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# LEARNERS' MOTIVATIONAL CHARACTERISTICS IN STATISTICS: A CAUSAL MODEL

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LEARNERS' MOTIVATIONAL CHARACTERISTICS IN STATISTICS:
A CAUSAL MODEL

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BY

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## ABSTRACT

This study explored learner characteristics related to motivation and cognition and their influences on cognitive engagement and achievement in statistics. Few previous studies have investigated the role of multiple variables, such as prior experience, self-efficacy, and goals in statistics, to examine how they influence statistics achievement in the context of one another. An examination of these variables together provides a better picture of the key influences motivational and cognitive engagement variables have on achievement in statistics. The present study examined the variables of (a) prior experience, (b) self-efficacy, (c) future consequences, (d) learning and performance goal orientations, (e) effort, and (f) deep and shallow processing strategy use in the context of one another in the domain of statistics to test the proposed theoretical causal model for achievement in statistics.

A total of 263 participants enrolled in three introductory statistics courses completed a two-part instrument measuring the variables of interest prior to their midterm exam. In order to assess the validity of the causal model, path analysis procedures outlined by Pedhazur (1982) were followed. Results of path analysis indicated the data fit the overidentified model well. A subsequent path analysis using a trimmed model also fit the data well. Results found that deep processing strategy use, self-efficacy, learning goals and prior experience have direct effects on achievement, and future career consequences, future graduate school consequences, and effort have indirect effects on achievement. Self-efficacy, by far, played the biggest role, directly and indirectly, in accounting for variance in many key variables related to achievement and achievement itself. Findings related to future consequences, a variable rarely investigated in statistics, provided support for theory and warrants further investigation of the role this variable plays in motivation. Suggestions for future research and the implications of these findings for teaching statistics are discussed.

# CHAPTER ONE

# INTRODUCTION

## Background of the Study

In the field of Social Science, students working on their degree tend to struggle with statistics more than other subjects in their curriculum. Statistics is one of the most challenging required courses for students to complete. Some students even choose to wait until the last possible semester before enrolling in the course (Roberts & Bilderback, 1980). When they do enroll, many students are anxious and spend many hours worrying about and studying the topic (Benson, 1989). Many of these students possess characteristics likely to negatively or positively affect their achievement in class. Some may have high anxiety, possess varied prior experience with statistics, hold negative or positive attitudes toward learning statistics, have low perceived ability and self efficacy beliefs for learning statistics and approach learning statistics using different goal orientations. To compound matters, most statistics courses now require students to compute statistical problems using a computer statistical package (Shannon, 1992). This often causes an increase in anxiety since many students often have limited computer skills and experience, especially with mainframe computers.

My interest in this subject domain is in examining learner characteristics that potentially influence learners' achievement in statistics. More specifically, I am interested in exploring learner characteristics related to motivation and cognition and their influences on cognitive engagement and subsequent achievement. Learner characteristics that affect motivation in a statistics course will likely affect subsequent cognitive engagement and achievement. Identifying the key variables that serve to either facilitate or hinder student cognitive engagement and achievement in statistics can be useful for statistics students and instructors who wish to address these variables prior to or during instruction. A literature review of research relevant to this topic found many variables that have been studied in connection with statistics achievement. These include (a) demographic variables, (b) prior experience, (c) prior achievement, (d) attitude toward statistics, (e) self-efficacy, (f) goals for learning, and (g) cognitive engagement. The diagram in Figure 1 depicts the influence and possible relationships a variety of learner characteristic variables have on student achievement in statistics. Learners enter with individual characteristics, such as prior statistics or math courses and associated achievement and goals for learning, and these characteristics likely play an important role in motivation, cognitive engagement, and achievement.

**Variables to be Investigated**

Several demographic type variables have been used in investigations of influences on achievement in statistics. Gender differences have been found in statistics achievement, but the findings are inconclusive. The number of prior statistics and math courses taken and associated achievements have been found to influence student attitude toward statistics and student achievement. The class rank of the student has also been found to be negatively related to attitudes toward statistics. This relationship is explained through the phenomenon that those with the poorest attitudes wait until the last possible semesters before enrolling in the course. Prior achievement, as reported by GPA, also predicted statistics achievement in several studies. While not previously investigated, it seems likely that the academic major of students could likely influence achievement through

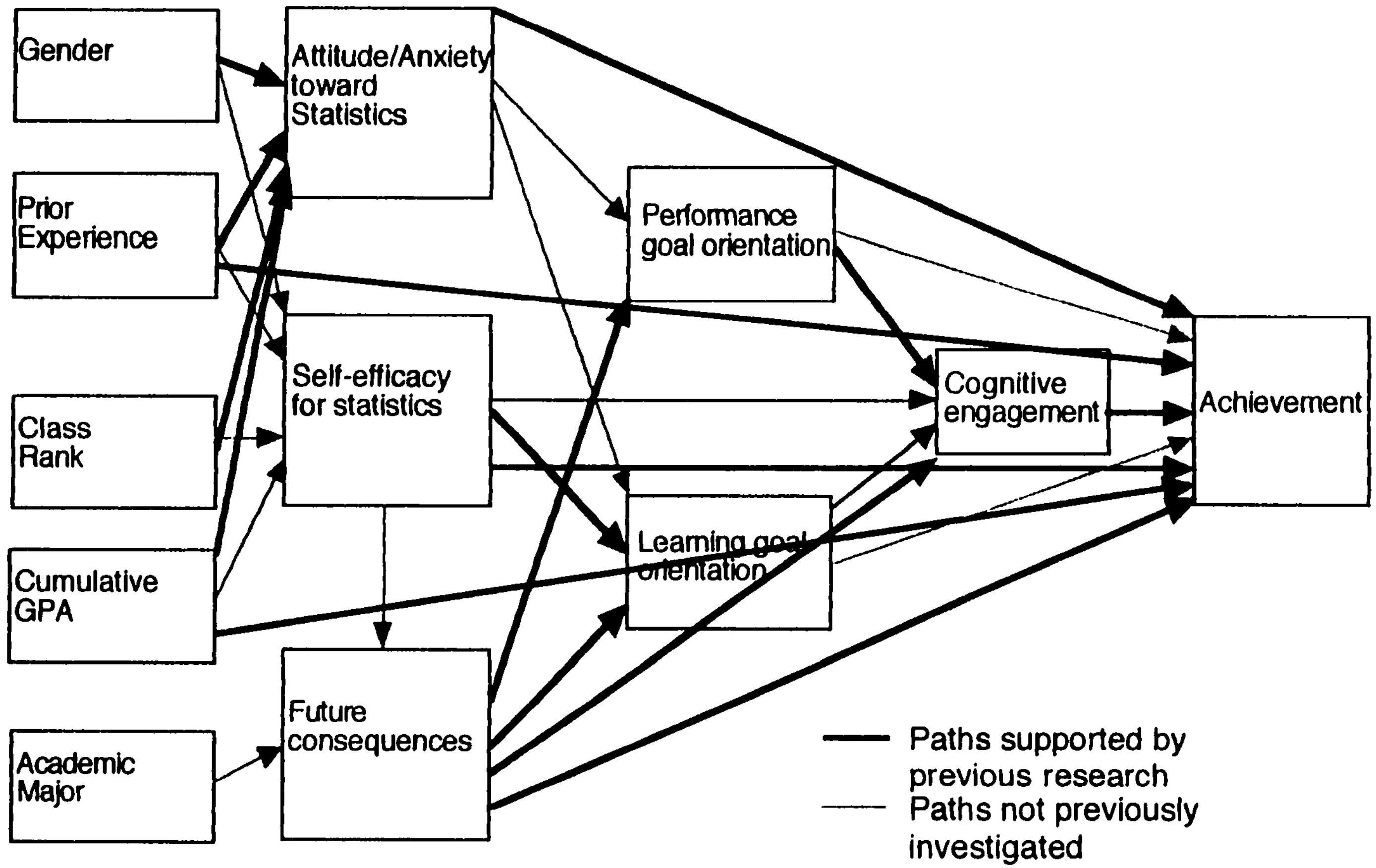


Figure 1. Path model of the influence of learner characteristics variables on student achievement in statistics.

various goals students may have for learning. Students in an academic major in which statistics knowledge is a critical skill for future career choices or advancements may adopt more advantageous goals for learning in statistics which may influence achievement.

Researchers have also investigated the relationship attitudes toward statistics have to cognitive engagement and subsequent achievement. Studies by Wise (1985) and Roberts and Bilderback (1980) found students with better attitudes did better in statistics courses. Students with negative attitudes toward statistics viewed statistics as an unfriendly topic and were not as successful as those students with positive attitudes toward statistics.

Self-efficacy may be another key variable related to student cognitive engagement and achievement. Bandura (1986) defined self-efficacy as an individual's personal assessment of his or her ability to successfully attain a specified action or goal. Bandura (1986) stated that the higher the self-efficacy a student possesses, the more likely he or she will be to engage in learning because he or she will exert more effort and tend to try harder when faced with challenging tasks. Students with low self-efficacy tend to give up easily and quit when faced with a challenge.

The variables of attitude and self-efficacy may also influence the goals with which students approach learning statistics. Dweck and Leggett (1988) discussed goal orientation theory and outlined two major ways students approach learning. First, students may approach learning with the goal of increasing their skill, competence, and knowledge. This is called learning goal orientation. Second, a student possesses a performance goal orientation when he or she approaches learning with the goal of impressing someone; looking good in front of others or avoiding looking bad. Students can possess both of these orientations to different degrees. For example, they may possess one or both of these qualities, can be high on one and low on the other, or can be high on both or low on both (Pintrich & Garcia, 1991). Therefore, students may enter introductory statistics courses wanting to learn statistics and understand it with learning goals, or wanting to get a high grade so that their professor or peers will think highly of them with performance goals, or have both motives. Students may be more or less involved in academic tasks or use different types of learning strategies depending on their goal orientation (Pintrich & Garcia, 1991).

These goal orientations are possibly influenced by the learner's attitudes and/or self-efficacy. A student with high efficacy and a good attitude is likely to approach learning with a goal of understanding and increasing competence in statistics. However, a student with low self-efficacy may learn just enough to pass the tests and participate in class so he or she does not look bad in front of his or her peers. While these two goal orientations are helpful in explaining the different ways in which students approach learning, they may not be sufficient in addressing all students. Goals students possess when they approach learning may not be as distinct as the learning goal and performance goal continuum.

According to Raynor (1974) students are motivated and tend to do better in subjects if they can predict that the topic will be useful in their future. Raynor found that students tend to do better in a course if they can link the subject to a future goal or understand its usefulness in the future. For example, students may approach learning in their statistics courses differentially depending on whether or not they believe that the skills learned will be useful in their future career or critical to advancement. Believing that statistics may be useful or critical knowledge will be more likely to lead them to adopt learning goals. So, students' perception of the future consequences of learning statistics that will motivate them to successfully complete the statistics course may include the goal of receiving their degree, the goal of obtaining the job they desire, or the usefulness of statistics in their future research endeavors. Maehr (1984) proposed that students with learning goals may tend to be future goal oriented. He also suggested that performance goals were linked to future goal orientation but this relationship would not be as strong as learning goals and future goal orientation.

The goals with which students approach learning statistics will likely influence the ways in which they engage in the material to be learned. Research has shown patterns of behavior which can be predicted from student goals. Butler (1987) and Elliott and Dweck (1986) have found that students with learning goals spend more time on learning tasks and persist longer when faced with difficulty when compared to students with performance goals. More importantly, a learning goal orientation increased the quality of engagement in learning. Cognitive engagement behaviors have been found to influence achievement in several studies. Research on cognitive engagement (Miller, Behrens, Greene, & Newman, 1993; Greene & Miller, 1996; Miller, Greene, Montalvo, Ravindran, & Nichols, 1996) indicates relationships between cognitive engagement variables and achievement. Miller and his colleagues identified that perceived ability, future consequences and learning goals were strongly correlated with meaningful cognitive engagement which in turn influenced achievement.

## Significance of the Study

All of the above variables combined result in multiple possible paths with indirect and direct influences on achievement in statistics. Figure 1 (see page 3) shows those that have been supported by previous research (shown by black line) and those that have yet to be studied in the domain of statistics (shown by gray line). Many studies have looked at these learner characteristic variables in isolation to predict their effects on student motivation, cognitive engagement, or achievement in statistics. Few studies, however, have looked at the role of multiple variables, such as prior experience, self-efficacy, and goals for learning in statistics to examine how they influence statistics achievement in the context of one another. An examination of these variables together provides a better picture of the key influences motivational and cognitive engagement variables have on achievement in statistics.

This study will be one of the first to examine this combination of motivational and cognitive engagement variables to predict achievement in statistics. By exploring how these variables are interrelated and serve to predict one another, instructors and students may be able to increase the emphasis on variables that serve to enhance motivation, encourage cognitive engagement and increase achievement. The more teachers and students of statistics understand key influential characteristics, the better they will be able to regulate learning of statistics. Some students may not be aware of their strengths and weaknesses or how these learner characteristics influence their achievement.

## Research Questions

This study will examine research questions related to the path model shown in Figure 2. These research questions are:

1. Of prior experience, self-efficacy, future consequences, performance and learning goals, deep processing, shallow processing and effort, which learner characteristics contribute directly or indirectly to variance in achievement in statistics?

2. What direct and indirect effects do prior experience, self-efficacy, future consequences, and performance and learning goals have on deep processing, shallow processing and effort?

3. What direct and indirect effects do self-efficacy and future consequences have on performance and learning goals?

4. Does prior experience predict self-efficacy and future consequences?

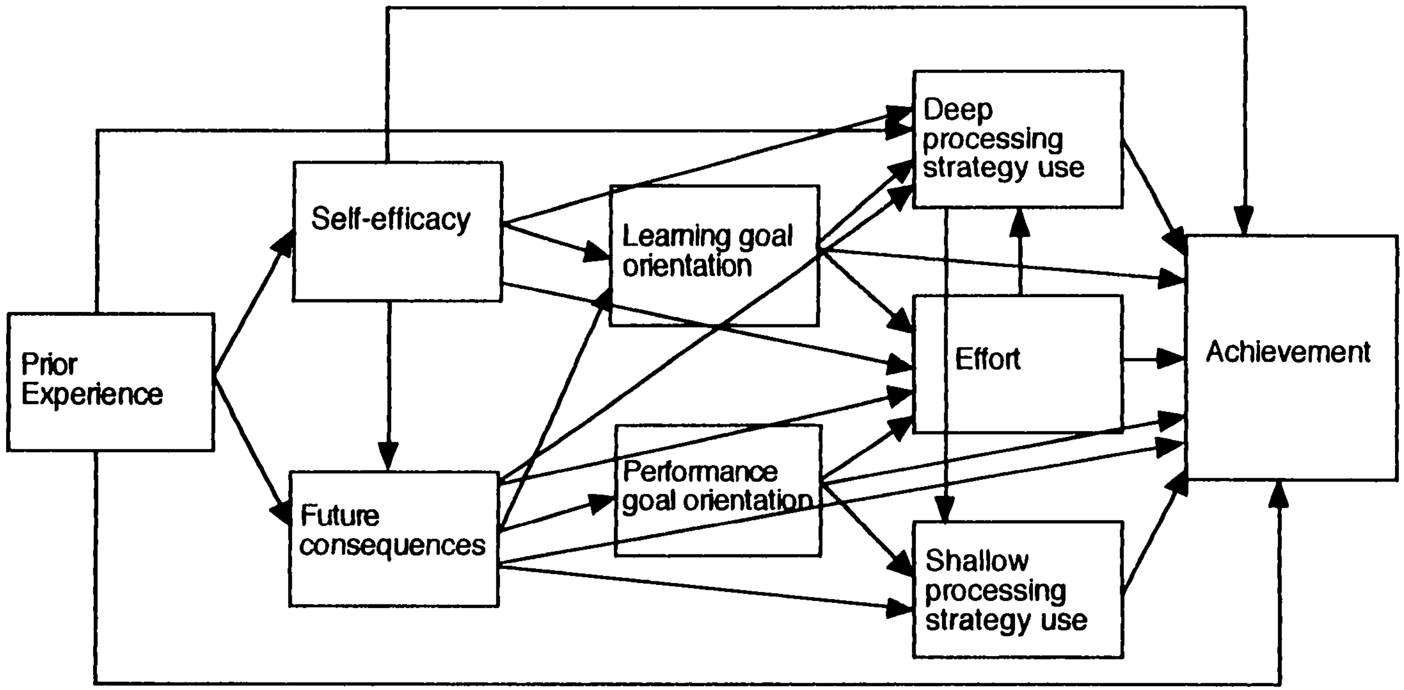


Figure 2. Initial path-analytic (overidentified) model: Influence of motivation and cognitive engagement variables on statistics achievement.

# CHAPTER TWO

## CURRENT LITERATURE

There are numerous studies that have examined the predictors of success in statistics achievement. Many suggested predictors are characteristics learners bring with them when enrolling in a statistics course. Other predictors include approaches to learning and strategies students use to learn statistics during enrollment in the course. What direct and indirect effects each of these predictors has on achievement, individually or in the context of one another, is still unclear. The following literature review elaborates on research related to the variables in Figure 1 (see page 3) by discussing the theories and research findings associated with each of these variables.

### Demographic Variables

Variables including gender, class rank of student, major, and full or part time status may influence statistics achievement. Fenster (1992b) found full/part time status and class rank of students to be significant predictors of performance in statistics courses. However, variables such as gender and major were not significant predictors of achievement. Fenster also found the number of hours in which students were enrolled to be a significant predictor of statistics achievement. Brooks (1987) found significant gender differences in statistics achievement, but Elmore and Vasu (1986), Ware and Chastain (1989a) and Woehlke and Leitner (1980) did not find gender to be a significant predictor of statistics achievement. No research has studied the influence of students' major on statistics achievement, however, it seems likely that this may influence performance in statistics through variables such as students' perceptions of the usefulness of statistics for their future career and other goals.

## Prior Experience and Achievement

Prior experience and achievement is likely to influence student learning especially when students are learning new but related tasks. Theories of cognition related to information processing suggest that previously learned relevant information held in long term memory that can be recalled facilitates the processing of new information (Woolfolk, 1995). Learners with prior knowledge possess information that allows them to understand incoming information from the sensory register (Woolfolk, 1995). This prior knowledge also makes the learner better able to integrate the new information with the old information and facilitates deep processing during cognitive engagement (Woolfolk, 1995).

Students enter statistics courses with different levels of prior experience and achievement in statistics or math courses. Fenster (1992a) hypothesized and found a strong positive relationship between learners' performance on a math aptitude test and their achievement in a statistics course. Fenster also found that achievement in statistics for individuals who had a prior statistics course was predicted from their attitude toward statistics, their math aptitude score, and years since taking a statistics course. However, gender and number of prior statistics courses were not significant predictors in this study. In a later study, Fenster (1992b) found prior statistics courses to be a significant predictor of performance in statistics with urban students.

Studies by Elmore and Vasu (1980; 1986) found that prior courses in statistics or math related course work significantly predicted statistics achievement over and above other variables such as spatial ability and feminist attitude. Elmore, Lewis, and Bay (1993) found a test of math ability to contribute significantly to the prediction of statistics achievement. Woehlke and Leitner (1980) found that performance on a basic mathematics pretest was a significant predictor of a final examination score in a masters level statistics course. Feinberg and Halperin (1978) also found measures of math achievement and previous experience in math were predictive of course performance in undergraduate statistics. Additionally, Harvey, Plake, and Wise (1985) found the number of math courses taken in high school and in college to be significantly and positively correlated with a first examination in a statistics course.

Giambra (1970; 1976) did not find that students' math background predicted success in statistics, but he did find that students' cumulative grade point average (GPA) predicted performance in introductory statistics. Ware and Chastain (1989a) also found students classified with a higher GPA had significantly higher statistics examination scores. Ware and Chastain (1989b) had similar findings of math background not contributing to differences in statistical interpretation or selection scores but GPA differences contributing to differences in statistical interpretation scores.

Prior experience and achievement are likely to influence the individual learner. There are mixed findings relating students' prior experiences and achievement to future achievement in statistics. Theory, however, would suggest that the more successful the prior experience and achievement, the more likely it is to positively affect student efficacy and attitude (Bandura, 1986; Maehr, 1984). Bandura's (1986) theory of self-efficacy and Maehr's (1984) theory of personal investment suggest that by having successful prior experiences and achievement, where the individual exerted a fair amount of effort and persistence, one's self efficacy and attitude toward a similar task is likely to be positive and his anxiety toward the task may be lower.

## Attitudes Toward Statistics and Statistics Anxiety

Learners' attitudes toward statistics have often been considered when investigating variables influencing cognitive engagement and subsequent achievement. An attitude is an internal state or disposition that influences individuals' choice of actions in a given situation (Green, 1994). An attitude is evident in behaviors such as approaching or avoiding certain situations or learning tasks. Attitudes have an affective and a cognitive component. In research on statistics learning, researchers have most often studied anxiety as the affective component of attitude influencing achievement and students' knowledge of the usefulness of statistics as the cognitive component of attitude influencing achievement (Green, 1994).

Green (1994) noted that many scales developed to measure attitudes toward statistics are assessing both the affective and cognitive components of attitude. The Attitude Toward Statistics (ATS) scale developed by Wise (1985) measures students' attitude toward statistics as a field of study and their attitude toward the statistics course in which they are enrolled. Green suggested that the first factor tends to tap the cognitive component while the second factor taps the affective component. In Green's (1994) study of graduate students in a statistics course, the only significant pretest predictor of grade was attitude toward statistics as a field ($r = .41$) while attitude toward the course was not a significant predictor of grade.

At posttest, both ATS factors were predictive of performance and predicted performance equally well (r = .53 for attitude toward the course and r = .52 for attitude toward the field). Wise (1985) found that student course grade was significantly and positively correlated with the attitude toward the course subscale (r = .27) and non-significantly correlated with the attitude toward the field of statistics subscale (r = -.04). Elmore, Lewis, and Bay (1993) found that the attitude toward the course subscale of the ATS contributed significantly to the prediction of statistics achievement in the context of computer usefulness and math ability measures while other variables were not significant (i.e., computer attitude, statistical anxiety, student prior knowledge, and demographic data).

Miller, Behrens, Greene, and Newman (1993) also measured attitude through subscales asking students about the intrinsic and extrinsic value they have of statistics. The four items measuring intrinsic valuing measured students' attitudes along the lines of the affective component described by Green (1994). For example, one item asked students to report the degree to which they agreed with the statement, "I found working with statistics enjoyable." The four items measuring extrinsic valuing measured students' attitudes along the lines of the cognitive component described by Green (1994). For example, one item asked students to report the degree to which they agreed with the statement, "Being able to use statistics will help me professionally." Miller et al. (1993) found that both intrinsic and extrinsic valuing were significantly and positively correlated with students' reported persistence in dealing with difficult problems (r = .36 and r = .30, respectively). They also found that students' reports of a more positive affect toward statistics through reports of intrinsic and extrinsic valuing were positively associated with their reports of perceived ability (r = .52 and r = .41, respectively) and learning goal orientations (r = .58 and r = .36, respectively). Intrinsic and extrinsic valuing also had significant and positive correlations with measures of self-regulation, including goal setting (r = .52 and r = .32, respectively), self-monitoring (r = .40 and r = .28, respectively), and strategy use (r = .50 and r = .36, respectively).

Miller et al. (1993) also conducted a multivariate analysis of variance assessing the impact of goal orientation and perceived ability on intrinsic and extrinsic valuing. They found students with learning goals reported more intrinsic and extrinsic valuing than students with performance goals. Also, students with high perceived ability reported higher intrinsic and extrinsic valuing than students with low perceived ability. Miller et al. did not include measures of achievement in statistics as a variable in their study, however, they did find that students' reported affects toward statistics were significantly and positively related to self-regulation variables, such as monitoring, strategy use, and goal setting, and measures of persistence. These variables are likely to influence achievement.

Other researchers have measured attitude as a unidimensional construct. Studies by Elmore (Elmore &Vasu, 1980; 1986) used the total score on the Fennema-Sherman Mathematics Attitude Scale as a measure of attitude in predicting statistics achievement. The 1980 study found the math attitude score was correlated significantly with statistics achievement (r = .426) but was not a significant independent contributor to statistics achievement in the context of several other variables. However, the 1986 study did find the math attitude scores to contribute significantly to prediction of statistics achievement over and above the contribution of spatial ability, math background, masculinity-femininity of interest pattern, gender, and attitude toward feminist issues.

Fenster (1992a) assessed attitude toward statistics using a single item measuring students' comfort level with statistics. He found a positive attitude toward statistics was positively associated with performance in statistics ($r = .24$). Ware and Chastain (1989a) measured attitude toward statistics using four items in which students rated the word "statistics" on the following four bipolar items: good-bad, cruel-kind, clean-dirty, and beautiful-ugly. They failed to find significant differences on test performance between people high and low on attitude toward statistics using this measure.

Roberts and Bilderback (1980) developed the Statistics Attitude Survey (SAS) to assess various components of statistics attitude including perceptions of how competent one is with statistics and the usefulness of statistical analysis. Roberts and Saxe (1982) found SAS scores were positively correlated with course grade ($r = .41$). They also found higher SAS scores were associated with having higher basic math skills, having had more previous math courses, and having more previous statistical knowledge.

Harvey, Plake, and Wise (1985) found measures of state anxiety were significantly correlated with and predictive of performance on statistics examinations. Further analysis indicated anxiety was the only significant predictor of achievement in statistics for graduate students, accounting for 21% of the variance. However, Elmore, Lewis, and Bay (1993) and Perney and Ravid (1990) did not find anxiety to predict statistics achievement for graduate students. Benson (1989) found gender, math self concept and past achievement to significantly predict statistical test anxiety, but she did not investigate its influence on achievement.

Research relating anxiety and learning (Green, 1994) has found that some anxiety in a learning situation can enhance student learning, but too much can be detrimental to a student. Eysenck (1979) has found that executive control processes in working memory such as monitoring and evaluating are adversely affected by anxiety. Roberts and Bilderback (1980) reported that statistics anxiety is prevalent among college students. Students who feel anxious about a class will feel the course is more difficult than it should be.

Mixed results have been reported relating measures of attitude and anxiety to measures of statistics achievement. A final conclusion as to the importance of attitude and anxiety is impossible. One problem lies in the variety of definitions and scales used to measure the constructs. Some researchers measure attitude and anxiety as a unidimensional construct while others measure them separately. Some studies analyzed attitude and anxiety in the context of one another and with other variables while other studies analyzed them independently. Finally, some of the studies reported above used measures of attitudes toward math rather than toward statistics. Any or all of these differences among these studies may have contributed to the mixed findings.

## Self-efficacy

Self-efficacy may be another key variable related to student cognitive engagement and achievement. Bandura (1986) defined self-efficacy as an individual's personal assessment of his or her ability to successfully attain a specified action or goal. Self-efficacy is one's confidence that he or she possesses the capabilities to organize and execute courses of action required to achieve expected types of performance. Bandura (1986) stated that the higher the self-efficacy a student possesses, the more likely he or she will be to engage appropriately in learning because he or she will exert more effort and tend to try harder when faced with challenging tasks. Students with low self-efficacy tend to give up easily and quit when faced with a challenge.

Self-efficacy has a strong influence on motivation and resulting achievement. Bandura (1986) reported that the greater one's self-efficacy, the greater the effort he or she will exert and the longer he or she will persist at difficult tasks. Efficacy research has concluded that people who possess different levels of self-efficacy behave differently (Bandura, 1986; Schunk, 1991). Those who perceive themselves as highly efficacious set goals and challenges that capture their interest and have high involvement in activities of their liking. Those who possess high self-efficacy tend to exert extra efforts when they perceive their performances fall short of their goals. They also tend to approach potentially threatening tasks non-anxiously. Their high self-efficacy tends to motivate behavior that produces accomplishment. In contrast, those who regard themselves as low in self-efficacy tend to shy away from difficult tasks, and they often lack effort and give up quite easily when faced with a challenge. Bandura (1986) informed us that those with low self-efficacy tend to dwell on their personal deficiencies and may suffer from much anxiety and stress.

Bandura (1986) proposed that the past experiences of success or failure on a given task are the most significant factor in determining self-efficacy. An individual's self-efficacy will significantly increase if he or she has had successful experiences with the same or similar tasks in the past. On the other hand, an individual's self-efficacy will decline drastically if he or she is not confident and believes himself or herself to be incompetent, especially if experiencing a past failure on the same or similar task. Schunk (1991) also provided empirical support for the theory that self-efficacy is influenced by prior accomplishments. In his study, providing feedback to learners as to their competency was an effective way of promoting self-efficacy and achievement. Bandura (1986) also cited vicarious experience, persuasion, and affective feedback as determinants of self-efficacy. One of the most prominent affective feedback measures is anxiety. Bandura stated that when the learner is faced with uncertain situations, his heart beats faster when his efficacy level might be low signaling to the learner that he or she is unsure of his or her competence.

Norwich (1987) observed the relationship between self-efficacy and a specific task performance in the field of mathematics learning. He found a moderate correlation between math self-efficacy and math performance. Randhawa, Beamer and Lundberg (1993) reported that mathematics self-efficacy was a mediator variable between mathematics attitudes and mathematics achievement. Cooper and Robinson (1991) examined self-efficacy beliefs and mathematics performance. They also determined self-efficacy was an important variable in outcome performance of mathematics. Hackett and Betz (1989) found that mathematics self efficacy measures were significantly and positively correlated with attitude toward mathematics and mathematics related topics. Their study used hierarchical regression analysis, and the results showed that mathematics self efficacy was a stronger predictor for mathematics achievement than the attitude of mathematics among students.

Miller et al. (1993) assessed students' perceived ability in statistics along with measures of goal orientation, valuing of statistics, persistence, and self-regulation variables. As reported above, they found perceived ability to be positively correlated with intrinsic and extrinsic valuing of statistics. They also found perceived ability was positively correlated with goal setting ($r = .65$), strategy use ($r = .52$), and monitoring ($r = .28$). They did not find a significant correlation between perceived ability and persistence which is contrary to Bandura's theory. A multivariate analysis of variance using the self regulation scores as a dependent variable and goal orientation and perceived ability as independent variables revealed students with high perceived ability reported higher levels of goal setting and strategy use than students with low perceived ability. A significant interaction was analyzed using multiple comparisons and found students with learning goals and high perceived ability reported higher levels of self-monitoring than students with learning goals and low perceived ability and students with performance goals and high perceived ability. Also, students with performance goals and high perceived ability reported lower levels of self-monitoring than students with performance goals and low perceived ability.

Self-efficacy is likely to have a considerable influence on cognitive engagement and achievement. Theory suggests the greater one's self-efficacy, the greater the effort individuals will exert and the longer they will persist at difficult tasks. As stated in the studies above, self-efficacy can be influenced by prior experience and achievement, attitude toward a given task, and anxiety. Most of the studies above related math self-efficacy to math achievement, but were reviewed due to the similarity often mentioned between the domains of math and statistics. The one study by Miller et al. (1993) was in the content domain of statistics and found perceived ability was related to valuing and several important self-regulatory activities that are likely to influence achievement. The relationship of efficacy to the valuing and goal setting variables also point to the potential for efficacy to influence learning, performance, and future consequence goals.

## Goals for Learning

### Performance and Learning Goal Orientations

Dweck and Leggett (1988) discussed goal orientation theory and outlined two major ways students approach learning. First, students may approach learning with the goal of increasing their skill, competence, and knowledge. This is called a learning goal orientation. Second, a student possesses a performance goal orientation when he or she approaches learning with the goal of impressing someone, looking good in front of others, or avoiding looking bad. Individual students can possess both of these orientations to different degrees. For example, they may possess one or both of these qualities, can be high on one and low on the other, or can be high on both or low on both. Therefore, students may enter statistics courses wanting to learn statistics and understand it, with learning goals, or wanting to get a high grade so that their major professor or peers will think highly of them, with performance goals, or have both motives.

Dweck (1986) indicated that the behavior of individuals with different goal orientations depends upon their perceived ability. She suggested that individuals with a helpless orientation focus on their inadequacies and their lack of ability.

These individuals see challenging problems as a threat to their self esteem. Learning goal oriented individuals are focused on mastering a task through strategies and effort in combination with their own ability. These individuals see problems as opportunities to learn something new. Performance goal oriented individuals, however, only want to demonstrate their competency and therefore only take on the tasks that look difficult to others but that they perceive as easy for themselves.

Learning and performance goal orientations are possibly influenced by the learner's attitudes and/or self efficacy. A student with high efficacy and a good attitude is likely to approach learning with a goal of understanding and increasing competence in statistics. However, a student with low self efficacy may learn just enough to pass the tests and participate in class so he or she does not look bad in front of his or her peers. While these two goal orientations are helpful, they may not be sufficient in addressing all students. Which goals students use to approach learning may not be as distinct as the learning goal and performance goal continuum.

**Future Consequences**

According to Raynor (1974) students are motivated and tend to do better in subjects if they can predict that the topic will be useful in their future. Raynor found that students tend to do better in a course if they can link the subject to a future goal or understand its usefulness in the future. Students may do better in statistics courses if they believe the skills learned will be useful in their future career. So, students' future goals which will motivate them to successfully complete the statistics course may include the goal of receiving their degree, the goal of obtaining the job they desire, or the usefulness of statistics in their future research endeavors. It also seems to reason that students' adoption of these types of goals could be influenced by the efficacy they possess to achieve in statistics and these future endeavors.

Raynor (1974) and Raynor, Atkinson and Brown (1974) indicated that students with positive future orientations achieved at higher levels on a learning task than students who did not see the future utility of their learning task. DeVolder and Lens (1982) indicated that the students who valued distant future goals more highly were the students with high grades and high levels of reported study effort, especially when compared with students with low grades and low levels of reported study effort. Research by Schutz and Lanehart (1992) and Schutz (1993) indicated that among college and high school students, long term educational goals, such as graduating or obtaining a masters or doctoral degree, were positively related to both achievement and reported self regulation and strategy use.

Support for Dweck's goal orientation theory and its application to statistics was found in a study by Miller, Behrens, Greene, and Newman (1993). They established that learning goal scores were positively correlated with measures of persistence ($r = .55$), goal setting ($r = .29$), and strategy use ($r = .39$), while performance goal scores were negatively related to self-monitoring ($r = -.27$) and not significantly related to any other self-regulatory behaviors. Further analyses found students with learning goals reported higher levels of strategy use than students with performance goals. They did not find the interaction between goal orientation and perceived ability as was expected based on theory. In this same study, measures of intrinsic and extrinsic valuing were used. These findings were discussed in the context of the influence of attitudes on cognitive engagement. However, items assessing extrinsic valuing are closely related to future usefulness and may also be applied to Raynor's theory discussed here. Miller and Brickman (1997) found evidence that future consequences have direct and indirect influences on cognitive engagement and achievement through their relationships to both learning and performance goal orientations. They also concluded perceived ability (self-efficacy) has direct and indirect influences on cognitive engagement and achievement. These studies identified another important factor in determining the success of individuals -- cognitive engagement. Students who adopted learning goal orientations in their statistics course tended to engage in meaningful cognitive activities that were likely to increase their achievement.

## Cognitive Engagement

Cognitive engagement, defined by Nolen (1988), is the use of different kinds of study strategies students use when faced with a task. Entwhistle and Ramsden (1983) distinguished two types of study strategies. Deep processing strategies involve identifying important information from unimportant information and finding a way to fit new information with already existing information. Deep level strategies are concerned with monitoring comprehension. Shallow level strategies involve simply trying to memorize all new information. Shallow level strategies are also concerned with rehearsing information. Entwhisle and Ramsden (1983) and Nolen (1988) concluded that deep processing strategies are more likely than shallow level strategies to lead to understanding and retention of meaningful material. Their particular interest was in factors associated with the use of deep processing strategies since the deep processing strategies are thought to lead to increased understanding of expository learning.

The goals with which students approach learning statistics will likely influence the ways in which they engage in the material to be learned. Research has shown patterns of behavior which can be predicted from student goals. Studies by Butler (1987) and Elliott and Dweck (1988) have shown that students with learning goals spend more time on learning tasks and persist longer when faced with difficulty. More importantly, a learning goal orientation increased the quality of engagement in learning. Pintrich and DeGroot (1990) found self efficacy and intrinsic valuing were positively related to cognitive engagement and achievement. Students who are interested in learning for their self improvement and for the increase in skills (learning goal orientation) tend to show an increase in the appropriateness of their cognitive learning strategies and self regulation. Students who are interested in showing their capability (performance goal orientation) tend to show no relation or negative relations to the use of deep cognitive learning strategies and self regulation (Miller et al., 1993; Nolen, 1988).

Miller et al. (1996) examined cognitive engagement in academic work from a multiple goals perspective in the domain of mathematics. In this two part study they identified five goal perspectives consisting of learning goals, performance goals, obtaining future consequences, pleasing the teacher, and pleasing the family. The additional variables observed were perceived ability in math, self-regulatory activities, deep or shallow strategies, and the amount of effort and persistence. In this study, Miller and his colleagues used self-regulation, persistence, deep and shallow strategies and effort as measures of cognitive engagement. In the first study, learning goals, perceived ability, pleasing the teacher, and future consequences significantly contributed to the prediction of self-regulation and accounted for 52% of the variance. Learning goals and future consequences contributed significantly to the prediction of deep processing strategy use and accounted for 32% of the variance. Learning goals significantly predicted reports of effort, and learning goals, perceived ability, and future consequences significantly contributed to variation in persistence. Finally, self-regulation, persistence and effort contributed significantly to prediction of achievement and accounted for 24% of the variance. A subsequent analysis of all variables and their influence on achievement revealed effort, future consequences, and perceived ability to be the best predictors of achievement and accounted for 40% of the variance.

The major difference between study one and study two by Miller et al. (1996) was that in study one all measures were collected at a single time. In the second study they assessed goals and perceived ability early in the semester and cognitive engagement variables several weeks prior to final examinations. The achievement variable was a measure of students' final percentage grade in the course. Results from this study indicated that (a) learning goals and future consequences predicted self-regulation and deep processing strategy use; (b) learning goals and perceived ability predicted effort; (c) learning goals, pleasing the family (negative weight), and the interaction of learning goal by perceived ability predicted persistence; (d) of the five cognitive engagement variables, persistence was the only significant predictor of achievement; and (e) with the addition of goal variables and perceived ability to cognitive engagement variables, only perceived ability and persistence predicted achievement.

While not in the domain of math or statistics, Greene and Miller (1996) conducted a study including many of the variables discussed above as relevant to statistics achievement. They examined the relationships among students' self reported goal orientation, perceived ability, cognitive engagement, and achievement in college level educational psychology courses. The resulting path model clearly indicated that perceived ability and learning goal scores were positively correlated with meaningful cognitive engagement which was positively correlated with achievement. Their study, similar to previous research, indicated performance goal orientations were positively correlated with shallow level strategy use. This shallow level cognitive engagement led to negative influences on achievement. Greene and Miller also found that deep level processing strategies suppressed the negative effects of shallow level strategies on achievement. Possible suggestions they pointed out for this is that learning goal oriented students tend to utilize both strategies when faced with learning situations and this will facilitate learning in various contexts. Performance goal oriented students utilized only the single dimension of shallow level cognitive strategies. They found that as a student with a learning goal orientation became more confident about his or her ability to learn, he or she tended to engage in deeper level strategies of cognitive engagement and self regulatory skills.

## The Current Study

All of the above variables combined result in multiple possible paths with indirect and direct influences on achievement in statistics. Figure 1 (see page 3) shows those that have been supported by previous research (shown by black line) and those that have yet to be studied in the domain of statistics (shown by gray line). It is important to note, however, that no study has used all of the variables in context of one another and some findings were in the domain of math rather than statistics. The inconsistent findings of the contribution of various learner characteristics in predicting cognitive engagement and achievement makes it difficult to determine the overall effects of each variable. An example of this is that attitude played an important role in student learning while in other instances it did not affect student learning. When cognitive engagement was measured, it consistently accounted for variance in achievement. So, it would be helpful to identify learner characteristics contributing most to cognitive engagement, especially within the context of one another. This study will examine variables (prior experience, self-efficacy, future consequences, learning and performance goal orientations, effort, and deep and shallow processing) in the context of one another in the domain of statistics to test the theoretical causal model in Figure 2 (see page 9) on achievement in statistics.

Some studies have tied efficacy and future consequences to goal orientation, however, little has been done in the domain of statistics. While the literature review above hypothesized that a variety of demographic variables will be important in contributing to variation in statistics achievement, the more theoretically sound and important one of these variables is individuals' prior experience in math and statistics. Other literature has looked at attitude as an important variable in predicting achievement. However, those studies examined attitude as an only variable or in combination with variables other than self-efficacy. When attitude and self-efficacy are observed together, it is hypothesized that they will be highly correlated to the point of multicollinearity. As a result, attitude will be looked at in later studies and will be omitted from this current study. This will allow for a more in-depth look at each variable in the model and how efficacy and future consequences influence goal orientations, cognitive engagement and achievement.

The current model is similar to Miller and Brickman's (1997) model of the impact of perceived instrumentality on immediate goals and cognitive engagement which indicated future consequences' and perceived ability's direct and indirect effects on goals, cognitive engagement, and achievement. The current model includes prior experience as measured by previous number of math and statistics courses, self-efficacy, future consequences, learning and performance goals, effort, deep processing, shallow processing and achievement. The proposed causal relationships among variables are as follows. Prior experience was hypothesized to have direct effects on self-efficacy, future consequences, deep processing, and achievement (Bandura, 1986; Miller & Brickman, 1997). Bandura stated that an individual's past experiences where a high degree of effort and persistency was applied will have high influence on a person's self-efficacy. Miller and Brickman also stated that prior experience will influence the goals to which one aspires. Theory related to deep processing and achievement also would hypothesize the direct relationship between prior experience and deep processing strategy use and related achievement. I also hypothesized that future consequences and self-efficacy will cause some variation in learning goals (Miller & Brickman, 1997). This would especially be true if future consequences are viewed as related to current academic achievement behavior. If so, this will also increase the likelihood that students' current goals focus on learning. Miller and Brickman (1997) found that future consequences also have direct effects on performance goals. The variables of self-efficacy, future consequences, and learning goals will predict variation in effort, and deep processing strategy use and achievement. Future consequences and performance goals will likely predict variation in shallow processing strategy use. Effort is hypothesized to have direct effects on deep processing strategy use and achievement, and cognitive processing strategy use (deep and shallow) should directly effect achievement. Finally, a path showing the influence of deep processing on shallow processing is included due to the previous findings by Greene and Miller (1996).

# CHAPTER THREE

# METHODOLOGY

## Participants

Participants were students enrolled in undergraduate statistics courses in the Psychology and Economics departments (PSY 2003, PSY 2113, and ECON 2843) at a large midwestern university. The three courses had varying enrollments and were taught by three different professors. There were a total of 263 participants, but due to missing data, data from a total of 197 participants were analyzed. Participant demographics are presented in Table 1.

The course, PSY 2003, is a general education course requirement for the university so the students represented a wide variety of majors. Instead of taking a general mathematics course for their general education requirement for the university, these students were taking introductory statistics to meet the requirement. For some majors, at least one course in statistics is required. PSY 2003 course requirements consist of five quizzes, evenly spread out through the semester. Attendance was mandatory and the students were given one excused absence for participation in this research.

PSY 2113 is an introductory statistics course designed especially for psychology and health science majors (nursing, physical therapy, dental, etc.). The PSY 2113 course is designed with midterm and final exams being the biggest part of the grade for the course. PSY 2003 and PSY 2113 students participated in a traditional lecture format three days during the week and they also met once a week for smaller lab/group work. Attendance in PSY2113 was also mandatory. Students were encouraged by the professors of both PSY 2003 and 2113 to

Table 1

Participant Demographics

| Gender | Percent | Prior Experience in Statistics | Percent |
|---|---|---|---|
| Males | 26.4 | No prior statistics course | 85.8 |
| Females | 69.5 | One statistics course | 10.6 |
| Not reported | 4.1 | Not reported | 3.6 |
| **Race** | **Percent** | **Prior Experience in Math** | **Percent** |
| Caucasians | 75.6 | No previous math courses | 7.1 |
| African-American | 7.1 | One math course | 32.5 |
| Asian-American | 4.1 | Two math courses | 31.5 |
| Native American | 6.1 | Three math courses | 17.3 |
| Other | 2.0 | Four math courses | 7.1 |
| Hispanic | 1.0 | Five math courses | 1.0 |
| Not reported | 4.1 | | |
| **Classification** | **Percent** | | |
| Freshmen | 12.2 | | |
| Sophomores | 32.0 | | |
| Juniors | 36.0 | | |
| Seniors | 14.7 | | |

participate in this research.

ECON 2843 is also a large lecture format course that meets twice a week with the professor and has smaller lab meetings once a week led by graduate students. The majority of the students were economics majors. The course had two exams evenly spaced out and a final. The second exam was similar in content to exam three in PSY 2003 and the midterm in PSY 2113. Attendance in this class was not mandatory.

All three courses were similar since they were introductory courses. Both psychology statistics courses used the same text book. The economics statistics course used a similar introductory text book and covered similar topics. Some of the topics included introductory research design, descriptive statistics, correlation, probability, and inferential statistics (t-tests and one way analysis of variance). All classes had assigned homework which was reviewed and discussed in the lab setting.

## Instrument

All variables in Figure 2 (see page 9) except achievement were measured using a researcher constructed instrument that can be viewed in Appendix A. The instrument was divided into two parts for data collection. The first part included demographic information and prior experience questions and 36 items measuring learning and performance goal orientations (7 learning and 8 performance), future consequences (10 items), and self-efficacy (11 items). Prior experience was measured as the combined number of math and statistics courses students reported taking. Examples of items measuring learning goal orientation, performance goal orientation, future consequences, self-efficacy are provided in Table 2. All items were randomly ordered and asked participants to respond using a seven point scale with "1" indicating that the participant strongly disagreed with the statement and "7" indicating the participant strongly agreed. The second part of the instrument included 25 items measuring cognitive engagement (16 deep and 9 shallow) and one item to assess effort. Examples of these items are provided in Table 2. All cognitive engagement items were randomly ordered and asked participants to respond using a seven point scale with "1" indicating that the participant strongly disagreed with the statement and "7" indicating the participant strongly agreed. Effort was measured using a 5 point scale asking students to rate their effort in statistics class compared to their typical amount of effort for school work. A score of "1" indicated extremely high effort and "5" indicated extremely low effort. The effort scores were reversed prior to data analysis. Variations of this questionnaire have been used by Miller and colleagues (Greene & Miller, 1996; Miller, Behrens, Greene, & Newman, 1993; Miller, Greene, Montalvo, Ravindran, & Nichols, 1996) on related research projects.

Achievement was measured as the percentage grade received on the midterm exam in each course. Because five quizzes were given throughout the semester in PSY 2003, I decided to treat the third quiz as the midterm exam. In ECON 2843 the second exam was treated as the midterm exam.

**Procedures**

Both instruments were administered to students enrolled in the introductory statistics courses previously discussed. Within the first three weeks of the semester, all students were asked to participate in the project, and information and consent forms (see Appendix B) explaining the project were handed out. Students

Table 2

Sample Items from Instruments

| Variable with Sample Items |
| --- |

Performance Goal:

One of my primary goals is to do well in this class because I don't want others to think I'm not smart.

One of my primary goals is to do well in this class because I want to look smart to my friends.

Learning Goal:

One of my primary goals in this class is to develop a good understanding of the statistical concepts I will be taught.

One of my primary goals in this class is to understand the concepts.

Future Consequences:

One of my primary goals is to do well in this class because doing well is necessary for admission to graduate school.

One of my primary goals is to do well in this class because good grades are important for graduate school admission.

One of my primary goals is to do well in this class because I want to understand the statistical concepts that will be involved in my future career.

I want to understand the statistical concepts because it will be useful in my future career.

Self-Efficacy:

I am confident I can understand the materials taught in this statistics course.

I feel confident in my ability to learn the material in the statistics course.

Deep Processing Strategy Use:

When I finish working on practice problems, I check my work for errors.

When I work a problem, I analyze it to see if there is more than one way to get the right answer.

Shallow Processing Strategy Use:

If I have trouble solving a problem, I'll try to get someone else to solve it for me.

When I run into a difficult homework problem, I usually give up and go on to the next problem.

(table continues)

| Variable with Sample Items |
|---|
| <u>Effort:</u><br>How would you rate your effort in this class compared to your typical amount of effort for school work?<br>a. Extremely high (probably as much effort as I've ever put into a class)<br>b. Fairly high (more effort than usual, but I have worked harder in other classes)<br>c. About average<br>d. Fairly low (less effort than usual, but I have put in less effort in other classes)<br>e. Extremely low (probably the least amount of effort I've ever put into a class) |

gave consent to the release of their exam scores and were assured confidentiality. The first part of the instrument was also administered during this class period. The second part of the instrument was administered the class period prior to the midterm exam. Students' scores from the midterm exam served as the measure of achievement. Achievement measures were obtained from the course instructors. Those students who did not wish to participate in the research project were not penalized.

## Data Analysis

### Instrument Reliability and Validity

Items on the instrument measuring the psychological constructs of self-efficacy, future consequences, and learning and performance goals were factor analyzed to determine that the items intending to measure the same construct share common variance. In addition, these subscales along with the cognitive engagement subscales were analyzed to determine subscale reliabilities. Means and standard deviations were also calculated and reported. Correlational analyses were performed among the subscales and other variables to examine some of the fundamental relationships predicted from theories. These findings are reported in the results section.

### Path Analysis

In order to assess the validity of the causal model presented in Figure 2 (see page 9), path analysis procedures outlined by Pedhazur (1982) were followed. Path analysis of data is designed to shed light on whether the causal model is consistent with the data. If inconsistency is found with the data, then the theory is questioned (Pedhazur, 1982). Path analysis also allows study of direct and indirect effects of variables hypothesized as causes of variables treated as effects. Path analysis does not discover or confirm causes but it applies to a causal model that is formulated by the researcher on the basis of knowledge and theoretical considerations (Pedhazur, 1982). Path analysis uses correlation to link two variables but it depends on reason, logic, and some background knowledge of the variables to link the variables in order to interpret their causality (Page, 1993). Having established links between variables, new vocabulary is required to further discuss the path analysis. The term exogenous variable is used when a causality arrow comes from it and no arrow leads into it; therefore, it could be considered a starting point. Exogenous variables are assumed to be determined by causes outside the causal model. Endogenous variables have causality arrows pointing to them and some of their variance is hypothesized to be explained by the exogenous or endogenous variable(s) from which the arrow originated (Page, 1993). The path coefficients are calculated by using multiple regression analyses in which each endogenous variable is regressed on the variables that are prior to it in the model and assumed to have a causal effect on it.

In this particular research, testing of the causal model was conducted using the overidentified model in Figure 2 (see page 9). This model is overidentified because some of the possible paths were dropped due to their not having hypothesized direct effects on other variables (Pedhazur, 1982). The validity of the overidentified model can be assessed using a Chi square goodness of fit test. This tests whether a specific model is consistent with the pattern of intercorrelations among the variables by seeing how well the path coefficients reproduce the correlation matrix in comparison to the just-identified (fully saturated) model in which all possible paths are included and analyzed. In this situation, rejection of the null hypothesis indicates that the model does not fit the data. If the overidentified model is found to fit the data well, the researcher has several choices. He or she could choose to adopt the overidentified model. In this case, the results have indicated that the theory withstood the test and it has not been disconfirmed (Pedhazur, 1982). Other researchers may choose to engage in further model trimming. Although, theoretically, the model has withstood the chi square goodness of fit test and fits the data, further refinement is conducted in which path coefficients that did not meet the criteria of statistical significance are deleted from the model. This new trimmed overidentified model is then used to determine the multiple regression analyses to compute and identify the new path coefficients associated with the causal paths that remain. Once again, the validity of the trimmed model is assessed using a Chi square goodness of fit test in comparison to the previous overidentified model. This approach allows for assessment of the trade off between parsimony and fit and may encourage further refinement of present theory if the more parsimonious model is found to fit the data well. This approach to path analysis was used to analyze the data in this study.

Once the fit of the model to the data was assessed, the direct and indirect effects each variable has on other variables in the model were calculated. Pedhazur (1982) suggests that the total effect (direct and indirect) a variable has on another should be reported because using only direct effects for interpretation may be misleading due to path coefficients being calculated in the context of all the variables that affect a given endogenous variable.

# CHAPTER FOUR

# RESULTS

This chapter is divided into three sections. The first section will discuss the reliability and validity analyses of the instrument that was used in measuring the motivational learner characteristics. Specifically, validity is addressed in detail including content validity and factor analysis results. Also, internal consistencies were calculated using Cronbach alpha reliability coefficients and are discussed. The second section presents descriptive statistics of interest including means, standard deviations, and subscale intercorrelations. The final section reports the results of the path analysis procedures.

## Instrument Validity and Reliability

Content validity experts completed a rating form (see Appendix C) to validate that items intending to measure efficacy, future consequences, and learning and performance goals appropriately represented one of the four conceptual definition categories. Content experts were given categories accompanied by the conceptual definitions generated from review of the literature. They were asked to read each item and indicate to which category it belonged. They also provided a rating from 1 (indicating not very sure) to 4 (indicating absolutely sure) that assessed how strongly they felt about their placement of the item into the category. Content experts were six doctoral students in their final year of study with advanced coursework in motivation and cognition, and one professor with research interests in motivation and measurement. All seven content experts agreed on the categorization of all but two items. The average ratings for their confidence in placement for the items to which everyone agreed were between 3.86 and 4.00.

This indicates that all experts were very confident in their categorization. For two of the items one of the content experts disagreed with the others but indicated he was not absolutely sure of the placement. The average ratings of the other participants with the hypothesized categorization was a perfect 4.00 on both. The decision was made to keep these two items and no items were deleted nor altered prior to administering the survey.

The instrument presented in the previous chapter and administered to the participants contained 36 items which were intended to measure the psychological constructs of future consequences, goal orientation for the class, and self-efficacy regarding statistics. The responses to these 36 items were examined using factor analysis to provide evidence that the items measuring the constructs shared common variance. A Principal Factor analysis with oblique rotation of the 36 items was computed for the 197 subjects without missing data. Oblique rotation was chosen because of the theoretically predicted correlations among efficacy, learning goal, and future consequences. Use of orthogonal rotation would have artificially eliminated the predicted correlations. Examination of the scree plot and eigenvalues (i.e., values greater than one) revealed five factors. The factors corresponded to the following constructs: learning goal, performance goal , self-efficacy, future consequences (toward graduate school), and future consequences (toward career). Although the future consequences questions were purposefully designed to focus on two areas, career and graduate school, only one factor was expected. In each case the items designed to measure these constructs loaded relatively high on the appropriate factors and did not load higher than .40 on any other factor. The items along with their factor loadings are reported in Table 3.

Table 3

Factor Analysis Results

| Factor, Subscale Reliability, Items, and Factor Loadings | |
|---|---|
| Performance Goal: (.915) | |
| One of my primary goals is to do well in this class because I don't want others to think I'm not smart. | .883 |
| One of my primary goals is to do well in this class because I want to look smart to my friends. | .828 |
| One of my primary goals in this class is to show people that I am smart. | .813 |
| One of my primary goals is to do well in this class because I don't want to look foolish or stupid to my friends, family or teachers. | .781 |
| One of my primary goals is to do well in this class because I don't want to be the only one who cannot do the work. | .757 |
| One of my primary goals is to do well in this class because I don't want to be embarrassed about not being able to do the work. | .719 |
| One of my primary goals in this class is to do better than other students. | .672 |
| One of my primary goals in this class is to score higher than other students. | .612 |
| Learning Goal: (.890) | |
| One of my primary goals in this class is to develop a good understanding of the statistical concepts I will be taught. | .850 |
| One of my primary goals in this class is to understand the concepts. | .843 |
| One of my primary goals in this class is to comprehend the material presented. | .742 |
| One of my primary goals in this class is to improve my ability to do statistical computations. | .720 |
| One of my primary goals in this class is to improve my knowledge of statistics. | .678 |
| One of my primary goals in this course is to acquire new skills. | .611 |
| One of my primary goals is to increase my understanding of how statistics are used in daily life. | .502 |

(table continues)

| Factor, Subscale Reliability, Items, and Factor Loadings | |
|---|---|
| Future School Consequences: (.870) | |
| One of my primary goals is to do well in this class because doing well is necessary for admission to graduate school. | .926 |
| One of my primary goals is to do well in this class because good grades are important for graduate school admission. | .917 |
| One of my primary goals is to do well in this class because getting into graduate school is important to me. | .820 |
| One of my primary goals is to do well in this class because good grades are important for getting into my future career. | .515 |
| One of my primary goals is to do well in this class because I want to understand the statistical concepts if I am accepted to graduate school. | .505 |
| Future Career Consequences: (.770) | |
| One of my primary goals is to do well in this class because I want to understand the statistical concepts that will be involved in my future career. | .709 |
| I want to understand the statistical concepts because it will be useful in my future career. | .658 |
| One of my primary goals is to do well in this class because doing well is necessary for getting the job I want after I graduate. | .653 |
| One of my primary goals is to do well in this class because it will help me get into the career I want after I graduate. | .472 |
| I want to understand the statistical concepts because it will be useful while in graduate school. | .378 |
| Self-Efficacy: (.904) | |
| I am confident I can understand the materials taught in this statistics course. | .872 |
| I feel confident in my ability to learn the material in the statistics course. | .843 |
| I am confident I can do a good job on the problems or homework given in my statistics course. | .821 |
| I am confident I will master the materials that are taught in the statistics course. | .805 |
| I am confident I can get at least a "B" (3.0) in this statistics course. | .726 |
| I am confident I can describe what correlation means. | .699 |
| I am confident I can understand what statistics are used for. | .660 |
| I am confident I know how to interpret statistical values. | .638 |
| I am confident I can identify the appropriate statistical test for a research question. | .615 |
| I am confident I can describe what probability means. | .589 |
| Compared with others in my class, I am confident I will learn a great deal more about the subject of statistics. | .354 |

Factor one accounted for 22.5% of the variance and represents students' self-efficacy in statistics. Factor two accounted for 15.4% of the variance and represents students' performance goal orientation. Factor three accounted for 11.7% of the variance and represents students' learning goal orientation. Factor four accounted for 9.7% of the variance and measures students' future consequences of statistics for graduate school. One of the items loading on this factor did not ask specifically about the consequences of statistics for graduate school. However, it asked about the importance of good grades for a future career which may explain its shared variance with those items referring to graduate school. Factor five accounted for 4.7% of the variance and appears to represent students' future consequences of statistics for career. Again, one of the items loading on this factor did not fall into the career domain but seemed as though it belonged in the graduate school domain. This item also had a relatively low factor loading and was subsequently dropped from further analyses. The total final communality estimate revealed that 64% of the variance was accounted for by all five factors.

The internal consistency of the subscales determined by the factor analysis was analyzed using Cronbach alpha reliability coefficients. The subscale reliabilities were: (a) performance goal, .915; (b) learning goal, .890; (c) self-efficacy, .904; (d) future school consequences, .870; and (e) future career consequences, .770.

**Descriptive Statistics**

Descriptive statistics, reported in Table 4, include the mean, standard deviation, and range for each subscale for the proposed path model. The intercorrelations among the subscales are reported in Table 5.

Table 4

Descriptive Statistics

| Variable | Mean | Standard Deviation | Range |
|---|---|---|---|
| Deep Processing | 5.25 | .67 | 3.63 - 6.81 |
| Shallow Processing | 4.24 | .67 | 2.67 - 6.44 |
| Efficacy | 5.56 | .80 | 3.18 - 7.00 |
| Effort | 3.34 | .91 | 1.00 - 5.00 |
| Future Career | 5.47 | 1.07 | 1.00 - 7.00 |
| Future School | 5.92 | 1.09 | 1.00 - 7.00 |
| Learning | 5.80 | .99 | 1.57 - 7.00 |
| Performance | 3.63 | 1.32 | 1.00 - 7.00 |
| Achievement | 77.18 | 14.48 | 37.00 - 100.00 |

Table 5

Intercorrelation Matrix of Path Model Variables

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1. Deep processing | | | | | | | | | |
| 2. Shallow processing | .22** | | | | | | | | |
| 3. Efficacy | .26** | -.01 | | | | | | | |
| 4. Effort | .28** | -.01 | -.16 | | | | | | |
| 5. Future career | .28** | .09 | .39** | .08 | | | | | |
| 6. Future school | .19* | .09 | .09 | .05 | .47** | | | | |
| 7. Learning | .40** | .10 | .43** | .11 | .55** | .26** | | | |
| 8. Achievement | .14 | -.05 | .12 | -.02 | .05 | .01 | -.09 | | |
| 9. Performance | .09 | .31** | .12 | .03 | .10 | .23** | .13 | -.09 | |
| 10. Prior experience | .05 | .02 | .01 | .07 | -.06 | -.07 | -.09 | -.08 | -.07 |

* p=.05, ** p=.01

The subscales measuring future career, future school, deep and shallow processing, efficacy, and learning goal were well above the midpoint of 3.5 on the 7-point scale with deep processing, shallow processing, and efficacy also having restricted ranges. The mean score for performance goal was 3.63, only slightly above the midpoint of the scale. Effort was measured on a 5-point scale and also had a reported mean above the midpoint. The measure of prior experience of participants indicated students had between 0 and 6 previous courses in math or statistics. However, the mean was far below the midpoint of the scale indicating the majority of the participants had low prior experience. Achievement measures ranged from 37 to 100 percent with a mean of 77.18 and a standard deviation of 14.48 indicating a "C" average on midterm examinations.

The intercorrelations among the path model variables (Table 5) are reported as Pearson product moment correlations to examine theoretical relevance. The data indicate a strong relationship between the learning goal orientation and deep processing strategy use subscales (.40). Deep processing strategy use also had significant positive relationships with efficacy (.26), effort (.28), future career consequences (.28), future school consequences (.19), and shallow processing (.22). Only performance goal orientation was significantly related to shallow processing strategy use (.31). All of these correlations have been reported in previous research. Self-efficacy was significantly and positively correlated with future career consequences (.39) and learning goal orientation (.43). Future career consequences was positively correlated with future school consequences (.47) and learning goal orientation (.55). Also, future school consequences had strong correlations with both learning (.26) and performance (.23) goal orientation subscales. Surprisingly, achievement was not significantly correlated to any other variables.

## Path Analyses

### Path Analysis of Overidentified Model

The overidentified model in Figure 3 was submitted to path analysis procedures described previously. I should note that Figure 3 is a revised version of Figure 2, previously presented, due to the above factor analysis results. The major modification was the future consequences variable. This single variable in Figure 2 was separated into two variables (future school and future career) in Figure 3 and the paths were drawn for each new variable. Each dependent variable was regressed on the variables that had causal paths leading to it using multiple regression procedures (Pedhazur, 1982). All variables were entered simultaneously. The results are reported in Table 6. A Chi square goodness of fit test described by Pedhazur (1982) was used to assess the validity of the model.

The Chi square test was not significant, $\chi^2 = 9.69$ compared to the critical $\chi^2$ $(10) = 18.31$ at $p = .05$, indicating the model provided a good fit with the data. The R-square for each of the dependent variables was: (a) self efficacy, $R^2 = .0001$; (b) future career consequences, $R^2 = .34$; (c) future school consequences, $R^2 = .01$; (d) learning goal orientation, $R^2 = .36$; (e) performance goal orientation $R^2 = .07$; (f) deep processing strategy use, $R^2 = .25$; (g) shallow processing strategy use, $R^2 = .14$; (h) effort, $R^2 = .07$; and (i) achievement, $R^2 = .14$.

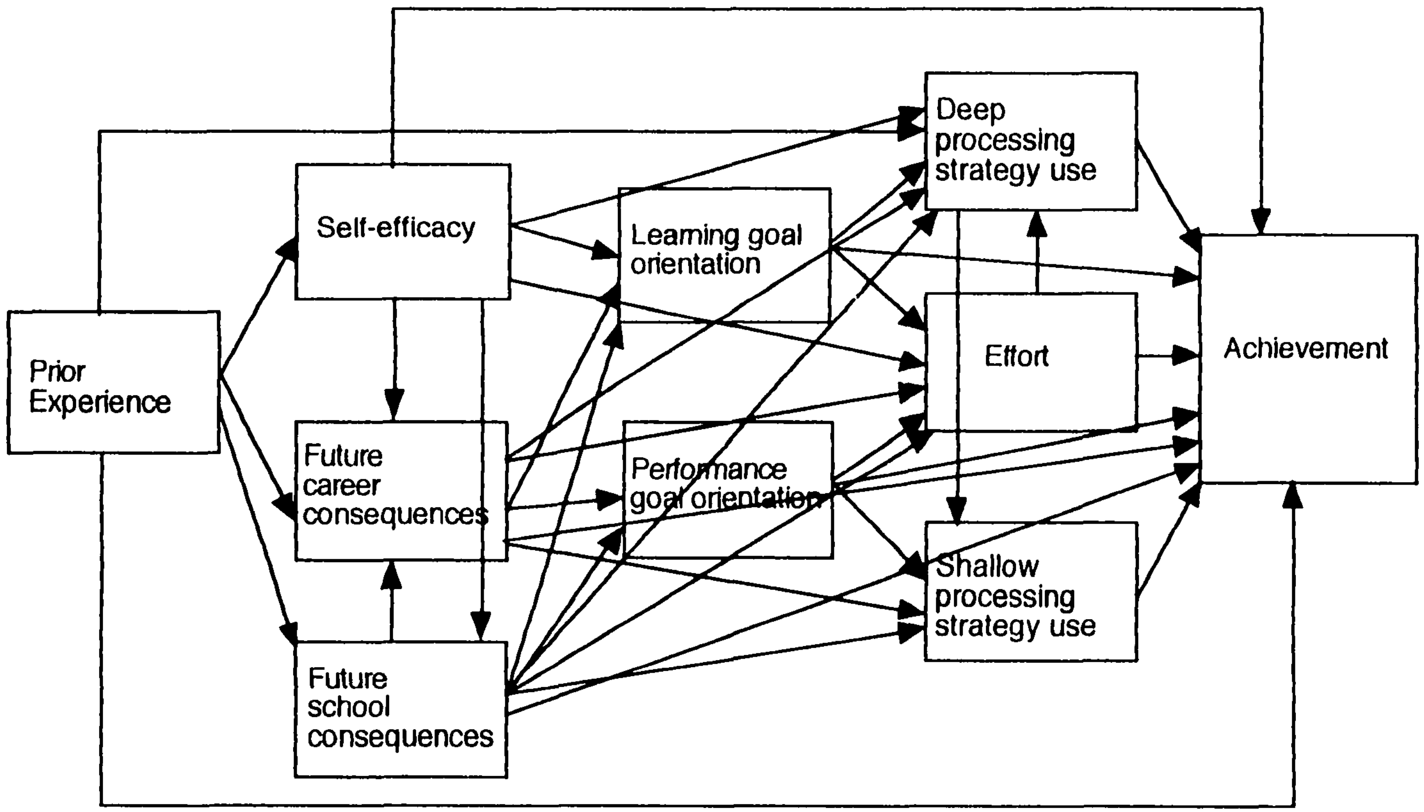


Figure 3. Revised path-analytic (overidentified) model: Influence of motivation and cognitive engagement variables on statistics achievement.

Table 6

Results of path analysis of overidentified model

| Paths (R-square) | Standard | Unstandardized | P-value |
|---|---|---|---|
| **On self-efficacy** (.0001) | | | |
| of prior experience | .01 | | >.05 |
| **On future career consequences** (.341) | | | .000 |
| of prior experience | -.04 | -.02 | .476 |
| of self-efficacy | .35 | .39 | .000 |
| of future school consequences | .44 | .40 | .000 |
| **On future school consequences** (.014) | | | .282 |
| of prior experience | -.08 | -.05 | .295 |
| of self-efficacy | .09 | .11 | .229 |
| **On learning goal orientation** (.359) | | | .000 |
| of self-efficacy | .26 | .30 | .001 |
| of future school consequences | .03 | .03 | .624 |
| of future career consequences | .43 | .44 | .000 |
| **On performance goal orientation** (.051) | | | .008 |
| of future school consequences | .25 | .17 | .005 |
| of future career consequences | -.06 | -.04 | .867 |
| **On deep processing strategy use** (.251) | | | .000 |
| of prior experience | .06 | .03 | .415 |
| of self-efficacy | .18 | .14 | .025 |
| of future school consequences | .25 | .17 | .391 |
| of future career consequences | .02 | .01 | .868 |
| of learning goal orientation | .27 | .17 | .003 |
| **On shallow processing strategy use** (.134) | | | .000 |
| of future school consequences | -.04 | -.02 | .761 |
| of future career consequences | .06 | .03 | .760 |
| of performance goal orientation | .31 | .21 | .000 |
| of deep processing strategy | .20 | .15 | .014 |
| **On effort** (.072) | | | .030 |
| of self-efficacy | -.28 | -.37 | .002 |
| of future school consequences | .02 | .02 | .833 |
| of future career consequences | .07 | .08 | .499 |
| of learning goal orientation | .20 | .23 | .039 |
| of performance goal orientation | .03 | .04 | .749 |

(tables continues)

| Paths (R-square) | Standard | Unstandardized | P-value |
|---|---|---|---|
| **On achievement** (.140) | | | .003 |
| of self-efficacy | -.21 | 4.33 | .017 |
| of future school consequences | .05 | .87 | .536 |
| of future career consequences | .11 | 1.97 | .274 |
| of learning goal orientation | -.35 | -6.07 | .001 |
| of performance goal orientation | -.07 | -1.76 | .353 |
| of shallow processing strategy | -.06 | -2.00 | .497 |
| of deep processing strategy | .24 | 6.36 | .007 |
| of effort | .03 | .49 | .690 |

**Path Analysis of Trimmed Model**

To provide parsimony in the model, those individual paths that were not significant were dropped from the model and a new trimmed overidentified model was proposed. This model is presented in Figure 4. The same multiple regression procedures were used to analyze this path model. The results are reported in Figure 5.

The Chi square goodness of fit test was not significant $\chi^2 = 16.60$ compared to the critical $\chi^2(19) = 30.14$ at $p = .05$ indicating the trimmed model provided a good fit with the data. All path coefficients remained significant on re-analysis. The R-square for each of the dependent variables was: (a) achievement, $R^2 = .117$; (b) future career consequences, $R^2 = .339$; (c) learning goal orientation, $R^2 = .358$; (d) performance goal orientation $R^2 = .050$; (e) deep processing strategy use, $R^2 = .244$; (f) shallow processing strategy use, $R^2 = .133$; and (g) effort, $R^2 = .069$. Due to both its parsimony and fit, this final model was used to calculate the direct and indirect effects of variables. Table 7 shows a decomposition of the direct and indirect effects on each of the possible variables in the model.

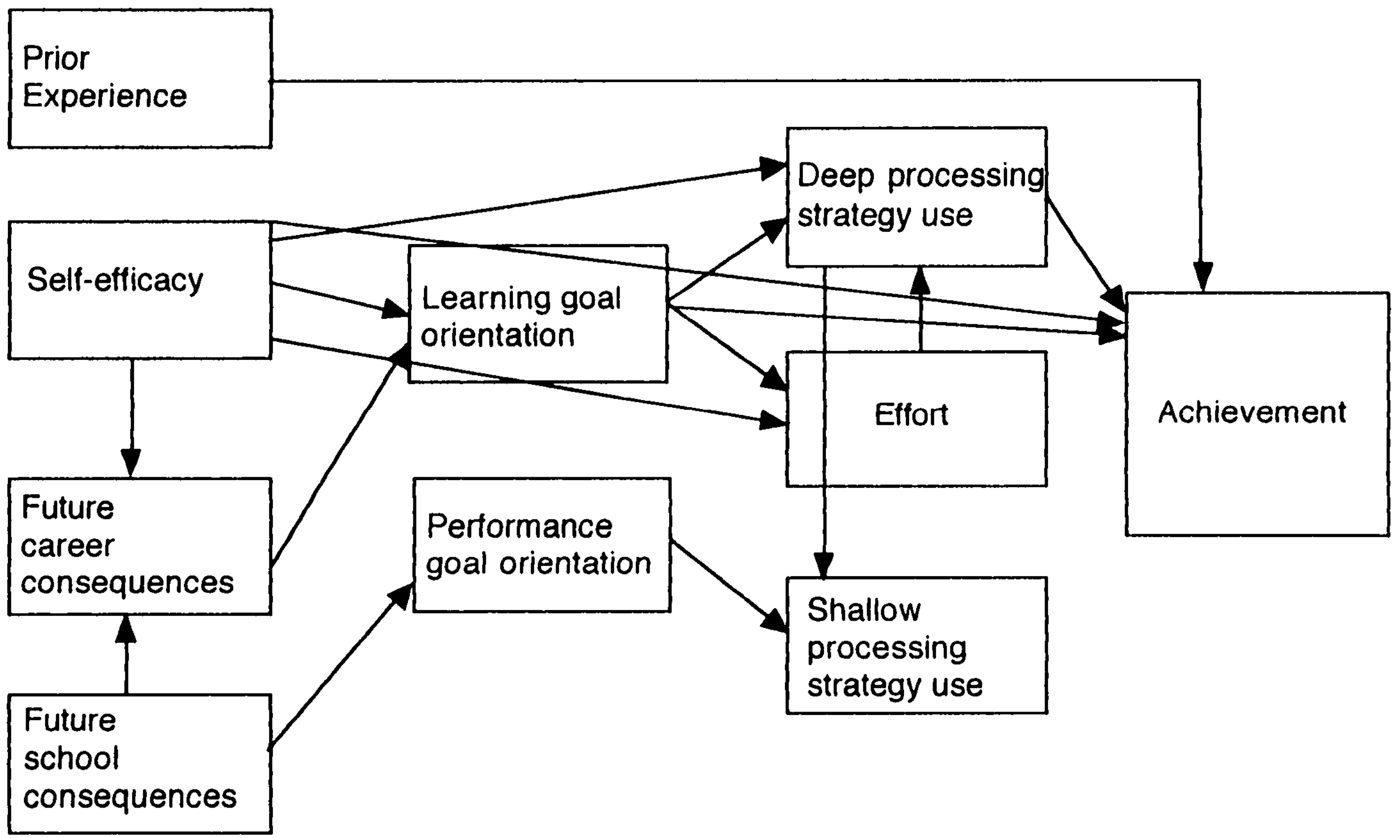


Figure 4. Trimmed path-analytic model: Influence of motivation and cognitive engagement variables on statistics achievement.

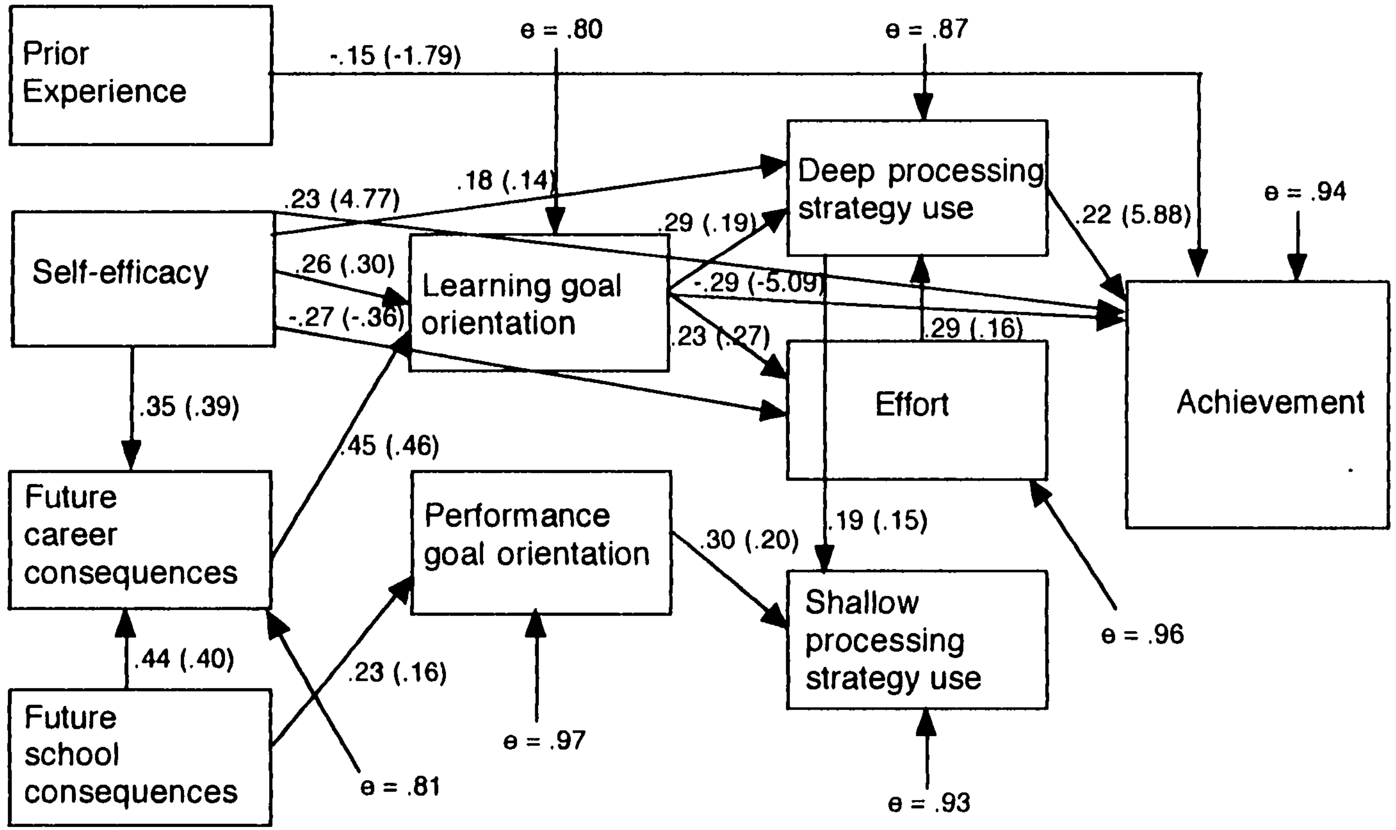


Figure 5. Trimmed path-analytic model with calculated standardized path coefficients (unstandardized coefficients in parentheses) and residuals.

Table 7

Direct and Indirect Effects of Model Variables on Goals, Cognitive Engagement, and Achievement

| Effect | r | Direct Effect | Indirect Effect | Total Effect | Noncausal Correlation |
|---|---|---|---|---|---|
| On Future Career | | | | | |
| of efficacy | .386 | .348 | .000 | .348 | .038 |
| of future school | .471 | .438 | .000 | .438 | .033 |
| On Learning Goal | | | | | |
| of efficacy | .430 | .256 | .157 | .413 | .017 |
| of future career | .553 | .451 | .000 | .451 | .102 |
| of future school | .263 | .000 | .198 | .198 | .065 |
| On Performance Goal | | | | | |
| of future school | .225 | .225 | .000 | .225 | .000 |
| On Effort | | | | | |
| of efficacy | -.162 | -.265 | .095 | -.170 | .008 |
| of future school | .052 | .000 | .105 | .105 | -.053 |
| of future career | .075 | .000 | .046 | .046 | .029 |
| of learning goal | .110 | .232 | .000 | .232 | -.122 |
| On Deep Processing | | | | | |
| of efficacy | .258 | .180 | .049 | .249 | .009 |
| of future school | .189 | .000 | .159 | .159 | .030 |
| of future career | .276 | .000 | .058 | .058 | .216 |
| of effort | .275 | .285 | .000 | .285 | -.010 |
| of learning goal | .404 | .286 | .066 | .352 | .052 |
| On Shallow Processing | | | | | |
| of efficacy | -.012 | .000 | .048 | .048 | -.060 |
| of future school | .086 | .000 | .031 | .031 | .055 |
| of future career | .085 | .000 | .067 | .067 | .018 |
| of learning goal | .097 | .000 | .067 | .067 | .030 |
| of performance goal | .312 | .296 | .000 | .296 | .025 |
| of effort | -.005 | .000 | .054 | .054 | -.059 |
| of deep processing | .219 | .190 | .000 | .190 | .029 |

(table continues)

| Effect | r | Direct Effect | Indirect Effect | Total Effect | Noncausal Correlation |
|---|---|---|---|---|---|
| On Achievement | | | | | |
| of efficacy | .123 | .234 | -.065 | .169 | -.049 |
| of future school | .008 | .000 | -.042 | -.042 | .091 |
| of future career | .049 | .000 | -.095 | -.095 | .103 |
| of learning goal | -.061 | -.290 | .078 | -.212 | .151 |
| of effort | -.022 | .000 | .063 | .063 | -.085 |
| of deep processing | .144 | .221 | .000 | .221 | -.077 |
| of prior experience | -.081 | -.151 | .000 | -.151 | .070 |

# CHAPTER FIVE

# DISCUSSION AND CONCLUSIONS

## Discussion

This investigation into the motivational characteristics influencing achievement in statistics provided support for the theoretical causal model presented. The model studied in this research focused on the motivational characteristics that impact achievement. The instrument used for this research had high reliability and validity. Results of path analyses indicate deep processing strategy use, efficacy, learning goal and prior experience have direct effects on achievement. Learning goal orientation, self-efficacy, and effort have direct effects on deep processing strategy use. Learning goal orientation is directly impacted by self-efficacy and future career consequences. These findings are consistent with previous studies (Miller et al, 1996; Miller & Brickman, 1997). This chapter will focus on the impact of these motivational learner characteristics on achievement and how one can foster these desirable characteristics in a classroom.

### Instrument Reliability and Validity

The validation of the instrument for this study is encouraging. Results from both the factor analysis and reliability analysis procedures provided evidence to support its validity and reliability. The findings indicated this instrument identifies at least five areas in which students distinguish their goals and efficacy. These areas are performance goal, learning goal, self-efficacy, and two types of future consequences. The split of future consequences can best be explained by the distinction of future consequences for graduate school from future consequences for career. In the future consequences for school, four of the five items asked about their entrance to graduate school. One question asked about the importance of grades for future career. In the future consequences for career, four of the five items dealt with the utility of statistical knowledge and skills for future career success while one asked about graduate school. The subscale reliabilities ranged from .77 to .92 indicating the items measuring each construct were internally consistent.

**Descriptive Statistics**

The high means on most subscales reported in Table 4 (see page 45) may be due to course instructors' emphasis on understanding the concept of statistics. Instructors gave concrete examples and often explained the applicability of the statistics material taught in their class. According to theory, these types of actions tend to foster learning goal orientations which will lead to more meaningful cognitive engagement. Also, since the majority of students were economics and psychology majors, they may have had some long term future consequence interest which also encourages learning goals and meaningful cognitive engagement. Social desirability may also play a part in these results. Students are less likely to report that they have performance goals and more likely to report behaviors or goals that present them as "good" students.

Self-efficacy and learning goal and deep processing strategy use were positively and significantly correlated with one another. Self-efficacy was positively correlated with learning goals and future career consequences. Other studies reported similar correlational findings as this current study (Greene & Miller, 1996; Miller et al, 1996; Nolen, 1988). Additionally, I found both types of future consequences (career and school) and learning goals were positively correlated similar to Miller and Brickman (1997). Deep and shallow processing strategy use may be correlated due to the possibility of students using both deep and shallow strategies when studying for their statistics course (Greene & Miller, 1996). It is not surprising that future career consequences and future school consequence are correlated since students likely view what they are learning in undergraduate course work will possibly be used in both graduate school and future careers.

**Path Analysis of Overidentified Model**

In the overidentified model, a total of 10 variables made up 37 individual paths among variables. Prior experience had a significant and direct effect on achievement, but all other paths from prior experience were non-significant. Bandura (1986) indicated one of the factors influencing self-efficacy is past experience. The results here contradict this existing theory since the path was non-significant. Prior experience also did not predict the future consequences variables. It may be that prior experience as measured by number of previous courses in math and statistics is not sufficient. Alternative ways of measuring this variable that indicate knowledge level may be a focus of future research.

The future consequences variables were fairly new variables in the context of this research so several possible paths were hypothesized that were non-significant. The path leading from self-efficacy to future school consequences was non-significant. In light of future school consequences' strong relationship to performance goal orientation, this finding is not surprising because previous studies by Greene and Miller (1996) did not find a significant relation between efficacy and performance goals. The significant path leading from future career consequences to learning goal orientation with all other direct paths from future career consequences being non-significant leads me to conclude that its direct effect on learning goal is the most important link. This relationship also leads to future career consequences having an indirect effect on many other key variables. Theoretically, it makes sense that future career consequences are not significantly related to a performance goal orientation while future school consequences are positively related to a performance goal orientation. Students probably view future career consequences in terms of the actual utility of statistics and know that they must learn and understand statistics in order to succeed. Also, students likely view future consequences for graduate school in terms of the grades needed for entrance, and therefore may tend to focus more on performance goals in the course.

The performance goal path leading into effort was non-significant. Performance goals tend to foster shallow processing and effort does not correlate with shallow processing strategy use but rather with deep processing strategy use. In addition, effort influenced achievement only through deep processing. Shallow processing had the expected negative relationship to achievement but this did not reach the level of significance.

To bring parsimony to the model, those paths that were not significant were dropped from the overidentified model. Nineteen paths were dropped from this overidentified model after results were analyzed. Most dropped paths were initially theoretically sound based on previous literature, but they did not have the expected direct influences on other variables. However, dropping these paths were not in complete contradiction to theory due to many of the variables having remaining indirect influences on other variables. When all these variables are analyzed within the context of one another, it is not unusual that some paths were non-significant.

This is due to an independent variable accounting for a greater chunk of the variance of a dependent variable and also being correlated to other independent variables.

**Path Analysis of Trimmed Model**

The trimmed model dropped 19 paths while providing parsimony and fit. Self-efficacy, by far, played the biggest role, directly and indirectly, in accounting for variance in many key variables related to achievement and achievement itself (future career consequences [35% direct], learning goal orientation [26% direct and 16% indirect], deep processing strategy use [18% direct and 5% indirect], effort [27% direct and 10% indirect], and achievement [23% of variance accounted for directly]).

In this model, learning goal orientation was positively affected by self-efficacy (accounting for a total of 41% of its variance) and future career consequences (accounting for 45% of variance) with future school consequences having a direct effect on performance goals (26% of variance accounted). Future school consequences directly accounted for 44% of the variance of future career consequences. Typically, admission to and success in graduate school tends to emphasize performance as measured by grades. Theoretically, this emphasis on grades, often seen as an indication of how well one is doing in comparison to others, would readily lead students to adopt performance goals. Entrance and success in most jobs and careers is most often determined by one's mastery and understanding of critical subject matter which, theoretically, would lead students to be likely to adopt learning goals.

Support for theory is also evidenced by learning goal orientation's positive relations with effort (accounting for 23% of the variance) and deep processing strategy use (directly accounting for 29% and indirectly accounting for 7% of the variance). Future school consequences is only indirectly related to deep processing strategy use (16% of the variance) through future career consequences and learning goal orientation. Performance goals directly accounted for 30% of the variance in shallow processing strategy use. Similar to Greene and Miller's (1996) findings, deep processing strategy use directly accounted for 19% of the variance in shallow processing strategy use. Students who are more motivated engage in more processing strategies thereby using both deep and shallow strategies. When engaged in learning, learning goal oriented students may tend to be more flexible depending on the context of the learning situation. Also, many deep processing strategies have components that include shallow strategies.

Efficacy directly accounted for 23% of the variance in achievement. Future school consequences indirectly accounted for 4% of the variance in achievement and future career consequences indirectly accounted for 10% of the variance in achievement. Learning goal directly accounted for 29% and indirectly accounted for 8% of the variance in achievement. Effort indirectly accounted for 6% of the variance in achievement, deep processing strategy use directly accounted for 22% of the variance in achievement, and prior experience directly accounted for 15% of the variance in achievement. Since using deep strategies does take effort, it is fitting that the path from effort to achievement goes through deep processing strategy use. Students who use shallow processing are not likely to exert much effort. Students could exert effort, however, if students do not study meaningfully, they may not succeed.

The results of this path analysis showed that when self-efficacy is measured within the context of learning goal and future career consequences it has a negative effect on effort. Apparently, the students with low efficacy reported they exerted extra effort in this course whereas those students with high efficacy reported they put forth relatively low effort in the course compared to other courses they were presently taking. Students with high self-efficacy seem to think the high effort is not needed since they feel confident about their ability in statistics. Unfortunately, there is no way to determine the difficulty level of the other courses individual students were taking. Future research assessing effort in a different manner may provide a finer grained analysis of its relationship with self-efficacy. Presently, these results raise the possibility that self-efficacy and effort may be curvilinearly related. This is a problem with path analysis which assumes linear relationships among variables. This analysis of self-efficacy and effort is more complicated than a simple linear relationship. Another possible explanation is overlap among the predictors that occurs in multiple regression. In this instance, the predictor variable (efficacy) explained some of the same variance as learning goal orientation and future career consequences and they are correlated among themselves. Regardless, high effort was necessary to encourage deep processing and subsequent achievement.

The path analysis also showed that learning goal orientation, when being measured within the context of self-efficacy and deep processing strategy use, has a negative effect on achievement. This may indicate that learning goals are necessary but insufficient to positively influence achievement by themselves. Pintrich and Garcia (1991) found that students who are concerned about learning were more likely to report use of deep processing strategies. Those students with learning goal orientations were more likely to plan as they prepared to study, to monitor their comprehension of what they were learning, and to correct any deficiencies in their understanding by reviewing the difficult materials. These students were more likely to better manage their time, study environment, and their effort. Those students with learning goal orientations were more likely to increase their achievement but only through appropriate effort and proper cognitive engagement. Without engaging in deep processing strategy use and exerting effort, students with learning goal orientations may be likely to negatively affect their achievement. This could be because they employed improper strategies or no strategies or put forth insufficient effort.

The model indicates students focus on two different aspects of future consequences, those related to career and those related to graduate school. Future school consequences are causally related to performance goals which in turn is related to shallow processing strategy use and unlikely to influence achievement. Future career consequences are causally related to learning goals which are directly and indirectly related to other variables including achievement. The model indicates that students who are high in self-efficacy are likely to be learning goal oriented and use deep processing strategies to master the subject in order to attain achievement.

## Suggestions for Future Research

The results of this study have generated some new questions about how motivational learner characteristics can affect student achievement. As discussed earlier, self-efficacy may be a key variable that accounts for not only variance in achievement, but also, variance in deep processing strategy use, effort, and learning goal orientation. Future study is needed on how factors influencing self-efficacy, (i.e., past experience, vicarious experience, persuasion, and affective feedback), can be manipulated in a classroom to see if higher efficacy can be fostered in classrooms to improve achievement.

Other future studies in the arena of future consequences are warranted. What variables could be identified which influence students' future consequences for career and graduate school, which in turn, especially in the case of future career consequences, would lead to adopting a learning goal orientation? This is a relatively new direction of research and the opportunity is certainly available for future study.

Another interesting future study could be looking at the use of study strategies regardless of goal orientation. Specifically, does instruction focused on deep processing strategy use help achievement when holding goal orientation and self-efficacy constant? Given two groups, one group could receive direct instruction on deep processing strategies while the others would not. Later, measures could be taken to see what type of strategies the groups used and compare the measure with achievement.

Specifically pertaining to this study, self-efficacy and prior experience should be reevaluated. Bandura (1986) stated prior experience is the foremost determinant in determining individuals self-efficacy. However, this part of the theory was not supported in this study. Perhaps the prior experience variable could be reevaluated using a more reliable and valid measure. Rather than simply measuring prior experience as the number of statistics and math courses, perhaps a measure of success in these prior courses will play a role in predicting self-efficacy as is hypothesized from theory. Similarly, the measure of effort could also be reevaluated to include measures of persistency. Also, theoretical and empirical work is needed on the complex relationship between self-efficacy and effort as mentioned earlier. Future research needs to look at the relationship more carefully to see how these two variables interact.

## Implications for Teaching

Self-efficacy had an influence on all "desirable" variables in the model. Bandura (1986) stated that the factors influencing self-efficacy are past experience, vicarious experience, persuasion, and affective feedback. One of the simple ways to increase self-efficacy that is right at the fingertips of teachers is what Bandura referred to as persuasion. Teachers need to encourage students that the task on hand is achievable, and encourage them that the knowledge they possess or will obtain during the course will be appropriate in meeting the challenge. Teachers need to point out to their students that achievement is possible through effort and persistence. One of the ways for teachers to do this is to design tasks which demonstrate to the students that they have the skills to master the given task. Exercises with an appropriate level of challenge where students will feel comfortable with their ability will help them to realize they can master the material. Teachers at this stage could also help students by providing direct or indirect instruction on some of the studying strategies that encourage deep processing. To provide vicarious experience, teachers could establish settings where students could observe other students with similar ability succeeding in tasks related to achievement. Give a challenging problem to a student who is capable of solving it and let others watch him successfully master the task. This may be threatening to some but according to the theory, this will raise self-efficacy among observers.

Bandura (1986) stated that when learners are faced with uncertain situations, their heart beats faster when their efficacy level might be low signaling to them that they are unsure of their competence. To improve students' affective feedback aspect of self-efficacy, teachers need to work on alleviating students' anxiety. Teachers need to give them practice in test taking or study skills that will reduce students' anxiety. Discussion of students' prior experiences of success and failure and their attributions for these may help pinpoint sources of anxiety or strategies that were helpful. Finally, emphasize that a little bit of anxiety is good since it is likely to motivate them to study.

Not only does the self-efficacy of students affect achievement, but the self-efficacy of teachers also tends to affect students' self-efficacy and subsequent achievement. Midgley, Feldlaufer, and Eccles (1989) reported that teachers with low self-efficacy were likely to have students with low self-efficacy and perceptions of ability. They also reported that a teacher's self-efficacy may have a subtle influence on students' perceptions of goals in the classroom. Students may perceive and adopt the same beliefs about themselves as the teacher who expresses these views. Therefore, raising instructors' efficacy is another possible way in which students may develop their own positive efficacy beliefs.

Teachers are active agents in fostering motivation to learn in their students through development of goals and efficacy in students that are consistent with quality involvement in learning and resulting achievement (Ames, 1992). The way teachers behave and the classroom atmosphere they establish determines if students will develop or possess a motivation to learn (Ames, 1992). Ames showed that the way the student perceives teacher behavior and the classroom environment will have an effect on his or her personal goal orientation and motivational patterns. Therefore, it is highly desirable that the teachers who want to promote meaningful learning allow their students choices of tasks, emphasize the intrinsic value of learning, and establish learning structures that support student autonomy and peer collaboration. These behaviors will likely lead students into high self-efficacy, future consequences for career and a learning goal orientation.

Teachers should emphasize the process of learning, encourage effort, and de-emphasize the consequences of making errors. Students who perceive their class as emphasizing a learning goal orientation, reported they used effective learning strategies, preferred tasks that were challenging, liked their classes more, and said that effort and success were synonymous (Ames & Archer, 1988). Ames and Archer believed that teachers should encourage and intervene often in order for students to set realistic but challenging goals which in turn, will further enhance the learning goal atmosphere in the classroom.

It is easy to say teachers should change their teaching approach, but to actually get them to change might be more difficult; also, teachers may not have the knowledge or techniques needed to establish a learning goal environment. Therefore, schools and universities may need to provide staff development workshops focused on encouraging and assisting teachers as to how they can best establish a learning goal atmosphere in the classroom. Even after all this, changing the classroom environment may not help some students who lack certain skills, lack critical learning strategies, or have low self-efficacy.

The findings of this study indicated that the students who are able to predict the usefulness of statistics in their future career were likely to have higher achievement. Looking at the path model, teachers can use some of the variables likely to influence self-efficacy to also influence students' future career consequences. Teachers can persuade students to "see" the utility of statistics in their future. Another way for teachers to assist students to focus on future consequences is for students to look at the people who are in the current field in which they aspire to be and find out how they use statistics. Emphasis on certain experiences and training those individuals have may induce students to desire similar experiences and training.

One important finding of this study implies that instructors need to make an attempt in teaching strategies that promote meaningful cognitive engagement through deep processing strategy use. Students are likely to engage in these behaviors if they have high self-efficacy, positive future consequences, a learning goal orientation, and are willing to put forth effort. The labs associated with each of the courses in which data were collected may provide the perfect opportunity for instructors to develop these desirable beliefs, goals, and skills. All three professors in this study voiced a concern that their classes had too many students and it was difficult for them to provide individual attention. However, they all had a lab/small group associated with the lecture class which was led by a graduate student. The lab setting may provide students with individual attention to receive instruction and engage in practice of deep processing study strategies, such as, reviewing previously solved problems to show it is a good way to study for a test, planning out how they should study the material prior to the test, ensuring they check their work for errors, and organizing their study time for the test. These graduate students may serve as excellent role models of positive self-efficacy beliefs and be able to inspire future consequences and learning goals that are likely to effect achievement.

## Conclusion

Learning is an active process requiring conscious and deliberate effort by all parties involved. Motivation is relevant to learning in that students must be motivated to engage in learning activities. The greater one's self-efficacy, the greater the likelihood of adopting a learning goal orientation and engaging in deep processing strategy use which results in higher achievement. The results of this study indicated positive relationships among the use of deep processing strategies, effort, and learning goals. If teachers encourage students to use deep and more complex cognitive strategies, students are likely to enhance their achievement.

An important implication for this finding is that one of the goals teachers of statistics or other subjects should have is to provide an atmosphere and environment conducive to a learning goal orientation. Any teacher who provides only a single instructional approach will surely be unable to effectively meet the needs of every student in the classroom. Therefore, in a more complex and difficult course, such as statistics, teachers need to put forth extra effort and energy in ensuring that students succeed in their classroom. In conclusion, the results of this study support the theoretical relationship and impact these variables have on one another while also supporting that certain motivational characteristics do support or improve achievement.

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# APPENDICES

Appendix A

Motivation and Cognitive Engagement in Statistics Questionnaire

Motivation and Cognitive Engagement in Statistics Questionnaire

Please circle the answer that is appropriate or fill in the blank with an appropriate answer.

1. Sex (Gender): Male Female

2. Ethnic background: Caucasian African-American

   Asian-American Hispanic

   Native American Other______________

3. Classification (Grade level):

   Freshman

   Sophomore

   Junior

   Senior

   Graduate Student

4. What is your current major? ______________________________________

6. How many prior math courses have you had in college? ______________________

7. Prior to this course, how many statistics courses have you had? __________

Part 1: Motivation in Statistics

Directions: The following statements represent goals that you might have for this class and beliefs you may have about your ability in statistics. Read each statement and indicate how much you agree that it is true of you in this class. Use the 7 - point scale below to indicate your response. Circle the number that corresponds to your answer.

| Strongly Disagree | Disagree | Somewhat Disagree | Undecided | Somewhat Agree | Agree | Strongly Agree |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1. One of my primary goals is to do well in this class because I don't want to be embarrassed about not being able to do the work. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 2. One of my primary goals in this class is to understand the concepts. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 3. One of my primary goals in this class is to develop a good understanding of the statistical concepts I will be taught. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 4. One of my primary goals is to do well in this class because I don't want to be the only one who cannot do the work. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 5. One of my primary goals in this course is to acquire new skills. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 6. One of my primary goals is to do well in this class because good grades are important for graduate school admission. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 7. One of my primary goals in this class is to increase my understanding of how statistics are used in daily life. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 8. One of my primary goals is to do well in this class because I don't want to look foolish or stupid to my friends, family or teachers. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 9. One of my primary goals is to do well in this class because doing well is necessary for admission to graduate school. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| Strongly Disagree | Disagree | Somewhat Disagree | Undecided | Somewhat Agree | Agree | Strongly Agree |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 10. One of my primary goals is to do well in this class because I don't want others to think I'm not smart. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 11. One of my primary goals in this class is to score higher than other students. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 12. One of my primary goals in this class is to improve my knowledge of statistics. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 13. One of my primary goals in this class is to improve my ability to do statistical computations. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 14. One of my primary goals in this class is to show people that I am smart. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 15. I want to understand that statistical concepts because it will be useful in my future career. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 16. One of my primary goals is to do well in this class because getting into graduate school is important to me. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 17. One of my primary goals in this class is to do better than other students. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 18. One of my primary goals is to do well in this class because I want to understand the statistical concepts if I am accepted to graduate school. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 19. One of my primary goals is to do well in this class because doing well is necessary for getting the job I want after I graduate. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 20. I want to understand the statistical concepts because it will be useful while in graduate school. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 21. One of my primary goals is to do well in this class because I want to look smart to my friends. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| Strongly Disagree | Disagree | Somewhat Disagree | Undecided | Somewhat Agree | Agree | Strongly Agree |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| | |
|---|---|
| 22. One of my primary goals is to do well in this class because good grades are important for getting into my future career. | 1 2 3 4 5 6 7 |
| 23. I am confident I can understand the materials taught in this course. | 1 2 3 4 5 6 7 |
| 24. One of my primary goals in this class is to comprehend the material presented. | 1 2 3 4 5 6 7 |
| 25. One of my primary goals is to do well in this class because it will help me get into the career I want after I graduate. | 1 2 3 4 5 6 7 |
| 26. One of my primary goals is to do well because I want to understand the statistical concepts that will be involved in my future career. | 1 2 3 4 5 6 7 |
| 27. I am confident I can understand what statistics are used for. | 1 2 3 4 5 6 7 |
| 28. I am confident I can get at least a "B" (3.0) in this statistics course. | 1 2 3 4 5 6 7 |
| 29. I am confident I can understand the materials taught in this statistics course. | 1 2 3 4 5 6 7 |
| 30. I am confident I can identify the appropriate statistical test for a research question. | 1 2 3 4 5 6 7 |
| 31. I feel confident in my ability to learn the material in the statistics course. | 1 2 3 4 5 6 7 |
| 32. Compared with others in my class, I am confident I will learn a great deal more about the subject of statistics. | 1 2 3 4 5 6 7 |
| 33. I am confident I can do a good job on the problems or homework given in my statistics course. | 1 2 3 4 5 6 7 |

| Strongly Disagree | Disagree | Somewhat Disagree | Undecided | Somewhat Agree | Agree | Strongly Agree |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |

34. I am confident I know how to interpret statistical values. 1 2 3 4 5 6 7

35. I am confident I can describe what correlation means. 1 2 3 4 5 6 7

36. I am confident I can describe what probability means. 1 2 3 4 5 6 7

Part 2: Cognitive Engagement in Statistics

Directions: The following questions ask about some of your specific behaviors as you study for this class during the semester. Respond to the statements along the following 7 - point scale. Circle the number that corresponds to your answer.

| Strongly Disagree | Disagree | Somewhat Disagree | Undecided | Somewhat Agree | Agree | Strongly Agree |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1. I find reviewing previously solved problems to be a good way to study for a test. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 2. Before the test in this class, I planned out how I will study the material. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 3. When I finish working a problem I check my answer to see if it's reasonable. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 4. When I work a problem, I analyze it to see if there is more than one way to get the right answer. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 5. When I finish working on practice problems I check my work for errors. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 6. I study example problems that have already been worked to help me figure out how to do similar problems on my own. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 7. I have a clear idea of what I am trying to accomplish in this class. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 8. If I have trouble solving a problem I'll try to get someone else to solve it for me. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 9. I try to complete homework assignments as fast as possible without checking my accuracy. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 10. If I have trouble understanding a problem I go over it again until I understand it. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 11. I classify problems into categories before I begin to work them. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| Strongly Disagree | Disagree | Somewhat Disagree | Undecided | Somewhat Agree | Agree | Strongly Agree |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| | |
|---|---|
| 12. If I have trouble solving a homework problem in the book I copy down the answer in the back of the book if it is available. | 1 2 3 4 5 6 7 |
| 13. I try to organize an approach in my mind before I actually start problems. | 1 2 3 4 5 6 7 |
| 14. I work several examples of the same type of problem when studying so I can understand the problems better. | 1 2 3 4 5 6 7 |
| 15. I try to memorize the steps for solving problems presented in the text/class. | 1 2 3 4 5 6 7 |
| 16. When I read something in the book that doesn't make sense, I skip it and hope that the teacher explains it in class. | 1 2 3 4 5 6 7 |
| 17. When I study for test in this class, I use solved problems in my notes or in the book to help me memorize the steps involved. | 1 2 3 4 5 6 7 |
| 18. When I read problems, I make sure I know what I am asked to do before I begin. | 1 2 3 4 5 6 7 |
| 19. When I study for test in this class, I review my class notes and look at solved problems. | 1 2 3 4 5 6 7 |
| 20. When studying for this class, I try to combine different pieces of information from course material in new ways. | 1 2 3 4 5 6 7 |
| 21. When I study I take note of the material I have or have not mastered. | 1 2 3 4 5 6 7 |
| 22. When I run into a difficult homework problem, I usually give up and go on to the next problem. | 1 2 3 4 5 6 7 |
| 23. I draw pictures or diagrams to help me solve some problems. | 1 2 3 4 5 6 7 |

| Strongly Disagree | Disagree | Somewhat Disagree | Undecided | Somewhat Agree | Agree | Strongly Agree |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |

24. I work practice problems to check my understanding of new concepts or rules. 1 2 3 4 5 6 7

25. If I have trouble solving a problem I'm more likely to guess at the answer than to look at examples in the book to try figure things out. 1 2 3 4 5 6 7

The following item is multiple choice. Select the ONE answer that best represents your view and fill in the circle on the answer sheet which corresponds to that answer.

26. How would you rate your effort in this class compared to your typical amount of effort for school work?
    a. Extremely high (probably as much effort as I've ever put into a class)
    b. Fairly high (more effort than usual, but I have worked harder in other classes)
    c. About average
    d. Fairly low (less effort than usual, but I have put in less effort in other classes)
    e. Extremely low (probably the least amount of effort I've ever put into a class)

Appendix B

Information and Consent Form

Information and Consent Form

You are being asked to participate in a study examining the roles of learners' motivational characteristics in statistics achievement. This study is being conducted by Steve Curda of the Department of Educational Psychology. This study intends to examine motivational and study strategy variables and how they predict achievement in statistics. By exploring how these variables are interrelated and predict one another, instructors and students may be able to increase the emphasis on variables that serve to enhance motivation, encourage appropriate study strategies and increase achievement.

If you choose to participate in this study you will be asked to give permission to release your midterm test score and complete a two-part questionnaire seeking your attitudes and beliefs about your own motivation in learning statistics by various goals and your perceptions about your ability in statistics. The result of the study will be compared with your midterm test grade to see if the goals and strategies you chose were effective. There is no foreseeable risk or discomfort associated with this study and you will not be harmed in any way.

Your participation in this study is voluntary and participation in this study is **not** a requirement for the course you are currently taking. There will be no penalty should you decide not to participate. There will be no extra credit associated with this research other than meeting the class research requirement for some of you. Additionally, should you change your mind about participating once you have begun, you may withdraw at any point without penalty; however, if you are doing this research for the class research requirement, you will not receive a credit.

Your responses to the questionnaires will be completely confidential. The questionnaires will be coded with a number to identify participants so that the separate pieces of information can be coordinated during analysis. The instructors will not have access to your responses on the questionnaires. At no time will your name or other identifying codes be made public. Once all the data has been collected, the data will be secured in a locked steel file in a locked office and will be destroyed after one year. If you have any additional questions about your rights, or about this research, you may contact Steve Curda, Department of Educational Psychology, 325-2599 for more information.

**Signature**

I hereby consent to participate in the study described above.

______________________________ Date:_______________

Please print your name

______________________________

Sign Here

Appendix C

Content Validity Rating Form

Content Validity Rating Form

Directions: The statements that follow are being considered for inclusion in a survey of observing motivational learner characteristics involved in learning statistics. Your assistance in reviewing the content of the statements by providing two ratings for each statement will be greatly appreciated. The conceptual definitions of the categories these statements are supposed to reflect as well as the rating instructions are below.

| Categories | Conceptual Definition |
|---|---|
| I. Learning Goal Orientation | Individual's approach to learning with the goal of increasing their skill, competence, and knowledge in the statistics course. |
| II. Performance Goal Orientation | Individual's approach learning with the goal of impressing someone, looking good in front of others or avoiding looking bad in front of others in the statistics course. |
| III. Future Consequences | Individual's approach learning with the goal of linking the statistics course to a future goal or understanding its usefulness in the future. For example, students may do better in statistics courses if they believe that the skills learned will be useful in their future career goal of receiving their degree, the goal of obtaining the job they desire, or the usefulness of statistics in their future research endeavors. |
| IV. Self-Efficacy | Assessment of individual's personal confidence that he or she possesses the abilities and skills necessary to successfully complete the statistics course. |

Rating Tasks

A. Please indicate the category that each statement best fits by circling the appropriate category numeral. (Statements not fitting into any category should be placed in category V.)
B. Please indicate how strongly you feel about your placement of the statement into the category by circling the appropriate number as follows:
    4 Absolutely sure
    3 Very sure
    2 Sure
    1 Not very sure

| | Categories | | | | | Rating | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1. One of my primary goals is to do well in class because I don't want to be embarrassed about not being able to do the work. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 2. One of my primary goals in this class is to understand the concepts. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 3. One of my primary goals in this class is to improve my ability to do statistical computations. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 4. One of my primary goals is to do well in this class because I don't want to be the only one who cannot do the work. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 5. One of my primary goals in this course is to acquire new skills. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 6. One of my primary goals is to do well in this class because good grades are important for graduate school admission. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 7. One of my primary goals is to increase my understanding of how statistics is used in daily life. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 8. One of my primary goals is to do well in this class because I don't want to look foolish or stupid to my friend, family or teachers. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 9. One of my primary goals is to do well in this class because doing well is necessary for admission to graduate school. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 10. One of my primary goals is to do well in this class because I don't want others to think I'm not smart. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 11. One of my primary goals in this class is to score higher than other students. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 12. One of my primary goals in this class is to improve my knowledge of statistics. | I | II | III | IV | V | 1 | 2 | 3 | 4 |

| | Categories | | | | | Rating | | | |
|---|---|---|---|---|---|---|---|---|---|
| 13. One of my primary goals in this class is to show people that I am smart. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 14. I want to understand the statistical concepts because it will be useful while in graduate school. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 15. I want to understand the statistical concepts because it will be useful in my future career. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 16. One of my primary goals is to do well in this class because getting into graduate school is important to me. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 17. One of my primary goals in this class is to do better than other students. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 18. One of my primary goals is to do well in this class because I want to understand the statistical concepts that will be involved in my future career. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 19. One of my primary goals is to do well in this class because doing well is necessary for getting the job I want after I graduate. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 20. One of my primary goals is to do well in this class because I want to understand the statistical concepts if I am accepted to graduate school. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 21. One of my primary goals is to do well in this class because I want to look smart to my friends. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 22. One of my primary goals is to do well in this class because good grades are important for getting into my future career. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 23. One of my primary goals is to do well in this class because it will help me get into the career I want after I graduate. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 24. One of my primary goals in this class is to comprehend the material presented. | I | II | III | IV | V | 1 | 2 | 3 | 4 |

| | Categories | | | | | Rating | | | |
|---|---|---|---|---|---|---|---|---|---|
| 25. One of my primary goals in this class is to develop a good understanding of the statistical concepts I will be taught. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 26. I am confident I can understand what statistics are used for. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 27. I am confident I can get at least a "B" (3.0) in this statistics course. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 28. I am confident I can understand the materials taught in this statistics course. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 29. I am confident I can identify the appropriate statistical test for a research question. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 30. I feel confident in my ability to learn the material in the statistics course. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 31. I am confident I will master the materials that are taught in the statistics course. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 32. Compared with others in my class, I am confident I will learn a great deal more about the subject of statistics. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 33. I am confident I can do a good job on the problems or homework given in my statistics course. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 34. I am confident I know how to interpret statistical values. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 35. I am confident I can describe what correlation means. | I | II | III | IV | V | 1 | 2 | 3 | 4 |
| 36. I am confident I can describe what probability means. | I | II | III | IV | V | 1 | 2 | 3 | 4 |