The Mediational Effect of Academic Self-Discipline (ASD) Between Academic Self-Efficacy (ASE) and College GPA

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Abstract

Drawing upon self-efficacy theory (Bandura, 1997), the purpose of this study was to examine academic self-discipline (ASD) as a mediator of the relationship between academic self-efficacy (ASE) and college Grade Point Average (GPA), as well as the feedback effect of previous academic performance on subsequent ASE and ASD. To test this research question, I used cross-sectional and longitudinal data with three time points from 560 first-year and second-year college students. The cross-sectional analysis confirmed ASD was a mediator of the ASE-GPA link. By contrast, the longitudinal analysis did not support the ASE → ASD → GPA associations, although a GPA feedback effect on ASE and ASD was found at time 2. The study findings suggest ASD may be a more practical and functional predictor than ASE of academic performance.

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

An increasing number of high school graduates are entering colleges and universities (U.S. Department of Education, 2009), but academic success in higher education remains a challenge for many of these students. For instance, only one out of every two students graduates within six years at 4-year universities (Carey, 2004; see also Robbins et al., 2004; 2006). These low graduation rates suggest that many who enter college are at risk for dropping out before graduation (Perry, 2005). Therefore, predicting academic success is an important issue in higher education. Unfortunately, traditional predictors, such as high school performance and standardized test scores, explain at best 25% of the variance in academic performance measures (Robbins et al., 2004). As such, psychologists have turned their attention to non-traditional predictors to understand individual differences in academic performance.

Self-efficacy is defined as perceived ability in specific domains of human lives (Bandura, 1997). Self-efficacy affects goal setting (e.g., Bandura & Cervone, 1983) and regulating behaviors to achieve the goals (Bandura, 1993). Individuals who have high self-efficacy set up challenging goals and use more resources to achieve these goals. In this regulating process, self-efficacy impacts effort and persistence that in turn affects performance (Bandura, 1997). To achieve goals, individuals who have high self-efficacy commit more time and effort to tasks and do not give up easily despite barriers or failing experience.

In an academic domain, academic self-efficacy (ASE) refers to perceived academic ability and is used as a predictor of academic performance. Meta-analytic studies confirm the positive relationship between ASE and academic performance. For instance, Multon et al. (1991) reported a .38 correlation between ASE and performance based on 36 studies in their meta-analysis. More recently, Robbins et al. (2004) published a more thorough meta-analysis about the relationship between ASE and college GPA. In their study, ASE had a .20 correlation with college GPA even after controlling for cognitive ability (i.e., standardized test scores) and high school GPA. In summary, ASE is an important motivational construct affecting academic performance above and beyond traditional predictors.

Although meta-analyses have generally confirmed the predictive power of self-efficacy on performance, the association is not always positive. Under certain conditions high self-efficacy may compromise subsequent performance (Schmidt & DeSchon, 2009; Vancouver et al., 2001, 2002; Vancouver 2005). Vancouver et al. (2001), for example, demonstrated that past successful performance increased self-efficacy, but self-efficacy had a negative influence on subsequent performance using a longitudinal, within-group experimental design. Similarly, Schmidt and DeSchon (2006) confirmed a negative relationship between self-efficacy and performance based on their within-group analysis. They also found that both prior performance and goal setting were moderators such that there was a positive relationship between self-efficacy and performance only when the participants were not satisfied with their performance and when their goals were not achieved. To unravel this paradox, researchers have conducted research on the processes of behavioral regulation that enable higher performance.

Academic self-discipline (ASD) refers to self-regulation behaviors in academic settings. ASD is specifically defined as perceived behavioral self-control regarding academic achievement, which includes effort and persistence. Bandura (1997) regarded personal self-discipline as another important factor contributing to human performance, because persistent behavioral effort is necessary to accomplish high performance, especially for long-term and challenging tasks (e.g., writing novels). Recently, Robbins et al. (2006) showed that self-perceptions of being hardworking and conscientiousness positively predicted academic performance in college students.

Bandura (1997) also posited that self-discipline likely mediates the association between self-efficacy and performance. Previous research has shown that self-efficacy induced self-discipline. Cervone and Peake (1986) showed that, in both college and high school students, self-efficacy was a significant predictor of subsequent persistent behavior (i.e., solving a cognitive task) in an experimental situation. They found that students with high self-efficacy demonstrated increased persistence compared to those with low self-efficacy. Robbins et al. (2006) also found that academic discipline, defined as students' amount of effort in schoolwork, significantly predicted 1st semester and 1st year college GPA after controlling for high school GPA and ACT scores. However, there are no studies that directly test self-discipline as a mediator between self-efficacy and college GPA over a longer time period.

Bandura (1982) further suggested that environmental input impacts self-efficacy and behavior in his triadic reciprocal determinism model. Experimental studies in organizational (Bandura & Jourden, 1991; Wood & Bandura, 1989) and educational (Schunk, 1981, 1982, 1983, 1984; Bouffard-Bouchard, 1990) fields show that manipulated feedback on participants' past performance affects their self-efficacy, behavioral persistence, and subsequent performance. Specifically, positive feedback improved self-efficacy, persistence, and performance in subsequent tasks. However, previous studies have only investigated manipulated feedback in experimental settings.

Past academic performance, as indicated by previous semester or year grade point average (GPA), should similarly function as relevant feedback. Unlike manipulated feedback, past academic performance is a more realistic form of student performance feedback. For instance, students who perform poorly in their first year may subsequently enroll in easier courses or elect to choose a different major (e.g., Allen & Robbins, 2008). However, the effect of previous year GPA as feedback on the following year's GPA has not been tested in college students.

Previous research on ASE, ASD, and academic performance has neglected two important questions. First, the mediational effect of ASD has not been explored. Second, the feedback effect of GPA on ASE and ASD has not been tested. Exploration of these two questions will strengthen the predictive validity of academic self-efficacy and academic self-discipline, two non-cognitive predictors of academic success. Thus, my dissertation first elucidates the psychological mechanisms of ASE and ASD and their relations with academic performance. Additionally, I will examine the impact of past performance on subsequent performance through self-efficacy and self-discipline using panel analysis with three waves of longitudinal data.

Literature Review

In this section, I review the literature on self-efficacy theory, the association between ASE and academic achievement, ASD, and the impact of feedback of previous performance on subsequent performance. The important terms used in self-efficacy theory and this study are presented in Table 1.

Table 1

Definitions of Terms

Terms	Definitions
Self-efficacy	Individuals’ subjective judgment about ability in a specific domain
Behavior	Action initiated by self-efficacy
Expected outcome	Individuals’ expected level of achievement which is partly affected by level of self-efficacy
Goal	Observable expected outcome
Performance	Objective results of behavior
Academic self-efficacy (ASE)	Students’ subjective judgment about their academic ability
Academic self-discipline (ASD)	Students’ subjective judgments about self-control regarding their academic behaviors including effort and persistence

Self-efficacy

Self-efficacy theory underscores the agentic function of the self in the relationship between environmental conditions and behavioral outcomes. Self-efficacy refers to individuals’ subjective judgment about their ability in a specific domain. Bandura (1974, 1978) proposed that human behaviors are not governed only by the environment, but are also affected by self-efficacy. Individuals can predict the outcome of their behaviors based on their subjective judgment about themselves. Depending on the level of confidence, individuals make decisions regarding whether to initiate behaviors. Vicarious learning referring to learning through modeling is strong evidence of the presence of self-efficacy as well as the mediational role of self-efficacy. The core point of vicarious learning is that individuals can learn without a behavior and reward corresponding to the behavior. Through vicarious learning, individuals can have the thought, “I can do if others can do” (Bandura & Barab, 1973).

According to self-efficacy theory (Bandura, 1977, 1982, 1986, 1997), self-efficacy controls initiating and maintaining goal oriented behaviors based on level of perceived ability. In a classic study, Bandura (1977) showed that self-efficacy was highly correlated with actual performance in snake phobic participants. Reducing participants’ snake phobia would be an expected outcome for the participants. Through vicarious and enactive learning, participants increased their self-efficacy and expected to be able to cope with seeing a snake. In this experiment, correlations between their self-efficacy to cope with a boa constrictor and actual approaching behaviors to the boa constrictor ranged between .80 to .90 in all three conditions (i.e., control, vicarious modeling, and enactive learning) after the treatment. This classic example confirmed the strong association between self-efficacy and actual behavior.

Because of the strong effect of self-efficacy on human performance, self-efficacy has been used in various settings as a precursor to behavior and the target of intervention. For example, in the clinical field, improving self-efficacy has been positively associated with improvements in anxiety disorders, including specific phobias (e.g., Hoffman, 2000; Bandura, 1982). Low academic self-efficacy also predicts depression in college students (Muris, 2002). In the industrial/organizational field, high self-efficacy is significantly associated with better job performance, job commitment, and higher job satisfaction (Ballout, 2009; Stajkovic & Luthans, 1998; Wood & Bandura, 1989).

Expected Outcomes and Goals

Bandura's original theory adopted the concept of "expected outcome" from expectancy-value theory (Ajzen & Madden, 1986) to explain self-efficacy as motivation of individuals for the outcome that they wish to have. Later, goal theory (Locke & Latham, 2002) was merged with self-efficacy theory. Both expectancy-value theory and goal theory postulate a future event, such as expected outcome and a goal. These future events motivate individuals to initiate action because they are meaningful to the individuals (expectancy-value theory) and rewarding (goal theory). Specifically for academic performance, self-efficacy has been referred to a motivational variable because level of perceived ability tailors expected outcomes and goals (Schunk, 1991).

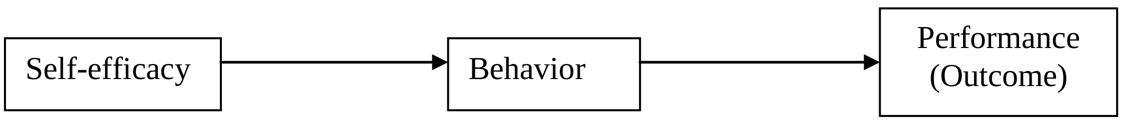
Although both expected outcomes and goals are assumed to be mediators, research supports a model with the goal as a mediating variable for self-efficacy on performance. Empirical results about the effect of expected outcome on performance were not consistent. For example, both self-efficacy and expected outcome independently and multiplicatively affected diabetes self-management in adolescents (Iannotti et al., 2006). Self-efficacy moderated the effect of expected outcome, in which high outcome expectancy did not predict high self-management if self-efficacy was low. However, Jensen et al. (1991) reported that there were no main and interaction effects of expected outcome on pain coping strategy. Williams and Kinney (1991) also found that expected outcome did not predict tolerance for pain when self-efficacy was controlled.

One possible reason for this dependency on self-efficacy or non-significant effects of expected outcome could be the method of measuring expected outcome. Expected outcome is often stated probabilistically (e.g., Millen & Bray, 2009) or conditionally (e.g., Jensen et al., 1991). For instance, an item measuring expected outcome is "If I were to keep myself busy with something interesting my pain would…" Expected outcome and self-efficacy are highly codependent (Jensen et al., 1991), which leads to difficulty differentiating expected outcome from self-efficacy. Furthermore, the causal relationship between self-efficacy and expected outcome has been questioned. Expected outcome may precede self-efficacy (Williams et al., 2010).

In contrast, the association between self-efficacy and goals is more stable. For example, self-efficacy interacted with self-set goals on physical performance (e.g., Bandura & Cervone, 1983) and goals mediated the effect of self-efficacy on job and academic performance (e.g., Fenollar et al., 2007; Fu et al., 2009). In specific, self-efficacy affects goal commitment (i.e., effort and persistence) as theorized in self-efficacy theory, which in turn predicts performance in a meta-analysis (Wofford et al., 1992). In terms of academic performance, the mediating role of goals has been supported (e.g., Lent et al., 1994; Brown et al., 2008). Goals can be defined more objectively and concretely than outcome expectations, so they are easier to operationalize regarding difficulty, proximity, and specificity (Locke, 1975).

In summary, expected outcome and goals have been utilized to explain how self-efficacy leads to behaviors. Both expected outcome and goals explain the effect of self-efficacy on performance, but the prediction of expected outcome on self-efficacy is weak. These mixed results could be caused by arbitrary definitions or the measurement of outcome expectations. Recently, research used goals to explore the effect of self-efficacy on academic achievement (e.g., Cellar et al., 2011; Diseth, 2011). Models and empirical results confirmed that self-efficacy is an important predictor for goal-oriented behaviors as well as the level of effort expended by individuals (Bandura, 1977). Figure 1 summarizes the causal relationships in self-efficacy theory.

Figure 1. The Basic Framework of Self-Efficacy Theory (Bandura, 1997)

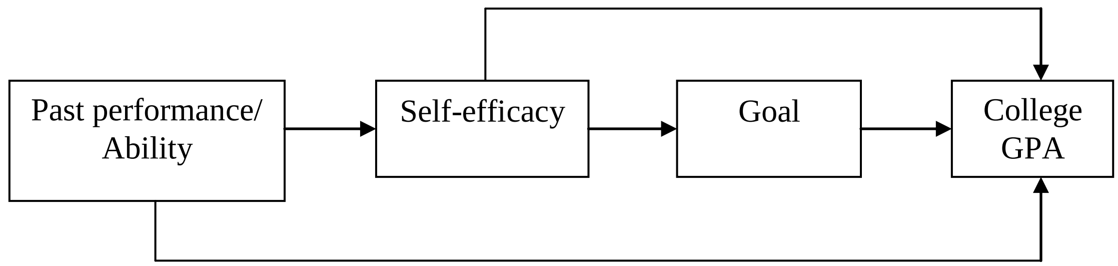


Academic self-efficacy and academic performance

In education, research focuses on the predictive validity of academic self-efficacy on academic performance (e.g., Bandura & Schunk, 1981; Schunk, 1991; Zimmerman, 2000). In an academic achievement model, academic self-efficacy is conceptualized as an intrinsic motivator for academic performance. Individuals with high self-efficacy confidently expect higher outcomes (e.g., better grades) and then put persistent effort (e.g., study hard) to achieve their expected outcomes (Schunk, 1991). The expected outcome is measured as an observable goal (e.g., to get an A in statistics class). In this model, the goal is a mediator between self-efficacy and actual outcome.

Individuals' cognitive and behavioral efforts to achieve their goals are critical components of human performance. Goal setting is affected by students' self-efficacy and influences their motivation to initiate behaviors. For example, students who have high academic self-efficacy set more challenging goals for themselves and work toward achieving these goals more persistently than students who have less challenging goals and, typically, lower academic self-efficacy. A path model by Brown et al. (2008) includes all these components except for the behavior (i.e., action) (see Figure 2).

Figure 2. Model of Academic Performance (Brown et al., 2008; Lent, 1994)



However, empirical research results for the mediating effect of goal setting on academic performance are mixed. Experimental studies conducted within a relatively short period of time with proximal and specific goals (e.g., the number of corrected answers for a cognitive task stimuli, specific grade for a writing course) support the mediating effect of goals (e.g., Bandura & Cervone, 1983; Zimmerman & Bandura, 1994; Zimmerman et al., 1992) such that individuals who have higher self-efficacy tend to choose challenging goals and show higher performance than individuals with low self-efficacy (e.g., Bandura, 1982, 1986, 1997, Bandura & Cervone, 1983, Locke & Latham, 1990, Wood & Bandura, 1989). In contrast, the relationship between the long-term goal of graduating college and college GPA was weak in a meta-analysis (β= -.04; Brown et al., 2008). Also, this goal did not have incremental predictive validity for GPA in college students after controlling for traditional predictors (Robbins et al., 2004). Furthermore, Brown et al. (2008) revealed that distal academic goals, such as time to graduation, did not predict college GPA. Because of the similarity (r=.49) of the two constructs, after controlling for the effect of self-efficacy on college GPA in the path analysis, the unique contribution of the goal was small.

Taken together, it appears that there is no clear pattern of the mediational impact of a goal on outcomes specifically for college GPA. Although goal setting is an important process in order to achieve an expected outcome, there are reasons that goals do not significantly predict college GPA. First, individuals set up goals based on their level of self-efficacy (Locke & Letham, 2002). In other words, self-efficacy and goal setting may share a significant amount of statistical variance, which can result in insignificant incremental predictive validity of that goal after the effect of self-efficacy is controlled for in a regression analysis (Brown et al., 2008). Second, students' academic goals can be changed by their mood (e.g., Cervone et al., 1994; Lane et al., 2005; Thelwell et al., 2007) and the goal setting needs to be multifaceted to be effective. For example, students need to have specific, challenging (Locke & Letham, 2002), and multiple goals to improve academic performance (Morisano et al., 2010). In a field study using quantitative methods, it is hard to measure these facets of goal setting for each individual and to test their effect on academic performance.

Although the underlying mechanism regarding how academic self-efficacy impacts college GPA is unclear, the predictive validity of academic self-efficacy on academic performance has been supported in both experimental and field studies in young adolescent and college student samples. In experimental research, increased self-efficacy predicted higher performance on cognitive tasks (Bandura & Schunk, 1981; Boufard-Bouchard, 1990; Zimmerman et al., 1992). In college samples, domain specific self-efficacy, such as math or science ability, predicted higher grades and career choice in related fields (Lent et al., 1986; Lent et al., 1991; Hackett et al., 1992). In a comprehensive meta-analysis (Robbins et al., 2004) the effect size (i.e., correlation) of academic self-efficacy on college GPA was .20 after controlling for traditional predictors.

As a whole, this empirical research supports the idea that academic self-efficacy is a strong non-traditional predictor of academic performance.

Effort, persistence, and academic self-discipline

Individuals' behavioral regulation is an important factor for achieving high performance both when learning a new skill and maintaining high performance at that skill. Literature about self-regulated learning distinguishes between effort and persistence as regulating behaviors that individuals can control (Sitzmann & Ely, 2011) which are necessary attributes for academic success in the long process of college education. Effort refers to time or number of trials to achieve relatively short-term goals such as quizzes, assignments, and midterm exams. In contrast, persistence is defined as a strong-willed characteristic to achieve relatively long-term goals despite barriers or failing experiences. Examples of long-term goals are earning a Ph.D., writing a novel, or learning a foreign language. Contribution of effort was found even in expert performance. For example, expert chess players or pianists spend significant amounts of time practicing to reach their high levels of performance and need to continually and consistently practice to maintain this level (Ericsson et al., 2009). The effect size of effort and persistence were .28 and .27 respectively related to performance in either educational or job related training settings for adult sample who were 18 or older (Sitzmann & Ely, 2011).

Although behavioral regulation is necessary to maintain high performance (Bandura, 1997; Ericsson et al, 2009; Sitzmann & Ely, 2011), previous research has not incorporated this mediational component in the academic self-efficacy model, specifically in predicting college students' academic performance. Earlier experimental studies demonstrated a significant positive relationship between self-efficacy and effort in children and young adolescents (e.g., Salomon, 1984; Bandura & Schunk, 1981; Schunk, 1981). In these experimental studies, time spent in a particular problem-solving context was used to measure effort or persistence. More recent studies focus on predictive power of ASE on college performance (e.g., Elias & MacDonald, 2009), but the instrumental role of behavioral regulation in self-efficacy theory has not been a primary interest. Specifically, the effect of ASE on behavioral regulation with a long-term interval has not been examined (Schunk, 1991).

In my dissertation, I test the mediational role of behavioral regulation in academic setting with using ASD. ASD, which includes both effort and persistence, is defined as a perceived behavioral self-control for academic performance. Although effort and persistence are conceptually two constructs, they can be one factor (Guan et al., 2006). ASD as a domain-specific adjustment characteristic that has discriminant validity from personality traits (McAdams & Pals, 2006). To my knowledge, there are no studies exploring ASD as a self-regulation construct that mediates the relationship between ASE and college GPA.

GPA as feedback for ASE and ASD

Past performance influences subsequent performance by acting as external feedback to the individual. External feedback provides information about learning or prior knowledge on how much individuals learned (Butler & Winne, 1995). Past performance with evaluative information predicts self-efficacy and subsequent performance (Heggestad & Kanfer, 2005). Interpretations about past performance can be manipulated by the researcher in an experimental setting, such as telling the participant that their score is relatively higher than others. This type of comparative feedback about performance also affects individuals' subsequent performance. A group who received supportive feedback such that their managerial performance progressively improved showed enhanced actual performance as well as satisfaction (Bandura & Jourden, 1991). Empirical research on this prediction using path analysis supports the mediating role of self-efficacy between past and subsequent managerial performance. Improved self-efficacy affected performance directly and indirectly through goal setting (Bandura & Jourden, 1991; Wood & Bandura, 1989). In academic skill development, positive feedback about past math calculations improved subsequent performance through increased self-efficacy in young children (Schunk, 1981, 1982, 1983, 1984).

To achieve success in college, students need to adjust quickly to their new academic environment, as well as to maintain their academic motivation and self-regulation throughout the college years. For first year students, academic self-efficacy is a predictor of academic and psychological adjustment (Chemers et al., 2001). Maintaining academic performance requires students to regulate ASE and ASD. Past GPA can be a factor influencing the regulation process through ASE and ASD. For example, attained past GPA functions as a piece of evaluative information about a student's level of achievement. The students can compare this evaluative information to his/her expected GPA as determined by academic self-efficacy. This internal comparison may lead to self-satisfaction if an individual's obtained GPA is higher than expected GPA (Bandura & Cervone, 1983). If obtained GPA is lower than expected GPA, students may feel self-doubt about their self-efficacy (Bandura, 1997) or work harder (i.e., high academic self-discipline) to achieve high academic performance.

To my knowledge, however, there are no longitudinal empirical data about the effect of past performance on ASE, ASD, and subsequent performance in college students. Specifically, the feedback effect of academic performance on ASD has not been explored even though feedback on deliberate practice is known as an important factor to improve subsequent physical performance in sports (Duffy et al., 2004, Ericsson et al., 1993, Law et al., 2007) as well as performance in the industrial and organizational psychology field (Wood, 2005). Thus, I propose a model where previous year GPA functions as past performance feedback that, in turn, affects subsequent GPA directly or indirectly through ASE and ASD. The exploration of the feedback effect of GPA on self-efficacy and self-discipline has important implications. First, it may reveal the mechanism through which past performance impacts student academic self-regulation. Second, by knowing how GPA affects ASE and ASD, counselors can potentially intervene in either self-efficacy or self-discipline with clients, as appropriate. For the analysis, I will use the data collected at three time points: Time 1 in 2008 (T1), Time 2 in 2009 (T2), and Time 3 in 2010 (T3).

Purpose of study

The two goals of this study were to examine the mediational effect of ASD on the ASE-GPA link, as well as to examine the feedback effect of previous GPA on ASE and ASD in first-year and second-year college students. Specifically, this study aimed to elucidate a mechanism of academic performance with two non-traditional predictors, ASE and ASD. In addition, the exploration of the feedback effect would provide an insight into the regulation of ASE and ASD based on previous academic performance. To test the effect of non-traditional predictors, ACT score as a traditional predictor of academic performance was controlled in these analyses. The mediation effect of ASD was tested in both cross-sectional and longitudinal analyses. Longitudinal analysis strengthens the validity of the mediation effect with extended time intervals among variables. The feedback effect was explored in longitudinal analysis only.

I. Cross-sectional hypotheses

ASD mediates between ASE and five semester GPAs (i.e., Spring 2008, Fall 2008, Spring 2009, Fall 2009, and Spring 2010) GPA after controlling for ACT scores.

II. Longitudinal hypotheses

1. Mediation effect
   a. T1 ASE predicts T2 ASD and T2 GPA (spring 2009 and fall 2009).
   b. T2 ASD predicts T2 GPAs (spring 2009 and fall 2009).
   c. T2 ASE predicts T3 ASD and T3 GPA (spring 2010).
   d. T3 ASD predicts T3 GPA (spring 2010).
2. Feedback effect
   a. Fall 2008 GPA predicts T2 ASE and ASD.
   b. Fall 2009 GPA predicts T3 ASE and ASD.

CHAPTER 2

METHOD

Participants

The total number of participants was 1,746 in 2008, 993 of whom were freshmen and 753 were sophomores. Among the participants, 655 (37.5%) students completed at least one more survey conducted either in 2009 or 2010. These 655 students serve as the participants based on the selection criteria that they needed to complete at least 2 surveys. Out of these participants, 371 (56.7%) were freshmen and 284 (43.3%) were sophomores in 2008. In this pool, 44 students graduated after the 2009 spring semester and 51 students graduated after the 2009 fall semester. Thus, the final sample size for this study was 560 after excluding the 95 (14.5%) students who were not eligible for the second or third survey due to graduation.

Out of the 560 students, 338 (60.4%) were freshmen and 222 (39.6%) were sophomores in 2008. The mean age was 19.89 (SD=3.325) in 2008 and the range of ages was 18 to 36. Most students were female (N=424, 75.7%) and white (N=449, 80.2%). There were 60 Asian (10.7%), 15 Black (2.7%), 14 Hispanic (2.5%), and 5 American Indian (.9%) students. Fifteen students were non-specific (2.7%), and 2 were missing (.4%). Among the 560 students, 129 students completed all three surveys. Three hundred thirty two students completed T1 and T2 surveys, and 99 students completed T1 and T3 surveys. The selection procedure of participants showed in Figure 3 and 4.

Figure 3. Participants Selection (All Freshmen and Sophomores)

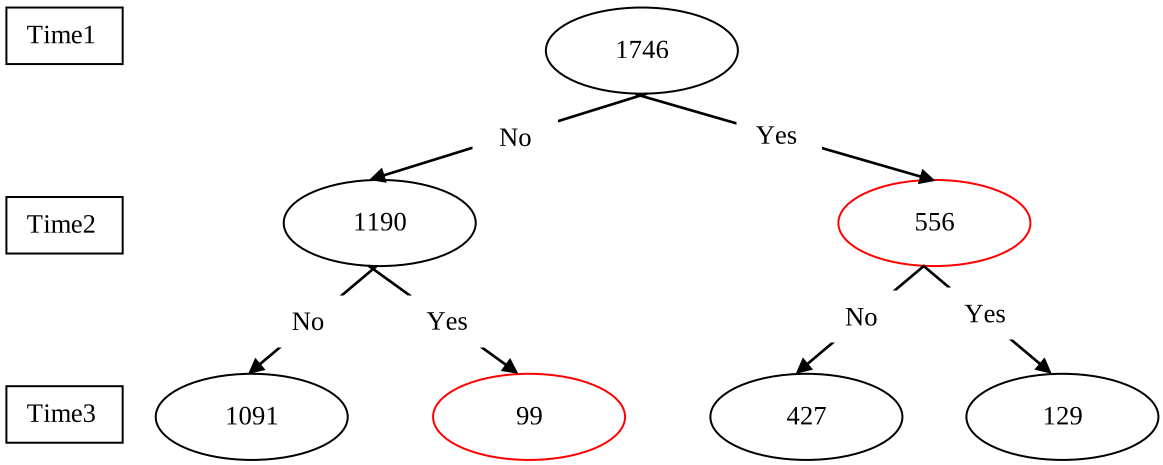
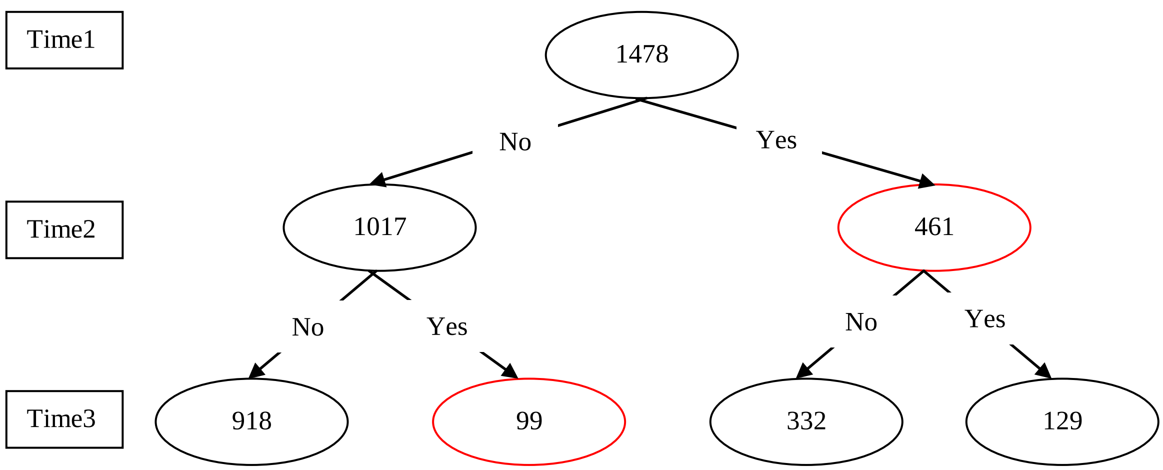


Figure 4. Participants Selection (All Eligible Freshmen and Sophomores)



Measures

ACT scores

ACT score were used as covariates as a traditional predictor. ACT scores were actual scores obtained from the college rather than self-reported scores. ACT has been reported to predict college GPA (.22-.37) as well as to measure cognitive ability (.07-.49).

(Robbins et al., 2004; Coyle & Pillow, 2008).

Academic self-efficacy (ASE)

The six-item Academic Self-Efficacy scale (Roeser, Midgley, & Urdan, 1996) was used to measure academic self-efficacy. Items are rated on a five-point scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*) with higher scores representing higher academic self-efficacy. An example item states, "I can master the skills taught in school this year." Other studies using this scale showed predictive validity for academic performance (e.g., Bong, 2001). Cronbach's alpha in this sample at T1 was .84 (*N*=560), T2 was .87 (*N*=461), and T3 was .86 (*N*=228). The items are presented in Appendix A.

Academic self-discipline (ASD)

A nine-item, five-point scale of academic self-discipline ranging from 1 (*strongly disagree)* to 5 (*strongly agree*) was created based on the conscientiousness subscale of the International Personality Item Pool (IPIP; Goldberg et al., 2006). This measure represented how much perceived effort and persistence a student has specifically in an academic setting by asking about diligence, responsibility, time management, organization skills, preparation for exams, and concentration. Higher scores represent higher academic self-discipline. Items include, "I keep working on a school assignment until it is finished" and "I do a thorough job of studying for exams." Cronbach's alpha in this sample was at T1 was .85 (*N*=560), T2 was .86 (*N*=461), and T3 was .86 (*N*=228). The items are presented in Appendix B.

GPA

All GPAs used in this study were semester GPAs, not cumulative GPAs. The five GPAs that were collected after the end of each semester from spring 2008 to spring 2010 were used as outcome variables. Each semester, some of the students' GPAs were missing (8 in spring 08 GPA, 11 in fall 08 GPA, 8 in spring 09 GPA, 46 in fall 09 GPA, and 27 in spring 10 GPA). Although there was not enough information about the reason why these students did have GPAs, dropping out for the specific semester was the most plausible reason.

Procedure

Data were collected using an online survey in April in 2008, 2009, and 2010. Email invitations were sent to all CLA students each year (N = 12,714 in 2008; N = 12,567 in 2009; N = 13,176 in 2010). The number of respondents in 2008 was 2848 (22.4%), 2571 (20.5%) in 2009, and 1604 (12.2%) in 2010. In 2008, there were 993 (34.9%) freshmen, 753 (26.4%) sophomores, 520 (18.3%) juniors, and 459 (16.1%) seniors. In 2009, there were 1504 (41.0%) freshmen, 617 (24.0%) sophomores, 446 (17.3%) juniors, and 327 (12.7%) seniors. In 2010, there were 623 (38.8%) freshmen, 382 (16.6%) sophomores, 267 (16.1%) juniors, and 259 (16.1%) seniors. All the surveys were voluntary and no compensation was given. Students' GPA data were collected separately by the registrar's office after the end of each semester from spring 2008 to spring 2010.

Data analytic plan

Two statistical approaches were adopted to test the research hypotheses in this study. In cross-sectional analysis, the mediational effect was tested with the bootstrapping method (Preacher & Hayes, 2008). In longitudinal analyses, panel analysis (Little et al., 2007) was used to test mediational and feedback effects. For both analyses, properly handling missing values was important to obtain unbiased results. The data has a high attrition rate, especially in T3 (59.3%). Detailed missing pattern analysis and the rationale for using Full Information Maximum Likelihood (FIML) to estimate path coefficients is presented in Appendix C.

Cross-sectional analysis

Five separate mediational analyses were conducted to test the effect of ASD. A predictor and a mediator were ASE and ASD respectively. Dependent variables were five GPAs (spring 2008, fall 2008, spring 2009, fall 2009, and spring 2010). ACT scores were entered as covariate for all the analysis. Instead of Baron and Kenny's (1986) mediational analysis, the bootstrapping method (Preacher & Hayes, 2008) was used. Bootstrapping is a non-parametric method; thus, it is free from the violation of assumptions of traditional inferential statistical procedures such as the normality assumption. Furthermore, this method is more powerful than Baron and Kenny's (1986) causal step strategy and Sobel test (1982). The gist of this method was to calculate the indirect effect from a predictor to an outcome variable through a mediating variable as well as the standard error with using sampling with replacement. Due to the non-parametric characteristic of the bootstrapping method, hypothesis testing is conducted by confidence interval. If the confidence interval contains zero, the null hypothesis (i.e., no mediation effect) is retained.

Longitudinal analysis

Panel analysis (Little et al., 2007) was used to test the research hypotheses with the longitudinal dataset. Panel analysis with longitudinal data is an ideal method to test multiple causal relationships with a single test. Panel analysis with longitudinal data is a stronger method to test mediational effects because it satisfies the temporal lag assumption between a predictor and a mediator, as well as between the mediator and a criterion variable. In addition, panel analysis with multiple time points estimates more accurate path coefficients. However, a major weakness is that the results of path analysis are sensitive depending on paths assigned by researchers who construct models. I added paths based on previous research and my hypotheses. Figure 5 shows the hypothesized model. The paths in the proposed model are described here:

(1) ACT predicts T1 ASE, ASD, and spring 2008 GPA.

(2) Previous ASEs predicts subsequent ASEs.

(3) Previous ASDs predicts subsequent ASDs.

(4) Previous GPAs predicts subsequent GPAs.

(5) T1 ASE and ASD, T2 ASE and ASD, and T3 ASE and ASD are covaried.

(6) T1 ASE predicts T2 ASD and T2 GPAs (hypothesis II 1 a).

(7) T2 ASD predicts T2 GPAs (hypothesis II 1 b).

(8) T2 ASE predicts T3 ASD and T3 GPA (hypothesis II 1 c).

(9) T3 ASD predicts T3 GPA (hypothesis II 1 d).

(10) Fall 2008 GPA predicts T2 ASE and ASD (hypothesis II 2 a).

(11) Fall 2009 GPA predicts T3 ASE and ASD (hypothesis II 2 b).

CHAPTER 3

RESULTS

Descriptive statistics

Descriptive statistics shows each variable's central tendency and variability. The mean ACT score was 26.27, which is higher than the average score (22.9) of the state of Minnesota, as well as the average of whole nation (21.0) in 2010 (ACT, 2010). However, the score is slightly lower than the average ACT score of College of Liberal Arts (CLA) students (27.3) who were admitted to the University of Minnesota in 2011. The range of ACT score across college was from 24.4 (Education and Human development) to 30.6 (Science and Engineering) (Sigler, 2012). Based on the university data, the participants in this study were not biased regarding their ACT scores.

The mean of ASE ranged from 4.05 to 4.19 and the mean of ASD ranged from 3.74 to 3.81. Mean ASE is higher than mean ASD, which may imply that students have stronger belief about their academic ability than their actual effort and persistence. The range of mean GPA was from 3.31 to 3.38. Table 2 shows descriptive statistics of variables in this study.

Table 2

Descriptive Statistics

	N	*M*	*SD*	*Range*
ACT	517	26.27	3.69	16-35
T1 ASE	560	4.05	.56	1.83-5.00
T1 ASD	560	3.75	.71	1.00-5.00
T2 ASE	461	4.08	.60	1.00-5.00
T2 ASD	461	3.74	.74	1.20-5.00
T3 ASE	228	4.19	.55	2.00-5.00
T3 ASD	228	3.81	.72	1.40-5.00
GPA08S	558	3.31	.57	.00-4.00
GPA08F	549	3.32	.52	1.11-4.00
GPA09S	552	3.34	.56	.69-4.00
GPA09F	514	3.35	.56	.00-4.00
GPA10S	533	3.38	.59	.00-4.00

Correlations

In this analysis, the pairwise deletion method was used. Thus, *N* sizes were reduced as time goes (T1 *N*=560, T2 *N*=461, T3 *N*=228). Zero-order correlations among variables indicated five distinctive patterns. First, ACT scores were correlated with GPA and ASE, but not ASD at all three-time points. The correlations between ACT and ASD were close to zero, which implied that academic aptitude measured by ACT (Coyle & Pillow, 2008) may be independent of academic effort and persistence. Second, the stability of ASE and ASD was established which is a required condition for causal relationships in longitudinal panel analysis. The range of correlations for ASE was from .49 to .60 and the range of correlation for ASD was from .58 to .68 between time points. Third, ASE and ASD were correlated cross-sectionally as well as longitudinally as expected. The range of cross-sectional correlations was from .32 to .43. The range of longitudinal correlation was from .19 to .32. Fourth, ASE and ASD are correlated with GPA across all three-time points. The range of the correlation between ASE and GPA was from .18 to .32. The range of the correlation between ASD and GPA was .14 to .26. Fifth, GPAs are highly correlated each other. The range was from .52 to .65. Pearson correlations among variables with reliabilities are presented in Table 3.

Table 3

Zero-Order Correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12
1 ACT	1											
2 AE1	$.28^{**}$	1										
3 AD1	-.02	$.32^{**}$	1									
4 Sp08	$.49^{**}$	$.32^{**}$	$.22^{**}$	1								
5 Fa08	$.44^{**}$	$.20^{**}$	$.21^{**}$	$.64^{**}$	1							
6 AE2	$.24^{**}$	$.49^{**}$	$.20^{**}$	$.31^{**}$	$.24^{**}$	1						
7 AD2	-.03	$.19^{**}$	$.64^{**}$	$.20^{**}$	$.26^{**}$	$.35^{**}$	1					
8 Sp09	$.37^{**}$	$.25^{**}$	$.21^{**}$	$.59^{**}$	$.61^{**}$	$.29^{**}$	$.26^{**}$	1				
9 Fa09	$.36^{**}$	$.21^{**}$	$.25^{**}$	$.56^{**}$	$.53^{**}$	$.24^{**}$	$.26^{**}$	$.61^{**}$	1			
10 AE3	$.24^{**}$	$.54^{**}$	$.30^{**}$	$.26^{**}$	$.37^{**}$	$.60^{**}$	$.32^{**}$	$.22^{**}$	$.22^{**}$	1		
11 AD3	-.02	$.20^{**}$	$.58^{**}$	$.14^{**}$	$.17^{**}$	$.28^{**}$	$.67^{**}$	$.20^{**}$	$.14^{**}$	$.43^{**}$	1	
12 Sp10	$.28^{**}$	$.18^{**}$	$.19^{**}$	$.52^{**}$	$.55^{**}$	$.23^{**}$	$.25^{**}$	$.59^{**}$	$.65^{**}$	$.29^{**}$	$.22^{**}$	1
α	-	.84	.85	-	-	.87	.86	-	-	.86	.86	-

Notes. AE1: T1 ASE, AD1: T1 ASD, Sp08: spring 2008 GPA, Fa08: fall 2008 GPA, AE2: T2 ASE, AD2: T2 ASD, Sp09: spring 2009 GPA, Fa09: fall 2009 GPA, AE3: T3 ASE, AD3: T3 ASD, Sp10: spring 2010 GPA

Cross-sectional analysis

To test the mediational effect, five separate regression models were tested for the five GPAs (i.e., 2008 spring, 2008 fall, 2009 spring, 2009 fall, 2010 spring). For 2008 spring and fall GPAs, T1 ASE and ASD were entered as predictors. For 2009 spring and fall GPAs, T2 ASE and ASD were used as predictors. For 2010 spring GPA, T3 ASE and ASD were predictors.

To strengthen the validity of the cross-sectional mediation effect, multicollinearity among independent variables was tested because high multicollinearity among independent variables undermines the mediational effect. Variance Inflated Factor (VIF) higher than 10 or tolerance lower than .01 would be problematic which would indicate that the predictors are identical (Cohen et al., 2003, p.422-424). The results indicated that none of the five sets of data for GPA had high multicollinearity. Multicollinearity test results were presented in Table 4.

Table 4

Multicollinearity

	GPA08S		GPA08F		GPA09S		GPS09F		GPA10S	
	VIF	Tol.	VIF	Tol.	VIF	Tol.	VIF	Tol.	VIF	Tol.
ACT	1.097	.912	.911	1.098	1.109	.902	1.106	.904	1.084	.922
ASE	1.218	.821	.820	1.219	1.276	.784	1.276	.784	1.332	.751
ASD	1.126	.888	.887	1.128	1.177	.850	1.174	.852	1.253	.798

Note. For GPA08S and GPA08F, T1 ASE and ASD were used; For GPA09S and GPA09F, T2 ASE and ASD were used; For GPA10S, T3 ASE and ASE were used.

Significant mediation effects of ASD for all five GPAs were found after controlling for ACT scores. 95% CI of indirect effect did not include zero for any of the five sets of analyses. In this analysis, Full Information Maximum Likelihood (FIML) was used to estimate parameters with handling missing values. As hypothesized, the effect of ASE went through ASD. For four GPAs (2008 fall, 2009 spring, 2009 fall, and 2010 spring), ASD fully mediated ASE. After controlling for the ACT and ASD, ASE was not a significant predictor of GPAs. ACT predicted both ASE and ASD in all five analyses, but the direction was negative for ASD. Students who had higher ACT score showed lower ASD. The indirect effects obtained by bootstrapping results were presented in Table 5.

Table 5

Mediational Effect

Indirect path	Indirect effect size	95% CI	
T1 ASE → T1 ASD → GPA08S	.077	.046	.117
T1 ASE → T1 ASD → GPA08F	.081	.044	.128
T2 ASE → T2 ASD → GPA09S	.087	.044	.143
T2 ASE → T2 ASD → GPA09F	.092	.053	.152
T3 ASE → T3 ASD → GPA10S	.157	.069	.275

Longitudinal analysis

Hypothesized model testing

Panel analysis (Little et al., 2007) with three time points was used to test the second set of hypotheses. The target model was specified based on the hypotheses with ACT as an exogenous variable and the other variables including ASE, ASD, and semester GPAs as endogenous variables. ASE and ASD in T1, T2, and T3 were covaried, which was consistent with the findings in the cross-sectional analysis. To test the feedback effect, the paths from fall GPAs on the following ASE and ASD were added in the hypothesized model. In the final model with the feedback effects, there was one exogenous variable and 11 endogenous variables. FIML was used to estimate path coefficients. With FIML, participants who have missing values in ASE, ASD, or GPA were not excluded in the analysis. However, 43 students who had missing values in endogenous variable (i.e., ACT scores) were excluded. The final sample size for panel analysis was 517.

Conventional methods were used to judge model fit such as χ^2, Mean Square Error of Approximation (RMSEA), and Comparative Fit Index (CFI). Because χ^2 test is sensitive to sample size, the other two auxiliary indices were supplemented. RMSEA shows the discrepancy between covariance in the population level and covariance generated from data (Byrne, 2004). Thus, the smaller value of RMSEA implies better fit. CFI compared the hypothesized model with the independence model, which is a null model with the most number of degrees of freedom without estimation (Byrne, 2004, p.117). Traditionally, RMSEA less than .05 is considered good fit, and values between .05 and .10 were acceptable. For CFI, values over .10 are considered as poor fit (see Hu & Bentler, 1999).

The hypothesized model fit was not statistically ideal, $\chi^2(37, N = 517) = 288.786$, $p < .001$; RMSEA =.115 (90% CI = [.103 .127]), CFI = .885. ACT predicted T1 ASE (β = .28, *SE* = .04, $p < .001$) and spring 08 GPA (β = .50, *SE* = .03, $p < .001$), but not T1 ASD (β = -.02, *SE* = .04, *n.s.*). As expected and shown in zero-order correlation analysis, ASE, ASD, and GPA are highly correlated across three time points (i.e., stability). The mediation effect of ASD was not supported in this analysis. T1 ASE did not predict T2 ASD (β = -.004, *SE* = .04, *n.s.*) and T2 ASE did not predict T3 ASD (β = .02, *SE* = .07, *n.s*). However, the feedback effect was supported, especially for self-efficacy. Fall 08 GPA predicted T2 ASE (β = .14, *SE* = .04, p = .001) and ASD (β = .11, *SE* = .04, p = .005). Fall 09 GPA predicted T3 ASE (β = .13, *SE* = .07, p = .044). Figure 6 shows the significant path coefficients.

Modified model testing

To obtain less biased results based on a better fitting model, a modified model was constructed based on the residual analysis (see Appendix D). In the modified model, ACT was entered as a covariate for all GPA, ASE, and ASD measures. Although covariance between ACT and ASD were not significantly high, ACT was controlled for all T1, T2, and T3 ASD to exclude the effect of a traditional predictor from the modified model. In addition, GPAs were covaried with each other. These two modifications have practical implications such that the effect of cognitive ability as traditional predictor was partialled out from all variables with this model. With GPAs being covaried, the shared method variance was controlled, which is unavoidable in longitudinal data analysis (Cole & Maxwell, 2003). Figure 7 shows the modified model.

With controlling for ACT effect and covariance among GPA, the revised model is well fitted to the data, χ^2 (23, N = 517) = 93.458, p < .001; RMSEA = .077 (90% CI = [.061, .094]), CFI = .968. The mediation effect of ASD was not supported in the modified model. Modified model resulted in three changes in findings. First, ASD significantly predicted GPA at all three time points. Second, the feedback effect for ASE in T3 disappeared, but feedback effects for ASE and ASD still remained in T2. Third, the prediction effect of T1 ASE on GPA 09 spring became non-significant. Because the modified model was more acceptable than the hypothesized model conceptually and statistically, these were considered as the final results of longitudinal analysis. Figure 8 shows the results of the modified model.

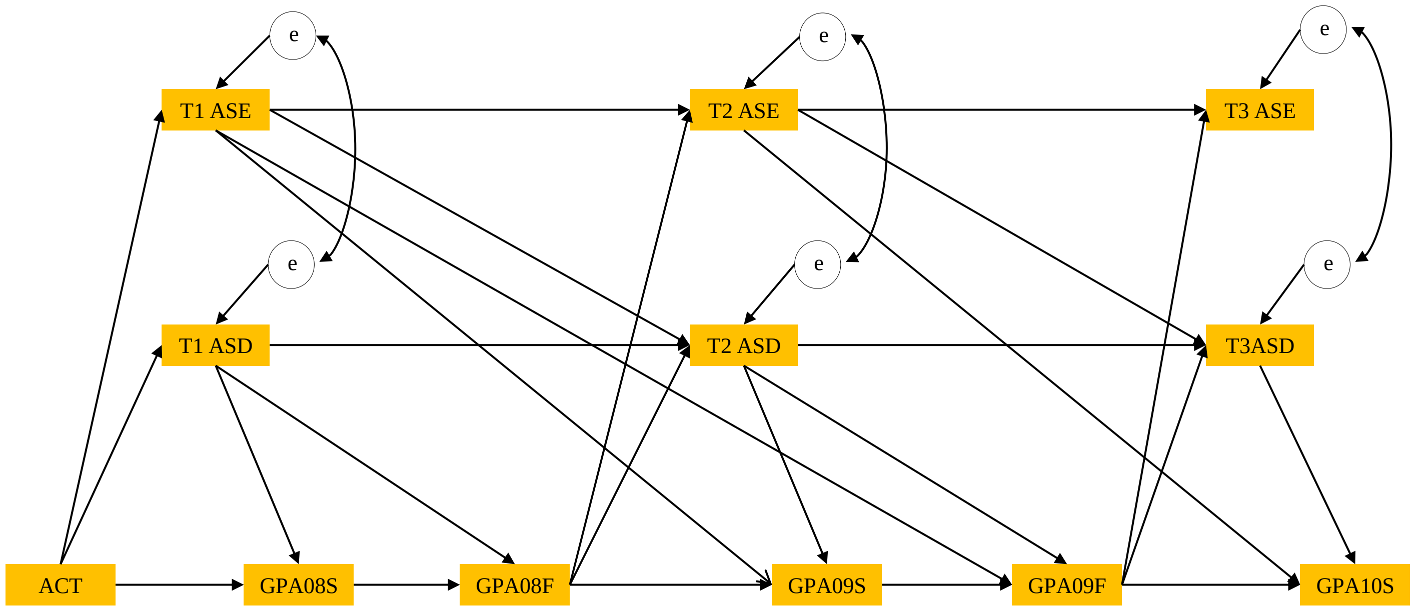


Figure 5. The Hypothesized Model

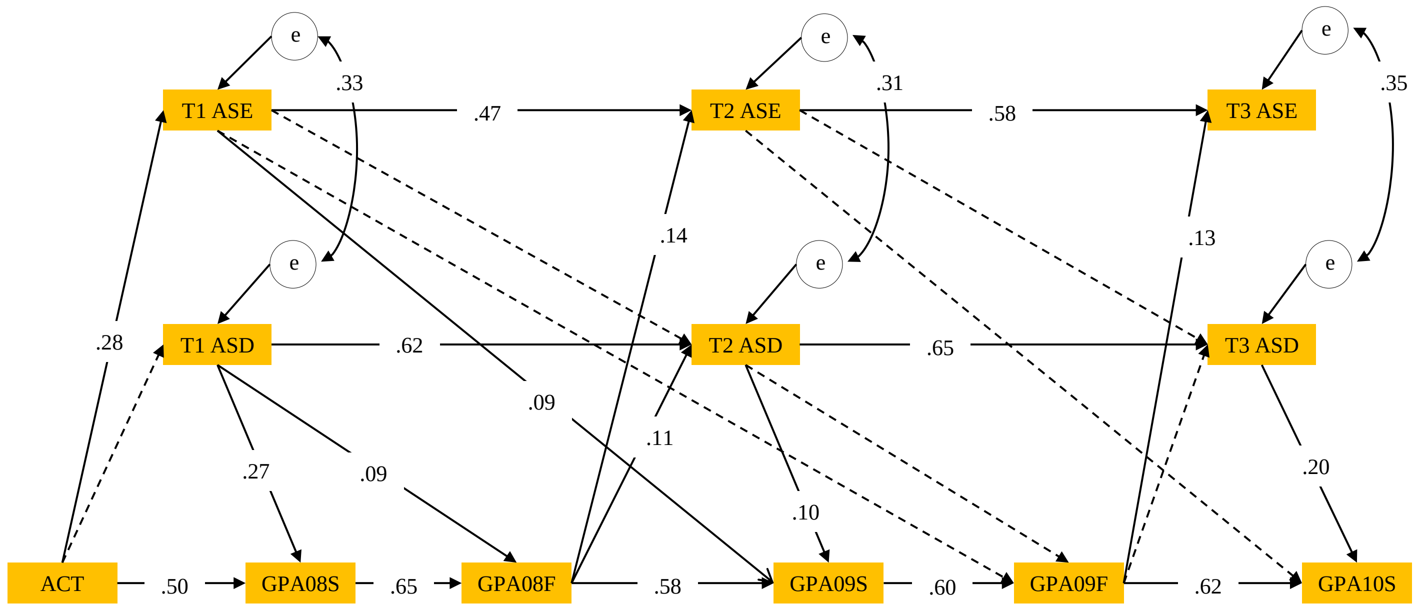


Figure 6. Path Coefficients of the Hypothesized Model

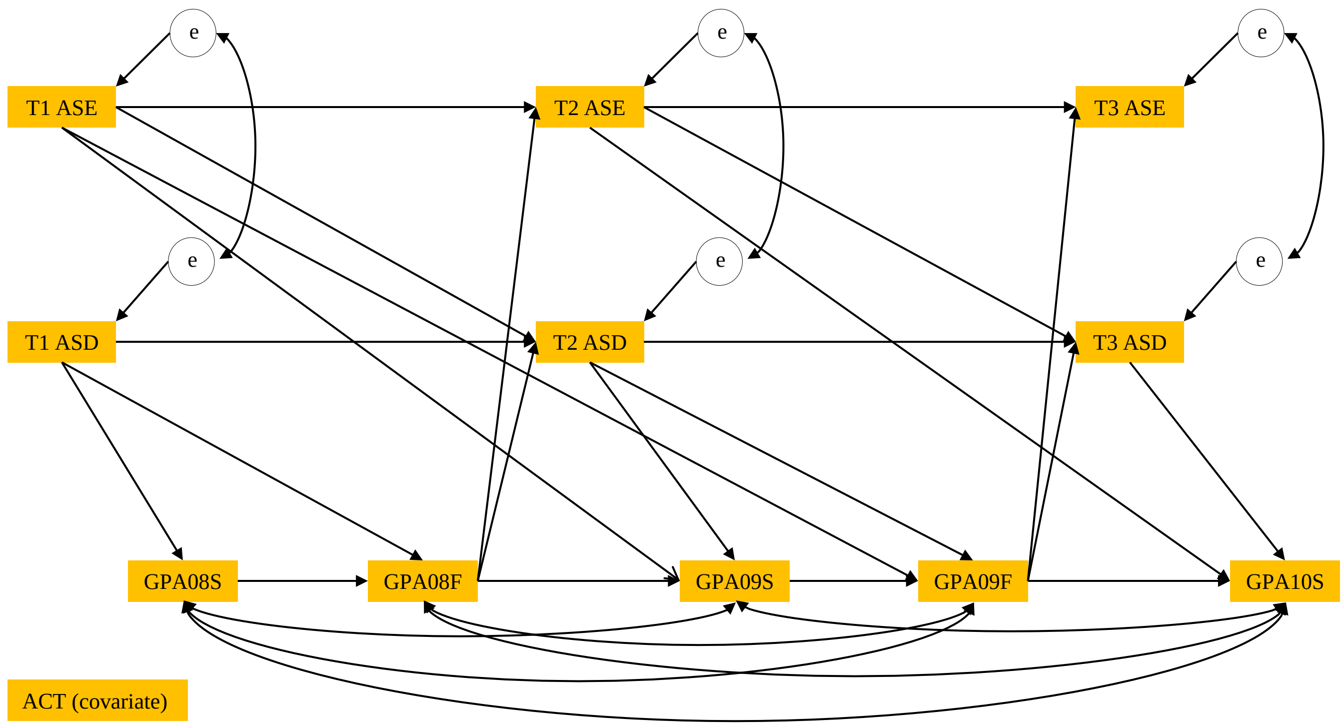


Figure 7. The Modified Model

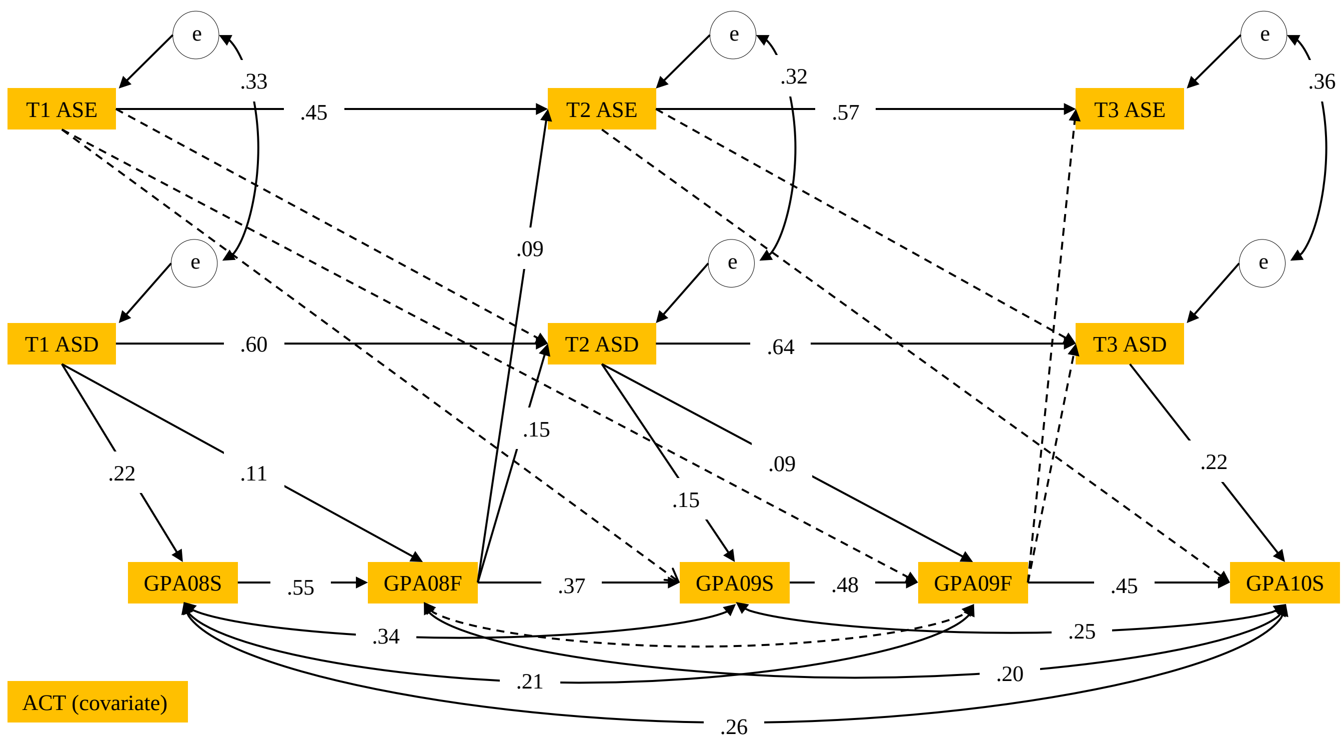


Figure 8. Path Coefficients of the Modified Model

CHAPTER 4

DISCUSSION

The two major purposes of this study were to investigate the mediational effect of ASD (i.e., perceived academic self-control) between ASE (i.e., perceived academic ability) and college GPA as well as the feedback effect of previous GPA on subsequent ASE and ASD. Results with cross-sectional data analysis supported the mediational effect of ASD for all five GPAs. However, the results with longitudinal data did not support the mediational effect. Specifically, previous year's ASE did not predict subsequent year's ASD and GPA. The feedback effect (i.e., the association of subsequent performance and subsequent ASE and ASD) was supported from fall GPA to subsequent year's ASD at T2 only. Based on both cross-sectional and longitudinal analyses, ASD was found as a non-traditional predictor for academic performance. ASD also was a stronger and more proximal predictor than ASE. In addition, GPA functioned as an evaluative feedback on ASE and ASD. Practical implications and limitations were also discussed.

Cross-sectional analysis

Cross-sectional analysis supported the hypotheses that ASE and ASD predicted college GPA after controlling for ACT scores. In specific, the effect of ASD on GPA was above and beyond the effect of ASE. Notably, ASD, as measured in April, had a mediational effect on spring semester GPA (one month later) and fall semester GPA (eight months later).

Mediational effect of ASD on spring GPAs

The cross-sectional analysis with spring GPAs showed that ASE and ASD were significant predictors for college GPA. ASE was expected to predict GPA, which has been consistently reported by previous empirical research (e.g., Robbins et al., 2004; Zimmerman et al., 1992). The hypothesis about the association between ASD and academic performance was supported in the mediational analysis. The two findings related to ASD were that ASE affected academic performance through ASD, and ASD positively predicted academic performance.

In self-efficacy theory, ASE initiates behaviors to achieve an academic goal (Bandura, 1997). The cross-sectional analysis supported this mechanism with ASD including effort and persistence. ASE positively predicted ASD that in turn entailed academic performance. For spring 2009 and 2010 GPAs, ASD was fully mediated the effect of ASE. In other words, after controlling for ACT score, ASD still explained spring 2009 and spring 2010 GPAs but ASE did not. These associations imply that ASD should be a practical tool to actualize ASE.

As a mediator, ASD was revealed as a significant predictor for GPAs. Previous research emphasized the association between effort and persistence and performance. For example, effort and persistence predicted learning (e.g., Sitzmann & Ely, 2011), physical education (e.g., Agbuga & Xing, 2008; Guan et al., 2006), and academic performance (e.g., Goodman et al., 2011; Richardson et al., 2012). Consistent with the research findings, this study showed regulating ASD in an academic setting was beneficial to produce higher performance.

Methodologically, this mediational model with spring GPAs had a weakness such that the time when ASD and ASE were measured was only a few weeks before the end of spring semester. Thus, the argument could be made that students' level of ASE and ASD reflected their cumulative scores around the time of survey. This argument can weaken the validity of this result. Students' expected GPA might affect their level of ASE and ASD. For example, students who did well in classes until the end of semester may report higher ASE and ASD than when they did not have information about their class performances. This data collection time issue may falsely strengthen the association. Thus, the same mediational model was tested with fall GPAs.

Mediational effect on fall GPAs

The cross-sectional analysis with two fall GPAs (2008 and 2009) confirmed that the suggested mediational model was valid. These results supported the association between ASD and college GPA as well. The time interval between the two predictors and GPA was long enough (i.e., 8 months) that students did not have any idea about their fall GPAs. ASD fully mediated the relation between ASE and 2008 and 2009 fall GPAs. Full mediation implied again that ASD should be a necessary component to have positive effect of ASE. Without ASD, ASE alone may not guarantee high academic performance. In conclusion, both sets of cross-sectional analyses supported the mediational model with ASD.

Longitudinal analysis

Even though the cross-section analysis supported the mediational effect of ASD, the causal association was still questionable due to the nature of study design (see Frazier et al., 2004). Specially, ASE and ASD were measured at the same time; thus, the direction of relations needed to be further explored. To examine the potential causal association between ASE and ASD, panel analysis with longitudinal data was conducted with the modified model (see Appendix D).

The longitudinal analysis confirmed the predictive effect of ASD found in the cross-sectional analysis and the feedback effect of fall GPA on ASD. However, the expected mediation of ASD in the longitudinal analysis was not found. In this section, findings from the longitudinal analysis as well as a methodological reason about the non-significant mediational effect of ASD are discussed.

Predictive power of ASD

The predictive effect of ASD on GPAs was the most distinctive finding from the longitudinal analysis. At all three time points, ASD predicted both spring and fall GPAs, which was consistent with the cross-sectional analysis. In the longitudinal analysis, the strong and proximal effect of ASD was reaffirmed. ASD predicted both spring and fall GPAs independently of previous year's GPA, ASE, and ACT scores. The long-term effect of effort and persistence with multiple time points has not been reported although effort regulation has been recently highlighted as a non-traditional predictor (Richardson et al., 2012).

Besides the relationship with ASD and GPA, another interesting finding was the weak relationship between ACT and ASD. This relationship is consistent with the finding in a recent study (*r* = .02; Allen et al., 2008). Even though there has been no theory developed on this association, the weak or negative correlation between conscientiousness and intelligence provides a clue to this result (Furnham et al., 2005). ACT is correlated with intelligence (Cohn et al., 2004; Coyle & Pillow, 2008; Harackiewicz et al., 2002) and ASD captures effort and persistence that are attributes of conscientiousness. Based on the previous research, it can be assumed that the null association between ACT and ASD would be expected. Cognitive ability and academic effort appear to be independent.

Non-significant mediational effect

Contrary to the cross-sectional results, the longitudinal analysis did not replicate the mediational effect of ASD. In particular, the direct effect of previous year's ASE on subsequent year's GPA was not significant. Previous year's ASE also did not explain subsequent year's ASD. This non-significant effect did not completely reject the mediational effect of ASD. A major explanation about the non-significant mediational relationship in the longitudinal analysis may be the long time interval between time points. The time interval of one year between ASE and ASD may simply be too long to have a significant association.

Previous research results do not provide a maximum time interval between self-efficacy and behaviors led by it. The duration of self-efficacy effect varies depending on outcome variables and the purpose of the studies. For instance, a physical exercise intervention study showed a long-term effect of improved self-efficacy that predicted level of exercise one year later (Neupert et al., 2009). However, memory performance studies conducted in experimental setting did not support the long-term effect of self-efficacy (e.g., Bandura, 1997). In a meta-analysis about self-efficacy and health outcome, the effect size declined as the time interval increased (Holden, 1991).

Regarding academic performance, the optimal interval is not known. Theoretically, Bandura (1997) commented that the ideal interval between ASE and the outcome variable would be short. Empirically, the long-term effect of ASE has been typically tested across only one semester (e.g., Chemers et al., 2001; Zimmerman & Bandura, 1994). Thus, the maximum interval between ASE and ASD as a mediator could be even shorter. Based on theoretical framework and empirical studies, it is reasonable to say that the one-year interval in this study may be too distant to examine the prediction of ASE both on ASD and GPAs.

Conclusion on the mediational effect of ASD

Based on both cross-sectional and longitudinal analyses, the mediational effect of ASD was partially supported. In the consideration of the long interval between time points, it is reasonable to argue that ASD mediated the effect of ASE on GPA during a short-term period, specifically less than one year based on the cross-sectional analysis. In conclusion, the mediation effect of ASD was not maintained with the one year interval.

Because the mediational effect of ASD was not confirmed in the longitudinal analysis, an alternative model was tested with ASD as a predictor (see Appendix E). This alternative model was less appropriate compared to the modified model. The alternative model testing reassured that ASD was more appropriate as a mediator rather than a predictor.

GPA as a feedback for subsequent performance

In the longitudinal analysis, the effect of previous GPA as an evaluative feedback on ASE and ASD was tested. The results partially supported the feedback effect of GPA on subsequent year's ASE and ASD. As hypothesized, the feedback effect both on ASE and ASD were significant at T2. The feedback effect on ASE supported the self-efficacy theory (Bandura, 1977) and was consistent with empirical findings that positive feedback improved self-efficacy (Bandura & Jourden, 1991; Schunk 1981, 1982, 1983a, 1984b; Wood & Bandura, 1989).

The feedback effect of previous GPA on ASD has not been previously reported. In this longitudinal analysis, academic performance (i.e., GPA) had a stronger association with ASD (.15) than with ASE (.09) at T2. The feedback effect of past GPA might be more influential on regulating the proximal predictor (i.e., ASD) rather than the cognitive distal predictor (i.e., ASE) in the theoretical framework proposed in this dissertation. With this feedback effect, ASD worked as a mediator between previous and subsequent GPAs. One interpretation would be that strong GPA associations might be related to hardworking although further explorations are required.

This result had an implication of an independent regulating system with ASD in academic performance, which was distinguished from ASE. In the self-efficacy literature, feedback given in experimental setting improved self-efficacy and persistence, which led to better performance in posttest (e.g., Schunk 1981, 1982, 1983a). No previous study has examined the feedback loop of previous performance, ASD, and subsequent performance in college students. In this analysis, students interpreted GPA as information about their ASD. Previous research results on expert performance supported this finding in that extensive practice and appropriate feedback about performance improves subsequent performance. For instance, the effect of practice explained the expertness of playing violin, gymnastics, and dart playing, which are often considered as a product of innate ability (Duffy et al., 2004; Law et al., 2007; Erricson, 1993). In contrast, mere repetition and non-concentrated studying does not produce high college GPA (Plant et al., 2004).

Implications

The results have implications for students, counselors, and administrators that ASD is a salient predictor of academic performance. College students are assumed to have cognitive ability to study based on their standardized scores. They also had high ASE as shown in this study at all three time points. However, some students may struggle with academic difficulties. The results demonstrated that ASE was not only a predictor of high academic functioning as traditionally emphasized as a target for intervention, but also being effortful and persistent (i.e., ASD) was even stronger and a more proximal determinant of academic achievement. Thus, students and counselors could focus on improving both ASE and ASD. Especially, for students who have high ASE but do not have good academic performance, ASD would be a perfect target for intervention.

This study also provided a clue about how students' ASD would work or be improved. Declaring a major in the early stage of college had potentially two benefits – utilizing GPA as information for self-regulating through ASD as well as maintaining stable academic performance (see Appendix F). Counselor should encourage students to set up academic goals. Setting up goals could lead students to use GPA as self-regulating information that affects ASD. Improved ASD was associated with better grades in the next semester. Furthermore, early decision-making about major selection is associated with stable academic performance.

Limitation and future suggestions

This study is not free from limitations. First, there are measurement issues specifically with regard to ASE and GPA. In this study, general ASE was used instead of specific ASE. ASE has often been defined based on a specific subject or domain such as learning, writing, and math (e.g., Finney & Schraw, 2003). Empirical studies have shown the utility of specific ASE. For example, course and content specific ASE has higher predictive power for midterm and final scores than general ASE (Bong, 2001). In this study, ASE might not accurately predict heterogeneous students' GPAs regarding their majors from English to physiology. Some majors emphasize more mathematics or sciences, but the other majors need more writing skills. Furthermore, by using aggregate GPA score as an outcome variable, different levels of difficulties in each major were not considered depending. Grading policy and the mean GPA can vary across different departments. Thus, more specific measures are encouraged to explore the relation based on a narrower scope with higher accuracy. For example, a specific or a bundle of academic self-efficacy scales and a term grade for a specific course could provide a less biased picture about the relationship.

Second, a high rate of missing values specifically at T3 is a potential problem. Previous literature did not say much about cut-off numbers of missing values for accurate estimation. Because of large sample size (N = 560), the estimation method in this study should work properly (Schafer & Graham, 2002). However, there is possibility of missing not at random (MNAR) in missing patterns because participants and non-participants in T3 had significant differences in their spring 09 and 10 GPAs that can be unobserved variables unless obtained by registrar's office. Multiple imputation (MI) and FIML are valid if the missing at random (MAR) assumption is satisfied. New methods are being developed to handle MNAR data that provide more accurate estimation (Schafer & Graham, 2002).

Third, as described earlier the time optimal distance among time points to explore the true mediational effect in panel analysis has not been found and used. This problem caused the conflicting results between cross-sectional and longitudinal results. Because of the strong mediational effect from the cross-sectional results, it is too haphazard to conclude that there is no true mediation effect of ASD in academic performance. During the one-year between measuring ASEs and ASDs including the long summer vacation, students can experience a dramatic number of changes developmentally and academically. In this longitudinal analysis, these changes are not reflected. A narrower time frame to measure ASE and ASD is necessary to test the true mediation effect of ASD such as within a semester or even a half semester. In addition, an alternative study design would be person-centered longitudinal design to explore individual change. Although this method does not focus on exploring the mechanism, it has major advantages: 1) figuring out significantly different changing patterns of variables (e.g., ASE, ASD), 2) detecting moderating variables predicting the divergent trajectories, and 3) practically, more specific intervention methods can be developed based on the different trajectories.

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Appendix A

Academic Self-Efficacy (ASE) Scale

**Please write the number from the scale that best corresponds to your answer.

1…………………	**2**…………………	**3**…………………	**4**…………………	**5**
Strongly disagree	**Disagree**	**Neither agree nor disagree**	**Agree**	**Strongly agree**

1. ____ I can master the skills taught in school this year.
2. ____ I can do even the hardest school work if I try.
3. ____ If I have enough time, I can do a good job on all my school work.
4. ____ I can do almost all the work in school if I don't give up.
5. ____ Even if the work in school is hard, I can learn it.
6. ____ I can figure out how to do the most difficult school work.

Appendix B

Academic Self-Discipline (ASD) Scale

**Please write the number from the scale that best corresponds to your answer.

1	2	3	4	5
Strongly disagree	**Disagree**	**Neither agree nor disagree**	**Agree**	**Strongly agree**

1. ____ I am a reliable and hardworking student.

2. ____ I keep working on a school assignment until it is finished.

3. ____ I efficiently work on school assignments.

4. ____ When studying, I make a plan and follow through with it.

5. ____ I do a thorough job of studying for exams.

Appendix C

Missing Pattern Analysis

Purpose

In order not to conclude with biased results with non-ignorable missing patterns, a series of missing pattern analyses were conducted. Examples of non-ignorable patterns of missing values are missing at random (MAR) or missing not at random (MNAR) (Schlomer et al., 2010). These terms refer to situations in which missing values are dependent on either observed variables (MAR) or unobserved variables (MNAR). In contrast, an ideal situation would be missing completely at random (MCAR) in which there was no systematic missing pattern.

In this study, two kinds of missingness were carefully examined to strengthen the validity of results. First, the missing values caused by non-participation at T2 and T3 were focused on between students who were included in the final analysis (N = 560, 37.9%) and who were not included (N = 918, 62.1%). Second, the missing values caused by attrition of participants in each time point among the eligible participants (N = 560) were examined. Specifically, at T2, 461 (82.3%) students responded and 99 (17.7%) students did not respond. In T3, 228 (40.7%) students responded and 332 students did not respond (59.3%).

Method

Missing value analysis was conducted based on chi-square tests of independence for categorical variables and independent samples *t*-test for continuous variables (Schlomer et al., 2010). For these two tests, the independent variable was missingness and dependent variables were demographic variables including gender and year in school, and the variables used in the analysis. More specifically, the analyses were conducted with three separate steps. First, participants (N = 560) and non-participants (N = 918) were compared regarding gender, year-in-school, and ACT scores. This analysis was used to explore if there was a significant difference in target variables between participants and non-participants at T1. Second, participants who completed T2 (N = 461) and who did not complete T2 (N = 99) were compared regarding gender, year-in-school, ACT, and spring 08 GPA. Third, participants who completed T3 (N = 228) and who did not complete T3 (N = 332) were compared regarding gender, year-in-school, ACT, spring 08 GPA, and spring 09 GPA. The second and third sets of tests showed if there was a discernable pattern in "wave nonresponses" (Schafer & Graham, 2002) at T2 and T3.

Results

The missing value analysis partially supported that the missing pattern was missing at random (MAR). To satisfy the condition for MCAR, no significant difference in observed dependent variables was expected. With categorical variables, there were no differences at T2 (gender: χ^2 (1, N = 560) = 1.70, p = .119; year in school: χ^2 (1, N = 1478) = .17, p = .68). However, ratio of gender was not equal between participants and non-participants at T1 (χ^2 (1, N = 1478) = 8.05, p = .005) and T3 (χ^2 (1, N = 560) = 5.20, p = .01). In the participant group, males were 136 (24.3%) and females were 424 (75.7%). In the non-participant group, males were 286 (31.2%) and females were 632 (68.8%). At T3, year in school was significantly different between participants and non-participants (χ^2 (1, N = 560) =10.71, p = .001). In the participant group, 119 (52.2%) students were freshmen and 109 (47.8%) students were sophomore in T1. In the non-participant group, 219 (66.0%) students were freshmen and 113 (34.0%) students were sophomore in T1.

This difference was expected due to graduation of sophomores in T1. Furthermore, the standardized residuals in each cell were small (<2.0). Based on the chi-square test, there was no strong evidence that the missing pattern was either MCAR or MNAR, but the missing pattern may follow MAR. Table 6 shows the chi-square test results.

In independent samples t-test, all other tests were non-significant except for three comparisons. Participants had higher ACT scores than non-participants at T1. Participants at T3 had higher spring 09 GPA and spring 10 GPA. Thus, missing pattern is not completely random based on participants' ACT and spring GPAs. However, this was not a sufficient condition to conclude that missing value was caused by students' academic performance. At T2, there was no significant difference between participants and non-participants. Furthermore, the effect sizes (Cohen's *d*) of the differences were small for ACT scores (.07) at T1 and spring 09 GPA (.35) at T3, small to medium for spring 10 GPA (.42) at T3. Based on the analysis with categorical and continuous dependent variables, the missing pattern could be MAR. Thus, FIML would be an appropriate method to analyze data (Schafer & Graham, 2002), which produces less biased results than listwise or pairwise deletion method. The independent t-test results shows in Table 7.

Table 6

Chi-Square Independence Test

Participants (N = 560) vs. Non-participants (N = 918)

		Non-missing	Missing	Total
Gender	Female	424 (1.2)	632 (-.9)	1056
	Male	136 (-1.9)	286 (1.5)	422
	Total	560	918	1478
Year	Freshman	338 (-.2)	564 (.2)	576
	Sophomore	222 (.3)	354 (-.2)	902
	Total	560	918	1478

T2 completers (N = 461) vs. T2 missing (N = 99)

		Non-missing	Missing	Total
Gender	Female	344 (-.3)	80 (.6)	424
	Male	117 (.5)	19 (-1.0)	136
	Total	461	99	560
Year	Freshman	286 (.5)	52 (-1.0)	338
	Sophomore	175 (-.6)	47 (1.2)	222
	Total	461	99	560

T3 completers (N = 228) vs. T3 missing (N = 332)

		Non-missing	Missing	Total
Gender	Female	184 (.9)	240 (-.7)	424
	Male	44 (-1.5)	92 (1.3)	136
	Total	228	332	560
Year	Freshman	119 (-1.6)	219 (1.3)	338
	Sophomore	109 (2.0)	113 (-1.6)	222
	Total	228	332	560

Note. Numbers in parenthesis are standardized residuals.

Table 7

Independent Samples t-test

Participants (N = 560) vs. Non-participants (N = 918)

	Non-missing		Missing				
	M(*SD*)	*N*	*M*(*SD*)	*N*	Mean diff.	*t*	*d*
ACT	26.27 (3.70)	517	25.31 (3.60)	776	.95	4.615**	.07

T2 completers (N=461) vs. T2 missing (N=99)

	Non-missing		Missing				
	M(*SD*)	*N*	*M*(*SD*)	*N*	Mean diff.	*t*	*d*
ACT	26.41 (3.70)	422	25.67 (3.65)	99	.40	-1745	.05
T1 ASE	4.09 (.56)	461	4.04 (.60)	99	.01	.646	.16
T1 ASD	3.74 (.73)	461	3.82 (.64)	99	-.73	1.005	.16
GPA08S	3.31 (.58)	459	3.33 (.57)	99	.02	.348	.06

T3 completers (N = 228) vs. T3 missing (N = 332)

	Non-missing		Missing				
	M(*SD*)	*N*	*M*(*SD*)	*N*	Mean diff.	*t*	*d*
ACT	26.24 (3.73)	215	26.29 (3.68)	302	-.05	-.150	.004
T1 ASE	4.08 (.55)	228	4.03 (.58)	332	.05	.901	.15
T1 ASD	3.78 (.69)	228	3.73 (.73)	332	.05	.724	.10
T2 ASE	4.03 (.55)	129	4.11 (.62)	332	-.08	1.415	.22
T2 ASD	3.75 (.72)	129	3.74 (.76)	332	.01	.203	.02
GPA08S	3.32 (.62)	227	3.30 (.55)	331	.02	.293	.05
GPA09S	3.41 (.49)	224	3.30 (.61)	328	.11	2.254**	.35
GPA10S	3.47 (.51)	227	3.32 (.65)	306	.15	2.839**	.42

**p < .01.

Appendix D

Model modification

Purpose

To investigate the poor model fit of the hypothesized model, residual analysis was conducted instead of specific modification indices such as the Lagrange Multiplier (LM) (Bollen, 1989, p. 293; Buse, 1982) generated by statistical software. Residual analysis provided a clue about how much covariances that were not hypothesized in the model contributed to the poor model fit (Muthen & Muthen, 2010, p. 644). Adding paths after exploring residuals between variables as well as theoretical consideration would reduce the possibility to commit Type 1 or Type2 error in model testing (Kline, 2010, p. 216).

Method

In this analysis, normalized residuals were used. Mplus provided both standardized residuals and normalized residuals that were residual covariances between two variables. Standardized residuals are z-statistics and normalized residuals were corrected for sample sizes and scale difference (Bollen, 1989, p. 256-252). In both residuals, high coefficients mean that the unexplained variance of two variables in a model were highly associated. In other words, connecting two paths would improve model fit. In this study, normalized residuals were utilized to investigate paths that should be added to improve model fit.

Results

As a result, two major sources of error variance were identified. First, residual covariances between ACT scores and GPA as well as between ACT scores and ASE at T2 and T3 were large. Previous empirical studies and meta-analyses supported these covariances. Standardized test scores were associated with college GPA (e.g., Hoffman & Lowitz, 2005; Kim, 2002; Robbins et al., 2004). Second, residuals among GPAs were significantly large. This association was expected and caused by common method variance. For example, spring 2010 GPA had a normalized residual of 5.99 with spring 2008 GPA, 4.96 with fall 2008 GPA, and 3.05 with spring 2009 GPA. The normalized residual with fall 09 was low (-.02) because the path between two variables was already included in the hypothesized model. The bivariate covariance matrix is showed in Table 8.

Table 8

Normalized Residual Matrix

	1	2	3	4	5	6	7	8	9	10	11	12
1 ACT	0											
2 AE1	0	0										
3AD1	0	0	0									
4 Sp08	0	2.11	0	0								
5 Fa08	2.65	1.03	0	-.01	.04							
6 AE2	2.20	-.38	.60	1.8	.22	-.11						
7 AD2	-1.02	.08	-.09	-.22	.02	.33	0					
8 Sp09	3.31	.61	.07	3.54	.09	1.31	-.06	.04				
9 Fa09	4.76	.39	1.57	5.45	3.17	.72	0	.12	.14			
10 AE3	2.12	3.11	2.27	2.24	2.52	-.58	1.41	.60	.22	-.02		
11 AD3	-.89	.11	3.03	.08	.79	-.37	.51	.63	.43	.85	.90	
12 Sp10	3.98	.04	.62	5.99	4.96	.39	-.36	3.05	-.02	.41	.61	-.13

Notes. AE1: T1 ASE, AD1: T1 ASD, Sp08: spring 2008 GPA, Fa08: fall 2008 GPA, AE2: T2 ASE, AD2: T2 ASD, Sp09: spring 2009 GPA, Fa09: fall 2009 GPA, AE3: T3 ASE, AD3: T3 ASD, Sp10: spring 2010 GPA

Appendix E

An Alternative Model Testing

Purpose

The purpose of testing the alternative model with ASE as a mediator was to resolve the issue of possible directionality from ASD to ASE. The problem came from the results of the longitudinal analysis because the modified model did not show the mediational effect of ASD. This result allowed for a reverse order effect with ASE as a mediator. This argument was supported only if ASD was conceptualized as a personality construct.

Research in individual differences has concentrated on the predictive validity of conscientiousness and its facets on academic performance. By definition, conscientiousness captures being hardworking, striving for success, and persistence (John & Strivastava, 1999). Empirical studies consistently have shown that conscientiousness predicts academic performances (Chamorro-Premuzic & Furnham, 2003; Poropat 2009, Trapmann et al., 2007). More specifically, the self-discipline facet in conscientiousness positively predicted college performance (O'connor & Paunonen, 2007). The mechanism underlying the effect of conscientiousness on academic performance has also been recently highlighted. In one study, conscientiousness was tested as a distal predictor of college performance with self-efficacy as a mediator (Noftle & Robins, 2007).

Method

The alternative model with ASE as a mediator was tested both cross-sectionally and longitudinally. The bootstrapping method was used for the cross-sectional analyses and the alternative model constructed based on the modified model was compared with the modified model in the longitudinal analysis. To compare the two non-nested models between the alternative and modified models, Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) were used.

Results

In the cross-sectional analyses with five GPAs, only the mediational effect of the first set with spring 2008 GPA was significant (95% CI = [.007, .057]), but the mediational effect was not significant in the other four sets with fall 2008, spring 2009, fall 2009, and spring 2010 GPAs. In the longitudinal analysis, the model fit of the alternative model was acceptable, χ^2 (23, N = 517) = 109.519, p < .001, RMSEA = .085, (90% CI = [.07 .102]), CFI = .960. In the alternative model, the mediational effect of ASE was not significant either.

Both AIC (6553.052) and BIC (6829.175) of the original model was lower than AIC (6569.113) and BIC (6845.235) of the alternative model. Following Raftery's (1995) guideline of a gap of 10 BIC scores, the original model was accepted as a better model than the alternative model. Figure 9 shows the alternative model results.

Discussion

The original model with ASD as a mediator fitted better than the alternative model with ASE as a mediator. In other words, the constellation of relationships in the original model was adequate. ASD was a more proximal predictor of GPA than ASE as expected. Based on the cross-sectional and longitudinal analyses, two assertions were supported. First, ASD does not appear to be a personality construct that is more distal than ASE. However, the discriminant validity of ASD from conscientiousness and its facets needs to be further explored. Second, ASE does not mediate the effect of ASD on academic performance. With conscientiousness, a meta-analysis result showed that the mediational model with self-efficacy as a mediator between personality and job-performance was not supported (Judge et al., 2007).

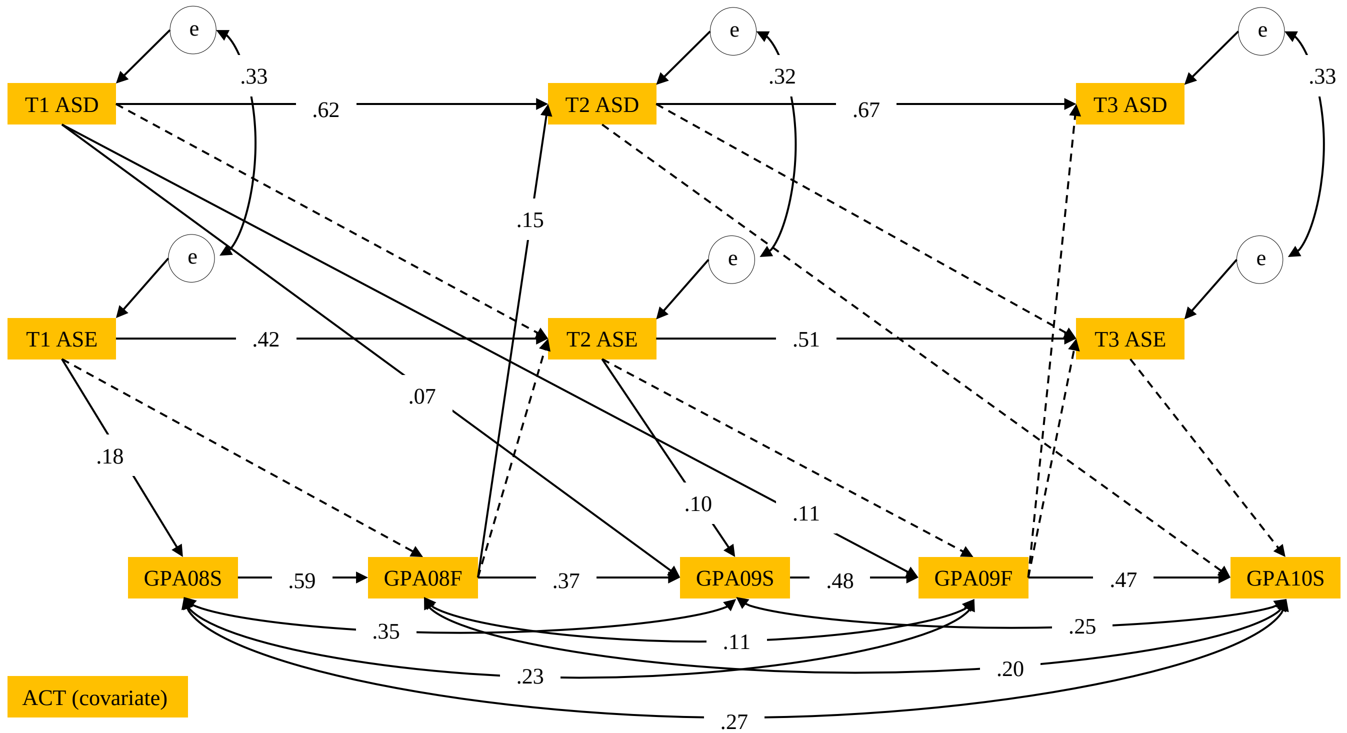

Figure 9. Alternative Model Result

Appendix F

Multigroup Analysis

Purpose

The purpose of this multigroup analysis was to explore the effect of major declaration on the feedback effect. Obtaining a college degree is a long-term goal and declaration major is the first step to achieve this goal. Declaring a major is related to students' interest in the specific subject (Allen & Robbins, 2008; Luzzo et al., 1999) as well as their aspiration to study. Students who have declared a major have better academic performance in college (e.g., Smith & Baker 1987; Weitz et al., 1955).

Previous research has indicated that the feedback effect was associated with goal setting (Locke & Letham, 2002). Self-set goals in particular play an important role as reference points for individuals to compare their desired and actual performance (e.g., Vancouver & Day, 2005) as well as increase effort (e.g., Fenollar et al., 2007; Fu et al., 2009). Different feedback effect depending on moderating variables has not been tested in previous research and the result section of this dissertation. Thus, with declaring major as a self-set goal, the feedback effect was tested for students who declared majors and who did not declare majors.

Method

To test if there is a different effect of feedback depending on students' major declaration, multigroup path analysis was conducted. Multigroup path analysis is used to compare the same model in different groups. The procedure of multigroup path analysis consists of two steps. First, the most and least constrained models were compared based on the chi-square difference test to explore if the grouping variable (i.e., major declaration) contributed to a significant difference, meaning the model differently fit in the two groups. Second, if a significant difference was found between the two groups, then the most constrained model was compared to the model with one less degree of freedom. Conceptually, these procedures allow to identify if the grouping variable is meaningful and to show which paths differently apply to the two groups. Although the focus in this analysis was the feedback effect, comparisons were repeated for every path in the modified model. Thus, all 42 paths were tested one at a time. In these comparisons, a significant difference suggests that the strength of a particular association was different between the two groups (see Byrne, 2004; Klassen et al 2010; Park & Huebner 2005).

Results

At the first step, it was found that the modified model was applied differently between the students who declared a major (*N*=264) and did not declare a major (*N*=253) ($\Delta\chi^2 = 81.542$, $\Delta df = 42$, $p < .05$). At the second step, all 42 models fit well to the data (RMSEA < .10 and CFI > .90). Seven paths were significantly different between the two groups (see Table 9). In specific, the strength of feedback from fall 2008 GPA to T2 ASD was different. The strength of association was bigger in the major declaration group (β = .23 vs. β = .06). The direct effect of T1 ASE on Spring 2009 GPA also was different. The association was only significant in the major undeclared group (β = -.05 vs. β = .12). The other five different paths were found in the associations among GPAs. Overall, covariances among GPAs were stronger for the group who declared a major. Table 10 shows the path coefficients in the two groups. Additionally, independent samples *t*-test between the two groups indicated that students who declared a major showed higher scores on T1 ASE and ASD as well as all five GPAs. As expected, students who declared a major had higher performance after controlling for ACT score than students who did not declare a major. Table 11 showed the independent samples *t*-test results.

Discussion

The major purpose of this multigroup analysis was first to see if major declaration as a proxy of a long-term goal had a differential effect on the modified model, and second to explore the differential effect of the long-term goal on feedback effect between the two groups. As expected, major declaration affected the feedback effect. The feedback effect of fall 2008 GPA on ASD at T2 was significant only for the group who declared a major. Additionally, two interesting differences were found. First, the direct effect of T1 ASE on spring 2009 GPA was significant only for the group who did not declare a major. Second, stability of GPA was different between the group groups. The covariances among GPAs were significant only for the group who declared a major.

The different feedback effect was an interesting finding. As both self-efficacy theory and goal theory hypothesized, a feedback effect on ASD was only found in the group who had a long-term goal (Locke & Latham, 2002). Furthermore, it would be interpreted that students who set up a long-term goal used feedback as a useful piece of information to improve to their next performance through ASD. In a similar study using exam scores as feedback, the feedback had a .29 correlation with the subsequent exam scores although the unique contribution of this feedback effect was not significant on increased effort or performance (e.g., VandeWalle et al., 2001). The non-significant effect may be caused by three goal orientation variables (i.e., learning, proving, and avoiding) in their path model. The results in this study suggested that long-term goal setting could be a moderating variable for the relationship between previous GPA and subsequent ASD.

On the differential effect of T1 ASE on spring 09 GPA, an explanation would be that different mechanisms operated between the two groups. Students who did not declare a major may not use ASD as much for their academic performance, but students who declared a major followed the mechanism with ASD as a mediator in this study. Based on the results of this analysis, major declaration may cause this difference. Further exploration would be needed to answer this phenomenon properly.

Another interesting finding is stability of GPA for students who declared a major. The strength of the association was stronger in the group who declared a major. The mean differences in GPA between two groups ranged from .12 to .18, which have medium to large effect sizes (i.e., Cohen's *d* ranging from .34 to .55). A positive association between academic goals and GPA improvement in a subsequent semester has been reported (e.g., Morisano et al. 2010), which has been replicated in the results. In addition, the results in this dissertation imply that the stability of GPAs may depend on major declaration status.

Table 9

Multigroup Analysis

Model/Path	*df*	χ^2	Δdf	$\Delta\chi^2$
Step 1				
Constrained	88	192.491	1	
All free	46	110.949	42	81.54^*
Step 2				
GPA08F → T2 ASD	87	184.303	1	8.19^*
T1 ASE → GPA09S	87	185.462	1	7.03^*
GPA09S → GPA09F	87	184.687	1	7.80^*
GPA08S ←→ GPA09S	87	178.001	1	14.49^*
GPA08F ←→ GPA09F	87	182.645	1	9.85^*
GPA08F ←→ GPA10S	87	188.905	1	3.59^*
GPA09S ←→ GPA10S	87	185.826	1	6.67^*

$^*p<.05$.

Table 10

Different Path Coefficients in Major Declared and Undeclared Groups

Paths	Coefficient (*β*)	
	Major declared	Major undeclared
GPA08F → T2 ASD	$.23^*$	.06
T1 ASE → GPA09S	-.05	$.12^*$
GPA09S → GPA09F	$.55^*$	$.41^*$
GPA08S ←→ GPA09S	$.23^*$	$.40^*$
GPA08F ←→ GPA09F	$.25^*$	-.08
GPA08F ←→ GPA10S	$.29^*$	.11
GPA09S ←→ GPA10S	.40	.13

$^*p<.05$.

Table 11

Independent Samples t-test for Major Declared and Undeclared Groups on ACT, ASE, ASD, and GPAs

	Major		No major				
	M(*SD*)	*N*	*M*(*SD*)	*N*	Mean diff.	*t*	*d*
ACT	26.53 (3.71)	264	26.00 (3.67)	253	.53	1.63	.04
T1 ASE	4.11 (.56)	298	3.98 (.56)	262	.13	2.84**	.41
T1 ASD	3.83 (.70)	298	3.67(.73)	262	.16	2.61**	.31
T2 ASE	4.14 (.63)	241	4.03 (.57)	220	.11	1.86	.30
T2 ASD	3.76 (.78)	241	3.72 (.72)	220	.04	.44	.07
T3 ASE	4.21 (.53)	139	4.18 (.60)	89	.03	.41	.10
T3 ASD	3.82 (.66)	139	3.81 (.81)	89	.01	.02	.02
GPA08S	3.40 (.52)	297	3.22 (.63)	261	.18	3.63**	.55
GPA08F	3.38 (.52)	291	3.26 (.53)	258	.12	2.58**	.44
GPA09S	3.42 (.53)	293	3.26 (.59)	259	.16	3.22**	.51
GPA09F	3.42 (.53)	280	3.28 (.59)	234	.14	2.73**	.45
GPA10S	3.44 (.60)	281	3.32 (.59)	252	.12	2.27**	.34

$^{**}p < .01$.