MOTIVATION AND PERFORMANCE IN COMPUTER SCIENCE:

TEST OF AN INTEGRATIVE THEORY

by

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ABSTRACT

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The purpose of this study was to design and empirically test a parsimonious integrative motivation theory. The theory integrates aspects of expectancy theory, social cognitive theory, goal-setting theory, and commitment theory. The theory was tested with 170 undergraduate students in an introductory computer science (CS) course.

The study tested relationships among the following variables: CS self-efficacy, mathematics ability, affective commitment to the CS class, goal orientation, effort, and performance. The study also tested the interactive effects of effort and ability on performance. Structural equation modeling was used to test the measurement model and a series of nested structural models. Findings supported the proposed integrative motivation theory and most of the hypothesized relationships. Future directions and contributions of this research are discussed.

This dissertation is dedicated to the loving man who kept me focused, gave me strength, and loved me unconditionally throughout the completion of this research.

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CHAPTER I

INTRODUCTION

Motivation is one of the most well researched topics in industrial/organizational psychology and educational psychology. These disciplines have produced numerous models of motivation with varying levels of empirical support. Several authors have created integrative theories of motivation (e.g., Locke, 1997; Meyer, Becker, and Vandenberghe, 2004), but they are highly complex and have rarely been tested empirically. This dissertation describes a parsimonious integrative theory of motivation and a research study designed to validate that theory.

Locke (1997) suggests that the motivation literature needs theoretical proliferation and theoretical integration. In understanding and predicting motivational processes in specific situations, *theoretical proliferation* is necessary because motivation is a complex human process that could never be fully explained by one theory. On the other hand, *theoretical integration* provides researchers with a broad foundation from which they can build a detailed model to fit their context. As researchers make new discoveries, integrative models of motivation should be adapted to fit new research findings. Because theoretical integration is important, I present an integrative theory of motivation below. I tested the validity of this theory using undergraduate students in a computer science class.

An Integrative Theory of Motivation

Motivation has been defined as "a set of energetic forces that originates both within as well as beyond an individual's being, to initiate work-related behavior, and to

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This dissertation adheres to the format of the *Journal of Applied Psychology*.

determine its form, direction, intensity and duration" (Pinder, 1998, p. 11). It focuses attention, produces effort, and results in persistence and behaviors aimed at reaching a particular goal (Mitchell & Daniels, 2003). Motivation has been a topic of study in the industrial/organizational psychology and educational psychology literatures for quite some time. Because of its extensive history, empirical results and theoretical models of motivation abound. Therefore, it is important for researchers in this area to use integrative motivation models.

Of all motivation theories, goal-setting theory (Locke, 1968) has the most potential for integrating other motivation theories (Pinder, 1998). Therefore, it is not surprising that Locke (1997) based his model of motivation on empirical findings in the goal-setting literature. Central constructs of Locke's model include: values/personality, self-efficacy, goal choice, goal and efficacy mediators, goal moderators, performance, and affective reactions (e.g., satisfaction, commitment). Much of Locke's model has received empirical support. Unfortunately, the model's complexity limits its use. Furthermore, newer models (e.g., Meyer et al., 2004) incorporate key components missing from Locke's model and goal-setting theory, such as the emotional aspects of motivation (e.g., organizational commitment).

Using Locke's (1997) model as a foundation, Meyer and colleagues (2004) proposed a new integrative model of motivation. This model incorporates the commitment literature and includes four new concepts: goal orientation or regulation, commitment to social foci, goal commitment, and the bases for commitment. This model is important because it provides a more thorough understanding of commitment and motivation. However, the model is difficult to test because it accounts for two complex human processes and the interplay between them.

In an effort to simplify the motivation literature further, I created an integrative theory of motivation with illustrative examples of variables for each construct (see Figure 1). This theory is designed to provide a testable sequence of factors involved in the motivation process. Each box in the model represents a category of motivation-relevant constructs. Variables within each category may also be related to one another. The proposed relationships between these general categories serve as a guide for testing motivation in any research setting.

In the following section, I briefly describe my integrative theory of motivation. A comprehensive discussion of the literature used to create the theory is beyond the scope of this paper (for reviews see Covington, 2000; Donovan, 2001; Eccles & Wigfield, 2002; Latham & Pinder, 2005; Maehr & Meyer, 1997; Mitchell & Daniels, 2003). Therefore, a broad description of the theory and its supporting evidence is presented next. Then, I provide a detailed discussion of the empirical findings related to the variables used in my dissertation.

Primary Motivators

The left-most category in the proposed integrative model, primary motivators, includes any construct that is central to the individual or is related to self-evaluation. It combines three antecedents from Locke's (1997) integrative model: needs, values/personality, and self-efficacy. Needs-based theories are among the earliest motivation theories (Mitchell & Daniels, 2003). Such theories include Maslow's hierarchy of needs, Alderfer's existence-relatedness-growth (ERG) theory, Herzberg's

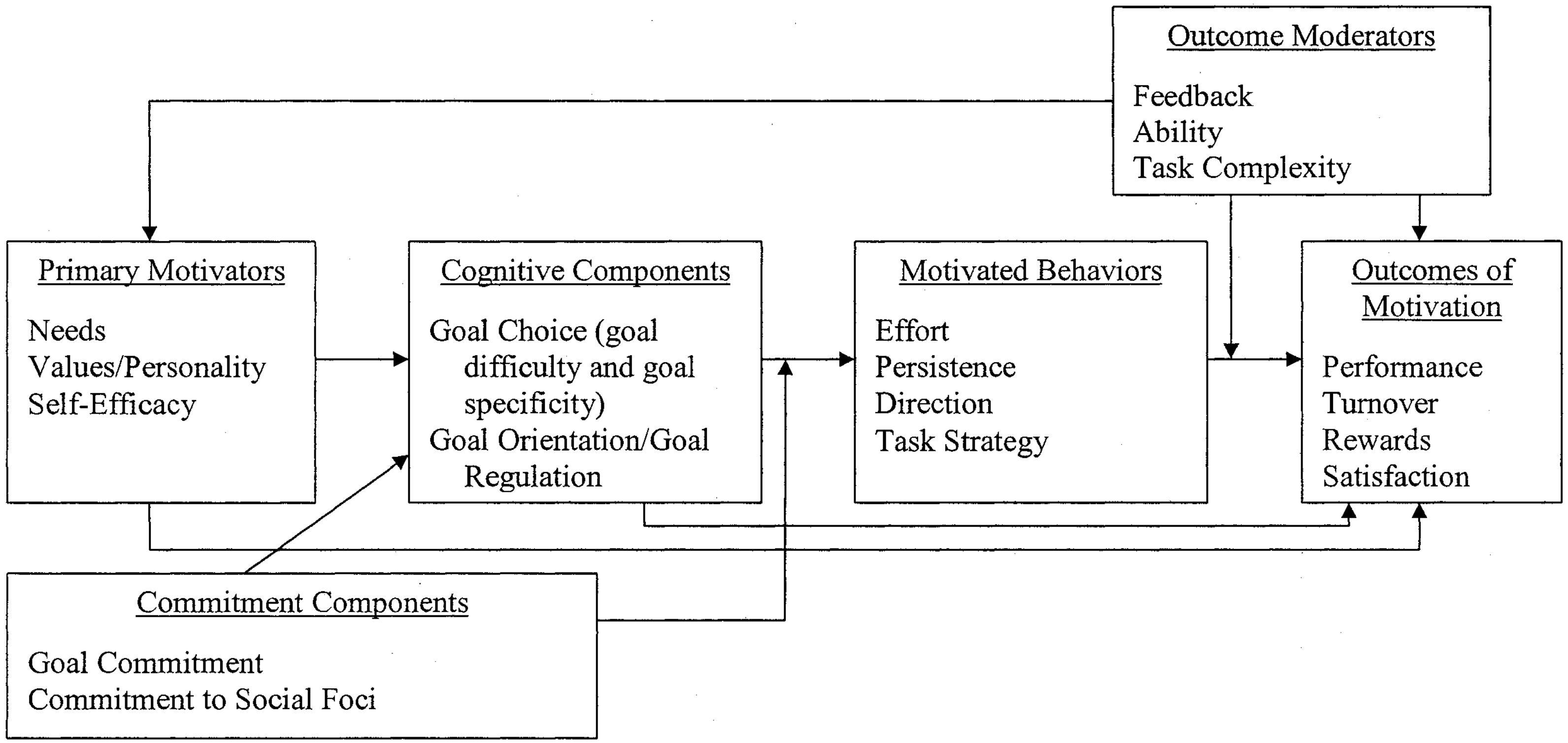

Figure 1. Integrative theory of motivation

two-factor theory (Steers, Porter, & Bigley, 1996), and McClelland's (1961) learned needs. More recently, traits (e.g., personality) and constructs related to self-evaluation (e.g., self-efficacy) are garnering attention from researchers (e.g., Phillips & Gully, 1997; Robbins et al., 2004; Schunk, 1991).

Locke's model suggests relationships among the variables within this category. For example, needs are related to values, and values/personality are related to self-efficacy. Researchers have found consistently that personality, primarily conscientiousness (Barrick & Mount, 1991; Schmidt & Hunter, 1998) and extraversion (Barrick & Mount, 1991), are related to performance. In addition, the four traits that comprise core self-evaluations (i.e., self-esteem, generalized self-efficacy, internal locus of control, and emotional stability) have high estimated true correlations with job performance (Judge & Bono, 2001). Furthermore, meta-analytic results show that achievement motivation, as defined as "the drive to strive for success and excellence" (Robbins et al., 2004, p. 267) has an estimated true correlation of .30 with college GPA. My model proposes that these relationships with performance occur through important cognitive components (e.g., goal orientation) and motivated behaviors (e.g., effort).

Cognitive Components

Cognitive components are those aspects of motivation that require conscious thought on the part of the individual. Therefore, constructs related to goal-setting are represented in this category. Goal-setting theory has been tested in different settings (laboratory, simulation, and organizations), with a variety of research designs (quasi-experimental, experimental, and correlational), in at least eight countries, and at multiple levels of analysis (individual, group, organizational unit, and entire organization). Such broad testing supports the generalizability of the theory (Locke & Latham, 2002).

The basis of goal-setting theory is that "most of human behavior is the result of a person's consciously chosen goals and intentions" (Mitchell & Daniels, 2003, p.231). A goal can be defined as "the object or aim of an action" (Locke & Latham, 2002, p. 705) or "something that a person tries to attain, achieve, or accomplish" (Pinder, 1998, p. 368). For the most part, research has confirmed the propositions of goal-setting theory and supported the effectiveness of goal-setting in work and academic settings. For example, Robbins and colleagues (2004) examined the relationship between academic goals and college GPA and between academic goals and retention, finding estimated true correlations of .18 and .34, respectively.

Figure 1 shows two example cognitive components: goal choice and goal orientation/goal regulation. "Goal choice" refers to goal difficulty and specificity (Locke, 1997). Goal orientation refers to the focus of individuals' goals, i.e., whether their goals are learning focused or performance focused (Dweck & Leggett, 1988). Goal orientation (see Dweck & Leggett, 1988) and goal regulation (see Deci & Ryan, 1985) are similar constructs and fit equally well into this category of the integrative theory (Meyer et al., 2004).

My integrative theory of motivation shows that the primary motivators are antecedents of the cognitive components. Empirical research supports this belief. Self-esteem (Levy & Baumgardner, 1991) and self-efficacy (Locke & Latham, 1990) are positively related to goal difficulty. In addition, Elliot and Church (1997) found that need for achievement was related to students' goal orientations. Zweig and Webster (2004) found that the big five personality variables were also related to goal orientation among undergraduates.

In turn, the cognitive components are proposed to influence motivated behaviors such as effort and task strategy. In a study of group processes, Weingart (1992) supported this proposed relationship, finding that goal difficulty was related to effort. In addition, Fisher and Ford (1998) found goal orientation was related to persistence and the use of a learning strategy. Ames and Archer (1988) also found a relationship between goal orientation and the use of learning strategies. Therefore, it follows that goal orientation and goal choice are key cognitive components that mediate the effects of the primary motivators on motivated behaviors.

The Link between Motivated Behaviors and Outcomes of Motivation

Motivated behaviors refer to behaviors that individuals use to produce an outcome. Locke (1997) refers to these behaviors as goal and efficacy mechanisms (mediators); they include effort, persistence, direction, and task strategy. The final central link in the proposed integrative theory suggests that these motivated behaviors predict various outcomes of motivation, primarily performance. For example, research has shown that effort (Fisher & Ford, 1998; VandeWalle, Cron, & Slocum, 2001) and effective learning strategies (Fisher & Ford, 1998) are positively related to test performance.

The variables within the outcomes category can also be related to each other. For example, research has demonstrated a significant relationship between job satisfaction and performance (Judge, Thoresen, Bono, & Patton, 2001).

Commitment Components

Commitment components include the affective influence of commitment on the motivation process. The first commitment component identified in my integrative theory is goal commitment. Meta-analytic results reported by Donovan and Radosevich (1998) suggest that goal commitment has a minimal moderating effect on the goal difficulty-performance relationship (R^2 = .03, Adj. R^2 = .02). However, Klein, Wesson, Hollenbeck, and Alge (1999) used a different approach to test for moderation, which allowed them to include many more studies in their meta-analysis. This second meta-analysis provided strong support for the moderated effects: the relationship between goal commitment and performance was significantly stronger for difficult goals (corrected r = .35) than for moderate (corrected r = .20) and low (corrected r = .18) goals (Klein et al., 1999). Consistent with these findings, the integrative theory proposes that goal commitment moderates the goal difficulty-motivated behaviors relationship. In figure 1, such moderating effects are depicted with an arrow pointing to a line.

The second commitment component is commitment to social foci. Meyer and colleagues (2004) conceptualized commitment as being directed toward social foci (targets), such as the organization, supervisors, or the team. Consistent with their theory, my integrative theory suggests that commitment to social foci predicts goal orientation. The details of this relationship are discussed later.

Outcome Moderators

The final category in the integrative theory of motivation refers to the goal moderators proposed by Locke (1997): feedback, ability, and task complexity. Research shows that feedback (Locke, Shaw, Saari, & Latham, 1981), ability (Phillips & Gully, 1997), and task complexity (Wood, Mento, & Locke, 1987) moderate the relationship between the motivated behaviors and outcomes of motivation (e.g., performance). These variables also have direct effects on some of the primary motivators, namely the self-evaluation constructs. Previous research suggests that both feedback (VandeWalle et al., 2000) and ability (Phillips & Gully, 1997; Thomas & Mathieu, 1994) influence self-efficacy.

Empirically Testing the Integrative Theory of Motivation

The proposed integrative theory is intended to be a heuristic for understanding the influence of motivation. To test the theory, I selected variables from the model's categories that were expected to be most relevant in my research setting—university students in computer science—and examined the relationships among them. Many researchers have argued for the value of using college students to study work-related processes (e.g., Campbell, 1986; Greenberg, 1987, Locke, 1986). In fact, Locke (1986) argues that similarities between students and employees are greater than their differences.

I chose the following setting-relevant variables to test the integrative theory: computer science (CS) self-efficacy, goal orientation, affective commitment to the CS class, effort, Scholastic Aptitude Test (SAT) math score, and course grade. Figure 2 displays these variables and how they fit into the integrative theory. The relationships depicted in the integrative theory represent potential relationships between constructs that fall into each component category. However, researchers using the integrative theory must consider which relationships are appropriate given the variables they choose to study. For example, a researcher who chooses to study goal commitment will need to test the moderating effect of this variable on the cognitive components-motivated behaviors

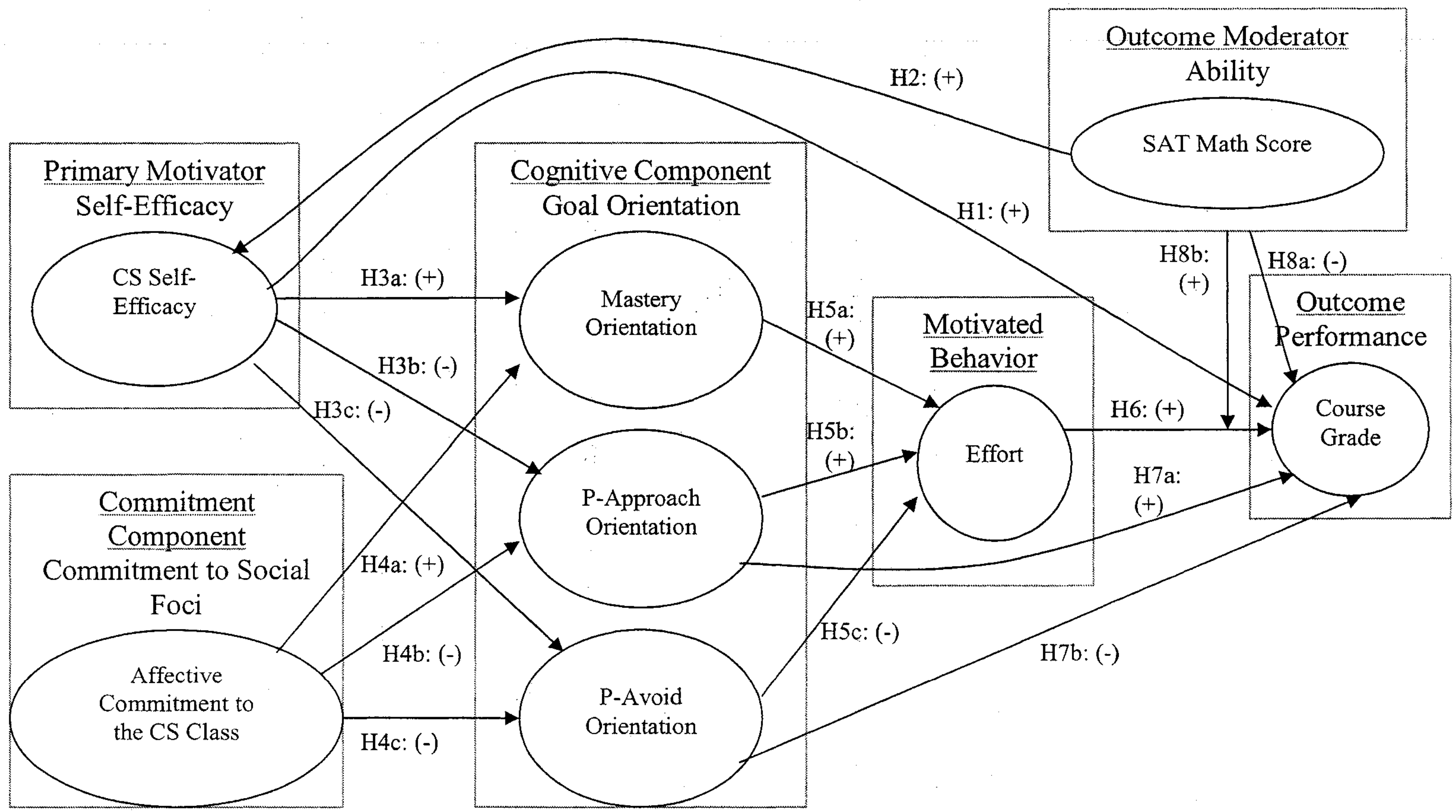

Figure 2. Hypothesized model used to test the integrative theory of motivation

relationship. On the other hand, I chose to study commitment to social foci. Therefore, the relationship of interest in my study is the direct relationship between commitment and goal orientation (the cognitive component in my study). In addition, research suggests that self-efficacy (the primary motivator in this study) has a direct relationship with performance (the outcome of motivation in this study). Therefore, I have included this direct relationship in my hypothesized model (Figure 2). However, some primary motivators may not have direct relationships with particular outcomes of motivation.

In Figure 2, the boxes represent the categories of the integrative theory (the name of each category is underlined). I list the construct I chose to study under each category name. Each construct was operationalized by a particular variable (represented by ovals in Figure 2). The lines between ovals represent the hypothesized relationships that were tested in this study. Below, I support these hypothesized relationships based on the extant literature.

Model Antecedents

Self-efficacy. Self-efficacy is defined as "beliefs in one's capabilities to mobilize the motivation, cognitive resources, and courses of action needed to meet given situational demands" (Wood & Bandura, 1989, p. 408). Social cognitive theory suggests that behavior is self-regulated, in part, through reactions to goal attainment or failure and self-efficacy (Latham & Pinder, 2005). Self-efficacy is the most researched component of social cognitive theory (Donovan, 2001). Meta-analytic research in industrial/organizational psychology reveals a positive relationship between self-efficacy and performance (.23 estimated true correlation; Judge & Bono, 2001). Educational research has also supported this relationship. For instance, Robbins et al. (2004) found self-efficacy to be related to college GPA and retention (estimated true correlations: .50 and .36, respectively). Bandura, Barbaranelli, Caprara, and Pastorelli (2001) also found that high academic self-efficacy was related to performance, course enrollment, and academic aspirations among 11-15 year olds. My integrative theory suggests that cognitive components and motivated behaviors mediate the self-efficacy-performance relationship. Studies have supported this assertion (for examples see Bandura, 1997, Locke & Latham,1990, and Wofford, Goodwin, & Premack, 1992). However, empirical findings also support a positive direct relationship between self-efficacy and performance (Breland & Donovan, 2005; Phillips & Gully, 1997; VandeWalle et al., 2001). Given previous findings, I expected the following result:

Hypothesis 1: CS self-efficacy will have a positive, direct relationship with course grade.

Previous research also supports a direct link between ability and self-efficacy among undergraduates even when self-set goals are included in the model (Phillips & Gully, 1997; Thomas & Mathieu, 1994). These findings suggest that ability will predict beliefs regarding capabilities in a related area. I represented ability with the math portion of the SAT because previous research suggests that math knowledge is a good predictor of computer science ability and performance (Butcher & Muth, 1985; Wilson & Shrock, 2001). This reasoning led to the following hypothesis:

Hypothesis 2: Mathematics ability will be positively related to CS self-efficacy.

Commitment to social foci. There are three types of commitment: 1) affective commitment, or "an emotional attachment to, identification with, and involvement in the organization;" 2) continuance commitment, or "the perceived costs associated with leaving the organization;" and 3) normative commitment, or "a perceived obligation to remain in the organization" (Meyer, Stanley, Herscovitch, & Topolnytsky, 2002, p. 21). Meta-analytic findings demonstrate that commitment is related to various outcomes, such as job satisfaction, turnover, and job performance. For each outcome, the relationship is strongest for affective commitment (Meyer et al., 2002). Meyer and colleagues (2004) proposed that commitment leads to performance through its influence on goal regulation/orientation. They referred to commitment as being directed toward social foci (targets), such as the organization, supervisors, or the team. In the hypothesized model (Figure 2), affective commitment to the CS class represents the commitment component.

Mediating Variable—Goal Orientation

The cognitive component I chose to include in the study was goal orientation. Goal orientation theory suggests that individuals have implicit theories that orient them toward a particular type of goal (Dweck & Leggett, 1988). A student with mastery goals (also called learning goals and task goals) is concerned with effort, improvement, and personal learning and growth. Conversely, performance goals (also called ego goals, ability goals, and relative-ability goals) focus on performance in comparison to others (Elliott, Hurton, Anderman, & Illushin, 2000). Researchers have identified two types of performance goals. Performance-approach goals are related to one demonstrating his/her ability in comparison to others. Performance-avoid goals are related to one trying to avoid looking unintelligent relative to others (Elliott et al., 2000). The integrative theory suggests there are two antecedents of goal orientation: self-efficacy and commitment to social foci. Theoretical and empirical support for these relationships is discussed next.

Self-efficacy and goal orientation. Studies have demonstrated that goal orientation is related to need for achievement (Elliot & Church, 1997) and personality (Zweig & Webster, 2004), but there are fewer studies connecting self-efficacy to goal orientation. Previous researchers (e.g., Phillips & Gully, 1997; VandeWalle et al., 2001) who have studied the self-efficacy-goal orientation relationship have examined the inverse of the proposed relationship (i.e., the influence of goal orientation on self-efficacy). However, examining the effects of self-efficacy on goal orientation is more appropriate given my research setting. Revisiting Kanfer's (1990) logic regarding goals, self-regulation, and performance explains why I believe this to be true.

Kanfer (1990) explained that "self-observation of one's effort and performance during task engagement provides information used to make inferences about ability" (p. 227). Individuals examine their performance and, if it is lower than the performance standard (indicating a performance discrepancy), they attribute their less than adequate performance to different things depending on their goal orientation. For example, individuals may be

> "…dissatisfied with their performance and their self-efficacy expectations decline. In addition, the attribution of the discrepancy as due to low ability appears to divert attention away from the task and toward off-task emotional processing (e.g., worry). Diminished self-efficacy reduces self-set goal difficulty levels, thereby decreasing effort devoted to the task" (Kanfer, 1990, p. 227).

Kanfer suggested that individuals with a mastery orientation focus on increasing their ability. Therefore, a performance discrepancy does not decrease their self-efficacy because they attribute the discrepancy to inadequate effort; a discrepancy leads these people to expend greater effort and maintain their previous goal levels. On the other hand, individuals with a performance goal orientation and low self-efficacy attribute poor performance to low ability, leading to goal abandonment and decreased interest in the task. For individuals with a performance goal orientation and high self-efficacy, performance has less of an effect on subsequent goal setting, i.e., these individuals maintain similar goal levels. These individuals may attribute the performance discrepancy to the situation, causing them to maintain their previous behaviors. Also, it may be that performance goals put a ceiling on how much these individuals' self-efficacy can increase, preventing them from increasing subsequent goal levels. Researchers who have tested the effect of goal orientation on self-efficacy were examining the first part of Kanfer's theory: how the goal orientations differentially influence self-efficacy.

Because students in this sample were enrolled in their first computer science class and we distributed the survey toward the end of the semester, it was more appropriate to examine the inverse of this relationship. Self-efficacy was assessed after students had received feedback on at least one exam and multiple programming assignments. At this point, their CS self-efficacy had been affected by their previous performance in this class and their performance attributions. I measured the effects of these new ability judgments on subsequent goal orientation. Therefore, individuals with higher CS self-efficacy should be more likely to have a mastery goal orientation than a performance goal orientation. This suggestion is represented with the following hypothesis:

Hypothesis 3: CS self-efficacy will be positively related to mastery orientation (Hypothesis 3a), negatively related to performance-approach orientation (Hypothesis 3b), and negatively related to performance-avoid orientation (Hypothesis 3c).

Commitment to social foci and goal orientation. In this study, I examined only affective commitment because it tends to be the commitment dimension that yields the largest relationships with other variables (Meyer et al., 2002). Consistent with Meyer et al. (2004), I propose that commitment toward social foci will influence corresponding goal orientations. That is, the primary bases for developing affective commitment are personal involvement and identification with the target as well as shared values with the target. Therefore, employees with high affective commitment to a target can be expected to have an ideal goal orientation (mastery orientation) toward that target. The social focus for this research setting is the participants' CS class. Therefore, students with high affective commitment to the CS class can be expected to have a mastery orientation toward that class. On the other hand, students with low affective commitment to the CS class are expected to have a performance orientation (possibly setting goals to do fairly well in comparison to others and to avoid looking unintelligent). These propositions lead to the following hypothesis:

Hypothesis 4: Affective commitment to the CS class will be positively related to mastery orientation (Hypothesis 4a), negatively related to performance-approach orientation (Hypothesis 4b), and negatively related to performance-avoid orientation (Hypothesis 4c).

Consequences of Goal Orientation

My integrative theory of motivation proposes that goal orientation is related to motivated behaviors such as effort. VandeWalle and colleagues (2001) found that mastery and performance-approach orientation were positively related to effort (measured by averaging self-assessments of amount of time, work intensity, and overall effort devoted to preparing for an exam). Performance-avoid orientation had a negative but non-significant relationship with effort. However, this result could be a function of the form of measurement used in their study, which combined three types of effort into one variable. Therefore, I tested this relationship by using just one of these dimensions—quantity of effort expended for the class. The corresponding hypothesis follows.

Hypothesis 5: Mastery orientation (Hypothesis 5a) and performance-approach orientation (Hypothesis 5b) will be positively related to effort, whereas performance-avoid orientation will be negatively related to effort (Hypothesis 5c).

Consistent with previous empirical results (Fisher & Ford, 1998; VandeWalle et al., 2001), higher levels of effort should, in turn, predict better performance. Therefore, I made the following hypothesis:

Hypothesis 6: Effort will be positively related to course grade.

Hypotheses 5 and 6 suggest that the goal orientation-performance relationship is mediated by effort. However, I also expected goal orientation to be directly related to performance, suggesting that effort is a partial mediator. Research has shown that performance-approach goals and performance-avoid goals are differentially related to undergraduates' exam grades (Elliot, McGregor, & Gable, 1999), final course grades, and GPA (Harackiewicz, Barron, Tauer, & Elliot, 2002). Performance approach goals are positively related, whereas performance-avoid goals are negatively related, to these outcomes (Elliot et al., 1999; Harackiewicz et al. 2002). Conversely, research has shown mixed results regarding the mastery orientation-performance relationship. Harackiewicz et al. (2002) found a non-significant relationship between mastery goals and college grades. However, Fisher and Ford (1998) found a significant positive relationship between mastery goals and performance. Fisher and Ford measured performance with a multiple choice test in a lab setting, whereas Harackiewicz and colleagues operationalized performance as the final course grade in a field setting. Because the Harackiewicz et al. study is more consistent with my study, I expected mastery orientation to be unrelated to course grade; thus, it is excluded from Hypothesis 7.

Hypothesis 7: Performance-approach orientation will have a direct, positive relationship with course grade (Hypothesis 7a) and performance-avoid orientation will have a direct, negative relationship with course grade (Hypothesis 7b).

The Role of Ability

Ability is clearly related to performance. Phillips and Gully (1997) found that ability influenced performance in two ways: 1) directly and 2) indirectly through its significant influence on self-efficacy. These relationships are represented in the hypothesized model, but I also propose that ability will moderate the motivated behaviors-outcomes relationship. Vroom (1964) originally conceptualized this relationship (Performance = f[Ability X Motivation]) based on limited empirical evidence. He suggested that when ability is low, increasing motivation will result in smaller increases in performance than when ability is high. Motivation and effort have often been confounded by researchers considering the two constructs to be equivalent (Brown & Peterson, 1994). However, few researchers have directly measured effort (Yeo & Neal, 2004); even fewer have tested the ability-effort interaction. Yeo and Neal (2004) tested the three-way interaction of ability, effort, and practice on performance. Holding practice constant, their results showed no significant relationship between effort and performance for low ability participants. However, for high ability participants, performance significantly increased as effort increased (Yeo & Neal, 2004). That is, increased effort did not compensate for very low ability. However, extra effort led to an increase in performance when ability was high. This discussion leads to the following hypothesis:

Hypothesis 8: Mathematics ability will affect performance directly as well as through a moderating relationship with effort: ability will have a direct positive relationship with course grade (Hypothesis 8a); ability will moderate the effort-performance relationship (Hypothesis 8b) such that the effort-performance relationship will be stronger for high ability individuals than it will be for low ability individuals (also displayed in Figure 3).

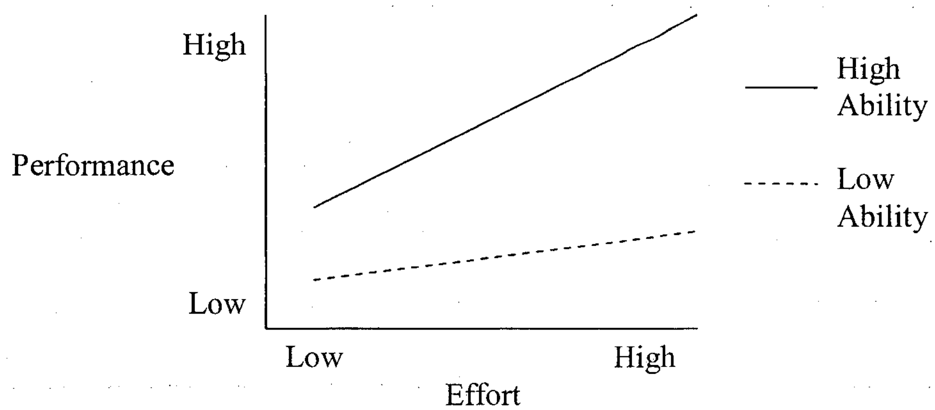

Figure 3. The expected ability-effort interaction effect on performance

CHAPTER II

METHOD

This study was part of a larger study funded by the National Science Foundation (NSF) called Increasing Success in Information Technology Education (INSITE). This project is testing a longitudinal intervention with the computer science (CS) departments at two universities in the Southeast. The project is designed to enhance inclusiveness for women and minority students by simultaneously addressing change in faculty and students, thus resulting in an increase in the retention of women and minority CS majors at the two institutions. Design of my study and selection of my measures was constrained by the need to fit my research into the larger study.

Participants

Participants in this study were chosen from the INSITE pool of participants. They were undergraduate students from one of the universities involved in the INSITE study and were enrolled in Introduction to Programming (the first programming course in the CS curriculum). The course instructor is a participant in the INSITE project so all students in that particular class were invited to participate in the study ($N = 223$). We received responses from 170 of these students (response rate = 76.2%). The instructor provided extra credit to students for their participation.

The respondents are predominantly mechanical engineering (24.1%), CS (22.9%), and civil engineering (15.3%) majors. Just over half of the sample is employed in addition to being a student (55.9%), 80.4% of whom are employed part-time (i.e., work under 26 hours per week). Participants represent the following races/ethnicities: White

(63.7%), Black/African American (20.8%), Asian/Pacific Islander (11.9%), Hispanic (1.8%), American Indian/Alaskan Native (1.2%), and Middle Eastern (0.6%). The majority of the sample is male (86.3%). On average, participants are 20.9 (*SD* = 4.63) years old. Table 1 presents demographic information for the full sample (*N* = 170) and the smaller portion of the sample with which the analyses were completed (*N* = 116).

Measures

All measures were context specific and each scale used the same referent: the class. A complete item list is provided in Appendix A.

Effort. This measure was created for this study. Students responded to three items (e.g., I exert a great deal of effort on assignments for this class) on a five-point agreement-type scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The coefficient alpha for this scale was .89.

SAT math score and course grade. Both SAT math score and course grade were obtained from the university's Office of Institutional Research. SAT math score was used as a raw score. The College Board reports that the reliability of the math portion of the SAT ranges from .91 to .93 (College Board, 2005). Therefore, reliability of the SAT math variable was set at .92 in the measurement and structural models. The Office of Institutional Research provides letter grades for final course grades. These letter grades were recoded into the following numeric values: F = 0, D- = 1, D = 2, D+ = 3, C- = 4, C = 5, C+ = 6, B- = 7, B = 8, B+ = 9, A- = 10, and A = 11. Course grade reliability was set at .95. Although course grade should have no measurement error, I chose the value of .95 to allow for potential transcription errors.

CS self-efficacy. This scale was taken from the Confidence in Learning CS subscale of the Computer Science Attitude Survey (Williams, Wiebe, Yang, Ferzli, & Miller, 2002). The negatively worded items from the original scale were not used in this

Table 1

Demographic Characteristics of the Sample

	Full Sample (*N* = 170)		Analyzed Sample (*N* = 116)	
Characteristic	*N*	%	*N*	%
Major				
Civil Engineering	26	15.29	15	12.93
Civil Engineering Technology	2	1.18	1	.86
Computer Engineering	9	5.29	7	6.03
Computer Engineering Technology	11	6.47	9	7.76
Computer Science	39	22.94	29	25.00
Electrical Engineering	16	9.41	11	9.48
Electrical Engineering Technology	1	.59	0	0
Environmental Engineering	3	1.76	1	.86
Mathematics or Physics	14	8.23	7	6.04
Mechanical Engineering	41	24.12	29	25.00
Political Science or Decision Sciences	2	1.18	2	1.18
Undecided	6	3.53	5	4.31
Employment Status				
Employed	95	55.88	61	52.59
Not employed	75	44.12	55	47.41
Race				
Black/African American	35	20.59	23	19.83
American Indian/Alaskan Native	2	1.18	1	.86
Asian/Pacific Islander	20	11.76	12	10.34
Hispanic	3	1.76	3	2.59
Middle Eastern	1	.59	0	0
White	107	62.94	76	65.52
Race not specified	2	1.18	1	.86
Gender				
Males	145	85.29	98	84.48
Females	23	13.53	18	15.52
Gender not specified	2	1.18	0	0

study because the negatively worded items merely repeated the positively worded items. Furthermore, a pilot study showed that removal of such items did not adversely affect reliability estimates. Students responded to six items (e.g., I have a lot of self-confidence when it comes to programming) on a five-point agreement-type scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The coefficient alpha for this scale was .90.

Affective commitment to the CS class. This scale was adapted and shortened from the Meyer, Allen, and Smith (1993) measure of occupational commitment. Items were adapted to assess students' commitment to the CS class rather than employees' commitment to their occupations. Students responded to three items (e.g., I am enthusiastic about this computer science class) on a seven-point agreement-type scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). The coefficient alpha for this scale was .89.

Goal orientation. This scale was assessed using items developed by Elliot and Church (1997). The goal orientation scale was comprised of 3 subscales: mastery, performance-approach, and performance-avoid goal orientation. Students responded to six items for each subscale on a seven-point agreement-type scale ranging from 1 (*not at all true of me*) to 7 (*very true of me*). Example items include: I want to learn as much as possible from this class (mastery orientation); it is important to me to do better than the other students (performance-approach orientation); I worry about the possibility of getting a bad grade in this class (performance-avoid orientation). The coefficient alphas for each subscale were .82 (mastery), .87 (performance-approach), and .77 (performance-avoid).

Procedure

As part of the overall INSITE project, the participating instructor provided the INSITE research team with students' email addresses. The researchers sent email invitations to every student asking them to participate in an online survey and sent weekly reminder emails to all potential participants (see Appendix B). The initial invitation contained a link to the survey. The first page of the survey gave a description of the project and instructions for completing the survey (see Appendix C). The survey was active for approximately five weeks. Participants received extra credit for completing the survey. At the end of the survey, a confirmation page appeared where participants were asked to enter their name, the CS course for which they were completing the survey, and their CS instructor's name. They were then instructed to print this page and turn it in to their instructor to receive extra credit for completing the survey.

Data Analysis Overview

Structural equation modeling (SEM) was used to test the hypothesized relationships and the overall fit of the hypothesized model. This data analytic strategy required the use of a parceling procedure to create indicators for the variables in the model and the Jöreskog-Yang (1996) procedure for testing the proposed interaction. In addition, I used a measurement model, structural model, and the resulting fit indices to examine the hypothesized model and relationships. Each of these aspects of the data analysis is described next.

Parceling. Parceling, an increasingly common practice in structural equation modeling (SEM), is a procedure in which item scores from two or more items are summed or averaged. Then, these composite scores are used as indicators (or manifest variables) in the SEM analysis in lieu of the directly observed item scores (Bandalos, 2002). Research suggests that parceling can have several beneficial effects on SEM results when used for items from unidimensional scales. The use of parcels, compared to the use of individual items, results in fewer model rejections, especially for sample sizes between 100 and 250, and better fit indices (specifically, the root mean squared error of approximation, comparative fit index, and chi-square test; Bandalos, 2002). These favorable effects occur, in part, because individual items tend to have more psychometric problems than parceled data, including lower reliability, lower communality, a smaller ratio of common-to-unique factor variance, greater likelihood of non-normal distributions, and fewer, larger, and less equal intervals between scale points (Little, Cunningham, Shahar, & Widaman, 2002). Furthermore, models based on parcels are more parsimonious, have fewer chances for residuals to be correlated or complex loadings to emerge, and lead to reductions in various sources of sampling error over models based on item-level data (Little et al., 2002).

In this study, scales containing three items (effort and affective commitment to the CS class) were not parceled and scales containing six items (CS self-efficacy, mastery orientation, performance-approach orientation, and performance-avoid orientation) were parceled. To justify parceling, maximum likelihood exploratory factor analyses were first conducted. Results of these analyses confirmed that each scale was unidimensional, supporting the appropriateness of the parceling procedure (Bandalos, 2002).

I used the congeneric method for creating parcels, which involves grouping items with more similar factor loadings into the same parcel. This procedure uses the standardized loadings provided by the completely standardized solution of a confirmatory factor analysis (Fletcher, 2005). In this study, each scale that was indicated by parcels consisted of six items. Therefore, I created parcels by grouping the two highest loading items into parcel 1, the next two highest loading items into parcel 2, and the two lowest loading items into parcel 3. Results of these confirmatory factor analyses and parcel assignments are provided in Appendix D. Simulation research suggests that the congeneric method is the most appropriate parceling strategy when using the Jöreskog and Yang (1996) procedure for testing interactions in SEM (Fletcher, 2005).

Jöreskog-Yang procedure. Jöreskog and Yang (1996) describe how to evaluate a latent variable interaction using LISREL 8. With their method, the indicators for the latent variables involved in the interaction are mean centered. Furthermore, they use one product indicator for identifying the latent interaction variable (i.e., the multiplication of the strongest indicators for each element of the interaction).

In this study, the two elements of the interaction are mathematics ability (indicated by the SAT math score item) and effort (indicated by 3 self-report items). The effort item with the strongest loading on the effort latent variable was item 1 (see Appendix A for item wording). Therefore, I computed a new variable (named "EFF1SAT") by multiplying effort item 1 and SAT score. *EFF1SAT* then served as the indicator for the latent interaction variable. Because the interaction term is made up of other variables in the model, several constraints for estimating the interaction term are required. Jöreskog and Yang (1996) describe these constraints and why they are necessary.

In addition, because two latent variables in the model (SAT score and grade) had just one indicator, I set the measurement error of those two indicators using the following formula: measurement error = variance*(1-reliability; see Allen & Yen, 1979). The SAT score reliability was set at .92. Course grade reliability was set at .95. To help clarify this procedure, Figure 4 shows the LISREL structural model for the interaction portion of the hypothesized model.

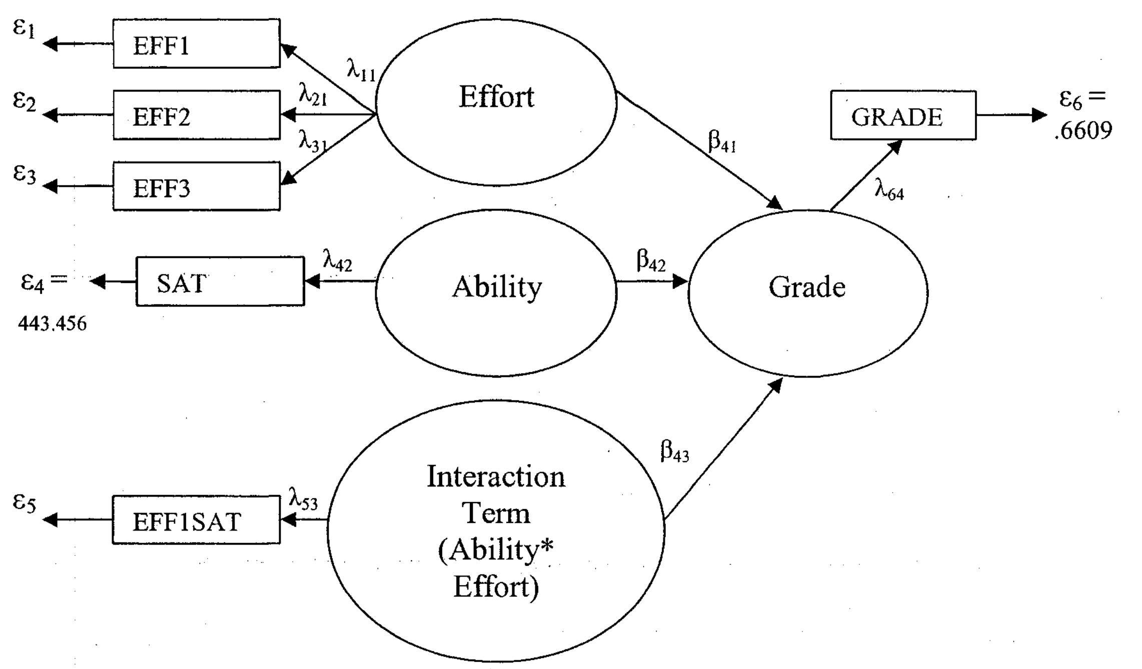

Figure 4. Interaction only model

Sample syntax for testing the model displayed in Figure 4 is provided in Appendix E. This syntax was adapted from Jöreskog and Yang (1996) to test the model from the y-side. Testing a model from the y-side is a technique that allows the researcher to more easily make adjustments to the syntax. LISREL treats all manifest variables in a y-side model as endogenous. Therefore, only one set of matrices is needed (e.g., only a lambda-y matrix is used rather than lambda-x and lambda-y matrices), which allows the researcher to fix and free different parameters with greater ease (Jöreskog & Sörbom, 1996). Because I used a nested model procedure to test the hypothesized model (see "nested model" section below), which meant I would have to change the syntax several times, it was most practical to write the syntax from the y-side.

Measurement model. I used LISREL 8.71 to test the hypothesized measurement model. The measurement model represents the regression of each indicator on its corresponding latent variable. The partial regression coefficients of the latent variables are provided in the lambda-x (Λ_x) matrix (Jöreskog & Sörbom, 1996). Previous research suggests that the measurement model should be tested prior to simultaneously testing the measurement model and structural model (Anderson & Gerbing, 1988). A maximum likelihood estimation method was used to test goodness of fit of the measurement model (Jöreskog & Sörbom, 1996).

Structural model. I used LISREL 8.71 to test the hypothesized structural model displayed in Figure 2. LISREL structural models involve manifest variables, latent variables, and error variances, allowing one to estimate relationships among latent variables while accounting for measurement error of those variables. Furthermore, LISREL provides regression coefficients for each hypothesized relationship among latent variables (i.e., parameter estimates) as well as estimates of the goodness of fit of the structural model (Jöreskog & Sörbom, 1996). The significance level of each parameter estimate is determined using a *t*-test. When a parameter estimate has a *t*-value greater than 2.00, the relationship is considered significant at $p < .05$. A maximum likelihood estimation method was used to test goodness of fit of the structural model (Jöreskog &

Sörbom, 1996). To further assess model fit, I examined several goodness of fit indices.

Fit indices. The chi-square (χ^2) test is the traditional overall fit test. It assesses the extent to which the sample and the fitted covariance matrix are discrepant (Hu & Bentler, 1995). Because the χ^2 test is actually a "badness of fit" test, smaller χ^2 values and a non-significant χ^2 test indicate a good fitting model (Hoyle, 1995). In addition, the χ^2 test can be evaluated by examining its value relative to the available degrees of freedom for the test (Hoyle, 1995). A model is considered to be a good fit when the ratio of the χ^2 to degrees of freedom is less than 2 (Tabachnick & Fidell, 2001).

I used three additional fit indices to assess model fit: the root mean square error of approximation (RMSEA), the non-normed fit index (NNFI), and the comparative fit index (CFI). RMSEA values less than or equal to .05 indicate a close fitting model; RMSEA values less than or equal to .08 indicate a reasonably well-fitting model (Browne & Cudeck, 1993). NNFI (Tucker & Lewis, 1973) and CFI (Bentler, 1990) values of .90 or greater suggest a good model fit. The NNFI and CFI have been shown to be unbiased estimators in small samples when using the maximum likelihood method (Hu & Bentler, 1995). Given the sample size in this study ($N = 116$), it was most appropriate to examine these fit indices.

Nested models. Experts in the area of structural equation modeling agree that it is better to examine multiple alternative models than a single model. Comparing models allows researchers "to determine the model with the best fit, rather than attempt to assess a single model's fit in some absolute sense" (Bollen & Long, 1993). I used three nested structural models (i.e., models that "contain the same parameters but the set of free parameters in one model is a subset of the free parameters in the other;" Hoyle, 1995, p.

8) to lend support to the proposed integrative theory. That is, a baseline model was tested in which the mediating effects of CS self-efficacy and goal orientation were not estimated. Then, a mediation model was tested in which the mediating effects were estimated. Finally, an interaction model was tested in which the mediating effects and the hypothesized interaction effect were estimated. The idea is that, as the model gets closer to the hypothesized model, the integrative theory is increasingly supported. The preferred way to choose among nested models is to conduct χ^2-difference tests (Hoyle & Panter, 1995). That is, one takes the difference between the resulting χ^2 and degrees of freedom for each nested model and determines whether the change in χ^2 ($\Delta\chi^2$) is significant given the change in degrees of freedom (Δdf).

CHAPTER III

RESULTS

Demographic Analysis

Using the full sample ($N = 170$), I examined differences between demographic groups on the study variables using one-way analysis of variance (ANOVA). These findings are reported in Table 2. Results show that CS majors in the sample, compared to non-CS majors, had significantly higher course grades, CS self-efficacy, affective commitment to the CS class, and mastery goal orientation, and lower performance-avoid goal orientation. Employed students were significantly lower than non-employed students on ability, course grade, and CS self-efficacy scores, and significantly higher on performance-avoid goal orientation scores. Due to sample sizes, the race/ethnicity comparison only tested differences between Black/African American and White students. These analyses showed that Black/African American students had lower ability, course grade, and CS self-efficacy scores, and higher performance-avoid goal orientation scores. Analyses revealed no significant differences between males and females on the study variables.

Outlier Analysis

Prior to data analysis, I conducted an outlier analysis using box plots to identify potential outliers and/or participants who responded haphazardly. I found that 4 participants responded haphazardly. That is, these individuals had 5 or more "outlier" responses and had clearly responded to survey items inappropriately (e.g., responded with 1's to every survey item). These 4 cases were removed, resulting in a sample of 166

Table 2

Differences between Groups on Study Variables

	Major		Employment Status		Race/Ethnicity		Gender	
Variable	CS	Non-CS	Employed	Not Employed	Black/ African American	White	Male	Female
Effort								
M	3.67	3.63	3.68	3.59	3.78	3.55	3.57	3.98
SD	.85	.83	.78	.88	.71	.87	.83	.73
Ability (SAT)								
M	593.45	582.87	570.66*	602.00	532.61*	604.34	585.61	585.00
SD	76.26	74.10	66.80	79.50	71.87	66.52	75.04	73.26
Course Grade								
M	8.07*	5.70	5.23*	7.47	4.17*	7.03	6.20	6.78
SD	3.65	3.45	3.78	3.09	3.37	3.54	3.67	3.51
CS Self-Efficacy								
M	4.02*	3.28	3.28*	3.66	3.14*	3.58	3.52	3.16
SD	.93	.85	.91	.91	.79	.93	.92	.93
Affective Commitment to the CS class								
M	5.84*	4.05	4.26	4.76	4.01	4.60	4.53	4.31
SD	1.43	1.41	1.59	1.61	1.35	1.69	1.60	1.73
Mastery Goal Orientation								
M	5.91*	4.66	4.82	5.15	4.88	4.95	4.98	4.94
SD	.82	1.11	.98	1.35	.94	1.29	1.17	1.22

(Table continues)

(Table continued)

Variable	Major: CS	Major: Non-CS	Employment Status: Employed	Employment Status: Not Employed	Race/Ethnicity: Black/ African American	Race/Ethnicity: White	Gender: Male	Gender: Female
Performance-Approach Goal Orientation								
M	4.70	4.47	4.41	4.66	4.45	4.49	4.55	4.39
SD	1.33	1.19	1.12	1.33	1.28	1.28	1.20	1.38
Performance-Avoid Goal Orientation								
M	3.37*	4.60	4.66*	3.88	4.83*	4.05	4.26	4.49
SD	1.31	1.12	1.03	1.40	1.07	1.30	1.29	1.25

Note. $N = 116$. SAT = Scholastic Aptitude Test (quantitative score only).
* Means are significantly different at $p < .05$.

participants. In addition to these 4 cases, 55 other cases had an outlier on 3 or fewer manifest variables (equaling 114 outlier responses). Due to the sample size, it was not practical to delete all 55 cases. I used 3 decision rules to determine whether outliers should be retained or changed. 1) If the "outlier" response provided valuable information to the study, it was retained. For example, only one participant scored an 800 on the math portion of the SAT so that person was considered an outlier. However, including a person with very high ability is important to the study. Also, few individuals reported very low effort (2 or less on the agreement scale). Therefore, very low responses to the effort items were deemed "outlier" responses. Again, including individuals with low effort was critical to the study. 2) In cases where the "outlier" response matched several other participants' responses (i.e., there was inter-participant consistency), I retained the outlier. 3) In cases where the "outlier" response was similar to the participant's other responses on the same scale (i.e., there was inter-item consistency), I retained the outlier. If an outlier did not meet one of these 3 criteria, I deemed it a genuine outlier. These decision rules yielded 40 true outliers (from 28 cases). Rather than deleting these 28 cases, I made these outliers less deviant using a procedure recommended by Tabachnick and Fidell (2001). I rescored the outlier so that it was one unit closer to the mean. This procedure was advantageous because it reduced the impact of the outliers without deleting valuable cases (Tabachnick & Fidell, 2001).

Missing Data

All of the variables had less than 2% missing data, with the exception of SAT math score. SAT scores were missing for 29% of participants because transfer students and international students are not required to provide the university with their SAT scores. Transfer students make up half of the university's undergraduate student body, so the 29% missing data are not unusual given this university's population (Z. Yang, personal communication, January 30, 2007). With such a large percentage of missing data in one variable, imputing the missing values is not recommended (Tabachnick & Fidell, 2001). Therefore, participants with incomplete data were removed and I completed the analyses with the remaining sample (N = 116). To justify the removal of these participants, I conducted one-way ANOVAs comparing individuals without SAT data to individuals with SAT data on the study variables. Results revealed no significant differences between these groups of participants on any of the study variables. All future discussions of results refer to analyses I conducted with the sample of 116 participants.

Power Analysis

MacCallum, Browne, and Sugawara (1996) provide procedures for estimating power in structural equation modeling. Their procedure uses degrees of freedom, the selected alpha level, and sample size to estimate power. Degrees of freedom are calculated with the following formula: $[(p(p+1))/2] - q$, where p is the number of observed variables and q is the number of estimated parameters. The hypothesized model had 21 observed variables and 79 estimated parameters, yielding 173 degrees of freedom. Given 173 degrees of freedom, alpha = .05, and N = 116, the power for testing the hypothesized model was .91.

Descriptive Statistics

Means, standard deviations, and intercorrelations among latent variables are presented in Table 3. Note that these intercorrelations are provided by the measurement model. Means, standard deviations, and covariances among manifest variables are

Table 3

Means, Standard Deviations, and Intercorrelations among the Latent Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
1. Effort[†]	.00	.91	----							
2. Ability (SAT math score)[†]	.00	74.45	-.07	----						
3. Course Grade	6.29	3.64	.03	.49*	----					
4. CS Self-Efficacy	3.46	1.01	-.02	.28*	.54*	----				
5. Affective Commitment to the CS class	4.50	1.77	.20*	.12	.47*	.65*	----			
6. Mastery Orientation	4.98	1.36	.35*	.07	.18	.48*	.70*	----		
7. Performance-Approach Orientation	4.53	1.38	.35*	.14	.23*	.26*	.23*	.54*	----	
8. Performance-Avoid Orientation	4.29	4.29	.30*	-.31*	-.50*	-.62*	-.56*	-.21*	.12	----

Note. $N = 116$. Intercorrelations provided by the measurement model. Ability-effort interaction term: $M = .15$; $SD = 53.43$.
[†]These variables were mean centered.
$*p < .05$.

provided in Appendix F. Covariances are provided because all analyses were conducted using the covariance matrix.

Hypothesized Model

Measurement model. The measurement model included three indicators (mean centered observed variables) for effort, one indicator (mean centered SAT math score) for ability, one indicator (course grade) for grade, three indicators (parcels) for CS self-efficacy, three indicators (observed variables) for affective commitment to the CS class, and three indicators (parcels) for each goal orientation variable (i.e., mastery, performance-approach, and performance-avoid orientation). The measurement model did not include the latent interaction variable or its indicator. It is acceptable to test the measurement model of unidimensional latent variables in the absence of the interaction term because unidimensional latent variables' loadings and error variances are unaffected by adding or removing other latent variables in the structural model (Ping, 1996). There is no need to examine measurement parameter estimates of the interaction term because the Jöreskog-Yang (1996) procedure requires the researcher to set or constrain those values (e.g., the loading of the indicator on the latent interaction variable is set to equal 1.0). The measurement model fit reasonably well, χ^2 (144) = 249.48, $p < .01$. Although the χ^2 is significant, the χ^2 to *df* ratio equals 1.73, which is below the recommended cutoff value (2.00; Tabachnick & Fidell, 2001). The other fit indices also indicate that the measurement model is a good fit: RMSEA = .07, NNFI = .95, CFI = .96.

The standardized factor loadings, corresponding *t*-values, error variances (Theta Delta values), and reliabilities for each indicator in the measurement model as well as scale reliabilities are displayed in Table 4. The measurement model with unstandardized

Table 4

Factor Loadings, t-values, Theta Delta, and Reliability Coefficients in the Measurement Model

Variables	Factor Loadings[†]	*t*-values	Theta Delta[†]	Reliability of Indicators	Reliability of Scales
Effort					.89
EFF1	.78	9.77	.39	.61	
EFF2	.85	10.95	.28	.72	
EFF3	.96	13.22	.08	.92	
Ability (SAT)	.96	13.95	.08	.92[a]	--
Course Grade	.97	14.41	.05	.95[b]	--
CS Self-Efficacy					.90
CSEP1	.94	13.19	.11	.89	
CSEP2	.90	12.29	.18	.82	
CSEP3	.77	9.68	.40	.60	
Affective Commitment to the CS Class					.89
AC1	.82	10.55	.32	.68	
AC2	.94	13.03	.12	.88	
AC3	.83	10.75	.31	.69	
Mastery Orientation					.82
MGOP1	.82	10.30	.32	.68	
MGOP2	.87	11.10	.25	.75	
MGOP3	.68	7.86	.54	.46	
P-Approach Orientation					.87
APPGOP1	.85	10.87	.27	.73	
APPGOP2	.89	11.46	.22	.78	
APPGOP3	.77	9.34	.41	.59	
P-Avoid Orientation					.77
AVDGOP1	.83	10.19	.31	.69	
AVDGOP2	.84	10.31	.30	.70	
AVDGOP3	.56	6.08	.69	.31	

Note. $N = 116$. EFF = Effort, SAT = Scholastic Aptitude Test (quantitative score only), CSEP = CS Self-Efficacy Parcel, AC = Affective Commitment to the CS Class, MGOP = Mastery Goal Orientation Parcel, APPGOP = Performance-Approach Goal Orientation Parcel, AVDGOP = Performance-Avoid Goal Orientation Parcel.
[†]Standardized estimates.
[a]Reliability set according to the College Board (College Board, 2005).
[b]Reliability set to account for potential transcription errors.

factor loadings and error variances is displayed in Figure 5. Each factor loading is high (greater than .77) with the exception of Performance-Avoid Orientation Parcel 3 (.56). In addition, each loading has a *t*-value greater than 2.00, demonstrating that each indicator loads significantly on its corresponding latent variable. The squared multiple correlations (R^2) in the measurement model indicate parcel or item reliability. I set the measurement error for SAT score and final course grade, which also sets the reliability. Therefore, the R^2 values for SAT and grade are .92 and .95, respectively. For the other indicators, the R^2 values range from .31 (Performance-Avoid Orientation Parcel 3) to .92 (Effort Parcel 3). Although some of the indicators' reliabilities are low, most are above .70.

Baseline structural model. The baseline structural model excludes the mediating effects of CS self-efficacy and goal orientation. I estimated only direct relationships between the antecedents (SAT score and affective commitment to the CS class) and the outcomes (effort and grade). The fit of this model was poor, χ^2 (184) = 461.38, $p < .01$, RMSEA = .11, NNFI = .88, CFI = .90, χ^2/df = 2.51. The baseline model and its standardized parameter estimates are displayed in Figure 6.

Mediation structural model. The second nested model I tested was the mediation structural model. This model estimates the hypothesized mediating effects of CS self-efficacy and goal orientation (i.e., all hypotheses, except the ability-effort interaction hypothesis, are tested). The mediation model fit reasonably well, χ^2 (174) = 307.32, $p <$ .01, RMSEA = .08, NNFI = .94, CFI = .95, χ^2/df = 1.77. The model and its standardized parameter estimates are displayed in Figure 7. A χ^2-difference test shows that the mediation model is a better fitting model than the baseline model (see Table 5). This

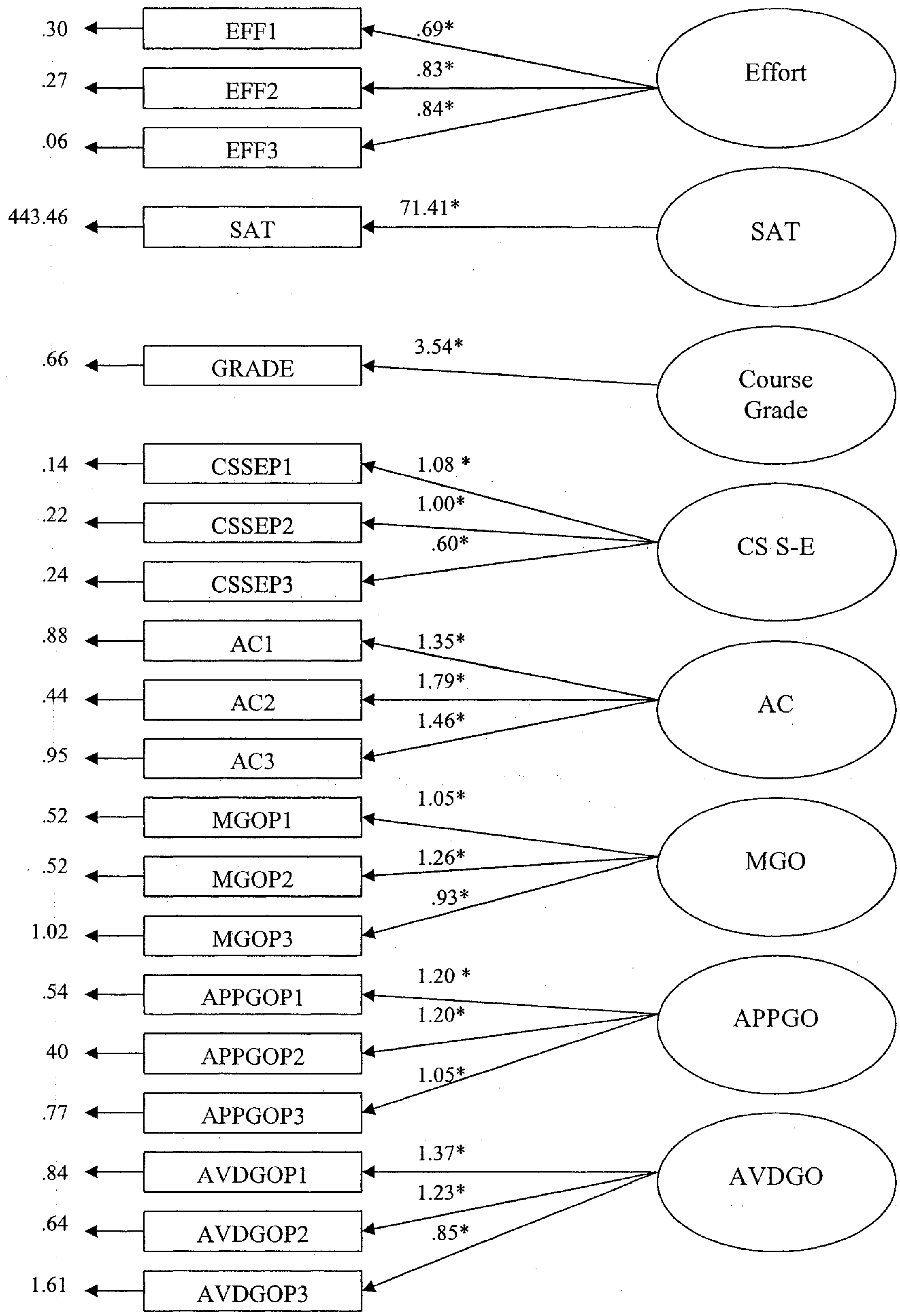

Figure 5. Latent variable measurement model with unstandardized estimates (* $p < .05$).

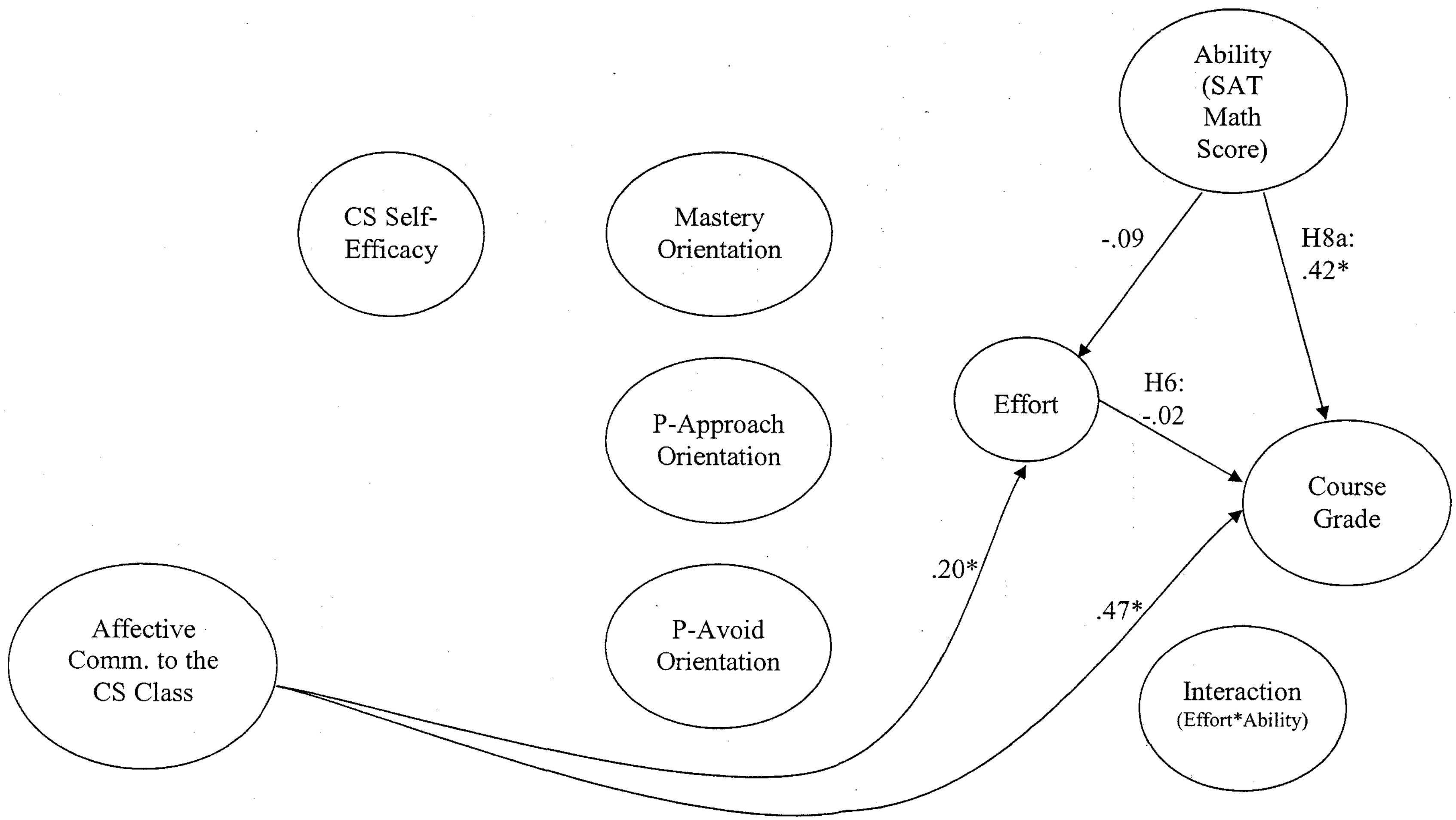

Figure 6. Baseline structural model without mediation. Hypotheses and standardized coefficients are displayed. ($N = 116$, * $p < .05$).

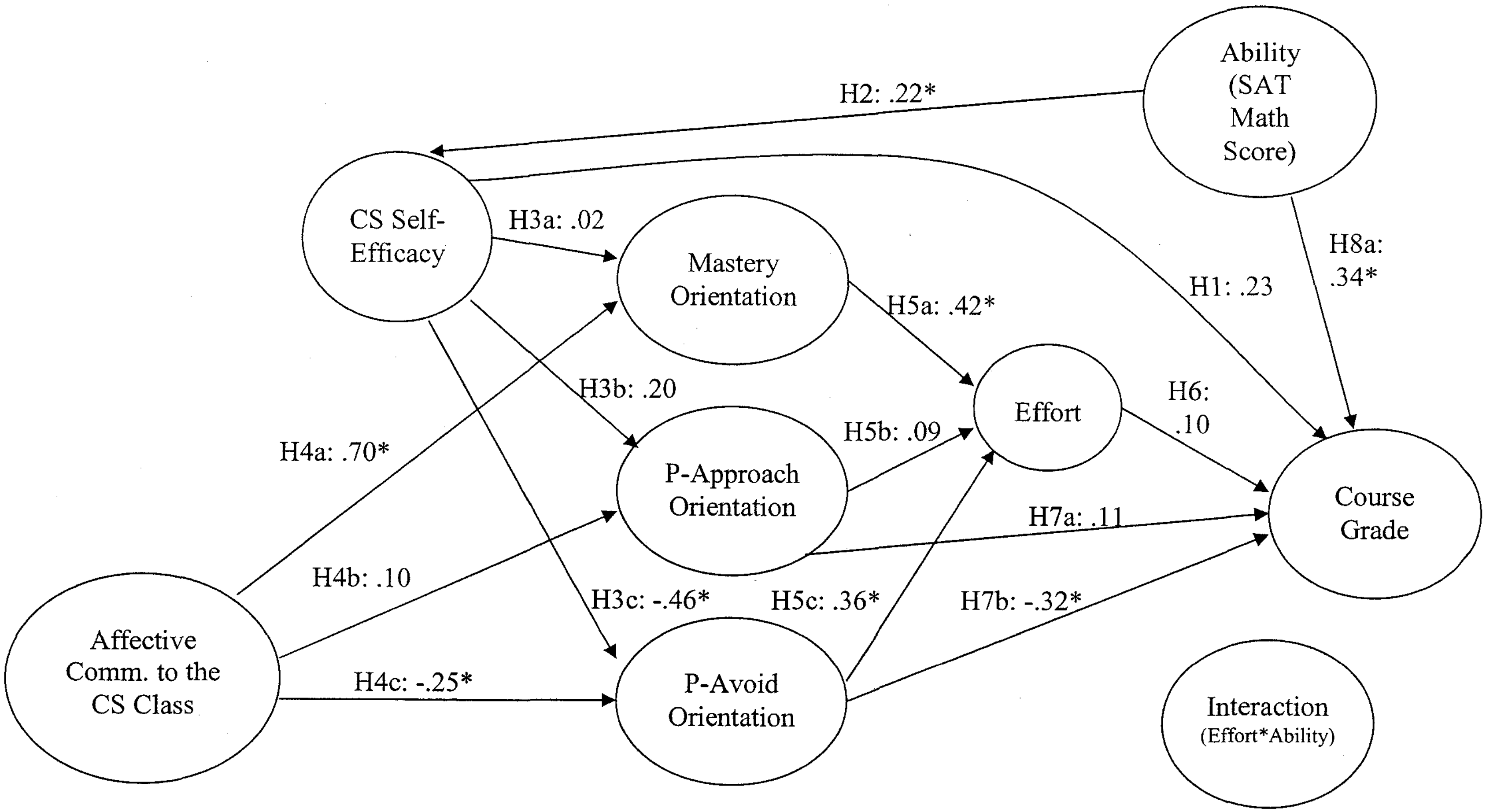

Figure 7. Mediation structural model. Hypotheses and standardized coefficients are displayed. ($N = 116$, * $p < .05$).

result supports the proposed hypothesized model because the model with mediating effects is a better fit for the data than the model without mediating effects.

Table 5

Nested Model Goodness of Fit Statistics and Comparisons

Nested Model	χ^2	*df*	$p <$	RMSEA	NNFI	CFI	$\Delta\chi^2$	Δdf
Baseline Model	461.38	184	.01	.11	.88	.90	----	----
Mediation Model	307.32	174	.01	.08	.94	.95	154.06**	10
Interaction Model	298.45	173	.01	.08	.94	.95	8.87*	1

Note. $N = 116$. A significant chi-square difference test suggests a significant change in goodness of fit between two models.
* $p < .01$.
** $p < .001$.

Interaction structural model. The final nested model to be tested is the interaction structural model. This model is consistent with the hypothesized model. That is, all hypothesized relationships, including the interaction effect, are tested in this model. The interaction model fit reasonably well, χ^2 (173) = 298.45, $p < .01$, RMSEA = .08, NNFI = .94, CFI = .95, $\chi^2/df = 1.73$. The model and its standardized parameter estimates are displayed in Figure 8. A χ^2-difference test shows that the interaction model is a better fitting model than the mediation model. This result lends further support to the hypothesized model and directly supports hypothesis 8b. The fit statistics and χ^2-difference tests for the nested models are summarized in Table 5. Given the model comparisons, the interaction model is the accepted model. Therefore, the findings reported below are based on the results obtained by testing this model.

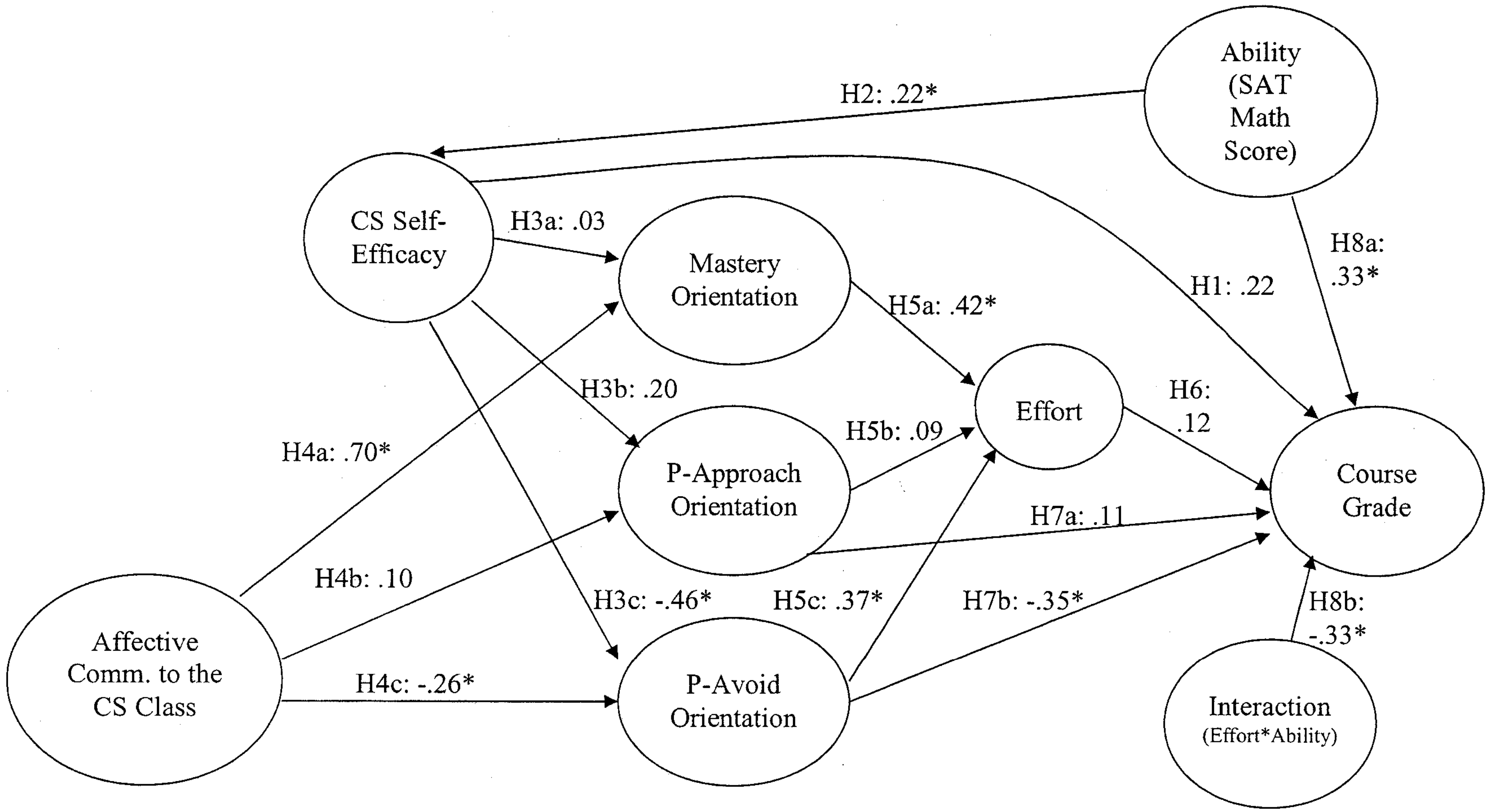

Figure 8. Interaction structural model. Hypotheses and standardized coefficients are displayed. ($N = 116$, * $p < .05$).

The direct relationship between CS self-efficacy and grade (hypothesis 1) was not significant. However, consistent with hypothesis 2, the direct relationship between ability and CS self-efficacy was significant and positive. In turn, CS self-efficacy was negatively related to performance-avoid orientation as predicted (hypothesis 3c), but was not significantly related to mastery (hypothesis 3a) or performance-approach orientation (hypothesis 3b). In addition, affective commitment to the CS class was positively related to mastery orientation (hypothesis 4a) and negatively related to performance-avoid orientation (hypothesis 4c) as predicted, but was not significantly related to performance-approach orientation (hypothesis 4b). As expected, mastery orientation (hypothesis 5a) was positively related to effort. I hypothesized that performance-avoid orientation would have a significant, negative relationship with effort (hypothesis 5c); the results showed a significant, but positive relationship. Also contrary to my hypotheses, performance-approach orientation was not significantly related to effort (hypothesis 5b) and effort was not significantly related to grade (hypothesis 6). In partial support of hypothesis 7, performance-avoid orientation had a direct, negative relationship with grade (hypothesis 7a), but performance-approach orientation was not directly related to grade (hypothesis 7b). Most of the non-significant findings involve performance-approach orientation. Consistent with hypothesis 8a, mathematics ability had a direct, positive relationship with grade.

Finally, the ability-effort interaction was significantly related to grade (hypothesis 8b). This relationship was expected to be positive, but the parameter estimate was negative. This result can be interpreted as the following: for every one unit decrease in mathematics ability (SAT math score), the relationship between effort and grade increases by .03, i.e., effort has a stronger effect on performance for low ability individuals than for high ability individuals. Given that ability and effort influence grade positively but the interaction is negative, the interaction is an *interference or antagonistic interaction* (Cohen, Cohen, West, & Aiken, 2003). That is, both ability and effort are positively related to performance, but the importance of high ability may be lessened by exceptional effort; effort and ability can compensate for one another. This suggests that "the whole is less than the sum of the parts; there is some partial trade-off between ability and [effort] in the prediction of [performance]" (Cohen et al., 2003, p. 255). The ability-effort interaction effect is displayed in Figure 9. In Figure 9, ability is split into high and low, such that participants who scored one standard deviation above the mean on the math portion of the SAT ($M = 585$) were categorized as "high ability" and participants who scored one standard deviation below the mean were categorized as "low ability." The points plotted in Figure 9 represent one standard deviation below the mean, the mean, and one standard deviation above the mean on each regression line.

There are two interesting things to note about the interaction effect. First, the slope of the line for low ability participants is steeper than the line for high ability participants. Consistent with the discussion above, this result suggests that effort can compensate for low ability; the effort-performance relationship is stronger for low ability people than it is for high ability people. I performed two follow-up regressions, which confirmed this suggestion. Using SPSS 12.0, I regressed performance on effort for both high ability participants (those with SAT scores above the mean) and low ability participants (those with SAT scores at or below the mean). The effort-performance relationship was stronger for the low ability group ($\beta = .24$) than it was for the high

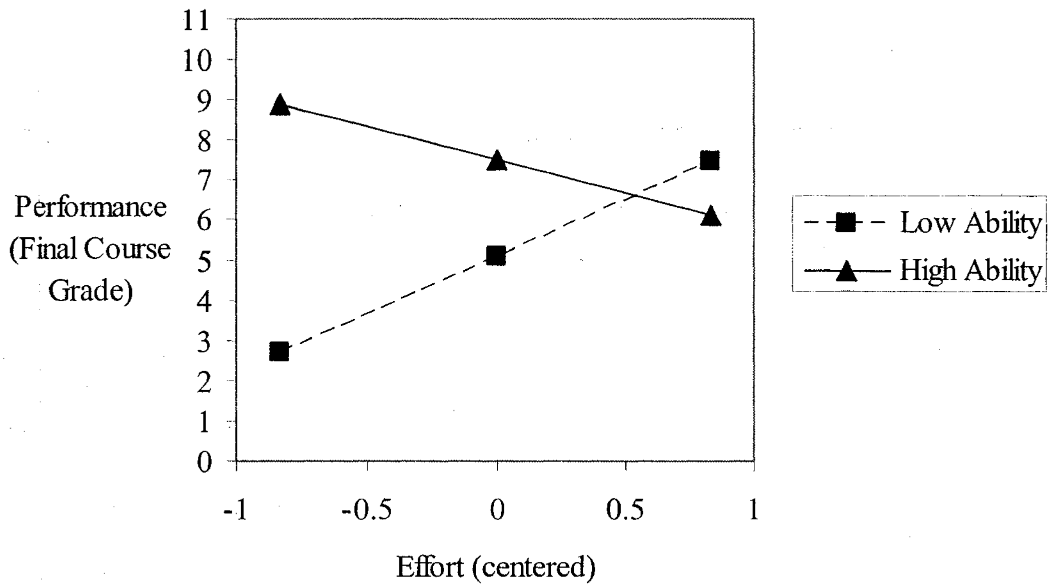

Figure 9. Ability (SAT math)-effort interaction effect on grade

ability group (β = -.17). This result is the exact opposite of the hypothesized relationship (that the effort-performance relationship would be stronger when ability is high).

Second, Figure 9 and the negative β-weight from the follow-up regression analysis suggest that, for high ability people, grade slightly decreases as effort increases. However, in the follow-up regression, the effort-performance relationship is non-significant among high ability participants. Thus, it is inappropriate to interpret this negative relationship because it could be due to chance.

I also examined the indirect effects suggested by the hypothesized model. These effects are displayed in Table 6. The indirect effect of CS self-efficacy on grade was significant (.17). Affective commitment also had a significant indirect effect on grade (.13). These results suggest that the relationships between CS self-efficacy and grade and commitment and grade were mediated by performance-avoid orientation. In addition, ability had a significant indirect relationship with performance-avoid orientation and grade. Therefore, consistent with the hypothesized model, CS self-efficacy mediated the relationship between ability and performance-avoid orientation, and CS self-efficacy and performance-avoid orientation mediated the ability-grade relationship. These results suggest that ability influenced grade in three ways: 1) through its direct relationship with grade, 2) by interacting with effort to influence grade, and 3) through its relationship with CS self-efficacy and performance-avoid orientation. Due to the non-significant relationship between effort and grade, the goal orientation variables did not have a significant indirect effect on grade through effort.

Table 6

Standardized Indirect Effects among the Latent Variables in the Interaction Model

	Ability (SAT)	CS Self-Efficacy	AC	MGO	APPGO	AVDGO
Effort	-.03	-.14	.20	----	----	----
Course Grade	.08*	.17*	.13*	.05	.01	.04
MGO	.01	----	----	----	----	----
APPGO	.04	----	----	----	----	----
AVDGO	-.10*	----	----	----	----	----

Note. N = 116. SAT = Scholastic Aptitude Test (quantitative score only), AC = Affective Commitment to the CS Class, MGO = Mastery Goal Orientation, APPGO = Performance-Approach Goal Orientation, AVDGO = Performance-Avoid Goal Orientation.
* $p < .05$.

The amount of variance in each variable that was explained by the model is provided in the squared multiple correlations (R^2) for structural equations matrix. These values are listed in Table 7. Ability accounted for a small portion of the variance in CS self-efficacy (5%). In terms of the goal orientation mediators, 51% of the mastery orientation variance and 43% of the performance-avoid orientation variance was accounted for by the model. Given the absence of significant relationships with performance-approach orientation, it is not surprising that only 8% of the variance in that variable was accounted for by the model. In turn, the goal orientation variables accounted for 30% of the variance in effort. Finally, the amount of variance in grade that was accounted for by the model was 56%.

Table 7

Squared Multiple Correlations (R^2) for Structural Equations in the Interaction Model

Effort	Ability (SAT)	Interaction (Effort* Ability)	Course Grade	CS Self-Efficacy	AC	MGO	APPGO	AVDGO
.30	----	----	.56	.05	----	.51	.08	.43

Note. $N = 116$. The squared multiple correlation (R^2) indicates the percent of variance in a variable that is being explained by the set of its predictors. SAT = Scholastic Aptitude Test (quantitative score only), AC = Affective Commitment to the CS Class, MGO = Mastery Goal Orientation, APPGO = Performance-Approach Goal Orientation, AVDGO = Performance-Avoid Goal Orientation.
* $p < .05$.

I tested an additional model in which non-significant paths from the interaction model were removed. This trimmed model was tested to determine whether a more parsimonious model was an equally good fit of the data. However, results showed that the trimmed model was a significantly worse fitting model than the interaction model, χ^2 (180) = 320.15, $p < .01$, RMSEA = .08, NNFI = .94, CFI = .95, χ^2/df = 1.78, $\Delta\chi^2$ = 21.7, Δdf = 7, $p < .01$. Therefore, although the removed parameters were not significant, they appear to contribute to the overall fit of the model.

Summary of Results

The best fitting model was the hypothesized interaction model that estimated the proposed mediation and interaction effects. It fit the data better than a model with only the mediating effects (mediation structural model) as well as a model with only direct effects (baseline structural model). The results support most of the hypothesized relationships. Higher ability was related to higher CS self-efficacy, which in turn was negatively related to performance-avoid orientation. In addition, participants with higher commitment to the CS class were more likely to have a mastery orientation and less likely to have a performance-avoid orientation. Both mastery and performance-avoid orientations were related to increased effort. However, performance-avoid orientation was negatively related to performance (course grade). Although effort was not significantly related to performance, the interactive effects of ability provide greater insight into this relationship. It appears that effort and ability had an antagonistic interactive relationship on performance. That is, effort and ability compensated for each other in effecting performance. Furthermore, the effort-performance relationship was stronger for low ability people than it was for high ability people.

CHAPTER IV

DISCUSSION

The purpose of this study was to design and empirically test an integrative theory of motivation. The theory integrates aspects of various motivation theories including expectancy theory, social cognitive theory, goal-setting theory, and commitment theory. The goal of this research was to provide researchers and practitioners with an empirically-supported model for understanding the underlying mechanisms through which motivation works.

The integrative theory suggests several components through which the motivation process occurs. Primary motivators, like personality and self-efficacy, influence cognitive components such as goal orientation and goal choice. Cognitive components affect motivated behaviors, like effort and persistence, which lead to outcomes of motivation (e.g., performance, turnover). Commitment components also play an important role in the motivation process through their direct and moderating effects on the cognitive components. Finally, several outcome moderators (feedback, ability, and task complexity) influence the relationship between the motivated behaviors and the outcomes.

To test the integrative theory, I chose one setting-relevant variable from each component and created a testable model containing relationships consistent with the theory. Other integrative motivation theories exist in the literature (e.g., Locke, 1997; Meyer et al., 2004), but there are few empirical tests of such theories in their entirety. Therefore, such a test of an integrative theory contributes to the motivation literature.

Overall Research Findings

Overall, the results provide support for the integrative theory and corresponding hypothesized model. A test of three nested models supported the utility of the integrative theory. The theory suggests that motivation cannot be explained through direct relationships alone. Each component of the model influences another component as the motivation process moves from constructs central to the individual (i.e., primary motivators) through cognitive and behavioral constructs to outcomes of motivation (e.g., performance). The value of including such mediating effects was supported by the data; the mediation model fit the data significantly better than did the baseline model, which excluded the mediating relationships. In addition, the integrative theory posits that these direct and indirect effects alone cannot fully explain motivation. Other constructs, like ability, moderate the relationship between motivated behaviors (e.g., effort) and outcomes of motivation. The value of including such interactive effects was supported by the data as well; the interaction model was a significantly better fit of the data than the mediation model. In addition to the overall test of the theory and hypothesized model, a majority of the proposed relationships were supported. These results are discussed next.

Self-Efficacy

Consistent with previous research (Phillips & Gully, 1997; Thomas & Mathieu, 1994), ability was directly related to self-efficacy such that individuals with higher math ability felt more confident in their CS skills. However, only an indirect relationship occurred between CS self-efficacy and performance. This result is contrary to some previous studies that found support for a direct link between self-efficacy and performance (Breland & Donovan, 2005; Phillips & Gully, 1997; VandeWalle et al., 2001). However, none of these researchers' models accounted for the ability-effort interaction effect on performance, and they all treated goal orientation as an antecedent to self-efficacy rather than as a mediator. I found that the ability-effort interaction effect was significantly related to performance, and the indirect effects suggested that performance-avoid orientation fully mediated the self-efficacy-performance relationship. Furthermore, Breland and Donovan (2005) and Phillips and Gully (1997) used general performance orientation rather than distinguishing between performance-approach and performance-avoid orientation. Given my results, this distinction is clearly important because these two goal orientations were differentially related to the other variables in the model.

Goal Orientation

There are two antecedents of goal orientation in the hypothesized model, CS self-efficacy and affective commitment to the CS class. The results partially supported the hypothesized relationships between these variables.

CS self-efficacy. Kanfer's (1990) theory of goals and self-regulation suggests that individuals' CS self-efficacy is affected by their previous performance and their self-attributions made in response to that performance. These new ability judgments, in turn, influence subsequent goal orientation. Given that the survey items were assessed at the end of the semester after students had received performance feedback, I expected to find a relationship between self-efficacy and goal orientation. However, this relationship was only supported for the self-efficacy to performance-avoid orientation link, such that individuals with greater confidence in their CS abilities were less likely to be performance-avoid oriented.

VandeWalle et al. (2001) found that performance-approach orientation had a non-significant relationship with self-efficacy and performance-avoid orientation had the strongest relationship with self-efficacy. They used self-efficacy theory to explain the significant effects for performance-avoid orientation. That is, unpleasant psychological arousal decreases self-efficacy (Bandura, 1997). Research has shown that a performance-avoid orientation is also related to unpleasant psychological arousal (e.g., test anxiety and worry; Elliot & McGregor, 1999). Therefore, this decreased self-efficacy continues to foster an avoidant orientation, which is evidenced by the significant negative relationship between self-efficacy and performance-avoid orientation found in this study and the VandeWalle et al. study.

The failure to find a significant relationship between performance-approach orientation and self-efficacy is consistent with some previous research. For instance, researchers have found that general performance orientation has weak correlations with other "primary motivators" such as internal locus of control (e.g., Phillips & Gully, 1997) and optimism (VandeWalle, 1996). Research suggests that general performance orientation has a significant, negative relationship with extraversion and openness to experience, but the behaviors associated with these relationships are more avoidant in nature (Zweig & Webster, 2004). For example, lower extraversion is related to decreased activity and interest, and increased avoidance of stimulation, which are behaviors characteristic of a performance-avoid orientation rather than a performance-approach orientation (Zweig & Webster, 2004). If performance-approach orientation is weakly related to a sense of self-determination, optimism, extraversion, and openness to experience, it is logical to expect it to be weakly related to self-efficacy. Individuals with a performance-approach orientation question whether past success will necessarily lead to future success (VandeWalle et al., 2001). Therefore, when a performance-approach oriented person receives positive feedback, he may doubt that this success has anything to do with his ability, leading to subsequent meager goal-setting. VandeWalle et al. (2001) suggest that negative feedback may also lead to meager subsequent goals because performance-approach oriented individuals believe that ability is difficult to develop and failure usually occurs because a task is challenging. This line of reasoning suggests that, in the face of positive feedback, performance-approach individuals' self-efficacy does not increase; in the face of negative feedback, they do not attribute the failure to themselves (i.e, self-efficacy does not decrease). In other words, after feedback, self-efficacy should have no relationship with performance-approach orientation as was the case in this study.

Previous research has demonstrated a significant, positive relationship between self-efficacy and mastery orientation (e.g., Breland & Donovan, 2005, Phillips & Gully, 1997; VandeWalle et al., 2001). However, I found a non-significant relationship between these variables. Ames and Archer (1988) provide a possible reason for the lack of a relationship. These researchers studied differences in classrooms that emphasized mastery goals versus those that emphasized performance goals. For example, in a classroom emphasizing mastery goals, the teacher allows students to learn from and fix mistakes on graded assignments and resubmit the assignment to increase their grade. In a classroom emphasizing performance goals, students are given just one opportunity to get the assignment right. Ames and Archer found that students' perceptions of mastery orientation were not related to self-perceptions of ability. This result suggests that, when students perceive a mastery goal emphasis in the classroom, that environment can override the contribution of perceived ability to achievement behaviors (e.g., goal setting). This discussion highlights a plausible explanation for the findings in this study. That is, it is possible that some of the students in the sample thought the CS class emphasized mastery of the material. Therefore, their confidence regarding the material was not related to their goal orientation; rather, regardless of their CS self-efficacy levels, they were working towards the mastery-type goals that they perceived were set forth by the instructor.

Affective commitment to the CS class. Another antecedent of goal orientation is affective commitment to the CS class. As expected, commitment was positively related to mastery orientation and negatively related to performance-avoid orientation. These results provide support for Meyer and colleagues' (2004) theory that integrates commitment with motivation theory. These researchers suggested that the primary bases for developing affective commitment are personal involvement and identification with the target as well as shared values with the target. Therefore, a person with such ideal feelings for a target will likely set ideal goals related to that target, i.e., mastery goals. On the other hand, individuals with low commitment to a target can be expected to have less than ideal goals, i.e., performance-avoid goals.

Based on the findings from this study, commitment influences performance-approach and performance-avoid orientations differently. Meyer and colleagues' (2004) propositions may explain why. They suggest that individuals who are committed to a target out of necessity (i.e., have continuance commitment toward the target) pursue goals to avoid the loss of a desirable outcome or to avoid an undesirable outcome. Therefore, they are externally regulated (i.e., engage in behavior to satisfy external demands or rewards, like earning a grade) and set goals that are prevention focused, demonstrating a performance-avoid orientation. In other words, individuals who feel continuance commitment toward a target will likely have a performance-avoid orientation toward the target. A post hoc regression analysis showed that CS majors in the sample had significantly higher affective commitment than non-CS majors ($\beta = .48$; major coded 0 for non-CS majors, 1 for majors). Given the research context, non-CS majors may feel less affective commitment but more continuance commitment to the class because they are committed out of necessity (i.e., the need to fulfill their degree requirement). Therefore, students with low affective commitment were more likely to emphasize performance-avoidant goals.

It appears that affective commitment has a polarizing effect on goal orientation. That is, high affective commitment leads to ideal goals and low affective commitment leads to avoidant goals, but commitment is not related to performance-approach goals. Meyer and colleagues (2004) propose that affective commitment is unrelated to goal-setting when individuals evaluate their behavior against external standards (i.e., demonstrate performance-approach orientations). These individuals' goal-setting is more likely predicted by normative commitment (Meyer et al., 2004). Although affective and normative commitment overlap to some extent, research suggests they are distinguishable constructs and have different relationships with some outcomes (Meyer et al., 2002).

Consequences of goal orientation. The hypothesized model presents two consequences of goal orientation: effort and performance. Consistent with previous research (VandeWalle et al., 2001), mastery orientation was positively related to effort. Contrary to the hypotheses, performance-approach orientation had a non-significant relationship with effort, and performance-avoid orientation was positively related to effort. Similarly, VandeWalle (1997) found a non-significant relationship between a desire to work hard scale and performance-approach orientation. The stronger relationship between mastery orientation and effort may occur because mastery oriented individuals are better able to stay focused on the task, enjoy expending effort on the task, and tend to believe that their effort will lead to success (VandeWalle et al., 2001). Such research suggests that a performance-approach orientation does not elicit strong enough feelings toward a task to produce increased effort.

The positive relationship between performance-avoid orientation and effort was inconsistent with previous research. VandeWalle et al. (2001) suggest that pessimism, anxiety, and disinterest in hard work are related to a performance-avoid orientation. Therefore, performance-avoid orientation should be related to decreased effort. However, it is also possible that the pessimism and anxiety could lead a performance-avoidant person to expend greater, but unconstructive effort. Students could be expending effort that is superficial in nature, making it ineffective in producing successful performance (Elliot & McGregor, 1999). This reasoning is supported by the significant negative relationship I found between performance-avoid orientation and performance. Another possibility is that these maladaptive characteristics (pessimism, anxiety, and disinterest in hard work) caused individuals to think they were putting forth a great deal of effort when they actually were not. Post hoc descriptive analyses support this suggestion; students who performed poorly in the class (i.e., earned a D+ or lower in the class) reported the same level of effort ($M = 3.50$) as students who performed very well in the class (i.e., earned a B+ or higher in the class).

Furthermore, effort was not significantly related to performance (course grade), suggesting that the entire sample may have been expending superficial effort or was inaccurately assessing their effort level. This result could be a function of the research setting. This class is the first programming course in the CS curriculum and it requires a great deal of work outside of class. Students may not be aware of how much effort they need to expend to do well in the class. Also, they may be expending more effort for this class in comparison to their other classes, but it is still not enough effort to increase their performance. On average, students reported effort of 3.64 on a five point scale. This mean suggests that students may have been reporting elevated effort levels or only students who expended high levels of effort chose to participate in the study.

Based on previous research (Harackiewicz et al., 2002), I did not hypothesize a direct relationship between mastery orientation and performance. However, other researchers have found a direct relationship between these variables (e.g., Fisher & Ford, 1998). To demonstrate with which previous findings my results aligned, I tested another model in which I estimated the mastery orientation-performance parameter. As expected, this path was non-significant. On the other hand, I hypothesized that both performance goal orientations would be directly related to performance. This hypothesis was only supported for performance-avoid orientation. The results showed that individuals who reported being more performance-avoidant earned lower grades in the class. This lends some support to the above-mentioned suggestions that performance-avoidant people were either inaccurately assessing their effort or were expending unconstructive effort.

The non-significant relationship between performance-approach orientation and performance may be due to the survey data collection time period; students completed the survey at the end of the semester after having received feedback on previous performance. Numerous studies suggest that feedback can cause the relationship between performance-approach orientation and performance to deteriorate from a significant positive relationship to a non-significant relationship (Elliot & McGregor, 1999; Ford, Smith, Weissbein, Gully, & Salas, 1998; VandeWalle, Brown, Cron, & Slocum, 1999; VandeWalle et al., 2001). For example, Elliot and McGregor (1999) found a significant, positive relationship between performance-approach orientation and performance on a midterm exam. However, this relationship was non-significant when performance was assessed on a second test at the end of the semester.

Feedback can reduce the effect of performance-approach orientation on performance because of the post-feedback attributions made by individuals with this type of orientation. Both performance orientations are associated with a belief that ability is difficult to develop, so when individuals with these orientations receive negative feedback, they have little hope for future performance (VandeWalle et al., 2001). Therefore, after negative feedback, individuals with a performance-approach orientation are discouraged and their subsequent performance drops enough to produce a non-significant relationship between performance-approach orientation and grade. Individuals with a performance-avoid orientation are motivated by their fear of failure. Therefore, if they receive negative feedback their morale takes an even harder hit, leading their subsequent performance to decline (as exhibited through a negative avoid-performance relationship).

Another explanation comes from Kluger and DeNisi's (1996) locus of attention theory. They suggest that when highly ego-centric people receive feedback, they reallocate their cognitive resources from focusing on the task to focusing on themselves. This reallocation of resources decreases individuals' ability to be successful on that task in the future. Since ego-involvement is a principal component of the performance goal orientations, it follows from this theory that, after feedback, performance oriented individuals reallocate their resources in an unproductive manner, causing their future performance to suffer (VandeWalle et al., 2001). The important point to make is that focusing on self-appearance leads to ineffective actions. For example, research has shown that performance-approach and performance-avoid orientations are related to hesitation to seek help to improve performance (Butler, 1993) and ineffective learning strategies (Ford et al., 1998).

This discussion suggests that being motivated by comparing oneself to others (performance-approach oriented) is not associated with lower performance. However, this type of motivation is not motivating enough to produce superior performance either.

Ability-Effort Interaction

The final hypothesized relationship to discuss is the ability-effort interaction effect on performance. Vroom (1964) originally conceptualized this relationship as Performance = f[Ability X Motivation], where motivation is often conceptualized as effort. He suggested that when ability is low, increasing motivation will result in smaller increases in performance than when ability is high. Consistent with this proposition, Yeo and Neal (2004) found that high levels of effort could not compensate for very low ability, whereas extra effort did lead to an increase in performance when ability was high. The results of the current study suggest that the effort-performance relationship was not significant for high ability participants, but was significant for low ability participants.

These contradictory results can be explained by examining the two research settings. Yeo and Neal tested the relationship with an air traffic control task that undergraduate students engaged in for a single 3-hour session. When completing this type of task in such a short time, one could expect there to be a cap on the level of performance low ability individuals can achieve regardless of their effort. However, the current study examined the interacting effects of effort and ability on performance in a semester-long class. The performance rating was students' final course grade, a culmination of their work over 16 weeks. Therefore, there is plenty of time for low ability individuals to expend enough effort to increase their performance. Furthermore, the activity Yeo and Neal used had greater variability in performance. Their participants' performance scores could range between -100 and 160 points and were based on whether they made correct or incorrect decisions and their response times. In my study, students could not receive a grade higher than an A, so the performance scores could only range from 0 (F) to 11 (A). Therefore, high ability participants' performance was capped at 11, giving them less room to show their superior performance than the high ability participants in Yeo and Neal's study. In my entire sample, 18% of the students earned an A; of the 57 students identified as high ability, almost 32% earned an A. It is possible that, if given the opportunity to achieve performance above an A, we would see differences among these students based on their effort levels.

Another explanation for these seemingly conflicting results is that the relationship cannot be explained by a linear trend. There may be some critical point along the performance scale where effort can no longer make up for low ability. Above this point on the scale, effort begins to predict performance for high ability people and no longer predicts performance for low ability people. In other words, my results hold true up to a certain level of performance, whereas Yeo and Neal's (2004) results hold true above that critical performance point.

Limitations and Future Research

There are a few limitations of this study that warrant attention. First, the generalizability of the results is limited. Because there was so much missing data for SAT score, individuals with no SAT score on file with the university were dropped from the analysis. The university does not require SAT scores from transfer and international students, so it is likely that the majority of the people who were removed from the analysis fell into one of those two groups of students. This non-random removal of students is a limitation of the study. However, one-way ANOVAs showed that those individuals who did not have SAT data were not significantly different than those individuals with SAT data on any of the study variables. Still, future research should test the proposed relationships with different samples.

Another limitation is that there were some group differences on the study's variables (see Table 2). For example, Black/African American participants had significantly lower SAT scores, course grades, and CS self-efficacy, and significantly higher performance-avoid goal orientation than White participants. Due to the small sample, I could not compare model fit between these two groups. I designed the integrative theory to be a general heuristic that would explain the motivation process in all settings and with all individuals. However, future research is required to support the validity of the integrative theory for different demographic groups in various settings.

A third limitation is one that is true of any research based on structural equation modeling. Any accepted model has various alternative models that are statistically equivalent. Equivalent models contain the same variables and are equally parsimonious to the accepted model so they cannot be statistically ruled out as acceptable alternatives (Hoyle & Panter, 1995). Due to this issue, authors are encouraged to explain what can and cannot be inferred from their results (Hoyle & Panter, 1995). As with any correlational study, causation cannot be inferred from the results of this study.

A fourth limitation is that the study is a snapshot in time and emphasizes specific variables from the integrative theory. Clearly, feedback is an important issue to the motivation process; thus, motivation evolves over time. Future research should consider examining motivation over a longer time period. Also, there are many other variables not tested in this study that fall into the component categories identified in the integrative theory. For example, there are additional outcomes to consider in the motivation process, such as retention/turnover and satisfaction. Researchers may find that mastery and performance-approach orientations and effort have more noteworthy effects on these outcomes than on performance.

The final limitation is the measurement of effort and its relationship with performance. Many researchers measure effort using self-report items. However, it is a problematic construct to measure because effort is relative; it is "in the eyes of the beholder." Furthermore, using a method other than self-report is not practical, especially if the goal is to use effort as part of an interaction term. Interaction analyses tend to require large sample sizes. Thus, directly observing participants' effort over a period of time and collecting diary accounts of effort are not practical research solutions.

Researchers should continue to consider these issues and work to develop methodologies in which effort can be measured more directly. Future research should also continue to examine the effort-performance relationship in different contexts. Based on the results of this study, future research should take care to consider the ability-effort interaction when studying the effect of effort on performance.

Contributions

In spite of these limitations, this study makes several contributions to the research literature as well as to practice. This research conceptualizes and provides empirical support for an integrative motivation theory that incorporates expectancy theory, social cognitive theory, goal-setting theory, and commitment theory. The integrative theory provides researchers, consultants, business leaders, and educators with a heuristic for understanding the complex process of motivation in a parsimonious model.

The test of the nested models and the use of SAT scores and final exam grades lend some support to the sequential order of the theory's components. Because ability was measured with archival SAT data, it can be viewed as a predictor of performance, and one could argue that it is also a predictor of CS self-efficacy. In addition, the mediation model fit better than the baseline model, demonstrating the importance of the mediating relationships represented in the theory. Furthermore, the interaction model was the best fitting nested model, supporting the inclusion of the outcome moderators.

Researchers interested in studying motivation can use the integrative theory to focus their research in a particular area of motivation or to ensure they are considering all important components in the motivation process. There are two important implications of the results for educators: 1) performance-avoid goals are detrimental to performance, so educators should work with students on appropriate goal-setting and on fostering climates that are not focused on simply avoiding failure and 2) effort can compensate for low ability, so educators should never assume that a student's lower ability is an insurmountable disadvantage. This second point is especially relevant for this study. Computer science departments have a culture for "weeding out" students who "just do not have the right abilities to be successful in CS." However, this study's results show that lower ability students can be successful in CS if they work hard enough. Finally, consultants can use the integrative theory to guide organization diagnosis. To help them fully understand their clients' "motivation problems," consultants can create interview or survey questions that measure the constructs represented in the integrative theory. Consultants then can use the responses to these items to develop thorough diagnoses.

CHAPTER V

CONCLUSION

Motivation has been defined as "a set of energetic forces that originates both within as well as beyond an individual's being, to initiate work-related behavior, and to determine its form, direction, intensity and duration" (Pinder, 1998, p. 11). This definition speaks to the complexity of motivation, which involves various subconscious and conscious thoughts and actions. Motivation researchers have worked for decades to understand this process, producing numerous models of motivation. My dissertation contributes to the study of motivation by providing theoretical integration in this area.

This study's findings highlight several key points. First, researchers must examine each dimension of goal orientation because these dimensions have different relationships with self-efficacy, commitment, effort, and performance. Second, commitment is a vital component in the motivation process. Finally, to enhance performance, individuals can compensate for lower ability by increasing their effort. Researchers and practitioners may do well to remember these points when considering the motivation process.

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APPENDIX A

QUESTIONNAIRE SCALES AND ITEMS

Scale	Questionnaire Items
CS Self-Efficacy	1. Generally I have felt secure about attempting computer programming problems.
	2. I am sure I could do advanced work in computer science.
	3. I am sure that I can learn programming.
	4. I think I could handle more difficult programming problems.
	5. I can get good grades in computer science.
	6. I have a lot of self-confidence when it comes to programming.
Effort	1. I try as hard as I can to succeed in this class.
	2. I exert a great deal of effort on assignments for this class.
	3. I put forth a great deal of effort to achieve my goals in this class.
Affective Commitment to the CS class	1. I regret having enrolled in this computer science class. – **R**
	2. I dislike being in this computer science class. – **R**
	3. I am enthusiastic about this computer science class.
Mastery Goal Orientation	1. I want to learn as much as possible from this class.
	2. It is important for me to understand the content of this course as thoroughly as possible.
	3. I hope to have gained a broader and deeper knowledge of computer science when I am done with this class.
	4. I desire to completely master the material presented in this class.
	5. In a class like this, I prefer course material that arouses my curiosity even if it is difficult to learn.
	6. In a class like this, I prefer course material that really challenges me so I can learn new things.

(*Questionnaire Scales and Items continue*)

(*Questionnaire Scales and Items continued*)

Performance-Approach Goal Orientation	1. It is important to me to do better than the other students.
	2. My goal in this class is to get a better grade than most of the students.
	3. I am striving to demonstrate my ability relative to others in this class.
	4. I am motivated by the thought of outperforming my peers in this class.
	5. It is important to me to do well compared to others in this class.
	6. I want to do well in this class to show my ability to my family, friends, advisors, or others.
Performance-Avoid Goal Orientation	1. I often think to myself, "what if I do badly in this class?"
	2. I worry about the possibility of getting a bad grade in this class.
	3. My fear of performing poorly in this class is often what motivates me.
	4. I just want to avoid doing poorly in this class.
	5. I am afraid that if I ask my TA or instructor a "dumb" question they might not think I'm very smart.
	6. I wish this class was not graded.

APPENDIX B

EMAIL INVITATION AND REMINDER

First Email Invitation

Dear Computer Science (CS) Student:

You are receiving this email because you are enrolled in at least one of the following classes at Old Dominion University (CS110, CS150, or CS250) or Norfolk State University (CSC101, CSC170, or CSC260). This email invites you to take advantage of the extra credit opportunity described by your professor.

The computer science (CS) departments at ODU and NSU are participating in an exciting research initiative funded by the National Science Foundation. The project is investigating the effects of new teaching techniques on retention of students enrolled in introductory CS classes. The goal of the project is to understand the factors that help retain CS students and ensure that all CS students have equal access to opportunities and feel included in the department. We hope that you will choose to share your opinions because they are important to us.

In order to receive credit for completing the survey, you will be asked to PRINT a confirmation page at the end of the survey and turn this in to your CS instructor. Please be sure to complete the survey using a computer where you have the ability to PRINT.

COMPLETE THIS SURVEY ONLY ONCE, even if you are required to complete the survey for more than one of your classes. If you are enrolled in more than one of the classes listed above, print the confirmation page for each one. Bring a copy of the confirmation page to each of your professors giving you extra credit for completion of the survey. You will receive your extra credit when you give the printed confirmation page to your professor.

The survey will be available only during the period (DATES). You must complete the survey before (CLOSING DATE) in order to receive extra credit.

The survey will take you about 30-40 minutes to complete. Be sure allow that amount of time before starting the survey because once you begin the survey you will not be able to exit and return where you left off.

Please click on the link below and you will be taken to the survey:

[LINK]

PLEASE DO NOT REPLY TO THIS EMAIL.

If you have any questions, you may contact:

Dr. Donald D. Davis
dddavis@odu.edu
Thank you for your participation
INSITE Research Team

Follow up email reminder sent weekly to everyone

Dear Computer Science Student:

We are writing to remind everyone enrolled in the following classes at Old Dominion University (CS110, CS150, or CS250) or Norfolk State University (CSC101, CSC170, or CSC260) to participate in our computer science department survey for extra credit.

We must send an email to everyone because we do not know who has already completed the survey. If you have already completed the survey, we thank you for your participation and apologize for sending you this message again.

The survey will take you about 30-40 minutes to complete. Be sure to allow that amount of time before starting the survey because once you begin the survey you will not be able to exit and return where you left off.

Please click on the link below and you will be taken to the survey:

[LINK]

PLEASE DO NOT REPLY TO THIS EMAIL:
If you have any questions, you may contact

Dr. Donald D. Davis
dddavis@odu.edu

Thank you for your participation
INSITE Research Team

APPENDIX C

SURVEY INSTRUCTIONS

The INSITE Project

INcreasing Success in Information Technology Education

INSITE Survey Introduction

This questionnaire asks you to describe your experience with the Computer Science (CS) department at your university. It is part of a research project sponsored by the National Science Foundation.

You have been selected to participate in this study because you are enrolled in one of the following introductory computer science classes at Old Dominion University (CS110, CS150, or CS250) or Norfolk State University (CSC101, CSC170, or CSC260). If you choose to participate in the survey, all of your responses will be stored in a secure database. Although reports that summarize the overall results of the study will be published, only the researchers will see your responses. Your individual responses will not be revealed to your CS professors. Your participation in the survey is entirely voluntary. You may withdraw from the survey at any time or simply omit any questions that make you feel uncomfortable.

By participating in this survey, you have the chance to tell the CS department at your university what you feel needs to be done to improve the department and what steps should be taken to develop a more inclusive environment for all students. By giving us permission to ask for your participation, your department is demonstrating how important it believes this research is. Please take the time to make your voice heard. You will be benefiting CS students at your university and potentially many others across the country as well. We thank you in advance for your time.

Completing the survey should take 30-40 minutes of your time. Please choose the answer that is most relevant for you.

COMPLETE THIS SURVEY ONLY ONCE, even if you are required to complete the survey for more than one of your classes. If you are enrolled in more than one of the classes listed above, print the confirmation page for each one. Bring a copy of the confirmation page to each of your professors giving you extra credit for completion of the survey. You will receive your extra credit when you give the printed confirmation page to your professor.

If you have any questions or if you just want additional information, please contact Dr. Donald Davis via email at dddavis@odu.edu or by calling him at (757) 683-4439.

APPENDIX D

CONFIRMATORY FACTOR ANALYSES FOR PARCELED SCALES

Table D1

CS Self-Efficacy: Maximum Likelihood Factor Loadings for Lambda X, Theta Deltas, Squared Multiple Correlations (R^2), and Parcel Assignments

Item[a]	Factor Loadings[b]	Theta Delta[b]	R^2	Parcel Assignment
Item 1	.83	.31	.69	2
Item 2	.85	.28	.72	2
Item 3	.72	.48	.52	3
Item 4	.90	.20	.80	1
Item 5	.74	.45	.55	3
Item 6	.91	.18	.82	1

Note. N = 116. All items loaded significantly on the latent variable.
[a]Item numbers correspond with Appendix A.
[b]Standardized values are provided.

Table D2

Mastery Goal Orientation: Maximum Likelihood Factor Loadings for Lambda X, Theta Deltas, Squared Multiple Correlations (R^2), and Parcel Assignments

Item[a]	Factor Loadings[b]	Theta Delta[b]	R^2	Parcel Assignment
Item 1	.89	.21	.79	1
Item 2	.82	.33	.67	2
Item 3	.83	.31	.69	1
Item 4	.74	.46	.54	2
Item 5	.62	.61	.39	3
Item 6	.62	.61	.39	3

Note. N = 116. All items loaded significantly on the latent variable.
[a]Item numbers correspond with Appendix A.
[b]Standardized values are provided.

Table D3

Performance-Approach Goal Orientation: Maximum Likelihood Factor Loadings for Lambda X, Theta Deltas, Squared Multiple Correlations (R^2), and Parcel Assignments

Item[a]	Factor Loadings[b]	Theta Delta[b]	R^2	Parcel Assignment
Item 1	.77	.41	.59	2
Item 2	.78	.40	.60	2
Item 3	.74	.45	.55	3
Item 4	.88	.22	.78	1
Item 5	.86	.26	.74	1
Item 6	.60	.64	.36	3

Note. $N = 116$. All items loaded significantly on the latent variable.
[a]Item numbers correspond with Appendix A.
[b]Standardized values are provided.

Table D4

Performance-Avoid Goal Orientation: Maximum Likelihood Factor Loadings for Lambda X, Theta Deltas, Squared Multiple Correlations (R^2), and Parcel Assignments

Item[a]	Factor Loadings[b]	Theta Delta[b]	R^2	Parcel Assignment
Item 1	.89	.22	.78	1
Item 2	.84	.29	.71	1
Item 3	.70	.51	.49	2
Item 4	.58	.67	.34	2
Item 5	.30	.91	.09	3
Item 6	.50	.75	.25	3

Note. $N = 116$. All items loaded significantly on the latent variable.
[a]Item numbers correspond with Appendix A.
[b]Standardized values are provided.

APPENDIX E

SAMPLE LISREL SYNTAX FOR TESTING AN INTERACTION WITH ONE PRODUCT INDICATOR FROM THE Y-SIDE

```
!Ability-effort (SAT math score) latent variable interaction effect on grade.
!From the Y-side using centered indicators for effort and SAT and EFF1*SAT as the
!indicator for the interaction.
!Syntax adapted from Jöreskog and Yang (1996)
DA NI=12 NO=166
RA FI=DATA_166.psf
SE
C_EFF1 C_EFF2 C_EFF3 C_SAT EFFBYSAT GRADE /
MO NY=6 NE=4 TE=SY TY=FR AL=FI PS=SY BE=FI
LE
Effort Sat Effbysat Grade
FR LY(2,1) LY(3,1)
VA 1 LY(1,1) LY(4,2) LY(5,3) LY(6,4)      !Fixing LY(5 3) is part of Constraint 5
FR BE(4,1) BE(4,2) BE(4,3)
FR PS(2,1)                                 !Constraint 1
CO AL(1)=PS(2,1)                           !Constraint 1
FI PS(3,1) PS(3,2)                         !Constraint 2, Redundant with MO AL=FI
CO PS(3,3)=PS(1,1)*PS(2,2)+PS(2,1)**2      !Constraint 3
CO TY(5)=TY(1)*TY(4)                       !Constraint 4
CO LY(5,1)=TY(4)                           !Constraint 5
CO LY(5,2)=TY(1)                           !Constraint 5
CO TE(5,5)= TY(1)**2*TE(4,4)+TY(4)**2*TE(1,1)  +  C    !Constraint 6
  PS(1,1)*TE(4,4) + PS(2,2)*TE(1,1)+TE(1,1)*TE(4,4)
CO TE(5,1)=TY(4)*TE(1,1)                   !Constraint 7
CO TE(5,4)=TY(1)*TE(4,4)                   !Constraint 7
FI TE(4,4) TE(6,6)                         !Fixing error for
VA 443.4566 TE(4,4)                        !single indicator
VA .6609 TE(6,6)                           !variables
PD
OU AD=OFF ND=4 IT=500 SC
```

APPENDIX F

MANIFEST MEANS, STANDARD DEVIATIONS, AND COVARIANCES

Variable	*Mean*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12
1. EFF1†	.00	.88	.78											
2. EFF2†	.00	.97	.57	.95										
3. EFF3†	.00	.88	.58	.69	.77									
4. SAT†	.00	74.45	.15	-4.72	-4.95	5543.21								
5. EFF1SAT	.15	53.43	.77	-1.06	.04	721.80	2854.97							
6. GRADE	6.29	3.64	.23	-.19	.11	124.72	-17.30	13.22						
7. CSEP1	3.17	1.14	.08	-.13	-.02	23.50	3.99	2.02	1.30					
8. CSEP2	3.25	1.11	.05	-.11	-.01	19.09	3.88	1.93	1.08	1.23				
9. CSEP3	3.97	.78	.03	-.08	.04	9.30	6.55	1.34	.64	.60	.61			
10. AC1	5.03	1.64	.18	.02	.16	13.42	17.62	2.89	1.07	1.02	.74	2.70		
11. AC2	4.36	1.91	.39	.10	.30	14.51	16.31	2.93	1.22	1.07	.77	2.43	3.66	
12. AC3	4.10	1.76	.44	.22	.34	10.47	11.20	2.00	.99	.94	.54	1.91	2.63	3.08
13. MGOP1	5.39	1.27	.41	.34	.39	-1.31	6.86	.31	.40	.42	.38	.75	1.16	1.16
14. MGOP2	4.76	1.45	.49	.26	.39	7.80	16.46	.80	.61	.54	.40	.99	1.53	1.35
15. MGOP3	4.77	1.37	.09	-.06	.04	12.75	4.37	1.41	.80	.72	.47	1.21	1.57	1.48
16. APPGOP1	4.33	1.41	.34	.19	.32	12.96	-3.83	.99	.44	.45	.23	.44	.56	.83
17. APPGOP2	4.75	1.36	.37	.25	.37	17.35	1.01	1.05	.21	.23	.21	.23	.19	.39
18. APPGOP3	4.50	1.37	.39	.29	.38	-1.42	1.63	.63	.32	.26	.25	.45	.60	.72
19. AVDGOP1	4.59	1.64	.14	.44	.27	-21.90	-4.90	-2.42	-.93	-.93	-.45	-1.09	-1.40	-1.11
20. AVDGOP2	4.69	1.47	.30	.49	.41	-34.12	-13.38	-1.99	-.74	-.61	-.33	-.81	-1.03	-.81
21. AVDGOP3	3.59	1.53	-.14	.19	-.04	-21.61	-6.04	-2.20	-.95	-.82	-.64	-1.15	-1.49	-1.05

(Table continues)

(Table continued)

Variable	13	14	15	16	17	18	19	20	21
1. EFF1†									
2. EFF2†									
3. EFF3†									
4. SAT†									
5. EFF1SAT									
6. GRADE									
7. CSEP1									
8. CSEP2									
9. CSEP3									
10. AC1									
11. AC2									
12. AC3									
13. MGOP1	1.62								
14. MGOP2	1.35	2.10							
15. MGOP3	.94	1.13	1.88						
16. APPGOP1	.64	.93	.65	1.98					
17. APPGOP2	.56	.66	.31	1.49	1.84				
18. APPGOP3	1.01	1.08	.50	1.20	1.23	1.87			
19. AVDGOP1	-.05	-.39	-.82	-.10	.20	.26	2.70		
20. AVDGOP2	.04	-.25	-.57	.11	.42	.45	1.73	2.15	
21. AVDGOP3	-.36	-.56	-.77	-.28	-.18	-.07	1.11	.92	2.34

Note. $N = 116$. Variance is displayed along the diagonal. EFF = Effort, SAT = Scholastic Aptitude Test (quantitative score only), CSEP = CS Self-Efficacy Parcel, AC = Affective Commitment to the CS Class, MGOP = Mastery Goal Orientation Parcel, APPGOP = Performance-Approach Goal Orientation Parcel, AVDGOP = Performance-Avoid Goal Orientation Parcel.

†These variables were mean centered.

$^{*}p < .05$

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EXPERIENCE

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- **Senior Research Assistant and Laboratory Manager**, Organization Research Group (ORG), Old Dominion University, Norfolk, VA (2002-2006)
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- **Organization Development (OD) Consultant**, Lohr & Lohr, Doctors of Optometry, Norfolk, VA (Fall 2005)

SELECT PUBLICATIONS, PRESENTATIONS, & TECHNICAL REPORTS

- Selgrade, K. A., & Bernas, K. H. (2007). *City of Norfolk: Workforce planning guide.* Norfolk, VA.
- Davis, D. D., Selgrade, K. A., & Major, D. A. (2006). *Gender and telework in information technology.* In E. Trauth (Ed.), Encyclopedia of gender and information technology (pp. 460-466). Hershey, PA: Idea Group Reference
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