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Predicting success in the undergraduate introductory computer science course using the Theory of Planned Behavior

Shaffer, Dale Owen, Ph.D.

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U·M·I
300 N. Zeeb Rd.
Ann Arbor, MI 48106

PREDICTING SUCCESS IN THE UNDERGRADUATE INTRODUCTORY COMPUTER SCIENCE COURSE USING THE THEORY OF PLANNED BEHAVIOR

by

Dale Owen Shaffer, B.S., M. Ed., M.S.

DISSERTATION

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PREDICTING SUCCESS IN THE UNDERGRADUATE INTRODUCTORY COMPUTER SCIENCE COURSE USING THE THEORY OF PLANNED BEHAVIOR

APPROVED BY

DISSERTATION COMMITTEE:

Thomas R. Koballa, Jr.

Thomas R. Koballa, Jr.

Lowell J. Bethel

Lowell J. Bethel

Frank E. Crawley

Frank E. Crawley III

G. H. Culp

George H. Culp

Nell B. Dale

Nell B. Dale

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> "Verses which do not teach men new and moving truths
> do not deserve to be read."

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Supervisor: Thomas R. Koballa, Jr.

This study identified predictors of success in the undergraduate introductory computer science course by using variables proposed by the Theory of Planned Behavior. The undergraduate introductory course follows the guidelines established by the Association for Computing Machinery Curriculum Committee Task Force for Computer Science 1. Success was operationalized as a grade of "C" or better in the course. Data was collected from two samples (n = 94, n = 19).

The Theory of Planned Behavior, an extension of the Theory of Reasoned Action, includes a perceived behavioral control component in an effort to allow the analysis of behavior which is non-volitional. The

Theory of Planned Behavior was shown to be an improvement over the Theory of Reasoned Action in the prediction of success.

The version of the Theory of Planned Behavior which considers perceived behavioral control to be an antecedent of intention and not of behavior was supported in this study both at the beginning and end of the semester. Behavioral intention was a significant predictor of success in the course at both the beginning and end of the semester.

The prediction of behavioral intention was examined. At the beginning of the semester, perceived behavioral control made a significant increase in explained variance above attitude and subjective norm, but the three together did not predict behavioral intention. Near the end of the semester, attitude towards the behavior and perceived behavioral control made significant contributions, and the three model variables predicted behavioral intention. The addition of the external variables gender, ethnicity, and Scholastic Aptitude Test Quantitative scores did not add significantly to the prediction of behavioral intention. The variables proposed by the Theory of Planned Behavior constituted good predictors of success for the female subgroup at the beginning of the semester, and for a number of subgroups at the end of the semester. Several specific beliefs contributed to the direct measure of related variables.

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Chapter 1: Introduction

This study attempted to identify predictors of success in an undergraduate introductory computer science course at Lander College in Greenwood, South Carolina and at the University of South Carolina, Columbia, South Carolina. The undergraduate introductory course was developed following the guidelines for Computer Science 1 (CS1) established by the Association for Computing Machinery Curriculum Committee Task Force for Computer Science 1. It is the first course taken by computer science majors at Lander College and the University of South Carolina and parallels the entry level computer science course offered by many other colleges.

Previous research concerning predictors of success in computer science will be closely examined in Chapter 2. Much of this research has been based in the cognitive domain. Studies have identified several potential predictors from the cognitive domain, including previous grade point average, Scholastic Aptitude Test scores, and programmer aptitude tests.

Cognitive predictors of success have been demonstrated by some previous studies to be useful as predictors of success in undergraduate introductory computer science courses. However, it is equally important to understand how affective factors influence students' success in undergraduate introductory computer science courses. Research in the affective domain has received considerable attention in the broader science education field but has been virtually ignored in computer science at the college level.

Therefore, this study was concerned with affective predictors of success in the undergraduate introductory computer science course. The theoretic framework of this study is provided by Ajzen's Theory of Planned Behavior.

Need for the Study

Overview.

In the late 1970s and early 1980s computer science educators were faced with large enrollments and scarce resources. Computer science educators needed a method to identify students who were likely to succeed in order to wisely utilize these scarce resources, such as computer equipment and faculty. Therefore prediction of success in the undergraduate introductory computer science courses was of great interest.

Today, enrollments in computer science programs have declined, but the demand for computer scientists has not (Duke, 1987). Now the interest in predicting success in the undergraduate introductory computer science course continues for different reasons. Computer science educators need predictors of success not only to eliminate high risk candidates, but also to improve recruitment efforts.

Previous studies have generally examined variables outside the affective domain. This is due in part to the fact that computer science education is a young field, since computers have existed for less than 50 years and have only gained widespread usage in the past 10 years. Researchers have virtually exhausted the search for predictors from the cognitive domain and are slowly recognizing the need to examine predictors from the affective domain. Yet the examination of predictors from the affective domain thus far has not utilized a methodology with strong theoretic underpinnings. The affective domain, however, has been widely recognized as being important in the broader science education field. This recognition is due to the fact that science education is a more mature field where research encompasses most aspects of the learning process. The lack of research in the affective domain in computer science education, coupled with the importance of such research in the broader science education field, demonstrates a need for research in this area. The lack of research in the affective domain is especially notable at the college level in computer science.

Need for predictors of success in computer science education.

The need for predictors of success in the undergraduate introductory computer science courses is centered on three areas: resource allocation, screening, and recruitment. Each of these areas has had an effect on programs in computer science.

Past research concerning predictors of success in the undergraduate introductory computer science courses was motivated by a desire to allocate scarce resources, specifically computer equipment and personnel (Gries, 1987), to students who were likely to succeed. The problem of scarce resources was exacerbated by the high enrollments in computer science programs nationwide (Duke, 1987). This situation was reflected several years ago at Lander College, a state supported liberal arts college of 2,500 students located in the Piedmont region of South Carolina.

When Lander College's computer science program began in 1982, available resources were at a minimum (A. B. Shiflet, personal communication, October 15, 1988). Zero microcomputers, ten terminals connected to a remote mainframe, and one faculty member were the extent of resources in the program. By 1983 the number of students majoring in computer science had grown to 188, which represented approximately 8% of Lander's enrollment (D. Dulniak, personal communication, October 12, 1988), while the amount of available resources expanded slightly. The lack of adequate resources coupled with the large number of majors severely limited the effectiveness of the program.

In the early 1980s, the computer science faculty at Lander College generally felt that many of the students had inadequate educational backgrounds and held misconceptions about the field of computer science (D. C. Platt, personal communication, July, 1988; J. Hinkel, personal communication, September, 1989). It was evident to many of the computer science faculty members that students in the undergraduate introductory course did not have an accurate idea of what lay ahead. The undergraduate introductory computer science course served as a screening device; the course often had failure rates in excess of 50%. Less than 15% of students entering the computer science program completed the entire course of study.

The computer science program at the University of South Carolina was experiencing similar problems during the early 1980s (D. B. Timney, personal communication, March 28, 1989). The University of South Carolina is a large, state supported university of about 26,000 students. In 1983 eleven faculty served 765 students in the undergraduate computer science major. Although these students had access to some resources at other locations on the campus, only 12 terminals were allocated for the use of computer science students. Cards for data input were used in the undergraduate introductory computer science course.

The educational background of computer science students at the University of South Carolina also did not measure up to the expectations of the faculty (D. B. Timney, personal communication, March 28, 1989). One of the faculty at the University of South Carolina felt that students during the early 1980s equated computer science with the computer game Pac Man.

Today these two reasons, screening and resource allocation, are becoming less important as the enrollments in computer science curricula nationwide decline (Duke, 1987). While easing the problem of resource allocation, the decline in the supply of computer science students has led to a decline in the number of computer science graduates entering the job market. Yet, the demand for computer scientists is greater than the supply (Duke, 1987). The number of computer-related jobs is expected to grow much faster than the average for all jobs through the year 2000 (United States Department of Labor, 1988).

To help equalize the supply of computer science graduates with the demand, computer science educators need an effective method of identifying potentially qualified students. Good predictors of success in the first undergraduate computer science course could be used to identify those students so that they could be recruited into the computer science major. This pool of potential candidates available for recruitment could come from those college students who are undecided as to the choice of undergraduate major or from high school students who indicate a preference for working with computers.

A need for good predictors of success in the undergraduate introductory computer science course is evident at Lander College. By 1988 enrollment in computer science at Lander College had declined to 66 students. This number represented about 2.5% of Lander's student population (D. Dulniak, personal communication, October 12, 1988).

Resource allocation and screening are no longer problems at Lander College. Over 40 microcomputers, 15 remote terminals, and four faculty members are available. High school students are now being exposed to computer science to a greater extent. Students entering the program are better prepared and possess fewer misconceptions about the field of computer science. Adequate predictors of success could be useful as a recruitment tool in this time of plentiful resources.

Likewise, screening and resource allocation no longer drive the need for good predictors of success in the undergraduate introductory computer science course at the University of South Carolina (D. B. Timney, personal communication, March 28, 1989). Fourteen faculty members serve the needs of 270 students. Computing resources include 73 microcomputers and seven terminals. Students entering the computer science program at the University of South Carolina have a better idea about the field of computer science.

The decline in enrollment in computer science programs at Lander College and the University of South Carolina mirrors a nationwide decline. Bailey and Hawkins (1989) found that the relative decline in enrollments in computer science programs nationwide between 1984 and 1987 was 30%. Their survey went on to identify, in the opinions of the individuals responsible for the programs, the factors which contributed to the decline. These factors, with the corresponding percentage of respondents so indicating, included the idea that computer science is more difficult than imagined (40%), students having an earlier exposure to computer science in high school (37%), and the notion that computer science has lost its glamour (33%). The respondents who indicated that earlier exposure to computer science in high school was detrimental to enrollments felt that it was due mainly to poorly prepared teachers (43%) and student discovery of a dislike of computer science (64%).

Need for predictors from the affective domain.

In general, researchers involved with the search for predictors of success in the undergraduate introductory computer science courses have identified several from the cognitive domain. Grade point average, Scholastic Aptitude Test (SAT) scores, and programmer aptitude test scores have been shown to be good predictors, explaining from 1% to 47% of the variance in student success. But a large amount of unexplained variance remains when these predictors are used. The unexplained variance may be accounted for by variables from the affective domain.

The use of predictors postulated by the Theory of Planned Behavior could explain a portion of this unaccounted variance. The Theory of Planned Behavior, which measures several variables in the affective domain, has been demonstrated to be a significant predictor of one non-volitional behavior as determined by grades in a business administration course (Ajzen & Madden, 1986). This theory, although rather new, provides a rich theoretic grounding. The Theory of Planned Behavior also has a proven track record in its predecessor, the Theory of Reasoned Action. The Theory of Reasoned Action has been shown to account for a large portion of the variance in a variety of volitional behaviors, including several science-related behaviors. A closer examination of studies using the Theory of Reasoned Action and the Theory of Planned Behavior will be made in Chapter 2.

The Theory of Planned Behavior provides a framework for the prediction of behavioral intention and behavior of either a volitional or non-volitional nature (Ajzen & Madden, 1986). For example, if the volitional behavior which is to be examined is the willingness of a person to regularly attend class, then behavioral intention is a measure of an individual's likelihood to perform the behavior of attending class regularly. Intention is measured before the person is actually placed into the situation of making the decision. Nevertheless, behavioral intention and behavior can be quite different. The individual could, when faced with a decision concerning attending a particular class, make a decision concerning the behavior that does not reflect an expressed intention. Some other variable could enter the situation, making the behavior non-volitional. For example, the person who has stayed up the previous night in an attempt to study for an exam may sleep through the class.

Volitional behavior is behavior over which the individual has complete control. For example, assuming a person has adequate funds to purchase a container of ketchup and is now standing in the supermarket aisle containing ketchup, the individual can exercise volitional behavior in the selection of the brand of ketchup. Non-volitional behavior, on the other hand, is behavior over which the individual has no control. A person stranded on a deserted island without a food source has little control over the behavior of eating.

Most behaviors fall somewhere between these two extremes. One may have a measure of control over what one wears today. But the weather, over which the person has no control, may effect the behavior. Each behavior, therefore, falls somewhere along the volitional - non-volitional continuum. The Theory of Planned Behavior measures behavior along the continuum.

The Theory of Planned Behavior utilizes three components to predict behavioral intention: attitude towards the behavior, subjective norm, and perceived behavioral control. Attitude towards the behavior is a measure of the person's attitude towards performing the specified behavior. A person's attitude is reflected in the answer to the question "What's in it for me?" In the class attendance example, the individual has probably formed attitudes towards attending class. These attitudes could range from totally acceptable to completely unacceptable in regards to the performance of the behavior. Subjective norm measures the individual's belief concerning what other individuals feel should be done about the behavior. One's subjective norm corresponds to the question "Do people who are important to me feel I should engage in the behavior?" The individual considering attending class may include in the decision factors such as parental approval. Perceived behavioral control is a measure of the individual's perception of the control the individual actually has over the behavior. It specifically considers one's impressions of the barriers met when attempting to perform the behavior. The level of control can fall anywhere along the volitional -

non-volitional continuum. The individual in the example may consider it likely that the alarm clock will fail to go off, precluding a decision entirely.

The effect of perceived behavioral control on behavior is thought to change over time. Perceived behavioral control may have no direct effect on the individual's behavior initially, but the effect may increase over time. In the example of predicting an individual's attendance, the person at the beginning of the semester may not be aware of certain barriers which may influence attendance. As the semester progresses barriers, such as the need to study for other courses, become more evident, increasing the direct influence of perceived behavioral control on behavior.

The Theory of Planned Behavior, therefore, utilizes three factors to predict behavioral intention. These variables, attitude towards the behavior, subjective norm, and perceived behavioral control, have not been used in the prediction of success in the undergraduate introductory computer science course, a behavior which is generally non-volitional.

Hence, an investigation using predictors from the affective domain specified by the Theory of Planned Behavior model could suggest the usefulness of predictors which have not been identified by previous research. It could also serve to increase the use of affective variables in computer science education research. If the variables suggested by the Theory of Planned Behavior are found to be effective in predicting success in the undergraduate introductory computer science course, further research which utilizes affective variables would indeed be warranted.

Interest in the effects of affective variables in conjunction with external variables has increased in science education (Crawley, in press; Crawley & Coe, 1990). The effect of affective variables on females, for example, could be quite different than for males. Therefore three external variables, gender, ethnicity, and Scholastic Aptitude Test Quantitative scores, were included in this investigation which examines variables from the Theory of Planned Behavior as predictors of success in the undergraduate introductory computer science course.

Statement of the Problem

This study tested the adequacy of variables proposed by the Theory of Planned Behavior as predictors of students earning grades of "C" or better in CS 230, Computer Science Principles I, at Lander College, a four year state supported liberal arts institution, and CSCI 145, Introduction to Algorithmic Design I, at the University of South Carolina, a state supported university, during the Fall 1989 semester. Each sample is analyzed separately since the two samples are from fundamentally different institutions.

The specific questions addressed in this study follow. Each question will be examined using data gathered at both the beginning and end of the semester.

1. Does the addition of perceived behavioral control (PBC) to behavioral intention (I) cause the prediction of the behavior (B) of earning the grade of "C" or better in the introductory undergraduate computer science course to be

a. not improved at the beginning of the semester (Equation 1)?

$$B \cong I \tag{1}$$

b. improved at the end of the semester (Equations 2 and 3)?

$$B \cong w_1(I) + w_2(PBC) \tag{2}$$

$$B \cong w_1(I) + w_2(PBC) + w_3(I * PBC) \tag{3}$$

The symbol $\cong$ represents a functional relationship; the w_i's are constants which represent the contribution of each variable.

2. Is a student's behavioral intention of earning a grade of "C" or better in the undergraduate introductory computer science course predicted by a linear combination of attitude towards the behavior (A_B) and subjective norm (SN)? Equation 4 summarizes this hypothesized relationship and Equation 5 hierarchically extends the hypothesis to include interraction effects.

$$I \cong w_1(A_B) + w_2(SN) \tag{4}$$

$$I \cong w_1(A_B) + w_2(SN) + w_3(A_B * SN) \tag{5}$$

3. Is a student's behavioral intention of earning a grade of "C" or better in the undergraduate introductory computer science course predicted by a linear combination of attitude towards the behavior, subjective norm, and perceived behavioral control? Equation 6 summarizes this hypothesized relationship and is a hierarchical

extension of Equation 4. Equation 7 hierarchically extends the hypothesis to include interraction effects.

$$I \cong w_1(A_B) + w_2(SN) + w_3(PBC) \tag{6}$$

$$I \cong w_1(A_B) + w_2(SN) + w_3(PBC) + w_4(A_B * SN) + w_5(A_B * PBC) + w_3(PBC * SN) + w_7(A_B * SN * PBC) \tag{7}$$

4. Is a student's behavioral intention of earning a grade of "C" or better in the undergraduate introductory computer science course predicted by a linear combination of attitude towards the behavior, subjective norm, perceived behavioral control, and specific external variables, namely gender (G), ethnicity (E), and Scholastic Aptitude Test Quantitative scores (SAT Q). Equation 8 summarizes this hypothesized relationship and is a hierarchical extension of Equation 6. Equation 9 includes the interraction effects.

$$I \cong w_1(A_B) +w_2(SN) +w_3(PBC) +w_4(G) +w_5(E) +w_6(SAT\ Q) \tag{8}$$

$$I \cong w_1(A_B) + w_2(SN) + w_3(PBC) + w_4(G) + w_5(E) + w_6(SatQ) + \text{interractions} \tag{9}$$

5. Is a student's behavioral intention of earning a grade of "C" or better in the undergraduate introductory computer science course predicted by a linear combination of attitude towards the behavior, subjective norm, and perceived behavioral control only, with the relative contributions of each variable dependent on:

a. the external variable gender (Equation 10)?

$$I \cong w_1(G)(A_B) + w_2(G)(SN) + w_3(G)(PBC) \tag{10}$$

b. the external variable ethnicity (Equation 11)?

$$I \cong w_1(E)(A_B) + w_2(E)(SN) + w_3(E)(PBC) \quad (11)$$

c. the external variable Scholastic Aptitude Test Quantitative test score (Equation 12)?

$$I \cong w_1(SAT\ Q)(A_B) + w_2(SAT\ Q)(SN) + w_3(SAT\ Q)(PBC) \quad (12)$$

6. Are the belief-based measures of attitude towards the behavior, subjective norm, and perceived behavioral control closely associated with the direct measure of attitude towards the behavior, subjective norm, and perceived behavioral control, respectively? This hypothesis will be examined only for variables which have significant relationships with behavioral intention as identified in hypotheses 2 and 3.

7. Does each belief-based measure of attitude towards the behavior, subjective norm, and perceived behavioral control make significant contributions to the respective direct measure? This hypothesis will be examined only for variables which have significant relationships between the direct and belief-based measures, as identified in hypothesis 6.

Definition of Terms

The following terms are defined within the confines of this study:

1. Attitude: "a learned predisposition to respond in a consistent manner with respect to a given situation" (Fishbein & Ajzen, 1975, p. 10).

2. Attitude towards a behavior: "a person's attitude towards performing the behavior under consideration" (Ajzen & Fishbein, 1980, p. 54). It is indirectly quantified by determining the sum product of each

behavioral belief and its corresponding outcome evaluation (Ajzen & Fishbein, 1980, p. 55). Attitude towards a behavior can be measured through appropriate questioning techniques and is operationalized in this study as the attitude towards earning a "C" or better in the introductory undergraduate computer science course.

3. Behavior: "observable acts of the subject" (Fishbein & Ajzen, 1975, p. 13). The behavior which was examined in this study was earning a grade of "C" or better in either CS 230, Computer Science Principles I, at Lander College or CSCI 145, Introduction to Algorithm Design I, at the University of South Carolina during the Fall semester of 1989.

4. Behavioral intention: "a person's intention to perform various behaviors" (Fishbein & Ajzen, 1975, p. 12). According to the Theory of Planned Behavior, behavioral intention is a function of three factors: attitude towards a behavior, subjective norm, and perceived behavioral control (Ajzen & Madden, 1986). Behavioral intention is operationalized in this study as a person's intention to earn a "C" or better in the introductory undergraduate computer science course. Behavioral intention reflects one's personal motivation to perform the behavior.

5. Belief: the information one has about an object. The strength of this belief is indicated by the perceived likelihood that the object has the attribute in question (Fishbein & Ajzen, 1975, p. 12).

6. Computer programming: "the process of planning a sequence of instructions for a computer to follow" (Dale & Weems, 1987, p. 2).

7. Computer science: "the systematic study of algorithmic processes that describe and transform information" (Denning et al., 1989). It is the field of knowledge which examines and promotes the use of computers

through the systematic development and improvement of the interface between information and humans.

8. Direct - full effects model: A predictive model which expands the prediction of behavioral intention from the variables proposed by the Theory of Planned Behavior to include specific external variables.

9. Direct - reduced effects model: A predictive model which does not include external variables in the prediction of behavioral intention.

10. Indirect effects model: A predictive model which blocks on specific external variables when predicting behavioral intention.

11. Perceived behavioral control: "a person's belief as to how easy or difficult the performance of a behavior will be" (Ajzen & Madden, 1986). It is quantified by taking the product of individual behavioral control beliefs. The control beliefs in this study are the beliefs associated with earning a "C" or better in the introductory undergraduate computer science course.

12. Subjective norm: "an individual's beliefs that certain referents think that the individual should or should not perform a behavior" (Fishbein & Ajzen, 1975, p. 16). It is quantified indirectly by determining the sum product of each normative belief and the individual's motivation to comply with the referent (Ajzen & Fishbein, 1980, p. 75). Subjective norm can be measured directly through appropriate questioning techniques. In this study, these normative beliefs are with respect to earning a "C" or better in the introductory undergraduate computer science course.

13. Undergraduate introductory computer science course: the first computer science course intended for, but not necessarily restricted to, undergraduate students majoring in computer science. The course must follow the recommended curriculum for CS1 as defined by the Association for Computing Machinery Curriculum Committee Task Force for CS1 (Koffman, Miller, & Wardle, 1984).

14. Volitional behavior: behavior which is completely under the control of the individual. The person can decide at will whether or not to exercise the behavior (Ajzen & Madden, 1986).

Chapter 2: Review of Related Literature

Before examining the predictors of success in the undergraduate introductory computer science course is made, a closer look at computer science education, and specifically the undergraduate introductory computer science course, is needed. The field of computer science is in a state of flux. In a National Science Foundation workshop examining undergraduate computer science education, it was stated that "unlike more established science and engineering disciplines, most of what was taught to undergraduates a decade ago is now largely superseded by new results" (Foley & Standish, 1988).

Efforts to establish the content of the undergraduate computer science curriculum reflect this turmoil. Through most of the 1980s, most undergraduate computer science curriculums across the country followed the model established by the Association for Computing Machinery (ACM) Curriculum Committee on Computer Science. This curriculum consists of objectives and outlines for courses in computer science, which includes the undergraduate introductory computer science course Computer Science 1 (Austing, Barnes, Bonnette, Engel, & Stokes, 1979). A further definition of the content of Computer Science 1 was provided by the ACM Curriculum Committee Task Force for Computer Science 1 (Koffman, Miller, & Wardle, 1984). This course emphasizes programming methodology and problem solving rather than language syntax, which was the main emphasis in the past.

The content of the undergraduate introductory computer science course is not yet settled. Challenges to the undergraduate curriculum, including Computer Science 1, have been issued. The ACM Task Force on the Core of Computer Science was established in 1986 to examine the emerging issues concerning curriculum content (Denning et al., 1988). Found within the report issued by this task force (Denning et al., 1989) is a recommendation to design the introductory computer science course with a lecture component to emphasize the enduring principles and a laboratory component which emphasizes the transient technology. In addition, the course should include "a rigorous, challenging survey of the whole discipline" (Denning et al., 1989). A member of the task force agreed that many of the components of the current Computer Science 1 would be considered prerequisite knowledge to the proposed new introductory course (A. J. Turner, personal communication, September 27, 1989).

Because of the inconsistent past and uncertain future of the content of the undergraduate introductory computer science course, it is difficult to clearly summarize past efforts at establishing predictors of success and to associate these efforts with current and future introductory courses. At least forty studies have examined methods to predict success in the first computer science course taken by an undergraduate student. These studies examined courses modeled after Computer Science 1 as defined by the Association for Computing Machinery Curriculum Committee Task Force (Koffman, Miller, & Wardle, 1984) and various language courses including COBOL, FORTRAN, and BASIC, all of which concentrated on syntax.

There is a distinct difference between Computer Science 1 and a computer language course. A course which follows the guidelines for Computer Science 1 teaches the beginning concepts of computer science such as programming methodology and problem solving using a language as the vehicle to do so. This language is often Pascal, but can be any structured, procedural language such as Modula-II or Ada. A language course, on the other hand, covers the use and syntax of that particular language. Yet both types of courses have served as introductory courses in computer science. Factors used as predictors of success in both types of courses will be addressed in this literature review.

In studies of the outcomes of these courses, success was considered the dependent variable and was operationalized in several ways. Success was operationalized in most studies as either a non-standardized examination or the final grade in the course. Both criteria may not adequately measure success; confounding variables such as test-taking skills and teacher differences may influence success. Several studies operationalized success as class ranking based on either an examination or the final grade. Other studies operationalized success as the dichotomy of either passing or failing the course. These two methods, ranking and dichotomizing grades, may be considered better methods of operationalizing success.

Most studies of success in the undergraduate introductory computer science course involved cognitive predictors. Demographic and cognitive predictors, several of which were chosen for use in this study, are examined in this review first. The balance of the review concentrates on predictors from the affective domain where most of the predictors of this study originate.

Demographics.

Eight studies examined the factors of age and gender as predictors of success in the undergraduate introductory computer science course (Table 1). Age and gender were significant predictors in only one study each (Lawson, 1985; Petersen & Howe, 1979); otherwise age and gender were not significant predictors of success, including two studies using the grade in Computer Science 1 (CS1) as the criterion for success. Petersen and Howe (1979) found that the number of siblings in the family, sibling birth order, parental occupation, and home town size had no significant correlation with success in computer science.

In an interesting study by Cramer (1984), success was operationalized as an exam taken in a FORTRAN course. The exam was divided into four portions covering production logic, production syntax, debugging

Table 1

Age and Gender as Predictors of Success in an Undergraduate Introductory Computer Science Course

Study and success operationalization	Sample Size	Age	Gender
Chin & Zecker (1985), scores on an exam in an introductory computer science course	32	-.17	-.04
Cramer (1984), scores on an exam in FORTRAN	105		
production syntax		-.13	
production logic		-.19	
debugging syntax		-.15	
debugging logic		-.06	
Lawson (1985), letter grade in BASIC or Prolog	496	-.18*	.12
Petersen & Howe (1979), letter grade in Introduction to Computers	113	-.05	-.05
	119	-.05	.22*
Salisbury (1986), letter grade in CS1[a]	107	-.18	-.04
Stager-Snow (1984), exam scores in a BASIC course	750	.01	.00
Werth (1986), grade in CS1[a]	58	-.08	.08
Wileman, Konvalina, & Stephens (1981), exam scores in PL/C	96	-.02	

[a]As defined by the ACM Curriculum Committee Task Force for Computer Science 1 (Koffman, Miller, & Wardle, 1984).

*$p<.05$ **$p<.01$

syntax, and debugging logic. Debugging syntax was a measure of the students' capability of recognizing correct syntax while debugging logic measured the students' ability to understand blocks of code. Both debugging syntax and debugging logic were implemented utilizing code examination by students. Production logic and production syntax were similar to debugging logic and debugging syntax, except that they involved programs that the students wrote during the exam. Production logic was a count of the number of logic errors in the student written programs; production syntax was a count of the number of uncompilable syntax errors. None of the subtests produced significant correlations with age.

Cognitive Predictors

Most of the previous research in the area of predicting success in the undergraduate introductory computer science course focused on predictors from the cognitive domain. These studies examined predictors from academic experience, standardized achievement tests, and programmer aptitude tests.

Previous academic experience.

Indicators of previous academic experiences, such as grade point average and class rank, have been shown to be predictors of success in an undergraduate introductory computer science course. Almost one half of the studies which examined previous academic experience found statistically significant results. These studies tend to demonstrate that prior academic experience is a good predictor of success in the undergraduate introductory computer science course, explaining up to 46% of the variance.

Overall high school grade point average has been shown to be a strong predictor of success in an undergraduate introductory computer science course (Table 2). With the exception of one study (Gathers, 1986), overall grade point average was found to be a statistically significant predictor of success in all studies, with the correlation coefficients ranging from .29 to .73. The Gathers (1986) study attempted to determine

Table 2

Overall High School Grade Point Average as a Predictor of Success in the Undergraduate Introductory Computer Science Course

Study and success operationalization	Sample	GPA
Butcher & Muth (1985), grade in CS1	269	.51*
Gathers (1986), grade in Pascal (ABC vs DF)	131	ns[a]
Lawson (1985), grade in BASIC or Prolog	496	.29**
Petersen & Howe (1979), grade in Introduction to Computers	113	.35**
	119	.31**
Whipkey (1984), exam in Pascal	88	.73**

[a]Gathers (1986) did not report correlations for relationships which were not significant.

*$p<.05$ **$p<.01$

the ability of overall grade point average to predict whether or not a student would earn the grade of A, B, or C, and did not produce significant results. Petersen and Howe (1979) found that high school grade point average and the grade in a course titled Introduction to Computers ranged in correlation from .31 ($p<.01$) to .35 ($p<.01$). Lawson (1985) found high school grade point average to significantly predict grades in BASIC or Prolog language courses (.29, $p<.01$). Butcher and Muth (1985) found a correlation of .51 ($p<.05$) when comparing high school grade point average to grade in Computer Science 1 (CS1). Whipkey accounted for 53% of the variance in exam scores when comparing high school grade point average to an exam in Pascal (.73, $p<.01$).

Grade point average in specific high school courses accounts for much of the variance in student success in the undergraduate introductory computer science course (Table 3). Grade point average in mathematics was significant in 4 studies. In a study by Armstrong, LeBold, and Linden (1986), high school mathematics grade point average was significantly correlated to the course grade earned by students in four programming courses. Three of the courses, involving different levels of FORTRAN, produced correlations ranging from .37 to .49 ($p<.05$). The fourth course, a combination of FORTRAN and Pascal, produced a correlation of .37 ($p<.01$). In six samples Koubek, LeBold, and Salvendy found correlations ranging from .21 ($p<.05$) to .41 ($p<.05$) when

Table 3

High School Math, Science, and English Grade Point Averages as Predictors of Success in the Undergraduate Introductory Computer Science Course

Study and success operationalization	Sample	Grade point average Math	Science	English
Armstrong, LeBold, & Linden				
(1986), letter grade in	1577[a]			
elementary FORTRAN		.37**	.35**	.35**
regular FORTRAN		.41**	.46**	.33**
honors FORTRAN		.49**	.60**	.44**
FORTRAN and Pascal		.37**	.36**	.20**
Butcher & Muth (1985),				
CS1 letter grade	269		.29*	
Cramer (1984), exam scores in				
FORTRAN	105			
production syntax		.06		
production logic		-.28*		
debugging syntax		-.32**		
debugging logic		-.31**		
Koubek, LeBold, & Salvendy (1985),				
letter grade in FORTRAN:				
(1980)	606	.38*	.30*	.23*
(1981)	339	.21*	.23*	.16*
(1982)	290	.27*	.26*	.25*
letter grade in Pascal and FORTRAN:				
(1980)	177	.33*	.34*	.21*
(1981)	125	.25*	.19*	.12*
(1982)	183	.41*	.41*	.32*

[a]The sample breakdown among the courses was not provided.

*$p<.05$ **$p<.01$

comparing mathematics grade point average with student grades in computer language courses.

The production syntax portion of Cramer's (1984) exam did not significantly correlate with high school mathematics grade point average. The other three sections, production logic, debugging syntax, and debugging logic, resulted in negative correlations from -.28 ($p<.05$) to -.32 ($p<.01$) when compared to mathematics grade point average. These were the only findings to show an inverse relationship between an examination score and undergraduate grade point average.

The correlation of success with high school science grade point average ranged from .19 to .60 in 4 studies, explaining up to 36% of the variance. The study by Armstrong, LeBold, and Linden (1986) demonstrated correlations from .35 ($p<.01$) to .60 ($p<.01$) between science grade point average and a grade in the four types of FORTRAN courses examined. Butcher and Muth (1985), when comparing the grade in Computer Science 1 to science grade point average, found a correlation of .29 ($p<.05$). The study by Koubek, LeBold, and Salvendy (1985) established correlations ranging from .19 ($p<.05$) to .41 ($p<.05$) when comparing science grade point average to the grade in computer language courses.

High school English grade point average and success in the undergraduate introductory computer science course correlated from .12 to .44, explaining up to 19% of the variance. The Armstrong, LeBold, and Linden (1986) study produced correlations from .20 ($p<.01$) to .35 ($p<.01$)

when using English grade point average to predict the grade earned in four types of FORTRAN language courses. The study by Koubek, LeBold, and Salvendy (1985), which compared English grade point average to the grade in several programming language courses, demonstrated correlations from .12 ($p<.05$) to .32 ($p<.05$).

Overall college grade point average and success in the undergraduate introductory computer science course have generally shown a high degree of correlation, as shown in Table 4. College grade point average was only significant as a predictor for non-freshmen students taking a computer science course since many freshmen have not attended college prior to taking the course. Correlation between the two variables ranged from .25 to .68, accounting for up to 46% of the variance. Two studies (Hostetler, 1983; Bauer, Mehrens, & Vinsonhaler, 1968) demonstrated correlations ranging from .37 ($p<.05$) to .68 ($p<.01$) when comparing college grade point average to the grade earned in FORTRAN. Werth (1986) and Salisbury (1986) found significant positive correlations (.25, $p<.05$, .54, $p<.01$) when using college grade point average as a predictor of the grade in Computer Science 1. The grade in various computer language courses was significantly correlated to college grade point average in a number of other studies (Correnti, 1969; Huse, 1986; Lawson, 1985; Petersen and Howe, 1979).

Table 4

College Grade Point Average as a Predictor of Success in the Undergraduate Introductory Computer Science Course

Study and success operationalization	Sample	Grade Point Average Overall	Math
Bauer et al. (1968), FORTRAN letter grade	68	.68*	
Correnti (1969), letter grade in various courses	261	.58**	
Cramer (1984), FORTRAN exam scores	105		
production syntax			-.14
production logic			-.23
debugging syntax			-.11
debugging logic			-.12
Hostetler (1983), letter grade in FORTRAN	79	.37**	
Huse (1986), letter grade in Introduction to Computer Science	105	.40**	
Koubek, LeBold, & Salvendy (1985), letter grade in FORTRAN:			
(1980)	606		.49*
(1981)	339		.56*
(1982)	290		.43*
letter grade in Pascal and FORTRAN:			
(1980)	177		.50*
(1981)	125		.41*
(1982)	183		.60*
Lawson (1985), BASIC or Prolog letter grades	496	.59**	
Petersen & Howe (1979), letter grade in Introduction to Computers	113	.51**	
	119	.65**	
Salisbury (1986), letter grade in CS1	107	.54**	
Werth (1986), letter grade in CS1	58	.25*	

*p<.05 **p<.01

Two studies have examined correlations between grade point averages in specific college disciplines and success in the undergraduate introductory computer science course (Table 4). A study by Cramer (1984) resulted in a nonsignificant correlation between college mathematics grade point average and an examination in FORTRAN. Koubek, LeBold, and Salvendy (1985), when comparing student grades in several computer language courses to math grade point average, demonstrated a significant correlation (.43, $p<.05$ to .60, $p<.05$), explaining up to 36% of the variance. Koubek, LeBold, and Salvendy (1985) also reported correlations ranging from .31 ($p<.05$) to .56 ($p<.05$) when using chemistry grade point average as the predictor of student grades in an undergraduate introductory computer science course, which explains up to 31% of the variance.

Compared to grade point average, a somewhat weaker correlation between high school rank and success in the undergraduate introductory computer science course was demonstrated by several studies (Table 5). Although several studies reported negative (Butcher & Muth, 1985; Petersen & Howe, 1979) or nonsignificant correlations (Koubek, LeBold, & Salvendy, 1985; Petersen & Howe, 1979) in portions of studies, generally significant correlations were found, accounting for up to 34% of the variance. The study by Armstrong, LeBold, and Linden (1986) produced correlations ranging from .27 ($p<.01$) to .59 ($p<.01$) by using high school rank to predict the grade earned in the four computer language courses examined. Most of the samples produced significant results in the study by Koubek, LeBold, and Salvendy (1985), where correlations ranged from .25 ($p<.05$) to .31 ($p<.05$) by comparing

Table 5

High School Rank as a Predictor of Success in the Undergraduate Introductory Computer Science Course

Study and success operationalization	Sample	Rank
Armstrong, LeBold, & Linden (1986),		
letter grade in	1577	
elementary FORTRAN		.33**
regular FORTRAN		.36**
honors FORTRAN		.59**
FORTRAN and Pascal		.27**
Butcher & Muth (1985), letter grade in CS1	269	-.31*
Koubek, LeBold, & Salvendy (1985),		
letter grade in FORTRAN:		
(1980)	606	.29*
(1981)	339	.25*
(1982)	290	.28*
letter grade in Pascal & FORTRAN:		
(1980)	177	.31*
(1982)	125	.06
(1982)	183	.25*
Leeper & Silver (1982), letter grade in introductory programming course	92	-.25*
Petersen & Howe (1979), letter grade in Introduction to Computers	113	-.31**
	119	-.21

*$p<.05$ **$p<.01$

high school rank to the grade earned in several computer language courses. Butcher and Muth (1985) found a correlation of -.31 (p<.05) between the grade in Computer Science 1 (CS1) and high school rank. In contrast, Butcher and Muth (1985) found a correlation of .44 (p<.05), accounting for 19% of the variance, when the high school rank was expressed as a percent of the total graduating class. Leeper and Silver (1982) found a significant negative correlation of -.25 (p<.05) when employing high school rank expressed as a percentage to predict the grade in an introductory computer science course.

The number of previous mathematics, science, and computer science courses taken by the students generally was not a definitive predictor of success in an introductory undergraduate computer science course. The number of high school mathematics and science courses was a significant predictor of success in two out of four samples in three studies (Table 6). Butcher and Muth (1985) found that the number of mathematics and science courses were significantly correlated (.28, p<.05) to the grade earned in Computer Science 1. In a portion of the study by Petersen and Howe (1979), it was found that the number of mathematics and science courses was correlated (.30, p<.01) to the grade in Introduction to Computers. The other part of the study by Petersen and Howe (1979) and a study by Cramer (1984) uncovered no significant correlation between the number of mathematics and science courses

Table 6

Number of Previous High School Courses Completed as a Predictor of Success in the Undergraduate Introductory Computer Science Course

Study and success operationalization	Sample	Math & Science	Math
Armstrong et al. (1986),			
letter grade in	1577		
elementary FORTRAN			.04
regular FORTRAN			.10
honors FORTRAN			-.05
FORTRAN and Pascal			.10*
Butcher & Muth (1985),			
CS1 letter grade	269	.28*	
Cramer (1984), FORTRAN exam scores	105		-.06 to .15
Konvalina, Stephens, & Wileman (1983), exam scores in PL/C	165		.19**
Lawson (1985), letter grade in BASIC or Prolog	496		.27**
Petersen & Howe (1979), letter grade in Introduction to Computers	113	.06	
	119	.30**	
Salisbury (1986), letter grade in CS1	107		-.05
Werth (1986), letter grade in CS1	58		.25*

*$p<.05$ **$p<.01$

taken and performance in a computer programming course. Armstrong (1986), in a series of studies attempting to predict student grades in four computer language courses, found that the number of semesters a student has taken science courses generally did not predict success, while the grade earned in science courses was a significant predictor, with correlations ranging from .35 ($p<.05$) to .60 ($p<.0001$).

The number of high school mathematics courses completed also did not clearly predict success in the undergraduate introductory computer science course (Table 6). Two studies (Cramer, 1984; Salisbury, 1986) and a portion of a third one (Armstrong, LeBold, and Linden, 1986) did not demonstrate a significant correlation. The portion of the study by Armstrong, LeBold, and Linden (1986) involving the course containing both Pascal and FORTRAN showed a significant correlation (.10, $p<.05$) when using the number of mathematics courses to predict the grade in the course. Several other studies produced significant correlations when comparing the number of high school mathematics courses to an exam in PL/C (Konvalina, Stephens, and Wileman, 1983; .19, $p<.01$) and grades in Computer Science 1 (Werth, 1986, .25, $p<.05$) and in BASIC or Prolog (Lawson, 1985; .27, $p<.01$).

The number of college mathematics courses taken also did not clearly predict success in the undergraduate introductory computer science course (Table 7). Three studies (Chin & Zecker, 1985; Salisbury, 1986; Werth, 1986) did not produce significant results. Three other studies found results at the .01 level of significance. Lawson (1985) found a correlation of .27 ($p<.01$) when using the number of college mathematics courses to predict the grade in BASIC or Prolog. When comparing an exam in a computer language course to the number of college mathematics courses, Alspaugh found a correlation of .41 ($p<.01$) while Konvalina, Stephens, and Wileman determined a correlation of .22 ($p<.01$).

Table 7

Number of Previous College Mathematics Courses Completed as a Predictor of Success in the Undergraduate Introductory Computer Science Course

Study and success operationalization	Sample	College Math
Alspaugh (1972), exam scores in Assembler and FORTRAN	50	.41**
Chin & Zecker (1985), exam scores in an introductory computer science course	32	.33
Cramer (1984), FORTRAN exam scores	105	-.15 to .06
Konvalina, Stephens, & Wileman (1983), exam scores in PL/C	165	.22**
Lawson (1985), letter grade in BASIC or Prolog	496	.27**[a]
Salisbury (1986), letter grade in CS1	107	.15
Werth (1986), letter grade in CS1	58	-.02

[a]Did not distinguish between high school and college math courses.
*$p<.05$ **$p<.01$

The number of previous computer science courses completed generally was not found to be a predictor of success in the undergraduate introductory computer science course (Table 8). Four studies did not find significant correlations. Two of these studies (Armstrong, LeBold, & Linden, 1986; Lawson, 1985) compared the number of previous computer

Table 8

Number of Previous High School Computer Science Courses Completed as a Predictor of Success in the Undergraduate Introductory Computer Science Course

Study and success operationalization	Sample	Computer Science
Armstrong, LeBold & Linden (1986),		
letter grade in	1577	
elementary FORTRAN		.16
regular FORTRAN		-.23
honors FORTRAN		-.16
FORTRAN and Pascal		-.10
Butcher & Muth (1985), grade in CS1	269	.02
Chin & Zecker (1985), exam in an introductory computer science course	32	.36*[a]
Konvalina, Stephens, & Wileman (1983), exam in PL/C	165	.18**[a]
Lawson (1985), grade in BASIC or Prolog	496	.03[b]
Salisbury (1986), grade in CS1	107	.06[b]

[a]Study included college computer science courses.
[b]Included both high school and college computer science courses.
*$p<.05$ **$p<.01$

science courses to a grade in Computer Science 1 while the other two (Butcher & Muth, 1985; Salisbury, 1986) compared the number of courses to the grade in a computer language course. Konvalina, Stephens, and Wileman (1983) found the correlation between the number of previous computer science courses and an exam in the language PL/C to be .18 ($p<.01$). A similar finding (.36, $p<.05$) was reported in a study by Chin and Zecker (1985) who used the number of courses to predict the score on an exam in a course titled Introduction to Computer Science.

Prior programming experience was not a clear predictor of success in an undergraduate introductory computer science course. Four studies (Chin & Zecker, 1985; Cramer, 1984; Salisbury, 1986; Werth, 1986) found that prior programming experience was not a significant predictor of success. Cramer (1984) operationalized success as the score received on a non-standardized examination in FORTRAN while Werth (1986) and Salisbury (1986) operationalized success as the final grade in Computer Science 1. Chin & Zecker (1985) operationalized success as an examination in Introduction to Computer Science. Cramer (1984) found success in a FORTRAN course to be negatively correlated with programming experience (-.39, $p<.05$; -.40, $p<.01$) while a study by Konvalina, Stephens, and Wileman (1983) found prior programming experience and success operationalized as an examination in the language PL/C to have a correlation of .18 ($p<.01$). Prior programming experience seems not to be a good predictor of success in the introductory undergraduate computer science course.

A study by Kersteen, Linn, Clancy, and Hardyck (1988) used a 'Computer Experience Questionnaire' as a predictor of grades in an introductory computer science course. The questionnaire included questions about a subject's previous computer usage and computer language knowledge. The explained variability in grades for the males in the two samples was 14% and 25%, while the scale did not explain a significant amount of variance for females in either sample.

In a similar study, Howerton (1988) found pre-college exposure to computers and computing to be a predictor of scores in an introductory computer programming course. Students who had a high school computing course scored significantly different from those students who did not ($F= 13.7$, $p<.001$). Those students who made regular use of a computer prior to college scored significantly better than those who did not ($F= 7.50$, $p<.01$). Students who owned a personal computer before attending college scored significantly better than those students who did not ($F= 4.24$, $p<.05$). A study by Franklin (1987) found that college students who had taken a high school computer science course performed significantly better ($F= -2.98$), $p<.01$) than those students who did not.

Many previous academic experiences were shown to be significant in predicting success in an undergraduate introductory computer science course. The predictor with the largest number of high correlation coefficients and the least number of nonsignificant findings was high school grade point average from specific courses.

Standardized achievement tests.

Many studies have established a significant correlation between standardized achievement test scores and success in an undergraduate introductory computer science course. These studies generally showed a significant correlation between success in the course and standardized achievement test scores.

A number of studies have shown significant results using the verbal portion of the Scholastic Aptitude Test (SAT) as a predictor of success in an undergraduate introductory computer science course (Table 9). Armstrong, LeBold, and Linden (1986) found correlations ranging from .10 ($p<.05$) to .35 ($p<.01$) when comparing SAT verbal scores to grades in computer language courses. Using the same operationalization of success, Koubek, LeBold, and Salvendy (1985) found correlations ranging from .12 to .25 ($p<.05$). Oman (1986) found that grades in BASIC and Pascal courses strongly correlate (.55, $p<.01$) with SAT verbal scores. Using an exam in a Pascal course to operationalize success, Whipkey (1984) found that SAT verbal scores were significant predictors (.42, $p<.01$) of success. The production syntax portion of the Cramer (1984) study

Table 9

Scholastic Aptitude Test as a Predictor of Success in the Undergraduate Introductory Computer Science Course

Study and success operationalization	Sample	Verbal	Math
Armstrong, LeBold, & Linden (1986),			
letter grade in	1577		
elementary FORTRAN		.10*	.12*
regular FORTRAN		.10	.28**
honors FORTRAN		.35**	.32**
FORTRAN and Pascal		.11*	.31**
Cramer (1984), exam scores in FORTRAN	105		
production syntax		-.28*	-.35*
production logic		-.04	-.17
debugging syntax		-.16	-.17
debugging logic		-.12	-.23
Koubek, LeBold, & Salvendy (1985),			
FORTRAN letter grade:			
(1980)	606	.18*	.30*
(1981)	339	.12*	.32*
(1982)	290	.14*	.16*
Pascal & FORTRAN letter grade:			
(1980)	177	.15*	.36*
(1981)	125	.19*	.19*
(1982)	183	.25*	.42*
Lawson (1985), BASIC or Prolog letter grades	496	.13	.33**
Leeper & Silver (1982), letter grade in unreported language course	92	.38*	.37*
Oman (1986), BASIC or Pascal letter grades	38	.55	.53**
Salisbury (1986), letter grade in CS1	107	-.12	.11
Whipkey (1984), exam scores in Pascal	88	.42**	.51**

*p<.05 **p<.01

determined a correlation of -.28 ($p<.01$) when comparing the SAT verbal scores to an exam in FORTRAN. Cramer's examination of production logic, debugging syntax, and debugging logic did not produce significant results. Leeper and Silver (1982) found a correlation of .38 ($p<.05$) when comparing SAT verbal scores to letter grades in a computer language course. Five studies (Armstrong, LeBold, and Linden, 1986; Cramer, 1984; Lawson, 1985; Oman, 1986; Salisbury, 1986) found nonsignificant correlations between SAT verbal scores and success in an introductory course.

The mathematics portion of the Scholastic Aptitude Test has also been shown to be a good predictor of success in the undergraduate introductory computer science course (Table 9). Armstrong, LeBold, and Linden (1986) found correlations ranging from .12 ($p<.05$) to .32 ($p<.01$) when comparing SAT mathematics scores to grades in computer language courses. Using the same criterion, Koubek, LeBold, and Salvendy (1985) found correlations ranging from .16 to .42 ($p<.05$). Oman (1986) determined that grades in BASIC and Pascal courses strongly correlated (.53, $p<.01$) to SAT mathematics scores. By operationalizing success as scores on an exam in a Pascal course, Whipkey (1984) found that SAT mathematics scores were significant predictors of success (.51, $p<.01$). The production syntax portion of the Cramer (1984) study determined a correlation of -.35 ($p<.01$) when comparing the SAT Quantitative scores to an exam in FORTRAN. Cramer's examination of production logic, debugging syntax, and debugging logic again did not produce significant results. Leeper and Silver (1982) found a correlation of .37 ($p<.05$) when comparing SAT mathmatics scores to success in a computer language course. Lawson (1985) found a correlation of .33 ($p<.01$) when comparing SAT mathematics scores to grades in a course covering BASIC and Prolog. The study by Salisbury (1986) and portions of the study by Armstrong, LeBold, and Linden (1986) found nonsignificant correlations between SAT mathematics scores and letter grades in introductory computer science courses.

The verbal section of the American College Test (ACT) also was shown to be a good predictor of success in the undergraduate introductory computer science course (Table 10). Butcher and Muth (1985) found the grade in Computer Science 1 to be correlated (.44, $p<.05$) to the verbal portion of the ACT. Gathers (1986), who attempted to predict a student's membership in either the passing group, with the grades of A, B, or C, or failing group, with D or F, determined the ACT to be a strong predictor (.83, $p<.01$).

The Mathematics portion of the American College Test tended to be a good predictor of success in the undergraduate introductory computer science course (Table 10). Butcher and Muth (1985) found the grade in Computer Science 1 to be correlated (.52, $p<.05$) to the mathematics portion of the ACT. Rhodes (1985) also uncovered a significant

Table 10

Standardized Achievement Tests as Predictors of Success in the Undergraduate Introductory Computer Science Course

Study and success operationalization	Test[a]	Sample	Verbal	Math
Alspaugh (1972), exam scores in Assembler and FORTRAN	SCAT	50	.20	.08
Bauer, Mehrens, & Vinsonhaler (1968), letter grade in FORTRAN	CQT	68	.37*	.53*
Butcher & Muth (1985), letter grade in CS1	ACT	269	.44*	.52*
Correnti (1969), letter grade in various courses	SUNY	261	.06	.27**
Gathers (1986), grade in Pascal (ABC vs DF)	ACT	131	.83*	ns[b]
Plog (1980), letter grade in COBOL	SCAT	52	total=.46**	
Rhodes (1985), letter grade in COBOL	ACT	unstated		.33*
Sauter (1986)	Norm	57		
COBOL syntax test score			.45*	ns[b]
COBOL logic test score			ns[b]	.41*

[a]American College Test (ACT), College Qualification Test (CQT), School and College Ability Test (SCAT), State University of New York Admissions Exam: Achievement (SUNY), and Normalization of SAT, ACT, and SCAT (Norm).

[b]not significant. The actual correlation was not reported.

*p<.05 **p<.01

correlation (.33, $p<.05$) by comparing the ACT to the grade in COBOL. Gathers (1986) determined the correlation to be nonsignificant when using the mathematics portion of the ACT to predict the grade group (A, B, or C grade vs. D or F grade) in computer language courses.

Other standardized achievement tests have also been found to be good predictors of success in the undergraduate introductory computer science course (Table 10). Bauer, Mehrens, and Vinsonhaler (1968) determined that the verbal portion (.37, $p<.05$) and the mathematics portion (.53, $p<.05$) of the College Qualification Test were correlated to the grade in a FORTRAN course. By comparing the grades in various computer language courses with the verbal portion of the State University of New York (SUNY) Admissions Exam: Achievement, Correnti (1969) found a nonsignificant correlation. The mathematics portion of this test correlated significantly (.27, $p<.01$) to the criterion (Correnti, 1969).

The high correlations in studies examining standardized verbal achievement test scores may be due to the similarities between designing a program and planning a writing project. These similarities tend to be supported in a study by Sauter (1986) who compared the normalization of the verbal sections of the SAT, ACT, and the School and College Ability Test to a COBOL syntax test, resulting in a correlation of .45 ($p<.05$), and a COBOL logic test, resulting in nonsignificant findings (Table 10). In the same study, Sauter (1986) uncovered almost the reverse when examining the mathematics scores; the COBOL syntax was not significant while the COBOL logic test was (.41, $p<.05$).

The results of operationalizing success in the undergraduate introductory computer science course as scores on the School and College Ability Test are mixed (Table 10). Plog (1980) found that the test, using both the verbal and mathematics portions, significantly predicted (.46, $p<.05$) students' grades in a COBOL course. Alspaugh (1972) determined that verbal and mathematics portions of the School and College Ability Test are not significant predictors of scores on an exam in an Assembler and FORTRAN course.

Standardized achievement tests have generally been consistent predictors of success in the undergraduate introductory computer science courses. In studies involving both verbal and mathematics portions of standardized achievement tests, the math portions are generally better predictors of success. There has been concern expressed that math ability is just one of many potential predictors of success in the undergraduate introductory computer science course (Sauter, 1986; Sharma, 1987).

Programmer aptitude tests.

Programmer aptitude tests have been generally found to be significant predictors of success in introductory computer science courses. These tests have explained from 4 to 50 percent of the variance. The Konvalina Stephens Wileman Computer Science Placement Test (KSW) was found to be significant as a predictor of success in five studies with correlations ranging from .36 to .56, explaining up to 31% of the variance (Table 11). Two studies, where success was operationalized as an examination in Computer Science 1 or Computer Science 2, reported correlations of .37 ($p<.05$; Greer, 1986) and .56 ($p<.01$; Konvalina, Wileman, & Stephens, 1983) when using the KSW. A third study

Table 11

Konvalina Stephens Wileman Computer Science Placement Test as a Predictor of Success in the Undergraduate Introductory Computer Science Course

Study and success operationalization	Sample	KSW
Greer (1986), exam scores in CS1&2	117	.37*
Konvalina, Wileman, & Stephens (1983), exam scores in CS1	382	.56**
Konvalina, Stephens, & Wileman (1983), exam scores in PL/C	165	.56**
Lawson (1985), letter grade in BASIC or Prolog	496	.36**
Salisbury (1986), letter grade in CS1	107	.21*
Stephens, Wileman, Konvalina, & Teodoro (1985), exam scores in BASIC	142	.36**
Stephens, Wileman, & Konvalina (1981), exam scores in PL/C	183	.47**
Wileman, Konvalina, & Stephens (1981), exam scores in PL/C	96	.49**

*$p<.05$ **$p<.01$

(Salisbury, 1986) compared students' grades in Computer Science 1 to scores on the KSW producing a correlation of .21 (p<.05). A series of three studies at the University of Nebraska at Omaha compared scores on an examination in PL/C with the KSW and found significant positive correlations ranging from .47 to .56 (p<.01) (Konvalina, Stephens, & Wileman, 1983; Stephens, Wileman, & Konvalina, 1981; Wileman, Konvalina, & Stephens, 1981). Lawson (1985) demonstrated a correlation of .36 (p<.01) when using scores on the KSW to predict grades in BASIC and Prolog courses. A study in the Phillipines (Stephens, Wileman, Konvalina, & Teodoro, 1985) established a correlation of .36 (p<.01) between scores on an examination in BASIC and scores on the KSW.

A number of other programmer aptitude tests have been employed to predict success in an undergraduate introductory computer science course (Table 12). Studies by Dale (1982) and Wolfe (1977) found the Wolfe: Programming Aptitude Test to be a significant predictor of success when used with female subjects; Wolfe (1977) found that the correlation was not significant for male students. Dale (1982) reported a correlation of .36 (p<.05) with an examination in Pascal while Wolfe (1977), using the grade in various programming courses, found a correlation of .71 (p<.01) which accounted for 50% of the variance.

The International Business Machines (IBM) Aptitude Test for Programmer Personnel (ATPP) was found to be a significant predictor of success in an undergraduate introductory computer science course in two studies (Table 12). Bauer, Mehrens, and Vinsonhaler (1968) found a correlation of .51 ($p<.05$) when using the ATPP to predict grades in FORTRAN. A correlation of .20 ($p<.01$) was reported by Correnti (1969) by comparing scores on the ATPP to student grades in various computer language courses. ATPP scores were not found to be a significant predictor of grades in a COBOL course in a study by Capstick, Gordon, and Salvadori (1975).

The Science Research Associates (SRA) Computer Programmer Aptitude Battery (CPAB) was determined to be significant in two out of three studies when used to predict success in the undergraduate introductory computer science course (Table 12). Dale (1982) reported a correlation of .46 ($p<.01$) when using overall scores on the CPAB to predict student scores on an examination in Pascal. Hostetler (1983), when using the CPAB to predict student grades in FORTRAN, found a correlation of .41 ($p<.01$) for the reasoning section and .48 ($p<.01$) for the diagramming section of the CPAB. Alspaugh (1972) found the CPAB to not be a significant predictor of examination scores in Assembler and FORTRAN language courses. Programmer aptitude tests have generally been found to be good predictors of success in the introductory computer science course. Correlations between programmer aptitude tests and success ranged from .21 to .71.

Table 12

Other Programmer Aptitude Tests as Predictors of Success in the Undergraduate Introductory Computer Science Course

Study and success operationalization	Sample	SRA Computer Programmer Aptitude Battery	IBM Aptitude Test for Programmer Personnel	Wolfe: Programming Aptitude Test
Alspaugh (1972), exam scores in FORTRAN and Assembler	50	.28		
Bauer et al. (1968), letter grade in FORTRAN	68		.51*	
Capstick et al. (1975), COBOL letter grade	46		.18	
Correnti (1969), letter grade in various courses	261		.20**	
Dale (1982), exam scores in Pascal	45	.46**		.36*
Hostetler (1983), letter grade in FORTRAN	79	.41-.48[a]		
Mazlack (1980), letter grade in FORTRAN	1350			.33**
Wolfe (1977), grade				in
various courses				
males	40			.21
females	30			.71**

[a]Hostetler's examination of the two part CPAB found the reasoning section coefficient to be .41 ($p<.01$) and the diagramming section to be .48 ($p<.01$).

*$p<.05$ **$p<.01$

Combinations of variables.

Several studies attempted to combine different variables from the cognitive domain in the prediction of success in the undergraduate introductory computer science course. Fowler and Glorfeld (1981) found that the variables grade point average, Scholastic Aptitude Test Quantitative scores, and the number of mathematics courses taken could be used to classify 75% of the students into grade groups of A, B, or C vs. D or F. Austin (1987) found that 87% of the sample of community college students taking a Pascal course were predicted into the correct course completion category, either pass or fail, by using a combination of the KSW Programming Aptitude Test, high school composite achievement, vocabulary and general information abilities, iconic pattern recognition ability, self-assessed math ability, cognitive style, and computer association measures. This model was updated and verified in a second study (Glorfeld, L.W. & Fowler, G. C. , 1982).

Bauer, Mehrens, and Vinsonhaler (1968) determined that, when using course grade as the criterion to measure success, college grade point average and a portion of the International Business Machine's Aptitude Test for Programmer Personnel predicted success (.76, $p<.05$). Butcher and Muth (1985) found that high school grade point average and the mathematics portion of the American College Test correlated (.60, $p<.05$) with the grade earned in a FORTRAN language course.

Campbell and McCabe (1984) determined that Scholastic Aptitude Test Quantitative scores, high school mathematics grades, and gender were the variables most predictive of whether a student continued study in computer science a year later, transferred to engineering or another science, or transferred to some other major. Approximately 68% of the subjects were correctly classified based on this model.

Cafolla (1987) used several cognitive predictors, including Piagetian formal operations, as predictors of success in the introductory undergraduate computer science course. Cafolla found that the Inventory of Piaget's Developmental Tasks and the Verbal Ability portion of the School and College Ability Test significantly explained 50% of the variability in student grades ($F=9.86$, $p<.001$). Formal operations, as measured by the Inventory of Piaget's Developmental Tasks, significantly correlated with student grades (.59, $p<.05$).

Summary.

A number of predictors of success in the undergraduate introductory computer science course exist within the cognitive domain. These predictors explain up to 53% of the variance in success when considered singularly and up to 57% when considered as combinations of predictors. This clearly leaves a large portion of the variance unexplained.

Affective predictors

Many studies have determined the importance of cognitive predictors of success in the undergraduate introductory computer science course. But the cognitive domain accounts for only about 50% of the variance in success. Clearly predictors from the affective domain need to be considered to account for the balance of the variance.

The affective area is composed of emotions and feelings. Included in the affective domain are tastes and preferences, attitudes, and morals and character (Ringness, 1975). Tastes and preferences can be temporary. A person's taste in literature can often be changed quite easily by the introduction of a different type of literature. Morals and character are very deeply internalized. The character of Napolean might be that of conquest.

Attitude falls somewhere between these extremes (Ringness, 1975). Attitudes are more stable than tastes, but not as internalized as morals. Attitude involves emotions and feelings as directed towards an object, person, or behavior. Attitude has been used frequently in education due to its relative stability and potential for change. Therefore when predictors of success in the undergraduate introductory computer science course from the affective domain are examined, attitude is of prime importance.

Definition of attitude.

Early theorists felt that the study of attitudes was so important that they closely associated the field of social psychology to the scientific study of attitudes (Allport, 1967, p. 3). Despite this clear indication of importance, attitudes have been characterized as ambiguous and confused. Fishbein and Ajzen (1975, p. 1) found that research in discrimination, voting opinions, consumer behavior, and interpersonal behavior, as well as absenteeism, turnover, and performance in industry have all come under the general rubric of attitude research.

Another problem during the early part of this century was the lack of a consistent definition of attitude to guide research (Fishbein & Ajzen, 1975, p. 1). Greenwald (1968) noted the large number of definitions of attitude and the lack of a clear single definition. Allport (1967, p. 7) found that definitions of attitude included the following:

> Readiness for attention or action of a definite sort [Baldwin, 1901];
>
> Mental postures, guides for conduct to which each new experience is referred before a response is made [Morgan, 1934];
>
> A mental disposition of the human individual to act for or against a definite object [Droba, 1933];
>
> A tendency to act towards or against something in the environment which becomes thereby a positive or negative value [Bogardus, 1931].

Related to this lack of a clear definition of attitude was the large number of methods employed to measure attitude. Fishbein and Ajzen

(1972) found over 500 different methods of attitude measurement in a survey of studies published between 1968 and 1970. This wide range of measurement procedures often produced conflicting results about the relationships between attitude and other variables (Fishbein & Ajzen, 1975, p. 5). The explicit definition of attitude is clearly a prerequisite to measuring attitudes.

Today, a generally accepted definition of attitude is "a learned predisposition to respond in a consistently favorable or unfavorable manner with respect to a given object" (Fishbein & Ajzen, 1975, p. 10). Attitude is more clearly understood by close examination of the components of the definition.

Attitudes are learned (Shrigley, Koballa, & Simpson, 1988). Cognition is directly involved in the development of attitudes (Shrigley, 1983). Consider the example by Sherif (cited in Shrigley, 1983) in which a broiling steak activates one person's salivary glands but in another, a vegetarian, feelings of nausea. The learned aspect of attitude explains why the smell of the cooking meat triggers pleasant anticipation in one person and makes a second feel ill. The residues of a person's experiences modify that individual's behavior. When attempting to predict these differences in behavior, each person's complete set of experiences generally cannot be measured. Consequently attitude, which reflects this past experience, is measured. Therefore attitudes are not innate, but are learned (Fishbein & Ajzen, 1975, p. 9).

Attitudes are predispositions, or a readiness to respond (Shrigley, 1983). A predisposition is the condition of having an inclination or tendency beforehand (Stein, 1984). This predisposition is general in nature, referring to an overall favorability of a behavioral pattern rather than an individual behavior (Fishbein & Ajzen, 1975, p. 8). For example, consider a person's generally pleasant predisposition towards driving a car compared to the specific lack of desire to drive a car in New York City during rush hour. Attitude's most discrete characteristic is the predisposition to like or dislike something (Shrigley, Koballa, & Simpson, 1988).

Attitudes have an associated object (Shrigley, Koballa, & Simpson, 1988). The object can range from abortion to acid rain, while attitude is the response to the object.

Attitudes are consistent. They are permanent enough to be stable, yet are temporary enough to be changed (Shrigley, Koballa, & Simpson, 1988). Fishbein and Ajzen (1975, p. 6) identify three types of consistency. First, the stimulus-response consistency implies that a person may be observed to respond in a consistent manner in the presence of a specific stimulus. Consider a person who abhors the drinking of alcohol. According to the stimulus-response consistency, this person should refuse a drink every time one is offered.

The second type, the response-response consistency, involves the degree of consistency between different responses to a given object (Fishbein & Ajzen, 1975, p. 6). If in the driving example the general attitude towards driving a car is compared to the attitude towards driving in New York City's rush hour, an inconsistency seems to be apparent in terms of driving attitude. But the behavior is consistent when considering the attitude towards driving on underutilized interstate highways.

Evaluative consistency over time is the third type of consistency (Fishbein & Ajzen, 1975, p. 7). In other words, a person on different occasions will perform different volitional behaviors in a consistent manner with respect to a given object. Consider a person's attitude towards close involvement in his preschool child's development. The person may show a tendency towards close involvement by reading to the child, helping the child do jigsaw puzzles, and helping the child master the computer as a learning tool. Each of these behaviors demonstrates a commitment to involvement in the preschool child's development.

These three components, consistency, predisposition, and learned, are important to the definition of attitudes. Each makes a significant contribution to the understanding of attitudes.

Attitudes should not be confused with beliefs and values (Shrigley, Koballa, & Simpson, 1988). Beliefs provide information, whereas attitudes are the feelings towards this information. Values are typically unidirectional whereas attitudes are bidirectional. For example, a person may value beauty, but may hold a positive or negative attitude towards the colors pink and purple when used on the exterior of a home.

Attitude is a latent variable (Ajzen, 1989). It cannot be directly measured, but can be inferred from measurable responses from the sample under consideration. These responses come from three categories: cognition, affect, and conation.

Responses from the cognitive category include those which reflect perceptions of and information about the attitude object (Ajzen, 1989). For example, considering the behavior of quitting smoking, a belief from this category might be that smoking is dangerous to one's health.

The second category, affective responses, deals with the feelings about the attitude object (Ajzen, 1989). An example from this category using the behavior of quitting smoking might be the feeling that a person who smokes is to be admired (or be considered disgusting).

Conative responses, the third category, include the behavioral inclinations with respect to the attitude object (Ajzen, 1989). Considering the behavior of smoking, a response from this category might be that a person prefers to sit in a non-smoking area of a restaurant.

The responses from these three categories, cognition, affect, and conation, make up the measurement of attitude (Ajzen, 1989). These responses can be considered the beliefs which are the first component of a causal chain. This chain, shown below, suggests that beliefs can predict attitudes, which predict intention, and intention predicts behavior.

Beliefs --> Attitudes --> Intention --> Behavior

Problems with attitudinal research in science education.

Koballa (1988c) suggests that science educators reevaluate the reasons for studying attitudes and give careful attention to the reasons offered by attitude theorists. These reasons, which are closely associated with the three components of attitudes, are that attitudes are relatively enduring (consistency), are related to behavior (predisposition), and are learned.

The study of attitudes in the field of science education is important. Their importance is especially notable when examining curriculum development and evaluation (Munby, 1983). Attitudes formed by people could have a profound effect on society. Koballa and Crawley (1985, p. 230) expressed concern over the attitudes towards science held by some segments of the population. These people often hold the view that "scientific investigation must be sharply curtailed if humankind is to survive" (Koballa and Crawley, 1985). These attitudes are often motivated by concerns over controversial issues such as nuclear energy and genetic engineering. Controversy has even erupted over the use of data from a hypothermia study and other scientific data gathered in Nazi concentration camps (Mills, 1988). Investigation of attitudes in the science education domain is clearly warranted if attitudes are to be improved.

Peterson and Carlson (1979), following a review of previous research, determined that attitude research in science education was chaotic and confusing. At least one investigator (Abelson, 1972) concluded that attitudes cannot predict behavior.

Several researchers have identified problems in attitude research in science education. Koballa (1988c) has identified a number of potential weaknesses, including invalid attitude instruments, poor research designs, the lack of theoretical frameworks, and the lack of specificity when identifying attitude objects. Munby (1983) determined that part of the problem lies in the sheer number of attitude scales and the lack of valid and reliable measures. Blosser (1984) and Schibeci (1984) reported similar findings. Several science educators have called for a moratorium on the production of attitude scales until these problems are adequately addressed (Blosser, 1984; Munby, 1983; Schibeci, 1984).

These criticisms have been addressed by researchers. Shrigley and Koballa (1987) have outlined the usefulness of Ajzen and Fishbein's (1980) Theory of Reasoned Action as the theoretic underpinning necessary to allow attitude research in science education to proceed. Shrigley and Koballa (1987, p. 16) believe that the Theory of Reasoned Action is the key to the "development of affective measures that link attitudes ... with behaviors."

The second concern, poorly designed attitudinal scales, is clearly delineated by Koballa (1986) who points out that instruments which have been developed in the past to measure attitudes towards science or computers are suspected to have little predictive value due to their measurement of attitudes towards a target, not a behavior. The Theory of Reasoned Action provides a methodology for designing attitudinal instruments which predict volitional behaviors and, therefore, is a significant improvement over past methods. In addition, the Theory of Reasoned Action provides for criterion-related validity by utilizing direct and belief-based measures of predictors, allowing for their comparison.

It is clear that Schibeci (1984) and many other researchers are aware of the problems of attitudinal research in science education. The answer to these difficulties probably lies within the framework provided by the Theory of Reasoned Action, which proffers a clear link between attitudes and behavior.

The Theory of Reasoned Action.

The Theory of Reasoned Action is used to understand and predict volitional behavior (Ajzen & Fishbein, 1980, p. 5). It is based on the premise that people are rational and utilize information available to them. Therefore people consider the implications of their actions prior to the action. Consequently, the best predictor of a particular behavior is the individual's intention to perform the behavior.

Application of the Theory of Reasoned Action is limited to behavior which is volitional. In other words, the individual must be able to perform the behavior under consideration without influence from other factors. For example, the theory can be used to examine the behavior of driving a car for those people who are licensed to do so, but not for the behavior of flying the space shuttle for the general public.

The Theory of Reasoned Action is based on a conceptual framework consisting of beliefs, attitudes, intentions, and behaviors (Fishbein & Ajzen, 1975, p. 15). Beliefs represent the cognitive dimension, containing information about performance of the behavior. Attitudes are representative of the affective dimension. They contain favorable or unfavorable evaluations concerning the performance of the behavior. Intentions are the future plans concerning the performance of the behavior. Behaviors are the observable actions. These four concepts, beliefs, attitudes, intentions, and behavior, are linked by a series of hypotheses which explain the associations. In the Theory of Reasoned Action, beliefs influence attitudes, which in turn influence intentions. Intentions, in turn, influence behavior.

There are four elements associated with the Theory of Reasoned Action (Ajzen & Fishbein, 1980, p. 34). These four elements help to clarify behaviors. The first element, action, is closely associated with the second element, target, which is where the action is directed. Depending how the target is considered, a study might find quite different results regarding reading books and reading novels by James Michener.

The third and fourth elements, context and time, are generally less recognized by researchers (Ajzen & Fishbein, 1980, p. 34). For example, a person who enjoys reading novels by James Michener at home on Saturday evenings might be quite opposed to reading them at 3 am in a New York subway. Clearly, context and time are elements of the behavioral criterion.

A person's intention, or behavioral intention, is the sole predictor of behavior (Ajzen & Fishbein, 1980, p. 90). But a better understanding of behavioral intention can be determined from two independent factors (Ajzen and Fishbein, 1980, p. 6, 90). Subjective norm, the social factor, is the perceived social support to perform or not perform the behavior (Ajzen and Madden, 1986). The personal factor, termed attitude towards the behavior, refers to the degree to which a person has a favorable or unfavorable evaluation of a behavior (Ajzen and Madden, 1986). These two factors do not in themselves predict behavior, but can be used to understand behavioral intention (Ajzen & Fishbein, 1980, p. 90).

The Theory of Reasoned Action considers attitude only towards a volitional behavior (Ajzen & Fishbein, 1980, p. 8). Attitudes towards objects, institutions, or people are not considered. For example, there is a clear distinction between a person's positive attitudes towards taxes (they provide roads, police protection, and so on) and the negative attitudes towards paying taxes. Taxes are objects, while paying taxes is a behavior.

These two factors, attitude towards the behavior and subjective norm, jointly help to explain behavioral intention. The relative importance of the attitudinal and normative factors is weighted in a predictive model to determine intention, which in turn predicts behavior. For example, a person who is leery of flying may fly largely due to peer pressure while a second person may be more willing to fly mainly due to positive personal attitudes towards flying (for example, she enjoys it). One's favorable intention to fly may be due to high subjective norm weight and low attitudinal weight, high attitudinal weight and low subjective norm weight, or high weightings of both factors. The function which expresses the behavioral intention component of the Theory of Reasoned Action is

$$B \cong I \cong w_1(A_B) + w_2(SN) \qquad (1)$$

where B is the behavior being examined, I is the behavioral intention, A_B is the attitude towards the behavior B, SN is the subjective norm, w_1 and w_2 are the relative combining weights associated with the attitudinal and normative factors, and $\cong$ represents the functional relationship (Fishbein & Ajzen, 1975, p. 301).

A person's attitude towards a behavior is the favorable or unfavorable feelings the person holds towards performing the behavior. Attitude towards the behavior can be measured by using a question involving a semantic differential scale such as (Ajzen & Fishbein, 1980, p. 55):

My attitude towards my having an abortion which will save my life is

favorable ____ : ____ : ____ : ____ : ____ : ____ : ____ unfavorable
extremely quite slightly neither slightly quite extremely

The determinants of attitude towards the behavior can be examined and compared to the direct measure described above. This comparison can be made by finding the sum of the salient beliefs about performing the behavior paired with the evaluation of the outcome by utilizing paired questions on a semantic differential scale. These salient beliefs and evaluations are integrated into an overall equation which describes the attitude towards the behavior component, as shown in Equation 2. This overall result is referred to as the belief-based measure of attitude towards the behavior.

$$A_B \cong \sum_{i=1}^{n} b_i e_i \tag{2}$$

In the above equation, b_i refers to the strength of the i-th salient belief held by the person concerning the performance of behavior B and e_i represents the degree to which that outcome is positively or negatively evaluated.

Equation 2 follows Fishbein and Ajzen's (1975, P. 222) expectancy-value model. This model is not causal, but rather helps to describe the relationship between attitude and the determinants of attitude. The model provides a way in which to combine different beliefs and their associated evaluations and compare them to attitude.

Subjective norm, which is the person's perceptions about the extent to which important others feel concerning his performing the behavior, is also evaluated using a direct method (Ajzen & Fishbein, 1980, p. 57). The direct method might ask:

Most people who are important to me feel that I

should ____ : ____ : ____ : ____ : ____ : ____ : ____ should not
extremely quite slightly neither slightly quite extremely

have an abortion which will save my life.

The determinants of subjective norm can also be measured in a belief-based manner similar to attitude towards the behavior. Questions using semantic differential scaling can be employed to determine a sum of the person's perceptions of the social support from individual sources paired with the person's motivation to comply with the individual sources. These normative beliefs and related compliance motivations can be summarized as follows:

$$SN \cong \sum_{j=1}^{x} b_j m_j \qquad (3)$$

where b_j refers to the j-th belief held by the person concerning what an important other feels about him performing the behavior and m_j represents the person's motivation to comply with this important other. Again, the expectancy-value model (Ajzen & Fishbein, 1975, P. 302) is utilized to combine these beliefs and associated motivations to comply.

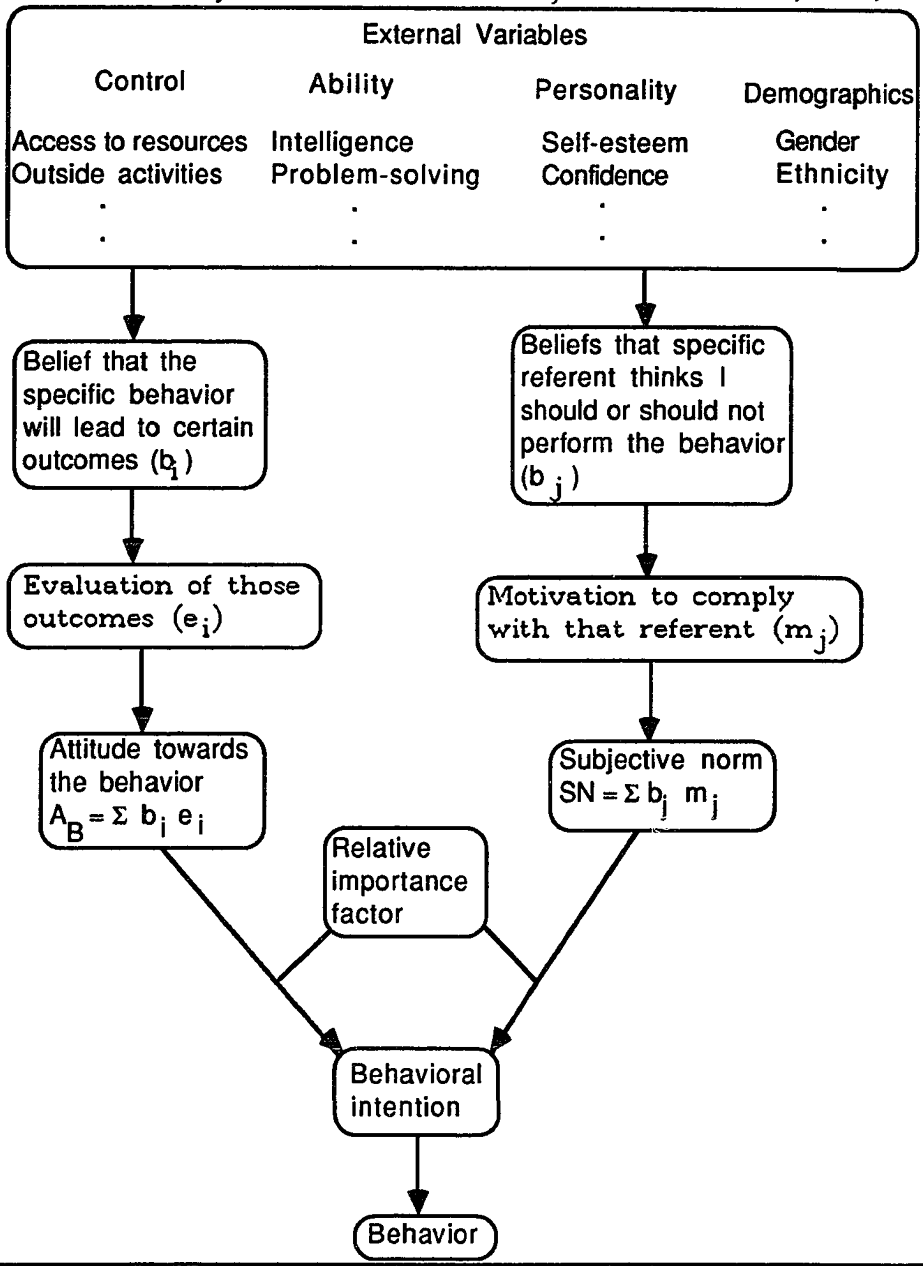
The direct and belief-based methods for identifying attitude towards the behavior and subjective norm should be significantly correlated.

Consequently, the results from the two methods are correlated to determine if a significant positive relation exists between them. In other words, A_B and $\Sigma b_i e_i$ are compared and SN and $\Sigma bjmj$ are compared.

The Theory of Reasoned Action is shown graphically in Figure 1. Note that external variables are considered to effect behavior indirectly through the variables attitude towards the behavior and subjective norm (Ajzen & Fishbein, 1980, p. 82). For example, consider the external variable age and its effect on the behavior of starting to smoke. A teenager may be more likely to begin smoking due to peer pressure than would a senior citizen. Peer pressure can be considered part of subjective norm in the Theory of Planned Behavior. Therefore age indirectly effects the behavior of smoking. In a similar manner, other external variables like personality traits, education level, and ethnicity can effect the behavior indirectly through the variables proposed by the Theory of Reasoned Action.

This theory has been demonstrated to have significant predictive capability in a number of studies. Ajzen (1985, p. 17) reviewed a series of studies and determined that the Theory of Reasoned Action affords an accurate prediction of intention and behavior when the behaviors are under volitional control. These studies researched areas ranging from birth control to military reenlistment to voting.

Figure 1 The Theory of Reasoned Action (Ajzen and Fishbein, 1980).



Use of the Theory of Reasoned Action in science education.

A number of studies have examined attitudinal factors in science education using the Theory of Reasoned Action. These studies have mainly examined student intentions to engage in several science-related behaviors. Many of these studies examine students' intentions to enroll in various science courses.

Koballa (1988a), in a study of eighth grade students' intentions to enroll in elective science courses, compared variables identified by the Theory of Reasoned Action to the Waring Attitude Towards Science Protocol, ability grouping, and science grades. Koballa found that no relationship existed when comparing attitude towards the behavior, subjective norm, and behavioral intention with ability grouping, science grades, and attitude measured by the Waring Attitude Towards Science Protocol (Table 13).

But two predictors of enrolling in elective science courses from the Koballa study came from the Theory of Reasoned Action (Table 14). Attitude towards the behavior (.58, $p<.0001$) and subjective norm (.48, $p<.0001$) produced significant correlations to behavioral intention. The combination of attitude towards the behavior and subjective norm accounted for 41% ($p<.0001$) of the variance in intention to enroll in elective science courses.

Table 13

Relationship Between Variables From the Theory of Reasoned Action and Other Variables When Variables are Used to Predict Student Intention to Enroll in Elective Science Courses

		Theory of Reasoned Action		
Study, science course, and sample	Other Variables	Attitude toward Behavior	Subjective Norm	Behavioral Intention
Crawley & Coe (1990), Any science course, 100	Gender			-.09
	Ethnicity			.05
	General Ability			-.07
	Science Ability			.22*
Koballa (1988a), Any science course, 174	Science Grade	.06	.03	.12
	Ability Group	.04	.10	.04
	Science Attitude[a]	.10	.00	.07
	Gender	.03	.03	.02
Koballa (1988b), Physical Science, 94 females	Science Grade	.05	.04	.11
	Ability Group	.12	.00	.09
	Science Attitude[a]	.20	.14	.06

Note. The above values represent the correlation between variables from the Theory of Reasoned Action and other variables when variables are used to predict student intention to enroll in elective science courses.

[a]Attitude to science was determined by the Waring Attitudes Towards Science Protocol.

*$p<.05$ **$p<.01$

A second study by Koballa (1988b) examined determinants of female junior high school students' intentions concerning enrollment in elective high school physical science courses. Again, Koballa found that no relationship exists between the Theory of Reasoned Action and the variables from the Waring Attitude Towards Science Protocol, ability grouping, and science grades (Table 13). Attitude towards the behavior was the best single predictor of intention to enroll (.53, $p<.0001$) with subjective norm producing a correlation of .32 ($p<.002$). Attitude towards the behavior and subjective norm together accounted for 40% of the variance (Table 14).

These two studies demonstrate the low collinearity between variables identified by the Theory of Reasoned Action and other potential predictor variables. They also show the apparent inadequacy of some predictors outside of the Theory of Reasoned Action as predictors of intention to engage in science-related volitional behaviors.

In a similar study, Crawley and Coe (1990) examined middle school students' intentions to enroll in a ninth grade science course. Attitude towards the behavior predicted the intention to enroll in a science course (.52, $p<.001$) at a higher correlation than subjective norm (.46, $p<.001$). The two factors in tandem accounted for 35% of the variance in behavioral intention (Table 14).

Table 14

Relationship Between Variables From the Theory of Reasoned Action and Student Intention to Enroll in Elective Science Courses

Study and science course	Sample	Attitude toward Behavior	Subject-ive Norm	Subjective Norm & Attitudes
Crawley & Coe (1990), Any science course	100	.52***	.46***	.59***
Koballa (1988a), Any science course	174	.58***	.48***	.64***
Koballa (1988b), Physical Science	94 females	.52***	.46**	.59**
Stead (1985), Any science course	71 males	.78*	.50*	.81*
Stead (1985), Any science course	81 females	.91*	.80*	.94*

[a]Attitude to science was determined by the Waring Attitudes Towards Science Protocol.

*$p<.05$ **$p<.01$ ***$p<.001$

Most other factors examined in the Crawley and Coe (1990) study did not predict intention to enroll in a high school science course (Table 13). Gender, ethnicity, and general ability were found to not be significant predictors of intention to enroll. General ability was determined by the school's placement of students into ability groups. Ability in science, as determined by the Science Research Associates Achievement Series, was a significant predictor of intention (.22, $p<.05$).

Stead (1985) found significant correlations between the predictors identified by the Theory of Reasoned Action and behavioral intention (Table 14). The related behavior was whether the student would choose to study science in subsequent courses or not. Attitude towards the behavior and subjective norm together correlated significantly with behavioral intention for both males (.81, $p<.05$) and females (.94, $p<.05$).

The intentions of physical science teachers to use investigative teaching methods were examined by Crawley (1988). Attitudes were found to be a significant predictor of teachers' intentions to use investigative teaching methods ($r=.53$, $p=.02$), while subjective norm was not ($r=.20$, $p=.39$).

Helgeson (1988) examined the intentions of elementary teachers to implement science activities which were suggested in staff development programs. It was found that the combination of attitude towards the behavior and subjective norm was significantly correlated to intention (.34, $p<.001$).

Ray (1988) examined determinants of student behavior with respect to laboratory and non-laboratory science learning activities. The related behavior was whether or not a student did the science-related activities the teacher requested. Attitude towards the behavior was significantly correlated with behavioral intention both when the requested activities were generated from the laboratory-based sample (.33, $p<.01$) and the non-laboratory based sample (.51, $p<.01$). Subjective norm was not significantly correlated with behavioral intention both when the requested activities were generated from the laboratory-based sample (.14, $p<.08$) and the non-laboratory based sample (.15, $p<.06$).

In an examination of microcomputer use by library and information science students, Walster (1986) found that the intentions of students to learn to use the computer were significantly predicted (.44, $p<.004$) by the combination of attitude towards the behavior and subjective norm. The intentions of students to use the computer were also significantly determined (.48, $p<.003$) by the combination of attitude towards the behavior and subjective norm. The study did not report the individual influences of attitude towards the behavior and subjective norm, nor did it report data on the actual behavior.

The Theory of Planned Behavior.

The Theory of Reasoned Action considers behavioral intention to be the antecedent to behavior (Ajzen, 1985). But intention will most likely predict behavior when two conditions occur. The first is a time consideration (Ajzen, 1985). Behavioral intention is a measure of the subject's intention immediately prior to the performance of the behavior. The correlation of intention and behavior can decrease with the passage of time. For example, the measure of intention to use aerosol spray containers before the public became aware of the dangers posed to the ozone layer could not be a good predictor of the behavior of using these containers after public awareness. Time can also have an effect on the intention-behavior relationship without the addition of new information. The weaker the level of commitment a person has the more likely the person is to change intention with the passage of time (Ajzen, 1985). Some people are more likely to change their intentions than others (Ajzen, 1985).

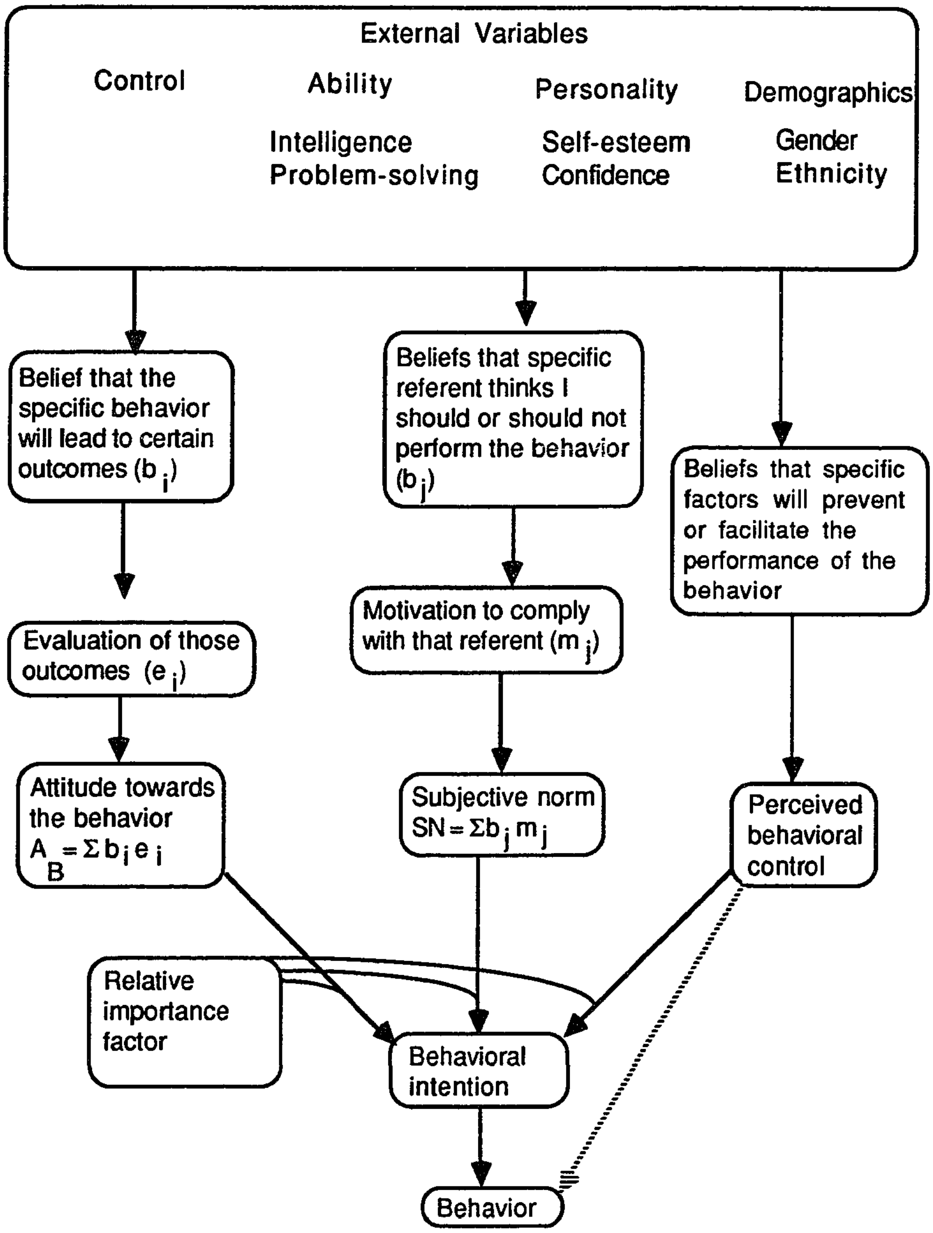
The second condition involves behavior that is under volitional control (Ajzen, 1985). This means that a subject must be able to easily perform the behavior if so inclined. For example, attitudes towards having an abortion cannot have much influence on behavior if abortion is illegal. Volitional control can vary from person to person. Many people can exercise little volitional control over addictive activities like smoking and drug abuse. Yet some individuals have been able to quit smoking through will power. Others are able to conquer alcohol addiction through support structures like Alcoholics Anonymous. Therefore the applicability of volitional control varies from person to person. The boundary conditions of time and volitional control place some limitations on the Theory of Reasoned Action.

When considering a certain behavior, a person does not either have or not have volitional control. For example, consider the behavior of hammering a nail through a piece of wood without bending the nail. If the only kind of wood available were seasoned oak, the level of volitional control would be small for most people since it is quite difficult to drive a nail through seasoned oak. Volitional control would be increased if the wood were green oak, which is easier to nail. Most people would have almost complete volitional control if they were using pine, which is very easy to drive a nail through.

Volitional control can, therefore, be represented as a continuum, with the behavior in question falling somewhere between complete volitional control and no volitional control. In the above example, the behavior of hammering a nail through green oak would probably fall somewhere between the two extremes.

The Theory of Planned Behavior (Ajzen, 1985, p. 29) is an extension of the Theory of Reasoned Action which attempts to address the volitional control issue. This new theory includes a perceived behavioral control component which is a measure of volitional control. The time boundary condition still remains in the Theory of Planned

Figure 2 The Theory of Planned Behavior (Ajzen and Madden, 1986).



Behavior. A diagram expressing the Theory of Planned Behavior is shown in Figure 2. Note that it is very similar to the Theory of Reasoned Action except for the addition of perceived behavioral control. The external variables are assumed to act through the variables attitude towards the behavior, subjective norm, and perceived behavioral control in a manner similar to the Theory of Reasoned Action. This figure shows two potential versions of the Theory of Planned Behavior (Ajzen and Madden, 1986). The first version does not include the line from perceived behavioral control to behavior and is based on the assumption that perceived behavioral control only effects intention. This version is expressed in the following equation which is an adaptation of Equation 1:

$$B \cong I \cong w_1(A_B) + w_2(SN) + w_3(PBC) \qquad (4)$$

The second version (Equation 5), which includes the line from perceived behavioral control to behavior, considers this link under the assumption that perceived behavioral control is a partial substitute for actual behavioral control. This link is suggested to be of increased importance as the amount of time decreases between the measurement of the variables and the occurance of the behavior under observation.

$$B \cong w_1(I) + w_2(PBC) \qquad (5)$$

In order to understand perceived behavioral control, it is necessary to examine the underlying construct, behavioral control. Behavioral control is an examination of the degree to which a subject is in control of actual behavior. It is important to determine, along with the subject's behavioral intention, an estimate of the degree of control over the behavior which the subject can exercise (Ajzen and Madden, 1986).

Perceived behavioral control is an extension of behavioral control in which the subject's beliefs as to how easy or difficult performance of a behavior would be are considered (Ajzen & Madden, 1986). Behavioral control is a very difficult variable to measure in many cases. Consider the difficulty in measuring the behavioral control involved with goals such as quitting smoking or losing weight. Therefore perceived behavioral control is used as an estimate of behavioral control (Ajzen, 1985, p.34).

Research in perceived behavioral control is rooted in an investigation by Phares (Lefcourt, 1976, p. 34). Phares found that the degree of control a subject felt over a task could be helpful in predicting that individual's judgments made in response to success and failure at the task. He developed a short Likert-type scale to measure locus of control which served as an impetus for further research. Locus of control measures assess the degree to which a person feels control over a given situation.

Research in locus of control had a strong role in the development of the perceived behavioral control aspect of the Theory of Planned Behavior (Ajzen & Madden, 1986). But there is an important difference to the two approaches. Locus of control scales measure a person's perceptions of his control over events in his life while perceived behavioral control examines a person's perceptions of environmental factors (Ajzen, 1985, p. 25). For example, a person may consider herself a safe driver, which can be measured by a locus of control scale. But this person may feel little control over safe driving due to the effect of drunk drivers, which can be measured by perceived behavioral control scales.

An even stronger connection exists between perceived behavioral control and self-efficacy beliefs (Ajzen & Madden, 1986). Self-efficacy beliefs involve a person's belief that one can successfully execute the behavior required to produce the outcome of interest (Bandura, 1977). Bandura has demonstrated that a person's behavior is strongly influenced by confidence in his ability to perform the behavior. This confidence in one's ability to perform a behavior is similar to perceived behavioral control (Ajzen and Madden, 1986). But a significant difference exists between the two concepts. Self-efficacy beliefs concentrate on factors internal to the individual, like confidence, while perceived behavioral control reflects external factors like time and internal factors such as ability and confidence (Ajzen & Timko, 1986).

Perceived behavioral control involves an assessment of control which is limited to the environmental factors which contribute to the performance of a behavior (Ajzen, 1985). Factors considered indirectly in perceived behavioral control include the time and opportunity for use of needed resources, cooperation from other people, will power, compulsions, and information, skill, and ability levels. These factors can influence the successful performance of an intended behavior.

Perceived behavioral control can be measured directly in a manner similar to the one used to measure attitude towards the behavior and subjective norm. Consider the prediction of the behavior of quitting smoking. Perceived behavioral control can be measured directly for this behavior as follows:

If I wanted to I could easily quit smoking.

likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely

extremely quite slightly neither slightly quite extremely

The individual determinants of perceived behavioral control can be assessed in a manner similar to those from the Theory of Reasoned Action to determine it's antecedents. A question like the following could be utilized to determine if this belief contributes to perceived behavioral control.

The addictive nature of nicotine will prevent me from quitting smoking.

likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely

extremely quite slightly neither slightly quite extremely

The scores from these control beliefs can be summed to determine the belief-based measure of perceived behavioral control. Equation 6 shows the formula to employ to sum these individual control beliefs.

$$PBC \cong \sum_{i=1}^{n} cb_i \qquad (6)$$

Use of the Theory of Planned Behavior

Two studies by Ajzen and Madden (1986) have compared the Theory of Reasoned Action with the Theory of Planned Behavior. The comparison of the two theories was undertaken to determine if perceived behavioral control added significantly to the prediction of behavioral intentions and behaviors where the degree of volitional control differs. The first study predicted the class attendance of undergraduate psychology students (Table 15) while the second predicted the earning of A's by students in three undergraduate business administration courses (Tables 16 and 17). Both studies demonstrated that the Theory of Planned Behavior predicted both behavioral intention and behavior more accurately than did the Theory of Reasoned Action due to the inclusion of the perceived behavioral control factor.

The second study reported by Ajzen and Madden (1986) also demonstrated the relationships of the predictor variables and the earning of A's with respect to time. The questionnaire which measured components identified in the Theory of Planned Behavior was administered near the beginning (Table 16) and near the end (Table 17) of the semester. The results of the two administrations (waves) of the questionnaire in the second study determined that the correlation between the predictors and intention did not change with time while correlation between the predictors and behavior was inversely related to time.

Crawley (in press), utilizing the Theory of Planned Behavior, found that attitude, subjective norm, and perceived behavioral control significantly contributed to the prediction of behavioral intention. The study examined the intention of teachers to utilize 50% of the activities and investigations acquired in a summer institute with their students during the following school year. When predicting behavioral intention,

Table 15

Hierarchical Regression in the Class Attendance Study by Ajzen and Madden (1986)

	r	R
Prediction of Intention		
Step 1- Theory of Reasoned Action		
-Attitude	.51**	
Subjective Norm	.35**	.55**
Step 2- Theory of Planned Behavior		
Attitude	.51**	
Subjective Norm	.35**	
Perceived Behavioral Control	.57**	.68**
Prediction of Behavior		
Step 1- Theory of Reasoned Action		
Intention	.36**	.36**
Step 2- Theory of Planned Behavior		
Intention	.36**	
Perceived Behavioral Control	.28**	.37**

Note. The above values represent the correlation between attendance and the theoretic component indicated.

*$p<.05$ **$p<.01$

Crawley found that predictors from both the Theory of Reasoned Action (R=.52, p=.0009) and the Theory of Planned Behavior (R=.54, p=.0007) were significant. He also found, using hierarchical regression techniques, the prediction of behavioral intention from the predictors from the Theory of Planned Behavior, including interactions, to be significant (R=.60, p=.0130).

Table 16

Hierarchical Regression in the Grades Study by Ajzen and Madden (1986) with Predictors Measured at the Beginning of the Semester

	r	R
Prediction of Intention		
Step 1- Theory of Reasoned Action		
Attitude	.48**	
Subjective Norm	.11	.48**
Step 2- Theory of Planned Behavior		
Attitude	.48**	
Subjective Norm	.11**	
Perceived Behavioral Control	.44**	.65**
Prediction of Behavior		
Step 1- Theory of Reasoned Action		
Intention	.26**	.26**
Step 2- Theory of Planned Behavior		
Intention	.26**	
Perceived Behavioral Control	.11	.26**

Note. The above values represent the correlation between grades and the theoretic component indicated.

*p<.05 **p<.01

The study by Crawley (in press) went a step further in an effort to better understand the effects of the predictors on behavioral intention (Table 18). Using an indirect model, external variables indicating gender, age, school level (secondary vs. elementary), and level of perceived behavioral control were examined in relation to the predictor variables. Crawley found that by limiting the sample to female participants,

Table 17

Hierarchical Regression in the Grades Study by Ajzen and Madden (1986) with Predictors Measured near the End of the Semester

	r	R
Prediction of Intention		
Step 1- Theory of Reasoned Action		
Attitude	.48**	
Subjective Norm	.30**	.49**
Step 2- Theory of Planned Behavior		
Attitude	.48**	
Subjective Norm	.30**	
Perceived Behavioral Control	.45**	.64**
Prediction of Behavior		
Step 1- Theory of Reasoned Action		
Intention	.39**	.39**
Step 2- Theory of Planned Behavior		
Intention	.39**	
Perceived Behavioral Control	.38**	.45**

Note. The above values represent the correlation between grades and the theoretic component indicated.

*p<.05 **p<.01

Table 18

Attitude Towards the Behavior and Subjective Norm as Predictors of Behavioral Intention by Blocking on Gender, Age, School Level, and Level of Perceived Control (Crawley, in press)

Group	$r_{AB \cdot I}$	$r_{SN \cdot I}$	R
All Participants	.49***	.32*	.49***
Gender			
Female	.62***	.32	.63**
Male	.28	.31	.36
School Level			
Elementary	.62**	.38	.63*
Secondary	.44**	.28	.47*
Age Group			
24 to 34	.68**	.31	.71*
35 to 44	.31	.26	.38
45 to 54	.18	.37	.37
Perceived Behavioral Control			
Low	.45*	.13	.46
High	.58*	.58**	.70***

*p<.05 **p<.01 ***p<.001

attitudes were the best predictor of behavioral intention, resulting in acorrelation coefficient of .62 (p<.001). Another very significant result was found when examining participants who felt that they had a high level of behavioral control. The correlation between behavioral intention and the combined predictive capability of attitude towards the behavior and subjective norm for this group was .70 (p<.001).

Schifter and Ajzen (1985) found that variables identified by the Theory of Planned Behavior significantly predicted intention and behavior concerning weight loss. They found that a combination of attitude towards the behavior, subjective norm, and perceived behavioral control predicted the intention to lose weight (.74, p<.01). The intention to lose weight correlated significantly (.25, p<.05) to the behavior of losing weight.

An additional study used aspects of the Theory of Planned Behavior. Ajzen and Timko (1986) found that the predictor perceived behavioral control significantly correlated with weight loss (.41, p<.01) while a locus of control measure did not.

A study by Dubanoski (1987) used aspects of both the Theory of Reasoned Action and the Theory of Planned Behavior to predict health behavior. The study measured adherence to a long-term preventive health regimen by measuring various predictors against intention and against behavior at one month and six months. Dubanoski (1987) found that the variables identified by these theories were generally not effective as predictors of health behavior. Attitude, subjective norm, and perceived behavioral control were adequate predictors of intention, but intention was not a reliable predictor of the behavior being investigated (Table 19). The study did not report the joint use of these variables to determine behavioral intention.

A study by Crowley (1989) examined, using the Theory of Planned Behavior, the factors which predict behavioral intention and the behavior of implementing school administrators' action plans for the transfer of in-service learning to the school setting. Crowley found that attitudes and subjective norm contribute to behavioral intention ($R^2 = .74$, $p<.05$), but that perceived behavioral control did not.

Attitude research in computer science education.

Science educators in the past decade have shown an increasing interest in affective areas (Schibeci, 1983). Yet very little investigation in attitudes has taken place in computer science education.

Attitudinal research in computer science education has not encompassed attitudes towards a behavior, but has tended to examine attitudes towards objects. Lawson (1985) found attitudes towards computers measured prior to a computer science course to be a predictor of attitudes towards computers measured after a computer science course. Lawson (1985) also found that attitudes towards computers did not predict the course grade. Stager-Snow (1984) found that student attitudes towards computers, as measured near the beginning of the semester by the Appreciation of Computers Questionnaire, predicted the scores on

Table 19

Components of the Theory of Planned Behavior as Predictors of Adherence to a Long-term Preventive Health Regimen (Dubanoski, 1987)

Group and Predictors	Behavioral Intention	Behavior After Month One	Behavior After Month Six
English Speaking Philippinos			
Attitude	.18**	.10	.06
Subjective Norm	.19**	-.07	.06
Perceived Behavioral Control	.21***	.08	.03
Intention		.07	-.02
Americans			
Attitude	.14*	-.09	.12
Subjective Norm	.43***	.23*	-.07
Perceived Behavioral Control	.06	.06	-.03
Intention		-.06	.08
Tagalog Speaking Philippinos			
Attitude	.13	.06	-.01
Subjective Norm	.27*	-.08	.09
Perceived Behavioral Control	-.09	.14	.04
Intention		.31	-.12
Koreans			
Attitude	.26**	.07	-.25
Subjective Norm	.30***	.05	.14
Perceived Behavioral Control	.12	.13	-.08
Intention		.22	.17

Note. The above values represent the correlation between the components of the Theory of Planned Behavior indicated and adherence to a long-term preventive health regimen (Dubanoski, 1987).

*p<.05 **p<.01 ***p<.001

the final exam in a Computer Science Introduction course (.19, $p<.05$). Measurement near the end of the semester using the same instrument resulted in a correlation of .37 ($p<.001$).

In another study, Correnti (1969), using the Survey of Study Habits and Attitudes, found a significant correlation between success in computer programming courses and teacher approval (.20, $p<.01$), and success in computer programming courses and education acceptance (.27, $p<.01$). Delay avoidance and work habits were not found to have a significant correlation with success in programming courses (Correnti, 1969).

A notable lack of attudinal studies in computer science with a good theoretic basis coupled with the wide interest in attitudinal research in the broader science education field suggests that this area is in need of further investigation.

Summary

In general, the search for predictors of success in the undergraduate introductory computer science courses, a non-volitional behavior, has produced some acceptable predictors from the cognitive domain. Grade point average, SAT scores and programmer aptitude tests are potential predictors. But a large amount of unexplained variance exists with the use of these predictors.

The Theory of Planned Behavior has been demonstrated to be a significant predictor of grades in a non-computer science course. The use of this predictor could explain the portion of this remaining variance which was not explained by variables from the cognitive domain. The first step is to determine if a relationship exists between the variables proposed by the Theory of Planned Behavior and success in the first computer science course.

The Theory of Planned Behavior is of special value since it is useful in the prediction of non-volitional behaviors. Prior to the introduction of this theory, research of affective variables in the quest of predicting success in the undergraduate introductory computer science course was stymied by the lack of an acceptable methodology with a strong theoretic basis. Results of the few affective studies undertaken make this point obvious. The strong theoretic undergirding coupled with a methodology designed for non-volitional behavior makes the Theory of Planned Behavior an excellent choice for the study of grade prediction.

Chapter 3: Procedure of the Investigation

This chapter describes the hypotheses, subjects, instrumentation, and procedures used in the study. The Theory of Planned Behavior (Ajzen, 1985) provided the theoretic underpinnings for the development and use of the instrument for measuring students' behavioral intentions, attitudes towards the behavior, subjective norms, and perceived behavioral controls regarding earning a grade of "C" or better in an introductory computer science course.

Hypotheses

The order in which the hypotheses appear corresponds to the Theory of Planned Behavior model. The first hypothesis examined the prediction of behavior, hypotheses two through five investigated the prediction of behavioral intention, and the remaining questions explored the antecedents of attitude towards the behavior, subjective norm, and perceived behavioral control.

The first hypothesis centered on the prediction of the behavior of earning a grade of "C" or better in the undergraduate introductory computer science course by examining the way in which perceived behavioral control effects behavior. The two possibilities, which reflect the two potential versions of the Theory of Planned Behavior, suggested that either perceived behavioral control contributes to behavior only through intention or that perceived behavioral control directly effects behavior. When measuring the variables from the Theory of Planned Behavior at the beginning of the semester, hypothesis 1a suggested that perceived behavioral control contributes to the behavior only through behavioral intention. When measuring the variables at the end of the semester, hypothesis 1b proposed that perceived behavioral control had a direct effect on behavior since students are probably better informed about the course.

Each of the following hypotheses were examined using data gathered at both the beginning and end of the semester. The second hypothesis explored the variables proposed by the Theory of Reasoned Action to determine if they contribute to the prediction of behavioral intention.

Hypotheses three through five explored the antecedents of behavioral intention by examining the variables proposed by the Theory of Planned Behavior in conjunction with specific external variables. Hypothesis three examined the addition of perceived behavioral control to the variables proposed by the Theory of Reasoned Action in the prediction of behavioral intention using a direct - reduced effects model, without including the effects of external variables.

The direct - full effects model, hypothesis four, explored the addition of several external variables to the prediction of behavioral intention. This hypothesis can be considered a method of determining if external variables do not directly effect behavioral intention as suggested by the Theory of Planned Behavior.

The fifth hypothesis utilized the indirect effects model. It explored the indirect effects of the external variables, gender, ethnicity, and Scholastic Aptitude Test Quantitative scores, and the variables from the Theory of Planned Behavior by blocking on the external variables.

The last two hypotheses examined in detail the composition of the predictors of attitude towards the behavior, subjective norm, and perceived behavioral control. The relationship between the direct measures and belief-based measures of the predictors was examined in hypothesis six. The seventh hypothesis attempted to determine the individual beliefs which contribute the most to each predictor. The hypotheses follow.

1. Adding perceived behavioral control (PBC) to behavioral intention (I) causes the prediction of the behavior (B) of earning the grade of "C" or better in the introductory undergraduate computer science course to be

a. not improved at the beginning of the semester (Equation 1).

$$B \cong I \tag{1}$$

b. improved at the end of the semester (Equations 2 and 3).

$$B \cong w_1(I) + w_2(PBC) \tag{2}$$

$$B \cong w_1(I) + w_2(PBC) + w_3(I * PBC) \tag{3}$$

The symbol $\cong$ represents a functional relationship; the w_i's are constants which represent the contribution of each variable.

2. Theory of Reasoned Action: A student's behavioral intention of earning a grade of "C" or better in the undergraduate introductory computer science course is predicted by a linear combination of attitude towards the behavior (A_B) and subjective norm (SN). Equation 4 summarizes this hypothesized relationship and Equation 5 hierarchically extends the hypothesis to include interraction effects.

$$I \cong w_1(A_B) + w_2(SN) \quad (4)$$

$$I \cong w_1(A_B) + w_2(SN) + w_3(A_B * SN) \quad (5)$$

3. Theory of Planned Behavior, Direct - Reduced Effects Model: A student's behavioral intention of earning a grade of "C" or better in the undergraduate introductory computer science course is predicted by a linear combination of attitude towards the behavior, subjective norm, and perceived behavioral control. Equation 6 summarizes this hypothesized relationship and is a hierarchical extension of Equation 4. Equation 7 hierarchically extends the hypothesis to include interraction effects.

$$I \cong w_1(A_B) + w_2(SN) + w_3(PBC) \quad (6)$$

$$I \cong w_1(A_B) + w_2(SN) + w_3(PBC) + w_4(A_B * SN) +$$
$$w_5(A_B * PBC) + w_3(PBC * SN) + w_7(A_B * SN * PBC) \quad (7)$$

4. Theory of Planned Behavior and External Variables, Direct - Full Effects Model: A student's behavioral intention of earning a grade of "C" or better in the undergraduate introductory computer science course is predicted by a linear combination of attitude towards the behavior, subjective norm, perceived behavioral control, and specific external

variables, namely gender (G), ethnicity (E), and Scholastic Aptitude Test Quantitative scores (SAT Q). Equation 8 summarizes this hypothesized relationship and is a hierarchical extension of Equation 6. Equation 9 includes the interraction effects.

$$I \cong w_1(A_B) + w_2(SN) + w_3(PBC) + w_4(G) + w_5(E) + w_6(SAT\ Q) \quad (8)$$

$$I \cong w_1(A_B) + w_2(SN) + w_3(PBC) + w_4(G) + w_5(E) + w_6(SatQ) + \text{interractions} \quad (9)$$

5. Theory of Planned Behavior, Indirect Effects: A student's behavioral intention of earning a grade of "C" or better in the undergraduate introductory computer science course is predicted by a linear combination of attitude towards the behavior, subjective norm, and perceived behavioral control only, with the relative contributions of each variable dependent on:

a. the external variable gender (Equation 10).

$$I \cong w_1(G)(A_B) + w_2(G)(SN) + w_3(G)(PBC) \quad (10)$$

b. the external variable ethnicity (Equation 11).

$$I \cong w_1(E)(A_B) + w_2(E)(SN) + w_3(E)(PBC) \quad (11)$$

c. the external variable Scholastic Aptitude Test Quantitative test score (Equation 12).

$$I \cong w_1(SAT\ Q)(A_B) + w_2(SAT\ Q)(SN) + w_3(SAT\ Q)(PBC) \quad (12)$$

6. The belief-based ($\Sigma\, b_i \cdot e_i$) measures of attitude towards the behavior, subjective norm, and perceived behavioral control are closely associated with the direct measure of attitude towards the behavior, subjective norm, and perceived behavioral control, respectively. This

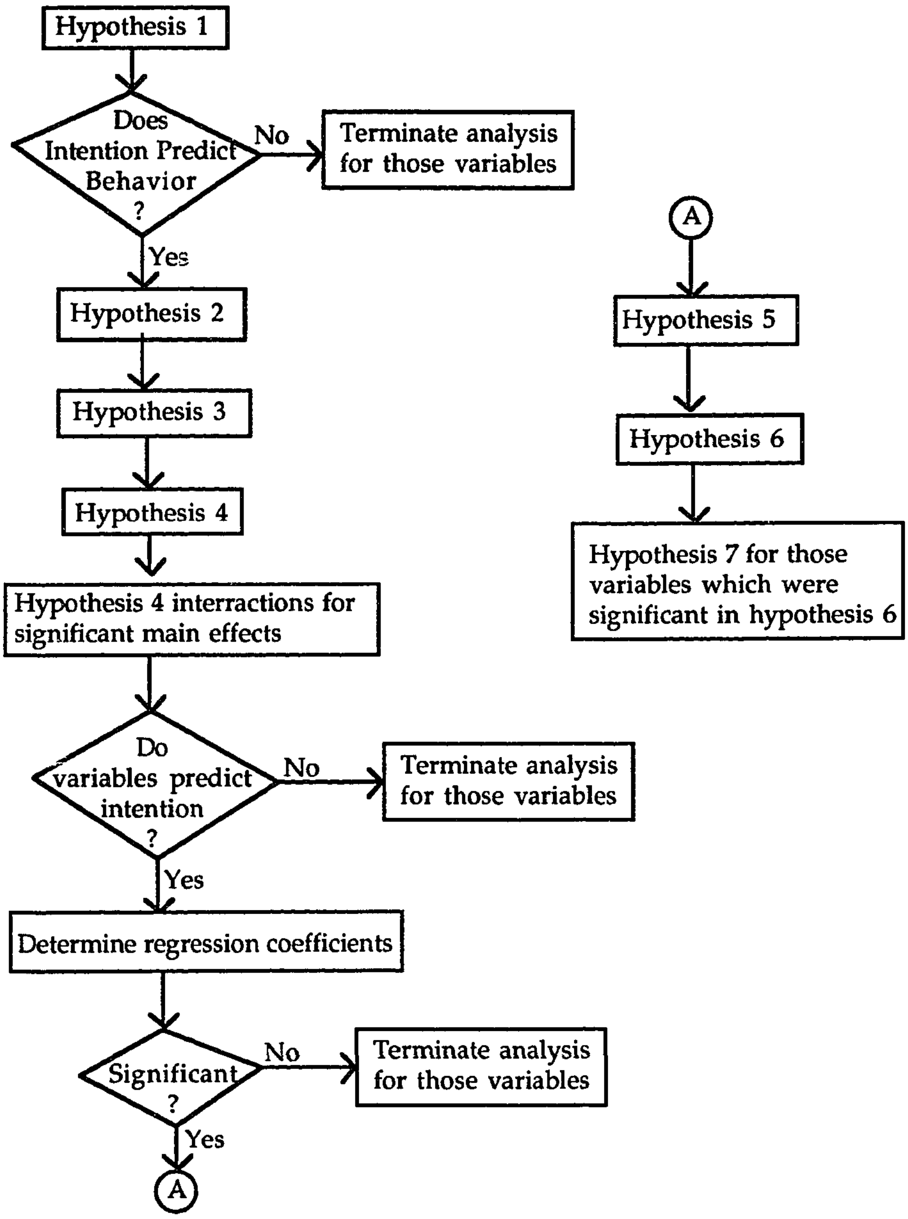
hypothesis will be examined only for variables which have significant relationships with behavioral intention as identified in hypotheses 2 and 3.

7. Each belief-based measure of attitude towards the behavior, subjective norm, and perceived behavioral control makes significant contributions to the respective direct measure. This hypothesis will be examined only for variables which have significant relationships between the direct and belief-based measures, as identified in hypothesis 6.

Not every hypothesis was examined for each data set since some hypotheses depended on the completion of one or more above it. A decision rule (Figure 3) was used to determine the specific analyses to be made. The decision rule is closely associated with the model of the Theory of Planned Behavior (Figure 2).

The decision rule first calls for the exploration of hypothesis 1. If intention does not predict behavior, then further analysis is terminated since the exploration of the determinants of intention would not be relevant. If intention does predict behavior, then an examination of hypotheses 3 through 5 is made. Analysis of hypotheses 5 and 6 is continued only for those variables which predict intention. Hypothesis 7 is examined only for those variables which were significant as a result of the analysis of hypothesis 6.

Figure 3 Decision Rules for the Hypotheses



Instrumentation

A scale was developed for use in this study to measure student beliefs, attitudes, subjective norms, perceived behavioral controls, and intentions using a procedure similar to the one proposed by Koballa, Crawley, and Shrigley (1987). The scale measured these variables with respect to the behavior of earning the grade of "C" or better in the undergraduate introductory computer science course.

The steps used to design this scale parallel the steps proposed by Ajzen and Fishbein (1980, Appendix A). Two samples were employed in the study. Below are shown the steps employed to design the scale for the Lander College sample. The method is similar for the University of South Carolina sample.

Defining the behavior of interest.

The behavior of interest in this study was defined in terms of its action, target, context, and time. The definition follows:

> Students earning the grade of "C" or better in either CS 230, Computer Science Principles I, at Lander College during the Fall semester of 1989.

Defining the corresponding behavioral intention.

The corresponding behavioral intention for this study was defined as follows:

As a student in either CS 230, Computer Science Principles I, at Lander College during the Fall semester of 1989, I intend to earn the grade of "C" or better.

Behavioral intention was measured on the instrument using a semantic differential scale (Osgood, Suci, and Tannenbaum, 1957). The semantic differential scaling technique results in integer values ranging from +3 to -3. The question appearing below appeared on the instrument to assess behavioral intention. A response of extremely likely resulted in a score of +3, quite likely a score of +2, and so forth. The question which directly measures behavioral intention following the Theory of Planned behavior is shown below.

I intend to earn a "C" or better in this class.

likely ______ : ______ : ______ : ______ : ______ : ______ : ______ unlikely
extremely quite slightly neither slightly quite extremely

Defining the corresponding attitude.

The corresponding attitude was defined as:

Attitude towards earning a grade of "C" or better in CS 230, Computer Science Principles I, at Lander College during the Fall semester of 1989.

Four semantic differential scales were employed to determine attitude. The question which appeared on the instrument to directly determine attitude and which is derived from the Theory of Planned Behavior follows:

My earning a grade of "C" or better is

beneficial	______ :	______ :	______ :	______ :	______ :	______ :	______	harmful
	extremely	quite	slightly	neither	slightly	quite	extremely	
good	______ :	______ :	______ :	______ :	______ :	______ :	______	bad
	extremely	quite	slightly	neither	slightly	quite	extremely	
rewarding	______ :	______ :	______ :	______ :	______ :	______ :	______	punishing
	extremely	quite	slightly	neither	slightly	quite	extremely	
wise	______ :	______ :	______ :	______ :	______ :	______ :	______	harmful
	extremely	quite	slightly	neither	slightly	quite	extremely	

Defining the corresponding subjective norm.

The corresponding subjective norm was defined as:

Social support associated with earning a "C" or better in CS 230, Computer Science Principles I, at Lander College during the Fall semester of 1989.

The following question was used to determine subjective norm directly as derived from the Theory of Planned Behavior.

Most people who are important to me think I

should ______ : ______ : ______ : ______ : ______ : ______ : ______ should not

extremely quite slightly neither slightly quite extremely

earn a grade of "C" or better in this course.

Defining the corresponding perceived behavioral control.

The corresponding perceived behavioral control was defined as:

> Environmental controls associated with earning a "C" or better in CS 230, Computer Science Principles I, at Lander College during the Fall semester of 1989.

Perceived behavioral control was directly measured on the instrument by the following questions which parallel the questioning techniques from the Theory of Planned Behavior:

How much control do you have over earning a "C" or better in this class?

complete______ : ______ : ______ : ______ : ______ : ______ : ______ very little

extremely quite slightly neither slightly quite extremely

For me to earn a "C" or better is

easy ______ : ______ : ______ : ______ : ______ : ______ : ______ difficult

extremely quite slightly neither slightly quite extremely

If I wanted to I could easily earn a "C" or better in this class.

likely ______ : ______ : ______ : ______ : ______ : ______ : ______unlikely

extremely quite slightly neither slightly quite extremely

Belief-based measures of attitude towards the behavior, subjective norm, and perceived behavioral control.

In an effort to provide indirect, or belief-based measures of attitude towards the behavior, subjective norm, and perceived behavioral control, it was first necessary to determine students' salient behavioral, normative, and control beliefs. An open-ended questionnaire provided these beliefs which were needed to construct the instrument.

The design of the questionnaire was adapted from two sources. The questionnaire followed the guidelines suggested by Ajzen and Fishbein (1980, chap. 6) in establishing the salient beliefs and evaluations associated with attitude towards the behavior and the normative beliefs and motivations to comply associated with subjective norm. Questions related to perceived behavioral control were designed in a manner similar to the one used by Ajzen and Madden (1986).

The open-ended questionnaire, which is shown in Appendix A, was administered to the twenty-seven students enrolled in CS 230, Computer Science Principles I, at Lander College during the Fall 1988 semester. The first three questions were used to identify students' salient behavioral beliefs. Questions four through six elicited students' salient normative beliefs. Beliefs affecting perceived behavioral control were determined by questions seven through nine.

Responses to the open-ended questionnaire, which are shown in Appendix B, were ranked within each category according to frequency following procedures proposed by Ajzen and Fishbein (1980, chap. 6).

Responses which could reasonably have been given by the same individual were combined. For example, a response of "parents" was combined with the response "family." Those responses which represented approximately 75% of the responses in each category were considered to be the variables underlying the three constructs and were used to develop the instrument.

This ranking and catagorization process can lead to some difficult decisions. For example, the category containing teachers and faculty (Appendix B, Subjective Norm) was not included since only the first 53 of the 67 responses were used to develop the instrument, which exceeds the 75% rule. Yet an argument could be made to include them.

The modal behavioral beliefs which represented approximately 75% of the responses from the open-ended questionnaire were then employed to construct the items on the instrument which indirectly measured attitude towards the behavior. For example, a belief which was identified was "earning a grade of 'C' or better would help the student get a good job." This behavioral belief was measured on the instrument by the following question:

My earning a grade of "C" or better in this course will help me to get a good job.

likely ______ : ______ : ______ : ______ : ______ : ______ : ______ unlikely
extremely quite slightly neither slightly quite extremely

Each behavioral belief could be more valuable to one person than to another. Therefore it is important to determine the value that each student holds for each behavioral belief. The outcome evaluation for the behavioral belief discussed above is:

Getting a good job is

good ______ : ______ : ______ : ______ : ______ : ______ : ______ bad

extremely quite slightly neither slightly quite extremely

The normative beliefs were measured in a similar manner. Each modal normative belief was used to design two questions, one which measured the normative belief and one which measured the motivation to comply. An example of the pair of questions follows:

It is important to my family that I earn a grade of "C" or better in this course.

{normative belief}

likely ______ : ______ : ______ : ______ : ______ : ______ : ______unlikely

extremely quite slightly neither slightly quite extremely

Generally speaking, I want to do what my family thinks is important.

{motivation to comply}

likely ______ : ______ : ______ : ______ : ______ : ______ : ______unlikely

extremely quite slightly neither slightly quite extremely

The belief-based measure of perceived behavioral control was based on the results of the open-ended questionnaire. Each modal belief associated with perceived behavioral control contributed one question on the instrument. An example of one of the questions follows:

My study habits will prevent me from earning a "C" or better in this course.

likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely
extremely quite slightly neither slightly quite extremely

The final instrument (see Appendix C) was divided into five areas. The five areas and the number of questions in each are shown in Table 20.

Table 20

Areas and Number of Questions on the Final Instrument

Area	Number of Questions
Intention	1
Attitude towards the behavior	
Direct	4
Belief-based ($\Sigma\, b_i \cdot e_i$)	
Behavioral beliefs	6
Outcome evaluations	6
Subjective norm	
Direct	1
Belief-based ($\Sigma\, b_j \cdot m_j$)	
Normative beliefs	4
Motivation to comply	4
Perceived behavioral control	
Direct	3
Belief-based	7
Demographics	8

Evaluating the instrument.

According to the Theory of Planned Behavior, a person's attitude towards a behavior can be determined indirectly by multiplying his evaluation of each of the consequences of the behavior by the strength of his belief, then summing these products (Ajzen, 1980, p. 67). As discussed in Chapter 2, this is expressed by the formula $A_B = \Sigma\ (b_i e_i)$ where b_i is the belief that performing behavior B would lead to outcome i and e_i is the evaluation of outcome i (Ajzen, 1985, p. 13). The products of the individual behavioral beliefs and evaluations are summed over all behavioral beliefs. For example, consider the behavioral belief concerning earning a grade of "C" discussed previously: it could lead to a better job. This behavioral belief and its related evaluation were examined on the final instrument using the following pair of questions which employs a semantic differential scale.

My earning a grade of "C" or better in this course will help me to get a good job. $\{b_i\}$

likely ______ : ______ : ______ : ______ : ______ : ______ : ______ unlikely
extremely quite slightly neither slightly quite extremely

Getting a good job is $\{e_i\}$

good ______ : ______ : ______ : ______ : ______ : ______ : ______ bad
extremely quite slightly neither slightly quite extremely

A score of 3 would be recorded for the extremely likely category, a 2 for quite likely, a 1 for slightly likely, 0 for neither, and negative values through -3 for the extremely unlikely category. The scores from the pair of questions concerning the better job were multiplied, then summed with other similar scores. This sum represented an individual's score for the belief-based measure of attitude towards the behavior.

Using the Theory of Planned Behavior, one's subjective norm can be determined by multiplying that individual's normative beliefs by the corresponding motivations to comply, then summing these products (Ajzen & Fishbein, 1980). Therefore within this study, subjective norm was ascertained using the formula $SN = \Sigma(b_j\, m_j)$ where b_j is the normative belief concerning referent j and m_j is the subject's motivation to comply with referent j (Ajzen, 1985, p. 14). For example, family was found to be a group of people who were likely to approve of students earning a grade of "C" or better. Therefore the following pair of questions was on the final instrument:

It is important to my family that I earn a grade of "C" or better in this course. $\{b_j\}$

likely ______ : ______ : ______ : ______ : ______ : ______ : ______unlikely

extremely quite slightly neither slightly quite extremely

Generally speaking, I want to do what my family thinks is important. $\{m_j\}$

likely ______ : ______ : ______ : ______ : ______ : ______ : ______ unlikely

extremely quite slightly neither slightly quite extremely

The results from each pair of questions were tabulated in a manner similar to the scores of attitude towards the behavior. This sum represented an individual's score for the belief-based measure of subjective norm.

The belief-based measure of perceived behavioral control was found by summing the results of a series of questions of the form which follows. Note that only two of the seven questions are shown below.

My study habits will prevent me from earning a "C" or better in this course.

likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely
extremely quite slightly neither slightly quite extremely

Attending class will help me to earn a "C" or better in this course.

adequate _____ : _____ : _____ : _____ : _____ : _____ : _____inadequate
extremely quite slightly neither slightly quite extremely

Questions four and five of the perceived behavioral control section were negatively worded and, therefore, needed to be scored differently. The "likely" response needed to reflect a score of -3 while the "unlikely" response the score of +3. To accomplish this, these questions were scored and entered into the computer in the same manner as the other questions. Then, using the SAS program (SAS Institute Inc., 1985a, 1985b), an instruction was executed to determine and use the multiplicative inverse of each response for these two questions.

Instrument validity and reliability.

The instrument validity was examined using two types of validity: content and predictive. Content validity is ensured by using the instrument design method from the Theory of Planned Behavior. As previously discussed, this method calls for designing questions generated by responses from the open-ended questionnaire. By carefully following the established methodology for instrument design from the Theory of Planned Behavior, the degree of content validity is high.

The predictive, or criterion-related, validity of the instrument is the centerpiece of this study. It will be determined by identifying how well the instrument can predict the behavior in question, earning the grade of "C" or better in the introductory undergraduate computer science course.

The reliability of the instrument will be more fully investigated in hypothesis 6. An examination between the direct measures and belief-based measures of attiude towards the behavior, subjective norm, and perceived behavioral control will be examined with that hypothesis. Test - retest reliability was not appropriate since the attitude, subjective norm, and perceived behavioral control were likely to change over the course of the semester due to the the participation of the subjects in the course.

Other variables.

The variables used in the study which were not measured directly by the instrument included SAT Quantitative scores and an indication of whether the student passed the course. The SAT Quantitative scores were reported by each subject, then each score was verified through student academic records at each institution. The variable which indicated whether the student earned the grade of "C" or better was reported by the instructor of the course.

The course grade is generally based on several components. Tests and quizzes generally comprise the majority of the grade, while other factors like programming assignments, other homework, and class participation are often used.

Experimental Design and Procedures

Subjects.

Two samples were used in the study. Included were 19 students in CS 230, Computer Science Principles I, at Lander College, Greenwood, South Carolina and 94 students in CSCI 145, Introduction to Algorithm Design I, at the University of South Carolina, Columbia, South Carolina during the Fall 1989 semester.

Lander College is a small, liberal arts institution located in the Piedmont region of the state. Most students commute from a five county area. Lander has traditionally been an open-admissions institution, but all students have completed a minimum core high school program including two years of algebra, two years of science, four years of English, and two years of foreign language. This open-admissions tradition is slowly giving way to criteria employing minimum performance indicated by class rank and Scholastic Aptitude Test (SAT) scores. The average SAT score for freshmen at Lander College during the 1988-1989 academic year is 829.

The University of South Carolina is a large, state-supported university located in the state capital of Columbia. The University of South Carolina requires the same minimum core high school program as Lander College, but has more stringent admissions criteria based on

SAT scores and class rank. The average overall SAT score for freshmen at the University of South Carolina during the 1988-1989 academic year is 958.

A more detailed description of the subjects, including gender, ethnic membership, and sample membership, is found in Table 21. Table 22 shows the mean and range for the age, high school and college grade point ratio, and the number of previous college credits. All of these variables were self-reported.

The two samples were not combined for several reasons. First, there were probably differences between the two instructors. These differences could include teaching style and grading methods. Second, there are differences between the two institutions. University of South Carolina generally has freshmen class sizes near 100 while Lander College class sizes are typically under 30. Different admissions criteria are applied. For these reasons, the samples were not combined.

Pilot Study.

A pilot of the actual study was implemented during the Spring semester of 1989 with 17 students in CS 230, Computer Science Principles I, at Lander College. The pilot study influenced the initial design of the study by showing the need for a larger sample. It was at this point that the University of South Carolina sample was included.

Correlations in the pilot study between behavioral intention and attitude towards the behavior (.04, $p<.88$), subjective norm (-.37, $p<.14$),

Table 21

Group Membership of Sample

Group	Lander College	University of South Carolina
Male	12	62
Female	7	32
Caucasian	16	55
Black	2	32
Other Minority	1	6
Total Sample	19	94

Table 22

Mean and Range for Selected Variables

Variable	Lander College	University of South Carolina
Age		
Minimum	17	16
Maximum	23	29
Mean	19.6	19.7
High School Grade Point Ratio		
Minimum	1.9	2.0
Maximum	3.7	4.0
Mean	2.9	3.3
College Grade Point Ratio		
Minimum	1.9	1.9
Maximum	3.5	4.0
Mean	2.6	2.7
Number of College Credits		
Minimum	0	1
Maximum	93	150
Mean	29.5	52.8

and perceived behavioral control (.03, p<.92) were not statistically significant at the beginning of the semester. At the end of the semester, correlations between behavioral intention and attitude towards the behavior were not significant (.27, p<.33), but the correlations between behavioral intention and subjective norm (.57, p<.03), and behavioral intention and perceived behavioral control (.58, p<.03) were.

Procedure.

Before the first questionnaire was administered, the subjects were informed of their selection for participation in the study and were told how the information gained in the study would be beneficial in the quest for predictors of success in computer science. They were also informed that the information gained from the questionnaires would remain confidential and would not effect their grades.

The first questionnaire was administered to 27 students in CS 230, Computer Science Principles I, near the beginning of the Fall 1988 semester. It was used to design the instrument as described under instrumentation. This instrument was reviewed by a person with considerable experience in the use of this type of instrument in science education. Following the review, the instrument was administered to 10 computer science students who had completed CS 230, Computer Science Principles I, in the previous semester in order to uncover ambiguous areas.

The instrument was administered to each of the two samples during the first week of class and again during the last week of class. During the first administration of the instrument students signed a form in which they agreed to participate in the study and to allow the investigator to collect pertinent information. The behavior, earning a "C" or better in the undergraduate introductory computer science course, was determined by obtaining students' grades from the instructor.

Scholastic Aptitude Test Quantitative scores were used to divide each sample into groups in order to allow blocking to be employed in hypothesis 5. The Lander College sample divided such that five students were in the low group (400 to 430), five in the middle group (510 to 540), and four in the high group (570 to 700). The University of South Carolina sample was divided into four groups such that 23 were in the lowest (290-440), 25 in the next (450 to 510), 21 in the next highest (520 to 580), and 23 in the highest group (590 to 730).

Statistical Analysis

Regression and correlation were used to test most of the hypotheses of this study. The Statistical Analysis System (SAS Institute Inc., 1985a, 1985b) was employed to analyze the data generated in the study. The significance level chosen for the study was .05.

Hierarchical regression techniques were applied to the data to test the first five hypotheses to measure the predictive capabilities of linear combinations of specific variables. These five hypotheses were concerned with the prediction of intentions and behavior. Correlation procedures were utilized to examine the last two hypotheses.

Summary

This chapter described the hypotheses, instrumentation, design, and procedures utilized in the implementation of this study. This study utilized regression techniques to test certain linear combinations of predictors of behavioral intention and behavior. Correlation was used to determine the association between direct and belief-based measures of the three predictors from the Theory of Planned Behavior.

The instrumentation section of this chapter described the development and scoring of the instrument used in this study. The instrument was based on the theoretic framework provided by the Theory of Planned Behavior (Ajzen, 1985). The procedure to develop the instrument, based on works by Ajzen (1985), Ajzen and Madden (1986), and Koballa, Crawley, and Shrigley (1987), included the collection of salient behavioral, normative, and control beliefs to determine which beliefs indirectly measure attitude towards the behavior, subjective norm, and perceived behavioral control. Questions on the instrument were formed from the individual beliefs as well as from more direct measures of attitude towards the behavior, subjective norm, perceived behavioral control, and intention.

Chapter 4: Results

This chapter describes the results of the study. The Theory of Planned Behavior (Ajzen, 1985) provided the theoretic basis for the study and the predictor variables attitude towards the behavior, subjective norm, and perceived behavioral control. These variables were used to predict behavioral intention, which was used to predict the behavior of earning a grade of "C" or better in an introductory undergraduate computer science course. Several other variables, including gender, ethnicity, and Scholastic Aptitude Test Quantitative scores, were used in conjunction with these variables.

The University of South Carolina sample generated results consisting of a larger quantity of significant findings than those from the Lander College sample. This may be attributed to the different sample sizes since sample size has a direct bearing on significance. The level of significance chosen for this study was .05.

Descriptive statistics will be examined first, followed by an examination of the hypotheses. A summary of the results concludes this chapter.

Descriptive Statistics

This section is devoted to the examination of the descriptive statistics. The means and standard deviations for the variables are provided. In addition, correlations between variables specified by the Theory of Planned Behavior and other applicable variables are given.

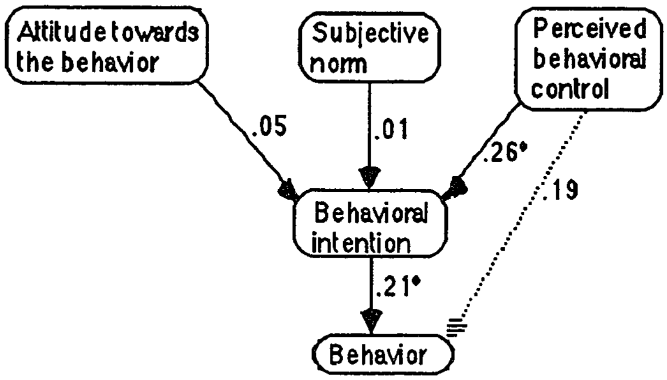
Figures 4 through 8 show the relevant correlations among variables suggested by the Theory of Planned Behavior. Most correlations were higher at the end of the semester than at the beginning. The findings tended to consist of a larger quantity of significant correlations for the University of South Carolina sample than for the Lander College sample.

Tables 23 and 24 show the mean and standard deviation for each major variable. Note the Range± indicates the possible range for each variable. For example, an individual score on the belief-based measure for subjective norm could have ranged from -36 to +36. The mean for each variable is in the top half of the range, and is often in the top quarter. The high mean value, coupled with a relatively low standard deviation, indicates that most individual scores of each variable were in the top half of the range.

Particular attention is drawn to the variable behavioral intention. At the beginning of the semester, the mean score in each sample was at least 2.5 out of a possible 3, with a standard deviation of approximately .5. The mean score at the end of the semester dropped at least .7 of a point, and a wider dispersion was indicated.

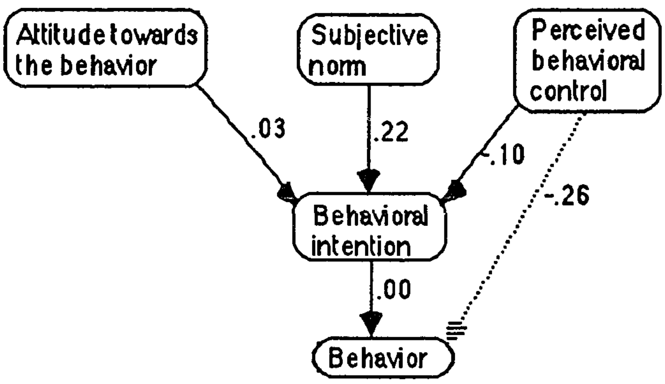
The score for grade in Tables 23 and 24 had a range from 0 to 4. The Scholastic Aptitude Test Quantitative Test scores had a possible range from 200 to 800.

Figure 4 Correlations Between Variables from the Theory of Planned Behavior at the Beginning of the Semester, University of South Carolina Sample



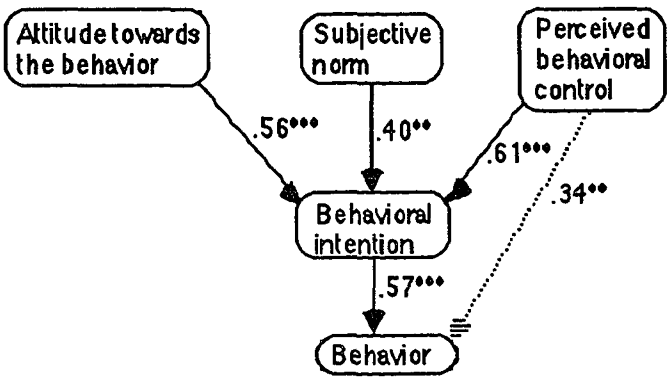
*p<.05

Figure 5 Correlations Between Variables from the Theory of Planned Behavior at the Beginning of the Semester, Lander College



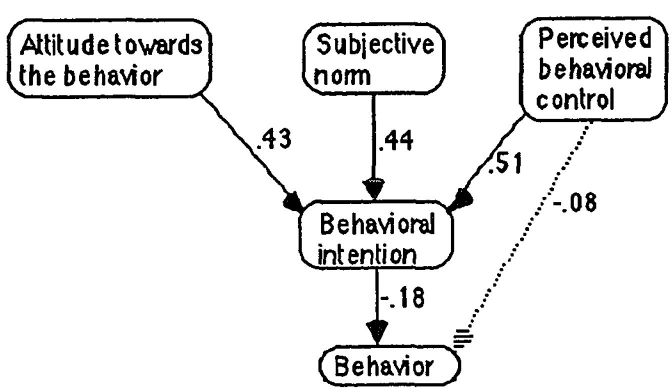
*p<.05

Figure 6 Correlations Between Variables from the Theory of Planned Behavior at the End of the Semester, University of South Carolina Sample



*p<.05 **p<.01 ***p<.001

Figure 7 Correlations Between Variables from the Theory of Planned Behavior at the End of the Semester, Lander College



*p<.05

Table 23

Means and Standard Deviations for Major Variables, University of South Carolina Sample

Variable	n	Range±	Mean	SD
At beginning				
Attitude towards the behavior				
Direct	94	12	10.20	2.43
Belief-based ($\Sigma\, b_i \cdot e_i$)	94	54	35.23	12.30
Subjective norm				
Direct	94	3	2.47	0.67
Belief-based ($\Sigma\, nb_i \cdot mc_i$)	93	36	11.02	8.66
Perceived behavioral control				
Direct	94	9	5.29	2.12
Belief-based ($\Sigma\, bc_i$)	93	21	13.99	3.82
Behavioral Intention	90	3	2.69	0.49
At end				
Attitude towards the behavior				
Direct	63	12	8.84	3.51
Belief-based ($\Sigma\, b_i \cdot e_i$)	63	54	24.11	14.41
Subjective norm				
Direct	63	3	2.17	1.04
Belief-based ($\Sigma\, nb_i \cdot mc_i$)	63	36	9.92	8.17
Perceived behavioral control				
Direct	63	9	4.32	4.15
Belief-based ($\Sigma\, bc_i$)	63	21	11.49	5.57
Behavioral Intention	61	3	1.95	1.62
Grade	94		1.62	0.49
SAT Quantitative score	86		528.60	98.95

Note: Range± indicates the possible range of results for each response.

Table 24

Means and Standard Deviations for Major Variables, Lander College Sample

Variable	n	Range±	Mean	SD
At beginning				
Attitude towards the behavior				
Direct	19	12	10.63	1.86
Belief-based ($\Sigma\ b_i \cdot e_i$)	18	54	33.72	13.86
Subjective norm				
Direct	19	3	2.53	0.77
Belief-based ($\Sigma\ nb_i \cdot mc_i$)	18	36	10.78	8.25
Perceived behavioral control				
Direct	18	9	4.39	2.17
Belief-based ($\Sigma\ bc_i$)	19	21	14.68	3.58
Behavioral Intention	18	3	2.50	0.51
At end				
Attitude towards the behavior				
Direct	16	12	9.81	2.81
Belief-based ($\Sigma\ b_i \cdot e_i$)	16	54	33.63	14.20
Subjective norm				
Direct	16	3	2.06	1.29
Belief-based ($\Sigma\ nb_i \cdot mc_i$)	16	36	11.19	9.48
Perceived behavioral control				
Direct	16	9	4.63	2.53
Belief-based ($\Sigma\ bc_i$)	16	21	12.06	5.60
Behavioral Intention	15	3	1.87	1.36
Grade	19		1.68	0.48
SAT Quantitative score	15		516.00	89.43

Note: Range± indicates the possible range of results for each response.

Table 25 indicates the mean and standard deviation for the individual behavioral beliefs. In the University of South Carolina sample, each mean declined over the semester while the standard deviation grew. In other words, the mean importance of each belief declined, while the dispersion of the responses grew. No general statement could be made about the Lander College sample.

The individual normative and behavioral control beliefs are shown in Tables 26 and 27. No general trend can be established by these data. Table 21 in Chapter 3 indicates the gender and ethnic makeup of the two samples.

Hypothesis Testing

This section examines the results of the hypothesis tests. Evaluation of most of the hypotheses was completed using hierarchical regression techniques to test the applicability of specific linear combinations of variables to predict behavioral intention and the behavior of earning a "C" or better in the introductory undergraduate computer science course.

Table 25

Means and Standard Deviations for the Salient Behavioral Beliefs

	Beginning			End		
Individual behavioral belief	n	Mean	SD	n	Mean	SD
University of South Carolina						
learn about computers	94	6.32	2.71	63	4.03	3.59
master course materials	94	5.91	2.00	63	4.38	3.08
get a good job	94	4.34	3.81	63	2.06	3.92
help grade point average	94	6.22	3.74	63	4.87	4.38
prepare for future						
computer science courses	94	6.68	2.56	63	4.75	3.51
build confidence in myself	94	5.75	3.21	63	4.02	3.40
Lander College						
learn about computers	19	5.89	4.38	16	5.93	3.09
master course materials	19	4.86	2.79	16	4.56	3.05
get a good job	19	3.89	2.71	16	4.81	2.71
help grade point average	18	6.44	3.18	16	6.25	2.89
prepare for future						
computer science courses	19	6.47	2.72	16	6.00	3.18
build confidence in myself	19	5.95	3.01	16	6.06	2.77

Note: The above table reflects the product of the individual behavioral belief and outcome evaluation.

Table 26

Means and Standard Deviations for the Salient Normative Beliefs

	Beginning			End		
Normative belief	n	Mean	SD	n	Mean	SD
University of South Carolina						
family	93	4.09	3.57	63	3.59	3.09
likely employer	94	4.19	3.55	63	2.65	3.40
friends	94	1.23	2.94	63	1.56	2.87
classmates	94	1.50	3.20	63	2.12	3.26
Lander College						
family	18	4.00	3.58	16	3.44	3.03
likely employer	18	3.89	3.48	16	4.44	3.54
friends	18	1.00	1.94	16	1.75	3.26
classmates	18	1.89	3.07	16	1.56	3.08

Note: The above table reflects the product of the individual normative belief and motivation to comply.

Table 27

Means and Standard Deviations for the Salient Behavioral Control Beliefs

	Beginning			End		
Individual control belief	n	Mean	SD	n	Mean	SD
University of South Carolina						
study habits	93	1.12	1.80	63	1.08	1.79
outside activities	93	1.13	1.58	63	1.37	1.82
getting special help	93	1.82	1.04	63	1.19	1.65
attending class	93	2.55	0.74	63	1.98	1.16
working to full potential	93	2.66	0.58	63	2.14	1.12
ability	93	2.30	0.83	63	1.76	1.43
access to resources	93	2.42	0.65	63	1.97	1.14
Lander College						
study habits	19	1.00	1.70	16	0.19	2.04
outside activities	19	0.74	1.66	16	0.13	1.96
getting special help	19	2.37	0.76	16	2.13	0.62
attending class	19	2.84	0.37	16	2.13	1.26
working to full potential	19	2.84	0.37	16	2.63	0.62
ability	19	2.32	0.58	16	2.19	0.83
access to resources	19	2.58	0.61	16	2.69	0.48

Hypothesis 1: The effect of the addition of perceived behavioral control to behavioral intention.

This first hypothesis examines the effect which perceived behavioral control has at the beginning and end of the semester on the behavior of earning the grade of "C" or better in the introductory undergraduate computer science course. It determines if perceived behavioral control is mediated by behavioral intention.

Perceived behavioral control is considered to be a measure of the actual control the student has over the behavior. It is suggested that, since students do not have adequate feedback concerning their course performance so early in the semester, perceived behavioral control would not add to the predictive capability of behavioral intention but would operate directly through behavioral intentions. At the end of the semester, the value of perceived behavioral control increases since it is expected to become a relatively good measure and reflect the individual's actual control.

The hypothesis is reflected in the equations below. Equation 1 represents the first portion of the hypothesis, namely that perceived behavioral control does not contribute to the prediction of behavior at the beginning of the semester. Equations 2 and 3 reflect the second portion of the hypothesis concerning the addition of perceived behavioral control at the end of the semester. Hierarchical regression was employed to determine if the addition of perceived behavioral control (PBC) and the interraction term (I * PBC) to behavioral intention

(I) significantly adds to the prediction of the behavior (B) at the beginning and end of the semester.

$$B \cong I \quad (1)$$

$$B \cong w_1(I) + w_2(PBC) \quad (2)$$

$$B \cong w_1(I) + w_2(PBC) + w_3(I * PBC) \quad (3)$$

Table 28 shows the hierarchical regression for the University of South Carolina sample which addresses the hypothesis at the beginning of the semester. Note that intention significantly predicts the behavior in question ($F = 4.00$, $p<.05$). The hierarchical addition of perceived behavioral control ($F = 2.80$) and the interraction between the two independent variables ($F = 1.92$) do not result in significant prediction of the behavior.

Table 29 shows the increment of explained variance due to the addition of each variable, with the variables measured at the beginning of the semester. The addition of either variable did not significantly add to the predictive capability of behavioral intention. Therefore the University of South Carolina sample supports the first portion of the hypothesis, namely that perceived behavioral control does not significantly add to the predictive capability of behavioral intention at the beginning of the semester.

The analysis for the Lander College sample at the beginning of the semester was quite different. Behavioral intention was not a predictor of

Table 28

Regression of Predictor Variables on Behavior at Beginning of Semester, University of South Carolina Sample

Predictors	Source	df	SS	MS	F	p	R^2
Intention							
	Hypothesis	1	.92	.92	4.00	.049	.04
	Error	88	20.94	.23			
Intention, Perceived Behavioral Control							
	Hypothesis	2	1.28	.64	2.80	.066	.06
	Error	87	19.88	.23			
Intention, Perceived Behavioral Control, Interraction							
	Hypothesis	3	1.33	.44	1.92	.133	.06
	Error	86	19.83	.23			

Table 29

Increment in Explained Variance at Beginning of Semester, University of South Carolina Sample

Additive Terms	Source	df	SS	MS	F	p	R^2
Perceived Behavioral Control							
	Hypothesis	1	.36	.36	1.58	.21	.02
	Error	87	19.88	.23			
Interraction							
	Hypothesis	1	.05	.05	.21	.65	.00
	Error	86	19.83	.23			

the behavior of earning a "C" or better in the undergraduate introductory computer science course ($F = 0$), as shown in Table 30. The addition of perceived behavioral control, however, resulted in the significant prediction of the behavior ($F = 4.16$, $p<.05$). The inclusion of the interraction term did not result in statistically significant findings ($F = 2.98$).

The increment of explained variance (Table 31) was significant ($F = 8.13$, $p<.01$) for perceived behavioral control, but not for the interraction term ($F = .77$). Since intention was not shown to predict behavior at the beginning of the semester, then conclusions based on the addition of perceived behavioral control are inappropriate.

Data collected from both samples do not support the second portion of the hypothesis. Table 32 shows the regression for the University of South Carolina sample. While behavioral intention is a significant predictor of the behavior ($F = 28.96$, $p<.0001$), the increment associated with the inclusion of perceived behavioral control ($F = .04$) and the interraction term (2.96) were nonsignificant (Table 33).

In the Lander College sample, intention was not a significant ($F = .43$) predictor of the behavior in question (Table 34). The increment associated with the inclusion of perceived behavioral control ($F = 4.39$) and the interraction term ($F = 0$) was nonsignificant (Table 35).

Within the confines of this study, perceived behavioral control does not add significantly to the prediction of the behavior of earning the grade of "C" or better in the introductory undergraduate computer

Table 30

Regression of Predictor Variables on Behavior at Beginning of Semester, Lander College Sample

Predictors	Source	df	SS	MS	F	p	R^2
Intention							
	Hypothesis	1	0.00	0.00	0.00	1.00	.00
	Error	16	4.00	.25			
Intention, Perceived Behavioral Control							
	Hypothesis	2	1.31	.68	4.16	.04	.37
	Error	14	2.21	.16			
Intention, Perceived Behavioral Control, Interraction							
	Hypothesis	3	1.44	.48	2.98	.07	.41
	Error	13	2.09	.16			

Table 31

Increment in Explained Variance at Beginning of Semester, Lander College Sample

Additive Terms	Source	df	SS	MS	F	p	R^2
Perceived Behavioral Control							
	Hypothesis	1	1.29	1.29	8.13	.01	.36
	Error	14	2.21	.16			
Interraction							
	Hypothesis	1	.12	.12	.77	.40	.04
	Error	13	2.09	.16			

Table 32

Regression of Predictor Variables on Behavior at End of Semester, University of South Carolina Sample

Predictors	Source	df	SS	MS	F	p	R^2
Intention							
	Hypothesis	1	4.04	4.04	28.96	.0001	.33
	Error	59	8.23	.14			
Intention, Perceived Behavioral Control							
	Hypothesis	2	4.04	2.02	14.26	.0001	.33
	Error	58	8.22	.14			
Intention, Perceived Behavioral Control, Interraction							
	Hypothesis	3	4.45	1.48	10.82	.0001	.36
	Error	57	7.81	.14			

Table 33

Increment in Explained Variance at End of Semester, University of South Carolina Sample

Additive Terms	Source	df	SS	MS	F	p	R^2
Perceived Behavioral Control							
	Hypothesis	1	.01	.01	.04	.85	.00
	Error	58	8.22	.14			
Interraction							
	Hypothesis	1	.41	.41	2.96	.09	.03
	Error	57	7.81	.14			

Table 34

Regression of Predictor Variables on Behavior at End of Semester, Lander College Sample

Predictors	Source	df	SS	MS	F	p	R^2
Intention							
	Hypothesis	1	.08	.08	.43	.53	.03
	Error	13	2.32	.18			
Intention, Perceived Behavioral Control							
	Hypothesis	2	.70	.35	2.47	.13	.29
	Error	12	1.70	.14			
Intention, Perceived Behavioral Control, Interraction							
	Hypothesis	3	.70	.23	1.51	.27	.29
	Error	11	1.70	.15			

Table 35

Increment in Explained Variance at End of Semester, Lander College Sample

Additive Terms	Source	df	SS	MS	F	p	R^2
Perceived Behavioral Control							
	Hypothesis	1	.62	.62	4.39	.06	.26
	Error	12	1.70	.14			
Interraction							
	Hypothesis	1	.00	.00	.00	.97	.00
	Error	11	1.70	.15			

science course near the end of the semester. This finding tends to refute the portion of the Theory of Planned Behavior in which perceived behavioral control influences behavior directly, as shown by the dotted line in Figure 2 (Chapter 2).

The predictive capability of behavioral intention was demonstrated for the University of South Carolina sample at both the beginning (Table 28) and end (Table 32) of the semester, but not for the Lander College sample (Tables 30, 34). Following the set of decision rules adopted for this study, the remaining hypotheses will be examined for the University of South Carolina sample only since behavioral intention did not predict behavior in the Lander College sample.

Hypothesis 2: Prediction of behavioral intention, Theory of Reasoned Action.

Hypothesis two examined the behavioral intention (I) of earning a grade of "C" or better in the undergraduate introductory computer science course and hypothesized that it was predicted by a linear combination of attitude towards the behavior (A_B) and subjective norm (SN). This hypothesis specifically tests the applicability of the variables proposed by the Theory of Reasoned Action both at the beginning and end of the semester.

Behavioral intention can be thought of as the individual's personal motivation to perform well in the course. A person who has a strong motivation to achieve the grade of "C" or better will have a high behavioral intention. The intent of this hypothesis is to explore the factors which contribute to this personal motivation, or behavioral intention. Equations four and five explore this relationship.

$$I \equiv w_1(A_B) + w_2(SN) \tag{4}$$

$$I \equiv w_1(A_B) + w_2(SN) + w_3(A_B * SN) \tag{5}$$

Tables 36 and 37 indicate that the variables attitude towards the behavior and subjective norm, and their interraction, do not predict behavioral intention in the University of South Carolina sample at the beginning of the semester. Attitude towards the behavior is not a statistically significant predictor of behavioral intention ($F = 2.23$). The addition of subjective norm ($F = 1.17$) and the interraction term ($F = .85$) do not result in significant relationships. Table 37 indicates that the increase in explained variance is not significant in either case. Therefore the variables proposed by the Theory of Reasoned Action are not good predictors of behavioral intention in the University of South Carolina sample at the beginning of the semester.

Examining the same variables measured at the end of the semester for the University of South Carolina sample reveals completely different results. Table 38 indicates that the variables attitude towards the behavior and subjective norm, and their interraction, do indeed predict behavioral intention ($F = 10.43$, $p<.0001$). But the inclusion of subjective norm ($F = 2.06$) and the interraction ($F = 1.82$) term does not add significantly to the predictive capability of attitude towards the behavior (Table 39).

Table 36

Regression of Predictor Variables from the Theory of Reasoned Action on Behavioral Intention, University of South Carolina Sample, Beginning of Semester

Predictors	Source	df	SS	MS	F	p	R^2
Attitude towards Behavior							
	Hypothesis	1	.53	.53	2.23	.14	.02
	Error	88	20.76	.24			
Attitude towards Behavior, Subjective Norm							
	Hypothesis	2	.56	.28	1.17	.31	.03
	Error	87	20.73	.24			
Attitude towards Behavior, Subjective Norm, Interraction							
	Hypothesis	3	.61	.20	.85	.47	.03
	Error	86	20.68	.24			

Table 37

Increment in Explained Variance, University of South Carolina Sample, Beginning of Semester

Additive Terms	Source	df	SS	MS	F	p	R^2
Subjective Norm							
	Hypothesis	1	.03	.03	.13	.72	.00
	Error	87	20.73	.24			
Interraction							
	Hypothesis	1	.05	.05	.21	.64	.00
	Error	86	20.68	.24			

Table 38

Regression of Predictor Variables from the Theory of Reasoned Action on Behavioral Intention, University of South Carolina Sample, End of Semester

Predictors	Source	df	SS	MS	F	p	R^2
Attitude towards Behavior							
	Hypothesis	1	48.64	48.64	26.52	.0001	.31
	Error	59	108.21	1.83			
Attitude towards Behavior, Subjective Norm							
	Hypothesis	2	52.35	26.18	14.53	.0001	.33
	Error	58	104.50	1.80			
Attitude towards Behavior, Subjective Norm, Interraction							
	Hypothesis	3	55.58	18.53	10.43	.0001	.35
	Error	57	101.27	1.78			

Table 39

Increment in Explained Variance, University of South Carolina Sample, End of Semester

Additive Terms	Source	df	SS	MS	F	p	R^2
Subjective Norm							
	Hypothesis	1	3.71	3.71	2.06	.16	.02
	Error	58	104.50	1.80			
Interraction							
	Hypothesis	1	3.23	3.23	1.82	.18	.02
	Error	57	101.27	1.78			

Equation 6 shows the only linear equation which would predict behavioral intention using these variables at the end of the semester. Subjective norm and the interraction term were not used since they did not significantly add to the prediction of behavioral intention. Table 40 shows the statistics relative to this linear equation.

$$I = -.28 + .26(A_B) \quad (6)$$

Hypothesis 3: Prediction of behavioral intention, Theory of Planned Behavior, direct - reduced effects model.

This hypothesis examined the behavioral intention (I) of earning a grade of "C" or better in the undergraduate introductory computer science course and hypothesized that it was predicted by a linear combination of attitude towards the behavior (A_B), subjective norm (SN), and perceived behavioral control (PBC) with variables measured both at the beginning and end of the semester. The direct - reduced effects model is utilized by excluding from consideration variables external to those provided by the Theory of Planned Behavior.

Table 40

Parameter Estimates for the Prediction of Behavioral Intention, University of South Carolina Sample, End of the Semester

Variable	df	Parameter Estimate	Standard Error	F	Prob > F
Intercept	1	-.28	.47	.37	.55
Attitude towards behavior	1	.26	.05	26.52	.0001

The hypothesis, which examined the variables proposed by the Theory of Planned Behavior, is reflected in the equations below. As with hypothesis 2, this hypothesis explored the components of intention, or personal motivation. Equation 7 is a hierarchical extension of Equation 4 due to the inclusion of perceived behavioral control. It aids in the comparison of the Theory of Reasoned Action and the Theory of Planned Behavior. Equation 8 hierarchically extends Equation 7 to include interraction effects.

$$I \cong w_1(A_B) + w_2(SN) + w_3(PBC) \quad (7)$$

$$I \cong w_1(A_B) + w_2(SN) + w_3(PBC) + w_4(A_B * SN) + w_5(A_B * PBC) + w_3(PBC * SN) + w_7(A_B * SN * PBC) \quad (8)$$

Using variables measured at the beginning of the semester, the addition of perceived behavioral control to attitude towards the behavior and subjective norm results in a significant increase in explained variance (Table 42, $F = 5.05$, $p<.05$), but the resulting combination does not form a set of predictors of behavioral intention which is statistically significant (Table 41, $F = 2.50$). Inclusion of the interraction terms is not statistically significant ($F = .70$), nor does it result in a statistically significant predictor of intention ($F = 1.46$). Therefore the variables proposed by the Theory of Planned Behavior together are not significant predictors of behavioral intention in the confines of this study when variables were measured at the beginning of the semester.

When examining those variables at the end of the semester, however, the variables proposed by the Theory of Planned Behavior are

Table 41

Regression of Predictor Variables on Behavioral Intention, University of South Carolina Sample, Beginning of Semester

Predictors	Source	df	SS	MS	F	p	R^2
Attitude to Behavior, Subjective Norm							
	Hypothesis	2	.56	.28	1.17	.31	.03
	Error	87	20.73	.24			
Attitude to Behavior, Subjective Norm, Perceived Behavioral Control							
	Hypothesis	3	1.71	.57	2.50	.06	.08
	Error	86	19.58	.23			
Attitude to Behavior, Subjective Norm, Perceived Behavioral Control, Interraction							
	Hypothesis	7	2.36	.37	1.46	.19	.11
	Error	82	18.93	.23			

Table 42

Increment in Explained Variance, University of South Carolina Sample, Beginning of Semester

Additive Terms	Source	df	SS	MS	F	p	R^2
Perceived Behavioral Control							
	Hypothesis	1	1.15	1.15	5.05	.03	.05
	Error	86	19.58	.23			
Interraction							
	Hypothesis	1	.16	.16	.70	.59	.03
	Error	82	18.93	.23			

significant predictors of behavioral intention ($F = 16.98$, $p<.0001$, Table 43), accounting for 47% of the variance. The addition of the interraction terms increased the explained variance to 53% ($F = 8.69$, $p<.0001$). Both perceived behavioral control and the interraction terms added significantly to the prediction of behavioral intentions (Table 44).

Regression weights associated with this hypothesis using variables measured at the end of the semester are shown in Table 45. When including the interraction effects, all but one of the parameter estimates are not statistically significant at the .05 level. Therefore further examination of a linear equation based on these variables is inappropriate.

When the interraction effects are not included, however, the parameter estimates have increased statistical significance. Perceived behavioral control is significant ($F = 14.92$, $p<.05$). The statistical significance of the other two variables is improved. The linear equation associated with this model is shown in Equation 9.

$$I \cong -.30 + .11(A_B) + .26(SN) + .17(PBC) \qquad (9)$$

Table 43

Regression of Predictor Variables on Behavioral Intention, University of South Carolina Sample, End of Semester

Predictors	Source	df	SS	MS	F	p	R^2
Attitude to Behavior, Subjective Norm							
	Hypothesis	2	52.35	26.18	14.53	.0001	.33
	Error	58	104.50	1.80			
Attitude to Behavior, Subjective Norm, Perceived Behavioral Control							
	Hypothesis	3	74.02	24.67	16.98	.0001	.47
	Error	57	82.83	1.45			
Attitude to Behavior, Subjective Norm, Perceived Behavioral Control, Interractions							
	Hypothesis	7	83.82	11.97	8.69	.0001	.53
	Error	53	73.03	1.38			

Table 44

Increment in Explained Variance, University of South Carolina Sample, End of Semester

Additive Terms	Source	df	SS	MS	F	p	R^2
Perceived Behavioral Control							
	Hypothesis	1	21.67	21.67	14.92	.0003	.14
	Error	57	82.83	1.45			
Interractions							
	Hypothesis	1	6.29	6.29	4.57	.0015	.06
	Error	53	73.03	1.38			

Table 45

Parameter Estimates for the Prediction of Behavioral Intention, University of South Carolina Sample, End of the Semester

Variable	df	Parameter Estimate	Standard Error	F	Prob > F
		With Interraction Effects			
Intercept	1	-.55	1.00	.31	.58
Attitude Towards Behavior (AB)	1	.12	.22	.32	.58
Subjective Norm (SN)	1	.46	.46	1.00	.32
Perceived Behavioral Control (PBC)	1	.39	.16	5.96	.02
AB x SN	1	0.00	.09	0.00	.97
AB x PBC	1	-.02	.03	.23	.63
SN x PBC	1	-.12	.07	2.58	.11
AB x SN x PBC	1	.01	.01	.26	.61
		Without Interraction Effects			
Intercept	1	-.30	.45	.45	.51
Attitude Towards Behavior (AB)	1	.11	.06	3.82	.06
Subjective Norm (SN)	1	.26	.17	2.34	.13
Perceived Behavioral Control (PBC)	1	.17	.04	14.92	.00

Hypothesis 4: Prediction of behavioral intention, Theory of Planned Behavior, direct - full effects model.

This hypothesis explores the possibility that a student's behavioral intention (I) of earning a grade of "C" or better in the undergraduate introductory computer science course is predicted by a linear combination of attitude towards the behavior (A_B), subjective norm (SN), perceived behavioral control (PBC), and specific external variables, namely gender (G), ethnicity (E), and Scholastic Aptitude Test Quantitative scores (SAT Q). The hypothesis follows the direct - full effects model, specifically including the variables which are external to the Theory of Planned Behavior. Equation 10 parallels this hypothesis; Equation 11 adds the interraction terms.

$$I \cong w_1(A_B) + w_2(SN) + w_3(PBC) + w_4(G) + w_5(E) + w_6(SAT\ Q) \quad (10)$$

$$I \cong w_1(A_B) + w_2(SN) + w_3(PBC) + w_4(G) + w_5(E) + w_5(SatQ) + \text{interractions} \quad (11)$$

When the variables attitude towards the behavior, subjective norm, and perceived behavioral control are measured at the beginning of the semester, the predictive capability of those variables is not appreciably improved by gender, ethnicity, and Scholastic Aptitude Test Quantitative scores (Tables 46 and 47). When the variables are measured near the end of the semester, again the predictive capability is not improved (Tables 48 and 49). The linear equation associated with this hypothesis was not examined since the external variables did not contribute to the prediction of behavioral intention.

Equation 11 was not explored since none of the external variable main effects were statistically significant. This decision was made based on the set of decision rules adopted for this study (Figure 3).

Table 46

Regression of Predictor Variables on Behavioral Intention, University of South Carolina Sample, Beginning of Semester

Predictors	Source	df	SS	MS	F	p	R^2
Attitude to Behavior, Subjective Norm, Perceived Behavioral Control							
	Hypothesis	3	1.71	.57	2.50	.06	.08
	Error	86	19.58	.23			
Attitude to Behavior, Subjective Norm, Perceived Behavioral Control, Gender, Ethnicity, SAT Quantitative scores							
	Hypothesis	6	2.32	.39	1.71	.13	.11
	Error	82	18.49	.23			

Table 47

Increment in Explained Variance, University of South Carolina Sample, Beginning of Semester

Additive Terms	F	p	R^2
Gender	1.75	.19	.02
Ethnicity	.55	.46	.01
SAT Q	.01	.93	.00

The lack of additional explained variance with the addition of these external variables tends to support the underlying assumption of the Theory of Planned Behavior. The assumption is that the effect of external variables is completely mediated by attitude towards the behavior, subjective norm, and perceived behavioral control.

Table 48

Regression of Predictor Variables on Behavioral Intention, University of South Carolina Sample, End of Semester

Predictors Source	df	SS	MS	F	p	R^2
Attitude to Behavior, Subjective Norm, Perceived Behavioral Control						
Hypothesis	3	74.02	24.67	16.98	.0001	.47
Error	57	82.83	1.45			
Attitude to Behavior, Subjective Norm, Perceived Behavioral Control, Gender, Ethnicity, SAT Quantitative scores						
Hypothesis	6	74.71	12.45	8.19	.0001	.48
Error	82	82.14	1.52			

Table 49

Increment in Explained Variance, University of South Carolina Sample, End of Semester

Additive Terms	F	p	R^2
Ethnicity	.23	.68	.00
Gender	.17	.68	.00
SAT Q	.07	.80	.00

Hypothesis 5: Prediction of behavioral intention, Theory of Planned Behavior, indirect effects model.

The fifth hypothesis examined a student's behavioral intention of earning a grade of "C" or better in the undergraduate introductory computer science course. It hypothesized that behavioral intention is predicted by a linear combination of attitude towards the behavior, subjective norm, and perceived behavioral control only, with the relative contributions of each variable dependent on the external variables gender (Equation 12), ethnicity (Equation 13), and Scholastic Aptitude Test Quantitative scores (Equation 14).

$$I \cong w_1(G)(A_B) + w_2(G)(SN) + w_3(G)(PBC) \tag{12}$$

$$I \cong w_1(E)(A_B) + w_2(E)(SN) + w_3(E)(PBC) \tag{13}$$

$$I \cong w_1(SAT\ Q)(A_B) + w_2(SAT\ Q)(SN) + w_3(SAT\ Q)(PBC) \tag{14}$$

The results of the indirect effects model were mixed when measuring the variables at the beginning of the semester. Table 50, which corresponds to Equation 12, shows that a strong relationship exists between the variables from the Theory of Planned Behavior and behavioral intention for females from the University of South Carolina sample. Twenty percent of the variability in behavioral intention was explained by the variables attitude towards the behavior, subjective norm, and perceived behavioral control for the females from this sample. Males from the University of South Carolina sample did not show a significant relationship between the variables.

Table 51 shows the parameter estimates. Note that the parameter estimate for the subjective norm variable is clearly nonsignificant (p<.66). Equation 15 shows the linear equation associated with the female sub-sample.

$$I \cong 1.15 + .07(A_B) + .06(SN) + .12(PBC) \qquad (15)$$

The regression for Equation 13 at the beginning of the semester is shown in Table 52. Ethnicity proved not to be a good blocking variable when predicting behavioral intention from the variables identified by the Theory of Planned Behavior within the confines of this study. This could be attributed to the small number of minorities in the sample.

Table 53 shows the regression for Equation 14 at the beginning of the semester. In each grouping based on Scholastic Aptitude Test Quantitative scores, no statistically significant results were found.

When the same blocking occurred using the variables proposed by the Theory of Planned Behavior measured at the end of the semester, the variables constituted good predictions in many cases. Blocking by gender (Table 54) was significant for both female (p<.0006) and male (p<.0005) subsamples. The variables attitude towards the behavior, subjective norm, and perceived behavioral control, therefore, are good predictors of behavioral intention for both males and females. The parameter estimates for the male and female sub-groups are shown in Table 55. The resulting linear equations are shown in Equation 16 for females and Equation 17 for males.

$$I \cong -.60 + .16(A_B) + .28(SN) + .14(PBC) \quad (16)$$

$$I \cong -.13 + .08(A_B) + .26(SN) + .18(PBC) \quad (17)$$

Blocking by the black ($p<.008$) and white ($p<.0001$) ethnic groups was statistically significant while, possibly due to sample size, the 'other' ethnicity group was not (Table 56). Therefore the variables proposed by the Theory of Planned Behavior are good predictors of behavioral intention for the black and white ethnic groups. Parameter estimates for the black (Equation 18) and white (Equation 19) sub-groups are shown below.

$$I \cong .18 - .03(A_B) + .31(SN) + .37(PBC) \quad (18)$$

$$I \cong -.71 + .17(A_B) + .35(SN) + .10(PBC) \quad (19)$$

When blocking by Scholastic Aptitude Test Quantitative scores, the groups below the score of 445 ($p<.0001$) and above 585 ($p<.004$) were statistically significant, while the two groups in the middle were not (Table 58). This implies that the variables attitude towards the behavior, subjective norm, and perceived behavioral control are good predictors of behavioral intention for the low and high groups based on Scholastic Aptitude Test Quantitative scores. The resulting parameter estimates for the two statistically significant groups are shown in Table 59. The associated linear equations are shown in Equation 20 for the 400 to 445 group and Equation 21 for 585 to 800.

$$I \cong -1.03 + .20(A_B) + .16(SN) + .20(PBC) \quad (20)$$

$$I \cong -.87 + .05(A_B) + .80(SN) + .16(PBC) \quad (21)$$

Table 50

Regression on Predictor Variables,University of South Carolina Sample, Beginning of the Semester: Indirect Effects Model, Gender

Sample	Source	df	SS	MS	F	p	R^2
Female	Hypothesis	3	2.60	0.87	3.46	.03	.28
	Error	27	6.75	0.25			
Male	Hypothesis	3	0.50	0.16	0.828	.48	.04
	Error	55	11.16	0.20			

Table 51

Parameter Estimates for the Female Sub-sample, University of South Carolina Sample, Beginning of the Semester

Variable	df	Parameter Estimate	Standard Error	T	Prob > |T|
Intercept	1	1.15	.51	2.24	.033
Attitude towards behavior	1	.07	.04	1.52	.141
Subjective norm	1	.06	.14	.44	.663
Perceived behavioral control	1	.12	.07	1.79	.084

Table 52

Regression on Predictor Variables, University of South Carolina Sample, Beginning of the Semester: Indirect Effects Model, Ethnicity

Sample	Source	df	SS	MS	F	p	R^2
Black	Hypothesis	3	0.89	0.29	0.89	.46	.10
	Error	24	7.97	0.33			
Other	Hypothesis	3	0.54	0.18	0.71	.68	.68
	Error	1	0.26	0.25			
White	Hypothesis	3	1.09	0.36	2.01	.12	.10
	Error	52	9.41	0.18			

Table 53

Regression on Predictor Variables, University of South Carolina Sample, Beginning of the Semester: Indirect Effects Model, Scholastic Aptitude Test Quantitative Scores

Score Range	Source	df	SS	MS	F	p	R^2
400-445	Hypothesis	3	.93	.31	.94	.44	.13
	Error	19	6.29	.33			
445-515	Hypothesis	3	.52	.17	.70	.56	.10
	Error	19	4.70	.25			
515-585	Hypothesis	3	.55	.18	.75	.54	.12
	Error	17	4.12	.24			
585-800	Hypothesis	3	.77	.26	1.55	.23	.20
	Error	19	3.14	.17			

Table 54

Regression on Predictor Variables, University of South Carolina Sample, End of the Semester: Indirect Effects Model, Gender

Sample	Source	df	SS	MS	F	p	R^2
Female	Hypothesis	3	38.18	12.73	8.84	.0006	.57
	Error	20	28.78	1.44			
Male	Hypothesis	3	37.04	12.35	7.71	.0005	.41
	Error	33	52.84	1.60			

Table 55

Parameter Estimates for Gender Sub-samples, University of South Carolina Sample, End of the Semester

Variable	df	Parameter Estimate	Standard Error	T	Prob > |T|
Females					
Intercept	1	-.60	.75	-.80	.43
Attitude towards behavior	1	.16	.09	1.71	.10
Subjective norm	1	.28	.26	1.09	.29
Perceived behavioral control	1	.14	.08	1.89	.07
Males					
Intercept	1	-.13	.60	-.22	.83
Attitude towards behavior	1	.08	.08	.96	.34
Subjective norm	1	.26	.24	1.12	.27
Perceived behavioral control	1	.18	.06	3.13	.00

Table 56

Regression on Predictor Variables, University of South Carolina Sample, End of the Semester: Indirect Effects Model, Ethnicity

Sample	Source	df	SS	MS	F	p	R^2
Black	Hypothesis	3	20.23	6.75	6.34	.008	.61
	Error	12	12.77	1.06			
Other	Hypothesis	2	0	0	.	.	.
	Error	0	0	.			
White	Hypothesis	3	58.99	19.66	12.27	.0001	.49
	Error	38	60.92	1.60			

Table 57

Parameter Estimates for Ethnic Sub-samples, University of South Carolina Sample, End of the Semester

Variable	df	Parameter Estimate	Standard Error	T	Prob > |T|
Black					
Intercept	1	.18	.76	.23	.82
Attitude towards behavior	1	-.03	.11	-.30	.77
Subjective norm	1	.31	.36	.87	.40
Perceived behavioral control	1	.37	.10	3.64	.00
White					
Intercept	1	-.71	.59	-1.26	.21
Attitude towards behavior	1	.17	.07	2.26	.03
Subjective norm	1	.35	.21	1.70	.10
Perceived behavioral control	1	.10	.06	1.83	.07

Table 58

Regression on Predictor Variables, University of South Carolina Sample, End of the Semester: Indirect Effects Model, Scholastic Aptitude Test Quantitative Scores

Score Range	Source	df	SS	MS	F	p	R^2
400-445	Hypothesis	3	23.02	7.67	24.69	.0001	.85
	Error	13	4.04	.31			
445-515	Hypothesis	3	16.28	5.43	1.26	.34	.26
	Error	11	47.45	4.31			
515-585	Hypothesis	3	12.12	4.04	2.97	.08	.47
	Error	10	13.60	1.36			
585-800	Hypothesis	3	16.31	5.44	8.06	.004	.69
	Error	11	7.42	.67			

Hypothesis 6: The belief-based measures of attitude towards the behavior, subjective norm, and perceived behavioral control are closely associated with the respective direct measures.

This hypothesis examined the relationships between the belief-based ($\Sigma\, b_i \cdot e_i$) measures of attitude towards the behavior, subjective norm, and perceived behavioral control and suggests that they are closely associated with the direct measure of attitude towards the behavior, subjective norm, and perceived behavioral control, respectively.

Table 59

Parameter Estimates for Scholastic Aptitude Test Quantitative Sub-samples, University of South Carolina Sample, End of the Semester

Variable	df	Parameter Estimate	Standard Error	T	Prob > |T|
400 - 445					
Intercept	1	-1.03	.59	-1.73	.11
Attitude towards behavior	1	.20	.05	4.18	.00
Subjective norm	1	.16	.22	.76	.46
Perceived behavioral control	1	.20	.06	3.38	.00
585 - 800					
Intercept	1	-.87	1.11	-.79	.45
Attitude towards behavior	1	.05	.09	.58	.58
Subjective norm	1	.80	.49	1.64	.13
Perceived behavioral control	1	.16	.08	2.01	.07

Based on the decision rule adopted for the study, the analysis was made only for the variables attitude towards the behavior, subjective norm, and perceived behavioral control measured at the end of the semester since measures of these variables at the beginning of the semester were statistically nonsignificant predictors of behavioral intention. The correlation between the direct and belief-based measures for attitude towards the behavior (.64, $p<.001$) and perceived behavioral control (.50, $p<.001$) were statistically significant. Subjective norm was not statistically significant (.16, $p<.22$). These correlations tend to parallel the finding that subjective norm does not add to the prediction of behavioral intention (Table 39) and the other two variables do (Tables 39 and 43).

Hypothesis 7: Each belief-based measure makes significant contributions to the respective direct measure.

This hypothesis suggests that each belief-based measure of attitude towards the behavior, subjective norm, and perceived behavioral control makes significant contributions to the respective direct measure. Due to the decision rule, this hypothesis was examined using variables measured at the end of the semester only. The beliefs concerning mastery of course materials ($F = 30.76$, $p<.01$,) and positive effect on grade point average ($F = 8.63$, $p<.01$) contributed to the direct measure of attitude towards the behavior (Table 60). The belief about the support structure provided by the family made a contribution to the direct measure of subjective norm ($F = 4.73$, $p<.03$, Table 60). The belief that "my own ability will help me" to earn a "C" or better contributed to perceived behavioral control when the variables were measured at the end of the semester ($F = 56.29$, $p<.0001$, Table 60).

Summary

This chapter described the results of the study. The Theory of Planned Behavior provided the theoretic basis for the study and the predictor variables which were used to predict behavioral intentions and the behavior of earning a grade of "C" or better in an introductory undergraduate computer science course. Several other variables, including gender, ethnicity, and Scholastic Aptitude Test Quantitative scores, were used in conjunction with these variables. Results from the University of South Carolina sample were generally more relevant than those from the Lander College sample.

The first portion of the chapter described the means, standard deviations, and correlations for variables relevant to the study. The balance of the chapter examined the hypotheses.

Hypothesis one explored the effect which perceived behavioral control has on the behavior of earning the grade of "C" or better in the introductory undergraduate computer science course. It suggested that perceived behavioral control has no direct effect on the behavior in question at the beginning or end of the semester. At the beginning

Table 60

Contributions to Attitude Towards the Behavior, Subjective Norm, and Perceived Behvaioral Control, University of South Carolina Sample, End of the Semester

Contributor	Source	df	SS	MS	F	p	R^2
To attitude towards the behavior							
master course	Hypothesis	1	256.27	256.27	30.76	.0001	.34
materials	Error	61	508.14	8.33			
help grade point							
average & master	Hypothesis	2	320.21	160.12	21.63	.0001	.42
course materials	Error	60	444.20	7.40			
To subjective norm							
family	Hypothesis	1	4.83	4.83	4.73	.03	.07
	Error	61	62.25	1.02			
To perceived behavioral control							
my own ability	Hypothesis	1	513.34	513.34	56.29	.0001	.48
	Error	61	556.31	9.12			

of the semester, behavioral intention predicted the behavior in the University of South Carolina sample, but the addition of perceived behavioral control and the interraction term did not add to the predictive capability. Behavioral intention did not predict behavior in the Lander College sample. Neither perceived behavioral control nor the interraction term significantly added to the predictive capability of behavioral intention in either sample at the end of the semester. The balance of the hypotheses were examined using data from the University of South Carolina sample only.

Hypothesis two suggested that the variables proposed by the Theory of Reasoned Action predict behavioral intention. When measured at the beginning of the semester, the variables do not predict behavioral intention. At the end of the semester, the variables do predict behavioral intention.

The third hypothesis proposed that the variables suggested by the Theory of Planned Behavior predict behavioral intention. When measured at the beginning of the semester, the variables do not predict behavioral intention. At the end of the semester, the variables attitude towards the behavior, subjective norm, and perceived behavioral control do predict behavioral intention.

Hypothesis four suggested that the addition of external variables improved the prediction of the variables proposed by the Theory of Planned Behavior. Both at the beginning and end of the semester, the variables gender, ethnicity, and Scholastic Aptitude Test Quantitative scores do not add to the predictive capability, supporting the portion of the theory which suggests that external variables are completely mediated by attitude towards the behavior, subjective norm, and perceived behavioral control when predicting behavioral intention.

The fifth hypothesis proposed that behavioral intention is predicted by a linear combination of attitude towards the behavior, subjective norm, and perceived behavioral control only, with the relative contributions of each variable dependent on specific external variables. The only subsample which resulted in statistically significant findings at the beginning of the semester was females. At the end of the semester, however, the male, female, black, and white subsamples were statistically significant. The lowest and highest ranges of the Scholastic Aptitude Test Quantitative score groups were significant as well.

Hypothesis six determined that two of the direct measures of the variables proposed by the Theory of Planned Behavior were significantly correlated to their respective belief-based measures when variables were measured at the end of the semester only. Attitude towards the behavior and perceived behavioral control were significant at the end of the semester only; subjective norm was not.

The last hypothesis examined the determinants of the predictors of attitude towards the behavior, subjective norm, and perceived behavioral control. At the end of the semester, two beliefs contributed to attitude towards the behavior while one belief contributed to subjective norm and one contributed to perceived behavioral control.

Chapter 5: Conclusions and Recommendations

Review of the Purposes, Design, and Procedures

This study attempted to identify predictors of success in an undergraduate introductory computer science course at Lander College in Greenwood, South Carolina and at the University of South Carolina, Columbia, South Carolina. The undergraduate introductory course was developed following the guidelines for Computer Science 1 established by the Association for Computing Machinery Curriculum Committee Task Force for Computer Science 1. It is the first course taken by computer science majors at the University of South Carolina and Lander College and parallels the entry level computer science course offered by many other institutions.

Previous research concerning predictors of success in computer science was examined in Chapter 2. Studies have identified several potential predictors from the cognitive domain, including previous grade point average, Scholastic Aptitude Test scores, and programmer aptitude tests.

Cognitive predictors of success have been demonstrated by previous studies to be useful. However, it is also important to understand if affective factors influence students' success in the undergraduate introductory computer science course. Research in the affective domain has received considerable attention in the broader science education field but appears to have been virtually ignored in computer science at the college level.

Therefore, this study examined affective predictors of success in the undergraduate introductory computer science course. The theoretic framework of this study is provided by Ajzen's Theory of Planned Behavior.

The hypotheses, instrumentation, design, and procedures utilized in the implementation of this study were described in Chapter 3. The study utilized hierarchical regression techniques to test certain linear combinations of predictors of behavioral intention and behavior. Correlation was used to determine the association between direct and belief-based measures of the three predictors from the Theory of Planned Behavior.

The instrument used in the study was based on the theoretic framework provided by the Theory of Planned Behavior (Ajzen, 1985). The instrument development procedure was based on works by Ajzen and Fishbein (1980), Ajzen (1985), Ajzen and Madden (1986), and Koballa, Crawley, and Shrigley (1987). Questions on the instrument were formed from the individual beliefs as well as from more direct measures of attitude towards the behavior, subjective norm, perceived behavioral control, and intention.

Findings and Conclusions

The hypotheses examined variables from the Theory of Planned Behavior as predictors of success in the undergraduate introductory computer science course. The external variables gender, ethnicity, and Scholastic Aptitude Test Quantitative scores were used to gain a better understanding of their effect on success in conjunction with the Theory of Planned Behavior variables. Specific findings of the study are provided below.

Behavioral intention is the best determinant of behavior.

Behavioral intention is the best predictor of success both at the beginning and end of the semester. This finding is supported by the first hypothesis using data from the University of South Carolina sample. Although 4% of the variance in success is explained by behavioral intention at the beginning of the semester, explained variance increases to 33% near the end of the semester.

Behavioral intention can be thought of as one's personal motivation to perform a specific behavior. The ability of motivation to predict the behavior of earning a "C" or better for the University of South Carolina sample was statistically significant at both the beginning and end of the semester, but increased over the semester as the subjects gained more information about the course. Personal motivation does play a role in grade prediction in the undergraduate introductory computer science course, and the role increases throughout the semester.

Perceived behavioral control is an antecedent of behavioral intention, not behavior.

The Theory of Planned Behavior model suggests that perceived behavioral control does not add to the predictive capability of behavioral intention at the beginning of the semester, but adds significantly to the prediction of behavior at the end of the semester. The data from the University of South Carolina sample measured at the beginning and end of the semester suggests that perceived behavioral control does not add to the prediction of behavior beyond the contribution of behavioral intention. However, perceived behavioral control does add significantly to attitude towards the behavior and subjective norm in the prediction of behavioral intention.

Perceived behavioral control is an antecedent of behavioral intention for the University of South Carolina sample. This implies that, within the domain of grade prediction in the undergraduate introductory computer science course, an individual's belief as to the difficulty level of the course effects one's personal motivation, not one's grade.

Attitude towards the behavior and subjective norm predict behavioral intention at the end of the semester.

Results of the study indicate that attitude towards the behavior and subjective norm do not predict behavioral intention at the beginning of the semester, but do at the end. The variance accounted for by the two variables at the end of the semester was 33%. Attitude towards the behavior alone accounted for 31% of the variance in behavioral intention, while the addition of subjective norm was not statistically significant.

It appears, therefore, that beliefs associated with certain referents concerning earning the grade of "C" in the undergraduate introductory computer science course are not important indicators of a person's motivation at the beginning or end of the semester. A person's attitude towards earning the grade of "C", however, does make an important contribution to the strengthing of personal motivation at the end of the semester.

<u>The Theory of Planned Behavior is an improvement over the Theory of Reasoned Action.</u>

The Theory of Planned Behavior is an extension of the Theory of Reasoned Action which includes a behavioral control component. This study determined that the Theory of Planned Behavior is an improvement over the Theory of Reasoned Action in the prediction of grades in the undergraduate introductory computer science course. The addition of perceived behavioral control to attitude towards the behavior and subjective norm accounted for 4% of the variance at the beginning of the semester and 14% at the end. This statistically significant increase in explained variance gives credence to the idea that the Theory of Planned Behavior is an improvement over the Theory of Reasoned Action.

<u>The addition of external variables did not improve the prediction of behavioral intention.</u>

The addition of the external variables gender, ethnicity, and Scholastic Aptitude Test Quantitative scores to the variables proposed by the Theory of Planned Behavior did not add to the prediction of behavioral intention. This finding is in support of the underlying assumption that external variables operate on behavioral intention through attitude towards the behavior, subjective norm, and perceived behavioral control, enhancing the applicability of the Theory of Planned Behavior in the study.

This finding also suggests that, when predicting behavioral intention of earning a "C" or better in the undergraduate introductory computer science course, demographic and cognitive variables effect behavioral intention through the major variables identified by the Theory of Planned Behavior.

<u>Variables predict behavioral intention following disaggregation by external variables.</u>

After disaggregating the data by each of the external variables, the variables proposed by the Theory of Planned Behavior were statistically significant predictors of behavioral intention for several subgroups. This process was done to better understand the attitudinal, normative, and behavioral control beliefs associated with related sub-populations.

The only statistically significant subgroup at the beginning of the semester was females. At the beginning of the semester, the model accounted for 28% of the variance in behavioral intention for females. The fact that the variables proposed by the Theory of Planned Behavior were significant predictors of behavioral intention for females at the beginning of the semester is not surpising. At least one study reported in Chapter 2 found differences based on gender (Crawley, in press). The model provides successful predictors of behavioral intention for females, but a post hoc analysis found that behavioral intention is not a statistically significant predictor of behavior (F=2.54, p=.12).

At the end of the semester, the model accounted for a significant portion of the variance in behavioral intention for several subgroups. Fifty-seven percent of the variance was accounted for in the female sub-group while 41% was accounted for in the male subgroup. The black (61%) and white (49%) subgroups had statistically significant accountings of the variance in behavioral intention. Eighty-five percent of the variance was accounted for in the lowest of four Scholastic Aptitude Test Quantitative score subgroups while 41% was accounted for in the highest sub-group.

Beliefs which contribute to attitude towards the behavior, subjective norm, and perceived behavioral control.

Two beliefs made statistically significant contributions to attitude towards the behavior at the end of the semester. The strongest single contributor was the belief concerning mastery of course materials, accounting for 34% of the variance in attitude towards the behavior. The belief that success in the course would help one's grade point average accounted for an additional 8% of the variance.

The first belief, mastery of course materials, implies that the individual has challenged oneself to perform well. A certain element of pride may also enter into this belief. The second belief, concerning the grade point ratio effect, may be considered a combination of the student's pride and firmly implanted goal to not just succeed in the course, but to excel. These beliefs may suggest that the students pride themselves on success and expect to do well in the course.

The belief involving family support structure was the strongest and the only statistically significant normative belief, accounting for 7% of the variance in subjective norm at the end of the semester. Subjective norm, however, did not add significantly to the prediction of behavioral intention. Therefore the fact that only one belief was statistically significant and accounted for a very small portion of the variance may indicate that the direct measure of subjective norm was not a good measure of the perceived social support to perform or not perform the behavior.

Only one belief, the belief in one's own ability, made a statistically significant contribution to perceived behavioral control at the end of the semester, accounting for 48% of the variance. This belief may be an indication of the underlying belief that a person's ability is established prior to the beginning of the course and does not change.

Theory of Planned Behavior as a predictor of success.

Predictors of success which can be administered prior to the beginning of a course are the most useful to computer science educators. This ability to predict success is important for a number of reasons, including the need to recruit able students into the course. Recruitment can only occur prior to the beginning of the course.

In this effort to identify predictors of success, data within this study which would be of most use was measured at the beginning of the semester. Data gathered at the end of the study is important to the understanding of student attitudes and intentions, but does not help in determining whether variables identified by the Theory of Planned Behavior can be useful in predicting success.

The findings suggest that in the area of undergraduate grade prediction in computer science, the behavior of earning a "C" or better can be accurately predicted from the variables proposed in the Theory of Planned Behavior, but the resulting portion of explained variance (4%) using this theory is much lower than that shown using other variables from other studies. This could mean that attitudes play a lesser role than was expected in the prediction of grades in the undergraduate introductory computer science course.

Usefulness of decision rules.

The use of the decision rules (Figure 3) was necessary to organize the potential directions of the study. For example, if behavioral intention did not predict behavior, then further study of the determinants of behavioral intention would be futile. The set of decision rules provided an underlying structure to the hypotheses by directing the course of hypotheses evaluation.

Summary.

Variables provided by the Theory of Planned Behavior model are statistically significant predictors of success in the introductory undergraduate computer science course near the end of the semester when subjects have the information necessary to make rational decisions. This is supported by a number of hypotheses using the University of South Carolina sample. Near the end of the semester, students have a more accurate idea of their likelihood of success in the course, which is reflected in their behavioral intention. At the end of the semester, 33% of the variance in success was accounted for by behavioral intention and 47% of the variance in behavioral intention was accounted for with the variables attitude towards the behavior, subjective norm, and perceived behavioral control.

Perceived behavioral control did not add to the contribution of behavior beyond the contribution of behavioral intention, both at the beginning and end of the semeter. This is somewhat contrary to the Theory of Planned Behavior, which suggests that the contribution above behavioral intention is significant close to the time of the measure of the behavior, but that an increase in time between the measure of the behavior and the measure of perceived behavioral control dimishes the usefulness of perceived behavioral control.

The Theory of Planned Behavior model is an improvement over the Theory of Reasoned Action. The inclusion of the perceived behavioral control variable increased the explained variance up to 14%.

External variables did not add to the prediction of behavioral intention. This supports one of the underlying assumptions of the model, that external variables operate through the variables proposed by the Theory of Planned Behavior.

The Theory of Planned Behavior model appeared to be appropriate for several subgroups of the sample. At the beginning of the semester, the model was useful for females only. Near the end of the semester, the female, male, black, white and the lowest and highest Scholastic Aptitude Test Quantitative scores subgroups had statistically significant results using the Theory of Planned Behavior model.

The Theory of Planned Behavior model supplies statistically significant predictors of the behavior of earning a "C" or better in the undergraduate introductory computer science course. But at the time when the prediction can be of the most use, at the beginning of the semester, the model accounts for only a small portion of the variance.

Post hoc data examination.

In order to better understand some of the components of attitude towards the behavior, subjective norm, and perceived behavioral control, further examination of the data from the University of South Carolina sample was made. This examination was initiated after the completion of data gathering and, consequently, is not part of the hypotheses.

An examination of the relationship between the direct and belief-based measures of the three variables was made first. The investigation was limited to those subgroups where the variables were significant predictors of behavioral intention. Therefore analyses were completed for the female sub-group at the beginning of the semester as well as the male, female, black, white, and the lowest and highest Scholastic Aptitude Test Quantitative scores subgroups at the end of the semester.

The results of this investigation are shown in Table 61. The correlation between the belief-based and direct measure of each variable for the female sub-sample at the beginning of the semester was not statistically significant.

At the end of the semester, the direct and belief-based measures of subjective norm were not statistically significant for any sub-group. The two measures of attitude towards the behavior were significantly correlated for the female (.64, p<.001), male (.65, p<.01), white (.74, p<.001), lowest (.71, p<.001) and highest (.69, p<.01) Scholastic Aptitude Test Quantitative scores sub-samples. The direct and belief-based measures of perceived behavioral control were significantly correlated for the female (.52, p<.01), male (.53, p<.001), black (.65, p<.01), white (.52, p<.001), and the highest Scholastic Aptitude Test Quantitative scores subgroups (.61, p<.05).

Table 61

Correlations By Selected External Variables Between Direct and Belief-based Measures of Variables Proposed by the Theory Of Planned Behavior

Sub-groups	Attitude towards Behavior	Subjective Norm	Perceived Behavioral Control
Beginning of Semester			
Female	-.10	.05	.18
End of Semester			
Female	.64***	.23	.52**
Male	.65***	.13	.53***
Black	.37	.19	.65**
White	.74***	.15	.52***
SAT Q to 440	.71***	.07	-.17
SAT Q over 580	.69**	.09	.61*

*p<.05 **p<.01 ***p<.001

The examination of the beliefs associated with the variables proposed by the Theory of Planned Behavior held by subgroups was taken a step further by examining the contribution each individual belief made to the associated direct measure. This evaluation was carried through for those sub-samples in which statistically significant correlations were established between the direct and belief-based measures of the variables. The analysis, therefore, included subgroups from the University of South Carolina sample with variables measured at the end of the semester. Only the statistically significant contributors were included.

Contributions to attitude towards the behavior are shown in Table 62. "Master course materials" was the only belief which made statistically significant contributions for females ($R^2 = .51$, $p<.0001$). The belief concerning preparing for future courses was the only belief to make a statistically significant contribution to attitude towards the behavior ($R^2 = .39$, $p<.0001$).

The white subgroup (Table 62) had three beliefs which made statistically significant contributions. The beliefs concerning mastery of course materials, grade point average help, and help to learn about computers accounted for 61% of the variance in the direct measure of attitude towards the behavior ($p<.0001$).

Only one belief in the lowest Scholastic Aptitude Test Quantitative subgroup made a statistically significant contribution. The belief that success would help the subject learn about computers accounted for 39% of the variance in attitude towards the behavior ($p<.01$, Table 62).

The highest Scholastic Aptitude Test Quantitative subgroup (Table 62) had two beliefs which made statistically significant contributions. The beliefs concerning help to learn about computers and grade point average accounted for 54% of the variance in the direct measure of attitude towards the behavior ($p<.0001$).

Each subgroup which had a statistically significant relationship between the direct and belief-based measures of perceived behavioral control had only one belief which made a statistically significant contribution to the direct measure of perceived behavioral control (Table 63). The belief which involves one's own ability accounted for 37% to 63% of the variance in perceived behavioral control in the five sub-samples. This belief appears to be held more strongly for females than males and for whites than for blacks.

These findings should be examined in light of the findings resulting from the hypotheses. It was determined that, for the overall sample, the beliefs concerning mastery of course materials and grade point average effect contribute to attitude towards the behavior. At least one of these beliefs contributed to the female, white, and high Scholastic Aptitude Test Quantitative scores subgroup. The other subgroups had other or no statistically significant beliefs which contributed to attitude towards the behavior.

Table 62

Contributions to Attitude Towards the Behavior by Specified External Variable, University of South Carolina Sample, End of the Semester

Contributor	Source	df	SS	MS	F	p	R^2
By females							
master course	Hypothesis	1	174.87	174.87	24.26	.0001	.51
materials	Error	23	165.77	7.21			
By males							
prepare for future	Hypothesis	1	163.83	163.83	22.97	.0001	.39
computer courses	Error	36	256.72	7.13			
By whites							
master course	Hypothesis	1	227.46	227.46	29.94	.0001	.43
materials	Error	40	303.87	7.60			
above & help	Hypothesis	2	275.22	137.61	20.95	.0001	.52
grade point average	Error	39	256.12	6.57			
above & help learn	Hypothesis	3	321.63	107.21	19.43	.0001	.61
about computers	Error	38	209.71	5.52			
By SATQ lowest							
help to learn	Hypothesis	1	87.5	87.5	10.26	.0055	.39
about computers	Error	16	136.5	8.53			
By SATQ highest							
help to learn	Hypothesis	1	33.42	33.42	6.40	.0252	.33
about computers	Error	13	67.92	5.22			
above & help	Hypothesis	2	55.14	27.57	7.16	.0090	.54
grade point average	Error	12	46.19	3.85			

*$p<.05$ **$p<.01$ ***$p<.001$

The belief associated with one's own ability proved to be the one belief which contributed to perceived behavioral control for the entire sample and for each subgroup examined. Therefore the strongest contributor to one's belief of the control over earning a "C" or better in the undergraduate introductory computer science course is the belief in one's own ability.

Table 63

Contributions to Perceived Behavioral Control by Specified External Variable, University of South Carolina Sample, End of the Semester

Contributor	Source	df	SS	MS	F	p	R^2
By females							
my own ability	Hypothesis	1	289.80	289.80	39.29	.0001	.63
	Error	23	169.64	7.38			
By males							
my own ability	Hypothesis	1	221.39	221.39	21.43	.0001	.37
	Error	36	371.98	10.33			
By blacks							
my own ability	Hypothesis	1	76.96	76.96	11.26	.004	.41
	Error	16	109.32	6.83			
By whites							
my own ability	Hypothesis	1	454.15	454.15	46.78	.0001	.54
	Error	40	388.32	9.71			
By SATQ highest							
my own ability	Hypothesis	1	117.94	117.94	16.70	.0013	.56
	Error	13	91.79	7.06			

*p<.05 **p<.01 ***p<.001

Implications

Ajzen's Theory of Planned Behavior model was successfully applied to the prediction of student attainment of the grade of "C" or better in the undergraduate introductory computer science course. Behavioral intention was determined to be the best predictor of the behavior, with perceived behavioral control not making a significant contribution beyond that of intention. The Theory of Planned Behavior has again been shown to be a useful model.

The Theory of Planned Behavior has been shown to be a better predictor of non-volitional behavior than the Theory of Reasoned Action. When predicting behavioral intention, the addition of perceived behavioral control to attitude towards the behavior and subjective norm was statistically significant at both the beginning and end of the semester.

The usefulness of external variables used to predict behavioral intention in conjunction with variables from the Theory of Planned Behavior has been shown to not be helpful. This finding is in support of the underlying assumption of the theory that external variables work through the attitudinal, normative, and behavioral control variables in the prediction of behavioral intention.

Can the Theory of Planned Behavior be helpful in predicting success in the undergraduate introductory computer science course? Data at the beginning of the semester instead of the end is employed since the usefulness of a predictor of success in the undergraduate introductory computer science course is predicated by the predictor being administered prior to the course. When considering the predictive capability of the variables proposed by the theory, only 4% of the variance in success can be attributed to behavioral intention. This explained variance is lower than variables from the cognitive domain.

Limitations

Many science education researchers are involved in understanding how attitudes influence behavior. This study differed from many other studies of this relationship between attitudes and behavior by examining a behavior which is not completely under the subject's control.

This study was pursued under the influence of several limitations. The first limitation has to do with the choice of the method to operationalize success in the study. Success was operationalized as earning a grade of "C" or better in the undergraduate introductory computer science course. This limitation is best illustrated by comparing this study to Ajzen and Madden's (1986) study of grade attainment, where success was operationalized as the behavior of earning an "A" in a business course as opposed to earning a "C" or better in a computer science course. One difference is that when considering the behavior of earning a grade of "A" in a course, many students may realize that the behavior is unobtainable for them. Near the beginning of the semester, all of the students in the Ajzen and Madden study expected to earn a "C" or better, but only 50% expected to earn an "A". Therefore the range of responses concerning one's intention to earn an "A" in a course is likely to be +3 to -3. But when measuring the intention of earning a "C" or better, as in this study, the scores clustered in the +2 to +3 range. Though the behavior of earning a "C" or better in a course is virtually every student's goal, not every student obtains the grade of "C" or better. In other words, all students in this study were highly motivated to perform the target behavior.

Second, the sample used in this study may be more homogeneous than those of other studies using the Theory of Planned Behavior. There appears to be a selection process resulting in a small percentage of the student population taking the undergraduate introductory computer science course. Students enrolling in this course have (1) graduated from high school in a college preparatory program, (2) taken algebra, biology, chemistry, and a foreign language in high school, (3) obtained adequate Scholastic Aptitude Test scores, (4) been accepted at the college or university, and (5) decided to take the course. The decision to take the course is often tempered by the perceived difficulty of the course compared to introductory courses outside of science. Studies using the Theory of Planned Behavior to examine pre-college science courses utilize samples which are less homogeneous. Therefore the applicability of the Theory of Planned Behavior in this sample may be less appropriate.

A third limitation is based on the fact that the study was made using variables from the affective domain. Variables outside the affective domain were introduced, but only from the standpoint of determining their effect in association with the variables from the Theory of Planned Behavior in the prediction of behavioral intention. Conclusions based on the suitability of the model variables in conjunction with specific cognitive and demographic variables when predicting the behavior of earning a "C" or better in the undergraduate introductory computer science course cannot be drawn since these analyses were not made.

A fourth limitation may lie in the design of the instrument itself. Although the procedures as outlined by Ajzen and Fishbein (1980) called for inclusion in the instrument of 75% of the responses to the open-ended questionnaire, possibly several other questions should have been included. In addition, the process of combining responses which could have been made by the same individual may have been handled differently by another researcher resulting in different findings. For example, should the combining of classmates and friends into one group not have been made? They roughly form the same group for many students, but not all classmates are friends. These arbitrary decisions made by researchers may have an effect on the results of the study.

A final limitation of the study concerns the generalizability of the findings. The selection of the subjects had more to do with geography than with random sampling techniques. But the institutions used in the study represent two completely different approaches to class size and type of student. The University of South Carolina uses somewhat more rigorous admissions standards than Lander College and typically has over 100 students in introductory courses. The average class size at

Lander College is approximately 20 students. These differences may indeed enhance the generalizability of the study.

This study did not result in a resounding endorsement of the predictive capability of the Theory of Planned Behavior in this situation. Ajzen and Fishbein (1980, ch. 6) suggest that inaccurate predictions may be caused by the theory being inappropriate in the context of the behavior under investigation. Further research may be necessary to determine if the theory is inappropriate in the undergraduate computer science context or if the problem lies in other areas.

Recommendations

Further study in the use of variables identified by the Theory of Planned Behavior is warranted to determine predictors of success in the undergraduate introductory computer science course. Further study may help to better determine the applicability of the variables proposed by the Theory of Planned Behavior as predictors of success in the undergraduate introductory computer science course.

This research is especially warranted to further analyze the effect of gender, specifically for females. Several studies (Campbell & McCabe, 1984; Kersteen, Linn, Clancy, & Hardyck, 1988; Petersen & Howe, 1979; Wolfe, 1977) have determined that gender is an important consideration when identifying predictors of success in the introductory undergraduate computer science course. Future studies need to examine gender not only as a predictor, but also as a variable for blocking. This importance is also reflected in the broader science education field (Crawley, in press).

The model provided by the Theory of Planned Behavior appears to be a valid model for the prediction of behavioral intentions of females enrolled in the introductory computer science course. This situation should be examined along with the fact that, in both samples, females made up approximately one third of the sample. This clearly indicates the underrepresentation of females in computer science classes at the two institutions and may reflect a problem which is present across the science curriculum and nationwide in scope. Females who have decided to take the undergraduate introductory course possibly have experienced a more selective social process than males. This process may have resulted in female students who have a better concept of their own behavioral intentions based on their individual behavioral determinants.

Further study of the way in which the variables proposed by the Theory of Planned Behavior operate in the prediction of the behavior of earning a "C" or better in the undergraduate introductory computer science course when used in conjunction with variables from the cognitive domain needs to be carried out. Again, for predictors to be useful to computer science educators, they must be valid near the beginning of the semester. Behavioral intention accounts for 4% of the variance in success at the beginning of the semester. Further study needs to be done to examine the variance in success in relation to behavioral intention and cognitive variables.

The study could have been improved by utilizing Ajzen's (1989, p. 252) improved method of identifying the determinants of perceived behavioral control. Using this method, the instrument would identify the individual control beliefs and associated perceived facilitating (or inhibiting) effects. Each pair would be multiplied, then summed across all pairs in a manner similar to attitude towards the behavior and subjective norm.

Variables proposed by the Theory of Planned Behavior have been shown in this study to be statistically significant predictors of success in the introductory undergraduate computer science course. Further study is needed to better understand how these variables operate for specific subgroups and in conjunction with cognitive variables in the prediction of success.

Appendix A: Open-ended Questionnaire

In this appendix, the open-ended questionnaire used to determine individual behavioral, normative, and behavioral control determinants is presented. The pagination of the questionnaire given to the subjects was different to what is presented here.

Computer Science Questionnaire

The following questions will be used to determine reasons why people enroll in computer science courses. This questionnaire will have no bearing on your course grade. You may continue any answer on the back if necessary.

1. What do you see as the advantages of earning a grade of "C" or better in this course?

2. What do you see as the disadvantages of earning a grade of "C" or better in this course?

3. Is there anything else you associate with earning a grade of "C" or better in this course?

4. Are there any groups of people who would approve of your earning a "C" or better in this course?

____

____

____

____

____

5. Are there any groups of people who would not approve of your earning a "C" or better in this course?

____

____

____

____

____

6. Are there any other groups of people who come to mind when you think about earning a "C" or better in this course?

____

____

____

____

____

7. What factors could prevent you from earning a grade of "C" or better in this course?

____

____

____

____

____

8. What factors could help you to earn a grade of "C" or better in this course?

____

____

____

____

____

9. Are there any other factors which could effect your ability to earn a grade of "C" or better in this course?

____

____

____

____

Appendix B: Results from the Open-ended Questionnaire

Attitude towards the behavior:

Advantages and disadvantages of earning a "C"

Responses used to form questions

to become better programmer	111	13
gain knowledge	1	
show knowledge	11111	
give me better understanding of computers	1111	

Resulting statement: My earning a "C" or better in this course will help me to learn about computers.

to get a good job	1111	7
high wages	1	
look good on resume	11	

Resulting statement: My earning a grade of "C" or better in this course will help me to get a good job.

show I can understand and learn from this course	111	6
prove I mastered course	1	
show I have not done my best	1	
demonstrate good background in computer science	1	

Resulting statement: My earning a grade of "C" or better in this course will show that I can master the materials presented in this course.

effect on grade point average	11111	5

Resulting statement: My earning a grade of "C" or better in this course will have a positive effect on my grade point average.

if I can do well here, then I can do well in other classes	1	4
to continue in field of computer science	111	

Resulting statement: My earning a grade of "C" or better in this course will better prepare me for future computer science courses.

confidence builder	1	3
feel better about myself	1	
accomplish long term personal goal	1	

Resulting statement: My earning a grade of "C" or better in this course will help me build confidence in myself.

Responses not used to form questions

lack of success	11	2
keep the scholarship I now have	11	2
class may be too easy	1	2
waste of time sitting through something I may already know	1	
people who fail may hate you	1	1
not required to repeat course	1	1
help to earn minor in computer science	1	1
make sure I get my work done	1	1
my ability to apply logic	1	1
show professor was good teacher	1	1

Total Responses - 50 $\quad$ 50 * .75 = 38

Subjective norm: Groups who approve or disapprove of earning a "C"

<u>Responses used to form questions</u>

parents	111111111111111	29
family	11111111111	
relatives	111	

Resulting statement: It is important to my family that I earn a grade of "C" or better in this course.

future employer	111111111111	12

Resulting statement: It is important to my likely future employer that I earn a grade of "C" or better in this course.

classmates	1	12
friends	11111111	
boyfriend	1	
students who failed the same course	11	

Resulting questions:

It is important to my friends that I earn a grade of "C" or better in this course.

It is important to my classmates that I earn a grade of "C" or better in this course.

<u>Responses not used to form questions</u>

teachers	11	9
faculty	11	
advisor	11111	
people who hand me my diploma	1	
Lander College	1	
me	111	3
people who hate computers	1	2
people in church	1	

<u>Total responses</u> - 67 67 * .75 = 50

Perceived behavioral control: Factors to prevent or help earning a "C"

<u>Responses used to form questions</u>

study habits	11111111111111	33
not doing homework	11111	
procrastination	1	
did not apply myself	1	
not keeping up	1	
lack of preparation	1	
doing assignments	1111	
keeping up with reading material	1	
hard work	11	
daily review	1	
listen in class, take notes, follow directions	1	
my spending time in lab	1	

Resulting statement: My study habits will prevent me from earning a "C" or better in this course.

outside activities	11	9
partying	11	
girlfriend	1	
work	1	
family problems	1	
spend too much time with friends	11	

Resulting statement: Outside activities, such as parties and work, will prevent me from earning a "C" or better in this course.

class attendance	1111111	7

Resulting statement: Attending class will help me to earn a "C" or better in this course.

special help from teachers	1	7
help from someone who knows about subject	1111	
group studying	11	

Resulting statement: Getting special help from the teacher or someone else who knows about the subject will help me to earn a "C" or better in this course.

fail to work to full potential	11	7
willingness to learn more	1	
poor attitude	1	
lack of interest	1	
slack attitude	1	
personal desire to do well	1	

Resulting statement: My willingness to work to my full potential will help me to earn a "C" or better in this course.

my ability	11111	5

Resulting statement: My own ability will help me to earn a "C" or better in this course.

a computer at home	1	5
modern computer	1	
good textbook	1	
access to computers	11	

Resulting statement: My access to adequate resources, like textbooks and computers, will help me to earn a "C" or better in this course.

<u>Responses not used to form questions</u>

professor's ability	1111	4
material too hard	11	3
material too time consuming	1	
demand from other classes	111	3
lack of knowledge from previous computer science courses	1	2
previous math courses	1	
good programming skills	1	2
high intelligence	1	
death, illness, ...	1	2
being sick	1	
thorough understanding of material	1	1
amount of sleep before a test	1	1

<u>Total responses</u> - 91 $91 * .75 = 68$

Appendix C: The Instrument

In this appendix, the instrument used to measure variables identified by the Theory of Planned Behavior is presented. Classifications of questions, which are in brackets {}, did not appear on the instrument which was used. The pagination of the instrument given to the subjects is different than what is presented here.

Computer Science Study, Permission to Participate

I am investigating ways in which earning a grade of "C" or better in this course can be predicted. For the study to be properly carried out, it is important that I collect information about you. Therefore I am requesting your permission to gather information about you such as your grade in this course, SAT scores, and responses to questionnaires. This information I collect will be used in a general way and will not be available for anyone else to examine, including the instructor of the course.

Please complete the statements below.

I [_____ agree]
[_____ do not agree] to the use of information about me in the study described above.

Signature ________________________ Date ___________

Your name (please print) _____________________________

What was your SAT quantatitive score? __________

I appreciate your cooperation and participation in this important study.

Dale Shaffer, Associate Professor of Computer Science

Computer Science Questionnaire

Name ______________________ Date _____________

Directions: In this questionnaire, rating scales with 7 places are used. Please make a mark in the place which best describes your opinion. For example, if you are asked to rate the weather in Greenwood on this scale, the seven places would be:

1. The weather in Greenwood is

   good _____ : _____ : _____ : _____ : _____ : _____ : _____ bad

   extremely quite slightly neither slightly quite extremely

If you think the weather in Greenwood is quite good, then you would place your mark as follows:

1. The weather in Greenwood is

   good ______ : __X__ : _____ : _____ : _____ : _____ : _____ bad

   extremely quite slightly neither slightly quite extremely

If you think the weather in Greenwood is slightly bad, then you would place your mark as follows:

1. The weather in Greenwood is

   good _____ : _____ : _____ : _____ : __X__ : _____ : _____ bad

   extremely quite slightly neither slightly quite extremely

If you think the weather in Greenwood is neither good nor bad, then you would place your mark as follows:

1. The weather in Greenwood is

   good _____ : _____ : _____ : __X__ : _____ : _____ : _____ bad

   extremely quite slightly neither slightly quite extremely

You will also be using a rating scale with likely-unlikely as end points. This scale is interpreted in the same way. For example, if you were asked to rate the weather in Greenwood in July on such a scale, it would appear as follows:

1. The weather in Greenwood is hot in July

   likely _____ : _____ : _____ : _____ : _____ : _____ : _____unlikely

   extremely quite slightly neither slightly quite extremely

If you think the weather in Greenwood is quite likely to be hot in July, then you would place your mark as follows:

1. The weather in Greenwood is

likely _____ : __X__ : _____ : _____ : _____ : _____ : _____ unlikely
extremely quite slightly neither slightly quite extremely

In making your ratings, please remember the following points:

1. Place your marks in the middle of spaces, not on the boundaries:

_____ : __X__ : _____ : _____ : _____ : _____ X _____
this not this

2. Be sure to answer all items-- please do not omit any.
3. Never put more than one mark on a single scale.

In this particular questionnaire we are concerned with your views towards earning a "C" or better in this course.

{intention}

1. I intend to earn a "C" or better in this class.

likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely
extremely quite slightly neither slightly quite extremely

This section deals with your attitudes towards earning a grade of "C" or better in this course.

{direct: attitude towards the behavior}

1. My earning a grade of "C" or better is

beneficial _____ : _____ : _____ : _____ : _____ : _____ : _____ harmful
extremely quite slightly neither slightly quite extremely

good _____ : _____ : _____ : _____ : _____ : _____ : _____ bad
extremely quite slightly neither slightly quite extremely

rewarding _____ : _____ : _____ : _____ : _____ : _____ : _____ punishing
extremely quite slightly neither slightly quite extremely

wise _____ : _____ : _____ : _____ : _____ : _____ : _____ harmful
extremely quite slightly neither slightly quite extremely

{behavioral belief set}

2. My earning a grade of "C" or better in this course will help me to learn about computers.

   likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely
   extremely quite slightly neither slightly quite extremely

3. My earning a grade of "C" or better in this course will show that I can master the materials presented in this course.

   likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely
   extremely quite slightly neither slightly quite extremely

4. My earning a grade of "C" or better in this course will help me to get a good job.

   likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely
   extremely quite slightly neither slightly quite extremely

5. My earning a grade of "C" or better in this course will have a positive effect on my grade point average.

   likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely
   extremely quite slightly neither slightly quite extremely

6. My earning a grade of "C" or better in this course will better prepare me for future computer science courses.

   likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely
   extremely quite slightly neither slightly quite extremely

7. My earning a grade of "C" or better in this course will help me build confidence in myself.

   likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely
   extremely quite slightly neither slightly quite extremely

{outcome evaluation set}

8. Learning about computers is

   good _____ : _____ : _____ : _____ : _____ : _____ : _____ bad
   extremely quite slightly neither slightly quite extremely

9. Mastering the materials presented in this course is

   good _____ : _____ : _____ : _____ : _____ : _____ : _____ bad
   extremely quite slightly neither slightly quite extremely

10. Getting a good job is

    good _____ : _____ : _____ : _____ : _____ : _____ : _____ bad
    extremely quite slightly neither slightly quite extremely

11. Taking a course which will have a positive effect on my grade point average is

good ______ : ______ : ______ : ______ : ______ : ______ : ______ bad
extremely quite slightly neither slightly quite extremely

12. Preparing for future computer science courses is

good ______ : ______ : ______ : ______ : ______ : ______ : ______ bad
extremely quite slightly neither slightly quite extremely

13. Building confidence in myself is

good ______ : ______ : ______ : ______ : ______ : ______ : ______ bad
extremely quite slightly neither slightly quite extremely

This section involves questions about how you think other people view your earning a grade of "C" or better in this course.

{direct: subjective norm}

1. Most people who are important to me think I

should ______ : ______ : ______ : ______ : ______ : ______ : ______ should not
extremely quite slightly neither slightly quite extremely
earn a grade of "C" or better in this course.

{normative belief set}

2. It is important to my family that I earn a grade of "C" or better in this course.

likely ______ : ______ : ______ : ______ : ______ : ______ : ______ unlikely
extremely quite slightly neither slightly quite extremely

3. It is important to my likely future employer that I earn a grade of "C" or better in this course.

likely ______ : ______ : ______ : ______ : ______ : ______ : ______ unlikely
extremely quite slightly neither slightly quite extremely

4. It is important to my friends that I earn a grade of "C" or better in this course.

likely ______ : ______ : ______ : ______ : ______ : ______ : ______ unlikely
extremely quite slightly neither slightly quite extremely

5. It is important to my classmates that I earn a grade of "C" or better in this course.

likely ______ : ______ : ______ : ______ : ______ : ______ : ______ unlikely
extremely quite slightly neither slightly quite extremely

{motivation to comply set}

6. Generally speaking, I want to do what my family thinks is important.

likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely
extremely quite slightly neither slightly quite extremely

7. Generally speaking, I want to do what my likely future employer thinks is important.

likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely
extremely quite slightly neither slightly quite extremely

8. Generally speaking, I want to do what my friends think is important.

likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely
extremely quite slightly neither slightly quite extremely

9. Generally speaking, I want to do what my classmates think is important.

likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely
extremely quite slightly neither slightly quite extremely

This last section deals with your view of the factors which might help or prevent you from earning a grade of "C" or better in this course.

{direct: perceived behavioral control}

1. How much control do you have over earning a "C" or better in this class?

complete _____ : _____ : _____ : _____ : _____ : _____ : _____ very little
extremely quite slightly neither slightly quite extremely

2. For me to earn a "C" or better is

easy _____ : _____ : _____ : _____ : _____ : _____ : _____ difficult
extremely quite slightly neither slightly quite extremely

3. If I wanted to I could easily earn a "C" or better in this class

likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely
extremely quite slightly neither slightly quite extremely

{belief-based: perceived behavioral control}

4. My study habits will prevent me from earning a "C" or better in this course.

likely _____ : _____ : _____ : _____ : _____ : _____ : _____ unlikely
extremely quite slightly neither slightly quite extremely

5. Outside activities, such as parties and work, will prevent me from earning a "C" or better in this course.

   likely ______ : ______ : ______ : ______ : ______ : ______ : ______ unlikely
   extremely quite slightly neither slightly quite extremely

6. Getting special help from the teacher or someone else who knows about the subject will help me to earn a "C" or better in this course.

   likely ______ : ______ : ______ : ______ : ______ : ______ : ______ unlikely
   extremely quite slightly neither slightly quite extremely

7. Attending class will help me to earn a "C" or better in this course.

   likely ______ : ______ : ______ : ______ : ______ : ______ : ______ unlikely
   extremely quite slightly neither slightly quite extremely

8. My willingness to work to my full potential will help me to earn a "C" or better in this course.

   likely ______ : ______ : ______ : ______ : ______ : ______ : ______ unlikely
   extremely quite slightly neither slightly quite extremely

9. My own ability will help me to earn a "C" or better in this course.

   likely ______ : ______ : ______ : ______ : ______ : ______ : ______ unlikely
   extremely quite slightly neither slightly quite extremely

10. My access to adequate resources, like textbooks and computers, will help me to earn a "C" or better in this course.

    likely ______ : ______ : ______ : ______ : ______ : ______ : ______ unlikely
    extremely quite slightly neither slightly quite extremely

Please provide the basic information requested below.

1. Indicate your gender. ____ male ____ female
2. How old are you? ____
3. What is your major? ____________________
4. What is your high school grade point average? _____ College grade point average? _____
5. Approximately how many college credits have you earned? ______
6. Have you taken CS 230, Computer Science principles I, before this semester? _____
7. Indicate your ethnicity: _____ black ____ white ____ other

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Vita

Dale Owen Shaffer was born in Johnstown, Pa on May 17, 1952, the son of Alma Schnars Shaffer and Frank Lynn Shaffer. After completion of high school in 1970, he entered Indiana University of Pennsylvania, where he earned the Bachelor of Science degree in Mathematics Education in 1973. From 1974 to 1977 he was employed as a mathematics instructor at the middle school level while completing the Master of Arts in Education degree, supervision emphasis, from George Washington University. A position as assistant principal at the middle school level followed in 1977. After the completion of the Master of Computer Science degree from the University of Virginia in 1980, he taught for one year at Piedmont Technical College, Greenwood, SC. Beginning in August of 1981, he began full-time consulting activities. The consulting generally centered on software development, systems analysis and design, and training using microcomputers; previous clients include Computer Haven, FL Aerospace, Southern Bank, Greenwood County Association for Retarded Children, Abbeville Human Services Administrators Council, Harcourt Brace Jovanovich, Inc., and Greenwood School District 50. He returned to teaching as Adjunct Instructor in 1982 and Assistant Professor of Computer Science in 1983 at Lander College, Greenwood, SC. He currently continues as Associate Professor of Computer Science at Lander College and consulting on a part-time basis. He has chaired the Task Force on Computer Science

Teacher Certification in South Carolina, and has been a reader for the Advanced Placement Computer Science exam. He entered the Graduate School of the University of Texas in 1985.

Permanent address: 613 Salak Road, Greenwood, SC 29646

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