INVESTIGATING A NEW MODEL OF TIME-RELATED ACADEMIC BEHAVIOR: PROCRASTINATION AND TIMELY ENGAGEMENT BY MOTIVATIONAL ORIENTATION

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CHAPTER I

INTRODUCTION

Procrastination, or task delay, is a significant issue in academic contexts. In an early and perhaps formative study of procrastination in academic contexts, Solomon and Rothblum (1984) found that 46% of students self-identified as high in procrastination on academic tasks. In a later follow-up study by the same researchers, Rothblum, Solomon, and Murakami (1986) found that 40% of students in a separate sample identified as high in procrastination by self-report. Onwuegbuzie (2004) studied procrastination among graduate students and similarly found 40-60% of those sampled were likely to procrastinate according to their self-report.

This issue of procrastination does not appear to be isolated to the United States or to Western contexts. Klassen, Ang, Chong, Krawchuck, Huan, Wong, and Yeo (2009) found that procrastination was similarly high in Canadian and Singaporean students, and the reported rates were similar to earlier research with students from the United States. In a sample of Turkish students, Ozer, Demir, and Ferrari (2009) found that 52% were high in procrastination by self-report, a number that is similar to the rates found in the United States, Canada, and Singapore. This research suggests this phenomenon is not culturally bound. Many students believe that procrastination is damaging to their performance, yet continue to procrastinate. For example, in Onwuegbuzie's (2004) study, of those that self-reported high levels of procrastination, 75% wanted to procrastinate less.

Researchers have been interested in the negative effects of procrastination. Rothblum, Solomon, and Murakami (1986) reported that those high in procrastination were significantly more likely to report high anxiety and a range of somatic complaints. Tice and Baumeister (1997) found that those who procrastinate more are likely to increase in stress over an academic term, and experience increases in somatic complaints and visits to healthcare providers. Among high-school students, Owens and Newbegin (2000) found depression was related to higher levels of procrastination. There are potentially negative academic effects of procrastination. Owens and Newbegin (2000) found a strong correlation between procrastination and overall course grades, and Tice and Baumeister (1997) found a negative relationship between level of procrastination and grade received on individual papers.

Background to the Research Problem

The research on procrastination has explained the phenomenon of procrastination in several ways: it is a function of personality, it is a protective mechanism, or it is a failure in self-regulatory behavior. Each perspective has been a powerful force in shaping the traditional model of procrastination, which the present study is a response to, and they are reviewed briefly here. However, each of these perspectives views the individual as relatively passive in the act of procrastination. That is, procrastination is a behavior that more or less *happens to* the individual, rather than a behavior the individual *chooses to engage in* for motivated purposes. Further, as will become clear in this brief review, the existing views of procrastination tend to cast the dilatory behavior as an extension of personality, of flaws in motivational profile, or of personal failures. These are all perspectives the present research is a response to and critique of.

Those researchers who have understood procrastination as a result of personality have viewed it as result of several types of maladaptive personality features. Some have viewed procrastination as a result of a sense of outward-focused or socially prescribed perfectionism (Flett, Blankstein, Hewitt, & Koledin, 1992; Onwuegbuzie, 2000; Saddler & Buley, 1999). Others have reported associations between neuroticism and procrastination (Hess, Sherman, & Goodman, 2000; Johnson & Bloom, 1995; van Eerde, 2003). Still others have reported negative relationships between procrastination and conscientiousness (Johnson & Bloom, 1995; Moon & Illingworth, 2004; van Eerde, 2003). In each of these views, a common theme is present: procrastination is *who the person is* just as much as is personality. That is, researchers tend to view personality as fairly immutable and stable across time in adults, and so the view that procrastination is an extension of personality places the person engaged in task delay as, in some sense, defective.

Another theoretical perspective views procrastination as a self-protective mechanism, allowing the individual to defer failure onto another source of blame exterior to performance ability. One such mechanism is that of self-handicapping, in which procrastination is used as a means of setting up an obstacle to success on which failure can later be blamed to protect the ego (Strube, 1986). Schraw, Wadkins, and Olafson (2007) found that students commonly report fear of failure as a reason for delaying tasks. Others have directly examined the relationship and found that self-handicapping and procrastination are related to one another (Beck, Koons, & Milgrim, 2000; van Eerde, 2003). Another self-protective mechanism is that of avoidant coping, in which the task is too stressful to approach, so it is avoided altogether. Several researchers have pursued this theory with results that support the idea that at least some students who procrastinate may be doing so due to an avoidant cognitive style (Alexander & Onwuegbuzie, 2007; Burns, Dittmann, Nguyen, & Mitchelson, 2000; Carden, Bryant, & Moss, 2004; Collins, Onwuegbuzie, & Jiao, 2008; Deniz, Tras, & Aydogan, 2009; Fritsche, Young, & Hickson, 2003;

Owens, & Newbegin, 1997). In this view, too, researchers tend to write about the individual as having mindsets that lead to procrastination. That is, procrastination is the natural extension of the way they think about the world around them (for example, it is overwhelming and procrastination is a way of avoiding it and displacing blame, yet this person is simultaneously thought to lack the cognitive skills to foresee the consequences of that task delay). This essentialization of procrastination as a part of who the person is deeply problematic, as the present study highlights.

Another theoretical view of procrastination places procrastination as an unintentional act, where it is a simple failure of one's ability to regulate behavior, so that self-regulation is the problem, not anxiety or fear of failure or personality flaws. In this conceptualization, procrastination results from an overall inability to keep up with tasks and regulate oneself fully enough to engage with and complete them. Some researchers have pursued this line of inquiry with results that seem to support a role of self-regulation in explaining some dilatory behavior (Brownlow & Reasinger, 2000; Senecal, Koestner, & Vallerand, 1995). However, the more promising research has occurred in the area of self-efficacy for self-regulation. That is, the student's belief in his/her ability to regulate his/her behavior, and the effect of that belief on procrastination in academic settings. Researchers in this area have found stronger relationships with procrastination and more stable relationships across cultures as compared with eiher self-regulation or self-efficacy alone (Klassen, Ang, Chong, Krawchuck, Huan, Wong, & Yeo, 2009; Klassen, Krawchuck, Lynch, & Rajani, 2008; Klassen, Krawchuck, & Rajani, 2008). However, here too the act of task delay is thought to *happen to* the individual, a result of their *constitutional inability* to self-regulate.

Statement of the Research Problem

Each of these perspectives seeks to understand procrastination as a function of some malfunction or flaw in the individual. What these perspectives leave behind is that each person has motives for engaging in dilatory behavior or engaging with tasks in a timely manner, and these behaviors do not necessarily represent a flaw in the personality structure or self-regulatory mechanisms of the individual. Even in those approaches which might have an element of motivation to them, such as avoidant coping and self-handicapping, the researchers in these areas treat the behavior as a kind self-unaware behavior, a natural extension of the flawed constitution of the individual. Although the person is, in their theory, procrastinating to avoid anxiety, the person is unaware of this fact for the most part. It is not a conscious motive for procrastination. Yet, there is evidence for the motivated nature of procrastination as a construct, and that people have conscious, active motives for engaging in procrastination (Choi & Moran, 2009; Chu & Choi, 2005; Ferrari, O'Callaghan, & Newbegin, 2005; Howell & Buro, 2009; Seo, 2009; Simpson & Pychyl, 2009). To leave motivation behind is to have an incomplete model of procrastination.

Any model of procrastination that does not include the concept of timely engagement is also incomplete. People do not fall on a continuum from very little procrastination to very much procrastination. Yet, this is how those working in the traditional, dominant model of procrastination have chosen to view them. This, too, creates an incomplete understanding of the phenomenon of interest. It is not possible to fully understand why, under what circumstances, and when people procrastinate without also understanding why, under what circumstances, and when people engage with tasks in a timely manner. What is needed, then, is a motivated, multidimensional model of procrastination and timely engagement.

Theoretical Framework

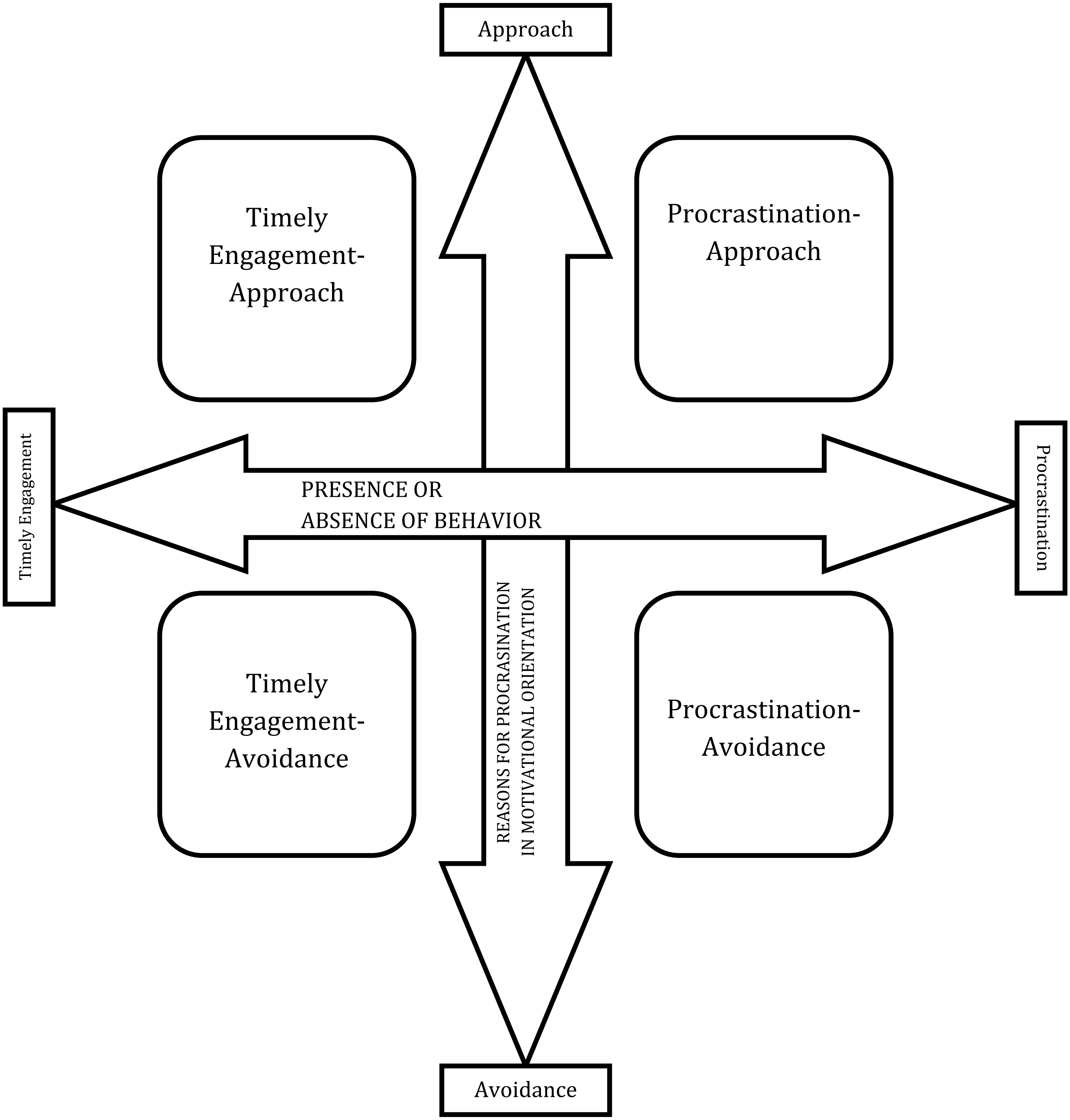
The present study builds on an existing model for the study of procrastination and timely engagement: the 2×2 model of time-related academic behavior (Strunk, Cho, Steele, & Bridges, 2012). This motivated, multidimensional model for the study of procrastination and timely engagement finds research support in two primary lines of inquiry. First is the field of active procrastination research. This research diverges from the traditional model of procrastination by asserting that some people intentionally engage in dilatory behavior for the purpose of gaining strategic advantage in tasks, or of creating a better end product for a given task (Choi & Moran, 2009; Chu & Choi, 2005; Ferrari, O'Callaghan, & Newbegin, 2005; Simpson & Pychyl, 2009). Choi and Moran (2009) have psychometrically differentiated active from generalized procrastination, and Chu and Choi (2005) found very low associations between active and generalized procrastination. Chu and Choi (2005) also found those engaging in active procrastination tend to be higher in self-efficacy and lower in extrinsic motivation than those engaging in general procrastination, supporting the idea that this type of procrastination is different in motivation and outcome.

A second line of inquiry that supports the development of the motivated, multidimensional model for the study of procrastination is that of goal orientation as related to procrastination. Using the 2×2 goal orientation framework, Howell and Buro (2009) found mastery-approach goals were negatively associated with procrastination, whereas mastery-avoidance goals were positively associated with procrastination. Seo (2009) found the same results with regard to mastery-approach and mastery-avoidance goals, but also found a positive association between performance-avoidance goals and procrastination. It appears, then, that there is a pattern of associations present in the literature with goal orientation and procrastination, and most specifically with the approach-avoidance subset of goals, as in Seo's (2009) study, both performance-avoidance and mastery-avoidance goals were positively associated with generalized procrastination.

What the traditional model of procrastination creates is a measurement model with one continuum. This continuum extends from very little procrastination or task delay to extreme procrastination or task delay. This continuum itself is incomplete. It leaves half of the spectrum of measurement in the behavior completely untouched, namely timely engagement. Instead, this measurement continuum should extend from extreme procrastination to extreme timely engagement. Yet, this measurement model would still be incomplete. The underlying motivation for that behavior must also be measured. The literature on active procrastination and goal orientation leads to a reasonable belief that an approach-avoidance continuum may be useful in capturing motivation toward procrastination and timely engagement. Thus, there are two concurrent measurement continuums used to apprehend the construct: one extending from extreme timely engagement to extreme procrastination, capturing the incremental steps between the two; the other extending from extreme approach motivational orientation to extreme avoidance motivational orientation, capturing the incremental steps between the two.

Figure 1

2×2 Model of Procrastination



In so doing, the two continuums become crossed, and a 2×2 framework for understanding procrastination and timely engagement is created. This is visually represented in Figure 1. On one side is procrastination, with two different motivational orientations. Procrastination-approach would be similar to what has been called active procrastination. This type of procrastination would be characterized by procrastination for the purpose of strategic gain, improvement in quality of work, or increased states of flow in work (Choi & Moran, 2009; Chu & Choi, 2005). Procrastination-avoidance would be similar to what has been described above as the traditional model of procrastination. This is the avoidant coping type of procrastination (Alexander & Onwuegbuzie, 2007; Burns, Dittmann, Nugyen, & Mitchelson, 2000; Carden Bryant & Moss, 2004; Deniz, Tras, & Aydogan, 2009), self-regulatory failure resulting in procrastination (Brownlow & Reasinger, 2000; Klassen, Ang, Chong, Krawchuck, Huan, Wong, & Yeo, 2009; Klassen, Krawchuck, Lynch, & Rajani, 2008; Senecal, Koestner, & Vallerand, 1995), or procrastination as self-handicapping (Beck, Koons, & Milgrim, 2000; Schraw, Wadkins, & Olafson, 2007).

On the other side is timely engagement, with two motivational orientations. Timely engagement-approach would be characterized by engaging with tasks right away in order to gain a strategic advantage or to create a better outcome in the final product. Timely engagement-avoidance would be characterized either by engaging with tasks in order to avoid the consequences of putting off starting or finishing them, by engaging with tasks in order to avoid the anxiety or fear of failure that comes along with not starting them in a timely manner, or possibly to get past unpleasant tasks as quickly as possible.

This is a more comprehensive model for studying the constructs of procrastination and timely engagement. By adding timely engagement to the spectrum of measurement with procrastination, a fuller picture may emerge of the types of behaviors that students are engaged in, and as a result, it may be possible to comprehend more fully the correlates and predictors of those behaviors. By adding the dimension of motivational orientation, it is possible to differentiate individuals not only on the basis of which behavior they are involved in (procrastination or timely engagement), and to what degree, but also *why* they are involved in that behavior, which may lead to an even more enhanced view of the predictors and correlates of procrastination and timely engagement.

The 2×2 model of time-related academic behavior is currently measured using the 2×2 Measure of Time-Related Academic Behavior (Strunk, Steele, Cho, & Bridges, 2012). This measure has been validated in previous research, showing convergent and divergent validity with a traditional, generalized measure of procrastination, and showing the best fit to the observed data among competing models using confirmatory factor analysis (Strunk, Steele, Cho, & Bridges, 2012). Additionally, the four 'types' of time-related behavior have been related to achievement goals, which demonstrated that the distinctions of behavior × motivation types offered meaningful distinctions in revealing previously unknown relationships.

Statement of Purpose

Research in the traditional model of procrastination has established a group of variables that seem useful in predicting procrastination at the generalized level (personality, self-efficacy, self-regulation, etc.). What this research does not provide is an understanding of these relationships when motivational orientation is taken into consideration, and when timely engagement is measured concurrently with procrastination. Further, the existing research treats procrastination as an extension of the individual's constitutional makeup. That is, researchers have typically thought of procrastination through a deficit theory lens. The present study has three purposes: First, to further validate the measurement model of the 2×2 Measure of Time-Related Academic Behavior. The second purpose of the study is to determine how the variables studied in the traditional model will relate to the 2×2 model of time-related academic behavior. When this was done with achievement goals, new and theoretically meaningful relationships emerged, and it is thought that the same may occur when examining the larger set of variables associated with generalized procrastination in traditional procrastination research. Third, the present study will examine how these relationships shift across time. Specifically, will predictive relationships remain stable across time? It is hypothesized that they will not. If procrastination is a natural extension of the deficits an individual has within himself/herself, then prediction across time should be stable. However, if there is a simple, strong relationship among motivation and procrastination, then it is reasonable at any point in time to expect prediction from motivation to procrastination and timely engagement, but not from motivation at one time point to procrastination and timely engagement at another. The repeated-measures prediction will help to assess the stability of prediction and, thus, the malleability of procrastination and timely engagement within individuals.

This study measured academic achievement, self-handicapping, self-efficacy, self-efficacy for self-regulation, Big Five personality type, avoidant coping style, and motivational orientation. Some of the key variables measured in this study will serve a dual role in exploring relationships in a new framework and model validation. For example, self-handicapping will be measured to determine how it functions differentially in relationship to the four different ‘types’ in the 2×2 model, but the theory would predict it should relate positively to avoidance-oriented procrastination. Other variables have no theoretically predicted relationships to the 2×2 model, such as the Big Five personality traits, which have been of much interest to researchers in traditional procrastination research, and are included here as exploratory variables.

This study offers promise to produce valuable practical and theoretical knowledge. That is, not only is a major goal of this study building a new model of time-related academic behavior, but building a model that offers practical insight for academic practice. Understanding the motivational and personal variables associated with different ‘types’ of time-related academic behavior may result in the ability to engage in early identification of students at-risk in academic environments, the design of targeted interventions, and direct work with students on malleable factors to improve their timely engagement with academic work. Of course, it may also be discovered that, of the 4 ‘types’ of time-related academic behavior, only certain types of behavior/motivation combinations are actually associated with negative outcomes, and that those same types are also predicted by other variables which have known interventions. This would offer significant practical information for educators. Simply having further understanding of the interaction between behavior type, motivational orientation, and correlate/predictor offers the promise of significant theoretical contribution to the field.

Research Questions

This study sought to investigate the 2×2 model of time-related academic behavior within the set of variables normally studied in traditional procrastination research. Accordingly, the research questions relate to how this model situates among these variables: How will the four ‘types’ of procrastination and timely engagement relate to openness, conscientiousness, extraversion, agreeableness, and neuroticism, as defined within the Big Five theory of personality? How will the four ‘types’ of procrastination and timely engagement relate to avoidant coping style? How will the four ‘types’ of procrastination and timely engagement relate to self-efficacy for self-regulation? How will the four 'types' of procrastination and timely engagement relate to self-handicapping? How will for the four 'types' of procrastination and timely engagement relate to academic self-regulation? How will the four 'types' of procrastination and timely engagement relate to approach versus avoidance orientation? Finally, how will these relationships change across time?

Definition of Terms

- **Avoidant Coping:** The coping style characterized by avoidance of stressful situations, avoiding performances altogether because of the stress they induce and the threat they pose, and preferring minimal information about the stressful situation or performance (Burns, Dittmann, Nguyen, & Mitchelson, 2000).
- **Big Five Theory of Personality:** This theory is widely used to describe normal personality, and includes Openness, Neuroticism, Conscientiousness, Extraversion, and Agreeableness. However, in procrastination research, the focus has been on:
    - **Neuroticism:** The difference between stable emotional development and maladjustment, including such things as negative affective experiences, fear, guilt and disgust (Costa & McCrae, 1992).
    - **Conscientiousness:** Self-control, organization, and planning. Has also been related to achievement, work-related behaviors, and compulsivity (Costa & McCrae, 1992).
- **Goal Orientation Theory:** Goal orientation theory, as expressed in the 2×2 framework, includes mastery-approach goals, mastery-avoidance goals, performance-approach goals, and performance avoidance goals (Elliot & Murayama, 2008, Dweck, 1986). In this framework, mastery-approach goals are those where a person seeks to gain competence or learning, performance-approach goals are those where a person seeks to perform up to a standard or

normative influence, mastery-avoidance goals are those where those where a person seeks to avoid incompetence, and performance-avoidance are those where a person seeks to avoid incompetence based on normative or external standards (Elliot & Murayama, 2008).

- **Procrastination:** Defined in this study as delay on tasks, usually time-sensitive tasks, and the putting off of starting or completing tasks.
- **Self-Efficacy for Self-Regulation:** One's belief in one's ability to self-regulate successfully (Klassen, Krawchuck, Lynch, & Rajani, 2008).
- **Self-Handicapping:** The structuring of the performance and pre-performance settings and environment so that the attributions will be more likely to be situational than dispositional. That is, this person will set the situation up so that failure is likely to be attributed to their behavior prior to the task than to their inability to complete the task successfully (Strube, 1986).
- **Self-Regulation:** Defined here as the ability to direct and control behavior in a given setting (Senecal, Koestner, & Vallerand, 1995).
- **Timely Engagement:** Defined in this study as the intentional engagement in a task in a timely manner, such as starting right away on a task or taking care to finish a task prior to its deadline. The opposite of procrastination.

CHAPTER II

REVIEW OF RELEVANT RESEARCH

The purpose of this study was to investigate a 2×2 model of procrastination and its relationship to personality, self-efficacy, self-regulation, self-efficacy for self-regulation, self-handicapping, motivational orientation, and how it changes within participants over time. These variables were selected because of their use in the traditional research on procrastination. There exist within the field of procrastination many strands of research, most of which comprise what is referred to here as the traditional model of procrastination. Each strand combines to form a rich picture of what factors make a person more likely to procrastinate, what the pattern of procrastination tends to be, and what some of the outcomes of procrastination are.

All of these strands form a picture of the 'traditional model of procrastination' that is mobilized in much of the research done to date on academic task delay. This picture is important because it is the picture that this study seeks to examine through a new lens, namely the lens of the 2×2 model of time-related academic behavior. There is also research relevant to understanding the background of this 2×2 model. This includes research on active procrastination, research on motivational orientation and procrastination, and research directly on the 2×2 model of time-related academic behavior.

The Traditional Model of Procrastination

Within the traditional model of procrastination is research on procrastination as related to personality, procrastination as a coping mechanism, procrastination as related to self-efficacy and self-regulation, research on somatic outcomes of procrastination, research on psychological outcomes of procrastination, and research on academic outcomes of procrastination. This research combines to provide a snapshot of what the traditional model is, how it views the individual, and how researchers working in this model conceptualize the phenomenon of procrastination.

Procrastination and Personality

Procrastination is often thought of as being related to personality in the literature, and this is apparently in the sense that dilatory behavior is thought to spring out of personality. That is, in this strand of research, often procrastination is conceptualized as an outgrowth of or symptom of other types of personality deficiencies. Primarily, these personality characteristics have been conscientiousness and neuroticism.

These personality constructs are defined by the theory and paradigm of measurement. There are two prominent measurement paradigms for personality that are mobilized in the procrastination literature: the Big Five theory of personality (Costa & McCrae, 1992), and the Eysenck and Eysenck Personality Inventory, with its three-factor system (Eysenck, Barrett, Wilson, & Jackson, 1992). Within the Big Five theory, conscientiousness is thought of as self-control, organization, and planning; it is also related to academic achievement, work-related behavior, and compulsivity. The three-factor Eysenck and Eysenck model does not measure conscientiousness. Neuroticism in the Big Five theory is though of in terms of the difference between stable emotional development and maladjustment, and includes negative affective experience, fear, anger, guilt, and disgust (Costa & McCrae, 1992). In the three-factor Eysenck and Eysenck system, neuroticism is characterized by anxiety, depression, guilt, low self-esteem, subjective tension, shyness, moodiness, and general emotionality (Eysenck, Barrett, Wilson, &

Jackson, 1992). It is worth noting, however, that there is a strong statistical correlation between neuroticism as measured in both models (Costa & McCrae, 1995).

Fee and Tangney (2000) found strong correlations between conscientiousness and procrastination while investigating the relationship of guilt and shame to procrastination. They found that procrastination was associated with lower levels of conscientiousness among a sample of college students using the NEO-PI-R measure of Costa & McCrae (1992). Johnson and Bloom (1995) similarly found a strong correlation between conscientiousness and procrastination among a sample of college students, with higher conscientiousness being associated with lower procrastination as measured by the NEO-PI-R. However, they also reported that conscientiousness was a better predictor of procrastination than neuroticism within the Big Five framework, though neuroticism was still significantly positively related to the level of procrastination. In a meta-analysis, Steel (2007) reported conscientiousness had the strongest relationship to procrastination across studies of any of the variables measured in the analysis (average r = -.62), and also reported a more modest relationship between neuroticism and procrastination across studies (average r = .24). Similarly, van Eerde (2003) also reported conscientiousness held the strongest relationship to procrastination across studies in another meta-analysis (average r = -.63), also reporting a significant relationship for neuroticism and procrastination across studies (average r = .24).

This smaller magnitude of relationship does not imply that neuroticism is not an important factor in explaining or predicting procrastination, however. For example, neuroticism may be a mediating variable in explaining procrastination, as Hess, Sherman, and Goodman (2000) report with the potential role of eveningness, or the tendency toward being up later in the evening, on procrastination. They found that, although eveningness did directly predict procrastination, this effect was mediated by neuroticism. In this study, neuroticism was measured in the Eysneck and Eysneck paradigm. Further, it is possible that neuroticism and conscientiousness operate differentially based on the goals of procrastination. Choi and Moran (2009) studied personality in the Big Five paradigm as a potential correlated variable to both active procrastination, reviewed in depth later in this review, and passive procrastination, and found that conscientiousness was significantly related to passive procrastination, but neuroticism was significantly related to active procrastination. This points to the need for the study of both variables in a model differentiated by motivation, as they may be related to different dimensions of motivational orientations.

Also worth noting in a discussion of the relationship of procrastination and personality is that it is possible that personality may only be related to type or baseline quantity of academic procrastination. Moon and Illingworth (2004) examined the longitudinal pattern of procrastination over a semester to determine what kinds of patterns in task delay would develop as the semester progressed. They also measured personality in the Big Five paradigm. They found that, although personality did relate to the baseline level of procrastination at the beginning of the semester, it did not appear to influence the curvilinear growth trend of procrastination over the course of the semester. That is, although personality influenced how much personality as a 'trait' a person started of with, in the researchers' analysis, the way in which procrastination grew and changed over time in response to the pressures of the academic term was the same.

In the present study, the primary critique of the personality explanation for procrastination comes from two sources. First, it is worth noting that there is considerable theoretical overlap between the construct of 'conscientiousness' and the idea of time-related academic behavior. For example, an item used to measure conscientiousness on the mini-IPIP asks the individual if he/she tends to “get chores done right away” (Donellan, Oswald, Baird, & Lucas, 2006). It is not surprising that this, then, is related to whether that same person will delay tasks. In other words, there is a measurement issue inherent in the constructs because they are apparently overlapping. Beyond that, a further critique is that personality is thought of as relatively stable in the literature, at least among adults. The resulting corralary is that, if personality is stable, and personality predicts procrastination, procrastination must be stable too. That is, personality comes to be viewed as an outgrowth of a deficient personal makeup that is relatively stable in nature. The individual is deficient in some way, which is why instructors, researchers, and others will observe dilatory behavior. One goal of the 2×2 model of time-related academic behavior is to challenge this viewpoint.

Procrastination as a Coping Mechanism

Procrastination has also been related to the idea of coping in the traditional model, and specifically related to coping in that procrastination is a means of coping with those tasks or roles that are too difficult or aversive to face, so they are delayed. Alternatively, procrastination may be viewed as coping through the idea that it is used as a way of externalizing failure in those tasks that a person views as too difficult or aversive, so procrastination becomes a self-handicapping mechanism. However, it is worth noting that this coping is rarely written about as an active or intentional process, but typically as unconscious or a self-protective defense mechanism rather than a motivated behavior to shield the self from failure.

The idea of procrastination as a coping mechanism is partially supported by its relationship to anxiety about academic tasks. Carden, Bryant, and Moss (2004) found a significant correlation between anxiety and procrastination, and further found that locus of control more directly predicted procrastination, and this prediction was mediated by anxiety. That is, whether a person perceived himself/herself to be in direct control of the outcome of the situation seemed to directly predict procrastination, with anxiety mediating the strength of this prediction. Collins, Onwuegbuzie, and Jiao (2008) found that perceived ability level in a given subject was predictive of procrastination in that subject area. They hypothesize this shows anxiety toward this task, and may be supportive of the coping mechanism hypothesis. Fritzche, Young, and Hickson (2003) found that increased anxiety was associated with increased procrastination. They created anxiety through feedback conditions and found that increased anxiety also increased procrastination on a writing task, in this randomized, experimentally manipulated study. Jackson, Weiss, and Lundquist (2000) found optimism was associated with lower levels of procrastination, and stress was associated with higher levels of procrastination, with optimism mediating the relationship between stress and procrastination. This further supports the idea that some students may procrastinate as a means of coping with anxiety or stress. Onwuegbuzie (2004) found that statistics anxiety was associated with higher levels of procrastination on statistics-related activities and assignments among graduate students, and Owens and Newbegin (1997) found that procrastination was directly related to anxiety levels among high school students. All of these studies highlight the potential relationship of procrastination to coping mechanisms, such as avoidant coping and self-handicapping, but other researchers have directly tested this association.

In studying the role procrastination plays as a means of avoidant coping, or coping by altogether avoiding the aversive stimuli, which in this case is an assignment or academic task, researchers have measured both procrastination and avoidant coping to test for associations. Alexander and Onwuegbuzie (2007) found higher levels of hope are associated with lower levels of procrastination, and suggest their results validate the idea that lower needs for avoidance coping lead to reduced procrastination. Burns, Dittmann, Nguyen, and Mitchelson (2000) directly measured both procrastination and avoidant coping, and found a negative relationship between the two, which was opposite of what was expected. The authors discuss these results in terms of the desire for control and procrastination, but there is no clear explanation for the negative association of avoidant coping and procrastination, which has been cited in the procrastination literature as a primary reason for the behavior.

Another potential means by which procrastination may be a coping mechanism is self-handicapping. In self-handicapping, the individual intentionally uses some behavior or other barrier to success to externalize failure, which the individual views as inevitable on a given task or set of tasks (Strube, 1986). Instead of general anxiety, then, this conceptualization of procrastination requires a fear of failure as an underlying deficit causing the task delay. In qualitative interviews, Schraw, Wadkins, and Olafson (2007) found fear of failure as a dominant theme in students' motivation to procrastinate on academic tasks. Others have directly measured self-handicapping and procrastination. Beck, Koons, and Milgrim (2000) found a strong correlation between procrastination and self-handicapping as measured by the Self-Handicapping Scale – Short Form (Strube, 1986). The authors suggest that the magnitude of correlation is so strong as to suggest that procrastination and self-handicapping are actually overlapping concepts, at least as measured in their study. Steel (2007) and van Eerde (2003) both report in meta-analyses a strong relationship between self-handicapping and procrastination across studies (average r = .46, in both meta-analyses).

Though perhaps a fear of failure or generalized anxiety are more malleable than one's personality, they are still here viewed as personal deficits being made manifest in the externalizing behavior of procrastination. Procrastination is not viewed as a behavior the individual has chosen to engage in to avoid an unpleasant task or to give an excuse, but rather a fear of failure or a debilitating anxiety have prevented the individual from engaging in a timely manner. The individual is constitutionally incapable of behaving in a more adaptive manner – he/she is deficient due to his/her fear or anxiety. This is a more pathologizing explanation of procrastination, to be sure. While this line of research does offer more room for intervention and change in procrastination, the 2×2 model of time-related academic behavior still offers a challenge to this viewpoint by understanding procrastination and timely engagement as largely intentional behaviors with particular motivations. Other researchers in traditional procrastination work have placed more emphasis on motivation by focusing on the role of self-efficacy and self-regulation in explaining procrastination, rather than viewing it as a protective coping mechanism.

Procrastination, Self-Efficacy, and Self-Regulation

Self-efficacy has been a direct research focus for some investigating the subject of procrastination. For example, Seo (2008) directly measured self-efficacy using an author-written scale, and found it not only directly predicts procrastination, but also mediates the relationship between procrastination and perfectionism. In meta-analyses Steel (2007) and van Eerde (2003) both found self-efficacy with a moderate relationship to procrastination across studies (average r = -.38 and -.44, respectively). Further, Chu and Choi (2005) found that self-efficacy operates differently based on type of procrastination, with higher self-efficacy being associated with active procrastination and lower self-efficacy associated with generalized procrastination.

Others have focused exclusively on self-regulation as a predictor of procrastination. Brownlow and Reasinger (2000) found that those high in procrastination seem to also have difficulty in self-regulatory abilities, and as such they hypothesize a causal relationship between self-regulatory failure and procrastination. Ferrari (2001) researched differences in procrastination under different cognitive load conditions, and suggests that his results point to a breakdown in self-regulatory ability when placed under time constraints by those high in procrastination. Milgram, Dangour, and Raviv (2001) tested the relationship of self-regulation as a function of self- versus other-determined time schedules, and found that the relationship of self-regulation to procrastination was mediated by whether the person had determined his/her own schedule, or whether it was determined for him/her, with other-determined schedules and strict compliance instructions producing less procrastination. Senecal, Koestner, and Vallerand (1995) found, among a sample of French-Canadian college students, that self-regulatory differences accounted for 25% of the variance in total procrastination scores, and that less autonomous forms of self-regulation were associated with higher levels of procrastination.

There is a third string of inquiry in this area that ties together self-efficacy and self-regulation into one integrated construct of ‘self-efficacy for self-regulation’, however. Some support for this idea is found in a study where self-efficacy and self-regulation were found to share considerable variance in predicting procrastination, suggesting they have substantial overlap (Strunk & Steele, 2011). Klassen, Krawchuck, and Rajani (2008) found that self-efficacy for self-regulation strongly predicted academic procrastination, and more strongly so than self-esteem, self-efficacy, or self-regulation. Similarly, Klassen, Ang, Chong, Krawchuck, Huan, Wong, and Yeo (2009) found that self-efficacy for self-regulation was highly predictive of procrastination, and in their sample of Canadian college students, academic self-efficacy was not, suggesting that it may be a more valid predictive construct than self-efficacy alone. Klassen and Kuzucu (2009) found similar results among a sample of Turkish college students, with self-efficacy for self-regulation being the strongest predictor of procrastination among those measured. Klassen, Krawchuck, Lynch, and Rajani (2008) investigated self-efficacy for self-regulation among a mixed sample of students with learning disabilities and those without learning disabilities, and found that in both groups self-efficacy for self-regulation was the strongest predictor of procrastination, and general academic self-efficacy was still a predictor among the group without learning disabilities, but not in the group with learning disabilities. All of the studies directly measuring self-efficacy for self-regulation cited above used the scale by Zimmerman, Bandura, and Martinez-Pons (1992).

This line of research, too, utilizes a deficiency discourse to understand why people procrastinate. Students lack sufficient self-regulatory skills, or do not have high enough self-efficacy beliefs to enable them to execute a successful course of action in a timely manner. This line of research offers perhaps the most malleable view of procrastination (maybe one could just teach self-regulation skills or build self-efficacy to lower procrastination or raise timely engagement). Still, this line of research fails to consider that procrastination may be intentional, a motivated behavior springing not from the deficiencies inherent in the individual performing the task delay, but instead arising from his/her motivational orientation to that situation based on his/her beliefs about it. This is another view that the 2×2 model of time-related academic behavior offers a challenge toward, viewing these behaviors as coming about as a result of the motivational orientation an individual holds, resulting formation of the intent to engage in a timely manner, or to procrastinate, which is performed as time-related academic behavior. However, all of the research reviewed to this point has been about predicting procrastination. Other research has focused not on predicting procrastination, but on what procrastination causes – the outcomes associated with dilatory behavior in an academic setting.

Somatic Outcomes of Procrastination

Some researchers have focused on the somatic outcomes associated with academic procrastination, primarily illness and healthcare visits. In their seminal study on academic procrastination, Rothblum, Solomon, and Murakami (1986) found that those who procrastinate more are also more likely to report physical complaints. Similarly, Tice and Baumeister (1997) found that as the semester progresses, people high in self-reported procrastination tend to delay tasks more and more on measured academic tasks such a date-stamped quizzes and assignments, and also experienced concomitant increases in illness-related complaints and visits to healthcare professionals. Of course, it might be argued that these somatic complaints could be associated with associated increases in anxiety, which would be a psychological outcome of procrastination. More researchers have focused on psychological outcomes of procrastination.

Psychological Outcomes of Procrastination

In fact, Tice and Baumeister (1997) found that not only does behaviorally measured procrastination increase over the course of the semester, with a concomitant increase in somatic complaints and visits to healthcare professionals, but at the same time, stress and anxiety also increase across the semester. These all followed the same growth curve across the course of the semester. Similarly, Rothblum, Solomon, and Murakami (1986) who also found higher levels of physical complaints among those who reported higher levels of procrastination found higher levels of test anxiety in those participants as well. Owens and Newbegin (2000) report a link between procrastination and depression, particularly with regard to math and English courses, though they do not establish the directionality of this relationship. Ferrari and Beck (1998) have a different take on the psychological outcomes of procrastination. They posit that procrastination leads to false excuse making on the part of the student as a means of putting of the work, and argue that these false excuses lead to negative affective outcomes. They found those high in procrastination use false excuses more often, and report higher levels of negative emotion.

Academic Outcomes of Procrastination

However, the area of outcome that is sometimes of greatest interest to educators is that of the academic outcomes associated with procrastination. Owens and Newbegin (2000) found that, in addition to the link between depression and procrastination cited above, there is a link to low math and English scores. However, their model does not make clear how depression, low scores, and procrastination may be directionally related to one another. Howell, Watson, Powell, and Buro (2006) found that students higher in self-reported procrastination were likely to turn in assignments later, and assignment grade was related to procrastination, but overall course grade was not related to procrastination in their study. In another study where procrastination was measured as turning assignments in on time or late, course grade was significantly predicted by procrastination, accounting for up to 44% of the variance in final course grade (Strunk & Spencer, 2012).

The 2×2 Model of Time-Related Academic Behavior

All of the research reviewed above forms a snapshot of what is referred to here as the traditional model of procrastination. In this model, the individual is thought of falling on a continuum that extends from ‘little procrastination’ to ‘extremely high procrastination’, and motivation is of little concern. There may be factors that predict where one falls on this continuum, but they are largely factors that might be categorized as deficiencies, like as failure to regulate oneself, low self-efficacy, high neuroticism, low conscientiousness, or (in the closest example to a motivational explanation) an inability to cope in a healthy manner, all of which might lead one to procrastinate and delay academic tasks.

What the 2×2 model of time-related academic behavior (described in more depth in Chapter I) contends is that people may fall anywhere on a continuum that actually extends from 'extremely high procrastination' to 'extremely high timely engagement'. That is, people might delay tasks, or they might engage in them in a timely manner, and it is not the same to say that a person chooses to engage in a task in a timely manner, and that that person only procrastinates very slightly. These two concepts are diametric opposites on the continuum, and it is inappropriate to describe timely engagement as 'little procrastination', as the traditional model would do, and currently does. In addition, to conceptualize of these behaviors as something that just happen, that emanate from the individual without thought or reason, is faulty logic. These are motivated processes, and the 2×2 model seeks to account for both of these issues (extending the continuum to timely engagement, and understanding underlying motivations) in a more comprehensive model of time-related academic behavior. The 2×2 model of time-related academic behavior builds on two lines of previous research, including active procrastination and motivational orientation in procrastination, and has previous research providing support for its validity.

Active Procrastination

One area of research that has begun to highlight the motivated nature of procrastination is the construct that has been called active procrastination. Active procrastination is built on the idea that not all procrastination is 'bad procrastination', but that sometimes people procrastinate to gain an advantage on a task, and do so intentionally with this goal in mind. Schraw, Wadkins, and Olafson (2007), though not investigating this construct, found some evidence for it in their qualitative study of procrastination. They found one of the more dominant themes that emerged from their interviews of students was that procrastination was often used to obtain a better state of ‘flow’ in work, and that students often procrastinated because they felt they worked better under time pressure. Neither of these themes would conform to the traditional model of procrastination, but reflect an underlying motivation to perform better on a given task as a result of procrastinating on that task. Chu and Choi (2005) directly investigated the idea of active procrastination and found almost no correlation between active and generalized procrastination, suggesting the two constructs were discrete and orthogonal. Further, they found that those high in active procrastination were higher in self-efficacy and lower in extrinsic motivation. This suggests that the differences are not only in reason for procrastinating, but also in the correlates associated with that motivational orientation. Choi and Moran (2009) further investigated a scale for active procrastination, finding it had almost no relationship to a generalized procrastination measure, and appeared to be statistically independent as a construct in their sample.

Motivational Orientation and Procrastination

Further evidence for the motivated aspects of procrastination can be found in literature examining the relationship of goal orientation to procrastination. It appears that different people may have different reasons in goal orientation theory for procrastinating, as well. Howell and Watson (2007) found that, of the four goal orientations, mastery-approach and mastery-avoidance most strongly predicted procrastination on two different scales for measuring procrastination. Further, these two scales predicted procrastination differentially, indicating the type of goal led to a different level of procrastination. These were generalized measures of procrastination, and the mastery-approach goals led to lower levels of procrastination, while mastery-avoidance goals led to higher levels of procrastination. Howell and Buro (2009) performed a similar analysis, but found both mastery-approach and performance-approach goals negatively predicted procrastination, while mastery-avoidance goals positively predicted procrastination. Seo (2009) found similar relationships, with mastery-approach and performance-approach goals negatively predicting procrastination, and mastery-avoidance goals positively predicting procrastination. All of these studies point out the role of underlying motivational orientation in procrastination.

Research on the 2×2 Model of Time-Related Academic Behavior

The 2×2 model of procrastination includes four 'types' of behavior: procrastination-approach, procrastination-avoidance, timely engagement-approach, and timely-engagement avoidance. These 'types' are created through the intersection of two continuums: behavior type (timely engagement to procrastination) and motivational valence (avoidance to approach). The crossing of these two continuums creates the quadrant in which the four 'types' are situated (see Figure 1). This model was created to address the two main issues with the traditional model of procrastination: it does not account for timely engagement behavior, and it does not consider underlying motivation.

To date, the research on this model has focused around the 2×2 Measure of Time-Related Academic Behavior (MPM; Strunk, Cho, Steele, & Bridges, 2012). This measure captures all four 'types' simultaneously, shows consistent factor structure, and has moderate-to-high reliabilities. The most recent work with this measure has focused on using it to validate the underlying theory. The MPM was administered along with the Achievement Goal Questionnaire (Elliot & Murayama, 2008), which measures the four achievement goal orientations, and the Procrastination Scale for Students (Lay, 1986), which measures procrastination in the traditional model. First, correlational analyses determined that the four 'types' on the MPM all related to the traditional procrastination measure as expected. Then, confirmatory factor analyses were used to determine if the measure held a four-factor structure, and the four 'type' structure was a good fit.

Finally, structural equation modeling was used to determine if the four 'types' related to the four goal orientations as expected, with the avoidance goal orientations predicting avoidance-oriented procrastination and avoidance-oriented timely engagement, and approach goal orientations predicting approach-oriented procrastination and approach-oriented timely engagement. This model was a good fit to the observed data, and produced better fit than all competing models (Strunk Cho, Steele, & Bridges, 2012). This study offers support for the underlying theory of the 2×2 model of time-related academic behavior, though more work is needed.

Summary

This review has presented two models for the understanding of procrastination. The first is the traditional model of procrastination, which understands the individual as passive recipient of biology, personality, and mental processes, which result in outward behaviors of procrastination. Procrastination is understood as a fault, which may be the result of other faults such as too much neuroticism, too little self-regulation, or too much anxiety. Furthermore, this model leaves no room for the construct of timely engagement, but rather classifies individuals on the continuum of 'little procrastination' to 'extreme procrastination'.

The second model presented is the 2×2 model of procrastination that offers an alternative view of the individual, where procrastination is a motivated construct, a result of goals that drive behavior. These goals will affect how the individual relates to the environment, including whether or not he/she chooses to delay academic tasks. Further, this model does not classify on the basis of 'little procrastination' to 'extreme procrastination', but rather from 'extreme timely engagement' to 'extreme procrastination', recognizing that people may choose to delay tasks, they may also choose to engage in them in a timely manner.

However, as is made clear in this review, there is a wealth of research on predictors and outcomes in the traditional model of procrastination. This model comes complete with personality research, self-regulation research, self-efficacy, research, outcomes research, even coping research. Yet, the alternative model, the 2×2 model of time-related academic behavior, has little research of this type. There are confirmatory factor studies, and a structural equation study appearing to confirm underlying theory. However, there is no research on the constellation of input variables and outcome variables such as what exists in the traditional model.

This is the purpose of this study – to extend on the existing work in the 2×2 model of procrastination and timely research by using the variables shown to predict procrastination in the new model. By doing so, it will be possible to demonstrate how the relationships found in that model change when the four 'types' of the 2×2 model are considered, and perhaps how they do not. This will allow for an exploration of the critiques of traditional procrastination research outlined in this review, and provide a fuller understanding of the four 'types' of time-related academic behavior and how they function. This fuller understanding of procrastination and timely engagement offers promise for research, but also offers promise for enhancing future practice in the area of procrastination. It is hoped that understanding how motivation and individual behavior type combine to affect the relationships both to predictors and outcomes that better practice with those who struggle with procrastination in the educational environment may be a future result.

CHAPTER III

METHOD

The purpose of this study was to study how the four 'types' of the 2×2 model of time-related academic behavior relate to the set of variables normally associated with the traditional model of procrastination. As such, this study examined the relationship of the 2×2 theory of procrastination and its four 'types' in relationship to the Big Five theory of personality, to self-efficacy for self-regulation, to avoidant coping style, to self-handicapping, to academic self-regulation, to approach and avoidance motivational orientation, and how these relationships change over time.

Participants

Undergraduate students actively enrolled in coursework at Oklahoma State University were recruited for participation through an email announcement to their University email account that was distributed to 5,000 students per semester for two semesters. Participants were offered an incentive for their participation in the form of entry into a drawing for one of four $50.00 cash awards. There were a total of 1,227 participants, though 102 of those did not complete the entire survey. A listwise deletion was performed of those who did not complete the survey because imputation was not possible as those data were not missing-at-random. Participants who skipped only some demographic questions remained in the data set. The average age of participants was 21.67 (*SD* = 5.39). There were 371 men and 752 women who participated, with 104 not reporting gender. In terms of ethnicity, 862 reported that they were 'White – non-Hispanic', 97 that they were 'American Indian or Alaskan Native', 57 that they were 'Hispanic, Latino, or Spanish

Origin', 44 that they were 'Black or African American – non-Hispanic', 34 that they were 'Asian or Pacific Islander', and 29 that they were of 'Other' ethnicities, with 104 not reporting ethnicity. There were 261 freshmen, 262 sophomores, 286 juniors, and 301 seniors in the sample, with 17 reporting 'other' as their college classification, and 100 not reporting college classification. The average GPA was 3.28 (*SD* = .53). All academic majors offered at the university were represented in the sample, and a distribution of those majors is found in Table 1.

Table 1

Participants by Academic Major

	Frequency	Percent
Accounting	39	3.2
Aerospace Administration and Operations	9	.7
Aerospace Engineering	20	1.6
Agribusiness	14	1.1
Agricultural Communications	8	.7
Agricultural Economics	5	.4
Agricultural Leadership	3	.2
American Studies	2	.2
Animal Science	53	4.3
Architectural Engineering	5	.4
Architecture	10	.8
Art	19	1.5
Athletic Training	13	1.1
Biochemistry	2	.2
Biochemistry and Molecular Biology	18	1.5
Biological Science	16	1.3
Biosystems Engineering	10	.8
Botany	5	.4
Career and Technical Education	1	.1
Chemical Engineering	12	1.0
Chemistry	2	.2
Civil Engineering	17	1.4
Communication Sciences and Disorders	18	1.5
Computer Engineering	11	.9
Computer Science	6	.5

Construction Management Technology	6	.5
Design, Housing, and Merchandising	29	2.4
Economics	7	.6
Education	48	3.9
Electrical Engineering	13	1.1
Electrical Engineering Technology	3	.2
Elementary Education	36	2.9
English	16	1.3
Entomology	4	.3
Entrepreneurship	8	.7
Environmental Science	9	.7
Finance	26	2.1
Fire Protection and Safety Technology	9	.7
Food Science	2	.2
General Business	11	.9
Geography	3	.2
Geology	7	.6
Health Education and Promotion	16	1.3
History	18	1.5
Horticulture	3	.2
Hotel and Restaurant Administration	19	1.5
Human Development and Family Science	51	4.2
Industrial Engineering and Management	9	.7
International Business	11	.9
Landscape Contracting	1	.1
Leisure Studies	4	.3
Liberal Studies	3	.2
Management	33	2.7
Management Information Systems	15	1.2
Marketing	33	2.7
Mathematics	9	.7
Mechanical Engineering	33	2.7
Mechanical Engineering Technology	7	.6
Microbiology, Cell and Molecular Biology	12	1.0
Multimedia Journalism	7	.6
Music	7	.6
Music Education	9	.7
Natural Resource Ecology and Management	13	1.1
Nutritional Sciences	29	2.4
Philosophy	2	.2

Physical Education	2	.2
Physics	3	.2
Physiology	11	.9
Plant and Soil Sciences	6	.5
Political Science	19	1.5
Psychology	72	5.9
Russian Language and Literature	2	.2
Secondary Education	15	1.2
Sociology	16	1.3
Spanish	7	.6
Statistics	3	.2
Sports Media	9	.7
Strategic Communication	27	2.2
Theatre	4	.3
University Studies	10	.8
Zoology	22	1.8
Total	1127	91.9
Missing	100	8.1

Based on the demographics of the University, chi-square tests were used to determine if this sample was representative of the population from which it was drawn. In terms of ethnicity, the sample significantly deviated from the population distribution ($\chi^2_5 = 43.687$, $p < .001$). Based on standardized residuals, it appears that there is a significant overrepresentation of those who identify as ‘American Indian or Alaskan Native’ (standardized residual = 2.513), ‘Asian or Pacific Islander’ (standardized residual = 3.771) and a significant underrepresentation of those who identify as ‘Other’ (standardized residual = -4.474). In all cases, the absolute residual was less than 40 individuals. Additionally, it is possible that some individuals identified as ‘Other’ by University statistics chose to identify with another ethnicity category on this survey. However, these deviations are not so large as to cause serious concern as to the representativeness of the sample in terms of ethnicity, although the chi-square test was statistically significant. Next the sample was tested for its representativeness in terms of gender for the University population. The chi-square test was again statistically significant ($\chi^2_1 = 151.597$, $p < .001$), with men being significantly underrepresented in the sample (standardized residual = -8.582). This points to a possible response bias as the random sample for email solicitation was gender-balanced. However, given the very large sample size, the unequal distribution of men versus women should not present an analytic problem. The issue is considering which men may have responded and which did not, given an overall response rate of approximately 12% to the survey invitation.

Instruments

The instruments selected for this study were chosen for their psychometric characteristics as well as their use in the procrastination literature. Almost all of the measures used in this study are widely used in procrastination research, and when this is not true it is clearly noted with rationale for including the measure. A notable exception is the 2×2 Measure of Time-Related Academic Behavior, which measures the 2×2 model of time-related academic behavior, and is the focus of the present study.

2×2 Measure of Time-Related Academic Behavior

This is a 25-item measure that includes items designed to assess each of the four areas of the 2×2 model of time-related academic behavior. It includes 7 items for procrastination-approach, 6 items for procrastination-avoidance, 7 items for timely engagement-approach, and 5 items for timely engagement-avoidance. This measure has shown good model fit in confirmatory factor analysis, and also showed fit to the theoretical model of approach and avoidance motivational orientation hypothesized in the theoretical framework. Additionally, in a previous study among 1496 participants, reliabilities were good, with procrastination-avoidance being the lowest ($\alpha = .81$), followed by timely engagement-approach ($\alpha = .85$), then procrastination-approach (α = .86), and finally timely engagement-avoidance (α = .87; Strunk, Cho, Steele, Bridges, 2012).

Motivated Strategies for Learning Questionnaire

The Motivated Strategies for Learning Questionnaire is a 56-item scale designed to measure motivation toward and strategies for learning. It contains subscales for self-efficacy, intrinsic value, test anxiety, cognitive strategy use, and self-regulation. The measure has shown adequate reliability in past research, with self-regulation the lowest (α = .74), followed by test anxiety (α = .75), cognitive strategy use (α = .83), intrinsic value (α = .87), and self-efficacy (α = .89; Pintrich & DeGroot, 1990). However, for the purposes of this study, only the self-efficacy and self-regulation subscales are of interest. Therefore, they were separated from the rest of the measure, for a total of 18 items, with 9 on each subscale. There is precedent for separating the scales in the procrastination research and this is not a novel methodological approach to the use of this scale (e.g. Howell & Watson, 2007; Klassen, Krawchuk, & Rajani, 2008; Klassen & Kuzucu, 2009). It is worth noting the self-regulation subscale does not measure general self-regulation ability or skill usage, but specifically self-regulation as applied to learning, which is the focus of the overall measure. This scale is, however, specific to skills or abilities, rather than other concepts of self-regulation. The same is true of the self-efficacy subscale, which measures self-efficacy as applied to the classroom and learning context.

Mini-IPIP Measure of Personality

The Mini-IPIP is a 20-item scale designed to measure normal personality as defined in the Big Five model. These scales show correlations above $r = .85$ with longer measures of personality in the Big Five model, and have reliability coefficients exceeding α = .70 (Donellan, Oswald, Baird, & Lucas, 2006). Although this measure is not the most commonly used in the field of procrastination, it is selected for the purposes of this study for its psychometric qualities and brief nature. The brief nature is particularly important given the large number of variables being measured in this study, and the fact that the shortest commonly used measure in the procrastination literature is 40 items (Saucier, 1994).

Mainz Coping Inventory

The Mainz Coping inventory includes eight scenarios, each of which is accompanied with ten items. These items are true-false instead of the more common Likert-type rating scale. This creates a binary measure on which a person is rated as either cognitive avoidance in coping style or vigilance in coping style. In the validation studies for this measure, Krohne (1989) reports internal consistency and test-retest reliabilities between .80 and .89, without specifying values by type of reliability. In the same validation study, coping strategy and type of stress reaction were highly correlated, as were physiological stress markers in pre-surgical patients. This measure is used in several studies investigating coping style in procrastination (e.g. Burns, Dittman, Nguyen, & Mitchelson, 2000), and so is selected to measure coping style in this study. However, due to the extreme length of the measure, only the two scenarios seemingly most relevant to the academic environment have been selected for inclusion in this study: the scenarios of the speech, and the exam. The others, including the dentist, the group of people, the job interview, the inexperienced driver, the mistake on the job, and the turbulent flight, were excluded for length considerations, while these two most relevant scenarios are included.

Self-Handicapping Scale – Short Form

The Self-Handicapping Scale – Short Form is a ten-item scale for assessing the degree of general self-handicapping, and has shown moderate reliability in validation studies ($\alpha = .70$; Strube, 1986). The short form scale demonstrates higher reliabilities and shows at least as strong of content validity in terms of correlations with related constructs when compared with the 20 item standard form Self-Handicapping scale (Strube, 1986). This scale the most commonly used for measuring self-handicapping in the procrastination literature, and so is selected for inclusion in this study (e.g. Beck, Koons, & Milgrim, 2000).

Achievement Goal Questionnaire

The Achievement Goal Questionnaire is a 12-item measure intended to assess goal orientation in a 2×2 framework of mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance goals. The measure includes three items for each type of goal, and in the validation studies by the measure's authors showed acceptable reliabilities (α = .88 or above) with a good model fit for the four-structure model (Elliot & Murayama, 2008).

Self-Efficacy for Self-Regulation

This is an 11-item measure taken from the Self-Efficacy scale by Zimmerman, Bandura, and Martinez-Pons (1992). The larger scale includes two subscales, but only the self-efficacy for self-regulation scale is selected for use in this study. The scale had a reliability of α = .87 in the original study by Zimmerman, Bandura, and Martinez-Pons (1992), and is the most commonly used scale for measuring self-efficacy for self-regulation in the procrastination literature (e.g. Klassen, Krawchuck, & Rajani, 2008). This scale is also commonly used in isolation from the rest of the original measure in the procrastination literature.

Demographic Questionnaire

Also included in the materials was the demographic questionnaire. This asked for age, gender, ethnicity, college classification, current grade point average (GPA), and college major. Gender and ethnicity were collected primarily for the purposes of determining representativeness of the sample. Because the University uses the U.S. Census categories for ethnicity, these categories were used on the demographic form to allow for direct comparison to the University diversity register for representativeness. For the same reasons of direct comparison, gender was only listed as “Male” or “Female”. Although these choices for ethnic and gender categories may not adequately capture participant self-identification and how those experiences may impact the phenomena of procrastination and timely engagement, for the purposes of this study ethnicity and gender are not objects of analytic interest. Rather, they are only collected to determine if the sample is adequately representative of the population from which it is drawn.

Grade point average was collected as a proxy for academic achievement. This is problematic for several reasons. First, there is no means of verifying the accuracy of self-reported GPA in this study. Other research has found around a 55-80% effect size for the relationship between self-reported and actual GPA (Frucot & Cook, 1994; Zimmerman, Caldwell, & Bernat, 2002). Further, GPA may not be an accurate measure of achievement as it is also related to other factors such as difficulty of a particular course of study, number of support systems a student may have, prior education in a subject area, and grading structure, to name a few. However, it is the closest available proxy measurement, and was used as a markedly imperfect way of glimpsing at achievement in this study.

College classification and college major were both gathered with the possibility in mind, though not a direct goal of the study, of analyzing the ways in which strategies differ across levels of analysis. That is, it is possible that people in different majors differ in motivation for procrastination and timely engagement, and differ in associated motivational and other variables. It is also possible that people differ in these same ways across the spectrum of college classification.

Procedure

Participants were recruited via an email message sent to students at Oklahoma State University who were actively enrolled in at least one traditional face-to-face course. The email announcement described the purposes of the research study, the type of information being collected, and described the inducement being used, which was entry into a drawing for a chance to win one of four $50.00 cash awards for participation in the study. The selection of a larger number of smaller awards, rather than a single award of larger cash value was to avoid any appearance of coercive potential to the inducement, and to increase the perception of potential to receive the award on the part of prospective participants, thus theoretically increasing response rates.

The email included a link to the online survey. This survey was hosted on Survey Monkey. The first page of the survey was the Informed Consent form, which also asked participants to signify their consent by creating their unique participant ID. This ID was used to match subsequent responses in future semesters to one another for the purposes of tracking longitudinal data. Instead of asking participants to remember their own ID, a system for creating an ID was used so that the same participant would create the same ID each time, thus taking the burden of remembering a unique ID off the participant, and ensuring accuracy of tracking. The ID was a combination of the first three letters of the participant first name, the first three letters of the participant last name, and the day of the month on which the participant was born (For example, John Smith born on August 8th would enter JohSmi08, with the system not being case sensitive). This still ensures confidentiality, keeps the study at the level where no personally identifiable information is collected, and allows for tracking of longitudinal data with accuracy. There were no cases where two participants entered the same ID in the same semester, with the exception of participants entering the IRB approval code, which was unfortunately the same number of digits as the participant ID they were to create. In all, 13 participants entered the IRB approval code instead of creating a unique participant ID.

After completing the informed consent and ID creation process, the participant began the measures. Each measure was presented on a separate page, including the demographic questionnaire. Each survey page required the participant to complete every question on the page to move on, but the participant had the option to exit the survey at any time. This was to minimize missing data, as the system would prompt a participant if they missed a question on a page. Also, this means data can be missing only if a participant stops the survey entirely, with the exception of the demographic questions. Upon completing the entire survey, the participant was directed to a separate survey that asked for first and last name and email address for the purposes of the drawing for the $50.00 cash award for participation. This was to ensure that the research database remained confidential and without any identifiable information.

At the end of the semester, the survey link was closed. Then, four names were randomly selected from the drawing database to receive the $50.00 award and were notified by email. This process was repeated for two semesters. All participants were treated in accordance with APA ethical guidelines, and the University Institutional Review Board approved these procedures (See Appendix A).

Data Analysis

The data analysis can be broken into three general categories or stages. First is the psychometric and measurement model work. This step is necessary because the 2×2 Measure of Time-Related Academic Behavior is essential to the theory-building that occurs in other analytic work, so the measurement model itself is important. Therefore, a number of techniques were used to determine the adequacy of the measurement model. First, confirmatory factor analyses (CFA) were used. Although the measurement model has already been subjected to confirmatory factor analysis in previous work (Strunk, Cho, Steele, & Bridges, 2012), it has only been confirmed in one sample. Thus, the replication of the CFA is important, and particularly replicating the CFA model in the present sample. Additionally, the measurement model was subjected to invariance studies using CFA multi-group techniques. Here the question became whether the measurement model is similar between the various groups represented in the data obtained for the present study. Measurement studies were also conducted for the other measures used to determine the adequacy of the measurement models proposed by the authors of those measures. Reliability analyses were also conducted for all scales used.

Having established the measurement models, the second analytic technique applied was to model structural relationships among the motivational and personality variables measured and the 2×2 model of time-related academic behavior. This process began with a hypothesized structural model, which was modified based on the observed data to create a final structural model. In this analysis, the models were then tested to see if data from the first time period predict outcomes at the second time period.

Finally, person-centered analyses were used to view the data in terms of how individuals perceive themselves and their behavior relative to their position on various motivational and personal variables measured in this study. This analysis gives a unique perspective about how the variables may interact within an individual as opposed to at the population level that captures some unique meanings that sets of variables take on in relation to other variables for groups of individuals.

CHAPTER IV

RESULTS

Because the 2×2 measure of time-related academic behavior was a focus of this study and the theory-building work is predicated on the soundness of this instrument, psychometric analysis was the first the first analytic emphasis. Several analyses were carried out to assess the structure and reliability of this instrument. Because previous work focused on establishing the validity of the instrument (Strunk, Cho, Steele, & Bridges, 2012), structural integrity and reliability of the instrument were a focus of analysis in the present study.

The second focus of analysis in this study was theory-building, with a particular emphasis on how factors previously established in traditional procrastination research would predict time-related academic behavior in the new 2×2 model. Additionally, an analytic focus in these structural equation models was on how these predictive models may give hints at malleable factors for educational intervention. Each set of variables (i.e., achievement goals, personality, and self-efficacy and self-regulation) was modeled separately, and then an integrated structural model was tested.

Finally, person-centered analyses were used to understand profiles of variables for groups of similar individuals and how these variables carry meaning for those groups of individuals. The nature of time-related academic behavior, achievement goals, and self-efficacy and self-regulation may be quite different for different people depending on how they view academic work and their environment, and person-centered analysis allows for exploration of these deeper interactions.

Psychometric and Confirmatory Factor Analytic Results for the 2×2 Measure of Time-Related Academic Behavior

The psychometric investigation of the 2×2 Measure of Time-Related Academic Behavior proceeded on two fronts: structural analyses, and reliability analyses. In structural analysis, there were two primary questions. First, would confirmatory factor analysis confirm the factor structure established in previous research? However, a secondary research interest was in the nature of the factor structure across groups. Namely, men and women seem to hold different attitudes toward procrastination, and procrastinate at significantly different levels, based on previous research (Brownlow & Reasinger, 2000; Flett, Blankstein, Hewitt, & Koledin, 1992; Meyer, 2000; Prohaska, Morrill, Atiles, & Perez, 2000; Ozer, Demir, & Ferrari, 2009; Senecal, Koestner, & Vallerand, 1995). Therefore, a structural invariance analysis was conducted between men and women. Further, although previous researchers have not considered the influence of classification on procrastination, some have shown a progressive change in procrastination across time (Moon & Illingworth, 2004), so a structural invariance analysis was also conducted by college classification. Finally, reliability analyses were conducted using traditional Chronbach's alpha, but also the congeneric model.

Confirmatory Factor Analysis

The confirmatory factor analysis was conducted using Mplus version 6.11 using maximum likelihood estimation. The initial model included all items loading as predicted on the 2×2 Measure of Time-Related Academic Behavior. Although this model produced adequate fit to the observed data ($\chi^2_{269} = 2206.86$, $\chi^2/df = 8.20$, CFI = .89, TLI = .88, RMSEA = .08, SRMR = .06), modification indices indicated large error covariances. The largest was between the errors of items 21and 12 (M.I. = 396.61). The content of these items both refer to a fear of failure as motive for procrastination, meaning the covariance could be due to either wording that is too similar, or an underlying facet related to fear of failure. After the model was modified to include this error covariance, the model fit improved (χ^2_{268} = 1770.89, χ^2/df = 6.61, CFI = .91, TLI = .90, RMSEA = .07, SRMR = .06). The largest remaining modification index indicated the addition of error covariance between items 23 and 3 (M.I. = 108.75). One of these items refers to the best possible result, and the other to being successful, so it appears there may be an underlying facet to the approach motivation causing these two items to have error covariance. The model was modified to include this error covariance, which further improved model fit (χ^2_{267} = 1657.64, χ^2/df = 6.20, CFI = .92, TLI = .91, RMSEA = .07, SRMR = .06). Finally, the largest remaining modification index indicated the addition of error covariance to the model between items 1 and 2. Item one refers to the effective utilization of time through procrastination, and item 2 to increased quality of work through procrastination. It is possible there is an empirical linkage between the idea of time use and quality in performance enhancement on the approach motivation. This error covariance was also added to the model. The final model included all items loading on the scales as predicted, plus three error covariances, and was a good fit to the observed data (χ^2_{266} = 1550.65, χ^2/df = 5.83, CFI = .93, TLI = .92, RMSEA = .06, SRMR = .06). Conventional cutoffs for the Comparitive Fit Index (CFI) are above .90, for the Tuck-Lewis Index (TLI) are above .90, for the Root Mean Square Error of Approximation (RMSEA) are below .08, and for the Standardized Root Mean Square Residual (SRMR) are below .08, though more conservative cutoffs for CFI and TLI are .95 (Schreiber, Stage, King, Nora, & Barlow, 2006). For a full listing of factor loadings and errors, refer to Table 2.

Table 2

Factor Loadings, Standard Errors, and Residuals for the 2×2 Measure of Time-Related Academic Behavior

Item	Est.	*SE*	Res.
Procrastination-Approach			
1. I more effectively utilize my time by postponing tasks.	.664	.018	.559
2. I delay completing tasks to increase the quality of my work.	.560	.022	.687
6. I put off starting tasks to increase my motivation.	.715	.016	.488
9. I feel a stronger state of "flow" in my tasks when working closer to a deadline.	.722	.016	.479
13. I intentionally wait until closer to the deadline to begin work to enhance my performance.	.831	.011	.310
18. I delay tasks because I perform better when under more time pressure.	.875	.009	.234
25. I rarely have difficulty completing quality work when starting a task close to the deadline.	.460	.025	.788
Procrastination-Avoidance			
5. I put tasks off for later because they are too difficult to complete.	.592	.021	.649
12. I put off completing tasks due to a fear of failure.	.532	.023	.717
14. I delay starting tasks because they are overwhelming to me.	.875	.010	.234
20. I avoid starting and completing tasks.	.556	.022	.691
21. I often delay starting tasks because I am afraid of failure.	.655	.019	.571
22. I delay starting tasks because they are overwhelming.	.909	.009	.173
Timely Engagement-Approach			
3. It is important to me to complete tasks on time because I want to achieve the best result possible.	.347	.027	.879
4. I work further ahead of the deadline, at a slower pace, because it helps me perform better.	.745	.014	.445
8. I believe I can successfully complete most tasks because I start work immediately after being assigned a task.	.775	.013	.399
17. I do my best work well ahead of the deadline.	.751	.014	.435
19. I start working right away on a new task so that I can perform better on the task.	.858	.009	.264
23. I complete my tasks prior to their deadlines to help me be successful.	.685	.017	.530
24. I begin working on difficult tasks early in order to achieve positive results.	.818	.011	.331
Timely-Engagement-Avoidance			
7. I start my work early because my performance suffers when I have to rush through a task.	.775	.013	.399
10. I do not start things at the last minute because I find it difficult to complete	.640	.018	.590

them on time.			
11. I begin working on a newly assigned task right away to avoid falling behind.	.829	.010	.320
15. When I receive a new assignment, I try to complete it ahead of the deadline to avoid feeling overwhelmed.	.797	.012	.364
16. On extremely difficult tasks, I begin work even earlier so I can avoid the consequences of putting it off for later.	.708	.016	.499

Note. Includes correlated errors for items 1 & 2 (.32), 12 & 21 (.59), and 3 & 23 (.32).

The model listed above represents the theoretical model proposed by Strunk, Cho, Steele, and Bridges (2012). There are, however, potentially competing models which must be evaluated as well, in order to determine what measurement continuums are necessary to capture the underlying constructs, and which model will be the best fit to the observed data. These competing models were selected to assess whether the procrastination-timely engagement dimension alone was a better fit to the data, whether the approach-avoidance dimension alone was a better fit to the data, and whether a three-factor solution would be a better fit to the data (i.e., if one of the behaviors was not differentiated by motivational orientation). As a result, four models were tested. They are as follows:

1. A model where only procrastination and timely engagement are differentiated, and approach and avoidance items are collapsed together. The result is a model where all procrastination-approach items and procrastination-avoidance items become a generalized procrastination scale, and all timely engagement-approach and timely engagement-avoidance items become a generalized timely engagement scale. This model was not a good fit to the observed data ($\chi^2_{271} = 3630.57$, $\chi^2/df = 13.40$, CFI = .81, TLI = .79, RMSEA = .11, SRMR = .09).
2. The second model tested differentiated the approach versus avoidance motivation, but did not differentiate procrastination versus timely engagement behavior. As a result, procrastination-approach and timely engagement-approach items created a single scale, and procrastination-avoidance and timely engagement-avoidance items created a single scale. This model was also not a good fit to the observed data ($\chi^2_{271} = 4692.69$, $\chi^2/df = 17.32$, CFI = .75, TLI = .72, RMSEA = .12, SRMR = .10).

3. The third model separated timely engagement by motivational orientation, but not procrastination. The result is timely engagement-approach and timely engagement-avoidance scales as predicted, and a general procrastination scale containing all items predicted to load on procrastination-approach and procrastination-avoidance. This model was also not a good fit to the observed data (χ^2_{269} = 3618.49, χ^2/df = 13.45, CFI = .81, TLI = .78, RMSEA = .11, SRMR = .09).
4. The fourth model separated procrastination on motivational orientation, but not timely engagement. As a result, procrastination-approach and procrastination-avoidance scales included items as predicted, and a general timely engagement scale was created with all of the items predicted to load on timely engagement-approach and timely engagement-avoidance. This model too failed to show good fit to the observed data (χ^2_{272} = 2235.01, χ^2/df = 8.66, CFI = .89, TLI = .88, RMSEA = .08, SRMR = .06).
5. The theoretical model as proposed by Strunk, Cho, Steele, and Bridges (2012), and described above. This model included all items loading on the scales as predicted, plus three error covariances, and was a good fit to the observed data (χ^2_{266} = 1550.65, χ^2/df = 5.83, CFI = .93, TLI = .92, RMSEA = .06, SRMR = .06).

The chi-square difference test and the difference in CFI were used to assess the empirical advantage of the final theoretical CFA model over the competing models. The final theoretical CFA model was a significantly better fit than model 1 ($\Delta\chi^2_5$ = 2079.92, p < .001, ΔCFI = .12), model 2 ($\Delta\chi^2_5$ = 3079.04, p < .001, ΔCFI = .28), model 3 ($\Delta\chi^2_3$ = 2067.84, p < .001, ΔCFI = .12), and model 4 ($\Delta\chi^2_6$ = 684.36, p < .001, ΔCFI = .04). In all cases, both the chi-square difference test and the difference in CFI support the empirical advantage of including both the behavioral differentiation and the differentiation on motivational orientation in the final measurement model, and demonstrate the empirical advantage of the theoretical model over potentially competing measurement models. For a comparison of fit indices for the potentially competing models, see Table 3.

Table 3

Comparison of Fit Indices for Potentially Competing Models

	χ^2/df	$\Delta\chi^2$	Δdf	CFI	ΔCFI	TLI	RMSEA	SRMR
1. 2×2 Model of Time Related Academic Behavior	5.83	-	-	.93	-	.92	.06	.06
2. 2 Factor Model of Procrastination and Engagement	13.40	2079.92	5	.81	.12	.79	.11	.09
3. 2 Factor Model of Approach and Avoidance	17.32	3079.04	5	.75	.28	.72	.12	.10
4. 3 Factor Model of Engagement with Two Motives and Generalized Procrastination	13.45	2067.84	3	.81	.12	.78	.11	.09
5. 3 Factor Model of Procrastination with Two Motives and Generalized Engagement	8.66	684.36	6	.89	.04	.88	.08	.06

Structural Invariance Analyses

Having confirmed the structure of the 2×2 Measure of Time-Related Academic Behavior, next the structural invariance of the measure was assessed. This was done using Amos version 18.0. First, invariance was assessed by gender. Previous research has indicated significant gender differences for procrastination both in attitudes and in magnitude of procrastination, so it was thought that the factor structure of the measure may vary based on gender. Four models were assessed: the unconstrained models, models with the measurement weights constrained to be equal, models with measurement weights and structural covariances constrained to be equal, and models with measurement weights, structural covariances, and measurement residuals constrained to be equal. This nesting of constraints allows for the assessment of differences in constrained versus unconstrained models to determine if the models vary, and if so, where that variance occurs. The difference in chi-square tests produced mixed results. The difference between the unconstrained model and the model with measurement weights constrained was significant ($\Delta\chi^2_{21} = 39.13$, $p = .009$), as was the difference between the unconstrained and the model with measurement variances and structural covariances constrained ($\Delta\chi^2_{31} = 56.47$, $p = .003$), and the difference between the unconstrained model and the model with measurement weights, structural covariances, and measurement residuals constrained ($\Delta\chi^2_{59} = 120.78$, $p < .001$). However, the difference between the model with measurement weights constrained and the model with both measurement weights and structural covariances constrained was not statistically significant ($\Delta\chi^2_{10} = 17.32$, $p = .07$). It is worth noting, though, that recently researchers have suggested the chi-squared difference test has significant limitations in determining structural equivalency, particularly as the chi-square statistic becomes less meaningful in very large samples (Byrne, 2008; Cheung & Rensvold, 2002; Little, 1997). As a result, the difference in the Comparative Fit Index (CFI) value was also used as a measure of structural equivalency. The CFI value changed by only .001-.002 between models, for a total change between all models of .004, suggesting structural equivalency (Cheung & Rensvold, 2002). A comparison of all fit statistics by model is found in Table 4. For the factor loadings and standard errors in the unconstrained model by gender, see Table 5.

Table 4

Fit Indices by Measurement Model for Invariance by Gender

Index	Unconstrained	Measurement Weights	Structural Covariances	Measurement Residuals
χ^2	1850.809	1889.955	1907.278	1971.591
df	532	553	563	591
χ^2/df	3.479	3.418	3.388	3.336
CFI	.924	.923	.922	.920
TLI	.914	.916	.917	.919
RMSEA	.047	.047	.046	.046

Table 5

Factor Loadings and Standard Errors by Gender in Unconstrained Model

	Men		Women	
Item	Est.	*SE*	Est.	*SE*
Procrastination-Approach				
Item 1	.645		.672	
Item 2	.470	.072	.597	.045
Item 6	.678	.096	.730	.062
Item 9	.618	.089	.763	.064
Item 13	.837	.101	.831	.062
Item 18	.887	.105	.871	.067
Item 25	.446	.084	.468	.060
Procrastination-Avoidance				
Item 5	.590		.598	
Item 12	.578	.114	.515	.078
Item 14	.888	.137	.870	.090
Item 20	.561	.108	.557	.072
Item 21	.704	.117	.632	.077
Item 22	.894	.139	.916	.096
Timely Engagement-Approach				
Item 3	.332		.345	
Item 4	.713	.409	.755	.351
Item 8	.708	.405	.802	.366
Item 17	.745	.409	.752	.326
Item 19	.847	.432	.862	.373
Item 23	.689	.319	.681	.255
Item 24	.828	.440	.814	.331
Timely-Engagement-Avoidance				
Item 7	.771		.778	
Item 10	.642	.062	.643	.047
Item 11	.821	.054	.831	.040
Item 15	.805	.060	.791	.040
Item 16	.687	.058	.717	.039

Next, structural invariance was assessed by college classification. This was tested because of previous research that demonstrates students' attitudes and orientations toward procrastination (thus, potentially all time-related academic behavior) change over time as they are exposed to the academic environment. As a result, it was necessary to assess if the structure of the instrument would be equivalent across college classification or if the structure would vary as students' perceptions of the academic environment and orientation to time-related behaviors change. Again the first test used was the chi-square difference test. The difference between the unconstrained model and the model with measurement weights constrained was not statistically significant ($\Delta\chi^2_{21} = 13.90$, $p = .874$), nor was the difference between the model with measurement weights constrained and the model with both measurement weights and structural covariances constrained ($\Delta\chi^2_{10} = 11.89$, $p = .293$), though the difference between the model with measurement weights and structural covariances constrained and the model with measurement weights, structural covariances, and measurement residuals constrained was statistically significant ($\Delta\chi^2_{28} = 53.58$, $p = .003$). Additionally, the difference between the unconstrained model and the model with measurement weights and structural covariances constrained was not statistically significant ($\Delta\chi^2_{31} = 25.79$, $p = .731$), though the difference between the unconstrained model and the model with measurement weights, structural covariances, and measurement residuals constrained was statistically significant ($\Delta\chi^2_{59} = 79.37$, $p = .04$). Again in the case of college classification, the chi-square difference test is treated with some hesitance due to critiques of its reliability, particularly in large samples. As a result, the CFI difference was also assessed. The overall difference in all four models was .001, with the first three models (unconstrained, measurement weights constrained, and measurement weights and structural covariances constrained) having a difference of less than .001, and the fourth model (with measurement weights, structural covariances, and measurement residuals constrained) having a difference from the other three of approximately .001. As a result, the four models were judged to be essentially equivalent. A complete listing of fit indices by model is found in Table 6, and the factor loadings and standard errors by classification for the unconstrained model are found in Table 7.

Table 6

Fit Indices by Measurement Model for Invariance by College Classification

Index	Unconstrained	Measurement Weights	Structural Covariances	Measurement Residuals
χ^2	2786.033	2799.936	2811.821	2865.398
df	1182	1203	1213	1241
χ^2/df	2.357	2.327	2.318	2.309
CFI	.908	.908	.908	.907
TLI	.906	.908	.909	.910
RMSEA	.035	.035	.035	.035

Table 7

Factor Loadings and Standard Errors by College Classification in Unconstrained Model

	Freshmen		Sophomores		Juniors		Seniors	
Item	Est.	*SE*	Est.	*SE*	Est.	*SE*	Est.	*SE*
Procrastination-Approach								
Item 1	.690		.578		.690		.690	
Item 2	.554	.042	.563	.097	.554	.042	.554	.042
Item 6	.707	.055	.729	.146	.707	.055	.707	.055
Item 9	.715	.055	.743	.147	.715	.055	.715	.055
Item 13	.829	.056	.836	.149	.829	.056	.829	.056
Item 18	.885	.058	.836	.164	.885	.058	.885	.058
Item 25	.448	.053	.495	.130	.448	.053	.448	.053
Procrastination-Avoidance								
Item 5	.608		.565		.608		.608	
Item 12	.544	.073	.485	.135	.544	.073	.544	.073
Item 14	.876	.085	.870	.166	.876	.085	.876	.085
Item 20	.585	.069	.494	.130	.585	.069	.585	.069
Item 21	.660	.073	.633	.138	.660	.073	.660	.073
Item 22	.903	.088	.915	.179	.903	.088	.903	.088
Timely Engagement-Approach								
Item 3	.357		.336		.357		.357	
Item 4	.741	.273	.758	.601	.741	.273	.741	.273
Item 8	.785	.283	.765	.603	.785	.283	.785	.283
Item 17	.750	.257	.762	.581	.750	.257	.750	.257
Item 19	.866	.291	.830	.601	.866	.291	.866	.291
Item 23	.706	.206	.626	.415	.706	.206	.706	.206
Item 24	.818	.270	.825	.570	.818	.270	.818	.270
Timely-Engagement-Avoidance								
Item 7	.784		.758		.784		.784	
Item 10	.652	.042	.609	.082	.652	.042	.652	.042
Item 11	.849	.036	.774	.074	.849	.036	.849	.036
Item 15	.811	.038	.742	.073	.811	.038	.811	.038
Item 16	.707	.308	.720	.067	.707	.308	.707	.308

Reliability Analyses

Reliability of the 2×2 Measure of Time-Related Academic Behavior was assessed through three methods: Cronbach's alpha, congeneric factor reliability in the SEM model, and test-retest reliability. The alpha coefficient is calculated on unit weighted scores which are more likely to be used by future researchers, and which are used in path analyses reported later in this study. It is also the most commonly reported reliability coefficient in the literature. All four subscales showed good reliability on Chronbach's alpha (DeVellis, 2003), including procrastination-approach (α = .87), procrastination-avoidance (α = .86), timely engagement-approach (α = .89), and timely engagement-avoidance (α = .87).

The reliability of the instrument was then assessed in the congeneric model in the SEM measurement model. This additional step was taken because this method allows for measurement weights to vary (alpha, measured in the tau-equivalent model, does not allow measurement weights to vary). This allows for more of the unique variance in the system to be accounted for in the measurement model, and often produces higher reliability coefficients (Graham, 2006). This is because more error is accounted for in the SEM measurement model, particularly the congeneric model, than in the essentially tau-equivalent model used by Chronbach's alpha. Because of this, the differences between the congeneric reliabilities from the SEM measurement model and Chronbach's alpha can be thought of as some rough estimate of the degree of reliability lost due to unique and error variance in the unit-weighted factor scores (Kline, 2010). Again, all four subscales showed good reliability, including procrastination-approach ($\hat{\rho}_{x_1x_2}$ = .87), procrastination-avoidance ($\hat{\rho}_{x_1x_2}$ = .85), timely engagement-approach ($\hat{\rho}_{x_1x_2}$ = .88), and timely engagement-avoidance ($\hat{\rho}_{x_1x_2}$ = .88). Additionally, in all cases the difference between alpha and rho was less than .01.

The test-retest reliability of the 2×2 Measure of Time-Related Academic Behavior was assessed among those participants who completed the measure twice (n = 131), approximately 15 weeks apart, though there is variation in the distance between administration as a result of the online survey methodology. Amos version 18.0 was used to assess the test-retest reliability of the measure within the SEM measurement model. All test-retest reliabilities were relatively strong. The lowest was the procrastination-avoidance scale (r_{12} = .78), followed by the timely engagement-approach scale (r_{12} = .81), the procrastination-approach scale (r_{12} = .82), with the highest being the timely engagement-avoidance scale (r_{12} = .85). Researchers have argued that it is difficult to set a criteria for test-retest reliability because the nature of the construct will dictate how much change is expected, and over what period of time that change is expected to occur (DeVellis, 2003; Furr & Bacharach, 2008). However, these test-retest reliability coefficients are sufficiently high to suggest a strong stability of the test across time, which also suggests some underlying stability of the construct of time-related academic behavior. This also suggests the measure may be useful in longitudinal prediction analyses, as were planned in the present study, because some stability in the measure and construct are required for such analytic techniques.

Measurement Analyses for Other Key Measures

Because other key measures, including the MSLQ, AGQ, and mini-IPIP were to be included in structural models, it was necessary to independently evaluate the measurement models for each of the measures. Confirmatory factor analyses were conducted for each of the key measures to establish the measurement model before proceeding to structural modeling with the 2×2 Measure of Time-Related Academic Behavior. Subsequently, the reliabilities were evaluated for each of the key measures and their subscales.

Measurement Analysis for the Self-Efficacy and Self-Regulation Scales of the Motivated Strategies for Learning Questionnaire

Two subscales of the MSLQ, the self-efficacy and self-regulation scales, were included in the present study. Those scales were subjected to confirmatory factor analysis according to the factor structure specified by Pintrich and DeGroot (1990). This structure included nine items (items 1-9) on self-efficacy and nine (items 10-18) on self-regulation. This model was not a good fit to the observed data (χ^2_{134} = 1714.45, χ^2/df = 12.79, CFI = .84, TLI = .82, RMSEA = .10, SRMR = .08). All items significantly loaded on their predicted scales. However, the largest modification index indicated item 5 cross-loaded on both latent variables (M.I. = 154.52). As a result, it was eliminated from the model. The resulting reduced model showed improved fit (χ^2_{118} = 1372.71, χ^2/df = 11.63, CFI = .87, TLI = .84, RMSEA = .10, SRMR = .07) but was still not a good fit for the observed data. The largest remaining modification index indicated the addition of an error covariance between items 15 and 16 (M.I. = 164.35). These items both reflect that, although the student is reading or paying attention in class, the content is not being retained or rehearsed, which may explain the error covariance between them. After adding this error covariance to the model improved model fit further (χ^2_{117} = 1198.15, χ^2/df = 10.24, CFI = .88, TLI = .87, RMSEA = .09, SRMR = .07), though it was still not a good fit for the observed data. An additional error covariance was indicated by the modification indices between items 2 and 9 (M.I. = 87.75) and was added to the model. These items are both very similar in content, reflecting a confidence in understanding course ideas or learning course content, which may explain why their errors covary. This refitting did improve model fit (χ^2_{116} = 1110.23, χ^2/df = 9.57, CFI = .89, TLI = .88, RMSEA = .08, SRMR = .06), but overall the model was still not a good fit to the observed data. Finally, an error covariance between items 2 and 5 was added to the model as indicated by the modification indices (M.I. = 75.04). These two items reflect a shared idea of confidence in understanding and execution, suggesting some latent connection between those ideas. The final model approached reasonably good fit to the observed data, though it did not reach conventional cutoffs for fit indices (χ^2_{115} = 1037.71, χ^2/df = 9.02, CFI = .90, TLI = .88, RMSEA = .08, SRMR = .07). The final model, being reasonably good fit to the observed data, was used in all subsequent analyses. The factor loadings, standard errors, and residuals can be found in Table 8. This measure demonstrated adequate reliability in the traditional Cronbach's alpha (essentially tau-equivalent) model, self-efficacy showing high reliability (α = .93) and self-regulation showing moderate reliability (α = .73). The congeneric reliability for self-efficacy was the same ($\hat{\rho}_{x_1 x_2}$ = .93), and for self-regulation it was higher ($\hat{\rho}_{x_1 x_2}$ = .75). The test-retest reliabilities of both scales were moderate, including self-efficacy (r_{12} = .57) and self-regulation (r_{12} = .65).

Table 8

Factor Loadings, Standard Errors, and Residuals for the MSLQ

Item	Est.	*SE*	Res.
Self-Efficacy			
1. Compared with other students in class I expect to do well.	.841	.010	.293
2. I'm certain I can understand the ideas taught in class.	.737	.015	.457
3. I expect to do very well in class.	.880	.008	.226
4. Compared with others in class, I think I'm a good student.	.810	.011	.344
5. I am sure I can do an excellent job ob the problems and tasks assigned for class.	.842	.010	.291
6. I think I will receive good grades in my classes.	.854	.009	.271
8. Compared with other students in class I think I know a great deal about the subjects.	.551	.022	.697
9. I know that I will be able to learn the material for class.	.762	.014	.420
Self-Regulation			
10. I ask myself questions to make sure I know the material I have been studying.	.614	.023	.623
11. When work is hard I either give up or study only the easy parts.	-.501	.027	.749
12. I work on practice exercises and answer end of chapter questions even when I don't have to.	.392	.030	.847
13. Even when study materials are dull and uninteresting, I keep working until I finish.	.674	.021	.545
14. Before I begin studying I think about the things I will need to do to learn.	.498	.027	.752
15. I often find that I have been reading for class but don't know what it is all about.	-.197	.033	.961
16. I find that when the teaching is talking I think of other things and don't really listen to what is being said.	-.348	.030	.879
17. When I'm reading I stop once in a while and go over what I have read.	.376	.030	.858
18. I work hard to get a good grade even when I don't like a class.	.650	.023	.577

Note. Includes correlated errors for items 9 & 2 (.29), 5 & 2 (.26), and 15 & 16 (.39). The latent factors are correlated at .63.

Measurement Analysis for the Self-Efficacy for Self-Regulation Scale

The measurement model for the self-efficacy for self-regulation scale was initially specified according to the model put forward by Zimmerman, Bandura, and Martinez-Pons (1992). This initial model was a poor fit to the observed data (χ^2_{44} = 810.76, χ^2/df = 18.43, CFI = .84, TLI = .79, RMSEA = .13, SRMR = .05). However, all items loaded significantly on the latent factor with moderate to large loadings. Therefore, the modification indices were examined, and they indicated the addition of an error covariance between items 6 and 7 to the model (M.I. = 455.44). Item six regards planning schoolwork, whereas item seven regards organizing schoolwork, which are highly related concepts. This relationship may explain the error covariance. After adding this error covariance to the model, the fit was much better, but still not a good fit to the observed data (χ^2_{43} = 386.46, χ^2/df = 8.99, CFI = .93, TLI = .91, RMSEA = .08, SRMR = .04). Therefore, the modification indices were examined again, and indicated the addition of an error covariance between items 2 and 3 to the model (M.I. = 65.28). Both of these items have to do with concentration on school, with item two adding the element of concentration among distractions. The shared content domain offers an explanation for the error covariance. Following this addition to the CFA model, the final model fit the observed data reasonably well (χ^2_{42} = 325.74, χ^2/df = 7.76, CFI = .94, TLI = .92, RMSEA = .07, SRMR = .04). This was the final model used in all subsequent analyses, and a table with factor loadings, standard errors, and residuals can be found in Table 9. The scale demonstrated good reliability using Cronbach's alpha (α = .85). The reliability remained stable when calculated under the congeneric model ($\hat{\rho}_{x_1 x_2}$ = .85). Additionally the test-retest reliability was moderate (r_{12} = .68).

Table 9

Factor Loadings, Standard Errors, and Residuals for the Self-Efficacy for Self-Regulation Scale

Item	Est.	*SE*	Res.
1. finish homework assignments by deadlines?	.549	.024	.698
2. study when there are other interesting things to do?	.672	.020	.549
3. concentrate on school subjects?	.762	.016	.419
4. take class notes of class instruction?	.545	.024	.703
5. use the library to get information for class assignments?	.437	.027	.809
6. plan your schoolwork?	.726	.017	.473
7. organize your schoolwork?	.670	.020	.551
8. remember information presented in class and textbooks?	.421	.027	.823
9. arrange a place to study without distractions?	.609	.021	.630
10. motivate yourself to do schoolwork?	.753	.016	.432
11. participate in class discussions?	.370	.028	.863

Note. Includes correlated errors for items 6 & 7 (.60) and 2 & 3 (.29).

Measurement Analysis for the Achievement Goal Questionnaire

The measurement model for the Achievement Goal Questionnaire was initially modeled based on Elliot and Murayama's (2008) CFA results. This model, however, was not a good fit to the observed data (χ^2_{48} = 690.69, χ^2/df = 14.39, CFI = .90, TLI = .86, RMSEA = .11, SRMR = .08). Because all of the items loaded significantly on the hypothesized latent factors, modification indices were examined. The modification indices indicated the addition of an error covariance between items 5 and 9 to the model (M.I. = 306.06). Items 5 and 9 are virtually identical in wording, with the change from "than it is possible to learn" to "than I possibly could," and this extreme similarity in item content seems to explain the covariance in error. After adding this covariance to the model, the final model was a reasonably good fit to the observed data (χ^2_{47} = 344.27, χ^2/df = 7.32, CFI = .95, TLI = .94, RMSEA = .08, SRMR = .04). This final model is used in all subsequent analyses. A table with factor loadings, standard errors, and residuals can be found in Table 10. The measure had moderate to good reliabilities using the essentially tau-equivalent model with Cronbach's alpha, including mastery approach (α = .83), mastery avoidance (α = .72), performance approach (α = .85), and performance avoidance (α =

.81). Under the congeneric model using the SEM measurement model, the measure demonstrated good reliability on three scales: mastery approach ($\hat{\rho}_{x_1x_2}$ = .84), performance approach ($\hat{\rho}_{x_1x_2}$ = .85), and performance avoidance ($\hat{\rho}_{x_1x_2}$ = .81). Mastery avoidance demonstrated low reliability in the congeneric model ($\hat{\rho}_{x_1x_2}$ = .56) This is an interesting finding, because mastery avoidance goals have traditionally demonstrated the lowest stability and measurability, leading many researchers to posit a three-factor goal structure of mastery goals, performance approach goals, and performance avoidance goals (Elliot, 2005). Because the alpha reliability, which uses the essentially tau-equivalent measurement model, was acceptable for this subscale, but the congeneric reliability is low, questions arise about the dimensionality of the instrument and its internal stability. These questions have been raised by others (Elliot, 2005), but bear further research. Test-retest reliabilities ranged from moderately low to moderately high for the measure, with the lowest being mastery-avoidance (r_{12} = .40), followed by performance avoidance (r_{12} = .49), mastery approach (r_{12} = .60), and finally performance approach (r_{12} = .61).

Table 10

Factor Loadings, Standard Errors, and Residuals for the Achievement Goal Questionnaire

Item	Est.	*SE*	Res.
Mastery Approach			
1. My aim is to completely master the material presented in class	.760	.016	.578
7. I am striving to understand the content of this course as thoroughly as possible.	.829	.014	.688
3. My goal is to learn as much as possible.	.802	.014	.644
Mastery Avoidance			
5. My aim is to avoid learning less than I possibly could.	.389	.030	.666
11. I am striving to avoid an incomplete understanding of course materials.	.768	.026	.590
9. My goal is to avoid learning less than it is possible to learn.	.508	.027	.258
Performance Approach			
4. My aim is to perform well relative to other students.	.816	.013	.644
2. I am striving to do well compared to other students.	.807	.014	.652
8. My goal is to perform better than the other students.	.797	.014	.635
Performance Avoidance			
12. My aim is to avoid doing worse than other students.	.824	.013	.679
10. I am striving to avoid performing worse than others.	.860	.012	.739
6. My goal is to avoid performing poorly compared to others.	.636	.020	.405

Note. Includes correlated errors for items 5 & 9 (.59).

Measurement Analysis for the mini-IPIP

The measurement model for the mini-IPIP was initially specified according to the model put forward by Donellan, Oswald, Baird, and Lucas (2006). This model, however, was not a good fit to the observed data (χ^2_{160} = 1397.59, χ^2/df = 8.73, CFI = .83, TLI = .80, RMSEA = .08, SRMR = .06). However, all items loaded significantly on their expected latent factors, so the modification indices were examined. The addition of an error covariance between items 10 and 15 was indicated (M.I. = 343.78). These two items both deal with the concept of abstract ideas. After adding this covariance to the model, the fit was improved, but the model was still not a good fit to the observed data (χ^2_{159} = 1053.189, χ^2/df = 6.62, CFI = .88, TLI = .85, RMSEA = .07, SRMR = .06). Another large modification index indicated the addition of an error covariance between items 2 and 12 (M.I. = 191.27). Both of these items relate to the content area of empathy or feelings others' emotions, using relatively similar wording. This covariance was added to the model, and the resulting model was a reasonably good fit to the data(χ^2_{157} = 815.60, χ^2/df = 5.19, CFI = .91, TLI = .89, RMSEA = .06, SRMR = .05), so it was determined no further modifications would be made. This final model was used in all subsequent analyses. A table with factor loadings, standard errors, and residuals can be found in Table 11. Using Cronbach's alpha, the subscales demonstrated moderate to good reliabilities including agreeableness (α = .81), conscientiousness (α = .73), imagination/intellect (α = .76), neuroticism (α = .68), and extraversion (α = .83). Reliabilities were also assessed in the congeneric model, in which for neuroticism was higher ($\hat{\rho}_{x_1x_2}$ = .69), but for all other scales was lower including agreeableness ($\hat{\rho}_{x_1x_2}$ = .77), conscientiousness ($\hat{\rho}_{x_1x_2}$ = .63), imagination/intellect ($\hat{\rho}_{x_1x_2}$ = .71), and extraversion ($\hat{\rho}_{x_1x_2}$ = .82). The relative lowering of reliability in the congeneric model may indicate that allowing the measurement weights to be freely estimated introduced more error into the system, indicated potential problems with dimensionality and the scale structure. Test-retest reliabilities were also assessed and ranged from moderately low for conscientiousness (r_{12} = .38) to moderately high for all other scales including agreeableness (r_{12} = .71), imagination/intellect (r_{12} = .73), neuroticism (r_{12} = .75), and extraversion (r_{12} = .69).

Table 11

Factor Loadings, Standard Errors, and Residuals for the mini-IPIP

Item	Est.	*SE*	Res.
Agreeableness			
2. Sympathize with others' feelings.	.632	.024	.601
7. Am not interested in other people's problems.	-.715	.021	.489
12. Feel others' emotions.	.562	.026	.684
17. Am not really interested in others.	-.810	.020	.345
Conscientiousness			
3. Get chores done right away.	.596	.026	.645
8. Often forget to put things back in their proper place.	-.671	.024	.550
13. Like order.	.581	.026	.663
18. Make a mess of things.	-.717	.024	.486
Imagination/Intellect			
5. Have a vivid imagination.	.760	.025	.423
10. Am not interested in abstract ideas.	-.412	.029	.830
15. Have difficulty understanding abstract ideas.	-.452	.028	.796
20. Do not have a good imagination.	-.829	.025	.312
Neuroticism			
4. Have frequent mood swings.	.756	.026	.428
9. Am relaxed most of the time.	-.452	.030	.795
14. Get upset easily.	.718	.022	.485
19. Seldom feel blue.	-.432	.017	.813
Extraversion			
1. Am the life of the party.	.626	.022	.608
6. Don't talk a lot.	-.764	.017	.416
11. Talk to a lot of different people at parties.	.721	.019	.481
16. Keep in the background.	-.821	.016	.326

Note. Includes correlated errors for items 2 & 12 (.53), and 10 & 15 (.54).

A summary table of the fit indices for the final model for each of these key measures can be found in Table 12. A table showing all reliability coefficients for all subscales of all key measures can be found in Table 13. All key measures showed fit approaching good fit to the observed data, and all showed acceptably good reliability, so these measures were used as specified in the CFA models in structural equation modeling (SEM).

Table 12

Summary of Fit Indices for All Key Measures Modeled

Scale	χ^2	df	χ^2/df	CFI	TLI	RMSEA	SRMR
2×2 Measure of Time-Related Academic Behavior	1550.65	266	5.83	.93	.92	.06	.06
Motivated Strategies for Learning Questionnaire	1037.71	115	9.02	.90	.88	.08	.07
Self-Efficacy for Self-Regulation	325.74	42	7.76	.94	.92	.07	.04
mini-International Personality Item Pool Questionnaire	815.60	157	5.19	.91	.89	.06	.05
Achievement Goal Questionnaire	344.27	47	7.32	.95	.94	.08	.04

Table 13

Summary of Reliability Coefficients for All Key Measures

	Scale	α	$\hat{\rho}_{x_1 x_2}$	r_{12}
2×2 Measure of Time-Related Academic Behavior	Procrastination-Approach	.87	.87	.82
	Procrastination-Avoidance	.86	.85	.78
	Timely Engagement-Approach	.89	.88	.81
	Timely Engagement-Avoidance	.87	.88	.85
MSLQ	Self-Efficacy	.93	.93	.57
	Self-Regulation	.73	.75	.65
	Self-Efficacy for Self-Regulation	.85	.85	.68
Achievement Goal Questionnaire	Mastery Approach	.83	.84	.60
	Mastery Avoidance	.71	.56	.40
	Performance Approach	.84	.85	.61
	Performance Avoidance	.81	.81	.49
mini-International Personality Item Pool Questionnaire	Agreeableness	.81	.77	.71
	Conscientiousness	.73	.63	.38
	Imagination/Intellect	.76	.71	.73
	Neuroticism	.68	.69	.75
	Extraversion	.83	.82	.69

Structural Modeling

Having confirmed the factor structure of the 2×2 Measure of Time-Related Academic Behavior and its structural invariance by gender and college classification, as well as the reliability of the instrument, structural modeling with predictor variables was then conducted. The relatively thorough investigation of the instrument in this study gives more confidence in the results of structural equation modeling (SEM) analyses, and is also likely to produce stronger predictive models in the SEM analyses.

The predictor variables were first analyzed in homogeneous sets, starting with self-efficacy, self-regulation, and self-efficacy for self-regulation, then moving to achievement goals, then to personality, and finally an integrated structural model was created and tested. Following these SEM analyses, predictive models across time (repeated-measures SEM) were conducted. All structural equation modeling was done using Mplus version 6.11 using maximum likelihood estimation. Because the online survey was constructed to force responses to all items on a given survey, it was not possible for data to be missing-at-random. Any participant with missing data would have completed early scales and not completed later scales. As a result, 91.6% of all cases with missing data were participants who completed the first scale (the 2×2 Measure of Time-Related Academic Behavior) and did not complete any additional scales. As a result, for the purposes of the structural equation models, participants were excluded if they were missing any of the variables included in the model (i.e., a listwise deletion). This resulted in the exclusion of 107 participants, or 8.7% of the sample, due to missing data. Because of the nature of the missing data, with complete scales missing, and in most cases all but one scale missing, data imputation was not a viable strategy.

Structural Modeling of Self-Efficacy, Self-Regulation and Self-Efficacy for Self-Regulation on the 2×2 Measure of Time-Related Academic Behavior

Self-efficacy and self-regulation were assessed using the MSLQ (Pintrich & DeGroot, 1990), and self-efficacy for self-regulation was assessed using the scale developed by Zimmerman, Bandura, and Martinez-Pons (1992). Because previous research had suggested that self-efficacy for self-regulation fully mediated the statistical effect of both self-regulation and self-efficacy on procrastination (Strunk & Steele, 2012), the hypothesized structural model was that self-efficacy and self-regulation would predict self-efficacy for self-regulation. It was then thought that all three of these variables (self-efficacy, self-regulation, and self-efficacy for self-regulation) would directly predict all four 'types' of time-related academic behavior. This hypothesized structural model can be found in Figure 2. The only modifications made to the hypothesized model was the elimination of one non-significant path from the model, that of self-regulation in predicting procrastination-avoidance. The path of self-efficacy in predicting self-efficacy for self-regulation was non-significant as well, but was left in the final model to demonstrate their relationship as it was strongly expected to be significant. All other paths were significant, and modification indices did not indicate any changes to the hypothesized model. Additionally, this model was a reasonably good fit to the data ($\chi^2_{1146} = 4149.24$, $\chi^2/df = 3.62$, CFI = .91, TLI = .90, RMSEA = .05, SRMR = .06). It is worth noting in this model, which is still a relatively good fit to the data, that neither the MSLQ nor the self-efficacy for self-regulation scale produce extremely good fit in stand-alone CFA analyses in this sample. This may produce relative poorer fit in the overall SEM model despite moderate to strong path coefficients in the full SEM model, and a good-fitting measurement model on the 2×2 Measure of Time-Related Academic Behavior. However, based on the relatively good fit of the overall SEM model and the moderate to strong path coefficients, it was concluded that this model was a good fit to the observed data and appeared to offer some meaningful explanation of the phenomenon.

Therefore, in the final model, procrastination-approach is predicted by self-efficacy (β = .18), self-regulation (β = -.15) and self-efficacy for self-regulation (β = -.32). Procrastination-avoidance is predicted by self-efficacy (β = -.14) and self-efficacy for self-regulation (β = -.42). Timely engagement-approach is predicted by self-efficacy (β = -.16), self-regulation (β = .30), and self-efficacy for self-regulation (β = .43). Timely engagement-avoidance is predicted by self-efficacy (β = -.22), self-regulation (β = .31), and self-efficacy for self-regulation (β = .41). Finally, self-efficacy for self-regulation is predicted by self-regulation (β = .64) and self-efficacy (β = .18). The structural model for self-efficacy, self-regulation, and self-efficacy for self-regulation predicting time-related academic behavior can be found in Figure 3.

Figure 2

Hypothesized Structural Model of Self-Efficacy, Self-Regulation, and Self-Efficacy for Self-Regulation Predicting Time-Related Academic Behavior

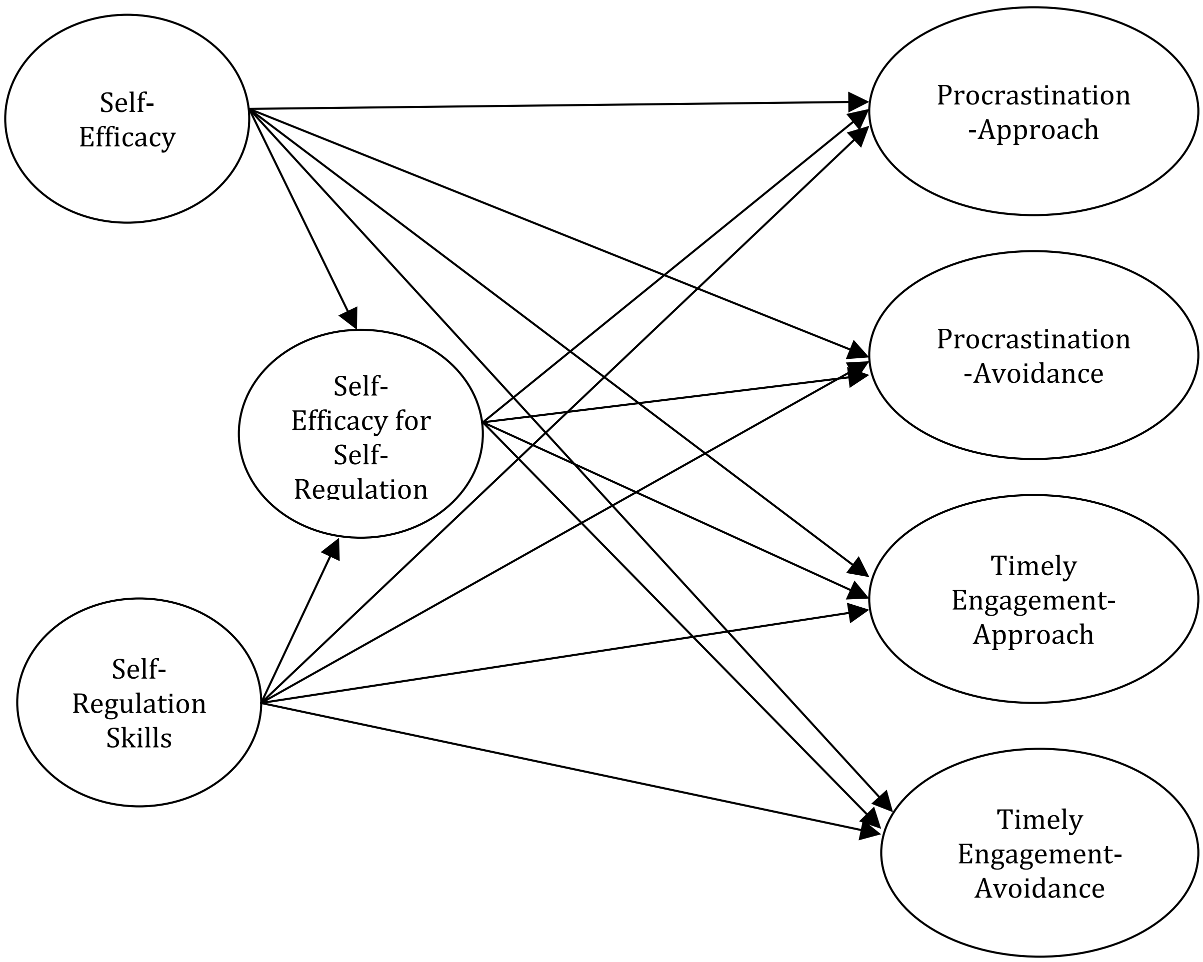
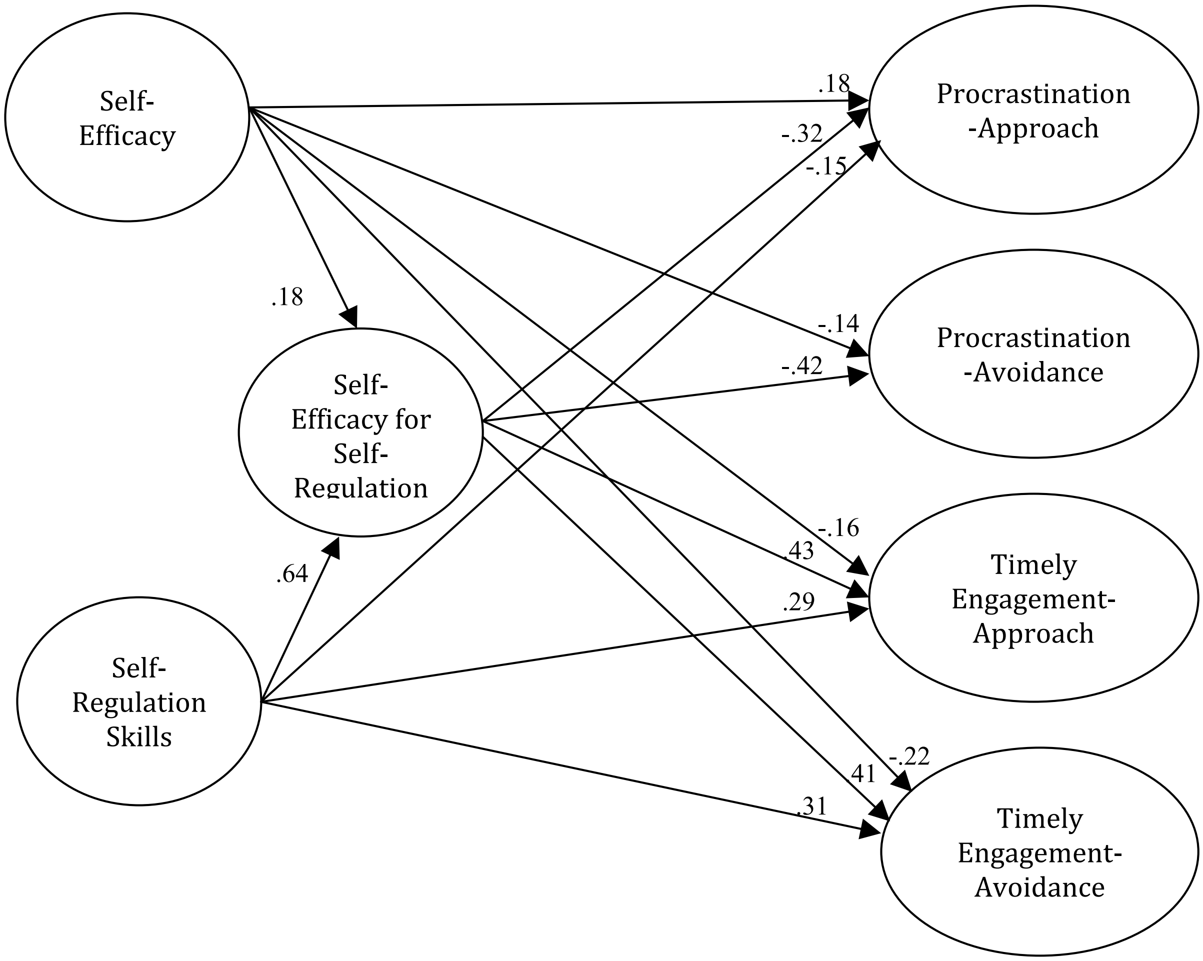


Figure 3

Structural Model of Self-Efficacy, Self-Regulation, and Self-Efficacy for Self-Regulation Predicting Time-Related Academic Behavior



Note. Includes error covariances between items 1 & 2 (.321), 12 & 21 (.551), 14 & 22 (.553), and 3 & 23 (.299) on the 2×2 Measure of Time-Related Academic Behavior, between items 6 & 7 (.591), and 2 & 3 (.281) on the Self-Efficacy for Self-Regulation scale, and between items 2 & 9 (.288), 2 & 5 (.264), and 15 & 16 (.399) on the MSLQ.

Structural Modeling of Achievement Goals on the 2×2 Measure of Time-Related Academic Behavior

Next, the structural relationships of achievement goals in predicting time-related academic behaviors were examined. Strunk, et al. (2012) previously examined these relationships. In their study, they found that procrastination-approach was negatively predicted by mastery-approach goals. Procrastination-avoidance was predicted by performance-approach goals, and negatively predicted by both performance-approach goals and mastery-avoidance goals. Timely engagement-approach was predicted by mastery-approach goals, and negatively predicted by performance-avoidance goals, and timely engagement avoidance was predicted by mastery-approach goals. In the present study, their results were used to guide the hypothesized structural model, but also it seemed reasonable to return to their original hypothesized structural model as a starting point. In their original model, mastery goals predicted timely engagement. This was because timely engagement was thought to be a learning strategy, used to increase learning for personal gain, whereas procrastination might be a performance strategy, with procrastination-approach association more strongly with performance-approach and its desire to be seen favorably in social comparisons, and procrastination-avoidance more strongly associated with performance-avoidance and its desire to avoid negative social comparisons in learning contexts. That original hypothesized model was used because it contained all but one of the paths from their final structural model, and had more potential for theory-building. In that model, mastery goals, in general, predict timely engagement, in general. Performance goals, in general, predict procrastination, in general. Then, avoidance goals predict avoidance-oriented behavior, and approach goals predict avoidance-oriented behavior. The result is the hypothesized structural model found in Figure 4.

Figure 4

Hypothesized Structural Model for Achievement Goals Predicting Time-Related Academic Behavior

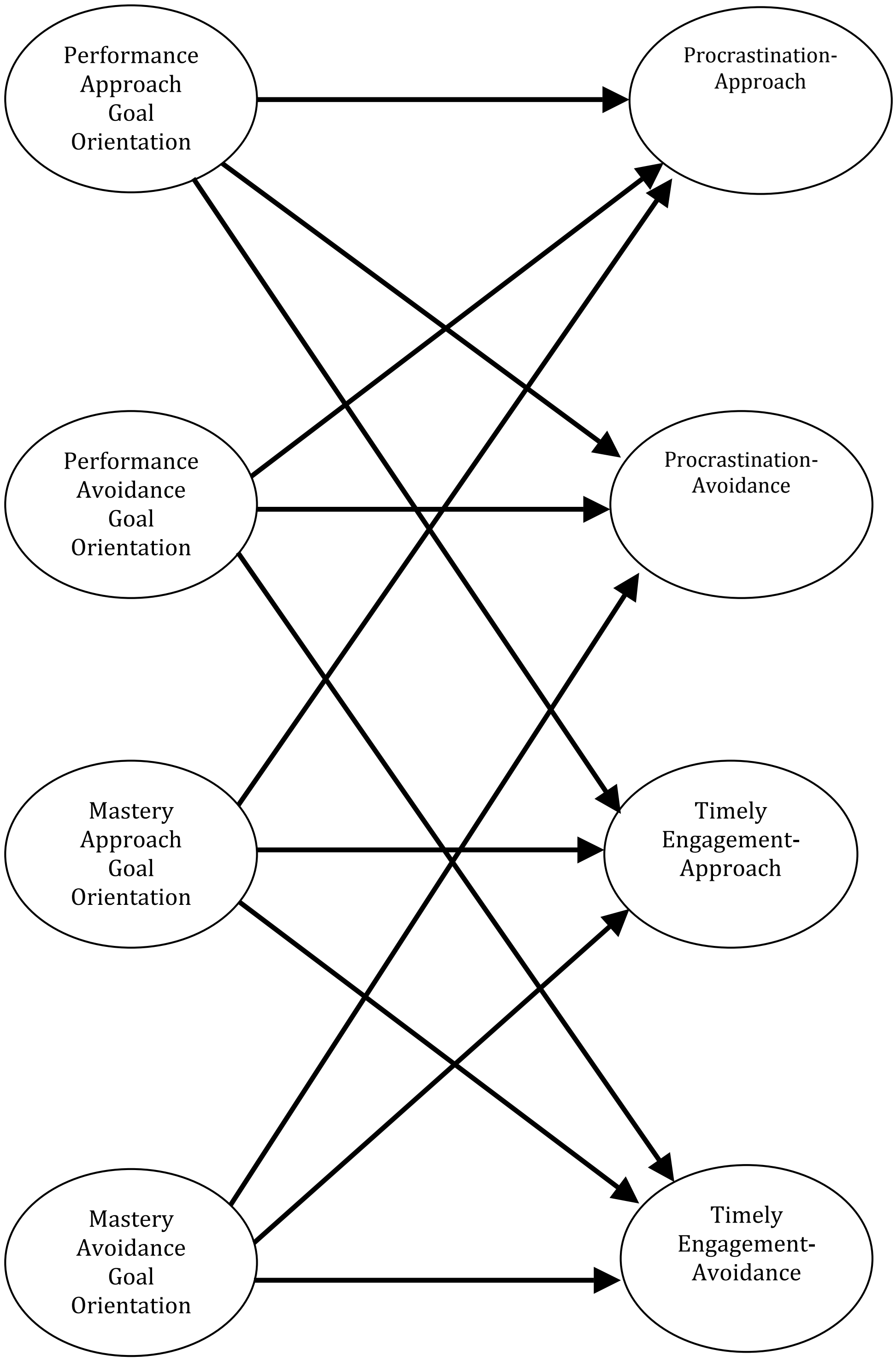
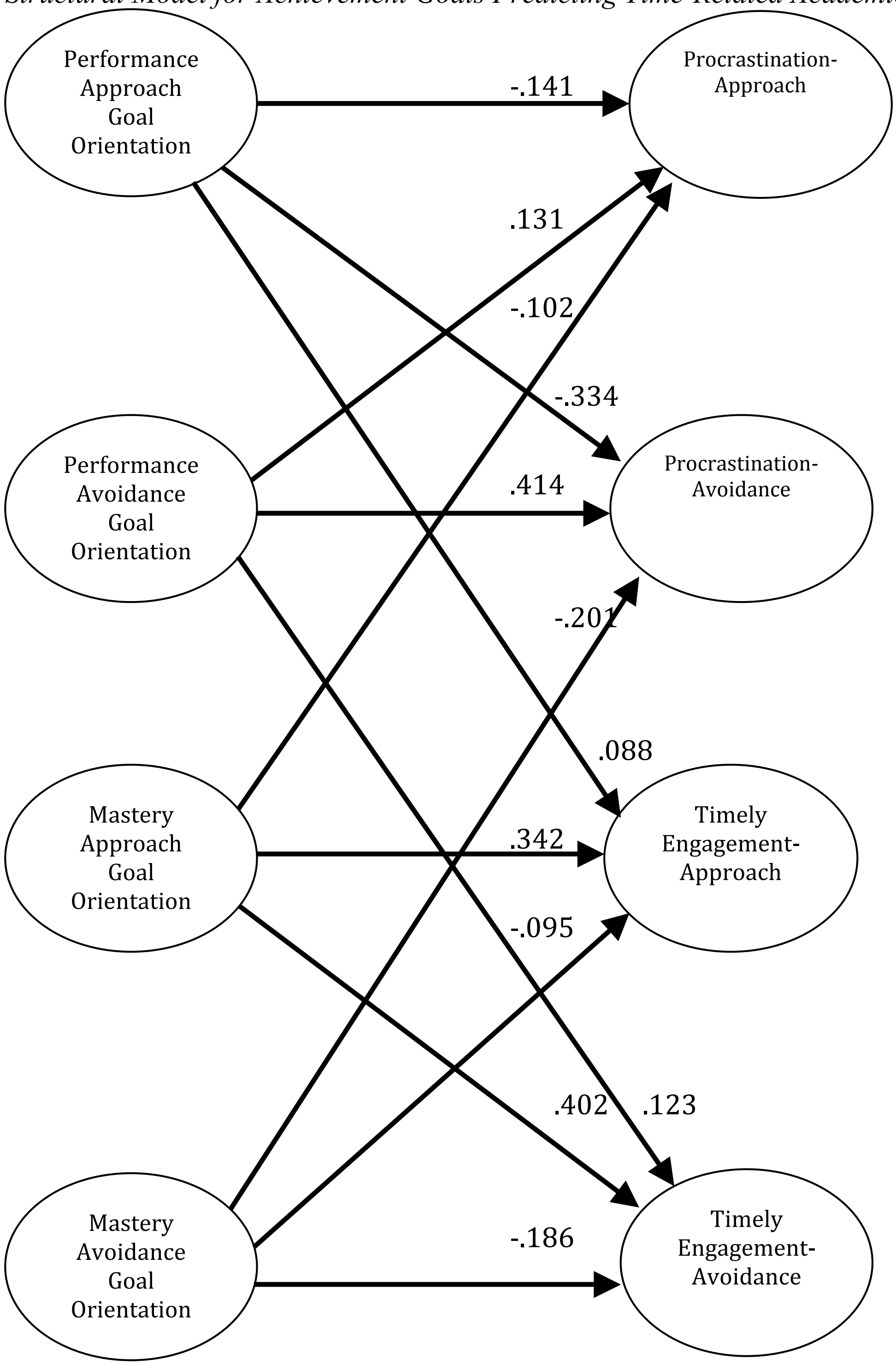


Figure 5

Structural Model for Achievement Goals Predicting Time-Related Academic Behavior



Note. Includes error covariances between items 1 & 2 (.32), 12 & 21 (.59), and 3 & 23 (.31) on the 2×2 Measure of Time-Related Academic Behavior, and between items 5 & 9 (.59) on the AGQ.

The hypothesized model was a good fit to the observed data (χ^2_{601} = 2386.09, χ^2/df = 3.97, CFI = .93, TLI = .92, RMSEA = .05, SRMR = .05). Additionally, the path coefficients were all statistically significant at the $p < .05$ level, and were moderate to large in size with few exceptions. Additionally, modification indices did not indicate any more paths that should be considered for addition to the model, so the hypothesized model was accepted as the final model. The final model with path coefficients can be found in Figure 5. In this model, procrastination-approach is predicted by performance-approach (β = -.14), performance-avoidance (β = .13), and mastery-approach (β = -.10). Procrastination-avoidance is predicted by performance-approach (β = -.33), performance-avoidance (β = .41), and mastery-avoidance (β = -.20). Timely engagement-approach is predicted by mastery-approach (β = .34), mastery-avoidance (β = -.10), and performance-avoidance (β = .08). Finally, timely engagement avoidance is predicted by mastery-approach (β = .40), mastery-avoidance (β = .12), and performance-avoidance (β = .30). For a structural diagram with all path coefficients, see Figure 5.

Structural Modeling of Personality on the 2×2 Measure of Time-Related Academic Behavior

Creating a hypothesized structural model for the Big Five personality variables of Agreeableness, Conscientiousness, Imagination, Neuroticism, and Extraversion was more difficult. Imagination, for example, held no relationship to procrastination in the literature. However, neither did agreeableness or extraversion, yet these variables have been associated with other variables that bear theoretical relationships to timely engagement like empowerment and workplace perseverance (Strunk & Strunk, in press). As a result, the hypothesized structural model was fully specified for extraversion, agreeableness, conscientiousness, and neuroticism in predicting all four ‘types’ of time-related academic behavior. It was expected, for example, that conscientiousness should negatively predict procrastination, but positively predict timely engagement. The opposite relationship was expected for neuroticism, with it being expected to positively predict procrastination and negatively predict timely engagement. What was not known was how this prediction would differentiate by motivational valence within behavior (e.g., how procrastination-avoidance would be predicted differently from procrastination-approach). This hypothesized structural model can be found in Figure 6. As a result, the hypothesized structural model was much more exploratory than the models proposed for other variables. However, SEM was still used because of the goal of building a larger, integrated structural model.

After removing non-significant paths, the model was a good fit to the observed data (χ^2_{914} = 3245.07, χ^2/df = 3.55, CFI = .91, TLI = .90, RMSEA = .05, SRMR = .05). In the final structural model, procrastination-approach was predicted by agreeableness (β = -.08), conscientiousness (β = -.31), and extraversion (β = -.09). Procrastination-avoidance was predicted by conscientiousness (β = -.34), neuroticism (β = .22), and extraversion (β = -.07). Timely engagement-approach was predicted by conscientiousness (β = .45). Finally, timely engagement-avoidance was predicted by conscientiousness (β = .42) and extraversion (β = -.06). It is worth noting in this model that one of the two variables that have been strongly associated with procrastination diverges in its prediction by motivational valence, with neuroticism not significantly predicting procrastination-approach, but having a moderate predictive relationship with procrastination-avoidance. The structural model with path coefficients can be found in Figure 7.

Figure 6

Hypothesized Structural Model for Personality Predicting Time-Related Academic Behavior

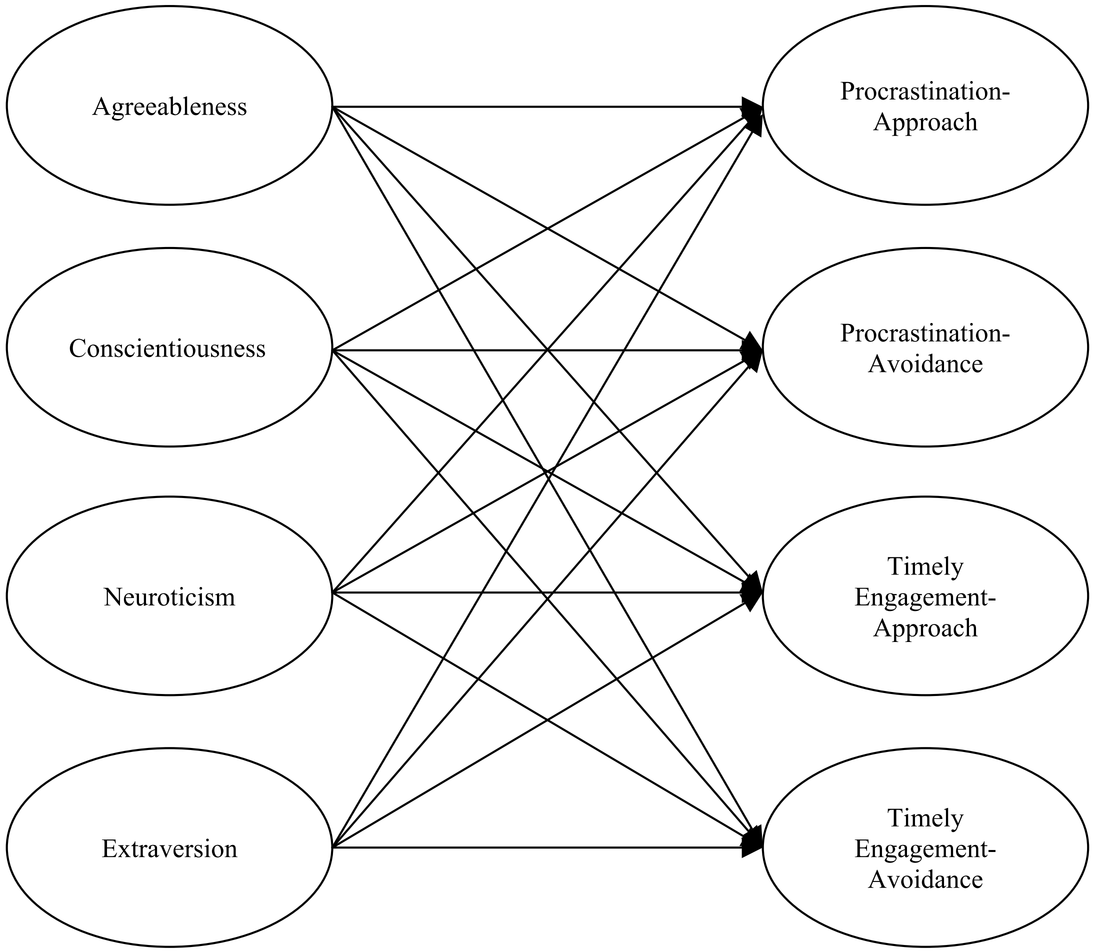
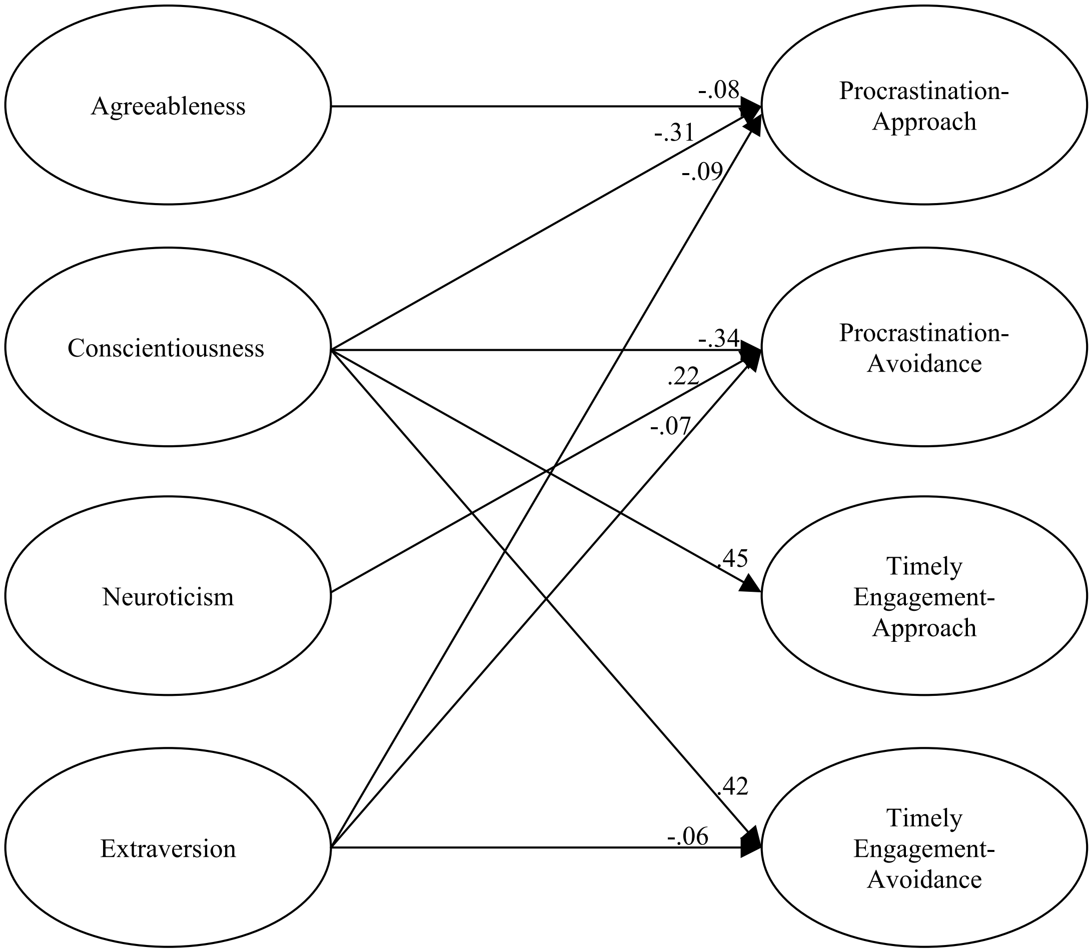


Figure 7

Structural Model for Personality Predicting Time-Related Academic Behavior



Note. Includes error covariances between items 1 & 2 (.32), 12 & 21 (.59), and 3 & 23 (.31) on the 2×2 Measure of Time-Related Academic Behavior, and between 2 & 12 (.53), 10 & 15 (.54), and 1 & 11 (.26) on the mini-IPIP.

Integrated Structural Modeling

Because the sets of variables had been modeled in homogeneous sets, it was necessary to hypothesize and test an integrated structural model based on the SEM results from those homogenous sets of variables and prior literature. In order to create the hypothesized structural model, first it had to be decided which variables would be placed more proximal in prediction to time-related academic behaviors, and which would be hypothesized to function as more distal in their prediction. Personality variables were placed in the most distal position for several reasons. First, this allowed the influence of personality on time-related academic behaviors to be modeled as mediated through motivation variables. This is consistent with the conceptual framework of the 2×2 model of time-related academic behaviors, which challenges the traditional notion that these behaviors naturally or essentially spring out of personality. Further, personality directly predicts things like achievement goals (Bipp, Steinmay, & Spinath, 2008), so mediation through motivation variables is reasonable to hypothesize. Then, although achievement goals directly predict time-related academic behaviors, as demonstrated in prior research (Strunk, Cho, Steele, & Bridges, 2012) and in the present study, the predictive strength is lower than it is for self-efficacy, self-regulation, and self-efficacy for self-regulation. Further, those variables should explain some of the relationship between achievement goals and time-related academic behaviors. That is, the kinds of goals one sets may predict how one uses time-related behaviors to obtain those goals, but that relationship should be mediated by how one perceives one's ability (i.e., self-efficacy for learning), and how well one is able to carry out those goals (i.e., self-regulation for learning), as well as one's perception of one's ability to self-regulate (i.e., self-efficacy for self-regulation). Therefore, in the hypothesized model, personality predicts achievement goals, which in turn predict self-efficacy and self-regulation, which in turn predict time-related academic behavior. In the original hypothesized model, all relationships were fully specified to explore possible cross-relationships, negative predictive relationships, and unexpected relationships. Further, at each level, fully specified predictive relationships were hypothesized between personality and time-related academic behaviors, achievement goals and time-related academic behaviors, and self-efficacy and self-regulation and time-related academic behaviors. Also in the hypothesized model, self-efficacy predicts self-regulation in line with Bandura's (1994) theorizing. This hypothesized model is not visualized in a figure due to the complexity of the hypothesized model.

Non-significant paths were then removed one at a time, starting with the smallest beta-weight, until all paths were statistically significant. The resulting model, although not an extremely good fit to the observed data (χ^2_{3244} = 9259.63, χ^2/df = 2.85, CFI = .88, TLI = .87, RMSEA = .04, SRMR = .06), was considered to be reasonably good in fit because of the relative fit of the measurement models involved in the latent variables. In the final model, procrastination-approach was predicted by agreeableness (β = -.12), conscientiousness (β = -.19), extraversion (β = .10), self-efficacy (β = .19), and self-efficacy for self-regulation (β = -.33). Procrastination avoidance was predicted by conscientiousness (β = -.20), neuroticism (β = .24), self-efficacy (β = -.11), and self-efficacy for self-regulation (β = -.33). Timely engagement-approach was predicted by conscientiousness (β = .22), self-efficacy (β = -.21), self-regulation (β = .30) , self self-efficacy for self-regulation (β = .34). Timely engagement-avoidance was predicted by conscientiousness (β = .20), extraversion (β = -.06), self-efficacy (β = -.27), self-regulation, (β = .30), and self-efficacy for self-regulation (β = .35). Then, self-efficacy for self-regulation was predicted only by self-regulation (β = .80), repeating the earlier result that self-efficacy did not significantly predict self-efficacy for self-regulation. Self-efficacy, in turn, was predicted by mastery avoidance goals ($\beta = .32$), performance approach goals ($\beta = .72$), and performance avoidance goals ($\beta = -.51$). On the other hand, self-regulation was predicted by mastery approach goals ($\beta = .60$), performance approach goals ($\beta = .24$), and performance avoidance goals ($\beta = -.11$). In terms of achievement goals, mastery approach goals were predicted by agreeableness ($\beta = .23$), conscientiousness ($\beta = .31$), imagination ($\beta = .20$), and extraversion ($\beta = -.10$). Mastery avoidance goals were predicted by agreeableness ($\beta = .10$), conscientiousness ($\beta = .12$), imagination ($\beta = .23$), and extraversion ($\beta = -.12$). Performance approach goals were predicted by agreeableness ($\beta = .16$), conscientiousness ($\beta = .28$), imagination ($\beta = .09$), and neuroticism ($\beta = .11$). Finally, performance avoidance goals were predicted by conscientiousness ($\beta = .11$), imagination ($\beta = .11$), and neuroticism ($\beta = .13$). The final structural model with path coefficients can be found in Figure 8.

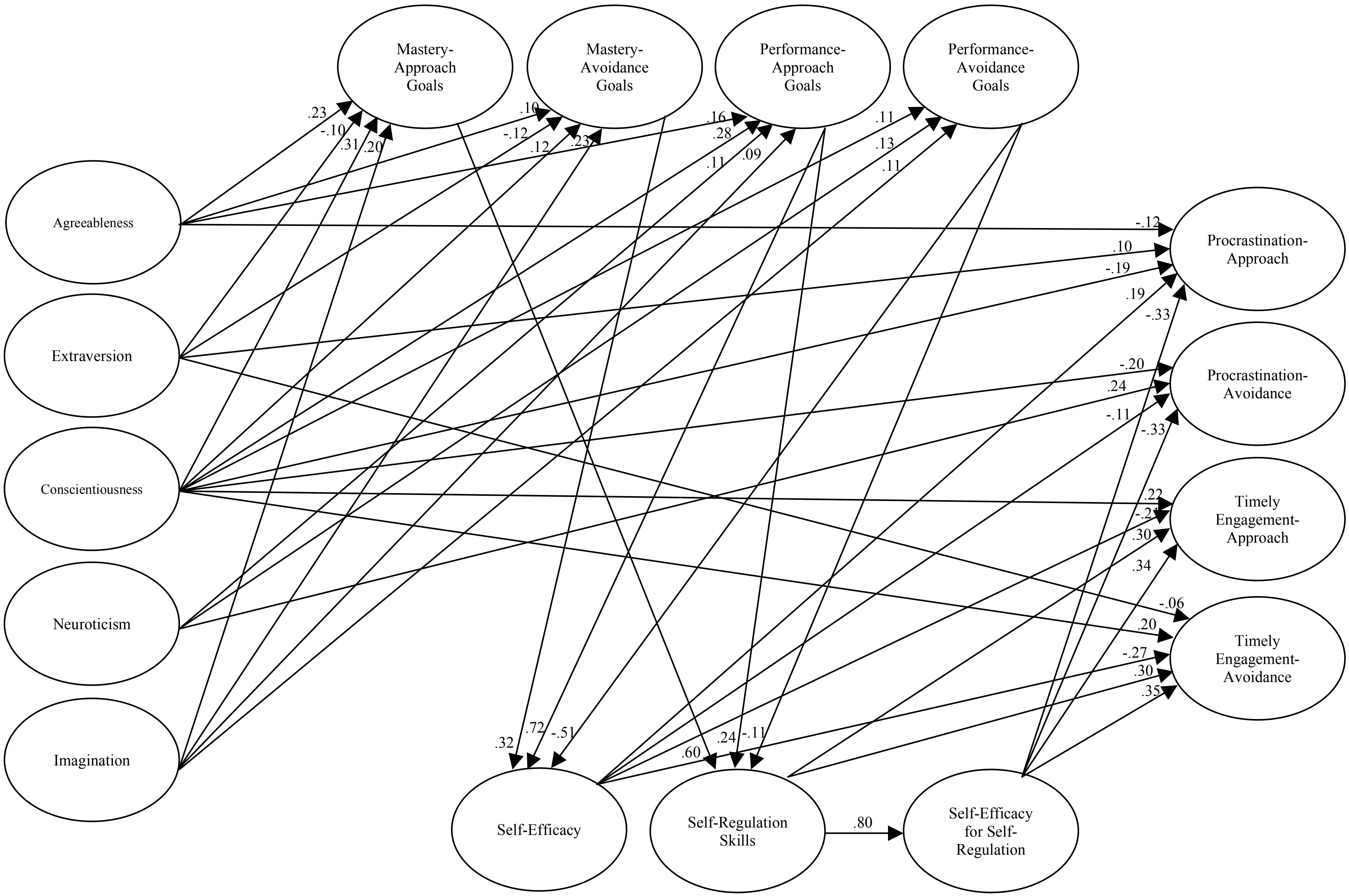
In this model, several indirect predictive relationships are modeled. First, self-regulation has an indirect predictive influence through self-efficacy for self-regulation. Self-regulation has an indirect predictive influence on procrastination-approach ($\beta = -.25$), procrastination-avoidance ($\beta = -.25$), and timely engagement-approach ($\beta = .27$). These relationships are highlighted in Figure 9.

Next, achievement goals have an indirect predictive influence through self-efficacy and self-regulation, as well as the further indirect influence through self-efficacy for self-regulation. These relationships are highlighted in Figure 10. Mastery approach goals indirectly influence procrastination-approach ($\beta = -.16$), procrastination-avoidance ($\beta = -.16$), timely engagement-approach ($\beta = -.13$), and timely engagement-avoidance ($\beta = .18$). Mastery avoidance goals also indirectly influence procrastination-approach ($\beta = .06$), procrastination-avoidance ($\beta = -.03$), timely engagement-approach ($\beta = -.06$), and timely engagement-avoidance ($\beta = -.07$). Then, performance approach goals indirectly influenced procrastination-approach ($\beta = .09$), procrastination-avoidance ($\beta = -.13$), timely engagement-approach ($\beta = -.08$), and timely engagement-avoidance ($\beta = -.12$). Finally, performance avoidance goals indirectly influenced procrastination-approach ($\beta = -.09$), procrastination-avoidance ($\beta = .06$), timely engagement-approach ($\beta = .06$), and timely engagement-avoidance ($\beta = .09$).

Finally, personality has an indirect predictive influence on time-related behavior. This influence is mediated through achievement goals, which is then mediated through self-efficacy, self-regulation, and self-efficacy for self-regulation. This pattern of relationship is highlighted in Figure 11. Agreeableness indirectly influences procrastination-approach ($\beta = -.02$), procrastination-avoidance ($\beta = -.06$), timely engagement-approach ($\beta = .06$), and timely engagement-avoidance ($\beta = .06$). Next, extraversion also has an indirect predictive influence on procrastination-approach ($\beta = .01$), procrastination-avoidance ($\beta = .02$), timely engagement-approach ($\beta = -.03$), and timely engagement-avoidance ($\beta = -.03$). Conscientiousness also has an indirect influence on procrastination-approach ($\beta = -.02$), procrastination-avoidance ($\beta = -.08$), timely engagement-approach ($\beta = .09$), and timely engagement-avoidance ($\beta = .08$). Then, neuroticism indirectly influences procrastination-approach ($\beta = .001$), but does not indirectly influence timely engagement-approach ($\beta < .001$) or timely engagement-avoidance ($\beta < .001$). Finally, imagination has an indirect predictive influence on procrastination-approach ($\beta = -.02$), procrastination-avoidance ($\beta = -.04$), timely engagement-approach ($\beta = .06$), and timely engagement-avoidance ($\beta = .05$). A summary table of total direct and indirect effects can be found in Table 14.

Figure 8

Structural Model for Integrated Model Predicting Time-Related Academic Behavior



Note. Includes error covariances between items 1 & 2 (.55), 12 & 21 (.55), 14 & 22 (.55), and 3 & 23 (.30) on the 2×2 Measure of Time-Related Academic Behavior, items 6 & 7 (.60) and 2 & 3 (.28) on the Self-Efficacy for Self-Regulation scale, items 2 & 9 (.29), 2 & 5 (.27), and items 15 & 16 (.40) on the MSLQ, items 2 & 12 (.53), 10 & 15 (.54), and 1 & 11 (.26) on the mini-IPIP, and items 5 & 9 (.59) on the AGQ.

Figure 9

Integrated Structural Model, Highlighting Indirect Influence of Self-Efficacy and Self-Regulation

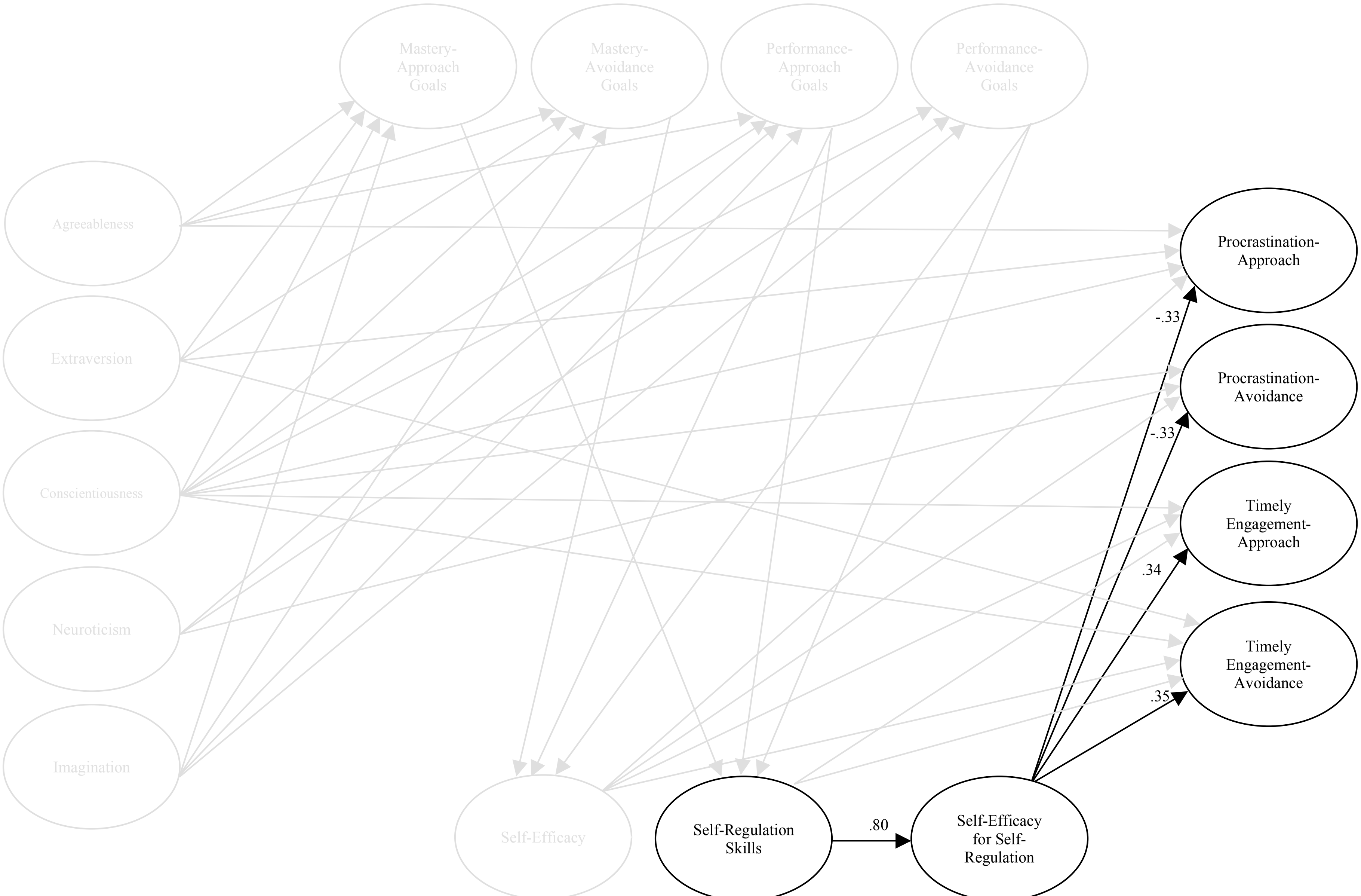


Figure 10

Integrated Structural Model, Highlighting Indirect Influence of Achievement Goals

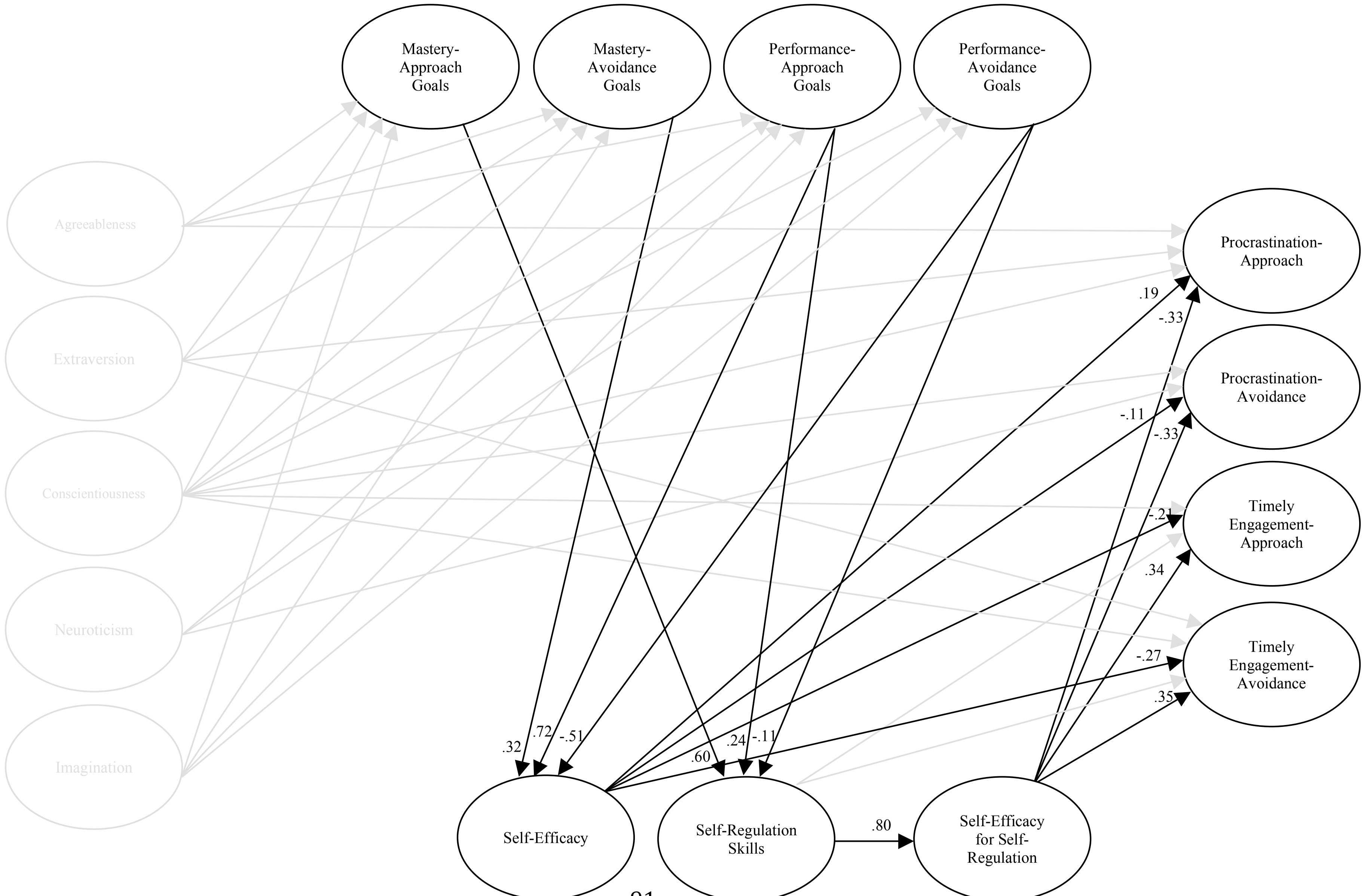


Figure 11

Integrated Structural Model, Highlighting Indirect Influence of Personality

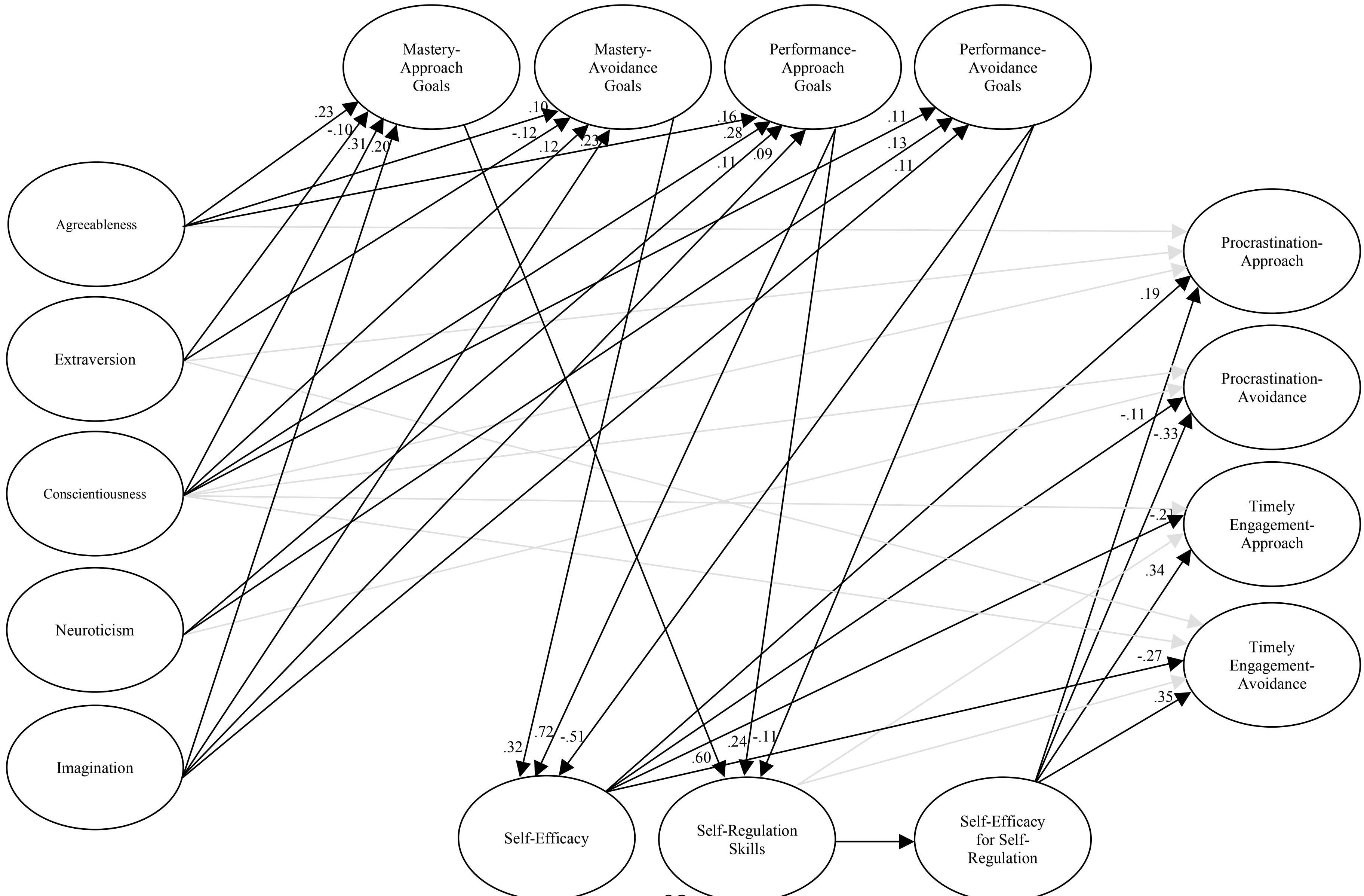


Table 14

Summary of Direct and Indirect Effects for Integrated Structural Model

	Procrastination-Approach			Procrastination-Avoidance			Timely Engagement-Approach			Timely Engagement-Avoidance		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
SESR	-.33		-.33	-.33		-.33	.34		.34	.35		.35
Self-Regulation		-.25	-.25		-.25	-.25	.30	.27	.57	.30		.30
Self-Efficacy	.19		.19	-.11		-.11	-.21		-.32	-.27		-.27
Self-Regulation		.26	.26		.26	.26	.30	.27	.57	.30	.28	.58
Mastery Approach		-.16	-.16		-.16	-.16		-.13	-.13		.18	.18
Mastery Avoidance		.06	.06		-.03	-.03		-.06	-.06		-.07	-.07
Performance Approach		.09	.09		-.13	-.13		-.08	-.08		-.12	-.12
Performance Avoidance		-.09	-.09		.06	.06		.06	.06		.09	.09
Agreeableness	-.12	-.02	-.14		-.06	-.06		.06	.06		.06	.06
Extraversion	.10	.01	.11		.02	.02		-.03	-.03	-.06	-.03	-.09
Conscientiousness	-.19	-.02	-.21	-.20	-.08	-.28	.22	.09	.31	.20	.08	.28
Neuroticism			.00	.24		.24			.00			.00
Imagination		-.02	-.02		-.04	-.04		.06	.06		.05	.05

Note. SESR is Self-Efficacy for Self-Regulation. All coefficients listed are standardized weights.

Path Modeling with Prediction of the 2×2 Measure of Time-Related Academic Behavior across Time

Because only 131 individuals completed both measurement points of the study (that is, completed a second set of surveys approximately 15 weeks later), structural equation modeling of the predictive relationships across time was not a viable option. This would require more specifications in the model than there were participants in the sample. As a result, path modeling was used to model the relationships from time one to time two. The time-related academic behavior measure, the outcome measure in this study, was taken from time two, while all other variables were taken from time one. Then, each of the structural models tested above was retested in a longitudinal path analysis to determine how these relationships changed across time.

Self-Efficacy, Self-Regulation, and Self-Efficacy for Self-Regulation Predicting Time-Related Academic Behavior across Time. The final structural model in Figure 3 was used as the initial hypothesized path model, with the exception that time-related behaviors were measured at time two, which was approximately 15 weeks after time one. This initial model produced multiple paths that were not statistically significant, and were subsequently removed from the final model. As a result, in the final reduced path model, procrastination approach was predicted by self-efficacy for self-regulation (β = -.23), as was procrastination-avoidance (β = -.56), timely engagement-approach (β = .42), and timely engagement-avoidance (β = .30). Self-efficacy for self-regulation was then predicted by self-regulation (β = .57), but not significantly predicted by self-efficacy (β = .13, p = .102). However, as in the SEM model, self-efficacy was left predicting self-efficacy for self-regulation in the model because of its strong theoretical relationship to demonstrate the non-significant relationship. The primary difference in this longitudinal path analysis as compared with the SEM model is that self-efficacy and self-regulation have no significant predictive relationship with any time-related academic behaviors, but only predict them indirectly through self-efficacy for self-regulation. A path diagram with path coefficients can be found in Figure 12.

Achievement Goals Predicting Time-Related Academic Behaviors Across Time. With achievement goals, too, the final SEM model for achievement goals predicting time-related behaviors found in Figure 5 was used as the initial hypothesized path model, with the exception that the time-related behaviors were measured at time two. The results of this path analysis were that no achievement goals predicted any time-related academic behaviors longitudinally. That is, while the SEM analysis showed significant prediction within a single time-point, this prediction does not occur across time, according to the path analysis. The path diagram with coefficients (none of which are significant at the $p < .05$ level) can be found in Figure 13.

Personality Predicting Time-Related Academic Behaviors Across Time. In order to assess the predictive power of personality on time-related academic behaviors across time, the final structural model from Figure 7 was used as an initial hypothesized path model with the exception that time-related academic behaviors were measured at time two. In this initial path analysis, the majority of paths were non-significant. In fact, only conscientiousness and neuroticism were significant predictors across time. Procrastination-approach was predicted by conscientiousness ($\beta = -.25$). Procrastination-avoidance was predicted by both conscientiousness ($\beta = -.26$) and neuroticism ($\beta = .18$). Timely engagement-approach was predicted by conscientiousness ($\beta = .30$), as was timely engagement-avoidance ($\beta = .25$). This path diagram with path coefficients can be found in Figure 14.

Figure 12

Path Model of Self Efficacy, Self-Regulation, and Self-Efficacy for Self-Regulation Predicting Time-Related Academic Behaviors across Time

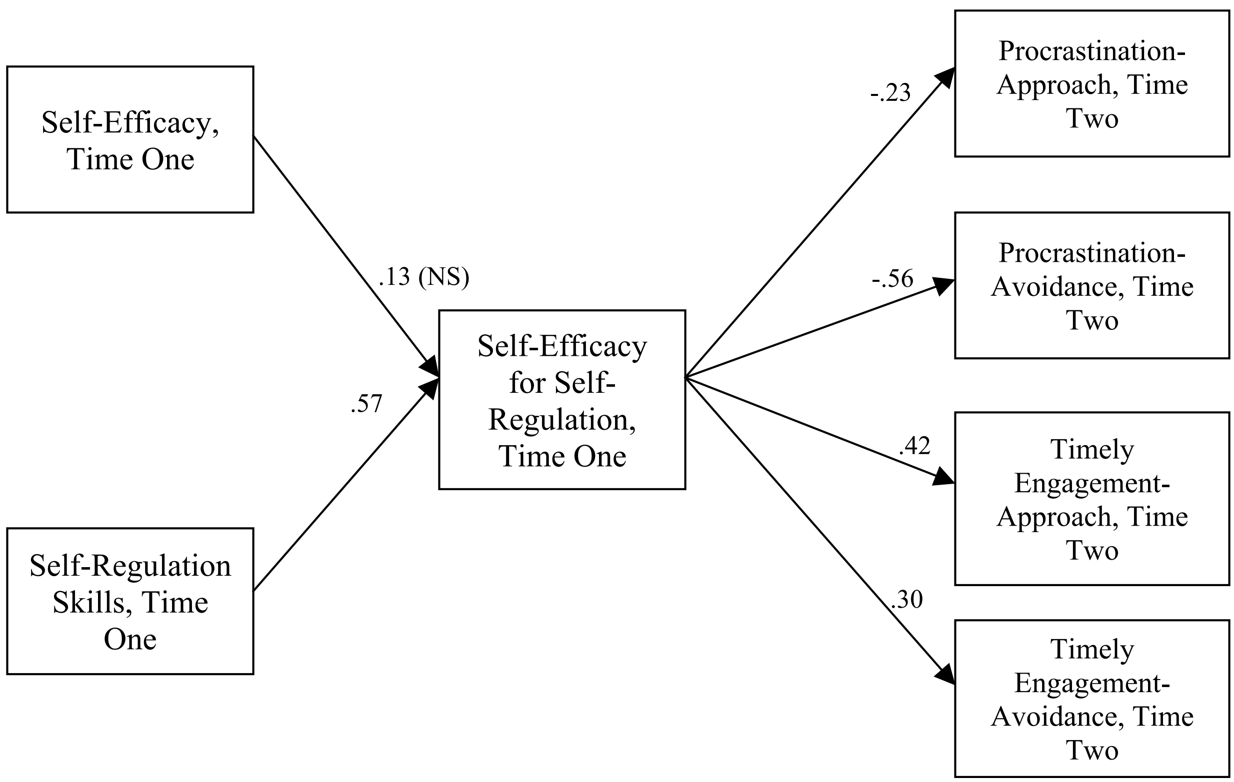
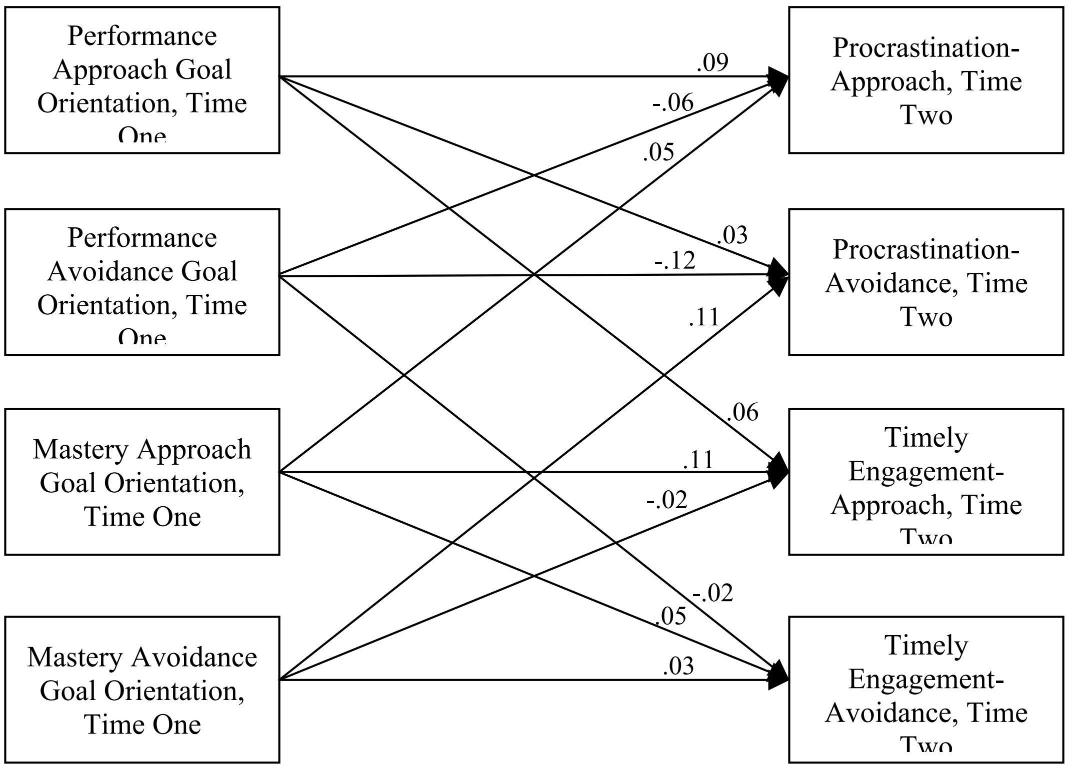


Figure 13

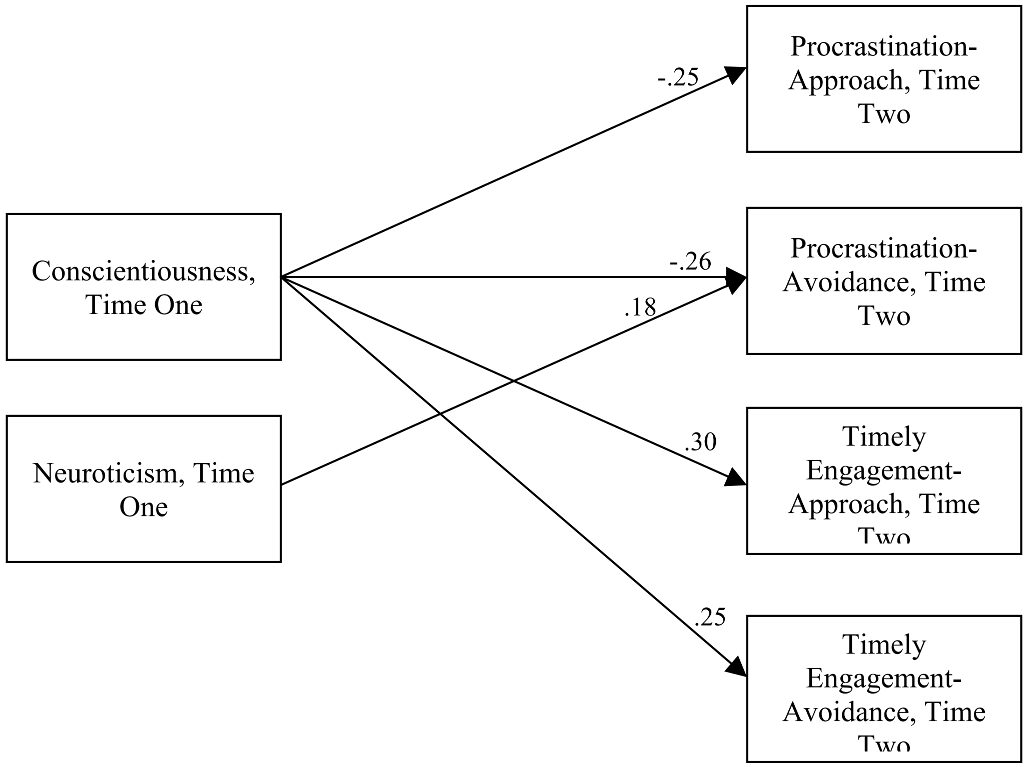
Path Model for Achievement Goals Predicting Time-Related Academic Behaviors across Time



Note. All weights are non-significant at the $p < .05$ level.

Figure 14

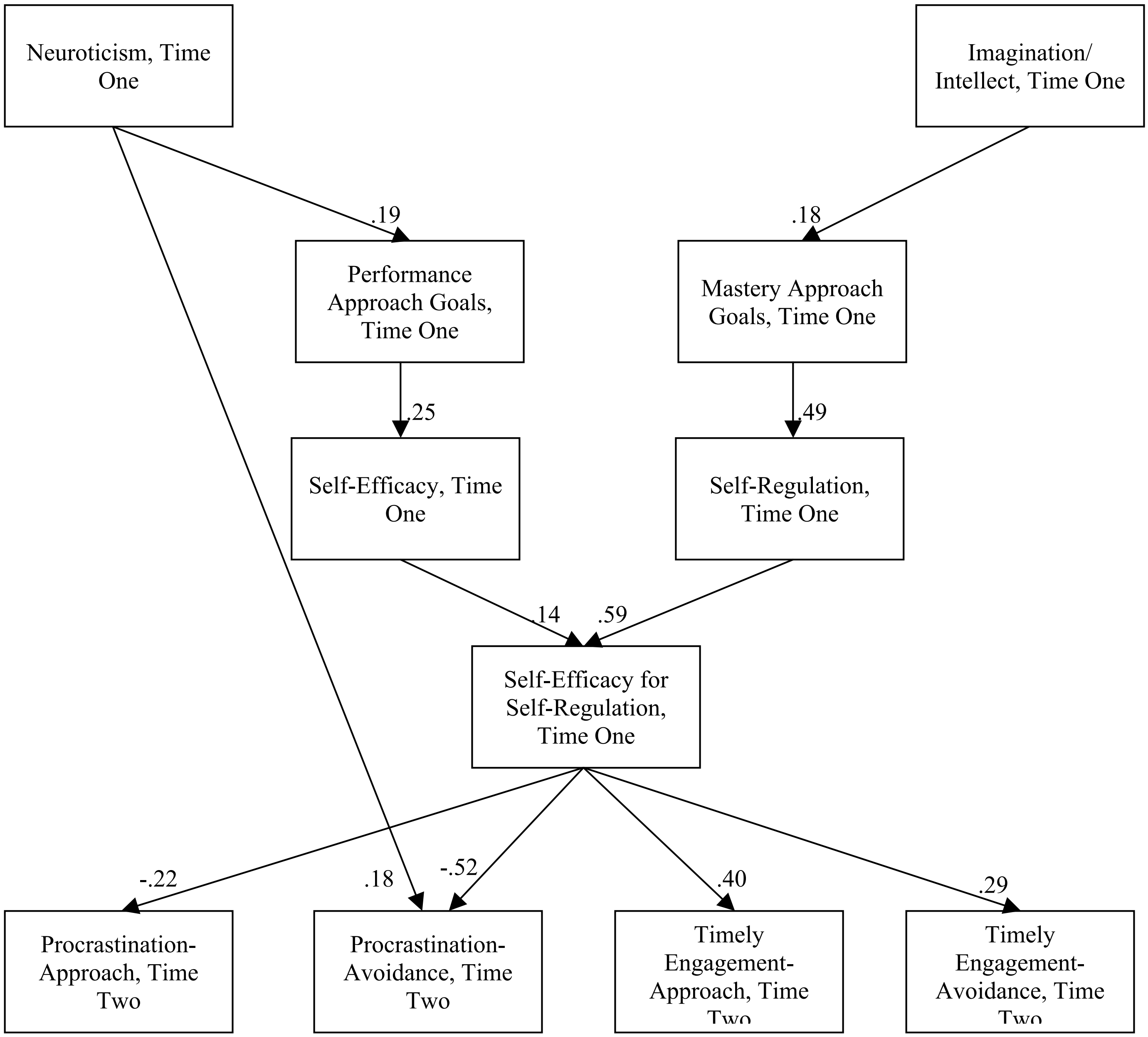
Path Model for Personality Predicting Time-Related Academic Behaviors across Time



Integrated Path Model Predicting Time-Related Academic Behaviors Across Time. Finally, the final integrated SEM model in Figure 8 was used as an initial hypothesized path model with the time-related academic behavior variables measured at time two. In this initial hypothesized path model, the majority of the paths were non-significant. So, the smallest path coefficient (agreeableness predicting mastery approach goals; β = .01) was removed and the model re-evaluated. Because there were many non-significant paths remaining, the smallest remaining path coefficient (imagination/intellect predicting performance avoidance goals; β = -.04) was removed and the model re-evaluated. This process was repeated in a step-wise fashion, resulting in the sequential removal of: extraversion predicting mastery approach goals (β = -.05), conscientiousness predicting performance avoidance (β = .05), performance approach predicting conscientiousness (β = .05), imagination/intellect predicting mastery avoidance goals (β = .06), agreeableness predicting performance approach goals (β = .06), imagination/intellect predicting performance approach goals (β = -.06), conscientiousness predicting mastery avoidance goals (β = -.10), agreeableness predicting mastery avoidance goals (β = .10), conscientiousness predicting procrastination-avoidance (β = .11), conscientiousness predicting mastery approach goals (β = .13), neuroticism predicting performance avoidance goals (β = .14), performance avoidance goals predicting self-efficacy (β = .14), mastery avoidance goals predicting self-efficacy (β = -.10), conscientiousness predicting timely engagement-avoidance (β = .14), conscientiousness predicting timely engagement-avoidance (β = -.01), and finally conscientiousness predicting procrastination-approach (β = -.06).

Figure 15

Path Model for Integrated Model Predicting Time Related Academic Behavior



As a result of this reduction, in the final model procrastination-approach is predicted by self-efficacy for self-regulation ($\beta = -.22$), procrastination-avoidance is predicted by neuroticism ($\beta = .18$) and self-efficacy for self-regulation ($\beta = -.52$), while timely engagement-approach ($\beta = .40$) and timely-engagement-avoidance ($\beta = .29$) are predicted by self-efficacy for self-regulation. Then, self-efficacy for self-regulation is predicted by both self-efficacy ($\beta = .14$) and self-regulation ($\beta = .59$). Self-efficacy is predicted by performance approach goals ($\beta = .25$) while self-regulation is predicted by mastery approach goals ($\beta = .49$). Finally, mastery approach goals are predicted by imagination/intellect ($\beta = .18$) while performance approach goals are predicted by neuroticism ($\beta = .19$). A path diagram with path coefficients can be found in Figure 15.

Person-Centered Analysis

Cluster analysis was selected to understand how participants grouped around sets of variables, and how those patterns of grouping could be meaningful in providing a picture of patterns of student interaction with motivation variables as well as time-related academic behavior. Participants were grouped into various clusters, ranging from two to ten, based on squared Euclidian distance using Ward's method. This analysis was conducted using the fours time-related academic behaviors, self-efficacy, self-regulation, and self-efficacy for self-regulation as the clustering variables. These variables were selected because in the integrated structural model, they were most proximal to time-related academic behaviors, which are the variables of most interest, and because they had relatively strong prediction on those behaviors. Then, three methods were used to assess which number of clusters to accept as the final solution. The clustering variables were entered into a MANOVA with the various groups, or clusters, as the independent variable. The solutions were assessed first by graphing the relative decrease in

R^2 and increase in mean square error as the number of groups was decreased to assess for a visual breakpoint in explained variance (Lathrop & Williams, 1987; Lathrop & Williams, 1989; Lathrop & Williams, 1990). Then, the change mean square error was graphed to assess for a visual breakpoint in the increase in total error in the system as a function of decreasing the number of groups. The graph for R^2 can be found in Figure 16, and for mean square error can be found in Figure 17. Based on these analyses, it was clear that either five or four clusters should be retained as the final solution. The final step in determining how many clusters to retain was to assess the theoretical meaningfulness of the clusters by assessing the differences among the five clusters, and then the four clusters, on the clustering variables. From this comparison, it was determined that the separation points in the four clusters were more interpretable and theoretically meaningful, thus making the relative difference in R^2 and MSE tolerable.

Using a multivariate analysis of variance (MANOVA) to control for Type I error rate, the clusters were analyzed for overall differences on the clustering variables (time related academic behavior, self-efficacy, self-regulation, and self-efficacy for self-regulation). There was a significant overall difference, as expected (Wilks' $\Lambda_{21,3187} = .12$, $p < .001$, $R^2 = .88$). These differences were then assessed at the univariate level using F tests. All clustering variables significantly differed across clusters, including procrastination-approach ($F_{3,1116} = 400.55$, $p < .001$, $\omega^2 = .52$), procrastination-avoidance ($F_{3,1116} = 236.42$, $p < .001$, $\omega^2 = .39$), timely engagement-approach ($F_{3,1116} = 826.26$, $p < .001$, $\omega^2 = .69$), timely engagement-avoidance ($F_{3,1116} = 1067.95$, $p < .001$, $\omega^2 = .74$), self-efficacy ($F_{3,1116} = 78.64$, $p < .001$, $\omega^2 = .17$), self-regulation ($F_{3,1116} = 112.64$, $p < .001$, $\omega^2 = .23$), and self-efficacy for self-regulation ($F_{3,1116} = 149.92$, $p < .001$, $\omega^2 = .29$). These univariate differences were then explored using Scheffe post-hoc analyses. For procrastination-approach, all clusters were significantly different from all other clusters ($p < .001$), except that cluster two and three were not significantly different ($p = .93$). For procrastination-avoidance, all clusters were significantly different from all other clusters ($p < .001$). For timely engagement-approach, all clusters were significantly different from all other clusters ($p < .001$), except for clusters two and three, which were not significantly different ($p = .24$). This was also true for timely engagement-avoidance, where clusters two and three were not significantly different from one another ($p = .46$), but all other clusters were significantly different from one another ($p < .001$). On self-efficacy, all clusters significantly differed from one another ($p < .001$) except for clusters two and four, which were not significantly different ($p = .15$). For self-regulation, all clusters were significantly different from one another ($p < .001$), with the exception that clusters three and four were not significantly different ($p = .68$). Finally, on self-efficacy for self-regulation, clusters three and four were not significantly different ($p = .81$) but all other clusters were significantly different from all other clusters ($p < .001$).

Next, the analysis was expanded to include other variables not used for clustering, but of analytic interest. The four achievement goals (mastery approach, mastery avoidance, performance approach, performance avoidance) were analyzed in a MANOVA to determine how they differed among the four clusters. The clusters significantly differed on achievement goals (Wilks' $\Lambda_{12,2945} = .85$, $p = .05$, $R^2 = .15$). Follow-up univariate F tests revealed that only mastery approach ($F_{3,1116} = 58.54$, $p < .001$, $\omega^2 = .11$) and performance approach ($F_{3,1116} = 42.79$, $p < .001$, $\omega^2 = .08$) goals significantly differed among the clusters. Neither mastery avoidance ($F_{3,1116} = 3.71$, $p = .14$, $\omega^2 < .001$) nor performance avoidance ($F_{3,1116} = 4.89$, $p = .07$, $\omega^2 < .001$) goals significantly differed among the clusters. Next Scheffe post-hoc tests were used to assess differences between clusters on the variables. For mastery approach goals, clusters three and four were not significantly different ($p = .88$), while all other clusters were significantly different from one another ($p < .001$). For performance approach goals, clusters two and four were not significantly different ($p = .12$), while all others were significantly different from one another (p's range from < .001 to .04).

The clusters also significantly differed on self-handicapping ($F_{3,1116} = 74.01$, $p < .001$, $\omega^2 = .16$). Scheffe post-hoc tests revealed that clusters three and four were not significantly different ($p = .99$), while all others were significantly different from one other ($p < .001$). A graph depicting the relative position of the four clusters on the variables on which they were significantly different can be found in Figure 18. The means and standard deviations on each measure by cluster can be found in Table 15.

Figure 16

Graph of R^2 by Number of Clusters for Cluster Analysis

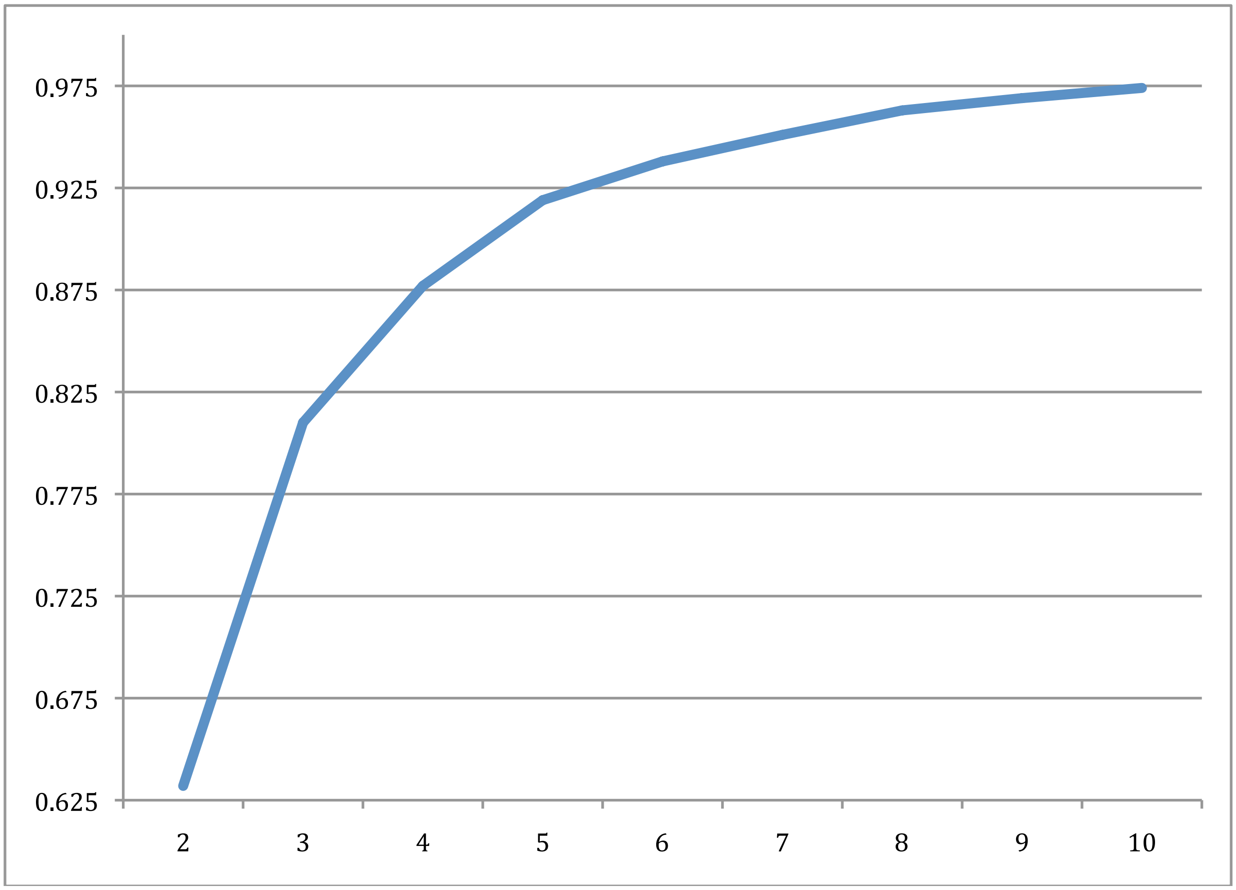


Figure 17

Graph of Mean Square Error by Number of Clusters for Cluster Analysis

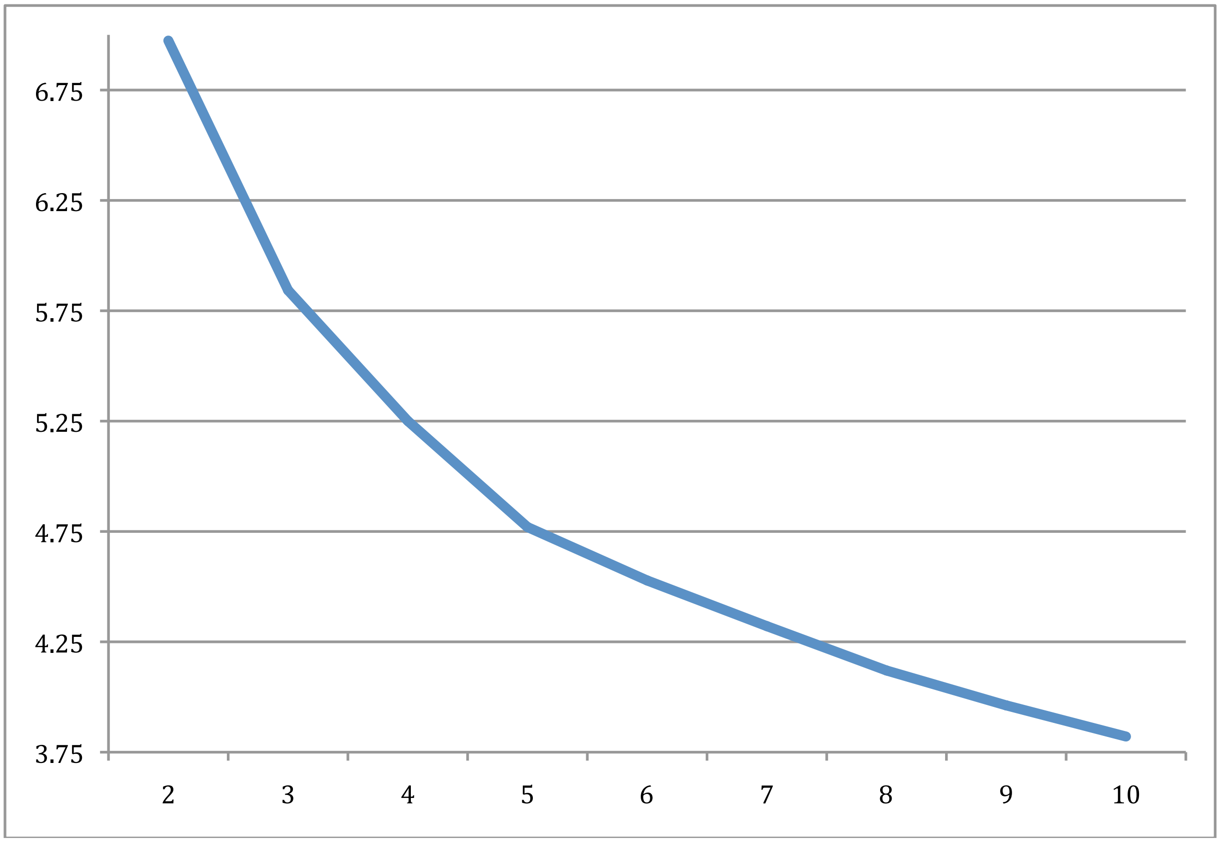


Figure 18

Means on Measures by Clusters

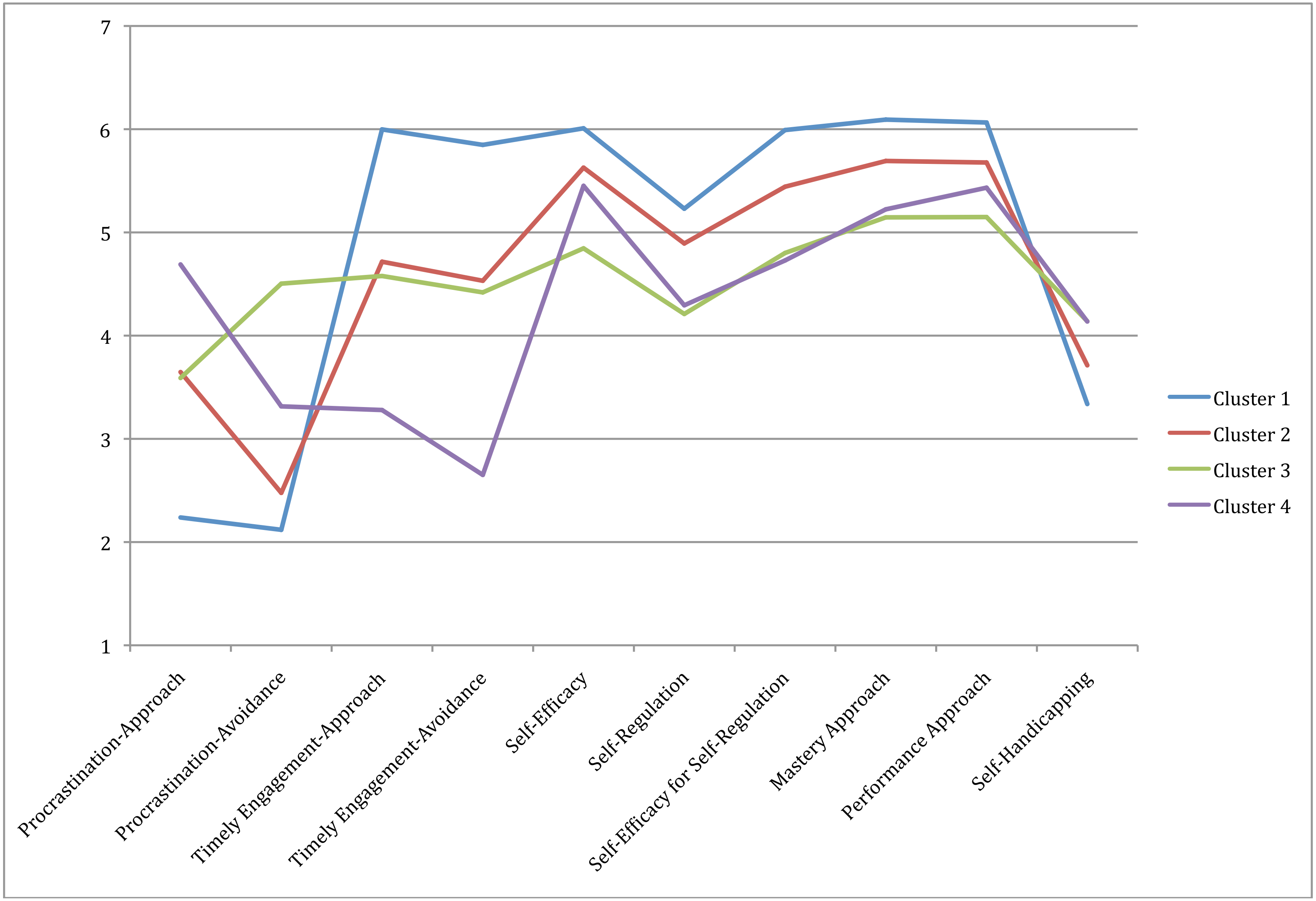


Table 15

Means (and Standard Deviations) for Measures by Clusters

	Timely Engagement	Mixed Strategies	'Classic' Procrastinator	'Active' Procrastination
Procrastination-Approach	2.24 (0.76)	3.65 (0.78)	3.59 (0.97)	4.69 (1.10)
Procrastination-Avoidance	2.12 (0.97)	2.48 (0.74)	4.50 (0.93)	3.31 (1.47)
Timely Engagement-Approach	6.00 (0.62)	4.72 (0.64)	4.58 (0.80)	3.28 (0.77)
Timely Engagement-Avoidance	5.85 (0.71)	4.53 (0.62)	4.42 (0.77)	2.65 (0.81)
Self-Efficacy	6.01 (0.74)	5.63 (0.72)	4.85 (1.05)	5.45 (1.00)
Self-Regulation	5.23 (0.84)	4.89 (0.63)	4.21 (0.70)	4.29 (0.89)
Self-Efficacy for Self-Regulation	5.99 (0.68)	5.44 (0.69)	4.80 (0.87)	4.73 (1.07)
Mastery Approach	6.09 (1.01)	5.69 (0.95)	5.15 (1.18)	5.22 (1.21)
Mastery Avoidance	4.59 (1.62)	4.49 (1.47)	4.64 (1.30)	4.38 (1.27)
Performance Approach	6.06 (0.99)	5.68 (1.00)	5.15 (1.23)	5.43 (1.35)
Performance Avoidance	5.34 (1.48)	5.10 (1.48)	5.04 (1.32)	5.16 (1.41)
Self-Handicapping	3.34 (0.81)	3.71 (0.74)	4.14 (0.69)	4.14 (0.85)

Next, the relative differences among the clusters were interpreted for their substantive and theoretical meaning. Cluster one demonstrated very low procrastination-approach and procrastination-avoidance scores, but very high timely engagement-approach and timely engagement-avoidance scores. They were also the highest group in self-efficacy, self-regulation, self-efficacy for self-regulation, mastery approach goals, and mastery avoidance goals, while being lowest in self-handicapping. This is an interesting pattern within-group because they have what may prove to be a typical timely engagement profile: that of the person who is motivated both by mastery of content and of performance relative to peers, who is high in self-efficacy beliefs about learning and self-regulation strategies, as well as actual implementation of self-regulation strategies. Moving to cluster two, a different profile emerges. Here there is a moderate mean score on procrastination-approach, low scores on procrastination-avoidance, and then moderately high on both timely engagement scales. This is paired with relatively high self-efficacy, moderately high self-regulation and high self-efficacy for self-regulation, and the second highest score of all clusters on performance approach and mastery approach goals, with very low scores on self-handicapping (though significantly higher than cluster one). This may be a demonstration of what was theorized by Strunk, et al. (2012) regarding the mixed use of procrastination and timely engagement as performance strategy with procrastination-approach being used on occasion, but timely engagement strategies being used on other occasions to enhance academic performances, though more work is needed to confirm that hypothesis. Cluster three scores moderately on procrastination-approach, moderately high on procrastination-avoidance and both timely engagement, and is then the lowest-scoring cluster on self-efficacy and self-regulation, as well as performance approach goals, while scoring higher than clusters one or two on self-handicapping. This group may be the closest observed in this sample to the classic 'procrastinator' theorized in the traditional model. However, it is interesting to note that while this cluster does score highest on procrastination-avoidance, they have mixed motivations, because they also score moderately high on the timely-engagement scales. However, the idea of low self-efficacy and self-regulation, as well as high self-handicapping being paired with high procrastination tendency appears to have occurred in this cluster. Finally, in cluster four is high procrastination-approach, and relatively lower procrastination-avoidance and timely engagement. In this cluster, too, there is a relatively high score in self-efficacy, though it is lower than in clusters one (but higher than cluster 4), but relatively low self-regulation (not significantly different, in fact, from cluster three). Self-efficacy for self-regulation is significantly lower, too than in clusters one or two, as are mastery-approach and mastery-avoidance goals, and self-handicapping is significantly higher. This profile of scores is in line with the research on what has been called active procrastination (Choi & Moran, 2009; Chu & Choi, 2005) with the exception of the lower performance goals relative to other clusters. However, the relatively high self-efficacy paired with high self-handicapping is also an interesting finding that warrants further investigation.

CHAPTER V

DISCUSSION

The present study had several research questions. First were research questions regarding the measurement properties of the 2×2 Measure of Time-Related Academic Behavior. Additionally, measurement modeling had to be conducted for other key measures including the self-efficacy and self-regulation subscales of the Motivated Strategies for Learning Questionnaire, the measure of self-efficacy for self-regulation, the mini-International Personality Item Pool questionnaire, and the Achievement Goal Questionnaire. In each of these cases, confirmatory factor analyses were fitted, modified, and refitted to determine the adequacy of the measurement model. Additionally, the reliability of each of these measures was assessed through several means, including Cronbach's alpha, congeneric reliability, and test-retest reliability. In this way, each key measure was subjected to a relatively intensive study of measurement adequacy.

The next set of research questions was how personality, self-efficacy, self-regulation, self-efficacy for self-regulation, and achievement goals would predict time-related academic behaviors. This was assessed using structural equation modeling with latent variables. Each set of variables was modeled separately, and then in an integrated structural model. Again each model was fitted, modified, and refitted, producing models in each case with relatively good fit.

The next set of research questions was how the predictive relationships explored with structural equation modeling would behave across time. That is, how the key measures at one time point would contribute to predicting time-related academic behaviors at a later time point.

This was explored by testing the same models produced in the structural equation models but with path modeling, with time-related academic behavior measured approximately 15 weeks later.

A final research question dealt with how participants would group around the variables and what meaning those groups would have for the various key measures. This was explored with cluster analysis. Each cluster was then compared for points of significant difference from the other clusters on the key measures, revealing patterns of difference with theoretical significance.

Summary of Key Findings

The study has key findings in several areas. These include the measurement analyses, both for the 2×2 Measure of Time Related Academic Behavior, which is a critical aspect of the present study, as well as for the other key measures. There are also structural models, including the models with latent variables (or SEM models) and the longitudinal path models testing those models' performance across time (models with observed variables). Finally, there are findings from the person-centered analysis, which in this case was cluster analysis.

Measurement Analyses

Measurement analyses for all key measures included testing the basic measurement model. However, also of interest was the reliability of the measure. This was assessed both in the traditional Cronbach's alpha (essentially tau equivalent) model, as well as the congeneric model, to determine how the measure performs under traditional measurement models, as well as within the SEM measurement model, which is used for many of the analyses. Finally, test-retest reliability was of interest because of the longitudinal prediction models tested.

2×2 Measure of Time-Related Academic Behavior. The 2×2 Measure of Time Related Academic Behavior was subjected to a series of measurement analyses, beginning with confirmatory factor analysis. First, the initial hypothesized structure was tested, and approached good fit, but was modified to include error covariances, which improved the fit of the model to the observed data. This final model was a good fit to the data. The final model was also compared with potentially competing models to determine if it offered an empirical advantage to a model with only procrastination/timely engagement, only approach/avoidance, or models with three latent factors (one with procrastination-approach, procrastination-avoidance, and generalized timely engagement; one with generalized procrastination, timely engagement-approach, and timely engagement-avoidance). In all cases, the 2×2 model was the best fit. This demonstrates that the 2×2 model offers an empirical advantage over other potentially competing models in terms of model fit. It also shows that it is necessary, in terms of model fit, to differentiate between both the behavior (procrastination/timely engagement) and motivational valence (approach/avoidance), and to do so for both behaviors, in order to achieve the best fit to the observed data.

The model was then subjected to structural invariance studies on two categories: gender and college classification. Previous research had demonstrated that men and women tended to differ on generalized procrastination measures (Brownlow & Reasinger, 2000; Flett, Blankstein, Hewitt, & Koledin, 1992; Meyer, 2000; Prohaska, Morrill, Atiles, & Perez, 2000; Ozer, Demir, & Ferrari, 2009; Senecal, Koestner, & Vallerand, 1995) and across time in school (Moon & Illingworth, 2004) making these logical selections for invariance studies. In both cases, the models were determined to be invariant. This meant that the measurement model did not differ between men and women, nor by college classification, so the same model could be used between groups.

Finally, the reliability of the instrument was subjected to analysis using three methods. First, the Cronbach's alpha reliability for all four subscales was calculated, with all four showing good reliability. The congeneric reliabilities from the SEM measurement model were also calculated, and were also good. Additionally, there was less than .01 difference between the two forms of reliability on all four subscales, suggesting the amount of error introduced in the unit-weighted scores used to calculate alpha is very low. This suggests the unit-weighted scores approach the reliability of the latent variables, which is important for the path analytic approach used in some subsequent analyses. Finally, the test-retest reliability of the instrument was quite high, suggesting that the measure maintains stability across measurements within-person.

Other Key Measures. The present study also used two subscales of the MSLQ, the mini-IPIP, the AGQ, and a measure of self-efficacy for self-regulation. All of these scales were also assessed for their measurement properties. In all cases, the CFA required modification due to error covariances, but in all cases, the measurement models approached good fit after refitting. Additionally, all subscales showed moderate or better reliabilities in both Cronbach's alpha and the congeneric model. A notable exception is the AGQ, in which mastery-avoidance showed much lower reliability in the congeneric model. This is unusual because typically reliabilities are the same or higher in the congeneric model, which suggests a problem with dimensionality in the AGQ. This is perhaps not surprising, however, because the issue of mastery-avoidance has been much discussed by theorists in this area, particularly in the way it is measured in the AGQ (Elliot, 2005). Further research is needed regarding the dimensionality, stability, and structure of the AGQ. It is further worth noting that the lowest test-retest reliability for any scale from any measure in the present study was for mastery-avoidance. A summary table of all reliability coefficients can be found in Table 13. Despite the measurement issues found in the AGQ, structural equation modeling proceeded with the model as refitted based on a desire to reflect the constructs represented in the literature, which have typically been measured by the AGQ.

Structural Modeling

Structural models included both the simultaneous SEM models with latent variables, as well as the longitudinal path models with observed variables. The SEM models are reported first as they were conducted to determine the nature of the relationship when measured simultaneously. This was then applied to the longitudinal path models to determine if these same predictive relationships would be found across time.

Self-Efficacy, Self-Regulation, and Self-Efficacy for Self-Regulation. The basic pattern of prediction was found as predicted self-efficacy for self-regulation. It negatively predicted procrastination-approach and procrastination-avoidance, while positively predicting timely engagement-approach and timely engagement-avoidance. This was in line with prior research that suggested a strong role of self-efficacy for self-regulation in predicting procrastination in general (Klassen, Ang, Chong, Krawchuck, Huan, Wong, & Yeo; Klassen & Kuzucu, 2009). It is also theoretically consistent that those with a higher belief in their ability to self-regulate will be less likely to procrastinate, in general, and more likely to engage in tasks in a timely manner, in general. Self-efficacy also significantly predicted all four 'types' of time-related academic behavior. In prior research, self-efficacy has been associated with lower levels of procrastination (Seo, 2008; Steel, 2007; van Eerde, 2003). However, in the present study, it is only directly associated with lower levels of procrastination-avoidance. That is, those with higher self-efficacy are less likely to procrastinate due to avoidance motivations. However, those with higher self-efficacy are *more* likely to procrastinate due to approach motivation. This is noteworthy as it highlights the need for the valence distinction in the construct. Interestingly, higher self-efficacy also predicted lower timely engagement-approach and timely engagement-avoidance. One possible explanation for this pattern could be that as self-efficacy for learning increases, the feeling that one *can* procrastinate and still achieve positive results (i.e., procrastination-approach) is more likely to occur, whereas with lower self-efficacy for learning, one might feel compelled to engage in a timely manner in order to learn at all, or to avoid negative outcomes. This result is somewhat consistent with Chu and Choi's (2005) findings in the area of active versus passive procrastination, wherein they found passive procrastination was associated with lower self-efficacy, but active procrastination with higher self-efficacy. For self-regulation, the results were largely as expected. Higher self-regulation predicted higher timely-engagement in both motivations. However, self-regulation did not directly predict procrastination-avoidance. This is noteworthy, as in previous research there has been a consistent association between self-regulation and generalized procrastination (Brownlow & Reasinger, 2000; Ferrari, 2001; Milgram, Dangour, & Raviv, 2001). This highlights again the need for differentiating the construct by motivational valence, because self-regulation did directly predict procrastination-approach, implying much of the association may be that those higher in self-regulatory skills are less likely to use procrastination as a performance strategy due to their repertoire of other available regulatory strategies. Also consistent with previous research, self-efficacy and self-regulation had an indirect influence (or were partially mediated by) self-efficacy for self-regulation (Klassen, Krawchuck, & Rajani, 2008; Strunk & Steele, 2011).

Achievement Goals. Achievement goals predicted time-related academic behavior in predicted manner, with no modifications to the model or removal of non-significant paths needed. Additionally, these results were largely in line with Strunk, et al. (2012) in which the four 'types' of time-related academic behaviors were predicted by the four achievement goals. The exception is that some paths were significant in the present study that did not rise to the level of statistical significance in their study. However, it is worth noting that these results show marked divergence from research with achievement goals in the traditional model of procrastination. In work predicting generalized procrastination from achievement goals, mastery approach and performance approach goals predicted lower levels of generalized procrastination, while mastery-avoidance goals predicted higher levels of generalized procrastination (Howell & Buro, 2009; Howell & Watson, 2007; Seo, 2009). The pattern of prediction is different when procrastination is differentiated by motivational orientation. For example, mastery approach goals do not significantly predict procrastination-avoidance. However, mastery approach goals do negatively predict procrastination-approach. Furthermore, prior research had suggested a positive relationship between mastery avoidance goals and generalized procrastination, yet in the present study, procrastination-avoidance is negatively predicted by mastery avoidance goals. There is an alternative interpretation for these results. Procrastination and timely engagement may be viewed by individuals as learning and performance strategies, particularly in the context of achievement goals. That is, one might think of putting off the start or completion of work as a means of either approaching or avoiding competence or comparative performance. For example, if one procrastinates because one thinks it will give him/her a strategic advantage, that is defined as procrastination-approach. However, this is closely linked with the idea of a performance-approach goal in that a person with performance approach goals might select procrastination as a strategy believing it will give him/her a strategic advantage. However, the idea of a strategic advantage is not likely to be positively associated with mastery, because mastery is about competence, understanding, and gaining ability, not strategy for performing well on a given task. So, it is then not surprising that the link between mastery goals and procrastination is negative. If a person has a mastery avoidance goal, being motivated by a fear of not learning as much as possible, for example, then it is logical that he/she will not procrastinate. Likewise, if a person has a mastery approach goal, and is seeking to learn as much as possible, the use of procrastination-approach strategies is counter to that goal. This pattern of prediction is shown in the SEM model, and theoretically shows the need for separating the behavior by motivation. Practically, this pattern of prediction is important as well. This demonstrates that it is not an inborn or innate characteristic of the person that drives him/her to procrastinate or engage in a timely manner. Rather, it seems, goals can drive the use of procrastination and timely engagement as a strategy to meet those goals.

Personality. Personality was modeled for its relationship with time-related academic behavior because of the history of explaining generalized procrastination as a function of the individual's personality (that is, generalized procrastination as a personality flaw) which the 2×2 model critiques (Choi & Moran, 2009; Hess, Sherman, & Goodman, 2000; Steel, 2007; van Eerde, 2003). In general, they found that conscientiousness predicted lower levels of generalized procrastination and neuroticism predicted higher levels of generalized procrastination. In the present study, additional personality variables were modeled because of the possibility that other patterns of prediction would emerge. Although significant predictive paths did emerge for agreeableness and extraversion, the largest Beta weight was -.09, and these are thus unlikely to be replicated or meaningful. As a result, the substantive results were that conscientiousness negatively predicted both procrastination-approach and procrastination-avoidance, and positively predicted timely engagement-approach and timely engagement-avoidance. Interestingly, neuroticism only positively predicts procrastination-avoidance. This is interesting not only because it shows that neuroticism is not associated with *all* procrastination, but also because Choi and Moran (2009) found that neuroticism was positively associated with 'active procrastination,' a construct that bears similarity to procrastination-approach. Yet, in the present study, there is no significant path between neuroticism and procrastination-approach. The prediction in Choi and Moran's study was relatively weak, and may thus not be generalizable. Additionally, the nature of the two constructs is somewhat differently, with their focus being on intentional 'active' procrastination for the sake of performance gains, and the nature of procrastination-approach being that all procrastination has some intention behind it, and seeking to ascertain whether that intention is rooted in approach or avoidance motivational valence. These differences may lead to the different pattern of prediction. However, the overall pattern of prediction suggests that people with different styles of personality may make different choices on which behaviors to engage in for learning. Conscientiousness seems to sway people between choices of timely engagement and procrastination, while neuroticism may change affect valence in the procrastination behavior. However, the integrated structural model offers more clues as the way in which personality might function to affect time-related academic behavior.

Integrated Structural Modeling. The integrated structural model presented an analytic challenge. However, what it enabled was the modeling of mediation of the influence of personality through achievement goals, self-efficacy, self-regulation, and self-efficacy for self-regulation. That is, though personality still showed some direct predictive influence, this was substantially diminished in the integrated model. The influence of personality flowed through achievement goals, then through self-efficacy and self-regulation, and through self-efficacy for self-regulation. This is important theoretically, because it suggests that perhaps personality may influence the kinds of goals that one sets for learning (i.e., mastery approach, mastery avoidance, performance approach, performance avoidance) which in turn will influence strategy use in the form of procrastination and timely engagement. Furthermore, the selection of those strategies will be mediated through the influence of self-efficacy (how well does one believe one can achieve the goals one sets) and self-regulation (what strategies for regulating ones own learning does one have available) and self-efficacy for self-regulation (how well does one believe one can utilize those strategies). Personality, then, can influence the goal, which will influence the time-related academic behavior. The influence of the goal is also mediated by the self-efficacy and self-regulation factors. All of this points to a much more nuanced intrapersonal understanding of how one arrives at the decision to delay a particular task. Further, this model makes clear that while personality will affect decisions about learning strategy, because personality is essentially one's basic orientation to the world and situations one encounters, but that influence filters through motivation, goals, and other factors.

Path Modeling Across Time. Next modeling across time was attempted. This necessitated a change to path models with observed (calculated) variables rather than latent variables due to the limited number of participants who completed surveys at both time points. In these path models, however, it was possible to determine if the same predictive paths would hold in predicting time-related academic behavior across time. In other words, if a person's personality, self-efficacy, self-regulation, self-efficacy for self-regulation, and achievement goals are known today, does that offer any meaningful insight into that person's likely time-related academic behavior 15 weeks from now? Secondarily, what is the theoretical meaning of those relationships that hold across time, and those that do not hold across time. The variable that demonstrated the best prediction across time was clearly self-efficacy for self-regulation, with

Beta weights that were at or near those for the simultaneous prediction model. Interestingly, in the same path model, self-efficacy and self-regulation did not significantly predict time-related academic behavior. However, self-regulation did significantly predict self-efficacy for self-regulation. Theoretically, this is consistent. One must first have access to self-regulatory strategies before one can feel confident in ones ability to use those strategies for learning. So, self-regulation is a strong predictor of self-efficacy for self-regulation. The finding that self-efficacy for self-regulation is the only significant longitudinal predictor of time-related academic behavior is not surprising, as it has been found to be a mediator for self-efficacy and self-regulation in prior research. It is, however, significant, as it implies that self-efficacy for self-regulation may be a more viable intervention point than self-efficacy or self-regulation alone.

For achievement goals, there was no significant predictive path. This finding may also be theoretically meaningful. The 15-week interval for collection was selected because this meant students would be in a new semester. As a result, they would also be in new courses, and may have formed new goals in those courses. If it is true that goals lead to strategy use in the form of time-related academic behavior, then when those goals shift in new academic environments, so would the use of time-related academic behaviors. This suggests two things: 1) Time-related academic behaviors are unlikely to be static, and 2) time-related academic behaviors may be context-dependent. Further, it makes the next finding with personality in the longitudinal path model not surprising.

Personality did predict time-related academic behavior longitudinally. However, only conscientiousness and neuroticism did so significantly, and the path coefficients were much smaller than in the original simultaneous SEM model. It is interesting to note the path coefficients here as they are very similar to those of the direct prediction of personality on time-related academic behavior in the integrated SEM model. The reason this is interesting is because it may imply that when the influence of contextually dependent (i.e., achievement goals) is mitigated by the passage of time and start of a new academic term, this is the leftover influence of personality on time-related academic behavior. However, the longitudinal integrated path model offers an interesting insight about the influence of personality.

In the longitudinal integrated path model, only neuroticism has any significant direct influence, and it is on procrastination-avoidance. This suggests that perhaps the personality trait of neuroticism tends to shift people toward avoidance as a strategy in performance scenarios, though more work would be needed to confirm that hypothesis. However, when self-efficacy, self-regulation, and self-efficacy for self-regulation are brought into the model, the influence of conscientiousness seems to be fully accounted for. That is, all of the variance that was accounted for by these personality factors is elsewhere accounted for by the motivation variables. Further, the only significant personality variables in this model are neuroticism and imagination/intellect. Again, their influence primarily flows through achievement goals in this model. The strongest prediction is from self-efficacy for self-regulation. The integrated model for the longitudinal path analysis again presents a more nuanced intrapersonal picture of a person whose goals are influenced by personality, and whose goals then influence motivation, which influences behavior. This model presents several promising points of intervention, including self-regulation, self-efficacy for self-regulation, as well as work with achievement goals.

Person-Centered Analysis

In the cluster analysis, four distinct clusters emerged. Each of these groups offers insight into how motivational variables and time-related academic behavior interact for individuals. These four clusters were interpreted as timely engagers, those engaged in strategic use of behavior, those who were involved in what has been classically called generalized procrastination, and what has been characterized in the literature as active procrastination. These clusters offer insight into the variables that may be points of intervention for procrastination and timely engagement, however. For instance, with achievement goals, although mastery avoidance and performance avoidance goals both significantly predict time-related academic behavior, they did not significantly differ among the clusters. This may suggest those goals are not ideal for intervention. Self-efficacy was also significantly lower in the classic generalized procrastination profile, and highest in the timely engagement profile. This may suggest the role of self-efficacy in supporting engaged behavior, beyond the structural models. Additionally, the active procrastination cluster showed a mean that was higher for self-efficacy, consistent with previous theory about procrastination-approach behavior. Self-efficacy for self-regulation was significantly lower in both of the procrastination profiles. This is noteworthy as self-efficacy for self-regulation is also a strong longitudinal predictor of procrastination, and this combination of findings may suggest self-efficacy for self-regulation as a point of intervention. Self-handicapping was higher in the procrastination clusters and lower in the other clusters, suggesting either that self-handicapping tendencies produce more procrastination behaviors, or that procrastination behaviors are means of fulfilling a self-handicapping strategy or goal. Taken together, these cluster analysis results offer insights into potential intervention work, including that self-efficacy for self-regulation may be a viable point for intervention, and that educators may be able to use established methods for reducing self-handicapping to increase time-engaged behavior and reduce procrastination. Furthermore, these results seem to support the theory that time-related academic behavior is an outgrowth of students' goals. That is, they behave in a timely engaged or dilatory manner based on the goals they have for the academic environment and they way they are motivated to engage with it. Time-related academic behaviors, then, become a way of actualizing those goals.

Conclusions

The present study points toward several conclusions. First is a new theoretical approach to the role of personality in influencing time-related academic behaviors. Analyses conducted in this study seem to support the idea that personality may actually be influencing goals and motivational orientation more than actual behavior itself. That is, a person's orientation to the world and basic disposition (personality) influences the kinds of goals he/she sets and how he/she is motivated toward educational settings. In turn, his/her motivation and goals will determine which behavior strategies (i.e., time-related academic behaviors) are performed. Further, conscientiousness is the strongest longitudinal predictor of time-related academic behavior in this study, but also has the lowest test-retest reliability. One possible explanation for this is that conscientiousness is not a core aspect of personality and a stable personal disposition, but shifts with the person as they move through different situations. Thus, conscientiousness will more closely align to goals and time-related academic behavior over time as the individual encounters different learning situations.

Viewing time-related academic behaviors as strategies that the individual performs to meet goals he/she has for learning also explains other patterns of prediction in the data. Self-efficacy for self-regulation was the best predictor of time-related academic behavior. This is logical if those behaviors are actually learning or performance strategies. The selection of strategy will be driven by what self-regulatory abilities one believes one has access to, and how effective one believes one can be in using those to learn and/or perform in the academic setting. This view of time-related academic behaviors as strategies also makes meaning of the clusters and their profiles of means relative to the other clusters. The goals and motivations of one cluster will drive the use of different strategies. This would theoretically be true within single individuals as well.

However, more is left to be uncovered about which strategies students select under which circumstances. For example, is it really possible to speak of a person who is an avoidant timely engager? Perhaps not – it seems from the results of the present study that as goals and motivation shift, so may time-related academic behaviors. That is, one is not identified by the behavior one performs today. This conclusion runs counter to the bulk of traditional procrastination research, which would seek to classify individuals, in a domain-general manner, as either high or low in procrastination. The 2×2 model proceeded from the notion that this was not sufficient, that motivational valence as well as timely engagement behavior needed to be accounted for. However, the present study offers results that seem to indicate this may also not be sufficient. Individuals have different goals depending on the class, the time of day, the instructor, and their motivation (including things like self-efficacy, self-regulation, and self-efficacy for self-regulation, but also including a large number of other variables such as expectancies, task value, self-determined motivation, and many others). All of these differences across situation may make a difference in how the individual selects strategies in the form of time-related academic behavior. This difference across situation is potentially suggested in the longitudinal analyses.

Implications and Recommendations

As a result of this reformulation of time-related academic behaviors as strategies for learning and performance, there are implications for theory, practice, and research. These grow from new findings in the present study, areas of practical significance in those findings, as well as limitations of the present study that warrant future research.

Implications for Theory

The addition of conceptualizing procrastination and timely engagement as strategies used for learning and/or performance is a significant shift theoretically from the traditional conceptualization of procrastination as a passive, pathological behavior. These strategies may, indeed, be maladaptive, but they are in many circumstances intentionally deployed as a result of the goals set, motivation of the student, and perceived resources available (i.e. self-efficacy, self-regulation, and self-efficacy for self-regulation). In this sense, there is a shift needed from theorizing about which pathologies or deficits in the individual lead to the irrational behavior of procrastination, to a theorizing about what goals, motivational orientations, and combinations of cognitive resources lead to the selection of one type of strategy over the other.

In this area, the present study does offer insight. Students seem to select procrastination as a strategy more often when they set performance avoidance goals. Mastery approach goals are associated with selection of timely engagement strategies. Additionally, when student feel they have access to self-regulatory strategies, and feel confident in their ability to use those strategies to enhance their learning, they are more likely to select timely engagement strategies and less likely to select procrastination strategies.

Implications for Practice

A goal of this study was to gain insight for educational practice and how best to structure instruction and intervention for time-related academic behavior, including future intervention research. Some of the implications for theory carry into this area. For example, knowing that students need adequate self-regulation strategies, increasing students' self-regulation ability may be helpful. Additionally, increasing actual ability in self-regulation is likely to increase self-efficacy for self-regulation, both logically and as demonstrated in the structural models. Self-efficacy and self-efficacy for self-regulation can also be intervened on in the classroom. For example, in a study on early intervention for procrastination, Strunk and Spencer (2012) applied an intervention asking students to select strategies to regulate their own academic behavior, write them down, and sign a contract regarding those behaviors. In their study, this simple exercise designed to increase self-regulation and accountability led to a significant decrease in late assignments and increase in overall course grade, with an average increase of about 14% versus the quasi-control group. More involved early work on self-regulation might result in even more significant results. Further, it is possible that working to increase students' self-efficacy directly may prove effective. Classrooms can also be structured to promote mastery approach goals, which may help lead to a context where students are more likely to select timely engagement as a strategy.

Another finding from the present study with direct application to practice is the distinction of procrastination-approach and procrastination-avoidance with respect to self-efficacy. Self-efficacy was negatively associated with procrastination avoidance (that is, higher self-efficacy was related lower procrastination-avoidance) but positively associated with procrastination-approach (that is, high self-efficacy was related to higher procrastination-approach). Knowing this brings to light a delicate balance that is needed with practices to increase self-efficacy. That is, it may be that when students are told they have the ability to succeed, particularly if that success is not cognitively associated with effort, they may be likely to use procrastination-approach as a strategy. This may be related to what Dweck and Molden (2007) describe in the incremental versus fixed approach to intelligence, where the fixed approach includes the mindset that intelligence is set and cannot be increased through effort, whereas the incremental approach is characterized by the mindset that intelligence and ability can be increased through effort. This may be related through the idea that some approaches to increasing self-efficacy may produce a fixed mindset, a self-efficacy that is high enough to produce procrastination-approach as viable strategy in the mind of the student, and thus lower performance for that student. One such example would be person-centered praise (Kamins & Dweck, 1999; Mueller & Dweck, 1998), which tends to produce a more fixed mindset. However, a teacher seeking to increase self-efficacy may be likely to use person-centered praise to help that student 'feel good' about himself/herself. In other words, the finding about self-efficacy presents a significant challenge for educators to find strategies that will increase self-efficacy, but through means that also increase effort and timely engagement, not simply belief in their abilities, which seems to lead to increased procrastination-approach. Though students believe that procrastination-approach is a performance enhancing strategy (Schraw, Wadkins, & Olafson, 2007), course performance is negatively associated with procrastination-approach behavior.

Recommendations for Future Research

Based on the results of the present study, there is much more research work needed in this area. First, a measure of time-related academic measures that is context-bound is needed. The 2×2 Measure of Time-Related Academic Behavior was developed in a domain-general manner because that is how all previous procrastination measures had been conceptualized. However, based on the results of this study, it seems that time-related academic behaviors vary over time, potentially based on the context and the goals and motivations associated with that context. Such a redefining of the measure would also allow for some refinement of the scale, which showed some issues in the CFA including correlated errors and a large chi-square to degrees of freedom ratio. Additionally, future research should focus on how contextual factors like task value and expectancies may influence time-related academic behaviors. Intensive intra-individual studies may offer insight into factors that educators can include in their instruction to influence these variables, as well. For example, following the same individual through more than one context (such as multiple classrooms) and measuring task value, achievement goals, self-efficacy, academic identity, and time-related academic behavior. As these contextual factors shift within a person, it is possible that the selection of strategy in the form of time-related academic behavior will also shift, giving new areas for intervention study.

Future research should also study the 2×2 Measure of Time-Related Academic Behavior in new samples, at other colleges and universities, and perhaps outside the educational environment. Because of the fact that it was developed exclusively using samples from one large Midwestern university, there may be limitations in generalizability as characteristics of students shift among universities and settings. These limitations and ways the model needs to be adapted should be studied in future research.

The present study also leaves room for intervention studies. What is the effect of teaching self-regulation skills on time-related academic behaviors? Can an effective intervention for self-efficacy for self-regulation be developed, and if so, how will it affect time-related academic behaviors? A number of intervention studies could be devised based on the present study to manipulate the variables that seem to most strongly influence time-related academic behavior within a given educational context to determine what steps educators can take to help their students engage with work in timely manner.

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APPENDIX A

Oklahoma State University Institutional Review Board

Date:	Tuesday, September 20, 2011
IRB Application No	ED11151
Proposal Title:	Building a New Model of Academic Behavior
Reviewed and Processed as:	Exempt

Status Recommended by Reviewer(s): Approved Protocol Expires: 9/19/2012

Principal Investigator(s):

Kamden K. Strunk	Diane Montgomery
413 Willard	424 Willard
Stillwater, OK 74078	Stillwater, OK 74078

The IRB application referenced above has been approved. It is the judgment of the reviewers that the rights and welfare of individuals who may be asked to participate in this study will be respected, and that the research will be conducted in a manner consistent with the IRB requirements as outlined in section 45 CFR 46.

☒ The final versions of any printed recruitment, consent and assent documents bearing the IRB approval stamp are attached to this letter. These are the versions that must be used during the study.

As Principal Investigator, it is your responsibility to do the following:

1. Conduct this study exactly as it has been approved. Any modifications to the research protocol must be submitted with the appropriate signatures for IRB approval.
2. Submit a request for continuation if the study extends beyond the approval period of one calendar year. This continuation must receive IRB review and approval before the research can continue.
3. Report any adverse events to the IRB Chair promptly. Adverse events are those which are unanticipated and impact the subjects during the course of this research; and
4. Notify the IRB office in writing when your research project is complete.

Please note that approved protocols are subject to monitoring by the IRB and that the IRB office has the authority to inspect research records associated with this protocol at any time. If you have questions about the IRB procedures or need any assistance from the Board, please contact Beth McTernan in 219 Cordell North (phone: 405-744-5700, beth.mcternan@okstate.edu).

Sincerely,

Shelia M. Kennison

Shelia Kennison, Chair
Institutional Review Board

VITA

Kamden K. Strunk

Candidate for the Degree of

Doctor of Philosophy

Dissertation: BUILDING A NEW MODEL OF TIME-RELATED ACADEMIC BEHAVIOR: PROCRASTINATION AND TIMELY ENGAGEMENT × MOTIVATIONAL ORIENTATION

Major Field: Educational Psychology

Biographical:

Education:

Completed the requirements for the Doctor of Philosophy in your major at Oklahoma State University, Stillwater, Oklahoma in December, 2012.

Completed the requirements for the Master of Science in Psychology at Evangel University, Springfield, Missouri in May, 2009.

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Experience: Graduate Teaching Assistant, Oklahoma State University
Graduate Research Associate, Oklahoma State University
Statistician and Research Consultant, University of Tulsa
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American Psychological Association
Association for Psychological Science

Name: Kamden K. Strunk Date of Degree: December, 2012

Institution: Oklahoma State University Location: Stillwater, Oklahoma

Title of Study: INVESTIGATING A NEW MODEL OF TIME-RELATED ACADEMIC BEHAVIOR: PROCRASTINATION AND TIMELY ENGAGEMENT BY MOTIVATIONAL ORIENTATION

Pages in Study: 145 Candidate for the Degree of Doctor of Philosophy

Major Field: Educational Psychology

Scope and Method of Study: The purpose of this study was to examine the nature of time-related academic behavior (i.e., procrastination and timely engagement) in the academic context. Specifically, this study aimed to build a new model for understanding these behaviors in a motivational framework by using motivational orientation to frame these behaviors. Participants were 1,227 undergraduate students enrolled in face-to-face courses at a large Midwestern university. Each participant completed a series of measures including the 2×2 Measure of Procrastination and Timely Engagement, two subscales of the Motivated Strategies for Learning Questionnaire, the Achievement Goal Questionnaire, a measure of Self-Efficacy for Self-Regulation, the mini-IPIP, and a demographic questionnaire through an online survey, and participants completed the same measures again 15 weeks later.

Findings and Conclusions: Findings include confirmatory factor analyses for all key measures. These indicated the four-factor model for time-related academic behavior was the best-fitting model to the observed data. Further, these raised questions about the existing models of achievement goals. Reliability analyses were also performed in three different models including the traditional tau-equivalent model (Chronbach's alpha), the congeneric model, and the test-retest model. Then, structural equation modeling was conducted to determine how well the variables would predict time-related academic behavior. Then, these models were retested using path analysis on the longitudinal data to determine how well this prediction holds up across time. Finally, cluster analysis was used for a person-centered view of the nature of the relationships among the variables. The findings present the view that self-efficacy for self-regulation may be one of the more important predictors of time-related academic behavior, that time-related academic behaviors seem to be related to the goals one has for the situation, and that personality is not a strong predictor across time, suggesting these behaviors are more malleable to intervention than previously thought. Implications for educational practice, theory, and future research are discussed.

ADVISER'S APPROVAL: Diane Montgomery, Ph.D.