, may motivate some students to expend extra effort in their studies which, in turn, increases their chances for academic success. Initial expectation, then, may set a self-imposed threshold that governs sufficing behaviors in some students.

Bennett and Seashore reported that ART scores increased with age for 8th through 12th graders. This study showed a



Table 42  
Cross correlations of all variables in the study.

	ACT	AGE	ART	CLASS	EXPECT	EXPER	EXPR	GPA	LOGIC	MAJOR	MATH	MATH2	PERS	REASON	SEX	STD
ACT	1	-.17	.392	-.10	-.452	.12	.42	.412	.25	*	.382	.521	-.01	.42	-.03	.472
AGE		1	-.07	.502	.14	-.19	-.10	-.10	.17	*	.01	-.12	.25	.01	.00	-.14
ART			1	-.09	-.24	.262	.05	.16	.331	*	.13	.351	.03	.21	-.08	.272
CLASS				1	.12	-.09	-.08	-.14	.05	*	.09	-.13	.11	.30	-.08	-.17
EXPECT					1	-.492	*	-.21	.301	*	-.402	*	*	*	.17	-.622
EXPER						1	*	.04	.14	*	.201	*	*	*	-.12	.312
EXPR							1	.32	*	*	*	.381	.421	.29	.02	.431
GPA								1	-.21	*	.19	.28	.18	.11	.352	.412
LOGIC									1	*	.01	*	*	*	-.371	.321
MAJOR										1	*	*	*	*	*	*
MATH											1	.23	.09	.00	-.08	.302
MATH2												1	.29	.20	-.11	.472
PERS													1	.24	.28	.25
REASON														1	-.34	.16
SEX															1	.13
STD																1

\* no correlation calculated  
1 significant at .01 level  
2 significant at .001 level

negative correlation of .074 (Table 42) of AGE with ART. This negative correlation may not be generalizable to the total college population, but may reflect a tendency of high ART students to take the class at an early stage in their programs, and low ART students to delay enrollment to a later point in time. Further inquiry would be needed to support the hypothesis that ART scores increase with age for the general population. Studies by Wileman, Konvalina, and Stephens (1981), Cheney (1980), Howell, Vincent, and Gray (1967), and Perry (1964) all reported finding correlations between reasoning related subcomponents of instruments and programming success. The rejection of  $H_1$  adds further support to the assertion that reasoning skills play an important part in programming success. The present study extends previous research by applying a test of a specific reasoning component, abstract reasoning. The findings show that there may be an important relationship between abstract reasoning skills and programming success. Furthermore, Table 42 shows that there is a correlation of 0.39, significant at the .001 level, between abstract reasoning scores and ACT-M scores. The table also reveals that abstract reasoning scores are significantly correlated with three other variables: EXPER, LOGIC, and MATH2. All four variables that showed significant correlations with abstract reasoning are highly correlated with academic success. This finding suggests that some commonality may

exist between these variables. Abstract reasoning may ultimately serve as the underlying liaison between the findings of several areas.

A multiple regression analysis was performed on the six significantly related variables to determine the relative weight of each independent of the others. Table 43 gives the results of the regression analysis. The regression was performed using a stepwise procedure with mean substitution for missing values. The table shows that of the six variables ACT-M scores, academic expectation, and high school grade point average account for the most variance. Notice also that abstract reasoning and math background completely drop from the analysis, indicating that their variance is covered by the other four. This is further support for the possibility that abstract reasoning skills may function as an important component of several key factors.

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Table 43  
Multiple Regression of  
ART, ACT, EXPECT, MATH, GPA, and EXPER  
with STD Dependent

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Step	MultR	Rsq	F(Eqn)	SigF	Variable	BetaIn
1	.4183	.1750	32.235	.000	ACT	.4183
2	.5133	.2635	27.006	0.0	EXPECT	-.3135
3	.5715	.3266	24.247	0.0	GPA	.2702
4	.5957	.3549	20.490	0.0	EXPER	.1805

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The findings that age, sex, academic major and academic class show no significant relationship to academic success are similar to those of Peterson and Howe (1979). Perseverance, as measured in this study, showed little relationship to academic success. This may be a result, however, of the small sample size and the narrow range of observed values.

### Implications

Student demand for computer science education at postsecondary institutions continues to strain institutional resources to a greater extent each year. The relatedness of training, employment opportunities, and high salaries has not gone unnoticed by subsequent generations of students, and will serve to maintain the current demand into the foreseeable future. To cope with the problem, administrators must formulate strategies to optimize resource allocation and utilization.

This study suggests a number of alternative considerations useful in the course of policy development and related decisional procedures. If the salient factors contributing to computer science success are definitively identified, a model can be developed which will aid in the effort to systematically address the ongoing problem of resource-demand disequilibrium in a more practical, timely

and rational manner. Identification of success factors may lead to changes in instructional strategies, and redeployment of human resources and institutional media so that maximum benefit can be derived from the limited resources available to educational institutions. Improved understanding of success may suggest, moreover, essential developmental criteria for new and responsive compensatory programs.

Factor identification may lead to better counseling and advising of students, both at the secondary and post-secondary level. Weaknesses in a student's profile can be identified, and remediations designed where feasible. When remediation is not possible or desirable, students can be realistically advised.

The identification of a relationship between math ability and computer science success has clear implications for college bound students and the institutions they enter. High school students, contemplating computer science as a profession, would do well to place emphasis on developing and refining math skills in order to increase their probability of success in a college computer curriculum. College computer science departments should note the relationship of math skills and computer science success, and review their current math pre/corequisites, stressing the importance of a solid mathematical foundation in their programs.

Aspiring computer professionals should seek to maximize computer exposure prior to postsecondary training. The exposure may enable them to better compete in college programs. Providing the requisite computer experience may require redeployment and/or augmentation of resources on the part of secondary educational institutions. High schools will need to periodically examine their technologies, related resources and systems of allocation in quest of a reasonable balance between user demand and organizational capabilities.

This study found no gender based differences in academic success rates. The finding suggests the need to encourage a more gender balanced enrollment than has traditionally been found in computer science classes.

#### Future Research

This study was designed to contribute to a progression of research targeted to the identification of critical factors that affect academic success in computer science education. Further research is needed to confirm and/or refine the significant variables in this and related studies, and to identify other potential factors which may be taken into account.

The data from this research revealed significant differences in success rates between students who had

completed four or more math classes and those with three or less. Is the difference merely attributable to the quantity increase in instruction, or are there other elements at work? Further research is needed to determine if success rates are affected by differing types of math classes (geometry, calculus, or algebra) in the students' backgrounds. Many studies have established math abilities as an important factor in computer science success. Future studies are needed to refine the relational potential of specific mathematical abilities.

This study showed a relationship between abstract reasoning skills and both computer science success and math abilities. Additional studies should be conducted to explore further abstract reasoning skills as components and/or integral subsets in both of these areas. Studies should explore the cause and effect relationship of abstract reasoning abilities as they pertain to math and computer science. Research is needed to determine if the study of math and computer science increases abstract reasoning ability levels.

The area of academic expectation showed promise as an avenue for future research. Follow-up studies are needed to examine the role that expectation plays in motivation and achievement among computer science students.

Previous studies reported mixed conclusions concerning the value of academic class and age as predictors of

academic success. Academic class showed some promise as a factor in this study. Further studies are needed to clarify the potential predictive value of these two related variables.

The questions raised by this study and related research suggest the need for continued inquiry. Additional studies may lead to the development of a knowledge base sufficient to inform institutional policy makers as they address resource and demand problems. A working model of factors would obviate sub-optimal planning and decisional processes with regard to computer science education.



**APPENDIX A**  
**ABSTRACT REASONING INSTRUMENT**

PLEASE NOTE:

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These consist of pages:

Appendix A, pages 104-109

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**APPENDIX B**  
**STUDENT PROFILE QUESTIONNAIRE**

## Student Profile 1

Number \_\_\_\_\_

1. Major \_\_\_\_\_ 2. Age \_\_\_\_\_ 3. Sex \_\_\_\_\_

4. Academic Class (circle one)  
1-Freshmen      2-Sophomore      3-Junior      4-Senior

5. High School GPA (on 4.0 scale) \_\_\_\_\_

6. Number of high school and college math classes you have  
taken? \_\_\_\_\_7. Do you (or your family) own a microcomputer?  
(Y/N) \_\_\_\_\_8. Previous computer experience? (circle one)  
1-none      2-some      3-extensive9. How would you characterize your logical reasoning  
skills?  
1-weak      2-average      3-strong10. What grade do you expect to receive in this class?  
1-A      2-B      3-C      4-D      5-F

### Student Profile 2

Number \_\_\_\_\_

1. Major \_\_\_\_\_ 2. Age \_\_\_\_\_ 3. Sex \_\_\_\_\_
4. Academic Class (circle one)  
 1-Freshmen      2-Sophomore      3-Junior      4-Senior
5. High School GPA (on 4.0 scale) \_\_\_\_\_
6. Number of high school & college math courses taken? \_\_\_\_\_
7. Do you (or your family) own a microcomputer? (Y/N) \_\_\_\_\_

For each of the following statements circle the response that best reflects your opinion. Where:

1=strongly disagree    2=disagree    3=agree    4=strongly agree

8. I often will keep working at something even if it seems hopeless.  
 1      2      3      4
9. I live by the saying, "Never give up."  
 1      2      3      4
10. I will finish in the top half of this class.  
 1      2      3      4
11. I dislike giving up on a task.  
 1      2      3      4
12. I consider myself open to new ideas.  
 1      2      3      4
13. If I cannot solve a particular problem, I would rather try an easier one than keep working on the harder task.  
 1      2      3      4
14. Success encourages me to attempt even more difficult problems.  
 1      2      3      4
15. I have well developed reasoning skills.  
 1      2      3      4
16. I have a strong math background.  
 1      2      3      4

17. It is important to finish something once it is started.  
1 2 3 4

18. I have worked with computers before.  
1 2 3 4

19. Unfinished tasks bother me until I get a chance to  
finish them.

1 2 3 4

**APPENDIX C**  
**ACT/SAT CONVERSION TABLES**

Table 44  
Act math score equivalents for SAT scores

ACT	SAT	ACT	SAT
1	220 - 230	19	430 - 440
2	240	20	450
3	250	21	460 - 470
4	260	22	480
5	270	23	490
6	280	24	500 - 510
7	290 - 300	25	520 - 530
8	310	26	540
9	320	27	550 - 570
10	330	28	580 - 600
11	340	29	610 - 630
12	350	30	640 - 650
13	360	31	660
14	370	32	670 - 680
15	380	33	690 - 710
16	390	34	720 - 730
17	400 - 410	35	740 - 750
18	420	36	760 - 780



**APPENDIX D**  
**SCATTERPLOTS**

Figure 1  
PLOT OF ART WITH STD

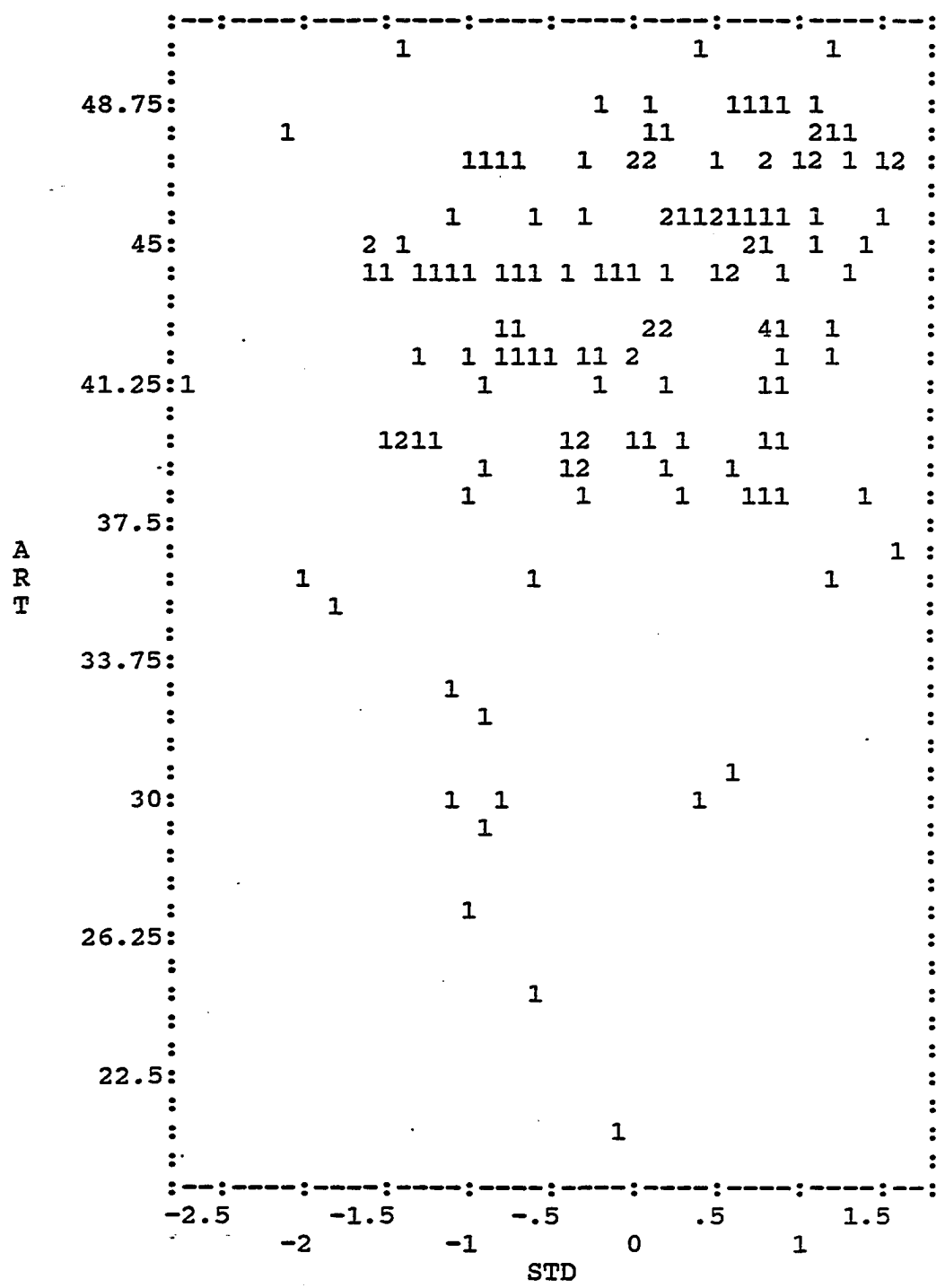


Figure 2  
PLOT OF ACT WITH STD

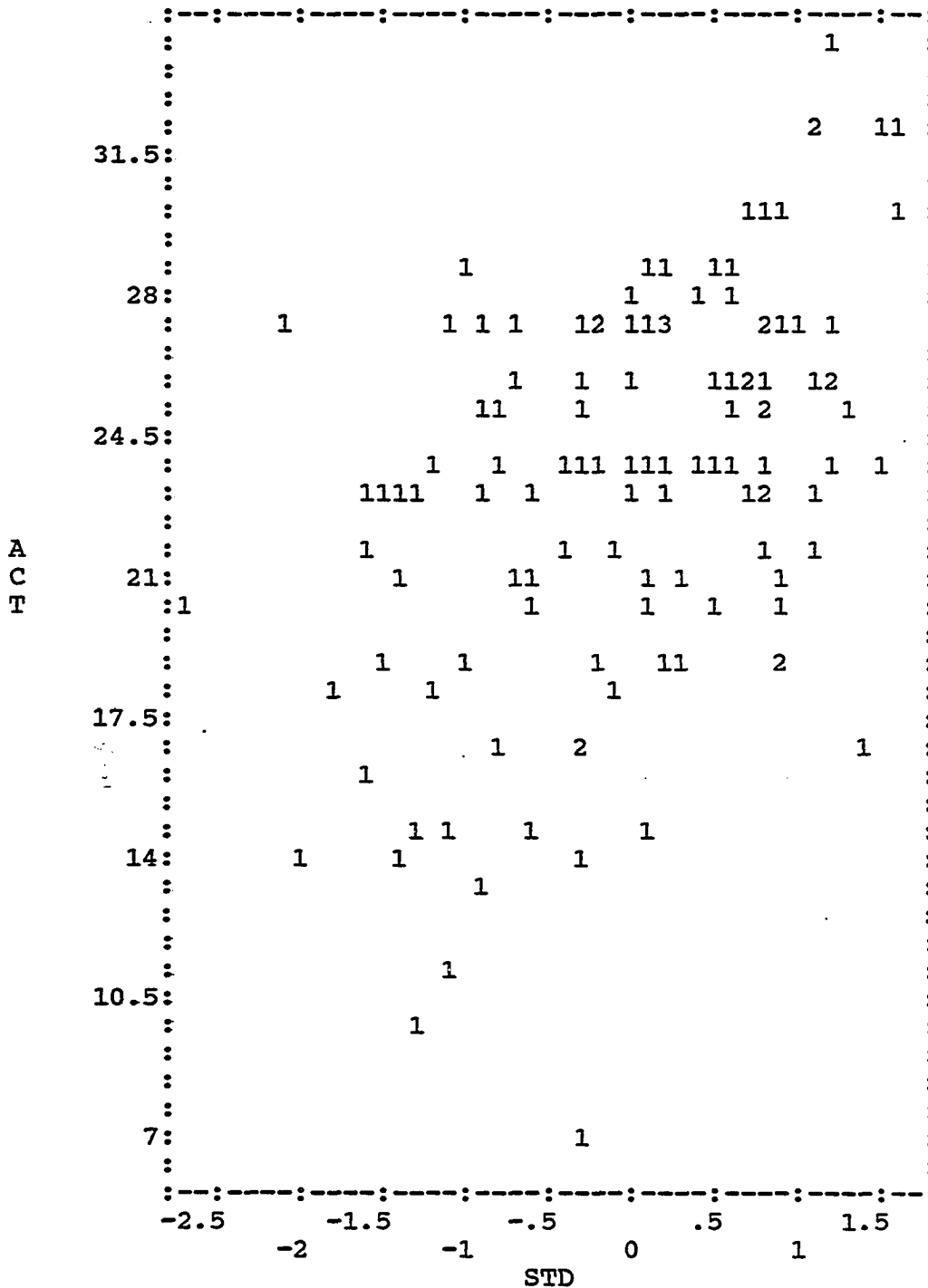


Figure 3  
PLOT OF SEX WITH STD

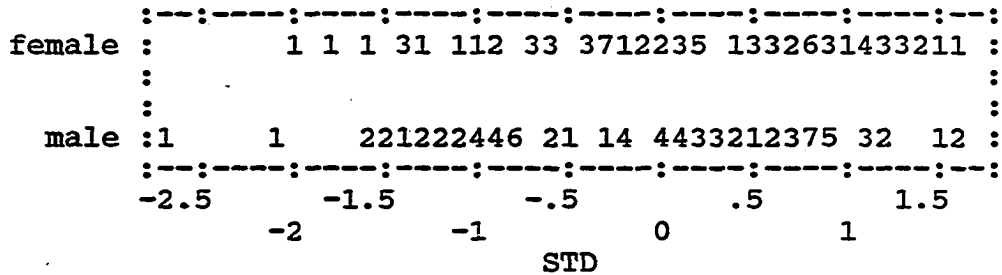


Figure 4  
PLOT OF CLASS WITH STD

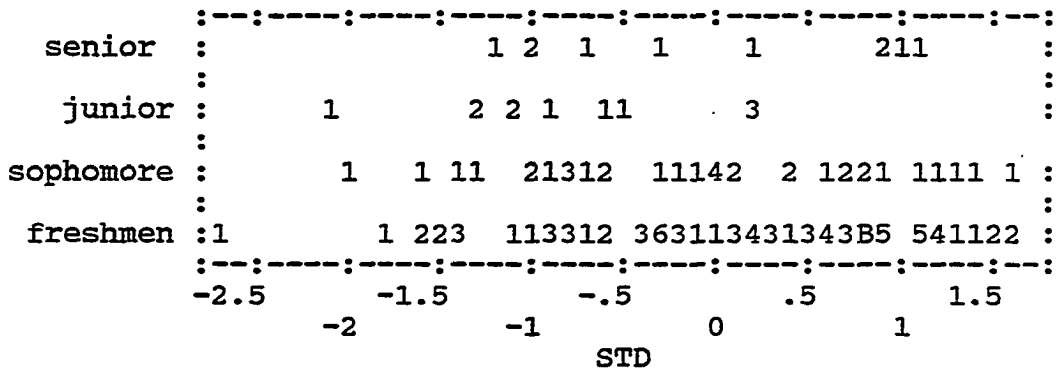


Figure 5  
PLOT OF MICRO WITH STD

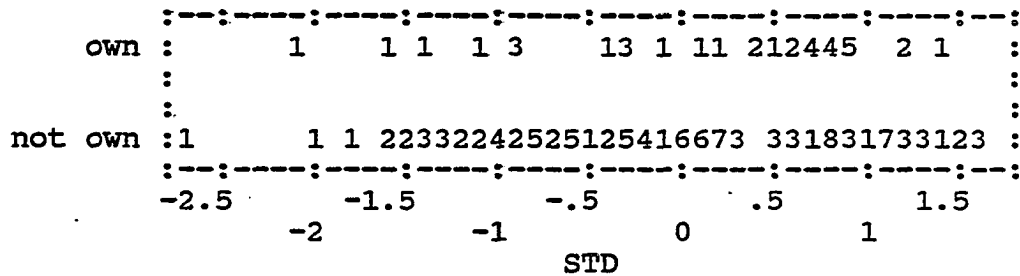


Figure 6  
PLOT OF AGE WITH STD

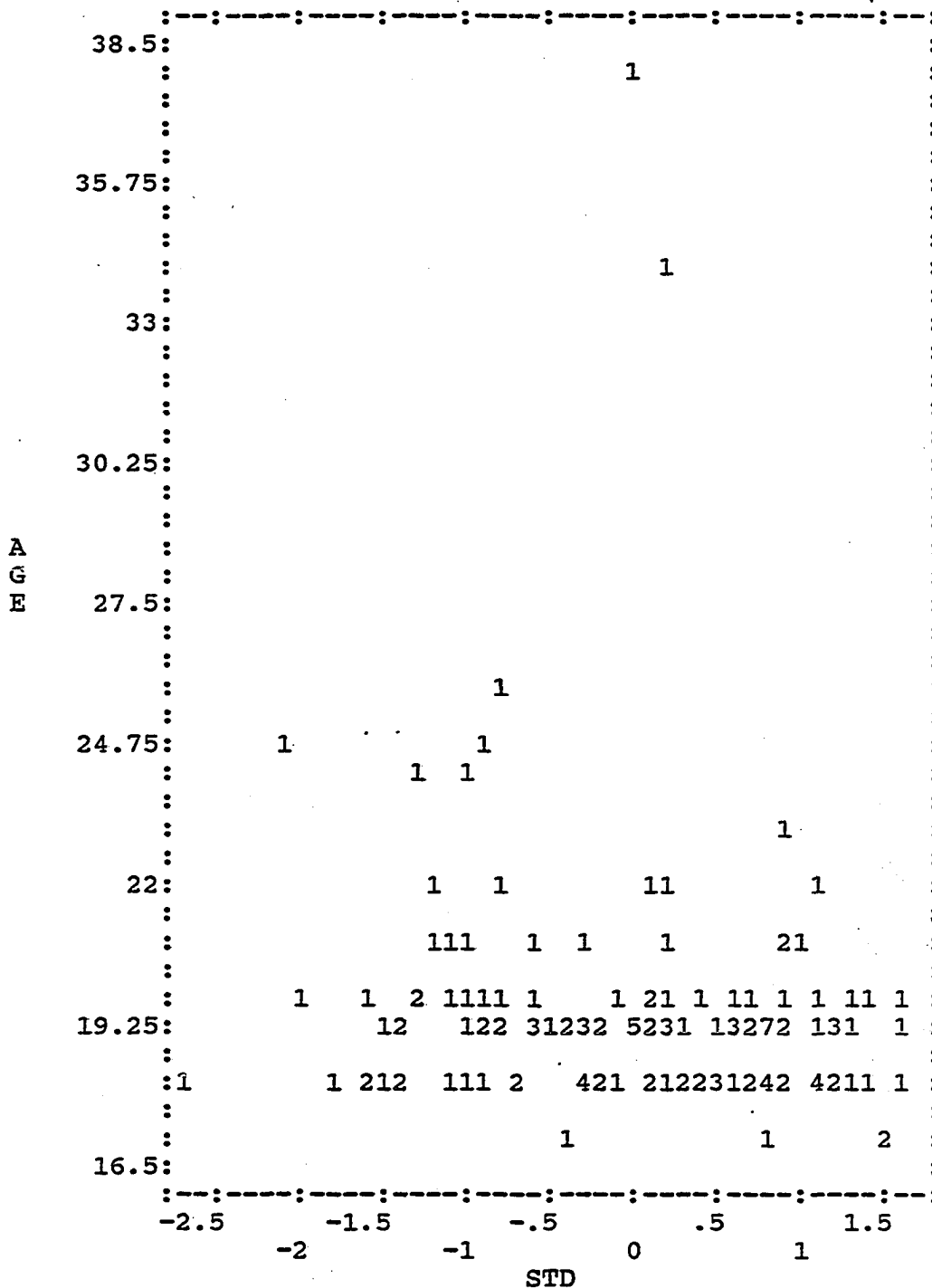




Figure 9  
PLOT OF EXPECT WITH STD

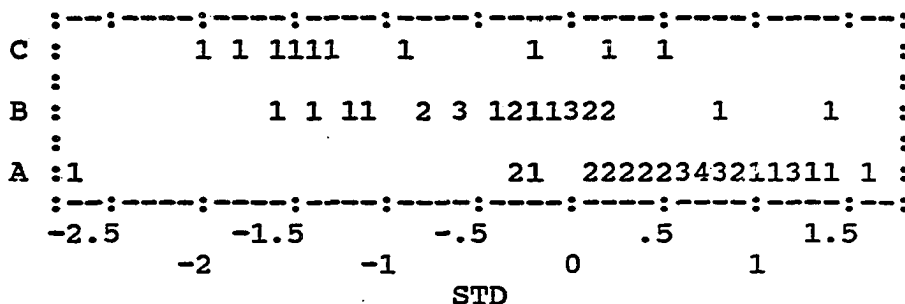


Figure 10  
PLOT OF EXPER WITH STD

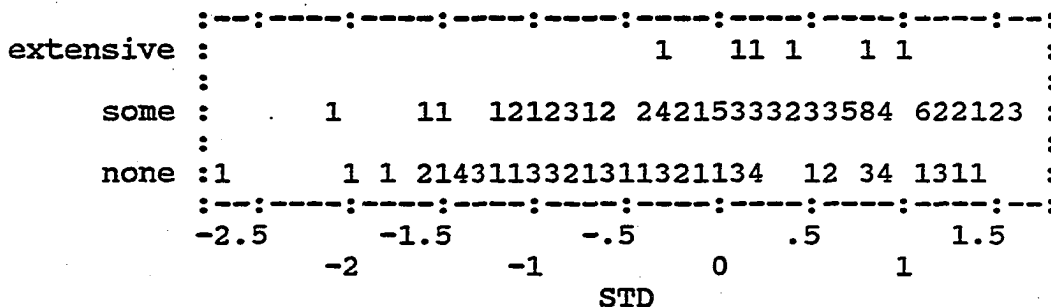


Figure 11  
PLOT OF MAJOR WITH STD

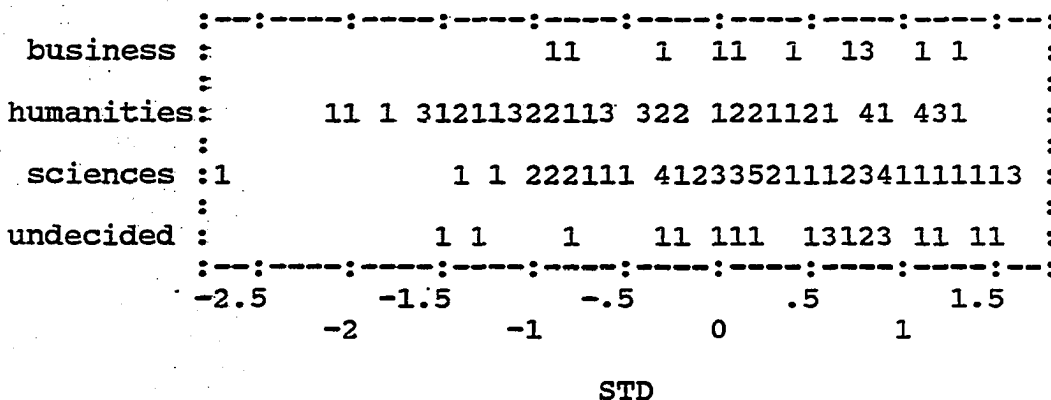


Figure 12  
PLOT OF GPA WITH STD

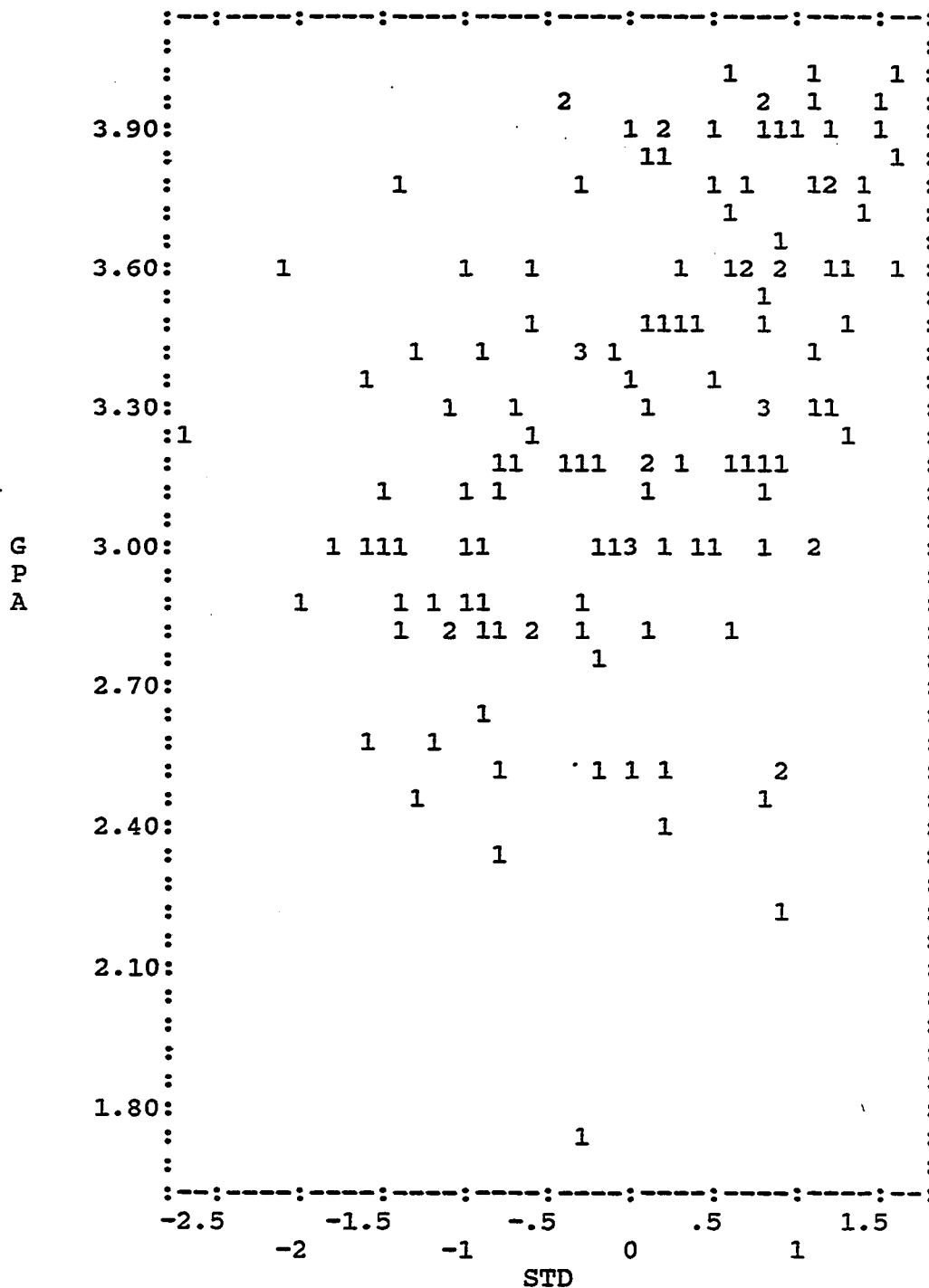




Figure 13  
PLOT OF MATH2 WITH STD

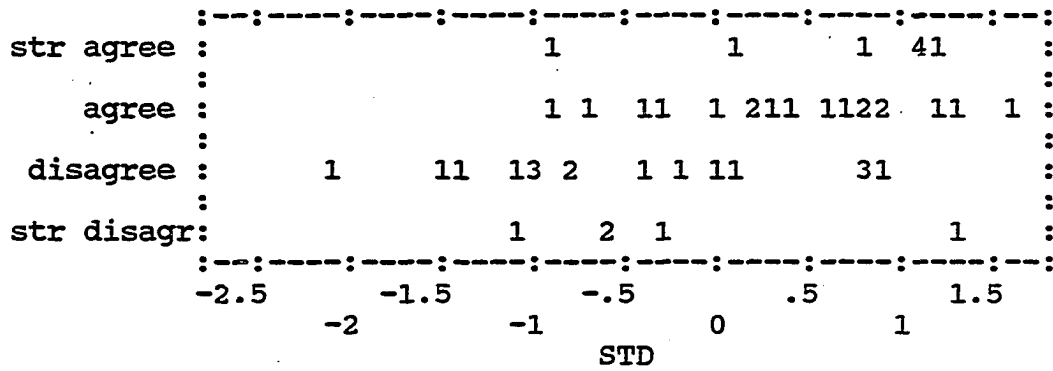


Figure 14  
PLOT OF REASON WITH STD

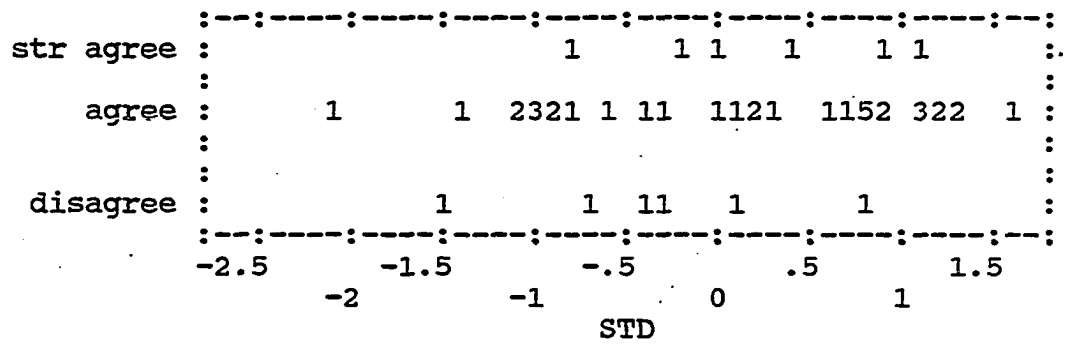


Figure 15  
PLOT OF EXPR WITH STD

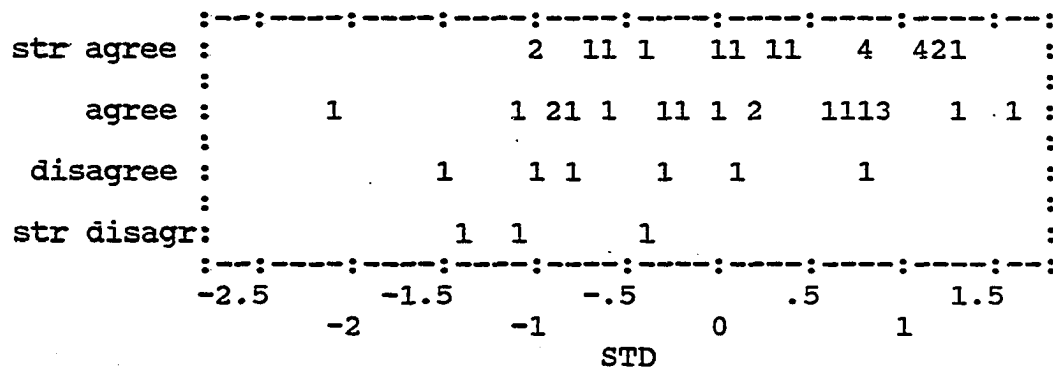
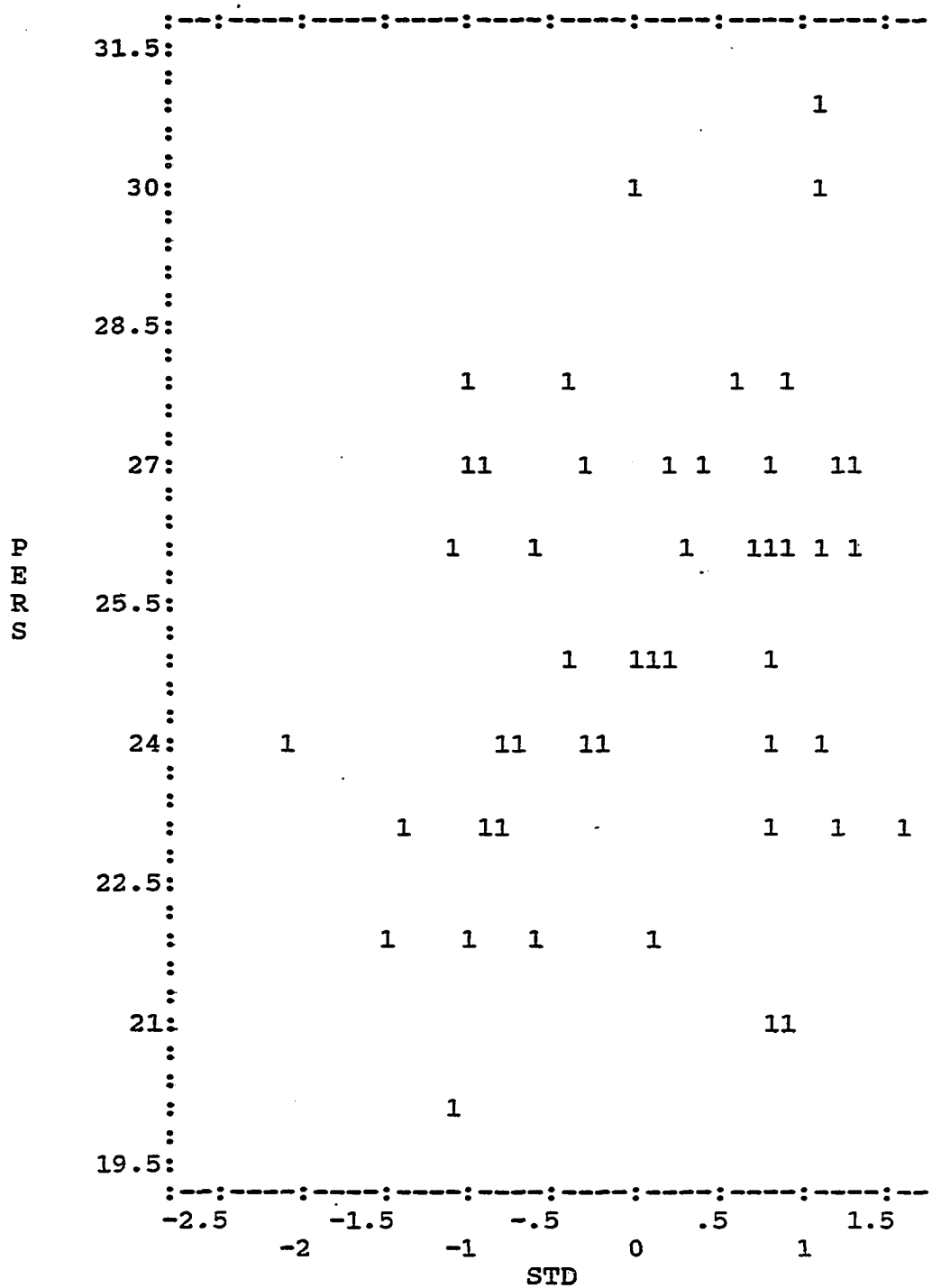


Figure 16  
PLOT OF PERS WITH STD



**BIBLIOGRAPHY**

- Alspaugh, Carol A. "Identification of Some Components of Computer Programming Aptitude," Journal for Research in Mathematics Education, March 1972, 89-98.
- Alspaugh, John W. "The Relationship of Grade Placement to Programming Aptitude and FORTRAN Programming Achievement," Journal for Research in Mathematics Education, January 1971, 44-48.
- Anastasi, Anne. Psychological Testing. New York: MacMillan Publishing Co., 1982.
- Astin, Alexander W. Predicting Academic Performance in College: Selective Data for 2300 American Colleges. New York: Free Press, 1971.
- Atkinson, John W., and Litwin, G. H. "Achievement Motivation and Test Anxiety Conceived as a Motive to Approach Success and a Motive to Avoid Failure," Journal of Abnormal Social Psychology, 60, 1960, 52-63.
- Austin, Gilbert R., and Ryan, Bruce. "Computer Assisted Guidance in Predicting Probable Admission to Institutions of Higher Education," Journal of Educational Data Processing, 4, 1971, 18-23.
- Barkin, Stephen. "An Investigation into Some Factors Affecting Information Systems Utilization." Unpublished Doctoral Dissertation, University of Minnesota, Minneapolis, Minnesota, 1974.
- Bateman, C. R. "Predicting Performance in a Basic Computer Course." Proceedings of the 5th Annual Meeting of the American Institute for Decision Sciences, Boston Mass., 1973.
- Bauer, Robert, Mehreus, W. A., and Vinsonhaler, J.R. "Predicting Performance in a Computer Programming Course," Educational and Psychological Measurement, 28, 1968, 1159-1164.
- Benbow, Camilla P., and Stanley, Julian C. "Consequences in High School and College of Sex Differences in Mathematical Reasoning Ability: A Longitudinal Perspective," American Educational Research Journal, Winter 1982, 598-608.
- Bennett, George K. Differential Aptitude Test. The Psychological Corporation, New York, 1974.

- Berger, Raymond M. "Selection of Systems Analyst and Programmer Trainees," Proceedings of the 6th Annual Computer Personnel Research Conference, June, 1968, 44-63.
- Bianchi, John R. and Bean, Andrew. "The Prediction of Voluntary Withdrawals from College: An Unsolved Problem," Journal of Experimental Education, 49, 1980, 29-33.
- Bork, Alfred M. "Learning to Program for the Science Student," Journal of Educational Data Processing, 8, 1971, 1-5.
- Bresdal, Pam. Unpublished self-study by the University of Iowa Computer Science Department, Iowa City, Iowa, 1985.
- Brillhart, L. "Computers: An Answer to Engineering Students Learning Styles at the Community College," Computer and Education, 1982, 247-255.
- Campbell, Patricia, F., and McCabe, George, P. "Predicting the Success of Freshmen in a Computer Science Major," Communications of the ACM, November, 1984, 1108-1113.
- Carlson, George R., and Steitberger, Eric. "The Construction and Comparison of Three Related Test of Formal Reasoning," Science Education, January, 1983, 133-140.
- Cheney, Paul. "Cognitive Style and Student Programming Ability: An Investigation," AEDS Journal, Summer 1980, 285-291.
- Cochran, William G. Sampling Technics. New York: John Wiley and Sons, 1963.
- Croxton, Federick, E., and Cowden, Dudley, J. Applied General Statistics. New York: Prentice-Hall, Inc., 1940.
- Denning, Peter J. "U.S. Productivity in Crisis," Communications of the ACM, 23, 1980, 617-619.
- Fennema, Elizabeth, and Sherman, Julia. "Sex Related Differences in Math Achievement, Spatial Visualization and Sociocultural Factors," American Education Research Journal, May 1977, 369-372.
- Fowler, George C., and Glorfeld, Louis W. "Predicting Aptitude in Introductory Computing: A Classification Model," AEDS Journal, Winter 1981, 96-109.

- Glorfeld, Louis W., and Fowler, George C. "Validation of a Model for Predicting Aptitude for Introductory Computing," SIGCSE Bulletin, 14, 1982, 140-143.
- Hannafin, Michael and Cole, Dennis D. "A Comparison of Factors Affecting the Elective Selection of Introductory Computer Courses," AEDS Journal, Summer 1983, 218-227.
- Hays, William L. Statistics. New York: Holt, Rinehart and Wilson, 1963.
- Hopmeir, G. "New Study Says CAI May Favor Introverts," Electronic Education, September 1981, 16-17.
- Howell, Margaret A., Vincent, John W., and Gay, Richard A. "Testing Aptitude for Computer Programming," Psychological Reports, 20, 1967, 1251-1256.
- Hunt, A. W. "A Decision Rule for Predicting Academic Success," Decision Sciences, 8, 1977, 270-286.
- Huysmans, J. H. "The Effectiveness of Cognitive Style Constraint in Implementing Operation Research Proposals," Management Science, September 1970, B92-B104.
- Jacobs, Stuart J. "Cognitive Predictors of Success in Computer Programmer Training," Proceedings of the 11th Annual Computer Personnel Research Conference, New York, 1973, 98 - 110.
- Johnson, James. "Information and Communications Technology in Teaching, Research and Administration: Perspectives and Recommendationd." Unpublished Report to the President of the University of Iowa, Iowa City, Iowa, September, 1982.
- Langston, Ira, W., and Watkins, Thomas, B. "SAT-ACT Equivalents." Unpublished Research Memorandum Prepared by the University Office of School and College Relations, University of Illinois, Champaign, Illinois, July, 1980.
- Konvalina, John, Stephens, Larry, and Wileman, Stanley. "Identifying Factors Influencing Computer Science Aptitude and Achievement," AEDS Journal, Winter 1983, 106-112.

- Konvalina, John, Stephens, Larry, and Wileman, Stanley. "Math Proficiency: A Key to Success for Computer Science Students," Communications of the ACM, 26, 1983, 377-382.
- Lawson, Anton E. "The Development and Validation of a Classroom Test of Formal Reasoning," Journal of Research in Science Teaching, 15, 1978, 11-12.
- \_\_\_\_\_. "Formal Reasoning, Achievement and Intelligence: An Issue of Importance," Science Education, January 1982, 77-83.
- \_\_\_\_\_. "The Nature of Advanced Reasoning and Science Instruction," Journal of Research in Science Teaching, December 1982, 743-760.
- Leeper, R. R., and Silver, J. L. "Predicting Success in a First Programming Course," SIGCSE Bulletin, 14, 1981, 147-148.
- Lemos, Ronald S. "Measuring Programming Language Proficiency," AEDS Journal, Summer 1980, 261-273.
- Light, Leah L. "Adult Age Differences in Reasoning from New Information," Journal of Experimental Psychology; Learning, Memory, and Cognition, September 1982, 435-447.
- Lindquist, Everett F. Design and Analysis of Experiments in Psychology and Education. Boston: Houghton Mifflin Company, 1953.
- Linn, Monica C. "Scientific Reasoning: Influences on Task Performance and Response Categorization," Science Education, 61, 1977, 357-363.
- \_\_\_\_\_. "Theoretical and Practical Significance of Formal Reasoning," Journal of Research in Science Teaching, December 1982, 727-742.
- \_\_\_\_\_. "Male-Female Differences in Predicting Displaced Volume: Strategy, Usage, Aptitude, Relationships and Experience Influences," Journal of Educational Psychology, February 1983, 86-96.
- Loyd, Brenda H., and Gressard, Clarice. "The Effects of Sex, Age, and Computer Experience on Computer Attitudes," AEDS Journal, Winter 1984, 67-77.

- Lusk, J., and Kersnick, M. "The Effect of Cognitive Style and Report Format on Task Performances: The MIS Design Consequences," Management Science, August 1979, 787-798.
- Mazlack, Lawrence J. "Identifying Potential to Acquire Programming Skill," Communications of the ACM, January 1980, 14-17.
- McNamara, W. J., and Hughes, J. L. "A Review of Research on the Selection of Computer Programmers," Personnel Psychology, 14, 1961, 39-51.
- Newsted, Peter R. "Grade and Ability Predictions in an Introductory Programming Course," SIGCSE Bulletin, June 1975, 87-91.
- Ory, John, C., and Poggio, John, P. "The Development and Empirical Validation of a Measure of Achievement Motivation." Paper presented at the Annual Meeting of the American Educational Research Association, Division D, Washington D.C., April 1975.
- Osborn, Herbert H. "The Assessment of Mathematics Abilities," Educational Research, February 1983, 28-40.
- Payne, David A., Rapley, Frank E., and Wells, Robert A. "Application of a Bibliographical Data Inventory to Estimate College Academic Achievement," Measurement and Evaluation in Guidance, October 1973, 152-156.
- Perry, D. K. "Programmer Selection Procedures," Santa Monica, Calif.: Systems Development Corporation, 1962.
- \_\_\_\_\_. "Training and Job Performance Validities of a Programming Trainee Selection Variables," Santa Monica, Calif.: Systems Development Corporation, 1964.
- Perry, D. K., and Cantley, G. "Computer Programmer Selection and Training in System Development Corporation," Santa Monica, Calif.: System Development Corporation, 1965.
- Petersen, Charles G., and Howe, Trevor G. "Predicting Academic Success in Introduction to Computers," AEDS Journal, Fall 1979, 182-191.
- Prichard, W. H. "Instructional Computing in the Year 2001: A Senario," Phi Delta Kappan, January 1982, 322-325.



- Ralston, Anthony. Introduction to Computer Science. New York: McGraw-Hill Book Co., 1971.
- Ralston, Anthony, and Shaw, Mary. "Curriculum '78 - Is Computer Science Really that Unmathematical?," Communications of the ACM, February 1980, 67-70.
- Reinstadt, R. N., Hammidi, B. C., Peres, S. H. and Ricard, E. L. "Computer Personnel Research Group Programmer Performance Prediction Study," Santa Monica, Calif.: System Development Corporation, 1965.
- Rothman, Stanley, and Mosman, Charles. Computers and Society. Chicago: Science Research Associates, 1972.
- Rowan, T. C. "Psychological Test and Selection of Computer Programmers," Journal of the ACM, 4, 1957, 348-354.
- Sharp, S., E. "Individual Psychology: A Study in Psychological Method," American Journal of Psychology, 10, 1898, 329-391.
- Sorge, Dennis H., and Wark, Lois K. "Factors for Success as a Computer Science Major," AEDS Journal, Summer 1984, 36-44.
- Staubly, J. A. "Selection Devices for Electronic Computer Programmers." Unpublished Report to the U.S. Dept. of Commerce, Bureau of the Census, Washington, D.C. 1963.
- \_\_\_\_\_. "Report on the Validity of the Federal Service Entrance Examination as a Selection Device for Digital Computer Programmers." Unpublished Report to the U.S. Dept. of Commerce, Bureau of the Census, Washington, D.C. 1963.
- Stephens, Larry J., Wileman, Stanley, and Konvalina, John. "Group Differences in Computer Science Aptitude," AEDS Journal, Winter 1981, 84-95.
- Stevens, Dorothy J. "Cognitive Processes and Success of Students in Instructional Computer Courses," AEDS Journal, Summer 1983, 228-233.
- Tillman, M. R. "An Examination of the Productive Validity of Several Potential Predictors of the Work Proficiency of Computer Programmers," Computer Personnel, August 1979, 3-6.