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Predicting achievement in computer science through selected academic, cognitive, and demographic variables

Ott, Carolyn Frances Pipkin, Ph.D.

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PREDICTING ACHIEVEMENT IN COMPUTER SCIENCE THROUGH SELECTED ACADEMIC, COGNITIVE, AND DEMOGRAPHIC VARIABLES

by

CAROLYN FRANCES PIPKIN OTT

A DISSERTATION

Presented in Partial Fulfillment of Requirements
for the Degree of Doctor of Philosophy in
Vocational Leadership in the Department
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1988

ACCEPTANCE

This dissertation, PREDICTING ACHIEVEMENT IN COMPUTER SCIENCE THROUGH SELECTED ACADEMIC, COGNITIVE, AND DEMOGRAPHIC VARIABLES, by CAROLYN FRANCES PIPKIN OTT, was prepared under the direction of the candidate's dissertation committee. It is accepted by the committee members in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Education, Georgia State University.

Harmon R. Fowler, Ed.D.
Major Professor

Date 4/5/88

Richard H. Barbe, Ph.D.
Committee Member

Date 4/5/88

Charles A. Burden, Ph.D.
Committee Member

Date 5 April 1988

Hugh T. Swogger, Ed.D.
Committee Member

Date 4/5/88

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Jerry Robbins, Ed.D.
Dean

Clifford I. Johnson, Ed.D.
Director of Graduate Studies

VITA

CAROLYN FRANCES PIPKIN OTT

ADDRESS: 5170 Lower Roswell Road
Marietta, GA 30068

EDUCATION:

B.A., Guilford College
M.Ed., Georgia State University
Ed.S., Georgia State University
Ph.D., Georgia State University

PROFESSIONAL EXPERIENCE:

1974-Present
: Educator
Teacher of Computer Science and Mathematics
Department Chair, Division Chair
Cobb County School District Task Force on the Use of Computers in Our Schools
Cobb County School District Education Technology Advisory Committee

1972-1974
: Self-employed Distributor of Imported Cigars

1957-1972
: Scientific Computing Professional
Programmer
Supervisor

PROFESSIONAL ORGANIZATIONS:

National Council of Teachers of Mathematics
Mathematical Association of America
American Vocational Association
Georgia Vocational Association
American Society of Professional and Executive Women
Kappa Delta Pi

PUBLICATIONS AND SELECTED PRESENTATIONS:

"Developing Pre-Technical Secondary Education Programs: Rationale, Content, and Methodology," Curriculum Consultant.

"Attracting the Gifted Student into Vocational Programs," Georgia Vocational Administrators' Conference

HONORS:

1987 Who's Who Among Professional and Executive Women

ABSTRACT

PREDICTING ACHIEVEMENT IN COMPUTER SCIENCE
THROUGH SELECTED ACADEMIC, COGNITIVE,
AND DEMOGRAPHIC VARIABLES

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CAROLYN FRANCES PIPKIN OTT

Purpose

This study was designed to identify selected student characteristics which correlate with achievement in a first course in computer science at the high school level and to develop a prediction model. Characteristics included brain hemisphere preference, brain quadrant dominance, cumulative grade-point average (GPA), mathematics proficiency, school ability, Jungian personality type, learning style preferences, grade level, and gender.

Methods and Procedures

A convenience sample of 63 students in a first course in computer science at a large suburban high school completed self-reporting questionnaires: Style of Learning and Thinking (SOLAT), Youth Form, by Torrance; Learning Style Inventory, by Dunn, Dunn, and Price; Herrmann Participant Survey Form, by Herrmann; and Personal Style

Inventory, by Hogan and Champagne. Academic and demographic data were taken from school records. The subject population was female and male students, grades 9 through 12, ages 14 to 18 years. Pearson *r* product-moment coefficients of correlation were calculated to determine attributes for inclusion in multiple stepwise linear regression analysis.

Results

A positive linear relationship was found with GPA (r = .82), score on the mathematics section of the Scholastic Aptitude Test (SAT-M) (r = .63), Otis-Lennon School Ability Index (SAI) (r = .55), preferred amount of light (r = .33), persistence (r = .33), responsibility (r = .30), Herrmann's left cerebral (r = .39), Herrmann's left brain total (r = .34), and the criterion variable, grade in course. Subsequent multiple stepwise linear regression with these attributes developed a model accounting for 79.6% of the variation within student achievement as measured by final grade in course. Other academic and demographic variables did not correlate with sufficient strength to reject the null hypotheses.

Conclusions

GPA provided the strongest indicator for success in a first course in computer science at the high school level (r = .82, R^2 = .68, p <.05). The correlations of SAI and

SAT-M with grade in course supported the rejection of the null hypotheses. With appropriate caution, a prediction model based on these three attributes accounting for 71.7% of variation in grade in course could be used as an advisement tool.

Acknowledgements

My appreciation and love go to my husband and sons for their patience and encouragement during the total graduate school experience. Without their support, this dissertation might never have been started nor completed.

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Chapter 1

Introduction

Achievement in any academic endeavor might be considered to be a function of more than one characteristic or attribute of the student. The purpose of this research was to determine which and to what extent selected attributes of the student correlate with academic achievement in a first course in computer science.

Significance of the Study

One of the objectives of education professionals has been the fostering of a successful academic experience for all students, regardless of ability level or prior academic achievement. Sequential school curricula have served as building blocks toward the accumulation of requisite skills for further study.

Introductory courses in elective subjects at the high school level do not have previous grades in the specific subject materials to serve as a guide for student placement or for teacher identification of student needs. A prediction formula as a function of academic aptitude and/or achievement measures would facilitate the meeting of individual student needs.

In the state of Georgia, high school curricula have been altered to include the option of computer education to meet one of the requirements for graduation under Georgia's Quality Basic Education Act of 1985, and some local educational agencies have offered computer science at the high school as a career option. The advisement for high school students which has been mandated by Quality Basic Education legislation could better meet individual student needs if advisors knew what factors lead to successful achievement in computer science. A prediction equation could be used to assist in the counseling of students who are interested in a career in computer science.

An observable phenomenon of low enrollment by female students has existed at the high school level in computer science classes. Research has been needed to determine if achievement in computer science was gender related or if this was a confounding variable.

The researcher has assumed that a student must be proficient in mathematics in order to succeed in computer science. Research has been needed to determine the validity of this assumption. Research to determine factors which correlate with achievement in computer science at the high school level could assist students in assuring success in elective courses and in making career decisions.

Problem

The specific problem in this study was to predict achievement in a first course in computer science in the high school through selected academic, cognitive, and demographic variables.

Research Questions and Related Hypotheses

The research questions and corresponding null hypotheses which were being researched are as follows:

Research Question 1: Does preferred learning style, operationally defined as learning preference, correlate with achievement in a first course in computer science?

Ho1: There is no significant correlation between preferred learning style and achievement in a first course in computer science in the high school.

Research Question 2: Is there a significant correlation between brain quadrant dominance, both left and right limbic system and left and right cerebral system, and achievement in a first course in computer science?

Ho2: There is no significant correlation between brain quadrant dominance and achievement in a first course in computer science in the high school.

Research Question 3: Does the grade achieved in a first course in computer science correlate significantly with style of learning and thinking, operationally defined by cerebral hemisphere preference: left, right, or integrated?

Ho3: There is no significant correlation between cerebral hemisphere preference and achievement in a first course in computer science in the high school.

Research Question 4: Is there a significant correlation between academic aptitude and achievement in a first course in computer science?

Ho4: There is no significant correlation between academic aptitude and achievement in a first course in computer science in the high school.

Research Question 5: Does mathematics aptitude correlate with achievement in a first course in computer science?

Ho5: There is no significant correlation between mathematics aptitude and achievement in a first course in computer science in the high school.

Research Question 6: Does the school grade level of the student correlate with achievement in computer science?

Ho6: There is no significant difference in grade in course between grade levels in school in a first course in computer science in the high school.

Research Question 7: Is there a significant correlation between the student's cumulative grade-point average (GPA) and achievement in a first course in computer science?

Ho7: There is no significant correlation between cumulative grade-point average (GPA) and achievement in a first course in computer science in the high school.

Research Question 8: Does student gender correlate with achievement in a first course in computer science?

Ho8: There is no significant difference in grade in course between male and female students in a first course in computer science in the high school.

Research Question 9: Is there a significant correlation between personal style and achievement in a first course in computer science?

Ho9: There is no significant correlation between personal style and achievement in a first course in computer science in the high school.

Definition of Terms

Brain quadrant dominance was defined operationally as a student's score on the Herrmann Participant Survey Form (1984) (see Appendix A).

Cerebral hemisphere preference was defined operationally as a student's score on Your Style of Learning and Thinking (SOLAT), Youth Form, by Torrance (see Appendix A).

Computer science was defined as the application of computer theory to the problems of business, industry, education, and research. It includes the use of computer systems and related software to solve problems.

First course in computer science was defined as the introduction of the student to structured computer programming in a graded environment at the high school level (see Appendix B).

High school was defined as a coeducational public secondary school of grades 9-12.

Mathematics aptitude was defined operationally as a student's score on the mathematics section of the Scholastic Aptitude Test (SAT-M) (see Appendix A).

Personal style was defined operationally as a student's Jungian typology, as measured by the Hogan and Champagne Personal Style Inventory (1980) (see Appendix A).

Preferred learning style was defined operationally as a student's scores on the subscales of the Learning Style Inventory (LSI), by Dunn, Dunn, and Price (1987) (see Appendix A).

Limitations of the Study

This descriptive research was defined to examine information about a heterogeneous population of high school students in the subject area of computer science. The use of a convenience sample and the restricted school population should be considered a limitation when generalizing findings to other populations.

No new data-gathering instruments were developed for this study, and instrumentation used for data gathering in research literature has been documented in the literature review. Any conclusions drawn from the results of this study should consider the assumptions which follow.

Assumptions

The following assumptions were made in conducting this study:

1. The following self-reporting questionnaires were the data-gathering instruments: (a) Your Style of Learning and Thinking (SOLAT), Youth Form, by E. Paul Torrance, to provide hemisphere preference data for the investigation; (b) Herrmann's Participant Survey Form, by Ned Herrmann, to provide brain dominance profile data for the investigation; (c) the Personal Style Inventory, by R. C. Hogan and D. W. Champagne, to provide Jungian personality type descriptor data for the investigation; and (d) the Learning Style Inventory, Form 9, by E. Dunn, K. Dunn, and G. E. Price, to provide learning preference data for the investigation. Information on these instruments is in Appendix A.

2. The data instruments used were reliable and valid for measuring the attributes they purport to measure.

3. The subjects answered the questionnaires truthfully.

4. The convenience sample provided data which were representative for analysis of grade in course as a function of the selected attributes.

5. A correlation study implies no cause and effect, and any prediction equation which resulted from the regression analysis should be used with appropriate caution.

Delimitations of the Study

The scope of the study was narrowed to a convenience sample of high school students in a first computer science course drawn from 9th through 12th grades. The school used a 4.0 grade-point-average system, with semester grades recorded as a numeric average on a scale of 100 points. The school was situated in a high socioeconomic community, with high academic expectations from home as well as from school staff. The school was located in a "bedroom" county adjacent to a major urban-international city. Approximately 88% of the school's graduates continue their education at a 4-year postsecondary institution, with a total of 94% continuing their education past the secondary level.

The computer science curriculum in the research setting was based on structured programming principles with emphasis on problem solving. The environmental setting was 68 to 72 degrees Fahrenheit, with overhead institutional lighting. The computer hardware was IBM-PC microcomputers, and the instructional language was MicroSoft BASIC. Class sessions met for 57 minutes each school day for one semester.

The study was restricted to students of one teacher to avoid the confounding variable of different instructors/ evaluators whose computer science background and expectations might differ significantly. The cognitive style of the teacher (Cafferty, 1981) and the method of instruction

(Domino, 1970; Linn & Dalbey, 1985) have been shown to have significant effects on student achievement.

The study was conducted without regard to subject maturation at the beginning of the study and developmental changes during the research period. The grades earned in the computer science course were calculated and submitted to school records prior to the scoring of any of the questionnaires. This precluded any subjective bias on the part of the researcher during the calculation and recording of student grades.

Research Design and Methodology

The research design was descriptive in nature. It was intended to assist in predicting achievement in computer science through selected academic, cognitive, and demographic variables. A convenience sample was selected from a population of students who elected to take a first course in computer science at the high school level.

Statistical Procedures

Correlation coefficients were calculated to determine the relationship between each attribute variable and the criterion variable. Subsequent multiple stepwise linear regression was performed with those attribute variables which correlated at a significant level.

The data reduction included descriptive statistics and analysis of variance (ANOVA). A significance level of

.05 was used as a threshold to fail to reject each null hypothesis or to reject each null hypothesis.

Chapter 2

Literature Review

Purpose

The purpose of this study was to identify student characteristics that correlate with achievement in a first course in computer science and to build a model to predict success in a first course in computer science at the high school level.

Brain Hemisphericity and Laterality Studies

Descartes surmised in the 17th century that the brain must act as a whole to yield a unified view of the natural world. During the 1860s and 1870s, Paul Broca, a French neurologist, and Karl Wernicke, a German neurologist, reported that severe damage to the left cerebral hemisphere caused disorders of language, and damage to the right cerebral hemisphere did not. Hughlings Jackson attempted in the 1880s to explain handedness by referring to a "leading" hemisphere (Zangwill, 1960).

Thus began the myth that man's left hemisphere was dominant because of its language center and the right hemisphere was mute and less important. In the 1930s investigators proposed that the left hemisphere was specialized for language, but the right hemisphere was specialized for many nonlinguistic processes. Zangwill (1960) drew the conclusion in the 1950s that cerebral dominance was a graded characteristic that varied in scope and completeness from individual to individual. The brain appeared to be a bilaterally symmetric organ, with each half being a mirror image of the other. This, however, was not true of its functions, as the left and right cerebral hemispheres have their own specialized abilities. Since the majority of people are right-handed, the left hemisphere was considered to be dominant. The preeminence of the left-half dominance theory remained virtually unchallenged until the 1960s.

Before that time, the prevalent view was that people had half of a thinking brain. The two-brain myth was founded on the premise that, since each hemisphere was specialized, each must function as an independent brain. In fact, just the opposite is true. Although the regions of the brain are differentiated, they integrate their activities. That integration gives rise to behavior and mental processes greater than and different from each region's special contribution.

The majority of researchers had concluded by the 1970s that each side of the brain was a highly specialized organ of thought, with the right hemisphere predominant in a set of functions that complemented those of the left hemisphere. Thus, the right hemisphere was declared to be as complex as the left hemisphere.

The physiological basis for current theories about hemispherical preference and cerebral dominance was the work of Roger W. Sperry, a Nobel Prize recipient in 1981 for his work on split-brain patients during the 1960s. Gazzaniga and Smylie (1984) reported on the research of Sperry and Gazzaniga on humans who had their brain hemispheres surgically separated. That research showed that in laboratory tests the right hemisphere was superior to the left in spatial tasks but was deficient in verbal tasks. Right-handers were more adept at identifying words displayed in the right visual field (left hemisphere control) and in recognizing faces or dot locations in the left visual field (right hemisphere control).

The left hemisphere plays a special role in understanding syntax, translating written words into their phonetic representations, and deriving meaning from complex relationships among word concepts and syntax. There is no activity in which only one hemisphere is involved or to which only one hemisphere makes a contribution. There is no evidence that either creativity or intuition is an exclusive property of the right hemisphere. Real creativity and intuition almost certainly depend on a collaboration between hemispheres (Levy, 1985).

There was a significant correlation between the more active hemisphere and the relative degree of verbal or spatial skills, but there was no evidence that people are purely "left brained" or "right brained." Not even those with the most extremely asymmetrical activity between hemispheres think only with the more activated side. When the left hemisphere is more active, verbal functioning is promoted to varying degrees. Similarly, spatial abilities are enhanced in those with a more active right hemisphere. While activation patterns and cognitive patterns were correlated, the relationship was far from perfect, indicating that differences in activity of the hemispheres are but one of many factors affecting the way we think. Normal people have not half of a brain, nor two brains, but one differentiated brain with each hemisphere contributing its specialized abilities. Descartes was correct: we have a single brain that generates a single mental self (Levy, 1980).

Models of hemisphere specialization were critically reviewed by Cohen (1973, 1982). She distinguished between those models that treat hemisphere specialization as absolute (a given function can only be performed by a particular hemisphere) and those that regard specialization as relative. The relative specialization models assert that both hemispheres can perform a given function, but one is faster or more efficient than the other.

Levy (1985), a biopsychologist who studied with Roger Sperry, is one of the leading authorities on hemispherical research of the 1980s. She contended that it is impossible to educate one hemisphere at a time in a normal brain. The communicating link between the two halves is the corpus callosum, a bundle of nerve fibers which ties the two hemispheres together.

What humans experience under normal conditions is the interplay of two separate minds through the corpus callosum connection. There is evidence that there is a rhythm to this interplay and that there may be ways of controlling that rhythm. When the electroencephalogram (EEG) was used to measure brain waves simultaneously on the right and left sides of the brain, one hemisphere dominated for a period ranging from 25 minutes to 200 minutes and averaging about 120 minutes (Levy, 1985).

Investigators at the University of California in San Diego and at Dalhousie University in Canada tested subjects at regular intervals on verbal (left hemisphere) and spatial (right hemisphere) tasks for periods of 8 hours and found that when the performance of verbal ability was high the spatial was low, and vice versa, indicating that the two hemispheres operated out of phase. The periods of dominance were found to last 90 to 100 minutes.

Both clinical and experimental evidence have linked the verbal and nonverbal codes to left and right hemispheres, respectively. A subject's performance on a task may depend not only on the way the stimuli are encoded but also on the strategy adopted to carry out the task.

Information processing theorists have distinguished between serial and parallel processing. Parallel processing is carried out simultaneously, and serial processing refers to cognitive operations carried out successively. Attempts have been made to map these two modes of processing onto the left and right hemispheres, respectively.

Bever (1975) drew a distinction between analytic and holistic (gestalt) modes of processing. Levy-Agresti and Sperry (1968) reported that the right hemisphere seemed able to grasp the shape of a three-dimensional form as a unified whole, whereas the left hemisphere concentrated on each of the edges and corners of the forms. The analytic versus holistic dichotomy has been confused with the serial versus parallel dichotomy, but the two are distinct.

The ability to speak and form thoughts into words rests primarily in the left hemisphere. The right side is host to motor skills, intuition, and emotion. As a problem solver, the right side looks at the whole situation, and often the solution materializes instantly. To a significant degree, men appear to be left-hemisphere dominant and women right-hemisphere dominant (Wonder & Donovan, 1983).

Ornstein (1977) referred to the linear and rational mode of consciousness as being specialized for analysis and the intuitive and arational mode as specialized for synthesis. It is only through the complementary functioning of the two modes that man reaches his highest creative achievements. It is the function of his verbal intellect to fit intuition into the linear mode so that ideas may be explicitly tested and communicated in the proper manner. Perhaps the search for a dichotomy of function between the left and right hemispheres was bound to fail because there is no reason why the brain should have evolved so conveniently.

Evidence of specialization between and also within each hemisphere (Newcombe & Ratcliff, 1979) has suggested that the different areas of left and right hemispheres may bear a different relationship to each other. It may be misleading to assume that the relationship between the hemispheres as a whole could be described in terms of any single principle.

Torrance (1981, 1986) and others have developed pencil-and-paper instruments to measure style of learning and thinking in an attempt to identify cerebral hemisphere preference as right mode, left mode, or integrated mode. Various forms of his self-reporting questionnaire (Torrance, 1972) for evaluating style of learning and thinking have been used in doctoral studies over the last 10 years. The external validity of the Torrance instrument to measure creativity has been challenged by Fitzgerald and Hattie (1983). Furthermore, they have asked what is implied with regard to creativity and cerebral laterality.

Laterality refers most often to the degree to which the two brain hemispheres specialize in different functions in a given individual. The measurement devices that have been developed to assess laterality presumably give an indication of the extent to which a given individual's right or left hemisphere is relatively better than the other at processing different types of information. The most difficult aspect of constructing a measuring instrument is to insure that only the tested hemisphere is aware of the phenomenon. Paper-and-pencil tests are limited in this regard when compared to tests such as dichotic listening or electroencephalogram (EEG) (Bejar, 1984).

It has been argued that laterality should be measured only on a nominal scale (Colbourn, 1978) so that only the direction and not the magnitude of any laterality effect will be taken into account. While measuring laterality on an interval or a ratio scale gives a false sense of quantification of underlying brain asymmetry, it is not necessarily wrong to use such a measure. A consistent difference in the laterality measure obtained by different individuals or groups means something. The level of measurement adopted by researchers has been intimately tied to the kind of theory that was developed to explain results and generate predictions. If the measurement of laterality were confined to a nominal scale, the kinds of theories which have been developed to account for the data would likely not have been able to do justice to between-group and within-group variation in performance (Beaton, 1985).

Bogen (1969, 1977) has favored the term propositional to describe left hemisphere functions and appositional to refer to those of the right hemisphere. Virtually all recent investigators have agreed that cerebral asymmetry is a matter of degree and not absolute. Bradshaw and Nettleton (1983) have argued in favor of some general distinction, such as the analytic/holistic one. They contended that verbal processing is largely the province of the left because of that hemisphere's possession of sequential analytic, time-dependent mechanisms.

Fundamentally, the left hemisphere has been characterized by its mediation of discriminations involving duration, temporal order, sequencing, and rhythm, and the right hemisphere has been characterized by its spatial aspects. The term analytic should be reserved for perceptual processing, which may be performed either sequentially or in parallel.

Oloumi-Capell's (1983) study conducted with a sample of graduate and undergraduate students at the University of Pittsburgh found significant differences at the .01 level between the means of the three hemisphere classifications (right, left, and integrated) with programming, test, and total class scores. Torrance's Your Style of Learning and Thinking (SOLAT) was used in that study.

Gustafson (1986) conducted research at the University of Georgia with a sample population of 40 graduate students in education enrolled in a one-quarter introductory computer course. A significant correlation was found between an integrated cerebral processing mode and a high score on the course project, but no significant correlation with final course grades and hemisphericity was indicated.

Payne and Evans (1985) studied the relationship of laterality to academic aptitude on a sample of 40 female college students. Scores from the Herrmann Brain Dominance Survey and the Torrance and Reynolds Your Style of Learning and Thinking (SOLAT) were correlated with grade-point average (GPA) and scores from Scholastic Aptitude Test--Mathematics (SAT-M), Scholastic Aptitude Test--Verbal (SAT-V), and total Scholastic Aptitude Test (SAT). Findings included a strong relationship between the Herrmann right cerebral and total cerebral scores with all SAT scores. Modest relationships were indicated between the limbic scores of the Herrmann Brain Dominance Survey and the SAT-M scores. No meaningful relationships between the Torrance and Reynolds SOLAT instrument scores and SAT scores were indicated, nor were there consistent relationships indicated between the measures of laterality and grade-point average (GPA).

Coppus (1978) conducted an exploratory study which indicated that, for a sample of 10 secondary school students, greater use of the left and integrated modes of cerebral hemispheric operation was related to higher achievement in computer programming. Torrance's Your

Style of Learning and Thinking (SOLAT) was the instrument used for determining cerebral hemisphericity.

Cody (1983) conducted research on learning style characteristics and hemisphericity with relationship to intelligence quotient (IQ) using the Dunn et al. Learning Style Inventory and Torrance's SOLAT. The gifted and highly gifted students demonstrated significant preferences at the .001 level for right hemisphere and integrated processing, as well as a preference for a minimum of structure and lecture.

Losh (1984) used the Torrance SOLAT to conduct a study to identify existing relationships between student hemisphericity and achievement as a computer programming student. He found no significant relationship between hemisphericity and performance in the sample of 106 students at the public postsecondary non-degree-granting area vocational-technical schools in Georgia.

Herrmann (1981), a management educator who has pioneered research on brain quadrant dominance within occupational groups, developed the Herrmann Participant Survey Form as an outgrowth of seeking information concerning both the cerebral and limbic levels. The survey designates two types of dominance for each hemisphere: (a) cerebral left--the analytic, logical, mathematical, technical, problem-solving person; (b) lower (limbic) left--the reliable, organized, planning, controlling, administrative, conservative person; (c) cerebral right--the creative, artistic, holistic, conceptual, synthesizing person; and (d) lower (limbic) right--the interpersonal, emotional, talkative, spiritual, sensitive, musical person.

The left dominance score has been found to relate positively with the sensing (S), judging (J), and thinking (T) scales of the Jungian typology explained below. The right dominance score has been found to relate positively with the intuition (N), perceiving (P), and feeling (F) scales (Bunderson, Olsen, & Herrmann, no date). When applied to teaching and learning, the Herrmann brain dominance characteristics are as follows: (a) left hemisphere--verbal, structured; (b) left cerebral--facts, rational, cognitive, quantitative; (c) left lower (limbic)--controlled, organized, sequential, procedural; (d) right hemisphere--nonverbal, experiential; (e) right cerebral--open minded, visual, conceptual, simultaneous; and (f) right lower (limbic)--feelings, emotional, expressive, interpersonal.

Personality Styles Research

Jung identified four pairs of dimensions of personality types as early as 1921, and subsequent work by Myers (1980) refined the type descriptors. Hogan and Champagne (1980) developed a self-scoring inventory based on the same descriptors.

The four pairs of dimensions in the Jungian typology are introversion/extroversion, intuition/sensing, feeling/ thinking, and perceiving/judging. Both dimensions of each pair are exhibited by each person, but one dimension of each pair is used more often. The individual's beliefs, values, and cognitive skills are more congruent with it than with the other dimension in that pair. The stronger dimension characterizes the person's personality and thought processes.

Hogan and Champagne (1980) described the strengths of each type:

1. The introvert (I) is independent, works alone, is diligent, reflects, works with ideas, is careful of generalizations, and is careful before acting.

2. The extrovert (E) understands the external, interacts with others, is open, acts, does, and is well-understood.

3. The intuitor (N) sees possibilities, sees gestalts, imagines, intuits, works out new ideas, works with the complicated, and solves novel problems.

4. The senser (S) attends to detail, is practical, has memory for detail and fact, works with tedious detail, is patient, and is careful and systematic.

5. The feeler (F) considers others' feelings, understands needs and values, is interested in conciliation, demonstrates feelings, persuades, and arouses.

6. The thinker (T) is logical and analytical, is objective, is organized, has critical ability, is just, and stands firm.

7. The perceiver (P) compromises, sees all sides of issues, is flexible and adaptable, remains open for changes, decides based on all data, and is not judgmental.

8. The judger (J) decides, plans, orders, controls, makes quick decisions, and remains with a task.

Lyons (1985) conducted an international study over a 3-year period with a sample of 1,229 professional programmers employed by over 100 different companies. He found that the Myers-Briggs personality type with the highest occurrence (almost 23%) was the combination of introversion, sensing, thinking, and judging (ISTJ). The next most frequently occurring types in his sample population were the two introversion-intuitive-thinking types, INTP and INTJ. These three types accounted for over 50% of the survey population.

Sitton and Chmelir (1984) used the Keirsey Temperament Sorter to see if a stereotype of data processors showed up in the professional ranks of four computer installations in Texas. In their sample of 27 volunteers, the most common personality type was extroverted-intuitive-thinking-perceiving (ENTP). Keirsey characterized the ENTP, which occurs in only 5% of the general population, as individuals who are good at analysis and who place a high value on innovation.

Bush and Schkade (1985) noted that in a study conducted at the University of North Carolina at Greensboro by White to determine personality type in professional computer programmers, the need for interpersonal skills persisted. The common thread between that study and the study in Texas was the occurrence of the thinking type personality. White's study concluded that computer professionals are thinking, judging, rational people who rely on their education, training, and experience to solve problems.

The difference in results between the Texas and North Carolina studies may be attributed to the corporate cultures in which the studies were conducted. Managers tend to hire people who fit their particular image of the successful professional. Over a period of time, the organization will tend to be dominated by that type of personality. It takes a variety of mental processes and personalities to solve problems in computer programming and information processing.

According to Corno and Haertel (1982), studies of expert programmers revealed that high general ability was a good predictor of success. Myers (1980) stated that in a study of 11th and 12th grade students the average IQ of intuitives topped the sensing types by 7.8 points for males and 6.7 points for females in academic courses in 30 Pennsylvania high schools.

Gender-Related Studies

Diamond discovered that hormones affect the dimensions of the cortex (cited in Weintraub, 1981). Diamond's findings provide strong anatomical evidence for Levy's theory: the cortex differs between men and women, largely because of hormones that early in life alter the organization of the two hemispheres. In test after test, Levy has found that abilities vary with gender. Men excel in spatial reasoning, and women do better with language. She concluded that during the prepuberty period of language development, the right hemisphere dominates the masculine brain and the left hemisphere dominates the feminine brain.

Waber (1977) of Harvard Medical School found that children reaching puberty earlier than normal have brains that are less lateralized--that is, their left and right hemispheres seem to share more tasks. Because females generally reach puberty 2 years before males, these findings have caused speculation that the corpus callosum of the female brain has less time to lateralize during puberty. If that is true, said Levy, it could help to explain female intuition, as well as male superiority in mechanics and mathematics. Of the students who scored 500 or better on the mathematics portion of the Scholastic Aptitude Test, males outnumbered females by more than two to one (Weintraub, 1981).

Oloumi-Capell's (1983) study indicated no significant differences at the .05 level between achievement in computer programming of males and females and that females are less likely than males to enroll in programming courses. Research on children and computers (Turkle, 1984) suggested that some of the problems that females experience in introductory programming have to do with the "social construction" of programming as male. Most men see programming as a logical, analytical activity, while females prefer a heuristic approach to creating desired results with the computer.

In a study by Jones (1984), males stereotyped computers and computing as a male domain, but no main effect for gender was found on the total cognitive scale or on the three cognitive subscales which she considered. Widmer and Parker (1985) documented a study in Kentucky which was based on an elective activity of a national computer programming contest. Participation was male dominated, with 248 males in a sample of 276 entrants; however, there was no significant difference between genders in the contest scores.

Based on the results of a study conducted in Virginia community colleges, Jones (1979) recommended that faculty and counselors advise students that gender, race, and age do not appear to be strong determinants of success in the first-year computer curriculum. Grade-point average and some measured student perception variables were found to be the most discriminating variables.

Williams (1984) concluded that differences between grade levels appeared to be greater than differences between the two genders in her assessment of affective and cognitive dimensions of the study subjects. The results indicated that in the cognitive dimension of computer literacy, gender and grade level appeared to have a significant effect, although the two effects were not interrelated.

Fertsch (1985) studied gender differences in computer attitudes and the relationships between these attitudes and grade level, mathematics achievement, computer courses, computer experience, and prior experience in programming and word processing. The exploratory study involved 115 middle school students enrolled in computer literacy courses in a suburban school district. Data analysis indicated no significant effects of gender upon any of the attitudes.

In a study designed to determine the instructional effectiveness of structured programming on the programming achievement in the BASIC language and logical thinking skills of 255 secondary school students (Little, 1984), the influence of gender and cognitive developmental level was also investigated. Formal operational students scored higher than concrete/transitional students on both the programming and logical thinking achievement measures. Females tended to score higher on the logical thinking measures than did males, and in the treatment group the mean differences between males and females on the programming achievement measure were reduced to zero. In the control group, males tended to score significantly higher than females on the programming achievement measure.

Learning Styles and Preferences Research

The theory that computer programming demands a syntactical and linguistic skill as well as deductive acuity finds support in the work of Dalbey and Linn (1986). The problem solving which precedes the writing of a computer program may be considered as logical and deductive (left brain activity), but a synthesis of the variables and their relationships relies on gestalt processing (right brain activity) in order to optimize the sequence of program steps and to provide the creative flourishes which characterize optimal use of the computer.

Meaningful learning is a process in which the learner connects new material with knowledge that already exists in the learner's memory (Bransford, 1979). The human cognitive system is made up of short-term memory and long-term memory. New information enters the human cognitive system from the outside by reception, availability, and activation. The learner must come into contact with the new material by bringing it into short-term memory, then search long-term memory for what Ausubel (1968) called "appropriate anchoring ideas," and transfer those ideas to short-term memory so they can be combined with new incoming information. Meaningful learning cannot occur if any one of these conditions is not met, and the learner will be forced to memorize each piece of new information by rote as a separate item to be added to memory.

The gestalt psychologists distinguish between two ways of learning to solve problems: rote memory and understanding. Understanding is defined here as the ability to use learned information in problem-solving tasks different from what was explicitly taught. The payoff for understanding comes in the transfer of the newly learned material to new situations.

One technique for improving novice programmers' understanding of new technical information is to provide them with a framework that can be used for incorporating new information. These novices lack domain-specific knowledge, and the framework method is aimed at insuring availability of knowledge in long-term memory. Since computer programming shares many of the characteristics of computational procedures in mathematics where use of concrete models has helped teach algorithms, it seems that the use of such models in teaching computer programming might be similarly successful.

Ausubel (1968) has argued that the use of advance organizers may enhance the learning of new technical prose. Reviews of the literature show that advance organizers tend to have their strongest effects in situations where learners are unlikely to possess useful prerequisite concepts. Studies show that advance organizers have a stronger effect on low knowledge or low ability learners, as compared with high knowledge or high ability learners.

Pommersheim (1984) conducted a study to investigate how BASIC computer programming achievement of high school students was related to a profile of cognitive style dimensions. He used 10 independent cognitive style sub-scores. Results indicated that males scored significantly higher than females, and a stepwise multiple linear regression was generated as a predictor of BASIC programming achievement based on two of the cognitive style subscores.

Rusnock's (1984) study with seventh-grade students as a sample population indicated that student cognitive profile type had a significant effect on student success in programming at both the comprehension and the creativity level. Instruction in the BASIC language was limited to one 40-minute period per week for 10 weeks.

Domino (1970) found that students taught in a manner consistent with the way they believed they learned best scored higher on tests, facts, knowledge, attitude, and efficiency than those taught in a manner dissonant with their orientation. Myers (1980) reminded researchers that, regardless of how a subject is taught, students tend to remember only the parts that capture their attention and interest.

Cognitive processing variables as predictors of student achievement in learning a computer programming language were studied by Cramer (1985) in a sample student population at the University of Georgia. Grade-point average (GPA) was found to account for a significant amount of the variance in the production and debugging of syntax and logic.

Thronson (1985) investigated the relationship between learning style and achievement in beginning computer programming classes with 314 students at the college level. The results of the study indicated that there was no systematic or significant relationship between learning style and course content or between learning style and achievement in the course.

Barrie (1985) conducted a study which examined the relationship between the learning styles of a sample of 288 adults and their learning achievement in a short-term course which introduced learners to the use of the computer. Kolb's Learning Style Inventory was used to measure learning styles. Evidence was found for the independence of learning style from all other demographic background and learning achievement variables. There was also a lack of linear correlation between each of the six learning style scores and final grade in the course. A major conclusion was that learning style does not differentiate people in ways that relate to a short-term learning situation.

In a study which compared learning computer programming with cognitive abilities and learning style, Daves

(1985) found that the relationship between converger learning style and programming achievement was not significant. The study found that there was a low positive correlation at the .05 level with abstract conceptualization and achievement (r = .268, n = 49). Tannenbaum (1982) determined that field-dependent high school students who were provided high structure performed significantly better when taught through complementary cognitive methods.

Trautman (1979) found in a sample population of junior high school students that whenever the instructional materials were matched correctly to the student's identified cognitive style, statistically significant academic gains were made. There was no difference between the relative achievement of analytic and global students when they each were taught through materials that matched their styles.

White (1980) studied the learning style preferences of technical education students and asked the following questions: (a) Do students from different subject areas differ in their preferences for course content? and (b) Do students from different subject areas differ in their preferences for modes of instruction utilized? Results of the study led her to recommend that learning style information not be used to guide students into a given technical college major program but that the information be used to assist students to achieve greater success in career fields of their choice.

Dunn et al. (1987) have researched the area of learning styles by looking at the range of personal characteristics that affect how individuals learn in the classroom. Their Learning Style Inventory (LSI) summarizes 22 of the environmental, emotional, sociological, and physical preferences a student has for learning, but it does not explain why preferences exist. It evidences how students prefer to learn, not the skills they use in their learning.

In order for programming to provide a beneficial intellectual environment, the presentation must have some aspects which are cognitively demanding. The planning and debugging skills which are an inherent component of programming demand a cognitive involvement which goes beyond rote and lower level thinking abilities. These skills, moreover, can be generalized and applied outside the domain of programming. Programming is a complex skill composed of distinct subskills and can have a variety of cognitive outcomes. The chain of skills and the development of those skills have been researched by Dalbey and Linn (1985).

Sheil (1981) said that the essence of the thinking ability necessary to write programs has been called "procedural reasoning" or "formal procedure specification." The development of this skill is de rigueur in the classes where the dissertation study was conducted. It has been noted that novice programmers have difficulty because they cannot keep up with the memory demands of a new language.

Programming requires organization of a large amount of complex and detailed knowledge about programming language syntax and semantics.

An evaluation of self-paced programming courses at University of California at Berkeley found that student final exam scores were higher than in the lecture version of the same course (Linn & Dalbey, 1985). The setting for the dissertation study was lecture style for the early lessons which covered introductory exercises and language syntax standards, followed by self-paced activities at the computer. Class time was a blend of structured problem-solving skills as well as programming syntax and semantics, with every programming exercise being keyed into the computer and debugged by the novice programmer.

Canning (1984) combined the Your Style of Learning and Thinking and the Myers-Briggs Type Indicator instruments in a study with 72 participants categorized as sensing (72%) and left-hemisphere preferenced (49%). There was no real difference in the mean cognitive style scores between left-hemispheric-preferenced and right-hemispheric-preferenced students in the sample. There was a significant difference in mean cognitive style scores between students classified as intuitive-feeling (NF) and students classified as sensing-thinking (ST).

Davis (1985) utilized the Myers-Briggs Type Indicator and the Dunn et al. (1987) Learning Styles Inventory (LSI) as instruments in her investigation of the relationship of personality types and learning style preference of high school students. The 44 significant correlations in her study showed that there was a linkage between personality types and learning styles.

Academic and Demographic Factors

In their article in the Communication of the ACM, Konvalina, Wileman, and Stephens (1983) reported on the design of an aptitude instrument for testing the key predictor for success in computer science courses. Their conclusion was that mathematics proficiency was the key to success.

In a study conducted with subjects at Eastern Oregon State College, Oman (1986) concluded that the key predictor of success in introductory computer science courses was mathematics proficiency. He found that 68% of the variability within the grade in the programming course could be accounted for by the student's score on the mathematics section of the SAT.

The relationships among computer programming ability, computer program content, computer programming style, and mathematical achievement in a BASIC programming course was the topic under investigation in a study by Duggar (1983). Significant differences were indicated in programming ability of algebraic versus geometric computer program content. Only algebraic mathematical ability was found to have a positive effect upon programming ability. The algorithmic style was found to be associated with both high programming ability and high mathematical achievement.

Results of a study at Mississippi State University (Bennett, 1983) indicated that there was a statistically significant relationship between the demographic variables of age, race, and gender and the criterion variable, grades, in a first course in computer science. There was a statistically significant relationship between the academic quality-point average and grades in a first course in computer science. There was also a statistically significant relationship between aptitude variables and grades. When the combination of demographic, academic, and aptitude variables was considered, a total of 47.08% of the variance in grades was explained.

Rice (1984) conducted a study which attempted to identify those demographic, aptitude, and psychological variables that discriminate between successful and unsuccessful high school computer programming students. The highest correlation between a predictor variable and final grades was $r = .514$ for grade-point average. The demographic variables age, gender, and grade level were not significantly related to the criterion variable. A multiple stepwise regression analysis of the data yielded an equation which indicated that approximately 48% of the variance of the criterion variable was accounted for by six significant variables.

Summary of Related Research

Table 1 provides a summary of referenced researchers and the attribute variables which were considered in the related studies. Results of these studies have been detailed in the review of literature.

Table 1

Summary of Related Research

	Attribute Variables[a]								
Researcher(s)	SAT-M	SA	CL	LS	BD	JT	GPA	GEN	GR
Barrie				*					
Bennett	*						*	*	
Cafferty				*					
Canning			*			*			
Cody		*	*	*					
Coppus			*						
Cramer				*			*		
Dalbey & Linn								*	
Daves				*					
Davis				*		*			
Domino				*					
Duggar	*								
Fertsch	*							*	*
Gustafson			*						
Jones, J.				*			*	*	
Jones, M.				*				*	
Little				*				*	
Losh			*						
Lyons						*			
Oloumi-Capell			*					*	
Oman	*								
Payne & Evans	*		*		*		*		
Pommersheim				*					
Rice							*	*	*
Rusnock				*					
Sitton & Chmelir						*			
Tanenbaum				*					
Thronson				*					
Trautman				*					
Turkle								*	
White, K.						*			
White, R.				*					
Widmer & Parker								*	
Williams								*	*
Ott (this study)	*	*	*	*	*	*	*	*	*

[a]SAT-M = mathematics section of the SAT, SA = schoolability, CL = cerebral laterality, LS = learning style, BD = brain dominance, JT = Jungian typology, GPA = grade-point average, GEN = gender, GR = grade level.

Chapter 3

Methods and Procedures

Purpose

The purpose of this study was to identify student characteristics that correlate with achievement in a first course in computer science and to build a model to predict success in a first course in computer science at the high school level.

Research Methods

The research method chosen was appropriate for a descriptive inductive study, since the attribute variables (X_i) could not be manipulated. The following independent variables were chosen which could influence the criterion variable (Y), grade in the course: X_1, subject's learning style preference; X_2, subject's brain dominance; X_3, subject's cerebral laterality; X_4, subject's academic aptitude; X_5, subject's mathematics proficiency; X_6, subject's grade level; X_7, subject's cumulative grade-point average; X_8, subject's gender; and X_9, subject's personality type.

Behavioral Research (Kerlinger, 1981) offers an explanation of multiple stepwise linear regression which fit the data analysis that was needed in this study. Kerlinger found multiple regression very adaptable with regard to educational research, since the mathematics is not weakened when scores are combined from different types of research. The prediction equation resulting from multiple regression is of the general form

$$Y' = a + b_1X_1 + b_2X_2 + \ldots + b_nX_n$$

where a is the intercept provided by the regression and b_i is the calculated coefficient of X_i.

The analysis in this study led to the use of the following generalized formula, since comparison for the purpose of arriving at conclusions about the relative importance of variables was desirable:

$$Y' = a + \beta_1X_1 + \beta_2X_2 + \ldots + \beta_nX_n$$

In multiple regression with the use of standardized regression weights (βs), the constant term no longer appears and the general form of the equation for the prediction of the criterion variable (y) becomes

$$Y' = \beta_1x_1 + \beta_2x_2 + \ldots + \beta_nx_n$$

This means, in effect, that scores have been transformed so as to be comparable (Pedhazur, 1982).

The coefficient of multiple correlation (R) expresses the magnitude of the relation between the best combination of all the independent (attribute) variables and the dependent (criterion) variable. R^2 expresses the variance between the observed (*y*) and the predicted (*y*') value of the dependent variable. R^2 is an index of the maximum amount of variance of *y* accounted for by all the *x*s. Residual variance (that which is not accounted for by the *x*s) is calculated by $1 - R^2$.

To determine estimates of the influence of all variables purged of the influence of a chosen variable, one must first calculate the R^2 of the joint effect of the attribute variables. Then one subtracts, in turn, the R^2 due to each attribute variable. The ideal prediction situation is high correlations between attribute variables and the criterion variable, not high correlations among the independent variables.

Population and Sample

The population of the study was composed of 74 students who elected during the 1987-88 school year to take the first course in computer science at a high school of 2,200 enrollment. The convenience sample (*n*) of 63 students resulted after data were collected from the defined population. Limiting the study to students of one instructor removed the confounding variables of teaching style and grade evaluation by more than one evaluator (Cafferty, 1981; Domino, 1970). Demographics of the sample are shown in Table 2.

Table 2

Sample Demographics

Grade Level	Male	Female	Total
9	18	0	18
10	15	1	16
11	4	6	10
12	15	4	19
Total	52	11	63

Data Instrumentation

The self-reporting questionnaires used in this study were the Learning Style Inventory (LSI), Grades 5-12, by Dunn, Dunn, and Price; Herrmann's Participant Survey Form (PSF) (1984); the Personal Style Inventory (PSI), by Hogan and Champagne (1979); and Your Style of Learning and Thinking (SOLAT), Youth Form, by Torrance. More information about each of these instruments is in Appendix A.

The LSI is a 104-item inventory which elicits from students the information about how they study and learn when provided options of doing so away from and within the school situation. The LSI was designed to get each student's preferences for different elements in 22 areas grouped according to four basic stimulants: the environment and one's emotional, sociological, and physical learning patterns. It was selected to provide data pertaining to learning style preferences.

The PSF is a 120-item inventory which asks the subject to describe personal characteristics such as key descriptors, hobbies, energy level, and introversion/extroversion and to respond to 20 statements of personal preferences on a Likert-type scale ranging from Strongly Agree to Strongly Disagree. Scoring provided a profile of the subject's use of the left cerebral, left limbic, right cerebral, right limbic, left hemisphere, right hemisphere, total cerebral mode, and total limbic mode. The score on the PSF provided brain dominance profile data.

The PSI is a 32-item questionnaire prefaced by "I prefer:" with two contrasting preferences for each item. Scoring data provided Jungian descriptors of personality types. Combinations of a typology from each pair constitute 16 composite identifiers. Jungian typology results described the personality style of the subject.

The SOLAT is a survey with two options for each of the 28 items. The subject is asked to mark if the statement is true for him/her. The subject may check either or both of the two options with each item. Scores for left hemisphere preference, right hemisphere preference, and integrated preference were obtained from this instrument.

Data Collection

Each of the students in the population was administered the four previously described self-reporting questionnaires. Each instrument was administered once, and subjects who missed one or more of the sessions were dropped from the population due to insufficient data, resulting in a convenience sample of 63 students. This was a voluntary activity and the scheduling of make-up sessions was inconvenient for the subjects, so no make-up sessions were held. Subjects were identified by student number to preserve the confidentiality of the data. Student data for the Otis-Lennon School Ability Index (SAI), scores on the mathematics section of the Scholastic Aptitude Test (SAT-M), gender, school grade level, and cumulative grade-point average (GPA) were obtained from school records.

Data Reduction

The researcher scored the PSI. Dr. Paul Torrance and his associates scored the SOLAT in the interest of laterality research and its relationship to achievement in computer science. Dr. Torrance also gave personal time to consult and advise before the research was begun. The PSF was scored by the Herrmann Corporation. Ned Herrmann, the developer of the PSF, gave personal consultation time prior to granting permission for the use of the instrument in this research.

The first phase of the data reduction consisted of descriptive statistics as well as simple correlation between each independent variable and its subscales ($\underline{X}_i$) and the dependent variable, grade in course. Attribute variables which produced a significant correlation ($\underline{p} < .05$) with grade in course were identified for inclusion in a multiple stepwise linear regression model. Analysis of variance was performed on the regression model, and standard error was calculated for each regression coefficient. Data reduction was performed on the Georgia State University UNISYS 1100/72 computer, using SPSS Batch System (Nie, 1983), a comprehensive software package for analyzing and displaying data.

Chapter 4

Analysis and Presentation of Data

Purpose

The purpose of this study was to identify student characteristics that correlate with achievement in a first course in computer science and to build a model to predict success in a first course in computer science at the high school level.

Analytic Methods

Correlation was determined by calculating Pearson *r*, the product-moment coefficient of linear relationship, for each of the attribute variables and the criterion variable, grade in course. Correlations were tested for significance from zero. The highest correlation between attribute variable and criterion variable was GPA, followed by SAT-M and SAI. These measures held highly significant correlations of .82, .63, and .55, respectively, when correlated with grade in course. Multiple stepwise linear regression permitted the construction of a model using the least-squares approximation of the criterion variable as a linear function of the attribute variables.

Data Analysis

This research study was designed to investigate nine operational hypotheses. Results are reported in this section for each hypothesis.

Ho1: There is no significant correlation between achievement in a first course in computer science at the high school level and the learning style characteristics measured by the Learning Style Inventory (LSI), by Dunn et al. (1987).

There was a failure to reject the null hypothesis for all of the learning style characteristics except amount of light needed (r = .33), persistence (r = .33), and responsibleness (r = .30). The null hypothesis was rejected for these three subscales. Descriptive data are shown in Table 3.

Ho2: There is no significant correlation between achievement in a first course in computer science at the high school level and the eight scores in the Herrmann Brain Dominance Profile which resulted from the Herrmann Participant Survey Form (1984).

There was a failure to reject the null hypothesis for six of the brain dominance scores. Significant correlations were indicated between grade in course and left cerebral (r = .39) and left brain total (r = .34), and the null hypothesis was rejected for these two measures. Data are presented in Table 4.

Table 3

LSI Correlations with Grade in Course

LSI Attribute	Pearson r
Prefers sound	-.22
Prefers light	.33*
Prefers warm temperature	.10
Prefers formal design	.15
Is motivated	.18
Is persistent	.33*
Is responsible	.30*
Needs structure	.06
Prefers peer-oriented learning	-.19
Prefers learning with adults	-.13
Prefers learning through several ways	-.02
Auditory preferences	-.03
Visual preferences	.04
Tactile preferences	-.07
Kinesthetic preferences	-.01
Requires food while learning	-.15
Functions better in morning than in evening	.07
Functions best in late morning	.02
Functions best in afternoon	-.05
Needs mobility	.02
Parent-figure motivated	.20
Teacher motivated	.14

*$p < .05$.

Note. $N = 63$, $\bar{y} = 80$, $s_y = 10$.

Table 4

Distribution by Brain Dominance

Quadrant	r	n	%	Grade in Course
Left cerebral	.39*	8	12.7	90
Left limbic	.11	17	27.0	79
Right limbic	.19	10	15.9	77
Right cerebral	.11	28	44.4	79
Total		63	100.0	
Left total	.34*	12	19.0	82
Limbic total	-.09	11	17.5	80
Right total	-.22	27	42.9	77
Cerebral total	.28	13	20.6	85
Total		63	100.0	

*p <.05.

Note. $N = 63$, $\bar{y} = 80$, $s_y = 10$.

<u>Ho3</u>: There is no significant correlation between achievement in a first course in computer science at the high school level and the three measures of hemispheric preference from Your Style of Learning and Thinking (SOLAT), Youth Form, by Torrance.

There was a failure to reject the null hypothesis due to less than significant correlation with the three measures of hemisphere preference and grade in course. Descriptive data are shown in Table 5.

<u>Ho4</u>: There is no significant correlation between achivement in a first course in computer science at the high school level and the score on the Otis-Lennon School Ability Index (SAI).

A significant correlation was indicated with SAI ($\underline{r}$ = .55) and grade in course, and the null hypothesis was rejected. Data are presented in Table 6.

<u>Ho5</u>: There is no significant correlation between achievement in a first course in computer science at the high school level and the score on the SAT-M.

A highly significant correlation ($\underline{r}$ = .63, $\underline{p}$ < .001) was indicated between SAT-M and grade in course, and the null hypothesis was rejected. Table 7 contains descriptive data.

<u>Ho6</u>: There is no significant correlation between achievement in a first course in computer science at the high school level as a function of the grade level in school.

Table 5

Distribution by Hemisphere Preference

Hemisphere	r	n	%	Grade in Course
Left	.15	18	28.6	83
Integrated	-.18	20	31.7	78
Right	-.11	25	39.7	80
Total		63	100.0	

Note. $N = 63$, $\bar{y} = 80$, $s_y = 10$.

Table 6

Distribution by School Ability Index (SAI)

SAI (x)	n	%	Grade in Course
80-89	2	3.2	70
90-99	4	6.3	68
100-109	16	25.4	75
110-119	17	27.0	82
120-129	15	23.8	83
130-139	8	12.7	85
140-149	1	1.6	96
Total	63	100.0	

Note. $N = 63$, $\bar{y} = 80$, $s_y = 10$, $\bar{x} = 115$, $s_x = 12$. $r = .55$ ($p < .001$).

Table 7

Distribution by SAT-M

SAT-M (x)	n	%	Grade in Course
200-290	4	6.3	63
300-390	10	15.9	72
400-490	21	33.3	81
500-590	19	30.2	83
600-690	7	11.1	89
700-800	2	3.2	90
Total	63	100.0	

Note. $N = 63$, $\bar{y} = 80$, $s_y = 10$, $\bar{x} = 474$, $s_x = 120$. $r = .63$ ($p < .001$).

There was a failure to reject the null hypothesis as a result of a calculated F in the analysis of variance of less than critical significance. Descriptive data are shown in Tables 8 and 9.

Ho7: There is no significant correlation between achievement in a first course in computer science at the high school level and the cumulative grade-point average (GPA).

A highly significant correlation (r = .82, $p < .001$) was indicated with GPA and grade in course, and the null hypothesis was rejected. Table 10 provides detailed data.

Ho8: There is no significant correlation between achievement in a first course in computer science at the high school level as a function of the gender of the student.

There was a failure to reject the null hypothesis as a result of a less than significant F in the analysis of variance. Tables 11 and 12 show descriptive data related to these results.

Ho9: There is no significant correlation between achievement in a first course in computer science at the high school level and the Jungian personality type of the student.

Data in Table 13 indicate less than significant correlation coefficients, which resulted in a failure to reject the null hypothesis.

Table 8

Analysis of Variance for Grade Level

Source	*df*	Sum of Squares	Mean Squares	*F*
SS_A	3	548.9	182.97	1.93
SS_W	59	5606.1	95.02	
Total	62			

Table 9

Distribution by Grade Level

Grade Level	*n*	%	Grade in Course
9	18	28.6	75
10	16	25.4	82
11	10	15.9	82
12	19	30.1	82
Total	63	100.0	

Note. $N = 63$, $\bar{Y} = 80$, $s_Y = 10$.

Table 10

Distribution by Grade-Point Average (GPA)

GPA (*x*)	*n*	%	Grade in Course
1.001-1.500	2	3.2	53
1.501-2.000	15	23.8	73
2.001-2.500	14	22.2	78
2.501-3.000	11	17.5	81
3.001-3.500	9	14.3	87
3.501-4.000	12	19.0	91
Total	63	100.0	

Note. $N = 63$, $\bar{y} = 80$, $s_y = 10$, $\bar{x} = 2.629$, $s_x = .743$. $r = .82$ ($p < .001$).

Table 11

Analysis of Variance for Gender

Source	*df*	Sum of Squares	Mean Squares	*F*
SS_A	1	300.0	300.0	3.13
SS_W	61	5855.0	95.9	
Total	62			

Table 12

Distribution by Gender

Gender	*n*	%	Grade in Course
Male	52	82.5	79
Female	11	17.5	85
Total	63	100.0	

Note. $N = 63$, $\bar{Y} = 80$, $s_Y = 10$.

Table 13

Distribution by Jungian Typology

Personality Style	r	n	%	Grade in Course
Introversion (I)	-.01	24	38.1	80
Extroversion (E)	.01	28	44.4	81
Balanced Component		11	17.5	77
Total		63	100.0	
Intuitive (N)	-.10	33	52.4	80
Sensing (S)	.10	23	36.5	80
Balanced Component		7	11.1	80
Total		63	100.0	
Feeling (F)	.02	32	50.8	78
Thinking (T)	-.02	25	39.7	73
Balanced Component		6	9.5	88
Total		63	100.0	
Perceiving (P)	-.17	38	60.3	80
Judging (J)	.17	21	33.3	83
Balanced Component		4	6.4	61
Total		63	100.0	

Note. $N = 63$, $\bar{y} = 80$, $s_y = 10$.

The most significant attributes (GPA, SAT-M, SAI, prefers light, persistence, responsibleness, left cerebral dominance, and left total dominance) were used to construct a multiple stepwise linear regression model. The results of the multiple regression analysis are summarized in Table 14. The R^2 value indicates the proportion of variation within the dependent variable that is explained by the attribute variables included in the model at that step.

The multiple regression model from this research accounted for 68% of grade variation with the inclusion of GPA at Step 1. The subsequent inclusion of responsibleness and SAI raised the R^2 value to .75 after Steps 2 and 3. The addition of the remaining five attribute variables to the model resulted in a final R^2 value of .79, indicating that 79% of grade variation may be explained by this model. An F test of the model yields a highly significant F statistic ($p < .001$). The analysis of variance of the regression model of the eight attribute variables from Table 14 is presented in Table 15. The t tests of the regression coefficients of the eight-variable model are presented in Table 16.

The intercorrelation of variables in a regression is of importance in the interpretation of data which resulted from the research. Optimum regression is possible when the intercorrelations of the attribute variables are low.

Table 14

Stepwise Multiple Regression Analysis,

Dependent Variable: Grade in Course

Step	Entered	R^2
1	Grade-point average (GPA)	.68*
2	Responsibleness	.71*
3	School Ability Index (SAI)	.75*
4	Need for light	
5	Left cerebral	
6	Persistence	.79
7	Left brain total	
8	SAT-M	

*$p < .05$.

Note. $N = 63$, $\bar{Y} = 80$, $s_Y = 10$, $s_{YX} = 5$.

Table 15

Analysis of Variance for Regression Model

Source	*df*	Sum of Squares	Mean Squares	*F*
Regression	8	4847.88	605.98	25.03**
Residual	54	1307.11	24.21	
Total	62			

$^{**}p < .001$.

Note. $N = 63$, $\bar{y} = 80$, $s_y = 10$, $s_{yx} = 5$.

Table 16

Regression Coefficients--Analysis of Variance

Variable	*b*	Standard Error of Regression Coefficient	*t* Test	Beta
(Constant)	11.149	8.799	1.267	
SAT-M	.012	.008	1.542	.144
Left brain total	.073	.050	1.456	.110
Persistence	.122	.077	1.595	.114
Left cerebral	-.058	.044	-1.320	-.114
Need for light	.119	.081	1.479	.102
SAI	.151	.067	2.265*	.186
Responsibleness	.190	.075	2.538*	.180
GPA	.008	.001	6.775*	.586

$^{*}p < .05$.

Note. $N = 63$, $\bar{y} = 80$, $s_y = 10$, $s_{yx} = 5$.

Table 17 gives the intercorrelations of the eight-variable model.

Reduction in the number of attribute variables to be included in the regression model was desirable because many of the variables which were in the research are not available in high school records. Another regression model was constructed using only three attributes: GPA, SAI, and SAT-M. The resulting model indicated that 68% of grade variation was explained by GPA, and a total of 72% was explained when these three variables were combined. The stepwise regression analysis is shown in Table 18. The analysis of variance for the regression model of the three attributes is shown in Table 19. The _t_ tests of regression coefficients of the three-variable model are presented in Table 20.

Table 17

Intercorrelations of Attribute Variables[a]

$\underline{X}$	GPA	RESPON	SAI	LIGHT	PERSIS	L-TOT	SAT-M	L-CER
GPA	1.00	.13	.48	.27	.27	.30	.60	.32
RESPON		1.00	-.03	.29	.31	.30	.09	.36
SAI			1.00	.11	-.01	.08	.59	.33
LIGHT				1.00	.24	.32	.19	.32
PERSIS					1.00	.49	.02	.25
L-TOT						1.00	.16	.70
SAT-M							1.00	.46
L-CER								1.00
s_x	.74	9.42	12.23	8.55	9.25	18.42	119.51	19.60
$\bar{X}$	2.63	51.14	115.38	52.35	47.33	91.91	473.65	63.75

[a]GPA = cumulative grade-point average; RESPON = Responsibleness; SAI = School Ability Index; LIGHT = Need for light; PERSIS = Persistence; L-TOT = Left brain total; SAT-M = score on mathematics section of the Scholastic Aptitude Test; L-CER = Left cerebral brain dominance.

Note. $N = 63$, $\bar{Y} = 80$, $s_y = 10$, $s_{yx} = 5$.

Table 18

Stepwise Multiple Regression Analysis (Three Steps)

Dependent Variable: Grade in Course

Step	Entered	R^2
1	Grade-point average (GPA)	.68*
2	School Ability Index (SAI)	.71*
3	SAT-M	.72

*p <.05.

Note. $N = 63$, $\bar{y} = 80$, $s_y = 10$, $s_{yx} = 5$.

Table 19

Analysis of Variance for Regression Model

(Three Variables)

Source	df	Sum of Squares	Mean Squares	F
Regression	3	4414.48	1471.49	49.88**
Residual	59	1740.51	29.50	
Total	62			

**p <.001.

Note. $N = 63$, $\bar{y} = 80$, $s_y = 10$, $s_{yx} = 5$.

Table 20

Regression Coefficients--Analysis of Variance

(Three Variables)

Variable	*b*	Standard Error of Regression Coefficient	*t* Test	Beta
(Constant)	36.94	6.697	5.516	
SAT-M	.01	.008	1.427	.137
SAI	.12	.071	1.713	.150
GPA	8.94	1.184	7.549**	.667

$^{**}p < .001$.

Note. $N = 63$, $\bar{Y} = 80$, $s_Y = 10$, $s_{YX} = 5$.

Chapter 5

Summary, Conclusions, and Recommendations

This chapter is divided into three major sections. The first section provides a summary of the purpose of the study, research methods, data analysis, and findings. The second section contains a discussion of the conclusions drawn from the findings of the study. The final section suggests recommendations as a result of the study and the conclusions.

Summary

Purpose of the study. The purpose of this research was to identify student characteristics that correlate with achievement in a first course in computer science and to build a model to predict success in a first course in computer science at the high school level. A primary goal of this study was to develop a model useful in predicting achievement in a first course in computer science that could be used as an aid in advising high school students prior to their entering a first course in computer science.

Research methods. Attribute variables for the study were selected following a review of related research, and appropriate data-gathering instruments were used to elicit information from the students in the sample population. The grade in the course was chosen as the criterion variable, and Pearson $\underline{r}$ product-moment correlation coefficients were calculated with each of the 40 attribute variables and the criterion variable. Statistically significant attributes were used to construct a multiple stepwise linear regression model for a prediction equation.

Findings. Findings are reported in relation to each of the study's hypotheses.

Ho1: There is no significant correlation between preferred learning style and achievement in a first course in computer science in the high school.

By studying the research question which was the basis for this hypothesis and evaluating the data which resulted from the research, there was a failure to reject the null hypothesis for all of the learning style characteristics except amount of light needed ($\underline{r}$ = .33), persistence ($\underline{r}$ = .33), and responsibleness ($\underline{r}$ = .30). The results indicated significant correlations with grade in course and these three attributes, and the null hypothesis was rejected for these three subscales.

Ho2: There is no significant correlation between brain quadrant dominance and achievement in a first course in computer science in the high school.

By studying the research question which was the basis for this hypothesis and evaluating the data which resulted from the research, there was a failure to reject the null hypothesis for six of the brain dominance scores. Significant correlations were indicated with grade in course and left cerebral ($\underline{r}$ = .39) and left brain total ($\underline{r}$ = .34), and the null hypothesis was rejected for these two measures.

Ho3: There is no significant correlation between hemisphere preference and achievement in a first course in computer science in the high school.

By studying the research question which was the basis for this hypothesis and evaluating the data which resulted from the research, there was a failure to reject the null hypothesis as a result of less than significant correlations with the three measures of hemisphere preference and grade in course.

Ho4: There is no significant correlation between academic aptitude and achievement in a first course in computer science in the high school.

By studying the research question which was the basis for this hypothesis and evaluating the data which resulted from the research, the null hypothesis was rejected as a result of an indication of significant correlation with SAI ($\underline{r}$ = .55) and grade in course.

Ho5: There is no significant correlation between mathematics aptitude and achievement in a first course in computer science in the high school.

By studying the research question which was the basis for this hypothesis and evaluating the data which resulted from the research, the null hypothesis was rejected as a result of an indication of a highly significant correlation ($\underline{r}$ = .63, $\underline{p}$ <.001) with SAT-M and grade in course.

Ho6: There is no significant difference in grade in course between grade levels in school in a first course in computer science in the high school.

By studying the research question which was the basis for this hypothesis and evaluating the data which resulted from the research, there was a failure to reject the null hypothesis as a result of an indication of less than critical value of $\underline{F}$ in the analysis of variance.

Ho7: There is no significant correlation between cumulative grade-point average (GPA) and achievement in a first course in computer science in the high school.

By studying the research question which was the basis for this hypothesis and evaluating the data which resulted from the research, a highly significant correlation ($\underline{r}$ = .82, $\underline{p}$ <.001) was indicated with GPA and grade in course. Therefore, the null hypothesis was rejected.

Ho8: There is no significant difference in grade in course between male and female students in a first course in computer science in the high school.

By studying the research question which was the basis for this hypothesis and evaluating the data which resulted from the research, there was a failure to reject the null hypothesis as a result of an indication of less than significant value of F in the analysis of variance.

Ho9: There is no significant correlation between personal style and achievement in a first course in computer science in the high school.

By studying the research question which was the basis for this hypothesis and evaluating the data which resulted from the research, there was a failure to reject the null hypothesis as a result of an indication of less than significant correlation coefficients with grade in course and the subscales on the personality inventory.

The prediction equation which resulted from the three-variable multiple regression analysis was:

grade in course = .67(GPA) + .15(SAI) + .14(SAT-M)

Conclusions

The primary goal of this study was prediction of achievement in computer science through selected academic, cognitive, and demographic variables. The classification of attribute variables is shown in Appendix C.

Academic variables. The results of this study indicate that much of the variation in achievement in a first course in computer science at the high school level can be accounted for by cumulative grade-point average (GPA), School Ability Index (SAI), and score on the mathematics section of the Scholastic Aptitude Test (SAT-M). The derived regression model based on these three attribute variables accounts for 72% of achievement in a first course in computer science, as measured by grade in course. The key predictor of success, as determined by this study, was GPA, which accounted for 68% of the variance in the criterion variable, grade in course.

Cognitive variables. The significant correlations of persistence and responsibleness confirmed researcher observations over a number of years in the classroom. These variables, combined with need for light and two left brain quadrant scores, were the only cognitive variables of significance in the study. These five attributes accounted for only 4% of the variance in the grade in course.

Demographic variables. None of the demographic variables in the study indicated significant correlation with grade in course, and none were included in the regression model for prediction.

Prediction equation. A multiple stepwise linear regression model with the three attribute variable scores most readily available in high school records produced the following prediction equation:

grade in course = .67(GPA) + .15(SAI) + .14(SAT-M)

This prediction equation may be used with substitution of GPA, SAI, and SAT-M directly from school records. Although useful, a predictive model should only be used in conjunction with other advising criteria. The model should be seen as a dynamic advising tool which may assist in assuring students of a successful academic experience in a first course in computer science at the high school level.

Recommendations

Based on this study and the conclusions, the following recommendations are made:

1. A study should be conducted of the relationship between predicted values from the regression equation and observed values of grade in course.

2. Research should be conducted on the prediction equation by further development of a regression model with GPA, SAI, and SAT-M. This would serve to update and improve predictions by adjusting for trends in student population and teaching methods.

3. The study should be replicated in urban, other suburban, and rural settings which may contain socioeconomic levels and educational expectations different from the research setting.

4. The study should be replicated with a larger sample to confirm the general applicability of the results of this study.

5. Caution should be exercised when the prediction equation is used, despite the indication that a high percentage of variance in grade in course may be accounted for by GPA, SAI, and SAT-M.

6. The study should be replicated in academic subjects other than computer science to verify the applicability of the prediction equation.

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Appendices

Appendix A

Data Gathering Instruments

Data-Gathering Instruments

The Herrmann Participant Survey Form (1984) is proprietary and may not be duplicated. Information related to that instrument, its administration, and its scoring may be obtained from:

Applied Creative Services, Ltd.
The Whole Brain Corporation
2075 Buffalo Creek Road
Lake Lure, NC 28746
(704) 625-9153

Your Style of Learning and Thinking (SOLAT) is provided by:

The Torrance Center
University of Georgia
422 Aderhold Hall
Athens, GA 30602

Information concerning the mathematics section of the Scholastic Aptitude Test is available from:

College Board Publications
P. O. Box 2815
Princeton, NJ 08541

Inquiries concerning the Learning Style Inventory (1987) should be directed to:

Price Systems, Inc.
P. O. Box 1818
Lawrence, KS 66044

The Personal Style Inventory (1980) is documented in The 1980 Annual Handbook for Group Facilitators, which is published by:

University Associates, Inc.
8517 Production Avenue
San Diego, CA 92121

Appendix B

Topical Outline, First Course in

Computer Science

Topical Outline, First Course in Computer Science

I. Course Concepts

A. Security of Computer Systems
B. Development of Digital Computers
C. Systems Analysis
D. Computer Hardware
E. Computer Software
F. Computer Careers

II. Programming Skills

A. Operating Systems
B. Structured Program Development
    1. Problem Definition
    2. Algorithm
    3. Program Coding
    4. Testing
    5. Documentation

III. Grading System

A. Notebook/Homework (15%)
B. Textbook Tests (30%)
C. Programming Assignments (35%)
D. Final Exam (20%)

Appendix C

Classification of Attribute Variables

Classification of Attribute Variables

Academic:

Cumulative grade-point average (GPA)

Otis-Lennon School Ability Index (SAI)

Scholastic Aptitude Test, Mathematics Section (SAT-M)

Cognitive:

Learning Style Inventory (Dunn, Dunn, & Price)

Participant Survey Form (Herrmann)

Personal Style Inventory (Hogan & Champagne)

Style of Learning and Thinking (Torrance)

Demographic:

Gender

Grade in school