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PREDICTING STUDENT PERFORMANCE IN A BEGINNING COMPUTER SCIENCE CLASS

By

Laurie Honour Werth

A dissertation submitted in partial fulfillment
of the requirements for the degree of

Doctor of Education

in

Post Secondary Education

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University of Nevada, Las Vegas

Summer 1985

The dissertation of Laurie Werth for the degree of Doctor of Education in Post Secondary Education is approved.

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ABSTRACT

Purpose of the Study. The purpose of this study was to determine factors which effectively predict success in a first course for computer science majors. A secondary goal was to provide a model of the successful computer science student in order to improve teaching and learning in the classroom.

Procedures. The sample consisted of 58 students enrolled in all three sections of Computer Science I, during Spring semester, 1985. Student characteristics selected included age, sex, previous high school and college grades, number of high school and college mathematics classes, number of hours worked, and whether the job was computer-related or involved programming. A measure of Piagetian cognitive development developed by Kurtz, the Group Embedded Figures Test (GEFT) and the Myers-Briggs Personality Index (MBTI) were administered early in the semester. These measures were correlated with the student's letter grade in the class using both Chi Square and Pearson's Product Moment Coefficient statistical tests.

Findings. Significant relationships were found between grade and the students' previous college grades and the number of high school mathematics classes ($p<.05$). The correlation between grade, and both number of hours worked and working as a programmer, approached significance ($p<.10$). Both the Group Embedded Figures Test ($p<.01$) and the measure of Piagetian Intellectual Development stages ($p<.05$) were also significantly correlated with grade in this rigorous Pascal programming class.

While there was no relationship between the personality type and grade, the Myers-Briggs results provided an interesting profile of the computer science major. On the Extroversion-Introversion, Sensing-Intuitive, and Thinking-Feeling indices, the students were considerably more introverted, intuitive and thinking than the population as a whole, though they were close to national norms on the Perception-Judging index. While computer science students were somewhat like engineering students, they more strongly resembled chess players, when these results were compared with other studies.

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To John, Johnny and Matthew.

CHAPTER I

INTRODUCTION

Background

The need to understand and use computers is rapidly becoming a necessity in our complex modern society. In a culture where information has become a major industry, a computer literate populace is as important as energy and raw materials. In his report to the National Science Foundation, "The Next Great Crisis in American Education: Computer Literacy," Andrew Molnar (1978) describes the national need to foster computer literacy. "Computer literacy is a prerequisite to effective participation in an information society and is as much a social obligation as reading literacy."

Very little is known about how people learn to use computers. Even the more restricted problem of teaching programming is not well understood. The scramble to provide ever improving computer hardware at an ever decreasing price, and to envisage and produce increasingly comprehensive computer applications, has left little time to learn what factors are important in computer programming instruction. However, a new science which applies the techniques of experimental psychology, together with the concepts of cognitive psychology, to the problems of computer and information science is emerging. Software psychology, defined as "the study of human performance in using computer and information systems," addresses a wide range of goals in order to "facilitate the human use of computers" (Shneiderman, 1980). Assessing programmer aptitude and ability are fundamental to improving both teaching and job performance. Aptitude tests for programmers have been available from the earliest days of computing, but little validity and reliablility testing has been done. In his "researcher's agenda," Shneiderman (1980) calls for both improvement and validation of programmer aptitude and ability tests. This would not only aid computing, but would also to improve the understanding of human thought processes in cognitive psychology.

In computer science instruction, the area which has drawn the greatest attention is beginning programming classes. However, existing studies have been only marginally successful in predicting student performance in these classes. The factors most frequently associated with success are high school and college grade point average, but these measures are too crude to use as predictors for computer programming. The IBM Programming Aptitude Test gives inconsistent results, as do factors such as college major, class, and numbers of math, science and computer science classes taken. Two pre-tests look promising, one based on mathematical reasoning (Konvalina, Wileman, & Stephens, 1983) and one based on Piaget's intellectual development levels (Kurtz, 1980), but these are preliminary and results indicate a need for further investigation.

Statement of the Problem

The purpose of the study was to determine factors which effectively predict success in a beginning computer science class. A secondary goal was to provide a model of the successful student in order to improve teaching and learning in the classroom. To accomplish this, the study investigated the relationship between selected personal, academic, and work-related variables and the student's grade achievement in a first college course in computer science. In addition, standard measures of cognitive development, cognitive style and personality factors were also given and compared to the student's grade in the course. The following questions served as a basis for collection and analysis of data:

a. Do the personal factors age and sex effect success in a beginning computer science class?

b. Do academic variables such as classification, high school grades, college grades, and prior mathematics classes effect success in a beginning computer science class?

c. Do work-related variables such as the number of hours worked, computer-related work experience, non-computer-related work experience, or computer programming work experience effect success in a beginning computer science class?

d. Does the cognitive development level as described by Piaget effectively predict success in a beginning computer science class?

e. Does the cognitive style factor, field dependence-independence effectively predict success in a beginning computer science class?

f. Does personality type as determined by the Myers-Briggs Type Indicator effect success in a beginning computer science class?

Hypotheses

The six main hypotheses, stated in the null form, are:

a. There will be no relationship between the students' demographic factors and their grade in the class.

b. There will be no relationship between the students' academic factors and their grade in the class.

c. There will be no relationship between the students' work-related factors and their grade in the class.

d. There will be no relationship between the students' cognitive development level and their grade in the class.

e. There will be no relationship between the students' cognitive style and their grade in the class.

f. There will be no relationship between the students' personality type and their grade in the class.

Research Hypotheses

It is expected that it will be possible to determine a student's probable success in the first computer science class on the basis of one or more tests of cognitive development level, cognitive style, or personality type administered prior to the course. Other factors such as age, sex, classification level (number of accumulated college hours), the number of mathematics classes taken in high school and college, the student's previous grades in high school and college, and the student's work experience may provide additional information helpful in determining a student's placement.

Significance of the Study

Enrollment in computer science classes has grown at an increasing rate, despite declining university budgets and limited numbers of computer science faculty (Mitchell, 1980). Students are often not prepared and attrition rates are high. Unfortunately, these student failures represent a waste of both university and student resources. Whether selecting a limited number of students from the large number trying to enroll or attempting to offer differing "levels" of classes based on student aptitude, some method of predicting performance is needed (Petersen & Howe, 1979; Konvalina, Wileman & Stephens, 1983). This problem will grow increasingly important as student interest and computer literacy requirements expand. Luehrmann, (1981) working on computer literacy curriculum for elementary and secondary school students, calls for faculty members and test developers "to construct innovative testing instruments within the next few years," for the variety of new courses that will be needed at the university level.

Several studies have shown that relatively few subjects operate at Piaget's higher, formal, cognitive level. McKinnon (1976) found that 50 per cent or more, of students entering a variety of different types of colleges, could not cope with abstract propositions. A large part of the high school and college curriculum assumes mastery of formal reasoning, and this lack of sufficient intellectual development is cited as the reason why many students have difficulty in school. Current methods are said to encourage the rote memorization of facts which soon dissolve due to the lack of an appropriate structure into which to integrate the ideas (Renner, 1976).

The importance of diagnosing the level of intellectual development of elementary and secondary students has resulted in the development of a number of Piagetian task evaluation devices, some of them suitable for group or classroom testing. The results have been incorporated into several science curricula based on Piagetian intellectual development level (Shayer & Adey, 1981). Others have applied Piaget to mathematics education, (Ginsburg, 1983) but very little work has been done in the area of computer science.

Cognitive style has been shown to have many applications in education (Witkin, Moore, Goodenough, & Cox, 1977). Not only does it describe differences in the way individuals process information, but cognitive style also correlates with career choice and social behavior. Field independence, the most studied measure of cognitive style, has been shown to relate to some kinds of problem solving and measures of analytic ability (Goodenough & Karp, 1961). Field independent individuals tend to choose careers in "structured" fields such as mathematics, science and engineering. Knowledge of a relationship between cognitive style and success in computer science could aid in understanding the cognitive processes involved in computer programming. But, to date, little work has been done.

Personality type, as measured by the Myers-Briggs Type Indicator, has been shown to correlate with grade point average and persistence in the major, at least in certain subgroups of students (Myers, 1962). More importantly, students in various fields often show a distinct and consistent profile of personality type. This information could be useful for comparing students with "successful" working computer scientists, as well as for counseling beginning students. Some engineering schools are using results of personality type studies to improve the teaching and learning styles of faculty and students (McCaulley, et al, 1983). Despite Weinberg's (1971) early efforts to arouse interest in the subject, very few studies of the psychology of computer programmers have been reported.

Assumptions

It is assumed that a student who has achieved Piaget's level of formal operations will be more successful than students who have not achieved this level.

Having attained Piaget's highest level of intellectual development, these students should be able to think abstractly and to draw logical conclusions better than the concrete or pre-operational level students who have not yet achieved these skills. This should aid them in writing computer programs, a task which is essentially problem solving. The computer programmer solves a verbally stated or written problem and translates his/her solution into instructions in a programming language.

Because field independence has been shown to correlate to some kinds of problem solving and analytic skills, as well as to a preference for careers in science-oriented subject areas, the field independent students should be more successful in programming computers than the field dependent student.

A profile of the Myers-Briggs personality type of the beginning computer science student will be of interest to both academic and industry personnel. Since much is known about the strengths and weaknesses of the different personality types and cognitive styles, such a model of the computer science student could lead to improved teaching and learning strategies.

Other assumptions include: the results will be generalizable to similiar populations of students; the tests choosen will measure intellectual development level, cognitive style and personality type; other factors such as personal, academic and work-related variables will also influence the student's grade in the class.

Research Plan

Personal, academic and work-related information were collected and tests of cognitive development, cognitive style, and personality type were administered early in the semester to all sections of the beginning computer science class at the University of Nevada, Las Vegas. Results were tabulated and correlated with the student's grade in the course at the end of the semester. Pearson's product moment coefficient and Chi Square tests were used to determine correlations between the factors. Pearson's R is the preferred bivariate correlational technique and has a smaller standard error than the other bivariate techniques. Chi Square is a nonparametric statistical test that is used for comparing frequency counts for data divided into categories. The personal, academic and work-related variables are all collected using multiple choice responses, and the continuous grades were made categorical by dividing them into groups by letter grade (with pluses and minuses). All variables were cross-correlated appropriately to determine if additional cross factor relationships exist. Because of the exploratory nature of the study, significance was examined at the .01, .05, and .10 levels.

Definition of Terms

Cognitive Processes are mental activities such as seeing, remembering, talking and solving problems. These processes receive, transmit and operate on information (Moates & Schumacher, 1980).

Intellectual Development Level is a term used by Piaget to describe the development of cognitive processes in children. He defines four levels, sensori motor, pre-operational, concrete operational and formal operational. Levels are determined by the nature of the tasks (selected by Piaget) the child is able to correctly complete (Ginsburg, 1979).

Information Processing Theory is primarily concerned with the mechanism, structures, and processes people employ in operating on environmental stimuli. It is founded on Gestalt Theory which is responsible for defining many of the basic phenomena of problem solving (Moates & Schumacher, 1980).

Information Processing Model is a model of human information processing used in problem solving. It is based on the computer model developed by Simon and Newell (1972) in their artificial intelligence studies (Klahr & Wallace, 1976).

Cognitive Style refers to differences between the way individuals process information. They are stable over time, cut across traditional boundaries, and include personality as well as cognitive elements (Witkin et al, 1977).

Field-Independence-Dependence is the most widely studied of the cognitive styles identified to date. It refers to a person's ability to disembed simple figures from a complex background (Witkin et al, 1977). The Group Embedded Figures Test (GEFT) is a pencil and paper measure of cognitive style designed to administered to groups.

Myers-Briggs Type Indicator (MBTI) is a self-report inventory which classifies people into dichotomous categories along four scales: Extroversion-Introversion, Sensation-Intuition, Thinking-Feeling, and Perception-Judgment. It is based on Jung's theory that human behavior is not random, but may be organized based on the way the individual prefers to use peception (awareness) and judgement (decision-making) (Myers, 1962).

Organization of the Study

Chapter I includes the background of the problem and its significance. The research plan, assumptions, and a definition of terms are also included. Chapter II includes a documented review of the literature pertinent to the study. Chapter III contains a brief description of the research design, the subjects, and the measures used.

Chapter IV reports the findings. Frequency counts and percentages are given for each factor and then each factor is correlated to the student's grade in the course. Results from each of the measures, Piagetian test of intellectual development, Group Embedded Figures Test, and Myers-Briggs Type Indicator, are also compared to the student's grade in the course. Finally, each of the factors is cross correlated with the results of each of the three measures of cognitive development, cognitive style and personality type. Chapter V summarizes the study and interprets the findings with respect to previous research. Limitations of the study and implications of the results are discussed.

CHAPTER II

RELATED RESEARCH

Introduction

This chapter begins by examining various existing studies of efforts to predict student performance in beginning computer science classes. Two pretests have been developed and used in these studies. One is based on mathematical reasoning, and one is based on Piaget's intellectual development stages.

Piaget's work is summarized briefly and some Piagetian research issues are discussed. Methodology questions are considered, especially those relating to measuring formal operational levels in adolescents and college students. The information processing model, proposed by those who feel that Piagetian tasks do not adequately describe more complex problem solving behavior, is outlined.

Cognitive style, as measured by the Group Embedded Figures Test, is discussed and its educational applications outlined. Finally, information on the Myers-Briggs Type Indicator measure of personality type is given.

Existing Studies

A number of investigators have looked at the problem of predicting student performance in a beginning computer science class. Many variables have been examined and several predictor examinations tested. These experiments are summarized in Table 1. There have been some conflicts in the outcomes, but results are helpful, both in answering questions concerning the organization of beginning computer classes, and in suggesting promising future research.

In the early 70's, Bateman found the IBM Programmer Aptitude Test (PAT), together with college GPA, classification (credits accumulated), SAT math score and major effective in predicting student grades (Bateman, 1973). Later, however, in a much larger study, Mazlack (1980) found the Programmer Aptitude Test unreliable as a predictor. Using Pearson Correlation Coefficients, he found no correlation between the three parts of the PAT and the grade components (quizzes, homework, midterm and final). In addition, he found no correspondence between the grade components and the student's academic discipline, gender or semester in school. Differences in these two studies might be due to the subject presentation or perhaps the advent of the microcomputer resulted in a different mix of students attempting a computer science course.

Table 1(a) A Comparison of Existing Studies

	Petersen & Howe 1979	Kurtz 1980	Barker & Unger 1983	Wileman Konvalina Stephens 1981	Konvalina Wileman Stephens 1983
Age				yes	yes
Gender	no				
Major	no	no			
Class	no	no			
GPA-college	yes				
CompSci					
Science					
Math	no	no			yes
HS GPA,rank	yes,yes			yes	yes
HS CompSci					
HS Math	yes				no
HS Sci	yes				
HS Eng					
ACT/SAT					
IQ	yes (GATB)				
Personality	some				
Cog.Style	(Thurstone Temperament Schedule)	no (hidden figure)			
Work exper.					no
# work hrs				no	no
Program?				no	no
Pretest		Piaget	Piaget2	Math	Math2
Signf?		yes	yes	yes	yes
Number	340	(na)	(na)	183	382
Final N	232	23	353	96	165
Statistics	StepRgr .40 Correl mixed	ANOVA F=19.9 ChiSqr 22 Correl .7954	ANOVA F=3.46 ChiSqr 7.257 Correl .11615	StepRgr .50	Correl .56 t-test 0.01 Regres .25
Depend.Var	Grade	Grade	Grade	Final	Final
Reliablity		ConfLev	ConfLev	K-R#20	K-R#20
Language	WATFIV	WATNOW	2 (na)	PL/C	PL/C
Other	2semster Literacy	25% Non English			

* (na) = not available

Table 1(b) A Comparison of Existing Studies (continued)

	Bateman 1973	Mazlack 1980	Newsted 1975	Fowler& Glorfld 1981,82	Hostler 1983	Cheney 1980
Age				yes,no		
Gender				no		
Major	yes	no		no		
Class	yes	no	no	no		
GPA-college	yes			yes	yes	
CompSci						
Science						
Math				yes	no	
HS GPA,rank			no			
HS CompSci						
HS Math						
HS Science						
HS English						
ACT/SAT	yes SAT-M SAT-V		no Entrance Exam	yes SAT-M		
IQ			no (self perceived)			
CS Work Exp.			yes			
Personality			no		yes 16PF	
Cog.Style						yes (Analytic)
Pretest	IBM	IBM		Wolfe	CPAB	
signf?	yes	no		no	yes	
Number	(na)	2000	472	200,150	120	(na)
Final N	71	1350	131	151,147	79	35
Statistics	StepRgr .60	Regres .40 Correl low	StepRgr .41	Logistic Discrim .7	StepRgr .65	Spearman .82 t test .01
Depend.Var	Grade	Grade	Grade	Grade	Grade	Grade
Reliablity			Split1/2		Cross Valid.	K-R#20
Language	FORTRAN	WATFIV	FORTRAN	(na)	WATFIV	BASIC
Other	Literacy 2semster	6semster	BDP	BDP	BDP	BDP

* (na) = not available

Table 1 (c) A Comparison of Existing Studies (continued)

	Campbell McCabe 1984	Nowaczy 1983	Sorge & Wark 1984	Whipkey Stephens 1984	Butcher & Muth 1985
Age		no			
Gender	yes	no	yes		
Major		no			
Class		no			
GPA-college					
CompSci					
Science					
Math					
HS GPA, Rank	yes		no		yes
HS CompSci	yes		no		no
HS Math	yes		yes		
HS Science	yes	yes	yes		yes
HS English	no	yes	yes		
ACT/SAT	yes SAT-M SAT-V		yes SAT-M SAT-V	yes SAT-M SAT-V	yes ACT all
IQ					
Personality		no anxiety		no MBTI	
Cog.Style		no LocusCtl			
Pretest		Logic	Trig		
Signif?		yes	yes		
Number	256	301	1323	(na)	372
Final N	(na)	286	1071	88	269
Statistics	Discrim. Analysis Wilk's L	ANOVA 3x6	Regres (na)	Regres .59 Correl moderate	Regres Correl mixed
DepVar	StayInCS	Grade Course	StayinCS	Grade	Grade Exam
Reliablity					
Language	Pascal	WATFIV		(na)	PL/1
Other	Persist Only	&COBOL &AdvProg	Persist Only		

* (na) = not available

The lack of correlation between grade and other factors is partially supported by other results and might be interpreted to imply that there is no need for different class sections for differing disciplines and levels of academic experience (Peterson, 1979; Kurtz, 1980). However, investigators at the University of Nebraska, Omaha found that previous math and computer science educational experience in both high school and college was significant, and they plan to add mathematics classes as a remedy for students who make a low score on their predictor exam (Konvalina, Wileman & Stevens, 1983). They also looked at work experience, both number of hours worked and programming experience, but found low correlations. However, they were comparing to the final exam grade, while most of the other studies used a composite course grade. A number of possible predictive factors have been identified in the various studies, but they have not all been compared consistently in the same study.

Two interesting predictive examinations have been developed. One, developed by Kurtz, uses Intellectual Development. This is the ability of students to think abstractly, a concept from Piaget (Kurtz, 1980). Drawing on the work of a number of cognitive development researchers, Kurtz constructed a test of 15 items in ten areas of formal reasoning to divide students into "late concrete", "early formal", and "late formal" intellectual development (ID) levels. In Kurtz's pilot study, all late formals made an A or A-, all late concretes received a C- or lower and most early formals made average grades, B to C+, with a few making higher or lower grades. The intellectual development score was largely independent of specific school achievement. While ID levels were higher for women than men, this sex difference was not significant in the ANOVA. The ID level explained 66 percent of the variance in the class grade with the means for the ID level significant at the .01 confidence levels. ID level explained over 80 percent of the variance in the total test scores, but only 39 percent of the variance in homework scores. These outcomes are high by behaviorial science standards, but results were available only for his class of 23 students.

Barker and Unger shortened the test and administered it to 353 students taught by 10 instructors in 15 sections learning two different programming languages (Barker & Unger, 1983). Their ID versus course grade correlation was only 0.11615 as compared to 0.7954 for Kurtz. The mean of the late concrete level and the means of the early and late formal levels was significantly different at the 0.05 level. Students considered late formal showed a trend to high performance (73 percent received an A or B), while students considered early formal, 55 percent received an A or B. Only 34 percent of the students considered late concrete received an A or B. Some of the variance in the second study is doubtless due to the wide variety between the instructors and between the two languages. Despite the lack of uniformity in these studies, the ID predictor shows promise and should be tested further.

The second predictor examination, developed by Wileman, Konvalina, and Stephens (1981), focuses on the important role of mathematical reasoning ability in predicting computer science aptitude. Their first exam contained 30 items and was divided into five components: reading comprehension, alphabetic and numeric sequences, logical reasoning, algorithmic execution, and alphanumeric translation. The exam is used to determine whether students will start in the beginning majors course (CS1 in Curriculum '78) or in the non-majors "Computers in Society" course. Based on their success, they revised the examination (four times in five years) to include additional demographic, academic and work factors together with 25 questions covering four components: sequences and logic, calculator simulation, algorithmic execution, and word problems (Konvalina et al, 1983). The most current version of the test yielded a correlation between the predictor and the final of .56. However, factors in the regression equation accounted for only 25 percent of the variance. Both predictor and final were tested for reliability using the Kuder-Richardson #20 measure with good results. Use of the predictor has reduced withdrawal rates in their beginning class from 40 to 23 percent. Since a copy of the exam is included with the article, it would be easy to validate this exam in other schools over a wide variety of students, classes and languages.

Many other aspects could be investigated in attempting to predict student performance. Newsted, interested in Weinberg's emphasis on work habits and personality, mailed a questionaire to three classes of students who had already completed the beginning Business Data Processing class (Newsted, 1975). Only 131 of 472 forms were returned and all factors are self-reported. Self-perceived ability and GPA were significant, while the time that a student spent on the class entered negatively, to explain 41 percent of the variance using a stepwise regression. Other personality factors, college status, experience and typing ability did not enter the equation. Newsted concluded that programming ability is more inate than suspected, and that students probably can learn to program in an interactive mode with far less direction than is given now.

The effects of personality factors on programming are just beginning to be investigated by software psychologists. In the behavioral sciences, there is interest in studying effects of self-esteem, cognitive style, locus of control, and other similiar factors, which might be relevant for predicting success in computer science. Little work has been done in investigating whether any of these variables affect success in programming classes.

Hostetler (1983) recently conducted a study in which he looked at the Computer Programmer Aptitude Battery (CPAB) and the Sixteen Personality Factor Questionnaire (16PF), both of which were significant in predicting success in a computer literacy course for business majors. The most important variables in the regresion were both subtests of the CPAB and the students's GPA. Mathematics background and several of the personality factors also entered the regression though they were not significantly correlated to grade and added little improvement to the regression. Cheney (1980) administered an instrument developed by Barker, which divided students into Analytic or Heuristic thinkers. Analytic students were found to perform significantly better on a programming examination given to a class of 35 business students. Another business data processing study by Fowler and Glorfeld

(1981) found GPA, the SAT math subtest, number of mathematics classes, and age to correlate to student grade. Using logistic discriminate analysis, they were able to correctly classify 75 percent of the students in the study. In a validation study (Glorfeld & Fowler, 1982), the model was effective in discriminating between high and low aptitude students, though it was decided to drop age from the model. Other variables examined, but not included in the model were sex, race, veteran status, marital status, major, student classification, and whether the course had been taken before. The Wolfe Programming Aptitude Test (WPAT) was given, but did not enter the model. While business students differ from computer science majors, these results give helpful information for predicting success in a first computer course. The introductory classes used in these studies includes programming, but other topics such as data processing concepts and the social implications of computers are usually included. These studies would be more relevant if an advanced course, which involved more computer programming, had been used.

It would also be interesting to follow students through several programming classes to see if initial evaluations of students in the introductory classes continue to be significant as they progress. This introduces considerable complexity, but several studies have shown that programmer behavior changes dramatically between the novice (one class) and intermediate (two or more classes) student (Moher & Schneider 1981; Brooks 1980). This would also help to determine factors which influence long term success in computer science majors, which is ultimately of greater importance.

Campbell and McCabe (1984) used discriminate analysis to examine differences between students who remained in computer science, engineering or other sciences and those who changed to dissimilar fields after their freshman year. SAT mathematics and verbal scores, high school rank, sex, and high school mathematics and science background were found to be significant. In a similar study conducted at Purdue over several years, Sorge and Wark (1984) found that sex, SAT scores and results of an algebra-trigonometry placement exam correlated with satisfactory progress in the computer science major. Neither class rank, nor average grade, nor number of semesters of high school mathematics, science and English added to the regression analysis, which defined satisfactory progress as enrolling in four consecutive computer science courses. Forty one percent of the students meeting their criteria still did not continue as majors however, and they suggest that factors other than academic ability must be involved.

Butcher and Muth (1985) were able to predict performance in an introductory computer science course using any two of high school GPA, ACT mathematics or ACT composite scores, but they explained only 37 percent of the variation in the grade with their regression equation. All of the ACT subtest scores, high school rank and percentile position, and number of high school math and science classes, all correlated with grade in the course, though size of high school and number of high school computer science classes did not. This study also looked to see how students who did not meet the department's new admission criteria would have fared, and found that one third of these students also did well in the course. Thus, they conclude, that motivation must be an important factor which should be considered.

There is no universal agreement on the importance of any one of the factors examined in these reports. Most studies showed student major, class (number of accumulated credits) and work experience not to be significant, while high school GPA, scores on national standardized tests and some predictor examination scores were significant in predicting success in beginning programming classes. It does seem puzzling that previous math, computer science or science classes taken gives such inconsistent results.

Studies which compare a number of these possibly predictive variables consistently are needed.

A good predictor examination would be a most worthwhile tool for computer science departments. Very few programmer examinations were found in the latest, Mental Measurements Yearbook (1978). Current achievement examinations include only the Certified Data Processor examination for business data processors, the Graduate Record Examination for computer science graduate students and the ETS Advanced Placement examination for high school students. The IBM exam attempts to predict success, but was shown significant in one study and not in another. Two promising examinations have been developed, but these need to be refined. The effects of personality were touched on in one study but a great many possibilities remain to be investigated. A review of general academic success factors studies would be useful in determining a possible starting point. Campuses vary widely, as do beginning computer science classes and grading methods. Clearly, much work remains to be done.

Piaget

In a professional career that spanned 60 years, Piaget produced over 40 books describing ideas in his two fields of interest, biology and epistemology. His research on the growth of children's intellectual development through their understanding of basic concepts in mathematics and science is of particular interest. Piaget believed that each person inherits physical structures which set basic limits on their intellectual functioning, though most of these functions improve through physical maturation. The newborn's reflexes are quickly changed into structures which incorporate the results of experience. One of Piaget's general principles of functioning states that all species have the tendency to organize their processes. Another describes the idea of adaption, which is made up of accommodation and assimilation. Accommodation relates to the organism's tendency to modify its structures according to the pressures of the environment, while assimilation describes the use of current structures to deal with the environment. Organisms strive for equilibrium, a balance between existing structures and the environmental requirements. Thus, Piaget is neither maturationist nor an environmentalist, but rather an "interactionist." That is, intellectual development results from an exchange between internal and external factors (Ginsberg & Opper, 1979).

Piaget outlines four stages of growth, sensori motor (birth to two years), pre-operational (two to seven years), concrete operational (seven to eleven years) and formal operational (twelve into adolescence). He describes the sensori motor period in terms of (six) stages through which infants move during the first two years. Children cannot skip a stage, but move gradually from one to the next. Behavior is not lost, but rather, new behavior is added at each stage. Piaget incorporated some ideas from Freud in his early work, but later, he moved from studying children using verbal exchanges to observing children's physical manipulation of their environment.

From age two to four years, the child gains the capacity to form abstract mental representations, the semiotic function. However, the preoperational child is not able to deal with several aspects of a situation simultaneously. Thus, the child is egocentric and has a tendency to group things which are unrelated, and to fail to see existing relationships. Through social interation the child begins to "decenter" and gain perspective. The five to seven year old can sort and even construct hierarchical organizations, but cannot comprehend "classes", or inclusion relationships. This comes later in the concrete operational stage, along with the ability to construct equivalent sets of objects, a task involving a number of operations. The concrete operational child gains the concepts of number, conservation and reversibility. Other important abilities include improved kinetic imagery, memory and cognizance, which greatly expands their understanding of the environment (Ginsberg & Opper, 1979).

Adolescents' formal (mental) operations reach a degree of equilibium, that is, their thought is flexible and they can deal with complex problems of reasoning. Unlike the concrete operational child, the adolescent can deal with hypothetical propositions. In these studies, adolescents were given problems based on simple principles of physics, chemistry and other sciences. Given some piece of apparatus, they were asked to explain how it worked. Each was allowed to manipulate the equipment while the investigator quietly recorded their activities, occasionally asking for clarification. Piaget developed two logical models of adolescent behavior, the 16 Binary Operations and the INRC group (Identity, Negation, Reciprocity, and Correlativity). These highly mathematical models describe rules used to manipulate or transform logical relations (Piaget & Inhelder, 1958). While not everyone agrees with his logical systems, few child development theorists have produced alternative models, despite the necessity of such a model for the development and testing of theories.

Piaget suggests that there are basic differences in scientific reasoning between young children and adolescents. With age, there are improvements in experimenting systematically, designing tests, isolating variables, appreciating problem complexity and drawing conclusions. Some adolescents and adults fail to demonstrate the use of formal operations, but he felt that this was due to lack of environmental stimulation or to experimental bias, or perhaps, he hypothesizes, all can use formal operatons when they are truly interested in the situation.

Four major factors are said to influence development. Mental development requires more than maturation; cultural factors also effect cognitive function. Second, both physical experience and "logico mathematical" experiences, are required. "Social transmission" (acquiring knowledge by reading, instruction, and so on), while important, is itself influenced by the individual's cognitive structures. Finally, Piaget stresses the role of internal conflict which leads the child through progressively more effective states of equilibrium. Piaget distinquishes between learning in the narrow sense, acquisition of particular responses in specific situations, and learning in the wider sense, gaining of more general cognitive structures. Development occurs as a result of self-regulating processes involving the four factors, not just through learning in the narrow sense (Ginsberg & Opper, 1979).

Piaget does not address education specifically, though many implications for education can and have been drawn from his research and theories. One of his major contributions is his extensive data on the development of basic mathematical, logical and scientific concepts in children, and as a result, on the general development of thinking.

Piagetian Issues

Piaget wrote extensively and modified his ideas throughout his career. Research, while already extensive, has only begun the experimental testing of his concepts. Although there is considerable agreement with his early stages, measuring formal operational levels in adolescents has met with less success. Methodological considerations, especially those surrounding group tests, make choosing a test of Piagetian development level difficult. Some researchers feel that Piaget's ideas are inadequate to explain complex problem solving situations and propose the information processing model instead. A brief description of the information processing model is provided below. How this model relates to computer programming, and whether it can be used to predict success in a beginning computer science class, are addressed in ;ater paragraphs.

Group Tests

Abundant research surrounds Piaget's theory of cognitive development. Several researchers' efforts have centered on relating developmental level with instructional strategy. However, Piaget favored individual interviews requiring special equipment and extensive interviewer training to determine development level. Unfortunately, this process is too time consuming for classroom use.

Recent efforts have concentrated on the writing of "pencil and paper tests" to be given to groups. Major group tests are outlined in Table 2.

Debate rages on the proper methodology for Piagetian tests. Nagy and Griffiths, in an extensive critical review, conclude that "there is questionable relationship between the observed products of mental effort and their underlying mental strategies." They feel that, rather than a one-to-one relationship, there is a many-many relationship between the student's solutions and their strategies. In their judgement, no effective group tests have been developed; existing standardized tests seem to

Table 2 Comparison of Piagetian Tests

	Raven	Staver &Gabel	Shayer Adey & Wylam	Lawson	Longeot	Gray
Date	1973	1979	1981	1978	1965	1973
Name	Raven's Test of Logic. Oper.	Piaget Logic. Opera tions	Test of Science Reason	Class- room Test of Log.Oper	Longeot	Piaget based written criter. refer.
Abbr.	RTLO	PLOT	TSR			
# Sub tests	7 classif seriate logic* compens propor. probab. correl.	4 conser ctlofvar combine propor.	(na)	15	4 propos. propor. combine classincl	3 propor. combine exclus.
#Items	(na)	(na)	(na)	15	28	36
Multiple	yes	yes +written	yes	no	yes	written
#Choices	3	4	(na)	-	3	-
Level	(na)	Formal	2A-3B	Formal	2A-3B	2A-3B
Valid?	FacAnal Expert	Intview CAT+L&T	Intview Discrim	KR-20 FacAnal	Intview FacAnal	Converg Discrim
Nagy Eval.	Not Satisf.	Not Satisf.	Best	Critical	Serious Doubts	Fair

(na) = not available

Note: 2A-2B early-late concrete
3A-3B early-late formal

be as effective. Problems with arbitrary scoring systems, lack of communication between the investigator and subject, and criteria changes between subtests are the major complaints.

Additionally, since the types of questions needed to understand an individual's thought processes are unique to the individual, only an interview is adequate to the task of determining intellectual development. Even so, the reviewers are nearly as critical of the interview studies as they are of the group test studies. The critics suggest that intellectual level depends on the subject, thus, researchers should study the concepts and strategies required in the particular subject area, rather than formal thought in general. While some have suggested combining the Gagnean and Piagetian models, Nagy and Griffiths (1982) believe that these models are too dissimilar.

After validity studies which compare written test results to individual interview results, Stefanich, Unrue and Perry (1981) are similarly reluctant to use the three instruments which they examined (Lawson's Classroom Test of Formal Operations, Burney's Logical Reasoning Test, and Ankney and Joyce's Reasoning Test), stating that the tests are of limited value for experimental study, especially when applied to individuals. They agree with Lawson

(1978) that the instruments should be used for helping teachers understand the nature of concrete and formal thought processes and for adapting current curriculum, teaching and evaluation methods to the Piagetian paradigm. In the design of their test, Shayer (1981) and Lawson (1978) sought to compromise by having an instructor use laboratory apparatus in a class demonstration format with the students responding to spoken questions by writing their answers in individual test booklets. PLOT (Piagetian Logical Operations Test) provides an objective, multiple-choice test with at least one cognitive trait presented via videotape in order to overcome the "inherent nonstandardizations associated with the clinical method" (Staver & Gabel, 1979).

Piagetian Tests and Cognitive Style

Neimark (1981) reviews a number of studies which give evidence of a "nonuniversal incidence of formal operations." Subgroups of the population which perform at a lower level include the aged, the less educated, members of other (especially non-Western) cultures, and in some studies, women. However, Neimark feels that critics who conclude that Piaget's theory is incorrect and must be forsaken are wrong, as the critics do not offer an alternative theory with which to replace Piaget's. She argues that performance bias introduced by cognitive style factors, such field dependence/independence, together with the ambiguous instructions used in most tests, provide sufficient explanation for failure to establish the existence of Piaget's final stage of adult thought. Neimark cites studies which provide evidence of such interaction between cognitive style and Piagetian task variables (Linn, 1978; Pascual-Leone and Goodman, 1974). Earlier stages are more easily explained due to more similar maturation and environment, together with more structured, less verbal, experimental procedures. She believes that using standardized tasks with familiar materials, objective responses and unambiguous procedures will result in higher incidences of formal behavior (Neimark, 1981).

In short, since the relationships may be due to intelligence or prior teaching or perhaps cognitive style factors, it is difficult to measure and use the formal level of cognitive development. Piaget (1972) may have thought so too. In one of his later papers, he suggest that there is more diversity of aptitude with age in adolescence and "our fourth period can no longer be characterized as a proper stage...". These factors must considered when planning research in this area.

Information Processing Model

Usage of the information processing model has grown rapidly in recent cognitive development research. Beilin (1981) argues that the importance of information processing theory has grown concurrently with the lessening of interest in Piaget's concepts. He postulates that the major difference is that Piaget was mainly concerned with questions about structure, while information processing researchers are mainly interested in questions about function. Groen and Kieran (1983) believe that "Piaget's theory is so subtle, ambiguous, and open to misinterpretation that it has simply been abandoned for a more manageable framework." In Piaget's later writings, he, himself, abandoned the idea that one must progress though a fixed set of stages. At an American conference on mental testing, Piaget stated that the child must tear down some partially reversible structures from the concrete stage and rebuild them in order to achieve formal operations (Green, Ford, & Flaser, 1971). Some of the pre-operational tasks, semi logics, are more closely related to formal operational thought than concrete. For these reasons, Groen and Kieran (1983) conclude that a synthesis of the two approaches, Piaget and the information processing model, might provide a better framework than either of the two individually.

Mathematics educators are also beginning to use the information processing conceptualizations. This paradigm allows consideration of the creative aspects, as well as drill and rote learning, both of which are required for the analysis of mathematical thinking processes (Davis, 1983).

Gestalt theory, a German school of psychology beginning in the early part of the century, was responsible for defining many of the basic phenomena of problem solving. The Gestalt psychologists studied the intuitive aspects of problem solving and showed how the pieces of a problem are used to structure a solution for it. The information processing model attempts to formalize these ideas so they are more testable. Information Processing theory, developed since World War II, depicts problem solving as a search through a problem space, where a problem space is all possible knowledge states that can be generated by applying the available operations to (pre-existing) knowledge states. There must be a selective search directed by a set of heuristics (Newell & Simon, 1972). The computer is used as a model for these problem solving processes. Computers are like humans in that they have:

1. Input and output devices for receiving information and displaying sorted or processed information;
2. A memory for storing information;

3. A processing unit for operating on information that is input or is in memory;
4. A control unit for ordering the processes (Moates & Schumacher, 1980).

A computer program is written which embodies the researcher's theory of the cognitive processes underlying the problem solving. The program is run and its results compared to those of a human solving the same problem. Thus, quite complex processes may be analyzed by comparing the computer's steps to those of humans. Computer programs have the advantage that they are objective, and all details must be explained precisely. While not perfect, these simulations allow researchers to clarify their thinking concerning problem solving processes (Moates & Schumacher, 1980).

Computer Programming

Little is known about cognitive processes in programming. Shneiderman (1980) suggests that programmers are expected to be able to compose, comprehend, debug, test, modify and design computer programs, as well as being able to learn new programming languages, operating systems, and hardware. Each of these skills is also required in a beginning programming class. Shneiderman proposes the use of the syntactic/semantic model, based on the information processing approach (Figure 1), as a framework for discussing the components of memory required for these tasks.

Short term memory holds information about the problem which the programmer has received from the outside world. Long term memory stores permanent knowledge, while working memory serves to integrate information from short term memory and long term memory. The problem solving process takes place in working memory, combining new information from short term memory, and existing information from long term memory, to form a solution.

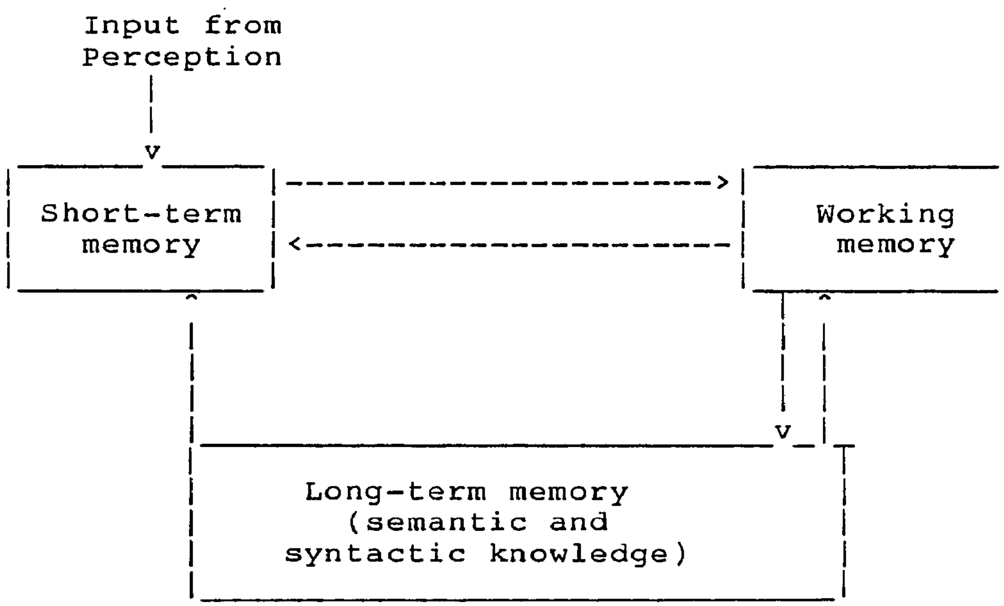

Figure 1. Components of memory in problem solving (Newell & Simon, 1972)

Semantic knowledge refers to the general concepts of programming which are independent of a particular programming language. Semantic knowledge is multileveled, ranging from low level ideas such as what an assignment statement does or what a subscripted variable is, to high level ideas such as binary searching strategies, sorting and recursion. Semantic knowledge is hierarchically organized and provides a structure upon which to assimilate new concepts and syntactic knowledge. (See Figure 2).

Syntactic knowledge contains the details of the programming language. Learning a first programming language involves assimilating both semantic concepts and specific syntatic information, while learning a second language generally requires learning only a new syntax. Syntactic knowledge is arbitrary and is easily forgotten, as it is not well integrated within the semantic knowledge

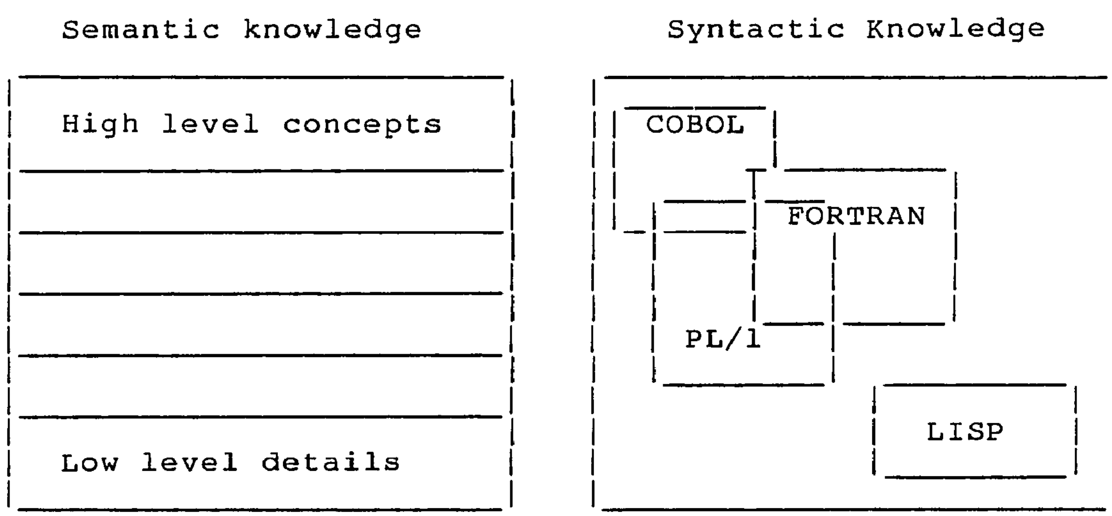

Figure 2. Syntactic and semantic knowledge in long-term memory (Shneiderman, 1980)

structure. Experienced programmers may learn a new language easily by relating it to their exisiting semantic knowledge; however, this semantic knowledge may interfere with learning a dramatically different programming language.

According to Shneiderman's syntactic/semantic model, program composition involves the following steps. The problem is given to the programmer, and it enters working memory through short term memory. There, general knowledge is recalled from long term memory and a solution developed. Ideally, a solution will evolve in a top down, or hiearchical fashion, starting from the highest, or most general level. The problem will be subdivided into subproblems and the process repeated until the desired solution is reached. Figure 3 illustrates the program composition process, the development of an internal semantic representation of a program.

When the internal semantics have been developed, writing the program is relatively straightforward. Program comprehension is a similar, multilevel process. The program can be understood at a high level with or without understanding the details, or the details can be understood without seeing the overall program structure. It is believed that programmers convert to internal semantics using the "chunking" process rather than by understanding the program line by line (Miller, 1956). Chunking encourages and is encouraged by the use of modular, structured programming, a basic concept taught in beginning computer science classes.

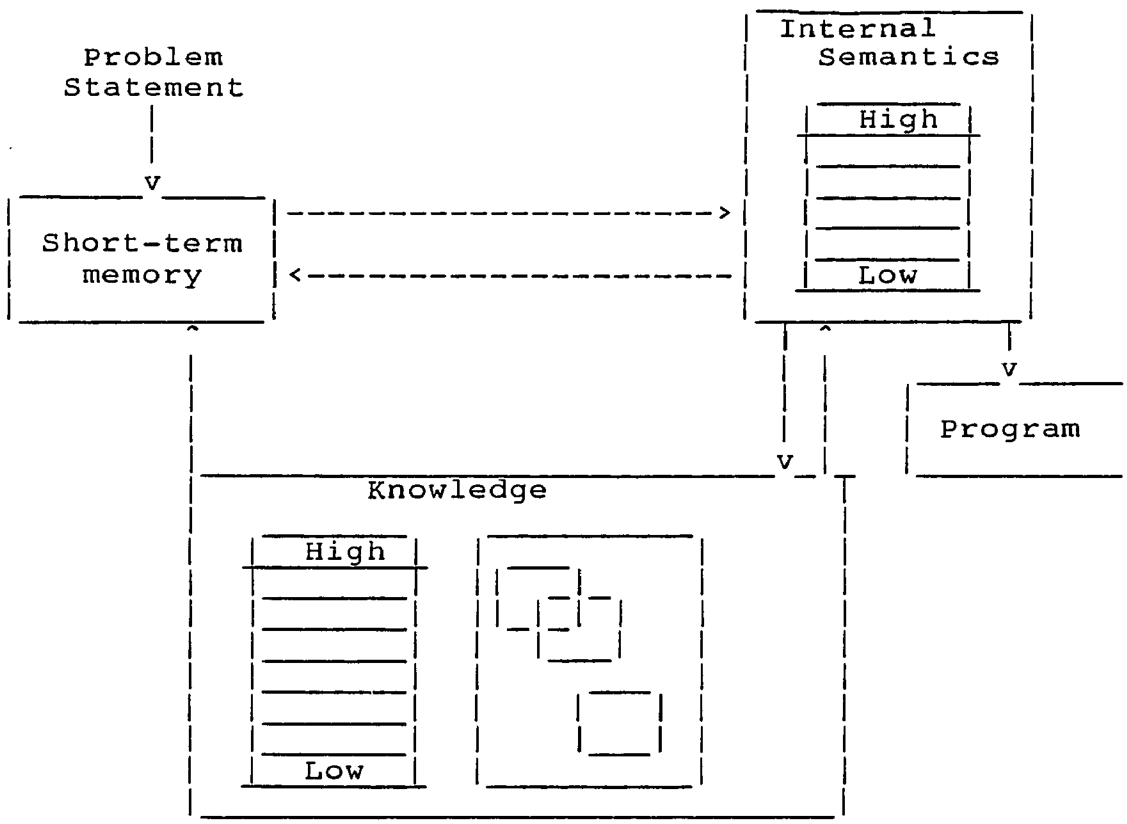

Figure 3. Program composition process (Shneiderman, 1980)

Debugging, or finding errors in a program, is a challenge in problem solving. Errors due to incorrect transformation of the internal semantics into program statements are signaled by unexpected results in the program's output. These must be detected and corrected by the programmer. Errors due to incorrect conversion of the problem into internal semantics may require that a new strategy must be developed and the composition tasks repeated. Program modification requires a combination of composition, comprehension and debugging skills. Beginning programmers must be taught a balanced combination of detailed syntactic and high-level semantic problem solving knowledge (Shneiderman, 1980).

The information processing model is of great interest to researchers and provides a more complete explanation of computer programming behavior. Computer programming is a form of problem solving in which the solution must be given as a series of instructions to the computer. Instructions are written using a simplified "programming" language, which has syntax and semantics, just as any "natural language does.

However, information processing model measurement, at this time, is limited to measuring such quantities as the speed of retrieval from long term memory, the number of items which can be "chunked" together, or memorization improvement skills. Intuitively, these do not seem to be as closely related to the reasoning skills required for computer programming as the abstract reasoning skills required to achieve Piaget's formal organizational level.

Cognitive Style

Cognitive style is a phrase used to describe differences between the way individuals process information. That is, how people think, solve problems, learn, perceive their environment, relate to others, etc. Cognitive style cuts across traditional boundaries used to compartmentalize human beings. They are stable over time. They are bipolar, and thus, a less threatening characterization than the usual ability measurements and designations (Witkin, Moore, Goodenough, & Cox, 1977).

Field dependence-independence, a term used by Witkin and his associates, refers to a person's ability to disembed simple figures from a complex background. It may be measured by a number of tests, including the Tilted Chair, the Rod and Frame Test, and a series of paper-and-pencil Embedded Figures Tests.

There is a high correlation between field independence and the analytical factor of the Wechler (IQ) test, though not with the attention concentration or verbal comprehension factor (Witkin, Oltman, Raskin, & Karp, 1971). Field independent learners find existing organization in a given situation, or if a pattern does not exist, they tend to impose structure on the field. Field dependent learners are the opposite. They are more likely to accept the field the way it is, and thus, may need more help in finding external structure or problem solving strategies. Witkin et al believe that field dependent individuals show greater continuity between self and nonself, which they term the "globally" experienced self, as opposed to the field independent individual who is more "articulated." In a similar fashion, field dependent persons are more responsive to social frames of reference and so enjoy being around other people, while field independent persons prefer a more impersonal or abstract orientation (Greene, 1976).

Studies at liberal arts colleges show little correlation between cognitive style and grade point average, though they do show a strong correspondence between field dependence-independence and career choice. Field dependent individuals favor a "people" emphasis in their job, and so choose a field such as business or one of the "helping" professions, such elementary school teacher or social worker. Field independent people tend to choose "structured" fields such as mathematics, science, engineering, the health professions, art or perhaps, teaching in these fields (Witkin, et al, 1977).

Sex differences are generally found. Women tend to be more field dependent than men, but women working for advance degrees in "male-dominated professions" were more field independent than women college graduates who were full-time homemakers in one study (Patrick, 1973).

Field dependence-independence, and especially its application to education, has been studied intensively in recent years. Field independent students prefer a more formal learning environment (Cawley, Miller, & Milligan, 1976) and show more intrinsic motivation (Grippin, 1976). In studies of college populations, field independent students achieve significantly higher grades and/or test scores in subjects such as mathematics, sciences, engineering and architecture, than do field dependent students (Witkin, et al, 1977).

Field dependent teachers are oriented toward student interaction, while field independent educators prefer the more cognitive aspects of teaching (Witkin, 1976). Numerous studies have shown a relationship between the cognitive style of the teacher, and the cognitive style of the student. A match in cognitive style encourages a greater interpersonal attraction due to share interests, shared personality characteristics and similar modes of communication (Witkin, et al, 1977). In another study, the highest grades are generally made by field independent students with field independent teachers, while the lowest grades were made by the field dependent student-teacher pairing. Naturally enough, students gave higher teaching evaluations to teachers of their matching cognitive style and lower evaluations where there was a mismatch of cognitive style (Daniel, et al, 1984).

While there is extensive research on cognitive style (Cox & Gall, 1981), little has been done to relate field dependence-independence to success in computer programming. Stevens (1983) found a significant relationship between score on the Group Embedded Figures Test and exam scores in a computer literacy course for teachers. The top one-third of 73 students were classified as field independent and the lower one-thind as field dependent in an analysis of variance study.

Hassell (1982) gave the Embedded Figures Test and two measures of programming ability to 28 sophomores and 19 seniors. The correlation was near .50 for the seniors on the two programming tasks, memorizing a program and finding errors in programs, but the correlation for sophomores was not significant.

Rogers (1983) did not find a significant relationship between grade in a beginning computer science course and the Group Embedded Figures Test (GEFT), but she gave the test to only 11 students, all but three of whom made the highest possible score.

Cognitive style has become increasing important in understanding not only of the cognitive processes involved in education, but also in understanding students' social behavior. Because of its high correlation with preference for, and success in, scientific fields sharing important characteristics with computer science, there is considerable potential correlation with success in computer science.

Personality Type

Weinberg, in his book (1971), introduced the idea that psychology and behavior played a significant role in computer programming, but few have followed his lead in exploring this aspect of understanding the computer programmer. Although Newsted (1975) did not find personality factors significant in his study, there is a personality test which has come into increasing use in educational testing and counseling.

The Myers-Briggs Type Indicator (MBTI) is a self-reporting instrument based on Jung's theory of personality type. Jung believed that human behavior was not random, but was orderly and consistent, based on the way people prefer to use perception and judgement. Perception includes the processes of becoming aware of people, things, or ideas. Judgement is how people come to conclusions about what they perceive. The MBTI includes separate indices for determining each of the four basic preferences which structure the individual's personality: Extroversion or Introversion, Sensing or Intuitive, Thinking or Feeling, Perceiving or Judging. Letters are used to represent the poles of these preferences: EI, SN, TF, and PJ. The Myers-Briggs instrument describes 16 types which result from the combinations of the four preferences. Everyone uses all eight preferences, but the four preferred modes are the ones most often and thus, the most successfully, used.

Myers (1962) states that using the Myers-Briggs Type Indicator (MBTI) adds little to efforts to predict grades, beyond that which is possible using SAT and high school grades. Using data from several of the outstanding liberal arts and engineering colleges in the country, she does show significant correlations between the intuitve and judging dimension and grade point average for students at most of the liberal arts colleges, but very few of the engineering colleges. Students at some liberal arts colleges also show a correlation for introversion and GPA. Students at two of the engineering colleges show a correlation for the judging dimension and GPA. The only business school listed shows a significant relationship between both the judging and thinking dimensions and GPA. Thus, Myers reports the main contributions to scholastic success are I, N and J. Intuitives who are also introverted, have the highest mean IQ's and GPA's, regardless of their other two dimensions.

Eight university engineering school and the Center for Applications of Psychological Type have formed a consortium to study the effects of psychological type differences, as measured by the Myers-Briggs Type

Indicator (MBTI), on the educational and career development of engineering students. Data collected on 3,718 students during 1980 and 1981, showed that engineering students strongly prefer thinking (74 percent) and judging (61 percent). In fact, almost half the sample fell into the four TJ types. Students were almost equally divided between the sensing types (53 percent) and the intuitive types (47 percent). The males were also more introverted (56 percent). These results, together with national norms from Keirsey and Bates (1984) and results from the Whipkey and Stephens (1984) study are compared in Figure 4.

	Myers (1962)	McCaulley (1983)	Whipkey & Stephens (1984)		
	National Norms	Engineer Students	Computer Students	Computer Majors	College Freshmen
Number	(na)	3,718	88	44	11,122
Type					
Introversion	25	53	50	41	45
Extroversion	75	47	50	59	55
Perceiving	50	39	52	55	47
Judging	50	61	48	45	53
Sensing	75	53	68	73	56
Intuitive	25	47	32	27	44
Thinking	50	74	43	43	33
Feeling	50	26	57	57	67

* (in percentages)

Figure 4. Myers-Briggs Personality Type Comparisons

There are differences of course. Percentages varied strongly between the different schools, the different branches of engineering, between males and females, and between different ethnic origins. Unfortunately, complete figures were not given, so comparisons are not possible.

Of the 2,045 students studied during the first year, 27 percent had either left school or changed majors. Atypical students had lower retention rates. The practical, organized SJ type were 34 percent of the entering students but 40 percent of the students who continued in engineering. Another study, comparing seniors to freshman over a six year period, showed that the predominate thinking-judging (TJ) students had increased their percentage from 46 percent of the freshman to 55 percent of the seniors, while the intuitive and feeling types had decreased from 17 percent to 9 percent. (McCaulley, Godleski, Yokomota, Harrisberger, & Sloan, 1983).

In a two year study of the effect of personality type on learning and problem solving in a linear circuit analysis class, interesting correlations for sensing and intuitive students were found (Yokomoto & Ware, 1982). If instructors included at least one conceptual problem that was <u>not</u> "just like the homework," the correlation between homework and exam scores was higher for intuitive types, while if the instructor wrote exam problems that were "just like the homework," the correlation was higher for sensing types. This difference was confirmed by interviews with individual students. Students who fell in the sensing type related that they studied by doing homework problems and often forgot to learn concepts and principles, while intuitve types reported that they believed concepts were more important and felt that they did not need to spend so much time doing homework problems as long as they understood the ideas. Students were counseled on these differences in learning style and some students reported improved class performance (McCaulley, et al, 1983).

Of the 882 students and 44 faculty tested at the Colorado School of Mines, there was considerable similarity between faculty and student in the three dimensions involving introversion-extroversion, perceiving-judging and thinking-feeling. There was substantial difference on the fourth dimension: faculty were 77 percent intuitive while the students were only 54 percent intuitive. In a small study of two classes of freshman engineering students, intuitive students in the class taught by an intuitve instructor did considerably better on the examinations than did the sensing students. The classes were almost identical in terms of type, but one instructor was primarily sensing and the other primarily of the intuitive personality type (Sloan & Jens, 1982).

Myers (1962) believes that the sensing-intuitve factor is the most important preference for the teaching learning process. Intuitives prefer theory and generalities, while sensing types like to work with concrete examples and experiential learning. Intuitive and introverted types average higher scores on aptitude tests than do their corresponding sensing and extroverted types. These standardized tests tend to favor the students who excel in dealing with abstract ideas (intuitives) and conceptual thinking (introverts). Since timed tests favor the intutives, Myers recommends that "power" tests be used instead. McCaulley (1983) argues that typical college admissions criteria do not adequately measure the skills of the either the realistic and practical, sensing, students or the successful, extroverted, business student. In fields such as engineering where these skills are an asset, not a liability, she believes that both admission criteria and classroom teaching should be changed to encourage these desirable traits.

Few studies which compare personality type to success in a beginning computer science course exist. Whipkey and Stephens (1984) gave the Myers-Briggs Type Indicator (MBTI) to 88 students in a first computer programming course at a small liberal arts college. They found a significant relationship between the average score on three examinations in the class and the students' SAT verbal score, SAT mathematics score and QPA (grade point average). They did not find a significant relationship between examination scores and Myers-Briggs personality types. The relationship did approached significance for the judging-perceiving index (R: $p < .10$); judging students tended to have higher exam scores than perceptive students. Using forward regression, their model explained 55 percent of the variance in the examination scores using only the grade point average; it explained only 59 percent of the variance using GPA together with both SAT and all four MBTI scores.

Compared to typical college freshman, these students are rather strongly extroverted, perceiving, sensing, and feeling. (See Figure 4.) Comparing the percentages from Myers (1962) (only male figures available) for engineers and liberal arts majors from highly selective schools, the male students exhibit double the percentage of sensing types expected. The high percentage of women very likely accounts for the higher percentage of feeling types, but evidently, both male and female sensing students are represented in unusually high numbers in this computer programming class. These students also demonstrate a rather high percentage of extroverted types, with computer majors even more extroverted than the average for the class - not the stereo-typical image of the computer programming student.

Engineering schools and computer science departments are faced with many of the same problems related to rising enrollments combined with limited resources. Despite the use of predictors such as high school grades and results on national tests, many students are lost during their college years. These students represent both lost resources and lost opportunities to students who were denied admission. These studies show that results from the Myers-Briggs Type Indicator may be helpful at least in predicting which students will persist in a given major. MBTI results may also be useful in making both students and faculty aware of the strengths and weaknesses of the various personality types, which could lead to improved teaching and learning strategies and ultimately, to more success in the classroom for students.

Summary

While existing studies of success in a beginning computer science class have looked at personal, academic and work-related factors, intellectual development, cognitive style and personality type, individually, no study has simultaneous compared the results of all of these possibly predictive variables, nor have the cross factor correlations been examined. A model which combines most or all of these characteristics of the beginning programmer can add greatly to our understanding of the cognitive processes involved in computer programming, as well as yielding valuable information for improving the teaching of computer science and ultimately improving the performance of students in a beginning computer science course.

CHAPTER III

RESEARCH DESIGN AND PROCEDURES

Statement of the Problem

This study investigated the relationship between selected personal, academic and work-related variables and the student's grade in a first college course in computer science. Standard measures of cognitive development, cognitive style and personality factors were also given and compared to the student's grade in the course. The purpose of the study was to determine factors which effectively predict success in a beginning computer science class. A secondary goal was to develop a model of the computer science student in order to improve teaching effectiveness. The following questions served as a basis for collection and analysis of data:

a. Do the demographic factors sex and age effect success in a beginning computer science class?

b. Do academic variables such as student classification, high school grades, college grades, number of years of high school mathematics, or number of college mathematics classses effect success in a beginning computer science class?

c. Do work related variables such as the number of hours worked, computer-related work experience, non computer-related work experience, or programming work experience effect success in a beginning computer science class?

d. Does the cognitive style factor, field dependence independence, effectively predict success in a beginning computer science class?

e. Does the cognitive development level as described by Piaget effectively predict success in a beginning computer science class?

f. Does personality type as determined by the Myers-Briggs Type Indicator effect success in a beginning computer science class?

Research Design

This study of success in a beginning computer science class was conducted using students in CSC 135, Computer Science I, during Spring semester, 1985, at the University of Nevada, Las Vegas. Early in the semester, students in all three sections of CSC 135 were given the Group Embedded Figures Test in class. They were also given the Piagetian Test of Intellectual Development, the Myers-Briggs Type Indicator and a demographic questionnaire to be completed at home and returned to class. A letter requesting their voluntary participation was included. See Appendix A for copies of the letter and questionnaire.

All demographic factors, including academic and work-related variables, as well as the measures of cognitive style, intellectual development and personality type were cross tabulated with the students grade in the class. Chi square and Pearson's product moment coefficient were computed for all relationships. In addition, demographic factors, including academic and work variables, were cross tabullated with the cognitive style, the intellectual development and the personality type measures. The Chi Square and Pearson's product moment coefficient were computed for these as well.

Subjects

CSC 135 is the first college level course for computer science majors. Students learn problem solving methods and algorithm development using the programming language Pascal. The course emphasizes program design, coding, debugging and documentation using techniques of good programming style. This course follows the curriculum recommended by the Association for Computing Machinery (ACM) and is the first semester of a two semester sequence tested by the Advanced Placement exam in Computer Science.

Students in Computer Science I were primarily computer science or computer science engineering majors, but there were a few students from other majors, largely business and science or engineering. There were a few undeclared majors and graduate students.

Measures

Personal, Academic and Work Data

Personal, academic and work-related data was collected using multiple choice questions. Requested information included: sex, age, a self-reported measure of high school and college grades, student classification, the number of high school mathematics classes, and the number of college mathematics classes. In addition, the amount of computer-related work experience, the total number of hours worked per week, and if appropriate, whether the job included programming or non-computer related work was requested. These questions provide a profile of the student population and they parallel data collected in some of the earlier studies.

Measure of Cognitive Style

The Group Embedded Figures Test (GEFT) (Witken, Oltman, Raskin, & Karp, 1971) is a standardized instrument which measures field dependence-independence. Field dependence indicates that the person's perception of an object or situation is strongly influenced by the overall organization, while the field independent individual is more likely to differentiate parts from the whole. This behavior is believed to hold over a broad array of activities. In particular, field dependence-independence has been shown to be related to problem solving tasks where the solution depends on the use of some object in a different context. There is also a high correlation between field dependence-independence and the analytical factor of the Wechsler (IQ) tests, though not with the verbal comprehension or attention concentration factors (Witken et al, 1971). Numerous studies have illustrated the educational implications of field dependence-independence with emphasis on the differences in both career choice and in teaching and learning style preferences. Field independent students tend to choose careers in mathematics, science and other "structured" fields and to avoid those with a "people" emphasis (Witkin et al, 1977).

The Group Embedded Figures Test is a timed test, requiring 12 minutes, not including instruction time. A high score on the GEFT indicates an ability to find a simple structure embedded in a complex structure. The measure consists of a number of complex line and shading drawings, and a set of simpler line drawings. For each complex drawing, the subject is asked to find and trace a simple drawing embedded in the complex drawing. There are three sections, but the first is only a two minute practice section and is not scored. Two sections of nine items each, to be traced in five minutes, are scored. The simple figure must be traced completely for the item to be scored as correct. Eighteen is a perfect score.

The GEFT is a group form of the "parent" test, the Embedded Figures Test (EFT). For college students, there is a high correlation between GEFT and EFT, though not so strong a correspondance with the original test, the Rod and Frame Test. The EFT has been in use for over thirty years and shows a high (split halves) reliability over many age groups (Witken, et al, 1971).

Measure of Intellectual Development (ID)

The second measure separates students into three categories, Concrete, Early Formal and Late Formal, according to Piaget's stage theory model (Inhelder & Piaget, 1958). This instrument, the Formal Reasoning Test, is not standardized, but has been used in two other investigations of students in computer science courses (Kurtz, 1980, Barker & Unger, 1983).

Kurtz, in his study of 23 students, found a good correlation (Pearson's R = .7954) between the Intellectual Development level and success in a first programming course. Barker and Unger, with a larger group of 353 students, did not find a high correlation (R = .11615), though the test did separate high achieving students from those with average and or below average achievement. Both recommend the instrument for advising students in computer science classes.

The test consists of 15 questions in the original form. Barker and Unger shortened the test to 11 questions by eliminating duplicate questions that measured the same ability. The shorter version was used in this study. The test was designed to be given during a 45 minute class period, with students taking as much time as desired. The eleven question groups with their ID level are:

Group	Number	Type	ID Level
1.	1.	Conservation of Volume	Late Concrete
2.	2.	Inverse Proportion	Early Formal
3.	3.	Probabalistic Reasoning	Early Formal
4.	4.	Permutations	Late Formal
5.	5.	Correlational Reasoning	Late Formal
6.	6.	Separation of Variables	Early Formal
7.	7-10.	Propositional Reasoning I	Late Formal
8.	11-12.	Deductive Logic	Early Formal
9	13.	Direct Proportion	Late Concrete
10.	14.	Combinations	Early Formal
11.	15-18.	Propositional Reasoning II	Late Formal

Some questions consist of several parts, all of which must be correct to receive credit. Two questions on propositonal reasoning are included and success on either one is counted as correct for that question type.

Test items were collected by Barry Kurtz from several different sources, which were availabe to him when he worked at the Berkeley Hall of Science with Anton Lawson and Robert Karplus, both of whom are well-known for their work in measuring Piagetian stages. In conversation with Dr. Kurtz on the reliability of a pencil and paper test of Piagetian ID level, he agreed that there were problems with such a test, but for a test for college students designed to measure only the upper levels, such a group test was feasible.

Scoring in the current study followed the method used by Kurtz and by Barker and Unger. Subjects were classified into three groups. Students failing to answer both the direct proportion and conservation of volume questions (1 and 13) were classifed as Late Concrete. Students were classifed as Late Formal if they were not classified as Late Concrete, and they received credit for three of the following four areas: correlation, permutation, deductive logic, and propositional logic (4, 5, 11-12, and 7-10 or 15-18). Otherwise, students were classifed as Early Formal.

Measure of Personality Type

The third measure uses Jung's theory of type to assign indices for determining each of four basic preferences which structure the individual's personality. The EI (Extroversion or Introversion) index shows whether the person is primarily an extrovert, who is oriented to the outside world of people and things, or an introvert, who is oriented to the inner world of concepts and ideas. The SN (Sensing or Intuition) index mirrors the person's preferred method of perceiving the outside world. That is, whether he/she is made aware of things directly through the five senses or indirectly through intuition and the unconscious. The TF (Thinking or Feeling) index reflects the person's preferred method of judging. That is, whether he or she prefers thinking or logic as opposed to feeling or value. The JP (Judging or Perceiving) index indicates whether the person uses judging or perceiving attitude in dealing with the outer world. That is, whether he/she prefers a planned, orderly way of life or a more flexible, spontaneous style of living (Myers, 1962).

The test consists of dual choice, forced answer, items. Subjects are encouraged to work rapidly, giving their first choice without agonizing, though the test is untimed. If a subject is not able to choose, without explanation or interpretation of the items, they were instructed to leave the item blank.

Each item yields one of two letters for one of the four personality indices. Each subject receives four preference scores, consisting of one letter for each personality index, EI, SN, TF, and JP. The choice of one of each pair of indices is based on the students answers to the dual choice questions.

For example, for the Introversion/Extroversion index, a typical question might look like:

When you are with a group of people, would you usually rather
(A) join in the talk of the group, or
(B) talk with one person at a time?

For the Intuitive/Sensing index, one question is:

Would you rather be considered
(A) a practical person, or
(B) an ingenious person?

Some questions involve choosing one word from a pair of words. For the Thinking/Feeling index, a typical choice of pair of words would be:

(A) justice mercy (B)

For the Judging/Perceiving index, a choice would be:

(A) systematic casual (B)

An answer of A to the first question would give the subject one point for Extroversion, while an answer of B would give a point for Introversion. An answer of A on the second question would give a point for Sensing, while B would count as Intutive. In the first word pair, A would count as Thinking with B counting as Feeling. Similarly, A would be credited as a Judging answer with B credited as Perceiving in the second word pair. The entire measure is scored on this basis.

At this point, contrasting index scores are compared, and the larger value choosen as the subject's "type" for that index. That is, if a subject answered 5 questions indicating an Extroverted personality type and 15 questions indicating an Introverted personality type, the subject would be considered to be Introverted or I. Ties are decided by choosing I not E, N not S, F not T and P not J. There is a slight adjustment in the score for TF based on the subject's gender.

This test is standardized and is often used in counseling students. Statistics are available for many types of students and schools. Reliability has been demonstrated using a logically-split-half procedure. Split half product moment correlations range from .80 to .94 with the median at .85 for freshman at high selective colleges, with figures from .76 to .88 with the median at .81 for regular academic 12th grade students. The TF index is somewhat less reliable than the others (Myers, 1962).

CHAPTER IV

FINDINGS

This study collected personal, academic and work-related data, as well as measures of cognitive style, intellectual development and personality type, for all three sections of the beginning course for computer science majors, CSC 135, during Spring semester, 1985 at the University of Nevada, Las Vegas. The purpose of the study is to determine if a relationship exists between any of this information and the student's grade in the class, where the grade is considered the measure of the student's success in the beginning computer science course. First the personal, academic and work-related factors are compared to the student's grade in the course. Then each of three standardized measures is compared to the student's grade to see if a relationship exists between an individual's grade in the course and their cognitive style as measured by the Group Embedded Figures Test, their Intellectual Development level as defined by Piaget, and their personality type as measured by the Myers-Briggs Type Indicator.

The semester began with 115 students in the three sections, of 49, 31, and 35 students respectively. The semester ended with 35, 19, and 27 students of whom 14 students failed. This left 26, 15 and 23 students in the respective sections. Two students in section one received an incomplete, leaving 62 students passing the course. Failing students were excluded because, for the most part, these students had simply disappeared. They typically left before the last exam(s) and project, so that their grade was not a true reflection of their work in the course. In several cases, these students had not been seen since the first day of the semester, but for some reason, they had failed to drop the course.

During the semester, data was actually collected from 71 students, of whom 62 completed the course. Four of these students failed, leaving 58 students in the study. Unfortunately, no data was collected from four students who completed the course with a passing grade.

In two of the class sections, the Group Embedded Figures Test (GEFT) was given in class on the day of the first exam. These two sections met for one hour and 15 minutes twice a week. Since the examination was only 50 minutes long, there was time for the timed Embedded Figures test before the exam began. The third section met for 50 minutes, three times a week. The GEFT was given the day after the exam in the third section, since they had already taken the exam the day before the other two sections. One make-up session was held for students not present the day the GEFT was given, and three students took it at that time.

The personal, academic and work data questionnaire, Piagetian measure and the Myers-Briggs measure were given to the students after they took the Group Embedded Figures Test. These measures were to be completed at home by the students and then returned to their instructor.

In several cases, it was not possible to get complete sets of data. One student failed to complete the Myers-Briggs and three students were not present the day the Group Embedded Figures Test (GEFT) was given. One additional student's GEFT score was dropped because that student was color blind (for blue and green) and complained that he could not see the blue drawings used in the measure. All students completed the Piagetian Intellectual Development measure. All missing data was excluded from the calculations.

Students were assured that these scores would not affect their grade in the course; in fact, the instructors would not even see the results. Results on the three measures were given to students who requested them.

Personal, Academic and Work Data

The personal, academic and work data reveals that the students in CSC 135 are predominately male (76 percent) and somewhat older than the average college student (26 percent are 19 or younger, 35 percent are 20 to 24, 19 percent are 25 to 29 and 20 percent are 30 or older). Personal, academic and work data frequency counts can be found in Table 3, parts (a) to (d), which follow. Individual factors are ennumerated as items A) to K).

Two thirds of the students rated themselves as above average (B), 22 percent as excellent students (A) and 12 percent as average or below (C or below) in high school. They rated themselves somewhat lower as college students, 53 percent as above average (B), 19 percent as excellent (A), and 28 percent as average or below (C or below). Academic performance is shown in Table 3 (a), items B) and C).

The class was made up of 19 percent freshman, 36 percent sophmores, 24 percent juniors, 10 percent seniors or students returning for a second degree, and 10 percent other, primarily graduate or high school students.

It may be seen that students are rather advanced in classification for a first class; however, students must be ready to take calculus before taking CSC 135. Thus many of the students are delayed in started the course. Other sources of upper division students are majors in business or science. Student classification counts are shown in Table 3 (b) item F).

Table 3 (a) Personal, Academic and Work Data

A) AGE

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
19 OR YOUNGER	1.	15	25.9
20 TO 24	2.	20	34.5
25 TO 29	3.	11	19.0
30 TO 34	4.	6	10.3
35 OR OLDER	5.	6	10.3
	TOTAL	58	100.0

B) HIGH SCHOOL ACADEMIC PERFORMANCE

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
A (EXCELLENT)	3.	13	22.4
B (ABOVE AVERAGE)	2.	38	65.5
C OR BELOW(AVERAGE OR BELOW)	1.	7	12.1
	TOTAL	58	100.0

C) COLLEGE ACADEMIC PERFORMANCE

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
A (EXCELLENT)	3.	11	19.0
B (ABOVE AVERAGE)	2.	31	53.4
C OR BELOW(AVERAGE OR BELOW)	1.	16	27.6
	TOTAL	58	100.0

Table 3 (b) Personal, Academic and Work Data (continued)

D) SEX

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
MALE	1.	44	75.9
FEMALE	2.	14	24.1
	TOTAL	58	100.0

E) NUMBER OF HOURS WORKED

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
NONE	1.	7	12.1
1 TO 13	2.	7	12.1
14 TO 26	3.	16	27.6
27 TO 39	4.	11	19.0
40 OR MORE	5.	17	29.3
	TOTAL	58	100.0

F) UNIVERSITY CLASSIFICATION

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
FRESHMAN	1.	11	19.0
SOPHOMORE	2.	21	36.2
JUNIOR	3.	14	24.1
SENIOR	4.	6	10.3
OTHER	5.	6	10.3
	TOTAL	58	100.0

Table 3 (c) Personal, Academic and Work Data (continued)

G) COMPUTER SCIENCE WORK EXPERIENCE

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
NONE	1.	28	48.3
SOME	2.	26	44.8
CONSIDERABLE	3.	4	6.9
	TOTAL	58	100.0

H) NON-PROGRAMMING WORK EXPERIENCE

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
NONE	1.	27	46.6
SOME	2.	24	41.4
CONSIDERABLE	3.	7	12.3
	TOTAL	58	100.0

I) PROGRAMMING WORK EXPERIENCE

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
NONE	1.	33	56.9
SOME	2.	23	39.7
CONSIDERABLE	3.	2	3.4
	TOTAL	58	100.0

Table 3 (d) Personal, Academic and Work Data (continued)

J) YEARS OF HIGH SCHOOL MATHEMATICS

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
0 YEARS	1.	1	1.7
1	2.	4	6.9
2	3.	6	10.3
3	4.	9	15.5
4 OR MORE	5.	38	65.5
	TOTAL	58	100.0

K) NUMBER OF COLLEGE MATHEMATICS CLASSES

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
0 YEARS	1.	2	3.4
1	2.	5	8.6
2	3.	11	19.0
3	4.	17	39.3
4 OR MORE	5.	23	39.7
	TOTAL	58	100.0

As is typical of a commuter campus, most students work to put themselves through school. Only twelve percent do not work, twelve percent work one to 13 hours, 28 percent work 14 to 26 hours, 19 percent work 27 to 39 hours and 29 percent work 40 or more hours a week. One of the sections is taught in the evening. This section accounts for most of the older students who are employed full-time. Number of hours worked is shown in Table 3 (b) item E). Forty-eight percent of the students have no computer- related work experience, 45 percent have had some, and seven percent have had considerable. Of students with non-programming work experience, 41 percent have some, and 12 percent have considerable non-programming work experience. Of students with programming work experience, 40 percent have some, and three percent have considerable experience. Work experience is shown in Table 3 (c) Items G), H), and I).

Two percent had no high school mathematics, seven percent had one year, 10 percent had two years, 15 percent had three years and 66 percent had four or more years of high school mathematics. Three percent had no prior college mathematics courses, nine percent had one course, 19 percent had two courses, 39 percent had three courses, and 40 percent had four or more college mathematics courses. Mathematics background is shown in Table 3 (d), items J) and K).

Cognitive Style

The Group Embedded Figures Test measures field dependence-independence and consists of trying to trace simple line drawings embedded in a more complex line and shading drawing. There are 18 items on the test, and one point is scored for each figure correctly traced. Two sections of nine drawings each are scored, for a total of 18 points. Five minutes is allowed to complete each section. Though most students finished before the time was up, no effort was made to distinquish between students on the basis of time. The results are shown in Table 4.

Field independence-dependence is one of a number of factors which are grouped under the heading, "cognitive style". Cognitive style is a pervasive part of the individual's psychological make-up and may affect many aspects of the individual's behavior. For example, the field independent subject is more likely to differentiate parts from the whole, and this has been shown to relate to problem solving tasks where the solution depends on the use of an object "out of context". Field independence also correlates with the analytical factor of the Wechsler tests, though not the verbal comprehension or attention concentration factors. Thus, this cognitive style factor may effect the way individuals perform a problem solving task such as computer programming.

Table 4 Group Embedded Figures Test Frequency Counts

GEFT ^ROUP EMBEDDED FIGURES TEST SCORES

CATEGORY LABEL	SCORE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
FIELD DEPENDENT	2.	1	1.7
	3.	1	1.7
	6.	2	3.4
	8.	4	6.9
	9.	3	5.2
	10.	3	5.2
	11.	8	13.8
	12.	4	6.9
AVERAGE	13.	1	1.7
	14.	5	8.6
	15.	4	6.9
	16.	3	6.2
	17.	9	15.5
FIELD INDEPENDENT	18.	5	8.6
	TOTAL	53	100.0

MEAN	12.755	MEDIAN	13.000
MODE	17.000	STD DEV	4.028
MINIMUM	2.000	MAXIMUM	18.000

Intellectual Development

The Formal Reasoning Test was used to measure Intellectual Development as described by Piaget in his theory of developmental stages. This test was written by Kurtz (1980) and modified by Barker and Unger (1983). Total number correct is shown as item A) in Table 5. These 18 questions are designed to group students into three categories based on their answers to 11 different types of mathematical and logical questions. Only two students missed both the direct proportion and conservation of volume questions (Questions 13 and 1) and were classifed as Late Concrete (three percent). Three students correctly answered three out of the four most difficult type of questions (Questions 4, 5, 11-12, and 7-10 or 15-18) and were classified as Late Formal (five percent). The remaining 57 students were classified as Early Formal (91 percent). Table 5, item B), shows the frequency counts and percentages for the three Piagetian stages, Late Concrete, Early Formal, and Late Formal.

The most difficult question type was the one on propositional reasoning. There were two examples of propositional reasoning (questions 7-10 and 15-18), and if either were correctly answered, students were given credit for that question type. Students who responded correctly to one did not necessarily get the other. The propositional reasoning questions are shown below.

Table 5 Intellectual Development Frequency Counts

A) TOTAL SCORE ON FORMAL REASONING TEST

CATEGORY LABEL	SCORE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
LOW	6.	2	3.4
	7.	2	3.4
	8.	7	12.1
	9.	4	6.9
	10.	12	20.7
AVERAGE	11.	8	13.8
	12.	11	19.0
	13.	5	8.6
	14.	4	6.9
	15.	2	3.4
HIGH	16.	1	1.7
	TOTAL	58	100.0

MEAN	10.776	MEDIAN	10.750
MODE	10.000	STD DEV	2.271
MINIMUM	6.000	MAXIMUM	16.000

B) INTELLECTUAL DEVELOPMENT STAGES

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
LATE CONCRETE	1.	2	3.4
EARLY FORMAL	2.	53	91.4
LATE FORMAL	3.	3	4.8
	TOTAL	58	100.0

If you were to <u>test</u> the following rule:

"If a card has a vowel on one side, then it has an even number on the other side."

1) $\boxed{E}$ Would you need to know what is on the other side?

CIRCLE Yes No

2) $\boxed{4}$ Would you need to know what is on the other side?

CIRCLE Yes No

3) $\boxed{K}$ Would you need to know what is on the other side?

CIRCLE Yes No

4) $\boxed{7}$ Would you need to know what is on the other side?

CIRCLE Yes No

If you were going to <u>test</u> the following hypothesis:

"If a rat has lipids in its blood, then it will be fat."

1) Given blood samples with lipids, would you need to know if they come from fat or thin rats?

CIRCLE Yes No

2) Given blood samples with no lipids, would you need to know if they came from fat or thin rats?

CIRCLE Yes No

3) Given several fat rates, would you need to know if there are lipids in these rates' blood?

CIRCLE Yes No

4) Given several thin rates, would you need to know if there are lipids in these rats' blood?

CIRCLE Yes No

Personality Type

The Myers-Briggs Test uses Jung's theory of type to assign indices for determining each of the four basic preferences which structure the individual's personality. By answering a number of dual choice questions about personal preferences, the subject accumulates points for each of the eight indices. Contrasting index scores are compared and the larger value choosen as the subjects's type for that index. Similar counts are made for each of the other indices. Thus a subject's score for this test is a group of four letters, E or I for Extrovert or Introvert, P or J for Perceiving or Judging, S or N for Sensing or iNtuitive, and T or F for Thinking or Feeling.

The Myers-Briggs test has been in use for over twenty years and data has been collected for many groups. National norms yield expected results of 75 percent extroverted to 25 percent introverted; sensing is usually found in about 75 percent, with 25 percent rated as intuitive. Perceiving-judging and thinking-feeling are both expected to be in about 50-50 ratios.

Each of the types and the 16 combinations of the four types is described in the various books devoted to this test (Myers, 1962; Keirsey & Bates, 1984). A summary of the frequency counts for each of the four indices is shown in Table 6.

Table 6 Personality Type Frequency Counts

EI - EXTROVERSION VS INTROVERSION

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
INTROVERSION	1.	36	63.2
EXTROVERSION	2.	21	36.8
	TOTAL	57	100.0

PJ - PERCEIVING VS JUDGING

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
PERCEIVING	3.	23	45.6
JUDGING	4.	31	54.4
	TOTAL	57	100.0

SN - SENSING VS INTUITIVE

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
SENSING	5.	28	49.1
INTUITIVE	6.	29	50.9
	TOTAL	57	100.0

TF - THINKING VS FEELING

CATEGORY LABEL	CODE	ABSOLUTE FREQ	RELATIVE FREQ (PCT)
THINKING	7.	44	77.2
FEELING	8.	13	22.9
	TOTAL	57	100.0

However, beginning computer science students differ dramatically from these norms. This study yielded a ratio of 63 percent introverted (I) to 37 percent extroverted (E), more like the reverse of the expected result of 25 percent (I) to 75 percent (E). Sensing-intuitives (SN) are generally found in a 75-25 ratio, but for CSC 135 students, the ratio is 49-51. Thinking-feeling (TF) is usually found in a 50-50 ratio, but among these beginning computer science students, the ratio is over three quarters thinking, with just under one quarter feeling. Only on the perceiving-judging (PJ) index was this group near the national norms of 50-50. They scored 46 percent perceiving to 54 percent judging. Thus, begining computer science students are far more introverted, intuitive, and thinking than the population at large. Comparison figures are summarized in Table 7. National norms were taken from Keirsey and Bates (1984).

In comparing beginning computer science students to other nationally normed groups, there were two groups, chess players and engineers, which seemed to show some of the same patterns as the computer science students.

Kelly's (in press) paper, "Chessmaster Personality and Type: Comparative Analyses with Average Players and Non-Players," yields some interesting Myers-Briggs figures for chess players. For the expected 75-25 EI ratio, average chess players are 28-72 and master players a more

Table 7 Myers-Briggs Personality Type Comparisons

(in percentages)

	National Norms	Chess Players Average	Chess Players Master	Engineering Students	Computer Science Students
Type	Keirsey & Bates (1984)	Kelly (in press)	Kelly (in press)	McCaulley (1983)	Current study
Introversion	25	72	82	53	63
Extroversion	75	28	18	47	37
Perceiving	50	46	35	39	46
Judging	50	54	65	61	54
Sensing	75	50	23	53	49
Intuitive	25	50	77	47	51
Thinking	50	77	78	74	77
Feeling	50	23	22	26	23

marked 18-82. Rather than the norm of 50-50 JP ratio, average players are 54-46, while master players are 65-35. In contrast to the expected 75-25 SN ratio, average players are 50-50 and masters 23-76. Rather than the norm of 50-50 for TF, average players are 77-23 and master players, 78-22. Thus, average chess players appear to have discrepancies from the national norms similar to those of beginning computer science students. Except for extroversion- introversion, beginning computer science students look very much like average chess players. They are far more introverted than the national norms, but not as introverted as chess players.

A much larger comparison of Myers-Briggs Type Indicator results for engineering students offers comparison figures for 3,718 students from eight different universities. These results vary between the different schools and between the different fields of engineering, but complete breakdowns were not given in the article (McCaulley et al, 1983). Engineering students differ from national norms in the same direction as computer science students, but are not as extreme, except for perceiving-judging. Male engineering students apparently prefer an orderly existence to the same degree that master chess players do, while this is the one dimension where computer science students are near the national norm. Myers-Briggs Type Indicator comparison figures are summarized in Table 7.

Grade in the Course

There are a number of significant relationships between the various measures and the student's grade, which is the measure selected to indicate success in this beginning computer science course. Both a Chi Square and Pearsons's Product Moment Correlation (Pearson's R) tests were performed. Since most of the data was categorical in nature, the student's letter grade with pluses and minuses were used as the dependent variable. The university grading system differentiates between plus and minus grades using the following scale:

Letter Grade	Grade Points
A	4.0
B+	3.7
B	3.0
B-	2.7
C+	2.3
C	2.0
C-	1.7
D+	1.3
D	1.0
D-	0.7
F	0.0

Failing grades were removed from the sample. Most students who see that they are not doing well in a class will drop. Consequently, the only failing grades were assigned to students who disappeared from the class without bothering to drop, in some cases very early in the semester. This is fairly typical behavior among students at this and other universities.

The student grade is made up of their scores on homework assignments, examinations, quizes, and a large final programming project. All three sections completed the same homework and project assignments as well as taking the same tests. There were 185 points assigned for homework, 100 points for the project, 60 points for quizes and 289 points for examinations. The final percentage was determined by the following weighting; homework 30%, quizes 10%, examinations 30% and the project 20%. Letter grades were assigned to these final percentages by the individual instructors.

One possible validity problem resulted when one instructor who was teaching two of the three sections, took another job about three quarters of the way through the semester. One of his sections was taken over by the second instructor, and the third section was assigned to a new instructor. Ideally, the results of this study should hold for any instructor, so this should not be a major problem. The assignments had already been decided upon and the original instructor wrote the last examination.

The biggest difference between the new and old instructor was in the assigning of the letter grades. Different letter grades were assigned for the same percentage scores by the different instructors. The original instructor was more lenient than the new instructor in assigning the letter grades. This is, of course, typical behavior in the university environment.

The three sections of CSC 135 in the Fall semester were taught by the same two instructors in the same fashion, and the letter grades were not assigned consistently in that semester either. Since each instructor graded his own examinations, there may be a (possibly similar) bias in the orignal point totals. Because of the grading discrepancies, however, comparisons between various grading schemes were examined and will be discussed at the end of this chapter. Three grading schemes are described in Table 11 and the statistical results compared in Table 12.

Complete copies of the cross tabulations between student grade and each of the other factors may be found in Appendix B. Results will be discussed in the same order in which the data has been covered previously. As each factor is discussed, its Chi Square and Pearson's R figures will appear with parentheses (Chi Square, Pearson's R). Cross tabulations with Chi Square and Pearson's R results and their respective significance may be found in Table 8.

Personal, Academic and Work Data

Student sex, age and high school grades do not show a significant relationship with grade in the course, but student's college grades do. The Chi Square was not

Table 8 Grade Cross Factor Correlation Summary
Letter Grade using Plus and Minus

Factor	Chi Square	Pearson's R
Sex	6.233	.0796
Age	30.573	-.0881
High School Grades	13.238	.0740
College Grades	22.854	.2523**
Classification	30.037	-.0216
Hours Worked	57.463***	.2029*
Computer Experience	14.613	.0967
Non Computer Work	15.753	-.1153
Programming Work	12.225	.1858*
High School Math	50.075**	.2520**
College Math	41.056	-.0191
Embedded Figures Score	122.958*	.3170***
Piaget Total Score	104.845**	.0886
Intellectual Development	27.793**	.2319**
Introvert-Extrovert	3.629	-.0602
Perceiving-Judging	11.443	.0532
Sensing-Intuitive	7.493	.1852*
Thinking-Feeling	9.677	.1514

* p <.10   ** p <.05   *** p <.01   See Appendix C

significant, but the Pearson's R was significant at the .05 level (R: p <.05). If a student does well in college in general, they will do well in this course also. This is not suprising and has been found in nearly all of the previous studies which looked at Grade Point Average. Student classification does not appear to be significant, that is, the freshman seem to do as well as the seniors. Rather than being more expert in computing because they are upperclassmen, many of the more advanced students come from the non-computer science majors.

The number of hours worked shows a significant positive relationship with the students' (letter) grade in the class (ChiSq: p <.01, R: p <.10). This may seem surprising, since it is often assumed that working will interfere with the student's ability to study, but it appears that the student that is dedicated enough to go to school while working (or to work while going to school) is very determined to get the most out of the class. This result is especially interesting because this particular class requires a great deal of time. Two programs a week is a typical assignment, and there is a large project at the end of the semester. The number of hours worked also shows a strong significant relationship with age (ChiSq: p <.01, R: p <.01). Motivation may well be the factor underlying this relationship.

The fact that a student's job involves computers does not have a significant relationship with the student's grade in the course. (A job may involve using a computer without requiring the student to program the computer.) Non-computer related work is also not significant, but programming work experience shows a slight relationship with success in the class, in the Pearson's R (R: $p < .10$), though not in the Chi Square test.

Another factor which many think may be related to success in computer science is the mathematical background of the student. The number of years of high school mathematics does have a significant relationship with class grade (ChiSq: $p < .05$, R: $p < .05$), but the number of college mathematics classes does not. It is tempting to think that this result may reflect the student's general academic background. Students who take a lot of mathematics in high school generally like mathematics and/or plan to go on to college. On the other hand, students may take a college mathematics courses for a variety of reasons. For example, taking many college courses may reflect an effort to remedy the lack of high school mathematics preparation. Students must be qualified to take calculus to take the beginning computer science course, so taking only a few college mathematics courses may indicate that the student already has a strong mathematics background, while taking a lot of courses may indicate a lack of preparation. As many as three classes may be required to qualify a student for calculus: Intermediate Algebra, Pre-calculus I and Pre-calculus II (trigonometry). There is no indication in the questionaire regarding the level of the college mathematics courses taken. Only the number of courses taken was requested.

However, when the correspondance between number of high shool mathematics classes and the the number of college mathematics classes is examined, a fairly strong positive relationship is seen (ChiSq: $\underline{p} < .01$ R: $\underline{p} < .10$). Of the students who took four years or more of high school mathematics (a total of 38 of the 58 students), 18 also took four or more college mathematics courses, 9 also took three college courses and 7 also took two college classes.

The differences found between number of high school mathematics classes and number of college mathematics classes continue to be a puzzle. The relationship between number of college mathematics courses and grade in the class is not significant, but it is negative. Age may again be a factor. There is a significant positive relationship between age and number of high school mathematics classes (R: $\underline{p} < .05$), as well as an even stronger relationship between age and number of college mathematics courses (ChiSq: $\underline{p} < .05$, R $\underline{p} < .01$). There is not a significant relationship between age and grade in the beginning computer science course, but the correlation is negative. Perhaps some are remedying background and some really like mathematics. Perhaps older students retook college mathematics courses to brush up, while younger students did not. Because of these confusing results, this is an area where more investigation is needed.

Cognitive Style

Scores on the Group Embedded Figures Test range from 2 to 18, with a mean of 12.76, a median of 13 and a mode of 17. It is clear that these students are field independent. The Group Embedded Figures Test (GEFT) measure showed significant relationship to class (letter) grade (ChiSq: $p < .10$, R: $p < .01$). When the GEFT scores (out of 18 possible) were subdivided into three categories (high, medium and low) the Chi Square correspondence was even more marked (ChiSq: $p < .01$, R: $p < .05$).

This significance is especially interesting, since the Group Embedded Figures Test correlates with some problem solving abilities and with the analytical section of the Wechsler test. It is the field independent student who appears to do well in a beginning computer science class. Results are summarized in Table 8.

Intellectual Development

The measure of Piagetian intellectual development stages shows a significant relationship with course grade (ChiSq: $p < .05$, R: $p < .05$), even though the measure did not diffentiate strongly between students. Only three students were judged to be Late Formal (five percent) and only two were Concrete (three percent) with the rest falling in the Early Formal category (91 percent). Because most students were in the same category (Early Formal), the total point score on the Piagetian test was also recorded and tested to see if there were a correlation with straight score on the measure. Here the Chi Square was seen as significant (ChiSq: $p < .05$) but the Pearson's R was not. The Piagetian Intellectual Development test was relatively difficult, with no students getting all 18 questions correct. The maximum score was 16, the minimum was 6, with the mean and median both at 10.8. The logic questions were especially difficult, with subjects required to get several questions in a question group correct to get credit for the question type. Results are summarized in Table 8.

Personality Type

There is not a significant relationship between the Myers-Briggs results and (letter) grade in the course. The sensing-intuitive measure did show a slight relationship with the course grade in the Pearson's R (R: $p < .10$), but not in the Chi Square test. This is likely due to the general correspondence between the intuitive measure and intelligence which is often seen (Myers, 1962). Results are summarized in Table 8, Grade Cross Factor Correlation Summary.

Summary

The personal, academic and work-related factors which show a significant relationship with success in a beginning computer science course are: the student's overall college grades, the number of hours worked, and the number of high school mathematics courses taken. Both the Piagetian Intellectual Development (ID) measure and the Group Embedded Figures Test (GEFT) appear to be good predictors of success in this course. There is no relationship between the Myers-Briggs Type Indicator and (letter) grade in the beginning computer science course.

Cross Correlations with Other Factors

Since both the Group Embedded Figures Test (cognitive style) and the Piagetian measure of Intellectual Development, showed a significant relationship with student's grade in the beginning computer science course, it is also interesting to see if these two measures show any of the same correlations that were seen between student (letter) grade and the other factors. These results are summarized in Table 9, GEFT and ID Cross Factor Correlation Summary - Cognitive Style and Intellectual Development.

Cognitive Style Correlations

Several correlations were seen between the Group Embedded Figures Test and the other factors. Computer related work experience (R: $p < .05$), programming work experience (R: $p < .01$) and number of high school mathematics classes (R: $p < .05$) show a significant relationship with the GEFT measure. Comparing these factors to student (letter) grade correlations, the only common factor is number of high school mathematics classes. Again, field independence does appear to be related to a liking for mathematics and computer work.

The only Myers-Briggs personality type factor showing a significant relationship with cognitive style was introversion-extroversion (R: $p < .05$). That is, field independent computer science students tend to be introverted. This apparently confirms the low need for social interaction seen in previous studies of field dependence-independence (Witkin et al, 1977).

Table 9 GEFT and ID Cross Factor Correlation Summary

Cognitive Style and Intellectual Development
Product Moment Coefficient - Pearson's R

Factor	Cognitive Style	Intellectual Development
Sex	-.0089	.1043
Age	-.0455	-.0675
High School Grades	.0668	.0912
College Grades	.0857	.0944
Classification	-.0263	.0026
Hours Worked	.1026	.0699
Computer Experience	.3052**	.0395
Non Computer Work	.1555	-.0564
Programming Work	.3513***	.0558
High School Math	.2663**	.3223***
College Math	.1347	-.1550
Embedded Figures Score	-	-
Piaget Total Score	.0583	.4500***
Intellectual Development	.0000	-
Introvert-Extrovert	-.2702**	.0777
Perceiving-Judging	.1528	.0543
Sensing-Intuitive	-.0777	.2957**
Thinking-Feeling	-.0168	.1092

* p <.10 ** p <.05 *** p <.01 See Appendix C

Intellectual Development Correlations

Only the number of high school mathematics classes (R: $p < .01$) shows a significant relationship with the Piagetian Intellectual Development measure, though it is strongly significant. This is not too surprising since the test involves knowledge of mathematics and logic. That Piagetian Intellectual Development stage does not correlate to number of college mathematics classes might be interpreted to strengthen the previous assumption that high school mathematics shows mathematics ability, while large number of college mathematics classes may show weakness in mathematics preparation, (even though there is at least one strong counterexample in the sample). The high correlation between the Piagetian stage and the total number of problems correct on the Intellectual Development measure is to be expected.

The only Myers-Briggs personality type factor showing a significant relationship with intellectual development is sensing-intuitive (R: $p < .05$). This may be due to the general correspondence between intuitive type and academic performance (intelligence scores, high grades, etc.) that is often seen in Myers-Briggs personality type studies (Myers, 1962).

Personality Type Correlations

The Personality Type variables, extroversion-introversion, perceiving-judging, sensing-intuitive, and thinking-feeling, show very interesting correlations with the various demographic, academic and work related variables. A model of the computer science student emerges, which in many cases corresponds to one's intuitive image. Results are summarized in Table 10, Personality Cross Factor Correlation Summary.

Extroversion-Introversion

The introversion-extroversion personality type variable shows a significant (negative) relationship with two personal, academic and work-related factors, namely, computer related work experience (R: $p < .10$), and number of college mathematics courses (R: $p < .05$). In fact, nearly all of the factors have negative correlations. Most of these negative signs come from the coding choosen. Introversion was given the lower code value (I=1, E=2). While not all the correlations are significant, the signs may be interpreted to mean that the introverted students tend to be male (male=1, female=2), younger in age, have higher high school and college grades (A=3, B=2, C=1), work fewer hours, are less likely to work either computer or non-computer related jobs, and have taken more high school math classes and fewer college math courses. The extroverted computer science student tends to be the opposite.

Table 10 Personality Cross Factor Correlation Summary

Myers-Briggs Personality Types
Product Moment Coefficent - Pearson's R

Factor	Introvert Extrovert EI	Perceiving Judging PJ	Sensing Intuitive SN	Thinking Feeling TF
Sex	-.0133	.1952*	.1530	.2727**
Age	-.0919	.3161***	-.1027	-.3851***
High Sch Grades	.0493	-.1368	.1774*	.1170
College Grades	.0981	.1403	.2336**	.2536**
Class	-.0836	.2784**	-.0948	-.2858**
No. Work Hours	-.1391	.3969***	-.1103	-.1572
Computer Work	-.1711*	-.0834	.0426	.1200
Non Comp. Work	-.0863	.1473	-.0931	-.0267
Program Work	-.1516	-.1060	-.0476	.1023
High Sch Math	.0925	.0723	.0619	-.0227
College Math	-.2340**	.2444**	-.3298***	-.4081***
GEFT Score	-.2702**	.1528	-.0777	-.0168
Piaget Score	.0989	.0873	.2807**	.0405
Piaget Stage	.0777	.0543	.2957**	.1092
Introvert-Extrovert	-	-.1768*	-.0498	.2783**
Perceiving-Judging	-	-	-.1953*	-.0898
Sensing-Intuitive	-	-	-	.2832**
Thinking-Feeling	-	-	-	-

* p <.10   ** p <.05   *** p <.01   See Appendix C

Scores on the Group Embedded Figures Test (GEFT) measure have a significant (negative) relationship with the introversion-extroversion factor. Thus, field dependent computer science students tend to be introverted. Neither the total score on the Piagetian measure nor the Piagetian stage have a significant relationship with the introversion-extroversion personality type factor.

Perceiving-Judging

The perceiving-judging variable shows a significant relationship with sex (R: $p < .10$), age (R: $p < .01$), student classification (R: $p < .05$), number of work hours (R: $p < .01$), and number of college mathematics courses (R: $p < .05$). The Chi Square test is also signficant for the number of hours worked (ChiSq: $p < .05$). Again, looking at the sign of the correlation, the judging (planned, orderly) computer science student tends to be older, have a higher student classification (these go together to a large extent), to work more hours, and to have taken more college level mathematics courses, while the perceiving student is the opposite. There is no significant relationship between the perceiving-judging factor and either the Group Embedded Figures Test or the Intellectual Development scores.

Sensing-Intuitive

There is a significant relationship between the sensing-intuitive variable and high school grades (R: $p < .10$), college grades (R: $p < .05$), number of college mathematics courses (R: $p < .01$). That is, the intuitive computer science student tends to have made good grades in high school and college, and has not taken very many college mathematics courses, while the sensing student tends to make lower grades in school and to have taken more college level mathematics courses.

The sensing-intuitive factor shows a significant relationship with both the total score on the Piagetian Intellectual Development measure (R: $p < .05$) and with the Intellectual Development stage designation (R: $p < .05$), though not with the Group Embedded Figures Test result. The Chi Square test is also significant for the ID stage (ChiSq: $p < .10$).

Thinking-Feeling

There is a significant relationship between the thinking-feeling variable and sex (R: $p < .05$), age (R: $p < .01$), college grades (R: $p < .05$), student classification (R: $p < .05$), and number of college mathematics courses (R: $p < .01$). The Chi Square test is also significant for sex (ChiSq: $p < .05$), age (ChiSq: $p < .01$), classification (ChiSq: $p < .10$), and college mathematics courses (ChiSq: p

$<.01$). That is to say, the thinking computer science student tends to be male and older, with a higher student classification. Their college grades are lower, and they have taken more college level mathematics courses. The feeling computer science student tends toward the opposite.

The thinking-feeling factor does not show significant relationship with either Group Embedded Figures Test score or Intellectual Development results. This applies to both total score and Piagetian stage designation.

The most interesting of the personality type cross factor correlations is the one with number of college mathematics courses. Few of the personal, academic and work-related factors exhibited a significant relationship with even one of the personality type indices, but number of college mathematics courses showed a significant relationship with all four of the personality type indices. Thus, the more college mathematics courses the computer science student takes, the more strongly introverted, sensing, judging, and thinking their Myers-Briggs Type Indicator profile becomes.

Personality Type Cross Correlations

There is a significant relationship between the introversion-extroversion factor and both the perceiving-judging (R: $p<.10$) and thinking-feeling (R: p

<.05) factors. The Chi Square test on the thinking-feeling factor is also significant (ChiSq: p <.10). That is, in this study, introverts tend to be more judging or to prefer more planned behavior, while extroverts tend to be more perceiving or to prefer more spontaneous behavior. Similarly, introverts tend to prefer a more thinking behavior, while extroverts tend to prefer a more feeling behavior.

The perceiving-judging factor does show a slight significant relationship with the sensing-intuitive factor (R: p <.10), though not with the thinking-feeling factor. There is a positive significant relationship between the sensing-intuitive factor and the thinking-feeling factor (R: p <.05), indicating that the intuitive computer science student tends toward feeling behavior, while the (physically) sensing student tends towards thinking behavior. The Chi Square test is also approaches significance for this relationship (R: p <.10).

Effects of Letter Grade Assignment

As described earlier in this chapter, the two instructors did not assign letter grades to the student's percentage grade in the same way. It would be desirable for any method of predicting success in a beginning computer science course to work regardless of small changes in the assigning of the letter grades.

While the three sections of CSC 135 had taken the same examinations and done the same homework assignments and projects, the letter grades assigned were not consistent between the instructors. One instructor graded the largest section using a straight percentage scale, 90-100% = A, 80 to 89% = B, etc. The other instructor graded the other two sections by looking at the distribution of the grades. He decided on letter grade based on groups of grades separated by gaps or breaks between similar scores. He also assigned higher letter grades to the same percentage scores than the first instructor. Since these are both common grading schemes, it was decided to see if there was a difference in number and kind of significant relationship between the three grading schemes: (A) based on straight percentages, (B) based on grade distribution and (C) the original study based on a mixture of the two grading schemes.

To study the impact of the difference letter grade assignment on this study, the numeric grade data was recoded using two additional schemes described above, schemes A and B. The actual letter grade assigned by the instructor and used in this study, is called Scheme C. The results of the two grade recoding schemes are compared in Table 11. Ranges used for each grade category are shown, along with the number of students falling in that

Table 11 Letter Grade Assignment Schemes

Grade	Number Scheme A	Number Scheme B	Ranges: Percentages Scheme A	Ranges: Distribution Scheme B	Code Value
A	6	13	92 - 100	90 - 100	11
A-	7	7	90 - 91	87 - 89	10
B+	6	3	88 - 89	85 - 86	9
B	6	3	82 - 87	76 - 84	8
B-	3	12	80 - 81	70 - 75	7
C+	4	7	78 - 79	66 - 69	6
C	8	7	72 - 77	52 - 65	5
C-	3	0	70 - 71	50 - 51	4
D+	3	0	68 - 69	49 - 49	3
D	5	0	62 - 67	42 - 48	2
D-	2	1	60 - 61	40 - 41	1
F	5	0	0 - 59	0 - 39	0

category under the given grading schme. Note that there were some failing grades under one of these grading scheme. Since these are "legitimate," failing grades were not treated as missing data and were not removed from the calculations. An examination of Table 12 shows little change in the correspondences found. The straight percentage scheme A would have added a slight increase in the college grade correspondences, but would have lost the slight relationship with the Myers-Briggs variables. The grade distribution scheme B would have reduced some of the correlations, but would not have major changes in the number and level of the significant relationships, except for improving the correlation with computer experience and the shift in significance from one Myers-Briggs factor to another. Thus, the study results do not depend heavily on the letter grade assignment scheme.

Table 12 Letter Grade Assignment Effects Summary

Product Moment Coefficient - Pearson's R

Factor	Percentages Scheme A	Distribution Scheme B	Study-Mixed Scheme C
Sex	.0472	.0239	.0796
Age	-.0141	-.0132	-.0881
High School Grades	.0788	.0984	.0740
College Grades	.3133***	.3188***	.2523**
Classification	.0953	-.0258	-.0216
Hours Worked	.0183	.0998	.2029*
Computer Experience	.2119*	.1761*	.0967
Non Computer Work	.0273	.0047	-.1153
Programming Work	.3020**	.2876**	.1858*
High School Math	.2033*	.2011*	.2520**
College Math	.0471	.0385	-.0191
Embedded Figures Score	.2721**	.2541**	.3170***
Piaget Total Score	.1517	.0922	.0886
Intellectual Development	.2180**	.2101*	.2319**
Introvert-Extrovert	-.0575	-.0742	-.0602
Perceiving-Judging	.0592	.0293	.0532
Sensing-Intuitive	.1516	.1596	.1852*
Thinking-Feeling	.1942	.2116*	.1514

* $p < .10$ ** $p < .05$ *** $p < .01$ See Appendix C

CHAPTER V

SUMMARY AND DISCUSSION

This chapter summarizes the study, and interprets the findings in the light of previous research. Limitations of the study and implications of the results are discussed. Future directions for research are suggested.

Summary

The purpose of the study was to provide a profile or model of the computer science student in order to determine which factors, if any, were effective in predicting success in a beginning computer science class. Variables included sex and age, high school and college academic performance, number of math classes, and work experience. Three measures were given to the students early in the semester and the results compared to the students' grade in the course. Predictor variables included (1) a measure of Piagetian intellectual development produced by Kurtz, (2) the Group Embedded Figures Test, a well-known measure of cognitive style (field dependence-independence) and (3) the Myers-Briggs Type Indicator, a frequently used measure of personality type based on Jung's theories.

All factors and measures were cross tabulated against the student's letter grade in the course. Both Chi Square and Pearson's product moment coefficent were computed for students in all three sections of CSC 135, Computer Science I, the first course for computer science majors. Data was collected for all but four of the 62 students who completed the course with a passing grade.

Each of the four kinds of data have been individually compared to student grade in various earlier studies, but no one study has collected all four kinds of data on the same group of students. The cross factor correlations are informative and give a stronger model of the successful computer science student.

Personal, Academic, and Work Data

The students in the current study were predominately male, and, typical of an urban or "commuter" campus, students were older and were frequently employed in non-university jobs. However, neither sex nor age showed a significant relationship with their grade in the course. High school grades and college classification (number of accumulated hours) were not significant, but college grades were (R: $p < .05$). It is not too surprising that the student who does well in college in general, would do well in this computer science course in particular. This same result was found in most of the similar studies of beginning computer science course success.

The number of hours worked showed the strongest Chi Square relationship to grade (ChiSq: $p < .01$), though the type of job did not seem to make much difference. Working as a programmer showed a slight correspondence in the Pearson's R only (R: $p < .10$).

The other strong correlation was between course grade and number of high school mathematics courses (ChiSq: $p < .05$, R: $p < .05$). Interestingly, the number of college math courses was not significant. The number of high school classes may give a better picture of the student's mathematics background than the number of college courses, since large numbers of college courses may indicate an attempt to remedy a weak background. The Chi Square result for number of college mathematics courses approached significance, and the Pearson's correlation, while not significant, was negative. This could be interpreted to support the weak background hypothesis. The strong relationship between age and both number of college mathematics courses and number of hours worked gives another clue. The older student may simply be more motivated or may be retaking mathematics as a refresher. The question of mathematics background clearly needs further investigation.

Looking at similar studies of success in a beginning computer science class, we see basically similar results, though there are important differences. Wileman, Konvalina and Stephens (1981, 1983) found age, grade point average (GPA), and number of college mathematics classes correlated with success in computer science class, while work experience and high school mathematics classes did not. The reversal on the mathematics background question is interesting. That number of hours worked is not significant is important, because the University of Nebraska, Ohmaha is also a commuter campus. In the first study, they reported that 40 percent of their students worked full time, somewhat higher than the 29 percent found in the current study. In their second study, more results were reported, with the age, high school performance and hours worked looking very much like the current study. Students were two-thirds male, similar, though not quite as high as the current study. Data was collected from 96 of 183 and 165 of 382 students starting the course, with about half of the students completing the course, as was found here.

There were, however, some differences between the two studies. Their course, while guided by the same ACM curriculum, covered assembly language and PL/C programming, rather than Pascal programming. One year of high school algebra was the only prerequisite. Thus, both the number of high school and college mathematics courses was much lower in their study than in the current study. This may well explain the differences found in the significance of the number of mathematics courses. Also, the dependent variable was the score on the final examination, rather than overall grade in the course. Their studies were conducted during Spring and Fall semesters, 1980.

Petersen and Howe (1979) found a correlation with both high school mathematics classes and GPA when compared with success in a beginnning computer science class, but did not find a correlation with gender and classification. They also found general intelligence (General Aptitude Test Battery) to relate to grade in the course, though they were looking at a computer literacy, rather than a computer programming, course. Other variables examined included biographical and temperament factors which were found to be not significantly related to grade. Their study was done during the Fall, 1975 and Spring, 1976, a long time ago considering the speed with which the field of computer science changes.

While the other studies differ from this one in many respects, there is some general agreement on the types of academic factors which are important. College GPA and mathematical background are the factors most often found to relate to student's grade in the first computer science class.

Because of the differences found in results on the number of college mathematics courses and the number of hours worked, these factors require further study. Information on the level of the high school and college mathematics classes is needed. A question on high school size might give an indication of the quality of preparation.

Information on prior computer science education would be valuable. Question #7 was to have read "How much prior education have you had in computer science?" A secretarial error converted it to "How much work experience have you had in computer science?" and this was not caught in time. It will be corrected before the questionaire is used again.

Some studies used SAT and ACT test scores and generally found them to correlate to grade in the course. These were not available for all students and so were not used in the current study. Because they would provide useful information which could be used in advising high school students before beginning a computer science major, an effort should be made to add this data.

Cognitive Style

Scores on the Group Embedded Figures Test (GEFT), a standardized measure of field dependence-independence, ranged from 2 to 18, the total points possible, with a mean of 12.76 (std dev = 4.03), a median of 13 and a mode of 17. The students appear to be relatively field independent and indeed, the relationship was significant (ChiSq: p <.10, R: p <.01) when compared to grade in the beginning computer science course.

Personal, academic and work factors which showed a significant relationship with cognitive style include: computer-related work (R: p <.05), programming work (R: p <.01) and number of high school mathematics classes (R: p <.05). Thus, field dependence-independence shows a correspondence with ability in and apparent preference for mathematics and computers, and is a significant predictor of success in a first computer science course.

There have been only a few studies which looked at cognitive style in relation to grade in computer science courses. Rogers (1983), did not find a significant relationship between grade and the GEFT, but she gave the test to only 11 students, all but three of whom made the highest possible score.

Stevens (1983) found a significant relationship (ANOVA: p <.01) between GEFT score and the sum of two exam scores (general literacy plus BASIC programming) in a computer literacy course for teachers. The top one-third of 73 students were classified as field independent and the lower one-third as field dependent in a 2 x 2 analysis of variance study. Cheney (1980), using an instrument written by Barkin, found a significant relationship between the score on the measure and score on a programming examination in a class of 35 business computer literacy students. The Barkin measure using a Likert scale for questions similar to those on the Myers-Briggs, divided students in snslytical problem solvers and heuristic problem solvers. Analytical problem solvers did better on the programming exam, which consisted of both multiple choice questions and a program to write. Hassell (1982) gave the Embedded Figures Test and two measures of programming ability to 28 sophomores and 19 seniors. The correlation was near .50 for the seniors on the two programming tasks, memorizing a program and finding errors in programs. The correlation for sophomores was not significant.

The Group Embedded Figures Test appears to be of importance in predicting students' grades in a beginning computer science course. Not only does field independence correlate to measures of problem solving and analytic abiltity such as the Wechler Analysis subtest (Witkin et al, 1971), it also corresponds to personality factors such as a reduced desire for social interaction and a higher level of intrinsic motivation (Grippin, 1976). Additional information about the role of cognitive style in computer programming could add greatly to our understanding of the cognitive processes involved.

Intellectual Development

The scores on the Piagetian measure of intellectual development ranged from 2 to 16 correct, out of a possible 18. The mean was 10.78 (std dev = 2.27), the median 10.75, and the mode 10. This test contains mathematics and logic questions designed to place students into one of Piaget's development stages. Based on the type of question correctly answered, student scores were translated into the Piagetian stages, Late Concrete, Early Formal and Late Formal. Two students (3 percent) were rated as Late Concrete and three as Late Formal (5 percent). The remainder were all Early Formal (91 percent). The Intellectual Development level showed a significant relationship with grade in the course (ChiSq: $p < .05$, R: $p < .05$). The total number of questions answered correctly was also significant (ChiSq: $p < .05$). While significant, the instrument is not very practical as a placement test, because there is no way to use the scores (as they were distributed in this study) to differentiate between students. The two Late Concrete students made a C+, as did one of the three Late Formals. Any student scoring in the Late Formal category will likely do well, but the Late Concrete students don't necessarily do poorly. The single D student received a score of 13 as compared to the top score of 16, and the two students with the lowest score of 6 points made a B and a B+, so there is not a clear cut off point even on the total score.

The only personal, academic and work factor which showed a significant relationship with the intellectual development stage was number of high school mathematics classes (R: $\underline{p} < .01$), but it was a strong correlation. This is to be expected given the mathematical nature of the test. Note the continued lack of agreement between number of high school and number of college mathematics courses.

Similar previous studies of success in a beginning computer science course, yielded results which conflicted with each other. Kurtz (1980), the developer of the measure, found a significant relationship between the Intellectual Development level and course grade for a class of 23 students. Barker and Unger (1983), who shortened the measure slightly to reduce duplicate question types, did not find a significant relationship for 353 students in 15 sections with 10 different instructors. However, the tool did separate the advanced students from the average and below average students, and they recommended its use, in combination with other data, for advising beginning computer science students.

Jean Rogers (1983) also adminstered this measure in her study of success in a beginning computer science course. She did not find a significant relationship, but she gave the measure to only 11 students, six of whom were rated Late Formal and five of whom were rated Early Formal.

While there are conflicting results in the use of this measure of intellectual development, there is enough of a correspondence to warrant further investigation, though perhaps with a different instrument. The significant relationships found in these studies, together with the significance of mathematical background found, demonstrate the importance of this topic in further research.

Personality Type

The profile of the beginning computer science student determined by the current study, using the Myers-Briggs Type Indicator, differed dramatically from the established national norms for the general population. Computer science students were found to be far more introverted, intuitive and thinking than the population as a whole, though they were about the same on the perceiving-judging index. Results are summarized in Tables 9 and 10. While there are some similarities between computer science students and engineering students, computer science students more closely resemble chess players than any of the other groups examined.

Student preferences on the extroversion-introversion, perceiving-judging, sensing-intuitive, and thinking-feeling indices did not, however, show significant relationship with their grade in the beginning computer science course, though Pearson's R on the sensing-intuitive factor approached significance (R: $p < .10$).

Interesting correlations with other factors and the Myers-Briggs results, give a more complete picture of the computer science student. There was a significant relationship between the extroversion-introversion factor and cognitive style as measured by the Group Embedded Figures Test (R: $p < .05$), and also between the sensing-intuitive factor and the Piagetian measure of intellectual development (R: $p < .05$). The association of introversion with field independence is likely similar to the low need for social interaction seen in previous GEFT studies (Greene, 1976). The correlation of intuitive with Intellectual Development is likely due to the frequent relationship seen between the intuitive type and academic success (Myers, 1962).

Judging students, those who prefer a carefully planned to a spontaneous or flexible existence, tended to be male, older and to work more hours. Intuitive students tended to have higher grades in both high school and college, while the thinking students tended to be male, older, and to have higher college grades. These relationships are often seen with the MBTI results (Myers, 1962). The most notable outcome was the one showing that the number of college mathematics courses demonstrated a significant relationship with all four of the Myers-Briggs indices. Introverted, judging, sensing and thinking students tended to have taken more mathematics courses. Given the importance of mathematics background, this is useful information.

While Myers-Briggs Type Indicator profiles of various (non-computer science) groups are readily available, few studies have attempted to predict academic success using MBTI results. One study compared general academic success (GPA) to Myers-Briggs profiles of first year students at a predominantly female campus in 1978 and 1979. For a sample of 1,812 freshman, students who prefered intuitive over sensing tended to obtain higher GPAs (Henstler, et al, 1981).

Whipkey and Stephens (1984) tested 88 students in three sections of a beginning programming course in a small liberal arts college and achieved grade prediction results similar to the current study. While SAT Mathematics, SAT verbal scores and GPA correlated strongly with grade in the class, only the perceiving-judging factor of the MBTI approached significance with grade in the course (R: $p < .10$).

However, the percentage of students preferring each of the factors differed significantly from the current study, so these results may not be very comparable. Rather than 63 percent introverted, they found 50 percent; rather than 46 percent perceiving, they reported 52 percent; rather than 49 percent sensing, they measured 68 percent; and rather than 77 percent thinking, they obtained 43 percent. The content of the class was not described in any detail, but there were 46 females to only 42 males, so this would account for some of the differences. This course may well have been more of a computer literacy or data processing class than a rigorous programming class such as CSC 135.

Two informal studies reported in a business data processing periodical, Datamation, gave only the predominant Myers-Briggs factors found and did not give complete sets of percentages or other information. The first of these studies looked at 27 volunteers from four Texas business computer installations. The study found that the most common type was ENTP (extroverted, intuitive, thinking and perceiving), a combination which occurs in only five percent of the general population (Sitton & Chmeliar, 1984). The Myers manual (1962) shows many studies of business students who are generally extroverted, so this may account for the differences from the current study.

The second Datamation study looked at 40 programmer analysts and 18 systems analysts from a Texas aerospace firm. This study found 74 percent to be thinkers and 70 percent to be judging as compared to 77 percent thinking and 54 percent judging in the current study. ISTJ was their most common type, with 25 percent in this category rather than the expected 6 percent. Sixteen percent were INTJ, whereas one percent of the general population usually falls in this category (Bush & Schkade, 1985). Interestingly, ISTJ and INTJ were the top two categories in the current study also, with 19 and 16 percent respectively. The CSC 135 students will likely become scientific programmers or programmer analysts. Some will be system programmers, but they will not generally be called system analysts, because that is a business job classification. Since the second Datamation study concerned an aerospace company, it may have tested scientific programmers, but the information given does not make this clear. A carefully planned study of working scientific and system programmers would provide valuable information which could then be compared with that obtained from computer science students. Differences between business and scientific programmers would be interesting as well.

While the Myers-Briggs Type Indicator does not appear to be very useful in predicting success in a beginning computer science course, the profile of the computer science student is quite distinct. If these personality type profiles continue, or grow even more pronounced, as students advance in the computer science program, this information would be helpful in advising beginning students. More importantly, the information could also be used to assist faculty in matching their teaching style to the learning style of the students. Comparing personality type with "successful" working programmers would be of interest to both academic and industry personnel.

Limitations

This study was exploratory in nature. Because of the small population and the lack of a theoretical foundation, only a causal-comparitive study was possible. While the results of this study should be interpreted cautiously, a better picture of the beginning computer science student is emerging, which should lead to important results in the future.

Because students who dropped the course were not considered, the study is biased toward the successful student. There is little that can be done since the grade in the course was the criteria for success. It would be interesting to compare the results of the students who dropped to those who remained in the class, however.

Methodological Limitations

The major problem with research design involved the voluntary nature of the data collection. There was considerable difficulty in getting the students to return the questionnaires to their instructors. The measures need to be reduced in length so that they may be completed in one 50 minute class period. While there was a high correlation between the students who completed the questionnaire voluntarily and the students who completed the course, the work involved in getting the questionnaires returned was frustrating and unnecessary. Completing the measures during class time will ultimately cause less interference for the instructor, as well as insuring more complete data collection. This was not a problem in pilot studies with my own students, but was a problem for the current study.

Implications and Recommendations

This study provides a profile or model of the computer science student which is useful from a number of points of view. The original purpose of predicting success in a beginning computer science course in order to make most effective use of limited resources has been well served. Important information on helpful student background was obtained, and two measures which show a significant relationship with grade were found. The knowledge gained will also prove useful in improving the teaching of computer science classes, a secondary goal of the study.

Additional information such as scores on national standardized tests such as the SAT and ACT need to be incorporated in the model. Information on the mathematics background has been shown to be important, but knowledge about the specific mathematics courses which are helpful would be valuable. Data on the number of science courses might also be useful. Information on student background needs to be refined. This kind of knowledge can be used to enforce prerequisites which will in turn, help students to be more successful.

The question of work experience is of considerable importance in a field where many are trying to add computer science skills while continuing to work at their current occupation. They may be studying to enhance their current job skills or because they want to change to a more rewarding profession. In any case, these students have shown that they can succeed in a rigorous computer science class. Indeed, because they are succeeding, despite the disadvantage of a heavy work load, any encouragement which can be offered, should be.

While motivation was not measured directly in the current study, it may be an important variable for the working students, and an attempt should be made to incorporate this factor into the model.

The significance of the Piagetian measure shows the importance of mathematics and logic ability in predicting success for the computer science student. Another measure might provide more specific information which can be more readily used than Kurtz's Formal Reasoning Test, but this factor clearly deserves further study.

Cognitive style, as measured by the Group Embedded Figures Test, apparently correlates to ability in and preference for both mathematics and computers. Interest in cognitive style in general, and field dependence-independence in particular, is growing rapidly, as measured by the large number of papers now available (Cox & Gall, 1981). The personal characteristics which correspond to field independence and the educational implication which have already been determined (Witkin et al, 1977), can be use to improve the learning environment for the computer science student. Additional study in this area should provide further insight into both the cognitive processes and the personality of the successful computer science student.

The Myers-Briggs personality types did not show a significant relationship to grade, but a better understanding of the rather dramatic profile of the computer science student shown in these results, holds tremendous promise for improving instruction in computer science. Engineering educators have already formed a consortium of eight universities to study the effects of psychological type differences, as measured by the Myers-Briggs Type Indicator, on the education of engineering students (McCaulley, 1983). Because of the similarities between engineering and computer science students, some of their ideas and suggestions can be applied directly to computer science education. Because of the differences, additional study is required to refine the model of computer science students and the factors which relate to success, not only while they are in school, but also after they are on the job.

Information about the "typical" personality of the computer scientist will be helpful in advising beginning computer science students. Computer science is a very diverse field which should hold opportunities for many types of individuals. Further study may reveal personality differences between the student "hacker," the more advanced, theoretically oriented student, the successful software engineer, and so on. This kind of information could even be used to broaden the range of personality types in computer science. It would certainly give hope to the students who do not fit the stereotypical image of the computer programmer that they might also find a place in the computer field.

An awareness of these personality type differences can help faculty improve their teaching as well. The type of student in a systems programming course will differ from that of the typical student in an artificial intelligence course. The student who prefers a theoretical foundations course will likely differ from the computer graphics student, and so on. Making these differences explicit to both faculty and student, together with educating them both on the prefered learning style of each type, could result in improved teaching and learning.

Extensions to the current study might include a long term study of persistence in the computer science major. How do the high aptitude students, who make As and Bs in this class compare to the lower aptitude student, who makes Cs and below? Do the average and below students finish the degree program? How many of these beginning computer science students complete their degree? What are the characteristics of the graduating computer science major? What about the graduate student in computer science? An interesting companion study would compare various factors between a general education computer literacy student, the beginning computer science major, and the advanced computer science student. Much work remains, but at least a start has been made.

APPENDIX A

Appendix A.1

Dear Student,

The tests which you are being asked to take are to be used to predict success in a beginning computer programming class. Many people are interested in what factors are important to success in computer programming. By comparing your scores on these tests to your grade at the end of this course, it will be possible to determine if the factors measured by these tests are important in a beginning programming course.

The Myers-Briggs Test is designed to measure preferences in four broad areas:

a) extroversion, liking social situations and being with large groups of people vs. introversion, liking individual and limited social interactions.
b) sensing, a liking for facts, experience and present realities vs. intuition, preferring theories, implications and future possibilities.
c) thinking vs. feeling choices and relationships.
d) a preference for orderly, scheduled, planned situations and events, vs. those which are spontaneous, unplanned and/or unstructured.

Since such preferences appeal to all individuals in varying degrees, there is literally no "right" or "wrong" choice for any of the items contained in this test. At the same time, it is not a personality test, nor does it contain items designed to assess personal topics of any sort. It measures only the broad preference areas cited above--and nothing more.

The Group Embedded Figures Test measures "field- independence" vs. "field-dependence," that is, the ability to separate out a simple figure concealed within a more complex figure. The final test measures intellectual development level as defined by the psychologist Piaget. These items measure knowledge of mathematics and logic concepts.

Since this is a professional research effort, every effort will be made to protect your privacy. (a) Response to these instruments is purely voluntary and based on informed consent; persons under 18 years of age should seek parental permission before completing it. (b) All results will be confidential; completed tests will be destroyed and all results recorded by coded number without reference to name or other identifying information, once the scores and the grade have been correlated. Published accounts will reflect only group results. (c) These scores will not be known to your instructor and will not affect your grade in the course in any way.

Thank you for taking the time to help the computer science department in our efforts to improve our course offerings. Your cooperation in this project is very much appreciated.

I've read the above and agree to participate in this research.

____

Appendix A.2

COMPUTER SCIENCE PLACEMENT EXAM

This placement exam is being tested for possible use by the computer science department. Your score will not effect your grade in this class in any way. We will compare your score to your grade in the class to see if this test effectively predicts students' grades. We appreciate your cooperation in this endeavor.

NAME ______________________________

CLASS ____________ INSTRUCTOR ________________ SECTION ______

Throughout this excercise, feel free to draw pictures or make notes wherever you like. Don't forget to mark the Scantron sheet with your selected answer.

1. What is your sex?

    a) Male b) Female

2. What is your age?

    a) 19 or younger b) 20 to 24 c) 25 to 29
    d) 30 to 34 e) 35 or older

3. Rate your high school academic performance using the following categories:

    a) A (excellent) b) B (above average)
    c) C or below (average or below)

4. Rate your current college academic performance using the following categories:

    a) A (excellent) b) B (above average)
    c) C or below (average or below)
    d) No previous college experience

5. How many hours per week do you work, on the average?

    a) None b) 1 to 13 c) 14 to 26
    d) 27 to 39 e) 40 or more

6. What is your current university classification?

   a) Freshman b) Sophomore c) Junior
   d) Senior e) Other

7. How much work experience have you had in computer science?

   a) None b) Some c) Considerable

8. How much work experience have you had that involved nonprogramming aspects of computers?

   a) None b) Some c) Considerable

9. How much work experience have you had that involved programming aspects of computers?

   a) None b) Some c) Considerable

10. How many years of high school math have you had?

    a) 0 b) 1 c) 2 d) 3 e) 4 or more

11. How many math courses have you had at the college or university level?

    a) 0 b) 1 c) 2 d) 3 e) 4 or more

APPENDIX C

Appendix B

Statistical Results

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * C R O S S T A B U L A T I O N O F * * * * * * * * * * * * * * *
SEX BY GRADE LETTER GRADE WITH +,-
* *

SEX	GRADE COUNT / ROW PCT / COL PCT / TOT PCT	D 1.0	C - 1.7	C 2.0	C + 2.3	B - 2.7	B 3.0	B + 3.3	A - 3.7	A 4.0	ROW TOTAL
MALE	1.	4	4	5	2	6	5	5	4	9	44
		9.1	9.1	11.4	4.5	13.6	11.4	11.4	9.1	20.5	75.9
		100.0	100.0	71.4	66.7	75.0	55.6	71.4	66.7	90.0	
		6.9	6.9	8.6	3.4	10.3	8.6	8.6	6.9	15.5	
FEMALE	2.	0	0	2	1	2	4	2	2	1	14
		0	0	14.3	7.1	14.3	28.6	14.3	14.3	7.1	24.1
		0	0	28.6	33.3	25.0	44.4	28.6	33.3	10.0	
		0	0	3.4	1.7	3.4	6.9	3.4	3.4	1.7	
	COLUMN TOTAL	4	4	7	3	8	9	7	6	10	58
		6.9	6.9	12.1	5.2	13.8	15.5	12.1	10.3	17.2	100.0

RAW CHI SQUARE = 6.23282 WITH 8 DEGREES OF FREEDOM. SIGNIFICANCE = .6212
PEARSON"S R = .07964 SIGNIFICANCE = .2762

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * * * * C R O S S T A B U L A T I O N O F * * * * * * * * * * * * * * * *
AGE BY GRADE LETTER GRADE WITH +,-

AGE	GRADE: COUNT / ROW PCT / COL PCT / TOT PCT	D 1.0	C - 1.7	C 2.0	C + 2.3	B - 2.7	B 3.0	B + 3.3	A - 3.7	A 4.0	ROW TOTAL
1. 19 OR YOUNGER	COUNT	1	0	3	2	0	4	2	2	1	15
	ROW PCT	6.7	0	20.0	13.3	0	26.7	13.3	13.3	6.7	25.9
	COL PCT	25.0	0	42.9	66.7	0	44.4	28.6	33.3	10.0	
	TOT PCT	1.7	0	5.2	3.4	0	6.9	3.4	3.4	1.7	
2. 20 TO 24	COUNT	1	1	3	0	3	3	2	4	3	20
	ROW PCT	5.0	5.0	15.0	0	15.0	15.0	10.0	20.0	15.0	34.5
	COL PCT	25.0	25.0	42.9	0	37.5	33.3	28.6	66.7	30.0	
	TOT PCT	1.7	1.7	5.2	0	5.2	5.2	3.4	6.9	5.2	
3. 25 TO 29	COUNT	0	1	0	1	3	2	0	0	4	11
	ROW PCT	0	9.1	0	9.1	27.3	18.2	0	0	36.4	19.0
	COL PCT	0	25.0	0	33.3	37.5	22.2	0	0	40.0	
	TOT PCT	0	1.7	0	1.7	5.2	3.4	0	0	6.9	
4. 30 TO 34	COUNT	1	1	0	0	1	0	2	0	1	6
	ROW PCT	16.7	16.7	0	0	16.7	0	33.3	0	16.7	10.3
	COL PCT	25.0	25.0	0	0	12.5	0	28.6	0	10.0	
	TOT PCT	1.7	1.7	0	0	1.7	0	3.4	0	1.7	
5. 35 OR OLDER	COUNT	1	1	1	0	1	0	1	0	1	6
	ROW PCT	16.7	16.7	16.7	0	16.7	0	16.7	0	16.7	10.3
	COL PCT	25.0	25.0	14.3	0	12.5	0	14.3	0	10.0	
	TOT PCT	1.7	1.7	1.7	0	1.7	0	1.7	0	1.7	
COLUMN TOTAL		4	4	7	3	8	9	7	6	10	58
		6.9	6.9	12.1	5.2	13.8	15.5	12.1	10.3	17.2	100.0

RAW CHI SQUARE = 30.57300 WITH 32 DEGREES OF FREEDOM. SIGNIFICANCE = .5338
PEARSON"S R = -.08309 SIGNIFICANCE = .2554

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * * * C R O S S T A B U L A T I O N O F * * * * * * * * * * * * * * * *
HS HIGH SCHOOL GRADES BY GRADE LETTER GRADE WITH +,-
* *

HS	GRADE COUNT ROW PCT COL PCT TOT PCT	D 1.0	C - 1.7	C 2.0	C + 2.3	B - 2.7	B 3.0	B + 3.3	A - 3.7	A 4.0	ROW TOTAL
A EXCELLENT	1.	1	1	3	0	1	1	3	2	1	13
		7.7	7.7	23.1	0	7.7	7.7	23.1	15.4	7.7	22.4
		25.0	25.0	42.9	0	12.5	11.1	42.9	33.3	10.0	
		1.7	1.7	5.2	0	1.7	1.7	5.2	3.4	1.7	
B ABOVE AVERAGE	2.	2	2	3	2	5	8	4	4	8	38
		5.3	5.3	7.9	5.3	13.2	21.1	10.5	10.5	21.1	65.5
		50.0	50.0	42.9	66.7	62.5	88.9	57.1	66.7	80.0	
		3.4	3.4	5.2	3.4	8.6	13.8	6.9	6.9	13.8	
C OR BELOW AVERAGE	3.	1	1	1	1	2	0	0	0	1	7
		14.3	14.3	14.3	14.3	28.6	0	0	0	14.3	12.1
		25.0	25.0	14.3	33.3	25.0	0	0	0	10.0	
		1.7	1.7	1.7	1.7	3.4	0	0	0	1.7	
COLUMN TOTAL		4	4	7	3	8	9	7	6	10	58
		6.9	6.9	12.1	5.2	13.8	15.5	12.1	10.3	17.2	100.0

RAW CHI SQUARE = 13.23807 WITH 16 DEGREES OF FREEDOM. SIGNIFICANCE = .6553
PEARSON"S R = -.07402 SIGNIFICANCE = .2904

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * * * * C R O S S T A B U L A T I O N O F * * * * * * * * * * * * * * * *
COL COLLEGE GRADES BY GRADE LETTER GRADE WITH +,-
* *

COL	GRADE COUNT ROW PCT COL PCT TOT PCT	D 1.0	C- 1.7	C 2.0	C+ 2.3	B- 2.7	B 3.0	B+ 3.3	A- 3.7	A 4.0	ROW TOTAL
A EXCELLENT	1.	2	0	0	0	0	1	2	1	5	11
		18.2	0	0	0	0	9.1	18.2	9.1	45.5	19.0
		50.0	0	0	0	0	11.1	28.6	16.7	50.0	
		3.4	0	0	0	0	1.7	3.4	1.7	8.6	
B ABOVE AVERAGE	2.	1	1	5	3	4	5	4	4	4	31
		3.2	3.2	16.1	9.7	12.9	16.1	12.9	12.9	12.9	53.4
		25.0	25.0	71.4	100.0	50.0	55.6	57.1	66.7	40.0	
		1.7	1.7	8.6	5.2	6.9	8.6	6.9	6.9	6.9	
C OR BELOW AVERAGE	3.	1	3	2	0	4	3	1	1	1	16
		6.3	18.8	12.5	0	25.0	18.8	6.3	6.3	6.3	27.6
		25.0	75.0	28.6	0	50.0	33.3	14.3	16.7	10.0	
		1.7	5.2	3.4	0	6.9	5.2	1.7	1.7	1.7	
	COLUMN TOTAL	4	4	7	3	8	9	7	6	10	58
		6.9	6.9	12.1	5.2	13.8	15.5	12.1	10.3	17.2	100.0

RAW CHI SQUARE = 22.85441 WITH 16 DEGREES OF FREEDOM. SIGNIFICANCE = .1177
PEARSON"S R = -.25288 SIGNIFICANCE = .0277

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * * * * CROSSTABULATION OF * * * * * * * * * * * * * * * *
WORK HOURS WORKED BY GRADE LETTER GRADE WITH +,-
* *

WORK	GRADE COUNT ROW PCT COL PCT TOT PCT	D 1.0	C- 1.7	C 2.0	C+ 2.3	B- 2.7	B 3.0	B+ 3.3	A- 3.7	A 4.0	ROW TOTAL
NONE	1.	1	1	2	0	1	1	0	1	0	7
		14.3	14.3	28.6	0	14.3	14.3	0	14.3	0	12.1
		25.0	25.0	28.6	0	12.5	11.1	0	16.7	0	
		1.7	1.7	3.4	0	1.7	1.7	0	1.7	0	
1 TO 13	2.	0	0	2	2	0	1	1	0	1	7
		0	0	28.6	28.6	0	14.3	14.3	0	14.3	12.1
		0	0	28.6	66.7	0	11.1	14.3	0	10.0	
		0	0	3.4	3.4	0	1.7	1.7	0	1.7	
14 TO 26	3.	1	0	2	0	1	7	2	1	2	16
		6.3	0	12.5	0	6.3	43.8	12.5	6.3	12.5	27.6
		25.0	0	28.6	0	12.5	77.8	28.6	16.7	20.0	
		1.7	0	3.4	0	1.7	12.1	3.4	1.7	3.4	
27 TO 39	4.	0	2	1	1	0	0	1	4	2	11
		0	18.2	9.1	9.1	0	0	9.1	36.4	18.2	19.0
		0	50.0	14.3	33.3	0	0	14.3	66.7	20.0	
		0	3.4	1.7	1.7	0	0	1.7	6.9	3.4	
40 OR MORE	5.	2	1	0	0	6	0	3	0	5	17
		11.8	5.9	0	0	35.3	0	17.6	0	29.4	29.3
		50.0	25.0	0	0	75.0	0	42.9	0	50.0	
		3.4	1.7	0	0	10.3	0	5.2	0	8.6	
	COLUMN TOTAL	4	4	7	3	8	9	7	6	10	58
		6.9	6.9	12.1	5.2	13.8	15.5	12.1	10.3	17.2	100.0

RAW CHI SQUARE = 57.46266 WITH 32 DEGREES OF FREEDOM. SIGNIFICANCE = .0038
PEARSON'S R = .20288 SIGNIFICANCE = .0633

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * * * * C R O S S T A B U L A T I O N   O F * * * * * * * * * * * * * * *

CLASS CLASSIFICATION BY GRADE LETTER GRADE WITH +,-

* *

CLASS	GRADE: COUNT / ROW PCT / COL PCT / TOT PCT	D 1.0	C − 1.7	C 2.0	C + 2.3	B − 2.7	B 3.0	B + 3.3	A − 3.7	A 4.0	ROW TOTAL
1. FRESHMAN	COUNT	1	0	2	1	0	3	1	2	1	11
	ROW PCT	9.1	0	18.2	9.1	0	27.3	9.1	18.2	9.1	19.0
	COL PCT	25.0	0	28.6	33.3	0	33.3	14.3	33.3	10.0	
	TOT PCT	1.7	0	3.4	1.7	0	5.2	1.7	3.4	1.7	
2. SOPHOMORE	COUNT	0	1	3	0	5	3	2	3	4	21
	ROW PCT	0	4.8	14.3	0	23.8	14.3	9.5	14.3	19.0	36.2
	COL PCT	0	25.0	42.9	0	62.5	33.3	28.6	50.0	40.0	
	TOT PCT	0	1.7	5.2	0	8.6	5.2	3.4	5.2	6.9	
3. JUNIOR	COUNT	2	2	1	1	1	3	0	1	3	14
	ROW PCT	14.3	14.3	7.1	7.1	7.1	21.4	0	7.1	21.4	24.1
	COL PCT	50.0	50.0	14.3	33.3	12.5	33.3	0	16.7	30.0	
	TOT PCT	3.4	3.4	1.7	1.7	1.7	5.2	0	1.7	5.2	
4. SENIOR	COUNT	1	1	1	0	1	0	2	0	0	6
	ROW PCT	16.7	16.7	16.7	0	16.7	0	33.3	0	0	10.3
	COL PCT	25.0	25.0	14.3	0	12.5	0	28.6	0	0	
	TOT PCT	1.7	1.7	1.7	0	1.7	0	3.4	0	0	
5. OTHER	COUNT	0	0	0	1	1	0	2	0	2	6
	ROW PCT	0	0	0	16.7	16.7	0	33.3	0	33.3	10.3
	COL PCT	0	0	0	33.3	12.5	0	28.6	0	20.0	
	TOT PCT	0	0	0	1.7	1.7	0	3.4	0	3.4	
COLUMN TOTAL		4	4	7	3	8	9	7	6	10	58
		6.9	6.9	12.1	5.2	13.8	15.5	12.1	10.3	17.2	100.0

RAW CHI SQUARE = 30.03736 WITH 32 DEGREES OF FREEDOM. SIGNIFICANCE = .5662

PEARSON"S R = -.02162 SIGNIFICANCE = .4360

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * * * * CROSSTABULATION OF * * * * * * * * * * * * * * * * *

CSEDUC PRIOR CS EDUCATION BY GRADE LETTER GRADE WITH +,-

* *

CSEDUC	GRADE COUNT ROW PCT COL PCT TOT PCT	D 1.0	C - 1.7	C 2.0	C + 2.3	B - 2.7	B 3.0	B + 3.3	A - 3.7	A 4.0	ROW TOTAL
NONE	1.	1	2	4	3	6	3	3	3	3	28
		3.6	7.1	14.3	10.7	21.4	10.7	10.7	10.7	10.7	48.3
		25.0	50.0	57.1	100.0	75.0	33.3	42.9	50.0	30.0	
		1.7	3.4	6.9	5.2	10.3	5.2	5.2	5.2	5.2	
SOME	2.	3	2	2	0	2	4	4	3	6	26
		11.5	7.7	7.7	0	7.7	15.4	15.4	11.5	23.1	44.8
		75.0	50.0	28.6	0	25.0	44.4	57.1	50.0	60.0	
		5.2	3.4	3.4	0	3.4	6.9	6.9	5.2	10.3	
CONSIDERABLE	3.	0	0	1	0	0	2	0	0	1	4
		0	0	25.0	0	0	50.0	0	0	25.0	6.9
		0	0	14.3	0	0	22.2	0	0	10.0	
		0	0	1.7	0	0	3.4	0	0	1.7	
	COLUMN TOTAL	4	4	7	3	8	9	7	6	10	58
		6.9	6.9	12.1	5.2	13.8	15.5	12.1	10.3	17.2	100.0

RAW CHI SQUARE = 14.61344 WITH 16 DEGREES OF FREEDOM. SIGNIFICANCE = .5531

PEARSON'S R = .09671 SIGNIFICANCE = .2351

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * * * * CROSSTABULATION OF * * * * * * * * * * * * * * *
NOCSWORK NON CS WORK HOURS BY GRADE LETTER GRADE WITH +,-

NOCSWORK (COUNT / ROW PCT / COL PCT / TOT PCT)	GRADE D 1.0	C- 1.7	C 2.0	C+ 2.3	B- 2.7	B 3.0	B+ 3.3	A- 3.7	A 4.0	ROW TOTAL
1. NONE	2	1	3	2	4	3	4	5	3	27
	7.4	3.7	11.1	7.4	14.8	11.1	14.8	18.5	11.1	46.6
	50.0	25.0	42.9	66.7	50.0	33.3	57.1	83.3	30.0	
	3.4	1.7	5.2	3.4	6.9	5.2	6.9	8.6	5.2	
2. SOME	0	2	3	1	4	5	3	1	5	24
	0	8.3	12.5	4.2	16.7	20.8	12.5	4.2	20.8	41.4
	0	50.0	42.9	33.3	50.0	55.6	42.9	16.7	50.0	
	0	3.4	5.2	1.7	6.9	8.6	5.2	1.7	8.6	
3. CONSIDERABLE	2	1	1	0	0	1	0	0	2	7
	28.6	14.3	14.3	0	0	14.3	0	0	28.6	12.1
	50.0	25.0	14.3	0	0	11.1	0	0	20.0	
	3.4	1.7	1.7	0	0	1.7	0	0	3.4	
COLUMN TOTAL	4	4	7	3	8	9	7	6	10	58
	6.9	6.9	12.1	5.2	13.8	15.5	12.1	10.3	17.2	100.0

RAW CHI SQUARE = 15.75272 WITH 16 DEGREES OF FREEDOM. SIGNIFICANCE = .4703
PEARSON"S R = -.11533 SIGNIFICANCE = .1943

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * * * * CROSSTABULATION OF * * * * * * * * * * * * * * *

PROGWORK PROGRAMMING EXPERIENCE BY GRADE LETTER GRADE WITH +,-

PROGWORK	GRADE COUNT ROW PCT COL PCT TOT PCT	D 1.0	C - 1.7	C 2.0	C + 2.3	B - 2.7	B 3.0	B + 3.3	A - 3.7	A 4.0	ROW TOTAL
	1.	3	2	4	3	6	5	3	4	3	33
NONE		9.1	6.1	12.1	9.1	18.2	15.2	9.1	12.1	9.1	56.9
		75.0	50.0	57.1	100.0	75.0	55.6	42.9	66.7	30.0	
		5.2	3.4	6.9	5.2	10.3	8.6	5.2	6.9	5.2	
	2.	1	2	2	0	2	4	4	2	6	23
SOME		4.3	8.7	8.7	0	8.7	17.4	17.4	8.7	26.1	39.7
		25.0	50.0	28.6	0	25.0	44.4	57.1	33.3	60.0	
		1.7	3.4	3.4	0	3.4	6.9	6.9	3.4	10.3	
	3.	0	0	1	0	0	0	0	0	1	2
CONSIDERABLE		0	0	50.0	0	0	0	0	0	50.0	3.4
		0	0	14.3	0	0	0	0	0	10.0	
		0	0	1.7	0	0	0	0	0	1.7	
	COLUMN TOTAL	4 6.9	4 6.9	7 12.1	3 5.2	8 13.8	9 15.5	7 12.1	6 10.3	10 17.2	58 100.0

RAW CHI SQUARE = 12.22522 WITH 16 DEGREES OF FREEDOM. SIGNIFICANCE = .7283
PEARSON"S R = .18584 SIGNIFICANCE = .0813

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * * * * C R O S S T A B U L A T I O N O F * * * * * * * * * * * * * * * *

HSMATH YEARS OF HS MATH BY GRADE LETTER GRADE WITH +,-

* *

HSMATH	GRADE COUNT ROW PCT COL PCT TOT PCT	D 1.0	C - 1.7	C 2.0	C + 2.3	B - 2.7	B 3.0	B + 3.3	A - 3.7	A 4.0	ROW TOTAL
	1.	1	0	0	0	0	0	0	0	0	1
0 YEARS		100.0	0	0	0	0	0	0	0	0	1.7
		25.0	0	0	0	0	0	0	0	0	
		1.7	0	0	0	0	0	0	0	0	
	2.	0	0	1	1	0	2	0	0	0	4
1		0	0	25.0	25.0	0	50.0	0	0	0	6.9
		0	0	14.3	33.3	0	22.2	0	0	0	
		0	0	1.7	1.7	0	3.4	0	0	0	
	3.	0	1	1	1	0	0	3	0	0	6
2		0	16.7	16.7	16.7	0	0	50.0	0	0	10.3
		0	25.0	14.3	33.3	0	0	42.9	0	0	
		0	1.7	1.7	1.7	0	0	5.2	0	0	
	4.	0	0	2	0	4	1	0	0	2	9
3		0	0	22.2	0	44.4	11.1	0	0	22.2	15.5
		0	0	28.6	0	50.0	11.1	0	0	20.0	
		0	0	3.4	0	6.9	1.7	0	0	3.4	
	5.	3	3	3	1	4	6	4	6	8	38
4 OR MORE		7.9	7.9	7.9	2.6	10.5	15.8	10.5	15.8	21.1	65.5
		75.0	75.0	42.9	33.3	50.0	66.7	57.1	100.0	80.0	
		5.2	5.2	5.2	1.7	6.9	10.3	6.9	10.3	13.8	
	COLUMN	4	4	7	3	8	9	7	6	10	58
	TOTAL	6.9	6.9	12.1	5.2	13.8	15.5	12.1	10.3	17.2	100.0

RAW CHI SQUARE = 50.07541 WITH 32 DEGREES OF FREEDOM. SIGNIFICANCE = .0219

PEARSON"S R = .25197 SIGNIFICANCE = .0282

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * * * * C R O S S T A B U L A T I O N O F * * * * * * * * * * * * * * * *
COLMATH COLLEGE MATH COURSES BY GRADE LETTER GRADE WITH +,-

COLMATH		GRADE: COUNT / ROW PCT / COL PCT / TOT PCT	D 1.0	C - 1.7	C 2.0	C + 2.3	B - 2.7	B 3.0	B + 3.3	A - 3.7	A 4.0	ROW TOTAL
	1.	COUNT	1	0	0	1	0	0	0	0	0	2
0 COURSES		ROW PCT	50.0	0	0	50.0	0	0	0	0	0	3.4
		COL PCT	25.0	0	0	33.3	0	0	0	0	0	
		TOT PCT	1.7	0	0	1.7	0	0	0	0	0	
	2.	COUNT	0	0	1	0	0	2	0	2	0	5
1		ROW PCT	0	0	20.0	0	0	40.0	0	40.0	0	8.6
		COL PCT	0	0	14.3	0	0	22.2	0	33.3	0	
		TOT PCT	0	0	1.7	0	0	3.4	0	3.4	0	
	3.	COUNT	0	0	1	1	0	3	2	1	3	11
2		ROW PCT	0	0	9.1	9.1	0	27.3	18.2	9.1	27.3	19.0
		COL PCT	0	0	14.3	33.3	0	33.3	28.6	16.7	30.0	
		TOT PCT	0	0	1.7	1.7	0	5.2	3.4	1.7	5.2	
	4.	COUNT	1	1	2	0	4	4	2	2	1	17
3		ROW PCT	5.9	5.9	11.8	0	23.5	23.5	11.8	11.8	5.9	29.3
		COL PCT	25.0	25.0	28.6	0	50.0	44.4	28.6	33.3	10.0	
		TOT PCT	1.7	1.7	3.4	0	6.9	6.9	3.4	3.4	1.7	
	5.	COUNT	2	3	3	1	4	0	3	1	6	23
4 OR MORE		ROW PCT	8.7	13.0	13.0	4.3	17.4	0	13.0	4.3	26.1	39.7
		COL PCT	50.0	75.0	42.9	33.3	50.0	0	42.9	16.7	60.0	
		TOT PCT	3.4	5.2	5.2	1.7	6.9	0	5.2	1.7	10.3	
	COLUMN TOTAL		4	4	7	3	8	9	7	6	10	58
			6.9	6.9	12.1	5.2	13.8	15.5	12.1	10.3	17.2	100.0

RAW CHI SQUARE = 41.05583 WITH 32 DEGREES OF FREEDOM. SIGNIFICANCE = .1310
PEARSON'S R = -.01915 SIGNIFICANCE = .4433

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * * * * * CROSSTABULATION OF * * * * * * * * * * * * * * *
PTOTAL PIAGET TOTAL SCORE BY GRADE LETTER GRADE WITH +,-
* *

PTOTAL		GRADE COUNT / ROW PCT / COL PCT / TOT PCT	D 1.0	C - 1.7	C 2.0	C + 2.3	B - 2.7	B 3.0	B + 3.3	A - 3.7	A 4.0	ROW TOTAL
	6.		0	0	0	0	0	2	0	0	0	2
LOW			0	0	0	0	0	100.0	0	0	0	3.4
			0	0	0	0	0	22.2	0	0	0	
			0	0	0	0	0	3.4	0	0	0	
	7.		0	0	0	1	0	1	0	0	0	2
			0	0	0	50.0	0	50.0	0	0	0	3.4
			0	0	0	33.3	0	11.1	0	0	0	
			0	0	0	1.7	0	1.7	0	0	0	
	8.		1	0	3	0	3	0	0	0	0	7
			14.3	0	42.9	0	42.9	0	0	0	0	12.1
			25.0	0	42.9	0	37.5	0	0	0	0	
			1.7	0	5.2	0	5.2	0	0	0	0	
	9.		0	0	0	0	1	0	1	0	2	4
			0	0	0	0	25.0	0	25.0	0	50.0	6.9
			0	0	0	0	12.5	0	14.3	0	20.0	
			0	0	0	0	1.7	0	1.7	0	3.4	
	10.		1	3	0	0	0	0	1	5	2	12
			8.3	25.0	0	0	0	0	8.3	41.7	16.7	20.7
			25.0	75.0	0	0	0	0	14.3	83.3	20.0	
			1.7	5.2	0	0	0	0	1.7	8.6	3.4	
	11.		1	1	0	0	1	3	1	0	1	8
AVERAGE			12.5	12.5	0	0	12.5	37.5	12.5	0	12.5	13.8
			25.0	25.0	0	0	12.5	33.3	14.3	0	10.0	
			1.7	1.7	0	0	1.7	5.2	1.7	0	1.7	
	12.		0	0	1	1	2	1	2	1	3	11
			0	0	9.1	9.1	18.2	9.1	18.2	9.1	27.3	19.0
			0	0	14.3	33.3	25.0	11.1	28.6	16.7	30.0	
			0	0	1.7	1.7	3.4	1.7	3.4	1.7	5.2	

Table B.1 Grade Crosstabulations (continued)

	13.	1	0	1	0	1	2	0	0	0	5
		20.0	0	20.0	0	20.0	40.0	0	0	0	8.6
		25.0	0	14.3	0	12.5	22.2	0	0	0	
		1.7	0	1.7	0	1.7	3.4	0	0	0	
	14.	0	0	1	0	0	0	2	0	1	4
		0	0	25.0	0	0	0	50.0	0	25.0	6.9
		0	0	14.3	0	0	0	28.6	0	10.0	
		0	0	1.7	0	0	0	3.4	0	1.7	
	15.	0	0	1	1	0	0	0	0	0	2
		0	0	50.0	50.0	0	0	0	0	0	3.4
		0	0	14.3	33.3	0	0	0	0	0	
		0	0	1.7	1.7	0	0	0	0	0	
	16.	0	0	0	0	0	0	0	0	1	1
HIGH		0	0	0	0	0	0	0	0	100.0	1.7
		0	0	0	0	0	0	0	0	10.0	
		0	0	0	0	0	0	0	0	1.7	
	COLUMN	4	4	7	3	8	9	7	6	10	58
	TOTAL	6.9	6.9	12.1	5.2	13.8	15.5	12.1	10.3	17.2	100.0

RAW CHI SQUARE = 104.84526 WITH 80 DEGREES OF FREEDOM. SIGNIFICANCE = .0307
PEARSON"S R = .08864 SIGNIFICANCE = .2541

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * * * * CROSSTABULATION OF * * * * * * * * * * * * * * * *
ID INTELLECTUAL DEVELOPMENT BY GRADE LETTER GRADE WITH +,-
* *

ID	GRADE COUNT / ROW PCT / COL PCT / TOT PCT	D 1.0	C - 1.7	C 2.0	C + 2.3	B - 2.7	B 3.0	B + 3.3	A - 3.7	A 4.0	ROW TOTAL
1. LATE CONCRETE	COUNT	0	1	0	1	0	0	0	0	0	2
	ROW PCT	0	50.0	0	50.0	0	0	0	0	0	3.4
	COL PCT	0	25.0	0	33.3	0	0	0	0	0	
	TOT PCT	0	1.7	0	1.7	0	0	0	0	0	
2. EARLY FORMAL	COUNT	4	3	7	1	8	9	7	6	8	53
	ROW PCT	7.5	5.7	13.2	1.9	15.1	17.0	13.2	11.3	15.1	91.4
	COL PCT	100.0	75.0	100.0	33.3	100.0	100.0	100.0	100.0	80.0	
	TOT PCT	6.9	5.2	12.1	1.7	13.8	15.5	12.1	10.3	13.8	
3. LATE FORMAL	COUNT	0	0	0	1	0	0	0	0	2	3
	ROW PCT	0	0	0	33.3	0	0	0	0	66.7	5.2
	COL PCT	0	0	0	33.3	0	0	0	0	20.0	
	TOT PCT	0	0	0	1.7	0	0	0	0	3.4	
	COLUMN TOTAL	4	4	7	3	8	9	7	6	10	58
		6.9	6.9	12.1	5.2	13.8	15.5	12.1	10.3	17.2	100.0

RAW CHI SQUARE = 27.79319 WITH 16 DEGREES OF FREEDOM. SIGNIFICANCE = .0335
PEARSON"S R = .23185 SIGNIFICANCE = .0400

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * * C R O S S T A B U L A T I O N   O F * * * * * * * * * * * * * * * * * *

EI EXTROVERT-INTROVERT BY GRADE LETTER GRADE WITH +,-

EI	COUNT / ROW PCT / COL PCT / TOT PCT	D 1.0	C - 1.7	C 2.0	C + 2.3	B - 2.7	B 3.0	B + 3.3	A - 3.7	A 4.0	ROW TOTAL
1. INTROVERSION	COUNT	2	3	4	1	5	6	6	4	5	36
	ROW PCT	5.6	8.3	11.1	2.8	13.9	16.7	16.7	11.1	13.9	63.2
	COL PCT	50.0	75.0	57.1	33.3	62.5	66.7	85.7	66.7	55.6	
	TOT PCT	3.5	5.3	7.0	1.8	8.8	10.5	10.5	7.0	8.8	
2. EXTROVERSION	COUNT	2	1	3	2	3	3	1	2	4	21
	ROW PCT	9.5	4.8	14.3	9.5	14.3	14.3	4.8	9.5	19.0	36.8
	COL PCT	50.0	25.0	42.9	66.7	37.5	33.3	14.3	33.3	44.4	
	TOT PCT	3.5	1.8	5.3	3.5	5.3	5.3	1.8	3.5	7.0	
COLUMN TOTAL		4	4	7	3	8	9	7	6	9	57
		7.0	7.0	12.3	5.3	14.0	15.8	12.3	10.5	15.8	100.0

RAW CHI SQUARE = 3.62937 WITH 8 DEGREES OF FREEDOM. SIGNIFICANCE = .8889
PEARSON'S R = -.06019 SIGNIFICANCE = .3233

* * * * * * * * * * * * * * C R O S S T A B U L A T I O N   O F * * * * * * * * * * * * * * * * * *

PJ PERCEIVING-JUDGING BY GRADE LETTER GRADE WITH +,-

PJ	COUNT / ROW PCT / COL PCT / TOT PCT	D 1.0	C - 1.7	C 2.0	C + 2.3	B - 2.7	B 3.0	B + 3.3	A - 3.7	A 4.0	ROW TOTAL
3. PERCEIVING	COUNT	2	2	5	2	0	5	2	4	4	26
	ROW PCT	7.7	7.7	19.2	7.7	0	19.2	7.7	15.4	15.4	45.6
	COL PCT	50.0	50.0	71.4	66.7	0	55.6	28.6	66.7	44.4	
	TOT PCT	3.5	3.5	8.8	3.5	0	8.8	3.5	7.0	7.0	
4. JUDGING	COUNT	2	2	2	1	8	4	5	2	5	31
	ROW PCT	6.5	6.5	6.5	3.2	25.8	12.9	16.1	6.5	16.1	54.4
	COL PCT	50.0	50.0	28.6	33.3	100.0	44.4	71.4	33.3	55.6	
	TOT PCT	3.5	3.5	3.5	1.8	14.0	7.0	8.8	3.5	8.8	
COLUMN TOTAL		4	4	7	3	8	9	7	6	9	57
		7.0	7.0	12.3	5.3	14.0	15.8	12.3	10.5	15.8	100.0

RAW CHI SQUARE = 11.44311 WITH 8 DEGREES OF FREEDOM. SIGNIFICANCE = .1778
PEARSON'S R = .05324 SIGNIFICANCE = .3470

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * * * * CROSSTABULATION OF * * * * * * * * * * * * * * * *

SN SENSING-INTUITIVE BY GRADE LETTER GRADE WITH +,-

SN / GRADE (COUNT, ROW PCT, COL PCT, TOT PCT)	D 1.0	C- 1.7	C 2.0	C+ 2.3	B- 2.7	B 3.0	B+ 3.3	A- 3.7	A 4.0	ROW TOTAL
5. SENSING	2	4	4	1	4	4	4	1	4	28
	7.1	14.3	14.3	3.6	14.3	14.3	14.3	3.6	14.3	49.1
	50.0	100.0	57.1	33.3	50.0	44.4	57.1	16.7	44.4	
	3.5	7.0	7.0	1.8	7.0	7.0	7.0	1.8	7.0	
6. INTUITIVE	2	0	3	2	4	5	3	5	5	29
	6.9	0	10.3	6.9	13.8	17.2	10.3	17.2	17.2	50.9
	50.0	0	42.9	66.7	50.0	55.6	42.9	83.3	55.6	
	3.5	0	5.3	3.5	7.0	8.8	5.3	8.8	8.8	
COLUMN TOTAL	4	4	7	3	8	9	7	6	9	57
	7.0	7.0	12.3	5.3	14.0	15.8	12.3	10.5	15.8	100.0

RAW CHI SQUARE = 7.49270 WITH 8 DEGREES OF FREEDOM. SIGNIFICANCE = .4845
PEARSON'S R = .18521 SIGNIFICANCE = .0839

* * * * * * * * * * * * * * CROSSTABULATION OF * * * * * * * * * * * * * * * * * *

TF THINKING-FEELING BY GRADE LETTER GRADE WITH +,-

TF / GRADE (COUNT, ROW PCT, COL PCT, TOT PCT)	D 1.0	C- 1.7	C 2.0	C+ 2.3	B- 2.7	B 3.0	B+ 3.3	A- 3.7	A 4.0	ROW TOTAL
7. THINKING	3	4	7	1	7	7	5	3	7	44
	6.8	9.1	15.9	2.3	15.9	15.9	11.4	6.8	15.9	77.2
	75.0	100.0	100.0	33.3	87.5	77.8	71.4	50.0	77.8	
	5.3	7.0	12.3	1.8	12.3	12.3	8.8	5.3	12.3	
8. FEELING	1	0	0	2	1	2	2	3	2	13
	7.7	0	0	15.4	7.7	15.4	15.4	23.1	15.4	22.8
	25.0	0	0	66.7	12.5	22.2	28.6	50.0	22.2	
	1.8	0	0	3.5	1.8	3.5	3.5	5.3	3.5	
COLUMN TOTAL	4	4	7	3	8	9	7	6	9	57
	7.0	7.0	12.3	5.3	14.0	15.8	12.3	10.5	15.8	100.0

RAW CHI SQUARE = 9.67735 WITH 8 DEGREES OF FREEDOM. SIGNIFICANCE = .2884
PEARSON'S R = .15140 SIGNIFICANCE = .1305

Table B.1 Grade Crosstabulations

* * * * * * * * * * * * * * C R O S S T A B U L A T I O N O F * * * * * * * * * * * * * * * * * *

GEFT EMBEDDED FIGURES TEST BY GRADE LETTER GRADE WITH +,-

* *

GEFT	GRADE COUNT ROW PCT COL PCT TOT PCT	D 1.0	C - 1.7	C 2.0	C + 2.3	B - 2.7	B 3.0	B + 3.3	A - 3.7	A 4.0	ROW TOTAL
	2.	0	0	0	0	0	0	1	0	0	1
LOW		0	0	0	0	0	0	100.0	0	0	1.9
		0	0	0	0	0	0	16.7	0	0	
		0	0	0	0	0	0	1.9	0	0	
	3.	0	0	0	0	0	0	0	1	0	1
		0	0	0	0	0	0	0	100.0	0	1.9
		0	0	0	0	0	0	0	16.7	0	
		0	0	0	0	0	0	0	1.9	0	
	6.	0	0	0	1	0	1	0	0	0	2
		0	0	0	50.0	0	50.0	0	0	0	3.8
		0	0	0	50.0	0	11.1	0	0	0	
		0	0	0	1.9	0	1.9	0	0	0	
	8.	0	1	1	1	1	0	0	0	0	4
		0	25.0	25.0	25.0	25.0	0	0	0	0	7.5
		0	25.0	14.3	50.0	14.3	0	0	0	0	
		0	1.9	1.9	1.9	1.9	0	0	0	0	
	9.	2	0	0	0	1	0	0	0	0	3
		66.7	0	0	0	33.3	0	0	0	0	5.7
		50.0	0	0	0	14.3	0	0	0	0	
	10.	0	0	0	0	1	1	1	0	0	3
		0	0	0	0	33.3	33.3	33.3	0	0	5.7
		0	0	0	0	14.3	11.1	16.7	0	0	
		0	0	0	0	1.9	1.9	1.9	0	0	
	11.	1	0	4	0	1	1	0	0	1	8
		12.5	0	50.0	0	12.5	12.5	0	0	12.5	15.1
		25.0	0	57.1	0	14.3	11.1	0	0	12.5	
		1.9	0	7.5	0	1.9	1.9	0	0	1.9	

Table B.1 Grade Crosstabulations (continued)

	12.	1	0	1	0	1	1	0	0	0	4
AVERAGE		25.0	0	25.0	0	25.0	25.0	0	0	0	7.5
		25.0	0	14.3	0	14.3	11.1	0	0	0	
		1.9	0	1.9	0	1.9	1.9	0	0	0	
	13.	0	0	0	0	0	0	0	1	0	1
		0	0	0	0	0	0	0	100.0	0	1.9
		0	0	0	0	0	0	0	16.7	0	
		0	0	0	0	0	0	0	1.9	0	
	14.	0	1	0	0	1	1	1	0	1	5
		0	20.0	0	0	20.0	20.0	20.0	0	20.0	9.4
		0	25.0	0	0	14.3	11.1	16.7	0	12.5	
		0	1.9	0	0	1.9	1.9	1.9	0	1.9	
	15.	0	0	0	0	0	0	0	1	3	4
		0	0	0	0	0	0	0	25.0	75.0	7.5
		0	0	0	0	0	0	0	16.7	37.5	
		0	0	0	0	0	0	0	1.9	5.7	
	16.	0	1	0	0	0	2	0	0	0	3
		0	33.3	0	0	0	66.7	0	0	0	5.7
		0	25.0	0	0	0	22.2	0	0	0	
		0	1.9	0	0	0	3.8	0	0	0	
	17.	0	1	1	0	0	1	3	2	1	9
		0	11.1	11.1	0	0	11.1	33.3	22.2	11.1	17.0
		0	25.0	14.3	0	0	11.1	50.0	33.3	12.5	
		0	1.9	1.9	0	0	1.9	5.7	3.8	1.9	
	18.	0	0	0	0	1	1	0	1	2	5
		0	[illegible]	[illegible]	0	0	20.0	0	20.0	40.0	9.4
		0	0	0	0	0	11.1	0	16.7	25.0	
		0	0	0	0	0	1.9	0	1.9	3.8	
	COLUMN	4	4	7	2	7	7	9	6	8	53
	TOTAL	7.5	7.5	13.2	5.3	13.2	17.0	11.3	11.3	15.1	100.0

RAW CHI SQUARE = 122.95831 WITH 104 DEGREES OF FREEDOM. SIGNIFICANCE = .0978
PEARSON'S R = .31702 SIGNIFICANCE = .0104

APPENDIX C

Statistical Tests

Chi-Square

Chi-square is a nonparametric statistical test. That is, it does not make any assumptions about the shape or variance of the population scores. The chi-square test is often used when the data are in the form of frequency counts which have been placed into categories (Borg & Gall, 1983).

The chi-square test is sometimes called a "goodness-of-fit-test," because it tests how well the observed frequencies fit the expected, or theoretical, frequencies. The independent variable should have two or more levels, and the dependent variable is a count which can be in the form of frequencies, proportions, probabilities or percentages. The categories should be descrete, or nonoverlapping, categories, with each responses falling into only one cell of the design (Shavelson, 1981).

Pearson's Product Moment Coefficient

Pearson's product moment correlation coefficient provides a measure of the strength of association between two variables. It takes on the values from -1 to +1, with the sign indicating the direction of the relationship, and the magnitiude indicating the strength of the relationship. A perfectly positive relationship will have the value +1, a perfect negative relationship will have a value of -1, while a value of 0 indicates no relationship between the variables (Shavelson, 1981). To interpret the signs on the correlations, verify the code values used in the calculations by looking at Tables 3 and 6.

The product-moment correlation, or Pearson's R, is generally preferred because it is stable; that is, it has the smallest standard error of the bivariate techniques. It is used when both variables are expressed as continuous scores, but can be calculated for variables, no matter how they have been measured (Borg & Gall, 1983).

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ABSTRACT

A Budget Analysis of Expenditure Patterns

for Non-Teaching Specialists

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The purpose of this study was to examine the expenditure patterns for certified personnel in selected school districts in the western United States over a ten year span. These certified positions were divided into the categories of District Administrator, Building Administrator, Classroom Teacher, and Specialists.

From the eight selected school district budgets for 1973-1974 and 1983-1984, the Average Daily Membership (A.D.M.), total budget expenditures, and per A.D.M. expenditures were calculated. Then the actual number of positions designated for each category, the actual dollar amount spent on those postiions, the percentage of the total expenditures, the per A.D.M. expenditures for that category, and the position-student ratios were calculated for each district for each of the years examined and for all four categories of certified staff.

Data was interpreted by making comparisons between the individual districts and between the large and small districts. Included in this interpretation was the effect of the inflation rate as measured by the Consumer Price Index on the spending over the ten year span. A comparison was made between what was actually spent and what should have been spent if inflation had been factored into the spending.

Several conclusions were reached based on the analyses and interpretation of the data and the review of the literature. The data demonstrated that significant growth had occurred in the number of certificated specialists employed, thus increasing the size of the non-classroom teacher category at a much faster rate than for any other category of certificated employee. This was particularly true for the larger districts. The phenomena of substantial specialist growth has not enhanced the position of the actual classroom teacher, while it has increased district expenditures substantially. In addition, the percentage of the total expenditures spent on the certified staff had deteriorated over the time period. Also, while the eight districts had increased their actual spending, only the four large districts kept pace or exceeded the inflation rate in their spending growth.

Apparently, significant personnel patterns can be revealed through the use of budget analysis and interpretation. Therefore, it was recommended that this study and studies like it be replicated or initiated to guarantee the very best personnel utilization for the purpose of quality education.