Summer 2011

Stability and Change in Goal Orientation and Their Relationship with Performance: Testing Density Distributions Using Latent Trait-State Models

Michael Charles Mihalecz
Old Dominion University

STABILITY AND CHANGE IN GOAL ORIENTATION AND THEIR RELATIONSHIP WITH PERFORMANCE: TESTING DENSITY DISTRIBUTIONS USING LATENT TRAIT-STATE MODELS

by

Michael Charles Mihalecz
B.A. May 1993, Rutgers, The State University of New Jersey
M.A. May 1998, The Catholic University of America
M.S. 2003, Old Dominion University

A Dissertation Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirements for the Degree of

DOCTOR OF PHILOSOPHY

INDUSTRIAL-ORGANIZATIONAL PSYCHOLOGY

OLD DOMINION UNIVERSITY
August 2011

Approved by:

James P. Bliss (Director)

Ivan K. Ash (Member)

Jeffrey T. Hansberger (Member)

ABSTRACT

STABILITY AND CHANGE IN GOAL ORIENTATION AND THEIR RELATIONSHIP WITH PERFORMANCE: TESTING DENSITY DISTRIBUTIONS USING LATENT TRAIT-STATE MODELS

Michael Charles Mihalecz
Old Dominion University, 2011
Director: Dr. James P. Bliss

Goal orientation has been proposed to influence a number of training and work outcomes. However, results have been inconsistent and predicted relationships are weaker than anticipated (Payne, Youngcourt & Beaubien, 2007). Weak findings may be due to inconsistencies in how goal orientation is conceptualized and operationalized (DeShon & Gillespie, 2005; Grant & Dweck, 2003; Kaplan & Maehr, 2007). One such inconsistency is the treatment of goal orientation as a stable trait or a malleable state. Issues of state-versus-trait have long fueled the person-situation debate in personality psychology. Fleeson (2001) offered a solution for integrating the two theoretical perspectives called the density distribution approach. By incorporating Fleeson's approach with Latent Trait-State (LTS) covariance matrix models (Steyer, Ferring, & Schmitt, 1992) this study tested the hypothesis that goal orientation, whether measured as a general trait, a domain-specific trait, or state, is density distribution. In addition, LTS models were hypothesized to provide a better method for examining the predictive relationship between goal orientation and achievement-related performance in an academic setting. Results were generally supportive of the first set of hypotheses, but not the second. Theoretical and practical considerations are discussed.

This dissertation is dedicated to my parents, Jane and John Mihalecz.

ACKNOWLEDGMENTS

I would like to thank my dissertation committee, James Bliss, Ivan Ash, and Jeffrey Hansberger, for their guidance. I want to give my committee chairman, James Bliss, additional thanks for his guidance, support and belief in me. I would also like to thank John Mathieu and Levent Dumenci for their helpful comments and Eric Heggestad for providing me access to the Motivational Trait Questionnaire.

I want to thank my parents for always being there and for sacrificing so that I did not have to go without. I also want to thank my friends for their encouragement throughout graduate school. Thank you all for helping to keep me motivated to finish this dissertation.

TABLE OF CONTENTS

Page

APPENDICES

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

Goal orientation has received considerable attention in the organizational literature over the past fifteen years (e.g., Button, Mathieu, & Zajac, 1996; Farr, Hofmann, Ringenbach, 1993; Kozlowski et al., 2001; Phillips & Gully, 1997; VandeWalle, 1997). According to DeShon and Gillespie (2005), "goal orientation has become one of the most frequently studied motivational variables in applied psychology and is currently the dominant approach in the study of achievement motivation (p. 1096)." It has been theorized to influence a number of training and work outcomes, for example knowledge-based learning, metacognition, self-efficacy, and task performance (Kozlowski et al., 2001; Salas & Cannon-Bowers, 2001, VandeWalle, 1997). However, empirical findings have been inconsistent and predicted relationships have been weaker than anticipated (Payne, Youngcourt & Beaubien, 2007). Weak findings may be due to inconsistencies in how the construct is conceptualized and then operationalized (e.g., DeShon & Gillespie, 2005; Grant & Dweck, 2003; Kaplan & Maehr, 2007).

One such inconsistency is the temporal stability of goal orientation. Despite the large amount of research, there remains poor agreement whether the construct is best described as a stable trait, a malleable state, or a quasi-trait that may be influenced by the situation. When the research has addressed both the trait-like and state-like attributes of goal orientation, they are often treated as dichotomously rather than a single underlying construct (e.g., Kozlowski et al., 2001). As an example, state goal orientation is commonly treated as a proximal outcome of trait goal orientation (Payne et al., 2007).

Issues of state-versus-trait have long been a concern in personality psychology and are referred to as the person-situation debate. Fleeson (2001) offered a solution to integrate both sides of the debate called the density distribution approach to personality, where personality attributes are a density distribution of states influenced by trait and situation. I hypothesized goal orientation to be better conceptualized as a density distribution than currently as a state or a trait. All goal orientation measures include trait-like and state-like variance which can be assessed longitudinally using latent trait-state (LTS) models, a structural equation modeling approach for deriving trait and state variance components.

The present study investigated the latent structure of goal orientation and its relationship with performance. First, it tested how well Fleeson's (2001) density distribution theory applies to goal orientation using LTS structural equation models. Second, it investigated whether LST modeling of density distributions provided additional value when examining the predictive relationship of goal orientation with achievement-oriented performance in an educational setting.

GOAL ORIENTATION

First researched in developmental and educational psychology and later adopted by organizational scholars (Button et al., 1996; Farr, Hofmann, & Ringenbach, 1993; Kozlowski et al., 2001), goal orientation has been proposed to influence various performance outcomes through the motivation-related strategies individuals adopt. While there is no single definition of goal orientation, DeShon and Gillespie (2005) identified five alternative definitions in the literature, alternately classifying goal orientation as goals, traits, quasi-traits, a mental framework, or beliefs. Defined as goals, goal orientation is the types of situationally specific achievement goals adopted and pursued in achievement settings (e.g., Elliot, 1999). As a trait, goal orientation is defined as a stable dispositional trait motivating individuals to develop or demonstrate ability in achievement situations (e.g., VandeWalle, 1997). The quasi-trait definition is similar. In this case, goal orientation is defined as a "somewhat stable individual difference factor that may be influenced by situational characteristics" (p. 28; Button et al., 1996). The forth definition is an *a priori* mental framework or achievement goal pattern describing how individuals perceive and respond in achievement situations (Ames & Archer, 1988). The final definition of goal orientation is an individual's beliefs concerning the malleability of his or her ability or intelligence. While only two of the definitions make explicit reference to stability or variability, these attributes are implied in details such as "situationally specific", "*a priori* mental framework or achievement goal pattern", and "individual's beliefs". Although there is no common consensus about stability, goal orientation has been defined as having both trait-like and state-like qualities. The definitions, while not drastically different, are one of several inconsistencies in the goal orientation literature.

In an effort to reconcile the multiple definitions and create a common ground, I combined compatible elements of the various definitions to create a broader definition of goal orientation. Goal orientation is a somewhat stable individual difference that describes how individuals perceive and act in achievement situations. It provides a mental model for how individuals cognitively and affectively construe achievement situations as well as how they attend to, interpret, evaluate, and act on achievement information. Furthermore, goal orientation describes the achievement goals that they pursue in efforts towards developing or demonstrating ability. The expression of goal orientation may be influenced by salient features of the situation. While this definition may be too broad to be useful

Goal orientation includes three dimensions which describe several types of goal strategies: learning, performance-prove, and performance-avoid. Learning goal orientation is associated with a belief that ability is malleable while the performance goal orientations are associated with a fixed ability. When an individual adopts a learning goal orientation (also known as mastery goal orientation), he or she seeks to improve knowledge or increase competence in a given activity (Button et al., 1996). A performance-prove goal orientation is the extent to which an individual seeks to demonstrate task competence for the purpose of favorable judgments, whereas a performance-avoid goal orientation is the extent an individual avoids negative judgments of their competence (Elliot & Harackiewicz, 1996; VandeWalle, 1997). The dimensions are modestly correlated but generally considered to be independent.

Individuals who adopt a learning orientation respond to challenges with increased effort and feedback seeking behavior (Button et al., 1996; VandeWalle & Cummings, 1997). According to Brett and VandeWalle (1999), individuals with a high learning orientation focus on development and refinement of skills and knowledge during training. Learning goal oriented individuals are concerned with increasing their competence and consider their ability in a given area to be malleable. They seek challenging tasks and increase effort under difficult conditions. When faced with failure, individuals with a learning orientation respond well to negative feedback and attempt to incorporate the information in future performance (Elliot & Dweck, 1988). Mistakes are viewed as opportunities to build competence.

Individuals who adopt a performance-prove orientation focus on comparing themselves favorably to others (Brett & VandeWalle, 1999). Such individuals have a preoccupation with performance and social comparison. They are concerned with securing favorable judgments of their competence. In addition, they are more interested in demonstrating their ability than acquiring skills or improving their ability.

Individuals who adopt a performance-avoid orientation are preoccupied with concealing their lack of ability and avoid negative judgments from others (Brett & VandeWalle, 1999). They avoid task difficulties (Phillips & Gully, 1997). In addition, they react to failure with low self-efficacy and avoid setting goals. Their beliefs promote a behavior pattern marked by inaction and they avoid unfavorable judgments. They seek situations that offer easy success. They avoid challenges and their performance declines in the face of obstacles. When faced with failure, individuals with a performance-avoid orientation attribute it to low ability, demonstrate negative affect, and may seek to withdraw from the activity. They view mistakes and negative feedback as a criticism of their competence. Similar to those adopting a performance-prove orientation, individuals with a performance-avoid orientation are preoccupied with the judgment of others in performance and learning situations.

To summarize, individuals adopting a high learning goal orientation are focused on their personal mastery of achievement-related tasks. High performance-prove individuals are directing effort to demonstrate their performance by competitive striving against others on achievement-related tasks. Finally, individuals high in performance-avoid goal orientation are preoccupied with avoiding failure in achievement-related tasks.

As mentioned previously, goal orientation research has been plagued by inconsistent findings that are difficult to reconcile (Elliot & Trash, 2001; Grant & Dweck, 2003). According to DeShon and Gillespie (2005), this is due to both conceptual and operational inconsistencies. One conceptual inconsistency would be the five competing definitions of goal orientation mentioned earlier. Another inconsistency, the stability of goal orientation, has resulted from the confusion surrounding the plurality of definitions. It has been conceptualized as a stable disposition, having the characteristics of a trait (e.g., Button et al., 1996; VandeWalle, 1997), and as transient, subject to situational influences and having the characteristics of a state (e.g., Dweck, 1986; Stevens & Gist, 1997). Adding to the inconsistencies and confusion surrounding goal orientation is the issue of domain specificity. Some researchers have conceptualized goal orientation as a trait existing within a specific context or domain, such as work, academics, or athletics rather than as a general trait (e.g., VandeWalle, 1996; 1997). An individual's level of academic-specific learning goal orientation may be different than his or her level of sports-specific learning goal orientation. The research on trait and state goal orientation are reviewed in more detail next.

Trait Goal Orientation

The majority of goal orientation research has treated the construct as a stable disposition and measured it though self-assessment questionnaires. Previous research has examined the relationship between trait goal orientation several motivational processes, including general self-efficacy (e.g., Chen, Gully, Whiteman & Kilcullen, 2000), domain-specific self-efficacy (e.g., VandeWalle, Cron, & Slocum, 2001), self-set goals (e.g., Chen et al., 2000), learning strategies (e.g., Ford et al, 1998; Kozlowski et al., 2001;

Schmidt & Ford, 2003), feedback seeking (e.g., VandeWalle & Cummings, 1997), and state anxiety (e.g., Chen et al., 2000; Horvath, Scheu, & DeShon, 2004). Other research has explored the relationship between trait goal orientation and other dispositions, such as the five-factor model of personality (e.g., VandeWalle, 1996) and need for achievement (Horvath et al., 2004). Research has also examined how well goal orientation predicts achievement-related outcomes such as learning (e.g., Bell & Kozlowski, 2002), academic performance, task performance (e.g., Yeo & Neal, 2004), and job performance.

As mentioned previously, trait research has also distinguished general from domain-specific goal orientations. Button et al. (1996) conceptualized goal orientation as a general trait. VandeWalle (1997), on the other hand, conceptualized goal orientation as domain-specific. This perspective is closer to Dweck's (2000) belief that individuals hold different goal orientation patterns depending on the context. It is also bears some resemblance to Button et al.'s view that goal orientation may be influenced by situational characteristics.

VandeWalle (1997) suggested that individuals can hold different goal orientations in the broad domains such as work, academics, and athletics. Measures with increased situational specificity may provide improved insight about the influence of motivational processes on learning and performance. According to Kanfer (1992), distal motivational constructs, such as self-efficacy or performance anxiety, are likely to impact outcomes through more specific and proximal versions of the motivational constructs, i.e., domain-specific self-efficacy and state anxiety.

State Goal Orientation

Some goal orientation research has conceptualized goal orientation as an internal state subject to situational influences. In these studies, goal orientation has been experimentally manipulated and/or recorded using self-report state measures.

Within an experimental setting, changes in goal orientation have been induced by manipulating one of a number of situational cues or aspects of the environment. Research has demonstrated that goal orientation can be influenced by manipulating situation cues through a variety of techniques (e.g., Chen et al., 2000; Gist & Stevens, 1998; Kozlowski et al., 2001; Kraiger, Ford, & Salas, 1993; Martocchio, 1994; Stevens & Gist, 1997). As an example, the manipulation employed by Kozlowski et al. (2001) induced change in state goal orientation and resulted in performance inconsistent with measured trait goal orientation. These techniques include comparing competitive versus individual reward structures (Ames, 1984; Ames, Ames, & Felker, 1977), comparing performance with or without an audience present (Carver & Sheier, 1981), and by comparing "test" instructions to "game" or neutral instructions.

In an effort to organize different goal orientation manipulations, Kaplan and Maehr (2007) placed situational cues that describe the types of manipulations into six categories which follow the acronym *TARGET*. Categories include the type of *task*, the *autonomy* in deciding how to complete the task, the type of *recognition* given for completing the task, the assignment of individuals to different *groups*, how task progress is *evaluated*, and *time* to complete the task.

But few studies claiming to manipulate goal orientation directly measure change in goal orientation. Instead they attribute changes in performance to goal orientation rather than goal type or feedback or whatever the study manipulated (e.g., Steven & Gist, 1997). Other studies measure trait goal orientation and treat experimental manipulations as moderators of the relationship between goal orientation and performance (Chen & Mathieu, 2008) or simply as another independent variable influencing one or more outcomes (e.g., Kozlowski et al., 2001).

In one notable exception, Steele-Johnson, Beauregard, Hoover, and Schmidt (2000) conducted a manipulation check and found that their goal orientation manipulation was related to perceptions of goal orientation. Participants reported that they felt they could improve their skills. Unfortunately, the researchers did not report details about the measure they used, such as the psychometric properties or a list of questionnaire items.

Some researchers have attempted to directly measure goal orientation states while also measuring goal orientation traits, which is similar to how affective traits and transient mood states are conceptualized in workplace emotion research (e.g., Judge & Kammeyer-Mueller, 2008). These studies demonstrate that state goal orientation measures possess different relationships with variables of interest than trait measures. For example, Boyle and Klimoski (1995) found state measures of goal orientation were related to an experimental manipulation, but that traits were not. As additional examples, confirmatory factor analyses (CFA) by Button et al. (1996) and Fisher and Ford (1998) provided evidence for the dual existence of trait and state orientation. Hansberger (1999) included all three levels of goal orientation specificity (i.e., general trait, domain-specific trait, and state) while examining dynamic driving performance and found that domain and state measures exhibited different relationships with performance as well as self-reported expertise. These studies provided evidence of construct validity for distinct trait and state elements of goal orientation.

Previous research suggests state goal orientation may alter the relationship between trait goal orientation and other variables of interest. Breland and Donovan (2005) found that state goal orientation mediates the relationship between trait goal orientation and self-efficacy. Although a main effect for both trait and state goal orientation directly influenced self-set goals, Ward and Heggestad (2004) found induced goal orientation moderated the relationship between trait and self-set goals. In a longitudinal study, Horvath et al. (2004) found a stronger relationship between state goal orientation and self-set performance goals than trait goal orientation and self-set performance goals during an undergraduate statistics course.

Meta-Analyses

The goal orientation literature is confusing at best. As mentioned earlier, conceptual and operational inconsistencies have resulted in muddy findings that are difficult to represent as a body of research. Fortunately, several meta-analyses have been conducted (Day, Yeo, & Radosevich, 2003; Payne et al., 2007; Rawsthorne & Elliot, 1999; Utman, 1997).

Two meta-analyses examined research experimentally manipulating goal orientation i.e., state goal orientation. Rawsthorne & Elliot (1999) identified differences in the effect of induced goal orientation states on behavioral and self report measures of intrinsic motivation. Performance goals were associated with significantly lower levels of a behavioral measure of intrinsic motivation during experimental free-choice period (i.e., task persistence; $d = -.17$), and a self-report measure of intrinsic motivation (i.e., self-report interest in an experimental task; $d = -.12$). The effect size was larger when limited to the studies inducing a performance-avoid versus a learning goal orientation (*d*

= -.46). When limited to the studies inducing a performance-approach versus learning goal orientation the effect size was not significant. Utman (1997) found a moderate effect size for an induced learning goal orientation lead to better task performance than an induced performance goal orientation ($d = .53$). However, the learning goal advantage was limited to relatively complex tasks. In addition, the learning goal advantage was larger when learning goals were moderately pressuring and when participants were tested alone.

Day et al.'s (2003) meta-analysis compared the two-factor model of trait goal orientation (e.g., Button et al., 1996) to the three-factor model (e.g., VandeWalle, 1997). The three-factor model explained more variance (11%) in performance than the 2-factor model (4%). Performance included job performance, scholastic achievement, athletic achievement, or performance on a laboratory task. Results indicated positive but small relationships between learning goal orientation and performance ($\rho = .10$) as well as between performance-prove goal orientation and performance ($\rho = .08$). The results also indicated a negative relationship between performance-avoid goal orientation and performance ($\rho = -.28$).

Payne et al. (2007) provide a more comprehensive meta-analysis. They examine the relationship of trait goal orientation and state goal orientation to a number of other variables, including several types of performance. Payne et al. assessed the temporal stability of trait goal orientation using sample-weighted means to calculate a coefficient of stability. They found the sample-weighted mean r for learning was .66, for performance-prove it was .70, and for performance-avoid it was .73. They also found that the longer the time between measures, the smaller the coefficients.

Payne et al. (2007) examined the relationship between trait goal orientation and multiple performance outcomes. They found a modest positive relationship between learning (performance on a test or exam) and learning goal orientation ($\rho = .16$), no significant relationship between learning and performance-prove goal orientation, and a modest negative relationship between learning and performance-avoid goal orientation ($\rho = -.17$). In addition to learning they also examined the relationship between academic performance and goal orientation. While learning is typically assessed through performance on a test or exam, academic performance is typically operationalized as a final grade in a course. Academic performance showed a modest positive relationship with learning goal orientation ($\rho = .16$), no relationship with performance-prove goal orientation, and a weak negative relationship with performance-avoid goal orientation ($\rho = -.06$). Contrary to theory, performance-prove goal orientation has virtually no relationship with learning or academic performance. In addition, learning and performance-avoid goal orientations had small effect sizes with learning and academic performance, falling short of the theorized relationship between goal orientation and training outcomes (e.g., Button et al., 1996; Farr et al., 1993; Kozlowski et al., 2001).

Payne et al. (2007) also found a small positive relationship between task performance and learning goal orientation ($\rho = .05$), no meaningful relationship between task performance and performance-prove goal orientation, and a negative but small relationship between task performance and performance-avoid goal orientation ($\rho = -.13$). Job performance had a small positive relationship with learning goal orientation ($\rho = .18$) and performance-prove goal orientation ($\rho = .11$), however the meta-analysis contained no studies that explored the relationship between job performance and performance-avoid goal orientation. Again, relationships between work performance outcomes and goal orientation were smaller than predicted (e.g., Button et al., 1996; Farr et al., 1993; Kozlowski et al., 2001).

The Payne et al. (2007) meta-analysis also examined the relationship between state goal orientation and the performance variables used in the trait meta-analysis. Learning had a moderate positive relationship with state learning goal orientation (ρ = .31), however the result is based on only 2 studies. Unfortunately, no studies included in the meta-analysis examined learning with performance-prove or -avoid goal orientations. Academic performance was not related to either learning or performance-prove goal orientations. No studies examined the relationship between academic performance and performance-avoid goal orientation. Payne et al. found that task performance was not related to state learning goal orientation, but did find that state performance-prove goal orientation yielded a small positive relationship with task performance (ρ = .16). No studies included in the meta-analysis examined state performance-avoid goal orientation and task performance. Small positive relationships were also found between job performance and state learning goal orientation (ρ = .22) and state performance-prove goal orientation (ρ = .09). Only one study examined the relationship between job performance and performance-avoid goal orientation and was therefore was not included in the analysis. The theorized relationship between state goal orientation and learning or task performance is tenuous at best.

Finally, Payne et al. (2007) examined the incremental validity of the three goal orientation factors on job performance beyond the influence of cognitive ability and the five-factor model of personality. Goal orientation predicted a small but significant amount of incremental validity in job performance above cognitive ability and the five-factor model of personality ($\Delta R^2 = .04$, $R^2 = .33$, $p < .01$. Learning goal orientation is largely responsible for the additional variance ($\beta = .23$, $p < .05$). Again, the predictive validity of goal orientation on job performance is less than anticipated (e.g., Button et al., 1996; Farr et al., 1993; Kozlowski et al., 2001).

Summary of Goal Orientation Literature

To summarize the literature, goal orientation reflects the particular goal-types individuals adopt in achievement situations. It consists of three largely-independent factors: learning, representing goals emphasizing the development of competence; performance-prove, representing goals emphasizing the demonstration of competence; and performance-avoid, emphasizing the avoidance of demonstrations of incompetence. Each dimension is associated with a different effect. In general, learning goal orientation is associated with adaptive response patterns. Performance-avoid associated with maladaptive response patterns, while performance-approach effects are highly variable. However, the empirical support for these assertions is mixed. According to the results of the meta-analyses, the relationships between goal orientation and important outcomes are often smaller and less consistent than expected.

Goal orientation has been treated as a trait *and* a state. When treated as a trait, the construct has been further divided into general and domain-specific traits. When operationalized as a state, it has been experimentally manipulated or directly assessed using state measures. Attempts to integrate the trait and state perspectives have examined the relationship between trait and state dimensions. Results suggest they are related yet distinguishable from one another. Both are related, albeit weakly, to performance.

Additionally, the relationship between trait goal orientation and performance is believed to be moderated by state goal orientation. Our understanding of the stability of goal orientation and its relationship with performance may be clarified by adopting a new paradigm, one different than the current state versus trait dichotomy. An alternative for integrating the different perspectives may be found in attempts to resolve the person-situation debate in personality psychology.

THE PERSON-SITUATION DEBATE IN PERSONALITY PSYCHOLOGY

The person-situation debate has been an ongoing argument in personality psychology. The core of the debate can be summarized into five points of disagreement (Fleeson & Leicht, 2006). First, the personality perspective argues that personality is a powerful predictor of future behavior and advocates the study of individual differences. The situation perspective argues that the situation is a more powerful predictor of behavior than personality. Second, the person perspective predicts that an individual will behave in a similar manner over time because behavior is determined by stable personality. The behavior may not be similar in absolute terms, but will be similar in relative or rank position. The situation perspective predicts that the behavior of an individual will vary considerably due to changes in the situation over time. Third, the person perspective has largely studied the structure of covariance structure between individual differences. The situation perspective has principally studied psychological processes that describe the sequence of events that start with a situation and end with a behavior and a resulting outcome. Forth, the person perspective emphasizes patterns of acting, feeling, and thinking over the cognitive determinants of the patterns. The situation perspective emphasizes several cognitive processes, including perception, interpretation, and adaptation. The final point of debate is where the perspective considers variance of interest to reside: between individuals or within an individual. For the person perspective, variance between persons is of interest; for the situation perspective, variance within one person and across time is of interest. Extensive and ongoing bodies of research support both perspectives (Cervone, 2005; Ozer & Benet-Martinez, 2006).

Both perspectives from the five points of disagreement that define the person-situation debate are also found in the goal orientation literature and can be identified in the five definitions mentioned earlier (i.e., goals, trait, quasi-trait, mental framework, and beliefs; DeShon and Gillespie, 2004). Similar to the first point of the debate, goal orientation is an individual difference that influences future behavior. However, the situation may induce changes in levels of goal orientation and affect achievement-related behavior. Parallel to the second point, goal orientation is treated as a stable trait but may be influenced by situational characteristics. Comparable to the third point, goal orientation has been studied in observational, quasi-experimental settings (i.e., Park, Schmidt, Scheu, & DeShon, 2007) and in true experimental settings (i.e., Kozlowski et al., 2001). Like the fourth point of the debate, several definitions of goal orientation emphasize patterns of acting feeling and thinking, such as the goals and trait definitions, while others highlight perception, interpretation and adaptation, like the quasi-trait, mental framework, and beliefs definitions. Finally, both the variance between and within subjects has been examined in goal orientation studies, similar to the fifth and last point of the person-situation debate. Fleeson (2001) developed a theory called the density distribution approach that integrates the two perspectives of the person-situation debate in personality psychology.

Integrating Person and Situation Perspectives

According to the density distribution approach to personality (Fleeson, 2001), personality is the "*accumulation* of the *everyday behavior* of an individual" (p.8). A core part of personality is an individual's *behavior.* An individual's personality should be described in *everyday* real situations. A large sample of an individual's actions must be *accumulated* and assessed because he or she does not act the same way in different situations.

The density distribution approach incldues three primary characteristics: the personality state, trait manifestation and distributions. The *personality state* is a construct that describes how an individual is acting, feeling and thinking at the moment. It is measureable in the same way that personality traits can be assessed, using the same content, breadth and scale. *Trait manifestation* is the term used to describe that traits are manifest in states. States are the form that traits take as they express themselves. According to Fleeson, the key to understanding traits is to explain the process in how traits manifest in states. Finally, an individual's state should be assessed on multiple occasions because he or she deviates from his or her behavior at least some of the time. This data forms a *distribution* or density distribution of state levels for the individual.

Fleeson (2007) proposed that state behavior is caused by several factors, which include psychologically active characteristics of the situation and internal physiological or cognitive structures that support an individual's typical way of acting (e.g., traits). Psychologically active characteristics of situations are defined as the characteristics of situations that elicit a change in states and alter the degree to which a trait manifests itself in that situation. The concept is similar to situational strength, "the implicit or explicit cues provided by external entities regarding the desirability of potential behaviors" (Meyer, Dalal, & Hermida, 2010; p. 122). While a situation characteristic may influence the current state of a psychological construct, the same characteristic may not be psychologically relevant to other constructs. For example, a situation containing a large group of friends may influence the current state of extroversion, but have little influence on another Big Five factor, neuroticism. Situations that share a specific domain (e.g., school or work) may still differ in the degree to which they contain a psychologically active characteristic. For example, different academic situations may not include the same characteristics that are psychologically active for goal orientation, such as performance expectations or type of feedback received following performance.

Psychologically active characteristics produce situation-state contingencies. A situation-state contingency is a systematic relationship between a state and a situation characteristic. Contingencies describe how an individual acts in one situation compared to him- or herself in another situation. Contingencies differ in the direction and magnitude they alter the level to which a trait is manifest in a state. For example, Kaplan and Maehr (2007) suggested six characteristics of situations that may influence different dimensions of goal orientation, and include the nature of the task, the amount of autonomy given in performing a task, the details of performance that are given recognition, collaboration versus competition, feedback strategies, and allocation of time. These characteristics may be situation-state contingencies for goal orientation. Each of these situational characteristics is believed to change the degree to which goal orientation is expressed. However, the direction and strength of each characteristic's influence is different relative to one another and to goal orientation dimension (e.g., learning, performance-prove, performance-avoid).

Fleeson has found support for the density distribution approach, finding significant levels of both within-person variability and between-person stability in interpersonal trust (Fleesson & Leicht, 2006) and scales of the Five Factor model of personality (Fleeson, 2001). In a study of the Five Factor model of personality, Fleeson (2007) found evidence of situation-based contingencies that influence the expression of trait manifestation. In addition, he found that the contingencies helped explain for the sizable with-person variability in behavior, individuals differed reliability in their contingencies and situational characteristics that served as contingencies differed by trait. Fleeson's theory may provide a new framework for thinking about goal orientation, help clarify conceptual and operational inconsistencies, and improve our understanding of how goal orientation relates with performance.

The next step is to identify an appropriate research method to test the applicability of the density distribution approach to goal orientation. Fleeson (2001), stated "if individual differences in behavior are best described as density distributions, a large amount of behavioral variability will be present within the typical individual, individual differences in distribution parameters will be highly stable, and within-person variability will be meaningful" (p. 1012). In a similar note, Dumenci and Windle (1998) stated that "a limitation to overcoming the trait-state dichotomy has been the development of measurement models and statistical procedures to simultaneously estimate parameters that correspond to both stable and labile features of behavior" (p. 405). Dumenci and

Windle suggest applying a class of longitudinal structural equation models known as latent trait-state (LTS) models.

LATENT TRAIT-STATE MODELS

LTS models assess stability and intraindividual differences in psychological attributes simultaneously (Steyer et al., 1992). These models have a longitudinal design, measuring attributes at multiple times. Figure 1 depicts a basic LTS model. In LTS models, a series of latent state variables (S_k) is extracted from one or more manifest variables (Y_k), one for each time period. The state represents an individual's level of an attribute at a particular point in time (k). The variance of the latent state variables is partitioned into two second-order factors: a common latent trait factor (T) representing stability over time, and an occasion-specific state residual (SR_k), representing the variability associated with the situation plus the interaction between person and situation. Variance unexplained by trait or occasion is random measurement error (ε). LTS models can account for stable patterns as well as situational variability.

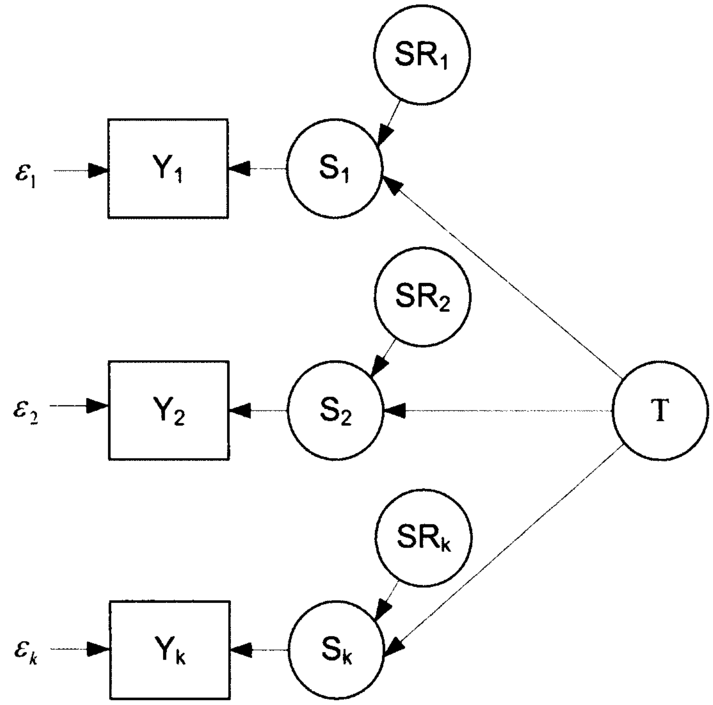

Figure 1. Simplified latent trait-state model.

Note. T = trait, S = state for *k* occasions in time, SR = state residual for *k* points in time, ε = random measurement error for *k* occasions in time, and any observable variable *Y*.

The most commonly used class of longitudinal models of change are latent growth curves models (e.g., Chan, 1998; McArdle & Epstein, 1987; Meredith & Tisak, 1990). In latent growth curve models, individual growth curves are decomposed into latent variables representing an intercept and one or more components of change. An alternative is LTS models. These models have been used to estimate situational and trait influences when measuring a number of psychological attributes, including organizational commitment (Tisak & Tisak, 2000), attitudes towards non-citizen workers (Steyer & Schmitt, 1990), test anxiety (Schermelleh, Keith, Moosbrugger, & Hodapp, 2004), personality scales from the Freiburg Personality Inventory (FPI), the NEO Five-Factor Inventory (NEO-FFI), and the Eysenck Personality Inventory (EPI; Deinzer et al., 1995), stress (Kenny & Zautra, 1995), depression (Davey, Halverson, Zonderman, & Costa, 2004), mood (Steyer & Riedl, 2004), primary emotions such as happiness, anger, fear, and sadness (Eid & Diener, 1999), psychopathology (Steyer, Krambeer & Hannöver, 2004), developmental psychopathology (Cole, 2006), and alcohol abuse (Dumenci & Windle, 1998).

LTS models were originally suggested by Herzorg and Nesselroade (1987) nearly twenty-five years ago. Several variant LTS models have been developed since that time. These models added autoregressive functions between states (e.g., Kenny & Zautra, 1995; Steyer & Schmitt, 1994) or occasions (Cole, Martin, & Steiger, 2005). Other adaptations have included first-order methods factors (Steyer et al., 1992) and the inclusion of 2 or more traits in hierarchical LTS models (Schermelleh et al., 2004). LTS models have also been adapted for categorical variables as latent class models (Eid & Langeheine, 1999), integrated with latent growth curve modeling (Tisak & Tisak, 2000) and generalized as a multitrait-multioccasion model (Dumenci & Windle, 1998).

Individuals are not measured in an environmental vacuum. Rather, they are assessed in a situation that has the potential to influence their scores on a measured variable regardless of whether that measure was intended to provide a score on a state or a trait. Allport (1937) originally conceived of traits as ranges of behavioral possibilities that are *activated according to situational demand.* Furthermore, Mischel (1968) noticed that individuals behave similarly in different situations only to the degree that the situations share similar features. Hertzog and Nesselroade (1987) noted that most psychological attributes are neither strictly traits nor states, but have both trait and state components.

LTS models are ideal for testing if Fleeson's (2001) density distribution theory describes goal orientation better than either state or trait conceptualizations. According to Fleeson, a trait is manifest in a state that shares the same content, breath, and scale. The state is also influenced by psychologically active characteristics of situations, which alter the level to which a trait is expressed. Trait manifestation is analogous to a latent trait, while a psychologically active characteristic of a situation is analogous to a latent state residual. Finally, both Fleeson's personality state and LST theory's latent state are comprised of trait and situational components.

LTS models may provide a method to integrate conceptualizations of goal orientation and explore the relationship between goal orientation and other variables. The expression of goal orientation (e.g., state goal orientation) is influenced by trait and characteristics of the situation. This can be modeled and tested using LST theory using goal orientation measures regardless of their intended level of temporal specificity (e.g., general trait, domain-specific trait, or state). The following section includes several hypotheses. They are divided into two groups: a) measurement model hypotheses and b) performance prediction hypotheses.

MEASUREMENT MODEL HYPOTHESES

Although trait measures are intended to assess goal orientation traits, when examined longitudinally, they will include both state-like and trait-like variance. When assessed across time, all goal orientation measures regardless of their intended level of stability include variance attributable to both sources. Trait measures will contain variance typically associated with states and, conversely, state measures will contain variance associated with traits. A trait goal orientation measure may have a larger latent trait variance component than latent state variance component, but it will still have both components. A state goal orientation measure will also have both latent state and latent trait variance components, while the latent state component will likely be the larger of the two. The LTS models will provide a better fit to the variance/covariance structure of goal orientation than a latent trait model or a latent state model. Therefore, I assert the following hypotheses.

H1a *A latent trait-state model will provide a better fit for general trait learning goal orientation than either a trait or state model.*

H1b *A latent trait-state model will provide a better fit for general trait performance-prove goal orientation than either a trait or state model.*

H1c *A latent trait-state model will provide a better fit for general trait performance-avoid goal orientation than either a trait or state model.*

H2a *A latent trait-state model will provide a better fit for domain-specific trait learning goal orientation than either a trait or state model.*

H2b *A latent trait-state model will provide a better fit for domain-specific trait performance-prove goal orientation than either a trait or state model.*

H2c *A latent trait-state model will provide a better fit for domain-specific trait performance-avoid goal orientation than either a trait or state model.*

H3a *A latent trait-state model will provide a better fit for state learning goal orientation than either a trait or state model.*

H3b *A latent trait-state model will provide a better fit for state performance-*

prove goal orientation than either a trait or state model.

H3c *A latent trait-state model will provide a better fit for state performance-avoid goal orientation than either a trait or state model.*

Hypotheses are grouped by the level of goal orientation specificity. Hypotheses 1a through 1c make assertions about general trait goal orientation, Hypotheses 2a through 2c relate to domain-specific trait goal orientation, and Hypotheses 3a through 3c concern state goal orientation. At each level of specificity there are hypotheses for learning, performance-prove and performance-avoid goal orientation.

Hypotheses 1a through 3c were tested by comparing the fit of LTS models to state and trait models within a longitudinal design. Previous studies have modeled goal orientation states and traits (e.g., Button et al., 1996; Fisher & Ford, 1998). However, they did not include a second-order model of a single measure. Instead, they included first-order models of multiple goal orientation dimensions.

PERFORMANCE PREDICTION HYPOTHESES

Steyer et al. (1999) suggested trait-state models could provide a useful methodological tool for answering different research questions of personality psychology. One research question is determining the proportion of variance in observable variables attributable to trait effects, situation and/or interaction effects, and measurement error. This suggestion was used to formulate Hypotheses 1, 2, and 3. Steyer et al. (1999) also suggested applying LTS models to evaluate how a trait, freed from situational influences or situation-based contingencies, correlates with other variables.

The relationship between trait goal orientation and performance is commonly assessed using a trait measure, either general or domain-specific, administered once. Performance data may be collected at the same time or may be collected on different occasions and be aggregated in some way. This presents two problems. The first problem is that trait measures contain both variance associated with trait goal orientation and variance associated with the situation. This decreases the accuracy of trait measure and diminishes its relationship with performance outcomes. The second problem is that scores on the trait goal orientation measure may not accurately individuals' scores during later periods of performance. An LTS model containing manifest variables (i.e., trait measures) administered repeatedly throughout the period of performance would provide a more accurate assessment of the relationship between goal orientation and performance. The Payne et al. (2007) meta-analysis included two achievement-oriented outcomes important in academic and training settings: learning and academic performance. The learning outcome should not be confused with learning goal orientation. Learning is the acquisition and of declarative and procedural knowledge while academic performance is how well an individual performs on academic tasks over time. LTS models will offer a better description of the predictive relationship of goal orientation with learning and academic performance. Therefore, I propose the following sets of hypotheses.

H4a *A latent trait-state model will provide a better fit than a trait model when examining the relationship between general trait learning goal orientation and learning in an academic setting.*

H4b *A latent trait-state model will provide a better fit than a trait model when* *examining the relationship between general trait performance-prove goal orientation and learning in an academic setting.*

H4c *A latent trait-state model will provide a better fit than a trait model when examining the relationship between general trait performance-avoid goal orientation and learning in an academic setting.*

H5a *A latent trait-state model will provide a better fit than a trait model for explaining the relationship between general trait learning goal orientation and academic performance.*

H5b *A latent trait-state model will provide a better fit than a trait model for explaining the relationship between general trait performance-prove goal orientation and academic performance.*

H5c *A latent trait-state model will provide a better fit than a trait model for explaining the relationship between general trait performance-avoid goal orientation and academic performance.*

H6a *A latent trait-state model will provide a better fit than a trait model for explaining the relationship between domain-specific trait learning goal orientation and learning in an academic setting.*

H6b *A latent trait-state model will provide a better fit than a trait model for explaining the relationship between domain-specific trait performance-prove goal orientation and learning in an academic setting.*

H6c *A latent trait-state model will provide a better fit than a trait model for explaining the relationship between domain-specific trait performance-avoid goal orientation and learning in an academic setting.*

H7a *A latent trait-state model will provide a better fit than a trait model for explaining the relationship between domain-specific trait learning goal orientation and academic performance.*

H7b *A latent trait-state model will provide a better fit than a trait model for explaining the relationship between domain-specific trait performance-prove goal orientation and academic performance.*

H7c *A latent trait-state model will provide a better fit than a trait model for explaining the relationship between domain-specific trait performance-avoid goal orientation and academic performance.*

Hypotheses are grouped by the level of goal orientation specificity and performance outcome. Hypotheses 4a through 4c concern the relationship between general trait goal orientation and learning in an academic setting. Hypotheses 5a through 5c relate to the relationship between general trait goal orientation and academic performance. Hypotheses 6a though 6c examine the relationship between domain-specific trait goal orientation and learning in an academic setting. Finally, Hypotheses 7a through 7c relate to the relationship between domain-specific trait goal orientation and academic performance. Similar to earlier hypotheses, these sets of hypotheses include learning, performance-prove and performance-avoid goal orientation.

Steyer, et al. (1999) suggested applying LTS models to determine how different LTS factors correlate with other variables. State measures are typically used to assess how an individual perceives, interprets and adapts to changes in the situation. Adding an LTS structure when modeling the relationship of a psychological state with performance could be promising. I predict that it will provide a more accurate representation of the influence of the situation on goal orientation expression and its relationship with two achievement-oriented outcomes: learning and academic performance. More specifically, I predict that:

H8a *A latent trait-state model will provide a better fit than a state model for explaining the relationship between state learning goal orientation and learning in an academic setting.*

H8b *A latent trait-state model will provide a better fit than a state model for explaining the relationship between state performance-prove goal orientation and learning in an academic setting.*

H8c *A latent trait-state model will provide a better fit than a state model for explaining the relationship between state performance-avoid goal orientation and learning in an academic setting.*

H9a *A latent trait-state model will provide a better fit than a state model for explaining the relationship between state learning goal orientation and academic performance.*

H9b *A latent trait-state model will provide a better fit than a state model for explaining the relationship between state performance-prove goal orientation and academic performance.*

H9c *A latent trait-state model will provide a better fit than a state model for explaining the relationship between state performance-avoid goal orientation and academic performance.*

Hypotheses 8a to 8c investigate the relationship between state goal orientation and learning in an academic setting, while Hypotheses 9a to 9c concern the relationship between goal orientation and academic performance. Like earlier sets of hypotheses, these include learning, performance-prove and performance-avoid goal orientation.

Figure 2 contains a summary of the study hypotheses. For the first nine hypotheses, Hypotheses 1a through 3c, I test measurement models of goal orientation and for the remaining 18, Hypotheses 4a through 9c, I assess how well the models predict performance in an academic (i.e., learning in an academic setting and academic performance). The hypotheses include the three dimensions of goal orientation (learning, performance-prove and performance-avoid) at three levels of specificity. Hypotheses 1a through 1c, 4a through 4c, and 5a through 5c pertain to general trait goal orientation. Hypotheses 2a through 2c, 6a through 6c, and 7a through 7c examine domain-specific goal orientation. And finally, Hypotheses 3a through 3c, 8a through 8c, and 9a through 9c examine state goal orientation.

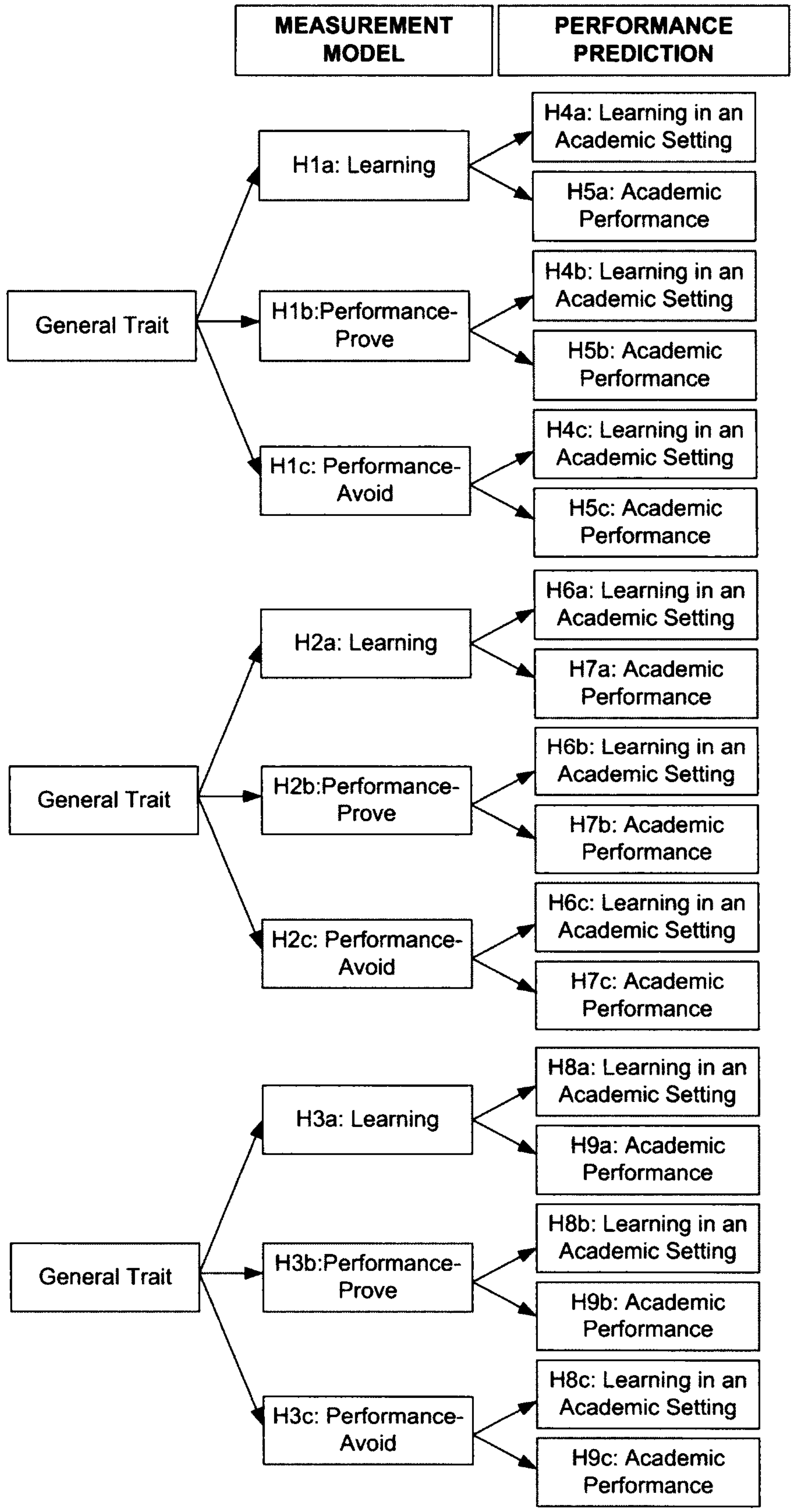

Figure 2. Summary of study hypotheses.

CHAPTER II

METHOD

The current study will assess how well Fleeson's (2001) density distribution theory describes goal orientation measured at three levels of specificity (general trait, domain-specific trait, and state) using LTS covariance matrix models.

PARTICIPANTS

Study participants were undergraduate students enrolled in an introductory psychology course at Old Dominion University during the fall semester of 2007. Enrollment for the course was 244 students with a slightly higher female enrollment. As a course requirement, students had to earn 4 research credits through volunteering as subjects in Psychology Department experiments or through written assignments. Participants were able to earn a total of 4 research credits through their participation, one for each period of data collection. Participation was voluntary and all responses were confidential.

DETERMINATION OF SAMPLE SIZE

There are several different rules-of-thumb for recommended sample size when using structural equation modeling. According to Kline (1998), sample size should be at least fifty plus eight times the number of latent variables in the model. The most complex model included in the hypotheses contains four state, one trait, and two method variables for a total of seven latent variables, requiring a minimum sample size of 106.

Another rule-of-thumb offered by Mitchell (1993) is having a sample 10 to 20 times larger than the number of variables in the model. This estimate would require a minimum of between 70 to 140 cases. Bentler (1985) recommends a minimum of 5 cases for each estimated parameter. The most complex model proposed contains 31 parameter estimates and would require 155 cases. With full student participation, a 25% dropout rate over the course of the study would leave 187 participants and a dropout rate of one-third (33%) would leave 167 participants. With dropout of over 40% (150 participants) the sample would still meet the requirements of the first two rules of thumb and come within 5 cases of the third.

Students enrolled in an introduction to psychology course were chosen as the sample because they provided the largest intact group in which individuals enrolled in a learning setting over an extended duration (14 weeks) could be followed. This was the most pragmatic option to meet or exceed recommended sample sizes estimates and accommodate the attrition common to longitudinal research.

MEASURES

Demographics

During time 1, participants were required to provide basic demographic information, including sex, age, academic major, and academic year.

Goal Orientation

Eight candidate goal orientation questionnaires were considered for the current study, including those from Button et al. (1996), Elliot (1999), Elliot and Church (1997), Elliot and McGregor (2001), Grant and Dweck (2003), Heggestad (1997), Horvath, Scheu, and DeShon (2004), and VandeWalle (1996; 1997). The selection of a goal orientation measure was based on four criteria:

1. The measure must have been developed through a documented psychometrically rigorous procedure driven by a sound understanding of theory.

2. The measure needs to include scales for learning, performance-prove, and performance-avoid goal orientations.

3. The measures must include scales for each of three levels of operationalization: general trait, domain-specific trait, and state. A measure could also meet this criterion if items from the scales are easily modifiable to assess goal orientation at all three levels.

4. The measure needs to contain scales with enough items to create multiple parcels. A parcel, also known as a testlet, is created by combining items from a scale into several smaller subscales. Parcels provide an increased likelihood of achieving a proper model solution and a better model fit when using structural equation modeling (Marsh, Hau, Balla, & Grayson, 1998; Rogers & Schmitt, 2004; Yuan, Bentler & Kano, 1997). According to Bandalos and Finney (2001), conducting a multi-factor confirmatory factor analysis (CFA) at the item level should be avoided. The covariance matrix of items can be

large enough to exceed the limits of structural equation software like Amos or LISREL. Furthermore, individual items have low reliability and may depart from normality, resulting in a confirmatory model that may not fit the data well (Bagozzi & Heatherton, 1994; Kishton & Widaman, 1994). A common solution is the use of parcels or item subscales. To meet this criterion, scales must include at least enough items to create three 2-item subscales.

All candidate measures met the first requirement. The second criterion excluded one of the more commonly used measures, the General Performance and Learning Goal scales (Button et al., 1996), which only contains scales for performance and learning orientations, as the name implies. Neither Elliot and Church's (1997) academic-domain measure nor a revised version of the measure (Elliot, 1999) met the third criterion. VandeWalle's (1997) work-domain and academic-domain (VandeWalle, 1996) measures did not meet the third or fourth criteria. Two 4-factor measures, by Elliot and McGregor (2001) and Grant and Dweck (2003), did not include enough items per scale to meet the fourth criteria. Horvath and colleague's (2004) general and domain-specific goal orientation measures also had too few items to meet the last criteria. Only one goal orientation measure met all criteria: the Motivational Trait Questionnaire (MTQ; Heggestad, 1997; Heggestad & Kanfer, 2000).

While it was originally intended as a measure of Kanfer and Heggestad's (1997) motivational trait framework, Heggestad and Kanfer (2000) recommend the MTQ as a measure of general goal orientation. The three main scales of the MTQ include personal mastery (learning goal orientation), competitive excellence (performance-prove goal orientation), and motivation anxiety (performance-avoid goal orientation). Ward and Heggestad (2004) used the MTQ as a measure of goal orientation while examining the relationships among general and domain-specific goal orientations, contextualized goals, and goal orientated situations. Most likely, the MTQ has not garnered wider use in published studies because it is a proprietary psychological assessment test with controlled distribution.

The full version of the MTQ contains 183 items, while a short form includes 48 items taken from the longer form. To assess general goal orientation, the current study included an abbreviated version of the measure containing six items from each of the three scales. This 18-item version contains items having the highest item-total correlation for each scale, based on the results of Heggestad (1997). Six item scales will allow the creation of two three-item parcels. A six-point Likert-type response scale, ranging from 1 (*very untrue of me*) to 6 (*very true of me*), will be used for each item. Scale values will be computed as an average of all items comprising the scale. The items for the abbreviated MTQ are presented in Appendix A.

Items from the abbreviated MTQ were modified to create an academic domain measure of goal orientation. For example, *in the class* was added to several items. As another example, items describing *standards* and *performance* were modified as *academic standards* and *academic performance*, respectively. All items retained a six-point Likert-type response scale. In addition, the instructions were modified from "this questionnaire asks you to respond to statements about your attitudes, opinions, and behaviors" to "this questionnaire asks you to respond to statements about your attitudes, opinions, and behaviors relative to college courses". The items for the academic domain instrument are in Appendix B.

The MTQ was also adapted to assess state goal orientation. According to Fleeson and Leicht (2006), state dimensions have the same content, breadth and scale as their trait counterparts. Individual items remained the same; the instructional set was modified. Rather than asking about general attitudes, the instructions asked participants to respond based on how they feel at that particular moment. The statement "In deciding on your answer for these questions, consider how you currently feel" was added to the directions. A copy of the state goal orientation instrument is in Appendix C.

Learning and Academic Performance

Operationalization of learning and academic performance was based on the meta-analysis by Payne et al. (2007). Learning is the acquisition of declarative and procedural knowledge and is frequently assessed in goal orientation studies as performance on a test of exam. Academic performance is broader than learning and indicates how well an individual performs on multiple academic-related tasks over a period of time. It is typically assessed as a final course grade or overall grade-point average. In this study I measured learning as an individual's score on the quiz or test administered closest in occurrence to one of the four administrations of the goal orientation measures. Learning measures included quiz 1 (Time 1), quiz 2 (Time 2), quiz 7 (Time 3), and final exam (Time 4). The length of time between the episode of performance and measure administration varied between 10 minutes (Time 4) and 5 days (Time 1). Based on Payne et al. (2007), academic performance was operationalized as final grade in the course. In the current study, final grade was comprised of a weighted average of eight quiz and 4 exam scores.

PROCEDURE

Participants were informed of the current study during the first class meeting of the semester. Goal orientation measures were administered to participants at four time periods during the course of the semester, including the first week of the course (Time 1), the week grades for the first test were posted (Time 2), a week without a major assignment such as a test (Time 3), and immediately before the final exam (Time 4). According to Davey (2001), the spacing of longitudinal data collection waves should represent occasions that reflect the full variability of the context across time. The spacing between the waves of data collection was based on presence or absence of aspects of a setting that influence goal orientation, such as after receiving performance feedback (Time 2) and performing under time pressure (Time 4; Kaplan & Maehr, 2007). The battery contained demographic items (sex, age, academic year, and academic major) as well as the questionnaires found in Appendices A, B, and C.

DATA ANALYSIS

Data Screening

Analyses proceeded in two phases. First, I screened the data and conducted a confirmatory factor analysis (FFA) of the scales. Second, I tested all hypotheses using structural equation modeling with Amos 17.0 (SPSS, 2009). Data screening included procedures outlined by Tabachnick and Fidell (2001): 1) check for data coding accuracy and univariate outliers by examining variable value frequencies as well as means and standard deviations, 2) test for nonlinearity and heteroscedasticity by checking pairwise plots, 3) identify nonnormal variables by checking skewness, kurtosis, and probability plots, 4) indentify multivariate outliers through Mahalanobis distance tests, 5) evaluate variables for multicolinearity and singularity, and 6) assess the degree of missing data and test for relationships between missing data and experiment variables. Logistic regression analysis was used to test for a pattern of missing data related to variables of interest and no relationship was found.

According to Schafer and Graham (2002), the most highly recommended approaches to address missing data include maximum likelihood (ML) and multiple imputation (MI). Missing data for the current study was addressed using the ML feature of Amos 17.0. Amos 17.0 employs a ML algorithm known as full-information maximum likelihood (FIML). ML provides a method to address the loss of statistical power associated with casewise or pairwise deletion or other ad hoc procedures and to address bias due to variables related to missingness (Collins, 2006). For all analyses, means were estimated as this is a requirement when estimating missing data using FIML.

A confirmatory factor analysis (CFA) was conducted on the scales for all four occasions to test the factor structure using Amos 17.0. CFA was conducted for several reasons. First, Byrne (2010) recommends conducting a CFA whenever using a measurement instrument with a new group. Second, items from the original general trait scales were modified to create state and domain-specific trait scale counterparts. This may have altered the covariance structure of the items. CFA results helped to ensure well fitting measurement models prior to hypothesis testing.

Model fit was evaluated through interpretation of several fit indices, including root mean square error of approximation (RMSEA), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI), and likelihood-ratio χ^2 test. Browne and Cudeck (1993) suggest a RMSEA < .05 is a good fit for a model, RMSEA < .08 is a reasonable fit, and RMSEA > .10 is a poor fit. According to Hu and Bentler (1999), models with CFI and TLI values > .95 display a good fit. Small χ^2 values relative to degrees of freedom also suggest a good fitting model (Bollen, 1989; Hu & Bentler, 1998).

Reliability (i.e., Cronbach's coefficient alpha) was computed using the FIML implied means and covariance matrices following Enders' (2004) recommended reliability reporting practices with missing data. Enders recommended reporting the reliability and a 95% confidence interval (CI) using the ML estimate of the means and covariance matrix.

A potential confound in multi-group or longitudinal research is lack of measurement equivalence/invariance (ME/I; Vandenberg & Lance, 2000). Assessing ME/I provides evidence that the same construct is being measured across time or between groups and is measured with equal precision. Violations of ME/I can be as harmful to statistical interpretation as the inability to establish reliability and validity. Golembiewski, Billingsley and Yeager (1976) outlined a typology describing different types of change when longitudinally measuring latent variables using self-report measures. *Alpha change* is a shift in reported scores. *Beta change* is a shift in the measurement scale. The final type of change, *gamma change*, is a shift in the definition of the construct being measured. Measures are not equivalent or invariant if beta or gamma change is found. Alpha change is an expected attribute of state or attitudinal scores. However, beta and gamma change make comparison of scores between occasions of measurement impossible, as scores are on different scales or measure different constructs.

All measures were tested for beta and gamma change using the multiple-group analysis feature of Amos 17.0. The procedure used to test for beta and gamma change was based on the approach outlined by Schmitt, Pulakos, and Lieblein (1989). Absence of gamma change is demonstrated if a measure has the same factor structure at each point in time. This is also known as configural invariance (Vandenberg and Lance, 2000). Another test for gamma change is equivalent factor variance-covariance matrices. Equality of factor loadings can serve as a test of beta change.

Gamma and beta change was assessed through several fit indices, including a χ^2 difference ($\Delta\chi^2$) test and CFI difference (ΔCFI) test. A significant $\Delta\chi^2$ is interpreted as evidence that measures are not equivalent. According to MacCallum, Roznowski, and Necowitz (1992), the $\Delta\chi^2$ test may be too stringent of a test for ME/I. Cheung and Rensvold (2002) suggest using ΔCFI as a more reasonable test alternative. According to their suggestion, evidence of equivalence should be based on a difference in CFI values having a value less than or equal to 0.01.

Hypothesis Testing

Estimation of correlated residuals in SEM is restricted to a small number of circumstances and, in most cases, should not be practiced (Landis, Edwards, Cortina, 2009). According to Cortina (2002) the practice of correlated residuals should only proceed when a strong *a priori* reason exists for doing so. One example would be the case of longitudinal data with identical measures across time periods (Landis et al., 2009). In this situation, residuals attached to identical items but at different occasions of measurement will correlate.

These constraints define the manifest variables as parallel across occasions of measurement. The resulting model is similar to the correlated uniqueness multitrait-multimethod model suggested by Kenny and Zuatra (2001) which they note as the preferred choice for initial estimations of LTS models.

When testing hypotheses in the current study, all models included a number of equality constraints. Based on the results of the ME/I tests, scales were treated as having several equivalent measurement properties across occasions. Equality constraints were added to like item factor loadings and the covariance between like item residuals were constrained to be equal. For example, the factor loadings for item 2 at Times 1, 2, 3, and 4 were fixed as equal. The covariances between item 2 residual at Times 1, 2, 3, and 4 were also fixed as equal. Appendices M through U illustrate the models used to test Hypotheses 1a through 3c with the described constraints.

Hypotheses 1a through 3c

Model fit. For the first group of hypotheses, a series of non-nested models using Amos's FIML estimation were tested using the covariance matrix of variables. For Hypotheses 1a through 3c, RMSEA, CFI and TLI were used to evaluate model fit using the same criteria outlined for the CFA analysis (e.g., good fit identified as CFI and TLI values > .95 and RMSEA < .05). The χ^2 goodness-of-fit test and RMSEA 90% confidence interval were also used to assess model fit. A non-significant χ^2 indicates a well fitting model. A well fitting model is also indicated by a narrow RMSEA confidence interval with a lower bound value at or near zero and an upper bound of < .08 (MacCallum, Browne, & Sugawara, 1996). For selecting the best fitting model, several alternative fit criteria were used.

When comparing non-nested models, as in the current study, a $\Delta\chi^2$ test is not appropriate. The $\Delta\chi^2$ test can only be used when testing fit among nested models. When testing non-nested models, alternative fit criteria are used to determine the better fitting model (Vandenberg & Grelle, 2009). Unlike the $\Delta\chi^2$ test, these criteria are not part of the null hypothesis approach to testing, but are based on alternative approaches to inferential statistics, including information-theoretic and Bayesian statistics (Burnham & Anderson, 2010).

The Akaike Information Criterion (AIC; Akaike, 1973, 1987) is an information-theoretic alternative for statistical model selection and inference. It is an approximately unbiased estimator of the expected Kullback-Leibler (KL) information of a fitted model. KL information, also called the KL distance or KL divergence, is a measure of information loss from information theory and probability theory. KL information, I(f, g), is a measure of the amount of information lost when using model g to approximate full reality, f. It is a measure of expected distance from approximating a model to reality. AIC is an asymptotically unbiased estimator of expected K-L distance. Burnham and Anderson (2010) recommend using AICC, a second-order information criterion, as an alternative to AIC when $n/K < 40$, where n is the sample size and K is the number of estimated parameters.

Another alternative criterion is the Bayesian Information Criterion (BIC; Schwartz, 1978). The BIC is also computed from the likelihood of seeing a model given the data, rewarded by goodness of fit and penalized for lack of parsimony (Burnham & Anderson, 2010). While BIC is more conservative than AIC, Burnham and Anderson (2004) recommend using the AIC in the social sciences. Their rationale is the BIC was developed according to the philosophy that a true model exists, but these types of models are not characteristic of the social sciences. In contrast, the AIC assumes that a best-fitting approximation is among the models tested.

All three criteria, AIC, AIC_C, and BIC, were computed for models for testing Hypotheses 1a through 3c. Following the procedure described by Burnham and Anderson (2010), all models were rank ordered by criterion value; the model with the smallest value was selected as the best for inference. The selected model minimizes the information lost when approximating full reality and is the best model given the candidate models and the data.

In addition to simple ranking, there are two types of evidence concerning the evaluation of alternative hypothesized models when using an information-theoretic approach: model probabilities and evidence ratios. Model probability is expressed as an Akaike weight (w_i). It is the probability that Model i is the K-L best model, given the model set and the data. Unlike an AIC value, model probability w_i is absolute, however, still conditional on the model set.

Akaike weight w_i is based on the AIC difference (Δ_i) between the AIC values for Model i and the best fitting model (model with the smallest AIC value; AIC_{min}). The Δ_i is the estimate of the expected K-L information between the best model and the ith model. K-L information is the distance from each model to full reality, whereas Δ_i is the relative distance or information loss between the ith model and the best model. The Δ_i values are then used to calculate w_i, model probabilities. These probabilities are another source of evidence in favor of model i as being the actual K-L best model in the candidate set. The second additional type of information-theoretic evidence is evidence ratios. The evidence ratio of Akaike weights for model i over model j can be calculated as w_i / w_j. The evidence ratio can also be expressed as the normalized probability that Model *i* is preferred over Model *j* as the K-L best model (Wagenmakers & Farrell, 2004). Based on the advice of Anderson (2008) concerning the ratio of estimated parameters to sample size, Δ_i, w_i, and evidence ratios were calculated for Hypotheses 1a through 3c using values for AIC_C rather than AIC.

Candidate models. The same set of non-nested models was used for each dimension of goal orientation (i.e., learning, performance-prove, performance-avoid). The selection of trait, state, and LTS models for the tests of alternative models was based on multiple methodological reasons, including theory and empirical research.

A latent trait model can be constructed containing a single trait on which manifest (i.e., observed) variables for all occasions are loaded. However, theory and previous research identify several reasons why a first-order autoregressive model is superior to a single latent trait model for longitudinal modeling of traits. First, using state and trait anxiety data Steyer et al. (1992) provide evidence that latent trait models provide a poor fit for longitudinal trait data. Based on model fit and the pattern of modification indices, they contend that the poor fit is due to situational and interactional effects. Second, a lack of invariance among structural means (i.e., changes in the latent mean) will result in a poor fit of a single latent construct to represent a construct over time. Furthermore, Hertzog and Nesselroade (1987) argue that first-order autoregressive models, or longitudinal Markov simplex models, are appropriate for longitudinal modeling of traits. This model contains an autoregressive function linking one occasion of measurement to the next, for example, the latent state at time one is autoregressed on the latent state at time two, the latent state at time 2 is autoregressed on the latent state at time three, and so on. The autoregressive coefficients may be interpreted as a stability coefficient. Herzog and Nesselroade state that these stability coefficients are determined by, but should not be equated with, intraindividual stability.

Kenny and Zuatra (2001) lament that too often researchers with longitudinal data only estimate one LTS model without considering alternatives. In a review of LTS modeling, Davey (2001) commented, "Only by considering and comparing across a range of theoretically and empirically meaningful models can the researcher gain insight into the dynamic processes at work in his or her data" (p. 268). Therefore, seven trait state and LTS models (Figures 2 through 7) were included for testing Hypotheses 1a through 3c. These models differ by the inclusion of equality constraints on higher-order loadings and an autoregressive function on state or occasion factors. All models are listed in Table 1.

There are several options for modeling states over time. The first option is a model containing a latent variable for each occasion of measurement. The second option would include the addition of a first-order autoregressive function connecting adjacent periods of measurement. First-order autoregressive models are a common method to represent and analyze longitudinal data.

Table 1

Set of Candidate Models for Testing Hypotheses 1a Through 3c

Model Number	Description
1	Trait model
2	State model
3	State model with first-order autoregressive state factors (state-AR model)
4	LTS model
5	LTS model with equality constraints on latent trait factor loadings (LTS-EC model)
6	LTS model with first-order autoregressive latent state factors (LTS-ARS model)
7	LTS model with first-order autoregressive occasion factors (latent TSO model)

Based on these reasons, a latent trait model (Figure 3) and two latent state models in testing the fit of alternate models (Figures 4 and 5) were included in the study. The first latent state model is a first-order autoregressive model, which may also be considered appropriate for longitudinal modeling of traits (Hertzog & Nesselroade, 1987). The second latent state model is based on Steyer et al. (1992) and is the higher-order autoregressive model described above. This model is referred to as the state-AR model. The autoregressive function defining this model may be due to a higher-order latent trait variable. However if the simpler model can describe the data just as well as or better than a more complex LTS model, it was selected as the superior model for reasons of parsimony.

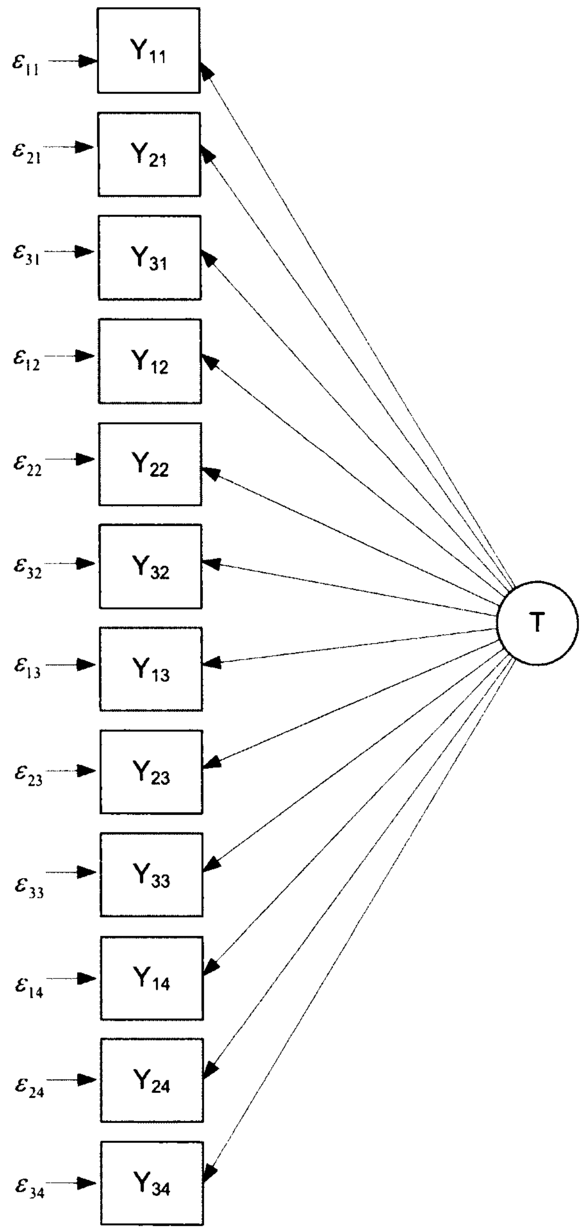

Figure 3. Model 1 for Hypotheses 1a through 3c: Trait model.

Note. T = trait for four waves and any observable variable Y_{ik}.

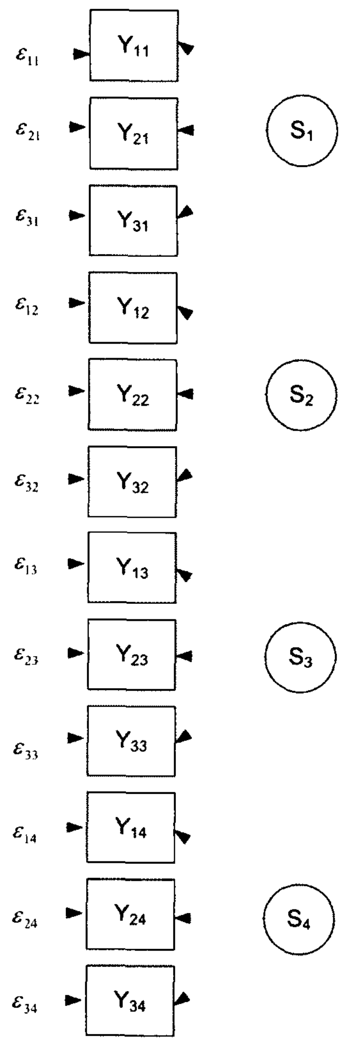

Figure 4. Model 2 for Hypotheses 1a through 3c: State model.

Note. S = state for four waves, and any observable variable Y_{ik}.

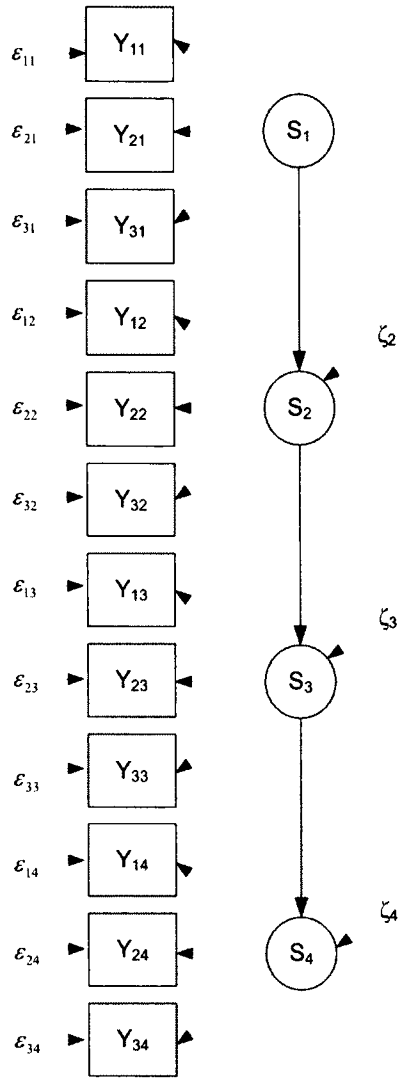

Figure 5. Model 3 for Hypotheses 1a through 3c: State model with first-order autoregressive state factors.

Note. S = state for four occasions, ζ_k = uniqueness factor for three occasions, and any observable variable Y_{ik}.

The first LTS model tested, Model 4, contained a state factor for each time period, a single trait factor, time-specific occasion factors, and random measurement error. A diagram of this model is located in Figure 6.

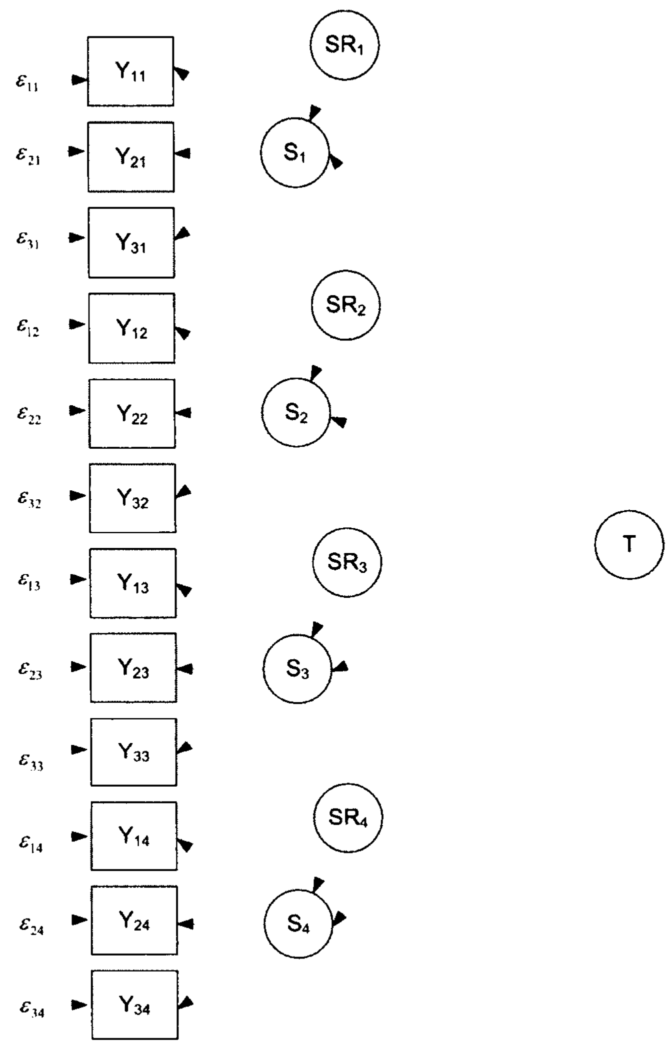

Figure 6. Models 4 and 5 for Hypotheses 1a through 3c: Latent Trait State model.

Note. T = trait, SR_k = state residual for four occasions across time, S_k = state for four occasions across time, ε = random measurement error for four occasions across time, and three manifest variables Y_{ik} for four occasions across time.

Model 5, the LTS-EC model, is identical to Model 4 with the exception of additional equality constraints on the factor loadings from the latent trait to the four latent states. The addition of the constraints serves to represent the stable and constant level of influence exerted by a trait over time.

Both Models 6 and 7, the LTS-AR and latent TSO models, contain an autoregressive component in the form of stability β coefficients. Autoregressive models have previously been used in analyzing stability and change in longitudinal data (Joreskog, 1979). They model stability by a variable measured at one period predicting itself or another variable at a later time. State-trait models with autoregressive state factors have been used to examine stressors and desirable experiences in the human lifecycle (Kenny & Zautra, 1995, 2001) as well as young adult anxiety and older adult mood states (Hertzog and Nesselroade, 1987).

Model 6, the LTS-ARS model, includes autoregressive state factors. This model would be most appropriate when a trait has a strong influence on a state and the strength of psychological active characteristics of the situation is weak. Model 6 is depicted in Figure 7.

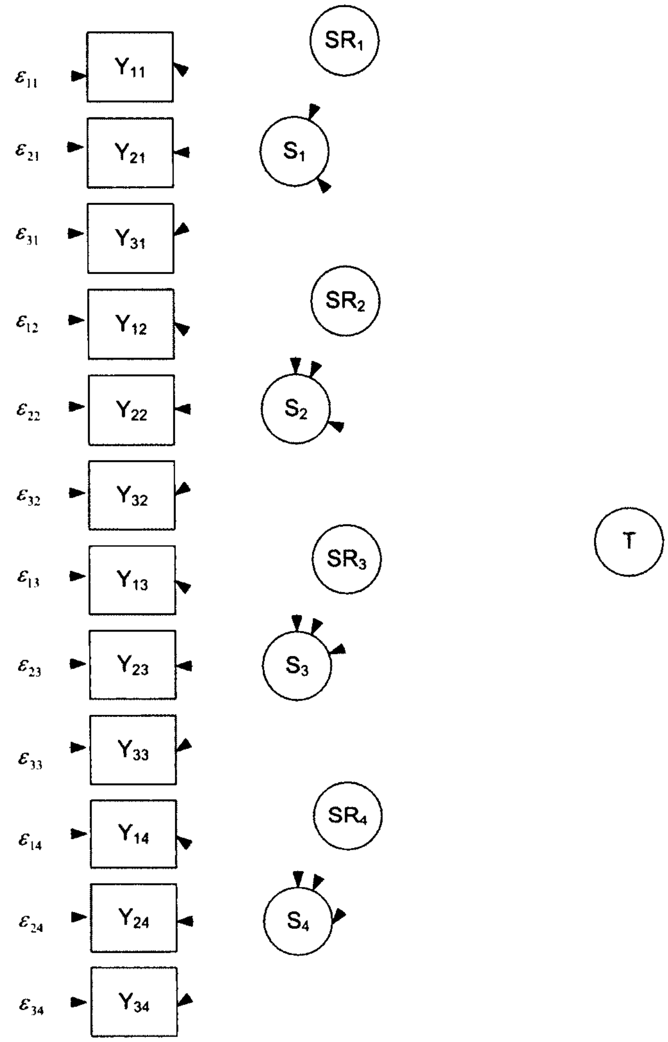

Figure 7. Model 6 for Hypotheses 1a through 3c: Latent Trait State model with autoregressive states.

Note. T = trait, SR_k = state residual for four occasions across time, S_k = state for four occasions across time, ε = random measurement error for four occasions across time, and three manifest variables Y_{ik} for four occasions across time.

Model 7 contains autoregressive occasion factors and is depicted in Figure 8. The model also contains residual factors (ζ_k) for the second through fourth occasion factors. Also, occasion residuals were constrained to be equal. This model includes the influence of a stable situation. This model would be most appropriate for a strong but stable situation, similar to the classroom setting in which the data for this study was gathered: the course was taught by a single instructor, included the same cohort of students, contained content the same general topic (Introduction to Psychology), and followed the same set of rules and expectations for classroom behavior and performance. According to Cole, Martin, and Steiger (2005), a LTS model with these constraints has the added advantage of reducing the number of improper solutions and reducing the standard error for all estimates. Cole et al. refer to the model as a latent TSO model.

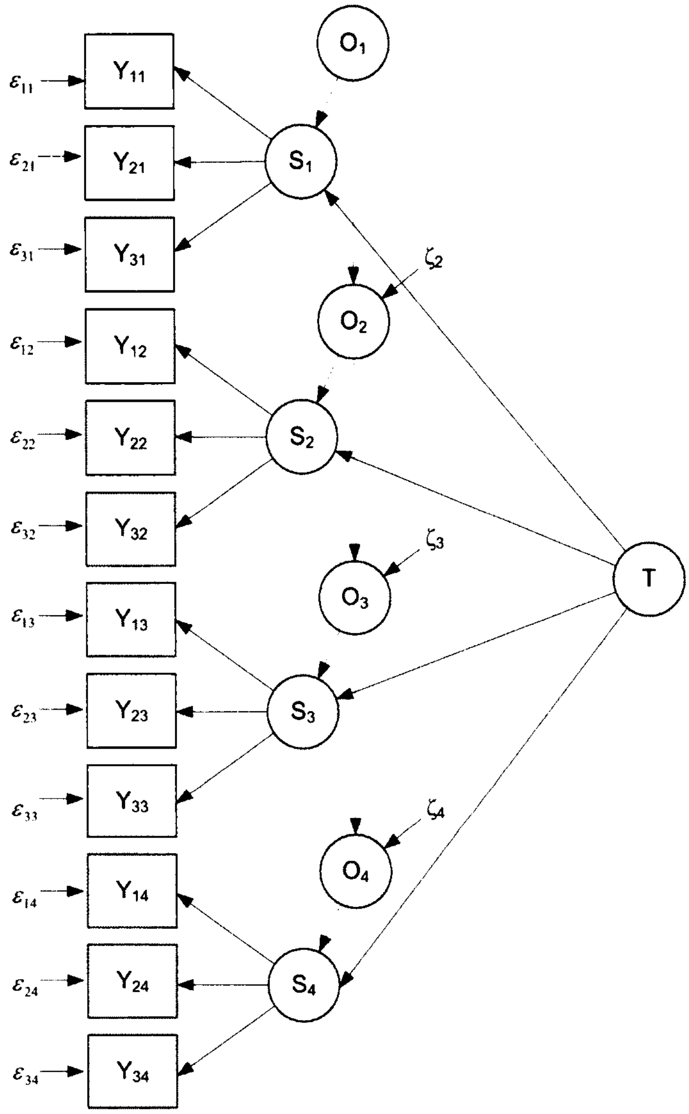

Figure 8. Model 7 for Hypotheses 1a through 3c: Latent State Trait Occasion model. *Note.* T = trait, O_k = occasion for four periods across time, ζ_k = uniqueness factor for three occasions, S_k = state for four periods across time, ε = random measurement error for four periods across time, and three manifest variables Y_{ik} for four periods across time.

Hypotheses 4a through 7c

Candidate models. Both Hypotheses 4a through 4c and Hypotheses 6a through 6c examined the predictive relationship between goal orientation and learning in an academic setting. However, they differed on the level of goal orientation specificity: general trait versus domain-specific trait, respectively. Table 2 lists the models used for testing Hypotheses 4a through c (i.e., general trait goal orientation predicting learning) and 6a through c (i.e., domain-specific trait goal orientation predicting learning). In the first model, goal orientation is modeled as a latent trait consisting of the manifest variables from Time 1. The four measures of learning corresponding to each of the four periods when the ability measures were administered. The four learning outcomes were operationalized as the first (Time 1), second (Time 2) and seventh (Time 3) quizzes and the final exam (Time 4). This model is illustrated in Figure 9.

Table 2

Set of Candidate Models for Testing Hypotheses 4a through 7c

Model Number	Description
1	Latent trait model
2	LTS model
3	LTS model with autoregressive occasion factors (latent TSO model)

For Model 2 (depicted in Figure 10), manifest variables from Times 2 through 4 and a LTS factor structure with equality constraints on the trait coefficients were added. This model is based on Model 5, used to test Hypotheses 1a through 3c. Model 3 was similar to the previous model with the addition of an autoregressive function on the occasion factors. This model is based on an autoregressive LTS models tested in earlier hypotheses (1a through 3c) and can be found in Figure 11.

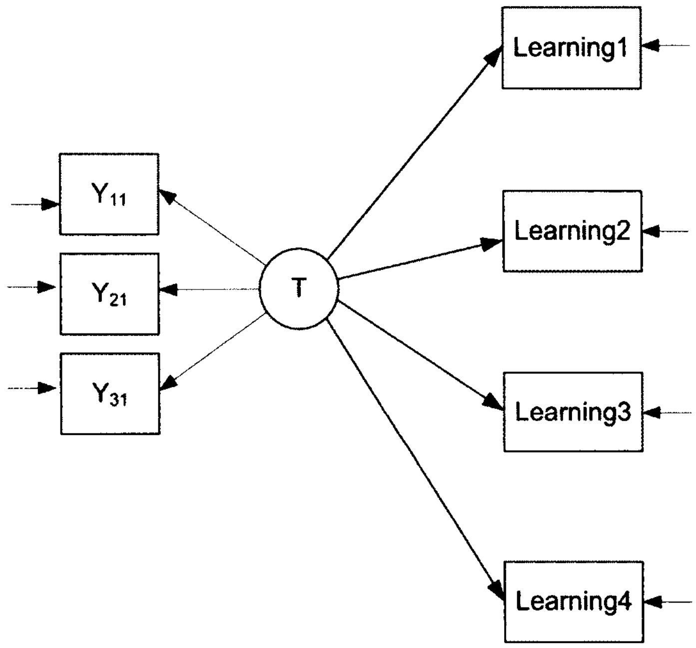

Figure 9. Model 1 for Hypothesis 4a through 4c and Hypothesis 6a through 6c: Relationship between latent trait model of goal orientation and learning.

Note. T = trait for three manifest variables Y_{ik} for one point in time, Learning1 = learning outcome for Time 1: Learning2 = learning outcome at Time 2; Learning3 = learning outcome at Time 3; Learning4 = learning outcome at Time 4.

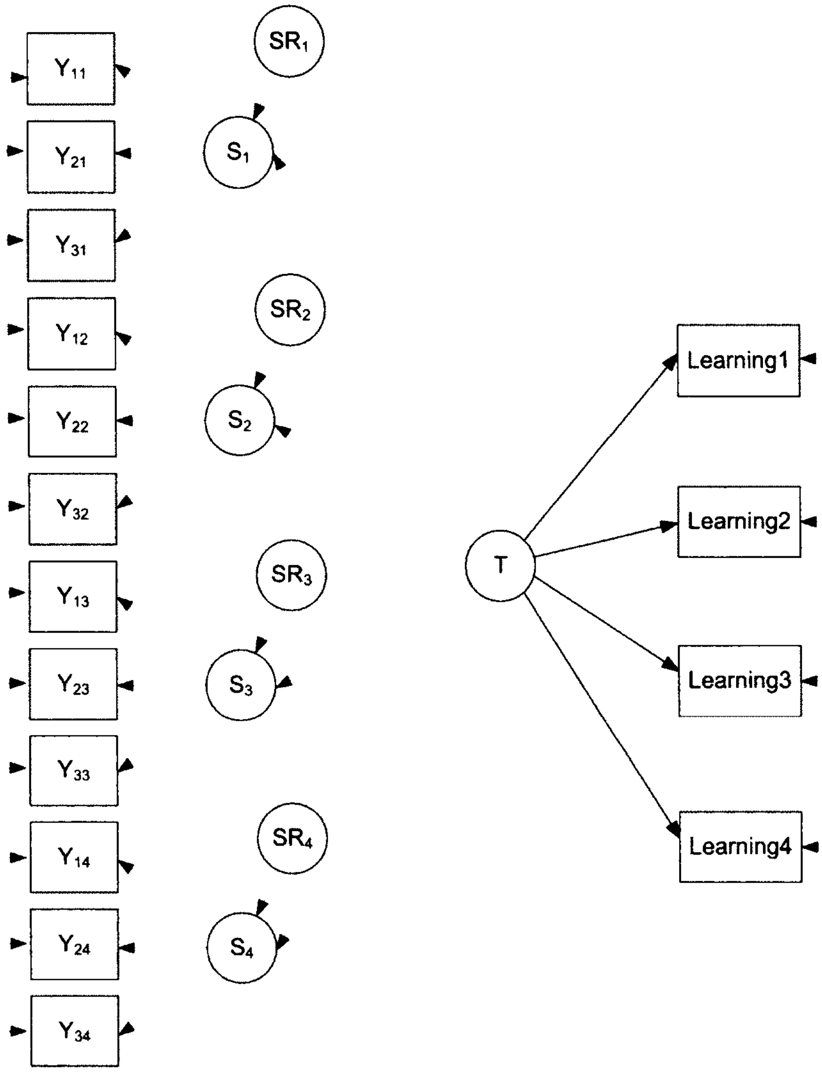

Figure 10. Model 2 for Hypotheses 4a through 4c and Hypothesis 6a through 6c: Relationship between LTS model of goal orientation and learning.

Note. T = trait, SR_k = state residual for four occasions across time, S_k = state for four occasions across time, and three manifest variables Y_{ik} for four occasions across time; Learning1 = learning outcome for Time 1: Learning2 = learning outcome at Time 2; Learning3 = learning outcome at Time 3; learning4 = learning outcome at Time 4.

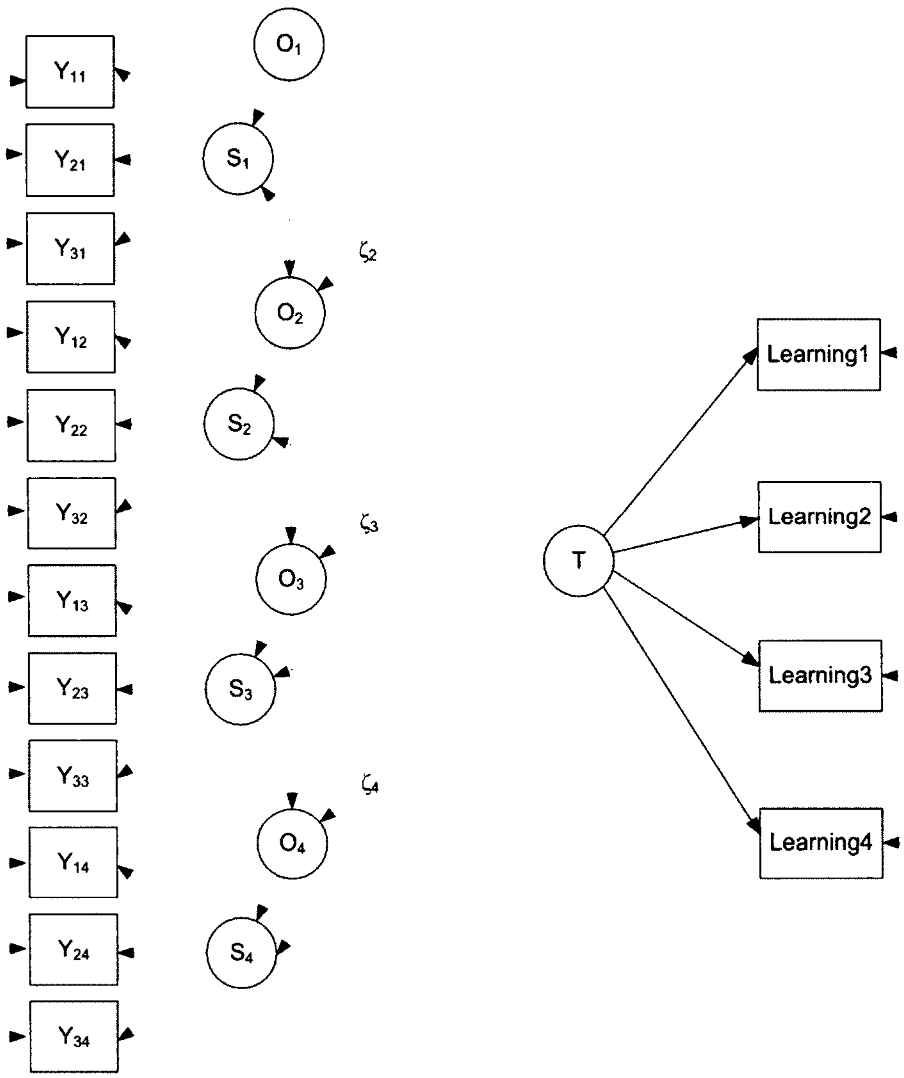

Figure 11. Model 3 for Hypothesis 4a through 4c and Hypothesis 6a through 6c: Relationship between LTS model of goal orientation and learning.

Note. T = trait, O_k = occasion for four periods across time, ζ_k = uniqueness factor for three occasions, S_k = state for four periods across time, and three manifest variables Y_{ik} for four periods across time; Learning1 = learning outcome for Time 1; Learning2 = learning outcome at Time 2; Learning3 = learning outcome at Time 3; learning4 = learning outcome at Time 4.

The models used to test Hypotheses 5a through 5c and Hypotheses7a through 7c were similar to those used for testing Hypotheses 4a through 4c. One difference being the learning outcome was replaced with academic performance. Academic performance was operationalized as final grade, which was the same as in the meta-analysis by Payne et al. (2007). In the current study, final grade consisted of a weighted average of four exam and eight quiz scores. Figures 12, 13 and 14 outline the alternative models used for testing Hypotheses 5a through c and Hypotheses 7a through c.

For Hypotheses 4a through 7c, Model 1 included only the observed variables from Time 1, while the alternative models contained the observed variables from all four occasions: Time 1, Time 2, Time 3, and Time 4. Model 1 is based on the psychometric concepts of true-score theory and latent-trait models (Allen & Yen, 1979) as well as simple linear regression (Pedhazur, 1997). In trait-score and latent-trait theories, latent-trait or true score values are assumed to give all the necessary information needed for measuring an individual level of the trait. Additional test scores will not improve measurement or prediction of an individual's trait score. Furthermore, prediction in simple linear regression precludes the need to measure traits from more than one occasion. Based on the assumptions of simple linear regression, scores of the same latent trait from additional occasions would not improve prediction.

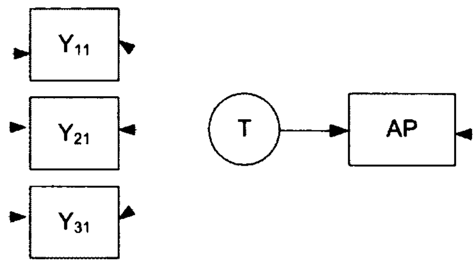

Figure 12. Model 1 for Hypotheses 5a through 5c and Hypotheses 7a through 7c: Relationship between latent trait model of goal orientation and academic performance.

Note. T = trait for three manifest variables Y_{ik} for one point in time, AP = academic performance.

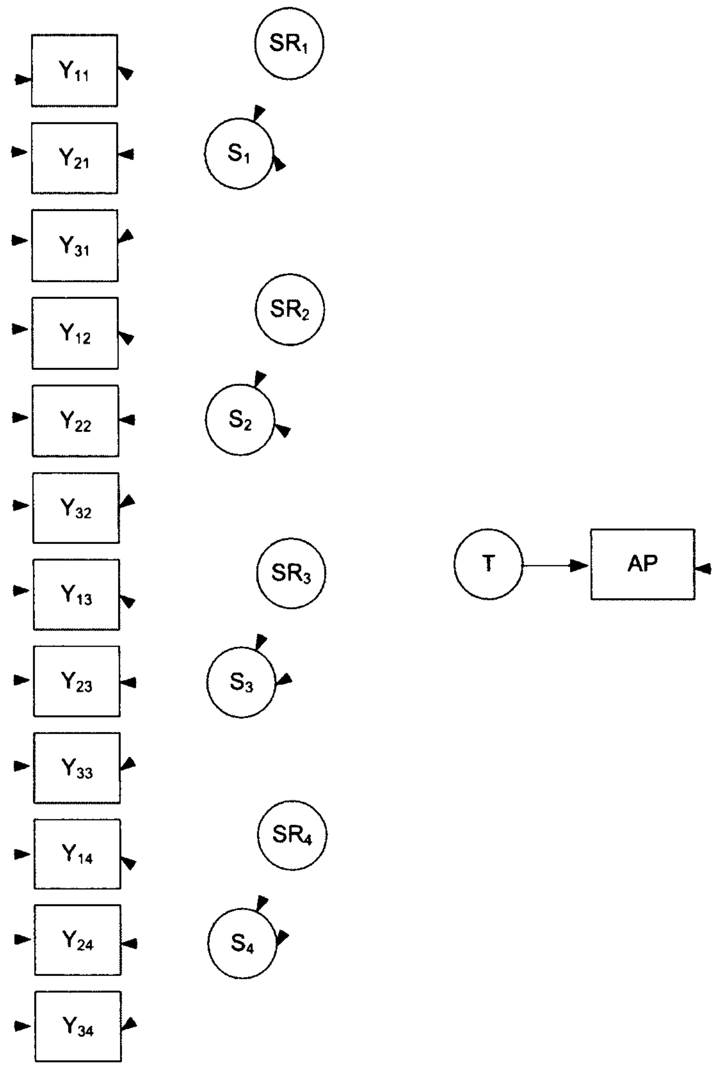

Figure 13. Model 2 for Hypothesis 5a through 5c and Hypotheses 7a through 7c: Relationship between LTS model of goal orientation and academic performance.

Note. T = trait, SR_k = state residual for four occasions across time, S_k = state for four occasions across time, and three manifest variables Y_{ik} for four occasions across time; AP = academic performance.

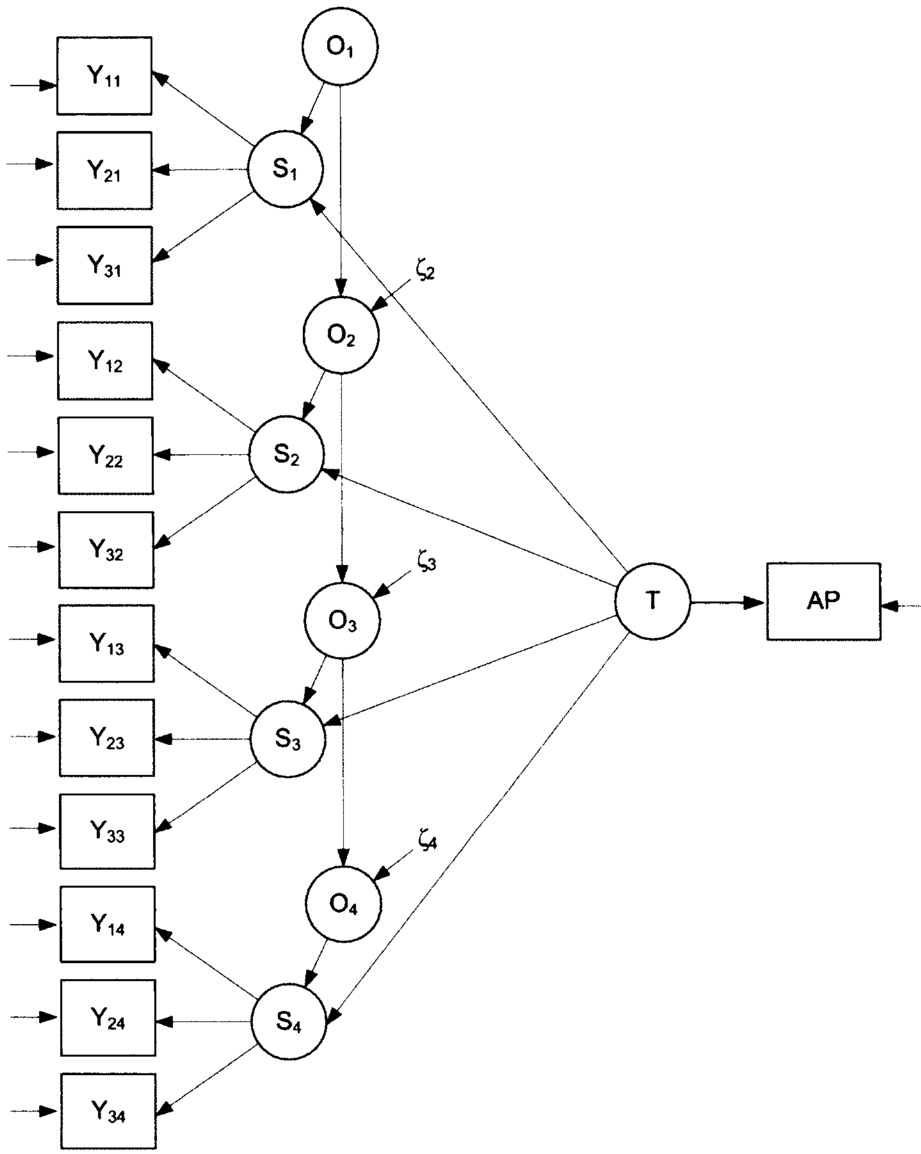

Figure 14. Model 3 for Hypothesis 5a through 5c and Hypotheses 7a through 7c: Relationship between LTS model of goal orientation and academic performance.

Note. T = trait, O_k = occasion for four periods across time, ζ_k = uniqueness factor for three occasions, S_k = state for four periods across time, and three manifest variables Y_{ik} for four periods across time; AP = academic performance.

Model fit. For Hypotheses 4a through 7c, the set of candidate models was tested using FIML estimation with the covariance matrix. Similar to the previous hypotheses, the same sets of models were used for the three dimensions of general trait goal orientation: learning, performance-prove, and performance-avoid. Models were non-nested and precluded the use of the chi-square difference test for selecting the best fitting model. In addition, Model 1, the latent state model, contained a subset of the variables from the covariance matrix and prevented the use of AIC and other alternative fit criteria.

For Hypotheses 4a through 7c, the best fitting model was selected using several criteria. First, alternative models were compared based on comments by Vandeberg and Grell (2009). They suggest that non-nested models, "in the best-case scenario", can be compared using benchmark fit indices such as RMSEA, TLI, and CFI. The best fitting model is identified in the event that it meets or exceeds all of the cut-off values identified for good fit while the alternative models fail to meet those benchmarks. Models were assessed for goodness of fit using the procedure listed for testing Hypotheses 1a through 3c. A good fitting model has a non-significant χ^2 goodness-of-fit test, a narrow RMSEA 90% confidence interval with a lower bound close to zero and upper bound < .08, CFI > .95, and TLI > .95). For the current study, a model was identified as the best fitting if it met or exceeded goodness-of-fit indices cut-offs for good fit and other models failed to meet the benchmark cut-offs.

However, fit indices only describe a model's lack of fit and do not reflect the extent to which the model is plausible (Byrne, 2010). According to Byrne, assessment of model quality should be based on multiple criteria. In a discussion of model assessment, Byrne mentions model usefulness when taking theoretical, statistical, and practical considerations into account. Therefore the usefulness of models in Hypotheses 4 through 7 will be evaluated by how well they predict outcomes identified by previous research. The second criterion for selecting the best fit was how well the model replicated or clarified the predictive relationship with learning and academic performance as noted in the Payne et al. (2007) meta-analysis. In the meta-analysis, they computed the estimated true mean correlation (ρ) between the three trait goal orientation dimensions (learning, performance-prove and performance-avoid) and two achievement-oriented outcomes (learning in an academic setting and academic performance). For predicting learning in an academic setting, learning goal orientation $\rho = 0.16$, performance-prove goal orientation ρ was not statistically significant, and performance-avoid = -0.17. For predicting academic performance, learning goal orientation $\rho = 0.16$, performance-prove goal orientation ρ was not statistically significant, and performance-avoid $\rho = -.06$. Goal orientation theory proposed that performance-prove goal orientation would predict the two achievement-related outcomes. Unfortunately, previous research has found the relationship to be small or more commonly, non-significant. LTS models may be more sensitive and better able to detect the relationship than commonly used trait models. In linear regression, the value of the standardized regression coefficient (β), which was computed in the SEM analysis of the current study, is the same as the correlation coefficient (r or population ρ), which was reported in the Payne et al. (2007) meta-analysis. The magnitude of both can be interpreted in the same way.

To summarize, when testing Hypotheses 4a through 7c, the selection of the best fitting alternative models was based on achieving cut-off values for RMSEA, CFI, and TLI. It was also based on whether a model included a statistically significant relationship with an achievement-related performance outcome and the magnitude of the regression coefficients (β) with that outcome.

Hypotheses 8a through 9c

Candidate models. A description of the candidate models used to test Hypotheses 8a through 9c is located in Table 3. For Hypothesis 8a through 8c, Model 1 was consisted of four latent states, one for each period of measurement. The criteria, learning in an academic setting, was modeled the same as earlier hypotheses (i.e., Hypotheses 4a through 6c). The latent state factors were associated with the learning outcome associated with the respective period of measurement. The model also contained regression paths connecting latent states at adjacent time periods, similar to Model 3 for Hypotheses 1a through 3c. A diagram of the model is located in Figure 15. Model 1 was tested against two alternative models that included an additional LTS structure for goal orientation (Figures 16 and 17). Model 2 included equality constraints on the structural paths from the latent trait to the latent states. Model 3 was the same as Model 2 with the addition of regression paths between occasion factors at adjacent time periods and equality constraints on the paths between occasions and states.

Table 3

Set of Candidate Models for Testing Hypotheses 8a through 9c

Model Number	Description
1	Latent state model
2	LTS model
3	LTS model with autoregressive occasion factors

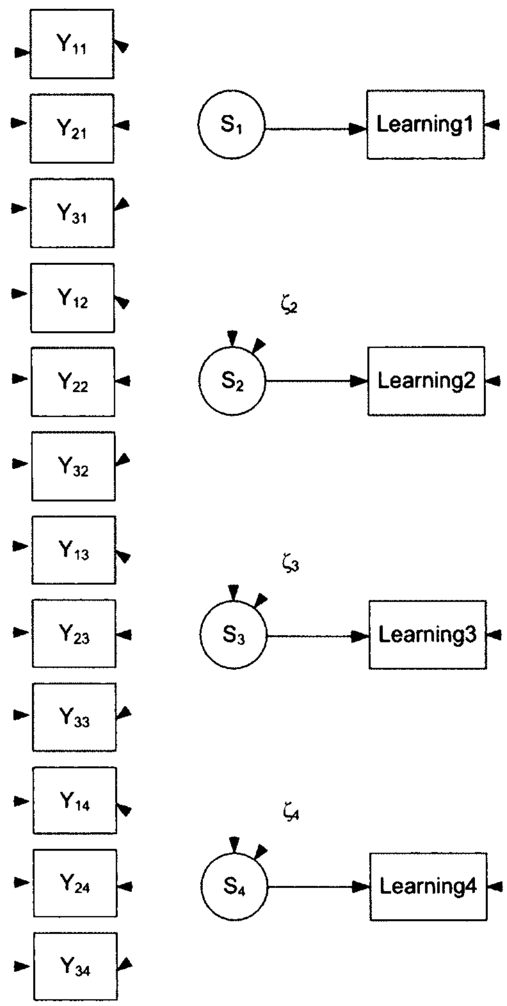

Figure 15. Model 1 for Hypotheses 8a through 8c: Relationship between latent state model of goal orientation and learning.

Note. S_k = state for four periods across time, ζ_k = uniqueness factor for three state, and three manifest variables Y_{ik} for four periods across time; Learning1 = learning outcome for Time 1; Learning2 = learning outcome at Time 2; Learning3 = learning outcome at Time 3; learning4 = Learning outcome at Time 4.

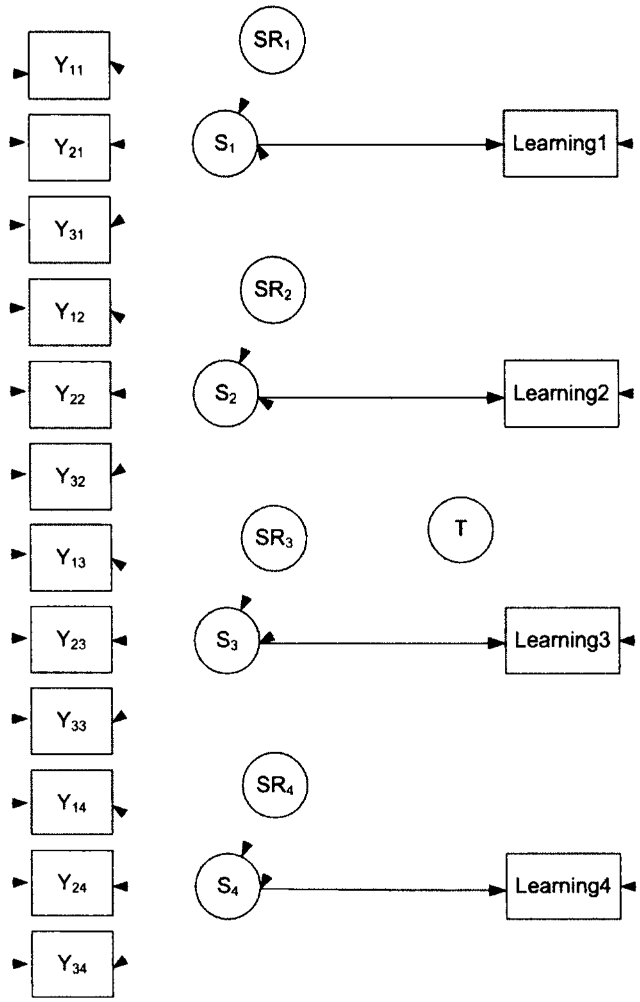

Figure 16. Model 2 for Hypotheses 8a through 8c: Relationship between LTS model of goal orientation and learning.

Note. T = trait, SR_k = state residual for four occasions across time, S_k = state for four occasions across time, and three manifest variables Y_{ik} for four occasions across time; Learning1 = learning outcome for Time 1; Learning2 = learning outcome at Time 2; Learning3 = learning outcome at Time 3; Learning4 = learning outcome at Time 4.

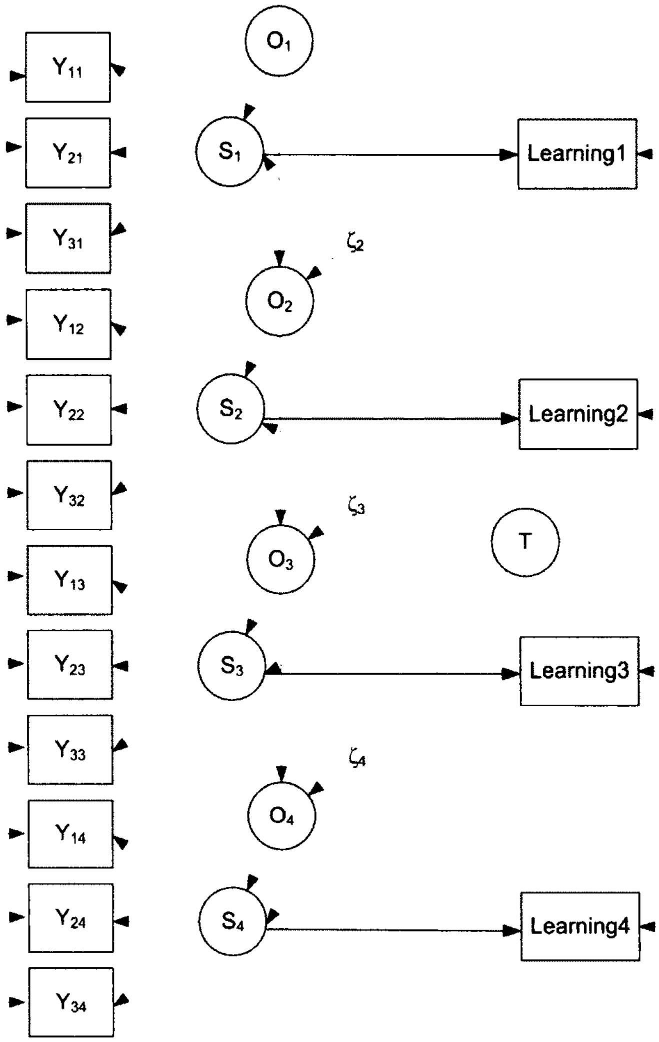

Figure 17. Model 3 for Hypotheses 8a through 8c: Relationship between LTS model of goal orientation and learning.

Note. T = trait, O_k = occasion for four periods across time, ζ_k = uniqueness factor for three occasions, S_k = state for four periods across time, and three manifest variables Y_{ik} for four periods across time; Learning1 = learning outcome for Time 1; Learning2 = learning outcome at Time 2; Learning3 = learning outcome at Time 3; learning4 = learning outcome at Time 4.

Hypotheses 9a through c were tested using three models nearly identical to those used to test Hypotheses 8a through c. The exception was the replacement of the four outcome variables, learning at Times 1 through 4, with a single variable, academic performance. Structural paths were added to the model, connecting the state factors with academic performance. Models 1, 2 and 3 are illustrated in Figures 18, 19 and 20, respectively.

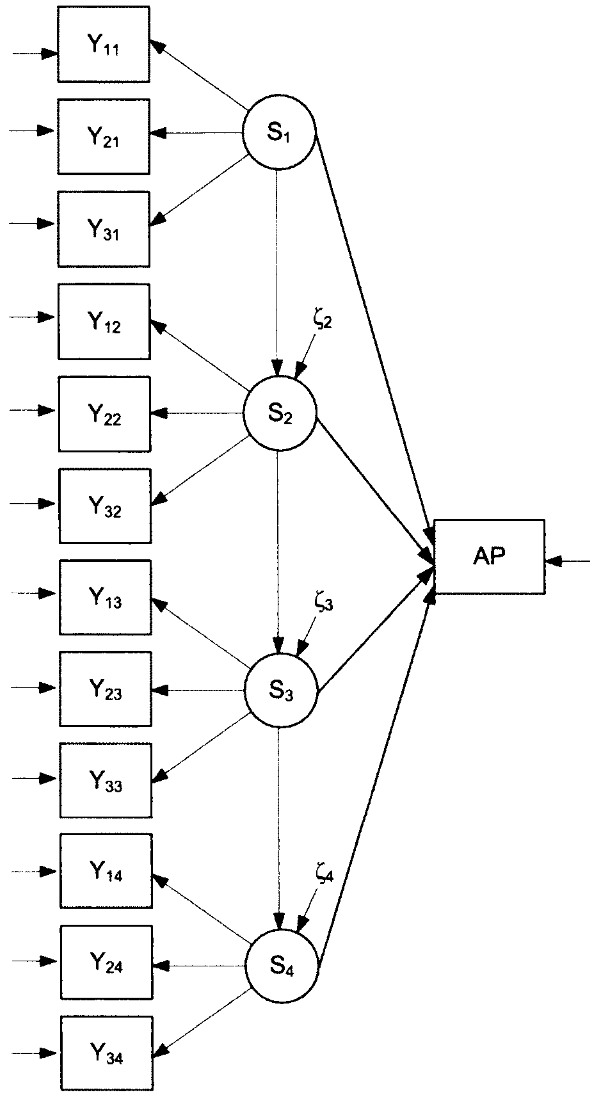

Figure 18. Model 1 for Hypotheses 9a through 9c: Relationship between latent state model of goal orientation and academic performance.

Note. S_k = state for four periods across time, ζ_k = uniqueness factor for three state, and three manifest variables Y_{ik} for four periods across time; AP = academic performance.

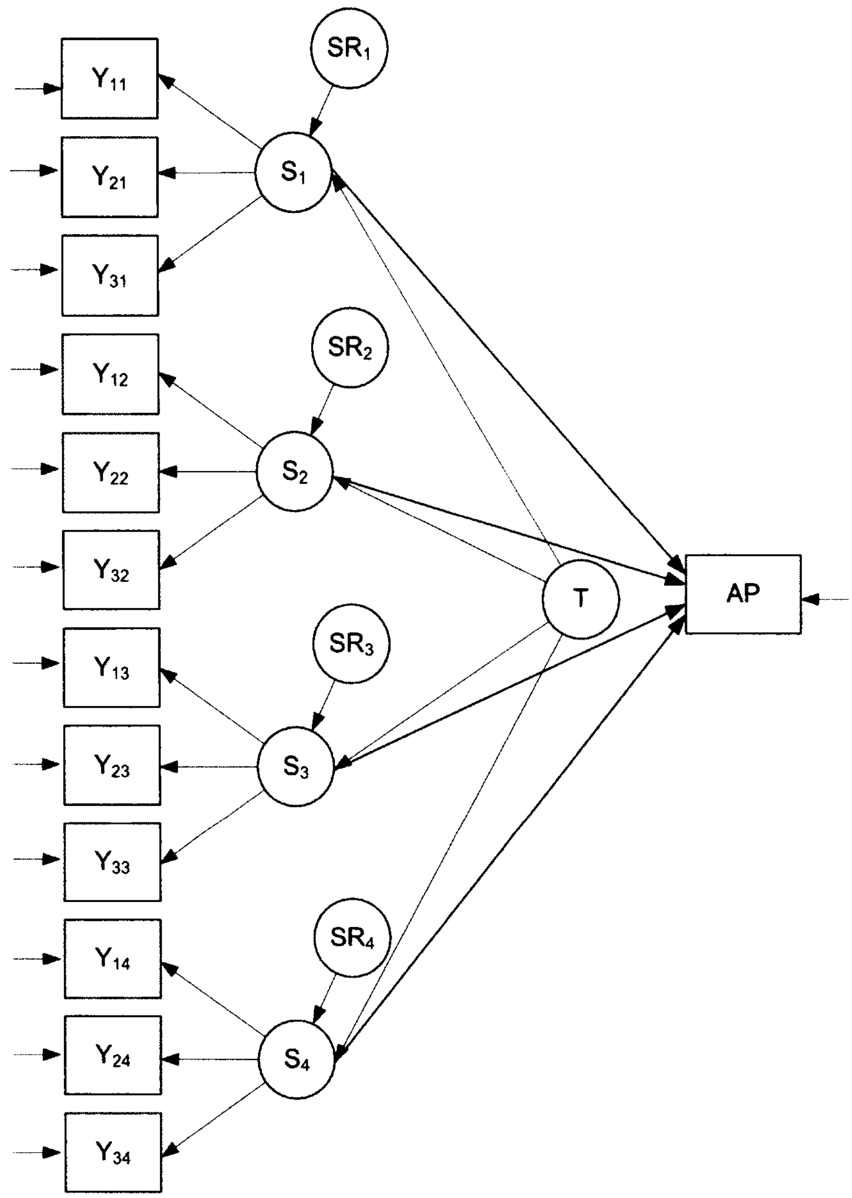

Figure 19. Model 2 for Hypotheses 9a through 9c: Relationship between LTS model of goal orientation and academic performance.

Note. SR_k = state residual for four occasions across time, S_k = state for four occasions across time, and three manifest variables Y_{ik} for four occasions across time; AP = academic performance.

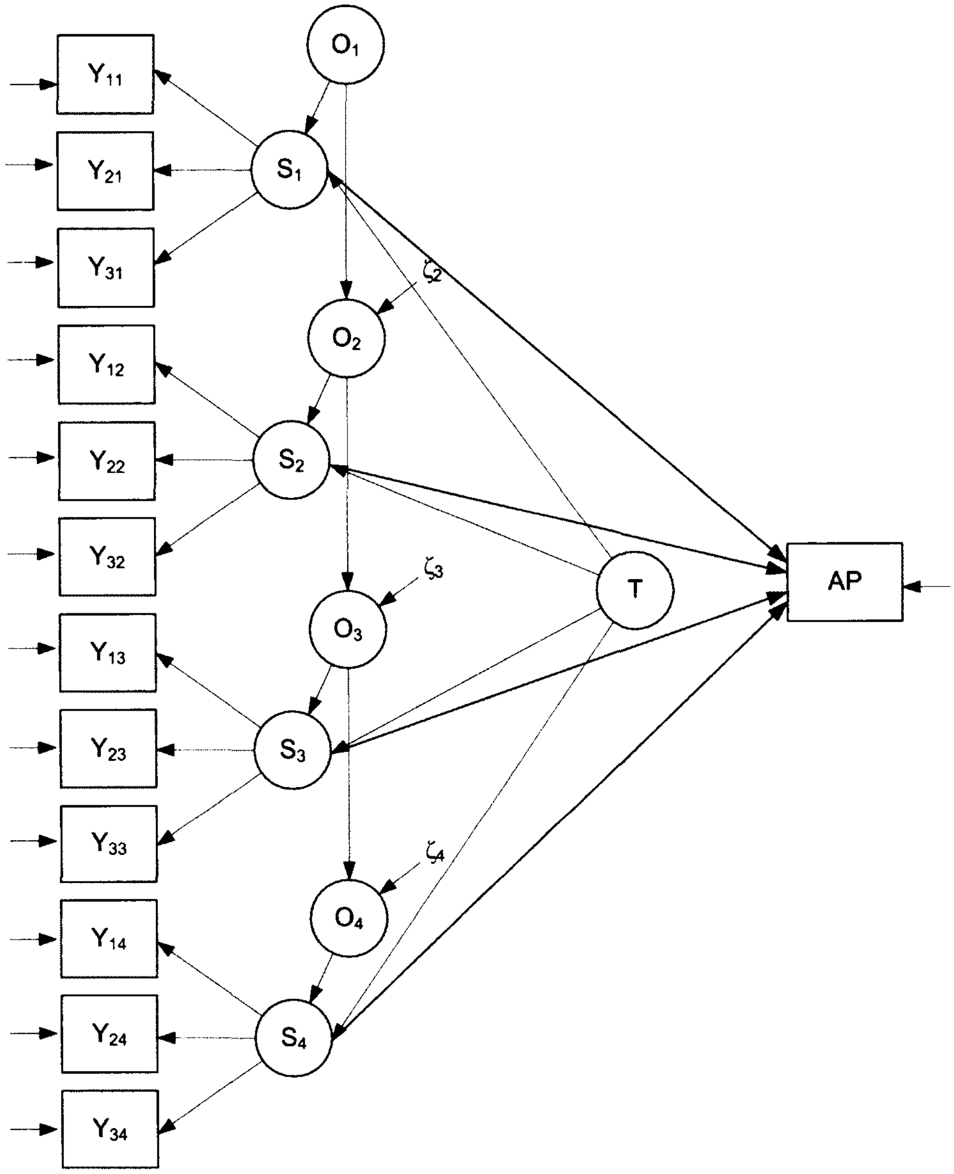

Figure 20. Model 3 for Hypotheses 9a through 9c: Relationship between LTS model of goal orientation and academic performance.

Note. T = trait, O_k = occasion for four periods across time, ζ_k = uniqueness factor for three occasions, S_k = state for four periods across time, and three manifest variables Y_{ik} for four periods across time; AP = academic performance.

Model fit. For Hypotheses 8a through c and 9a through c, a set of alternate models tested using SEM with FIML estimation using the covariance matrix. Models were assessed for goodness of fit using the procedure listed for testing previous hypotheses. A good fitting model has a non-significant χ^2 goodness-of-fit test, a narrow RMSEA 90% confidence interval with a lower bound close to zero and upper bound < .08, CFI > .95, and TLI > .95). The selection of the best fitting model was based on whether a model included a statistically significant relationship with an achievement-related performance outcome and the magnitude of the regression coefficients (β) with that outcome.

CHAPTER III

RESULTS

PRELIMINARY ANALYSES

Data Screening

Prior to analysis, all data for goal orientation measures were examined for fit between their distributions and the assumptions of multivariate statistics following the procedures outlines by Tabachnick and Fidell (2001). None of the data deviated from normality nor met criteria indicating multicolinearity. General trait data contained no deviations from normality. No univariate or multivariate outliers were present. For all general trait scales the number of cases varied from 229 at Time 1 to 173 at Time 4.

Several cases with extremely high or low z scores (+/- 3.29) on domain-specific goal orientation scales were found and identified as univariate outliers. One case was dropped from analyses of the learning scale at time period 1, six cases were dropped from the analyses of the performance-prove scale (one at Time 1, two at Time 2, two at Time 3, and one at Time 4), and four cases were dropped from the analyses of the performance-avoid scale (one at Time 1, two at Time 3, and one at Time 4). Three cases were identified through Mahalanobis distance as multivariate outliers. Scores on the variables causing the cases to be outliers were deleted. After all outliers were deleted, between 173 and 228 cases were left for the four time periods for the learning scale, between 172 and 228 cases remained for the four time periods for both the performance-prove and performance-avoid scales.

Several cases with extremely low or high z-scores on domain-specific goal orientation scales were identified as univariate outliers. One case was dropped from analyses of the learning scale at time period 4, three cases were dropped from the analyses of the performance-prove scale (one at time periods 1, 2, and 4), and two cases were dropped from the analyses of the performance-avoid scale (one at time periods 2 and 3). After all outliers were deleted, between 172 (learning and performance-prove scales at Time 4) and 228 (learning and performance-avoid scales at Time 1) cases were left for the four time periods for the learning scale, between 172 and 227 cases remained for the four time periods for both the performance-prove scale, and 173 and 228 cases remained for the four time periods for the performance-avoid scale.

CFA Results

Results of the CFAs for all measures, including $\chi 2$, *df*, RMSEA, CFI, and TLI, can be found in Appendices D through L. Three models were compared: 6-item, 5-item, and 4-item. For all measures, a 4-item version demonstrated the best fit across the four occasions of measurement. Based on the results of the CFAs, two items were cut from each scale to improve fit. Modification indices, typically used to identify items responsible for poor model fit, were not available. When using Amos, modification indices cannot be computed using a dataset with missing data. Instead, poor factor loadings and large error variances were used to identify items contributing to poor model fit. Item factor loadings for the nine 4-item goal orientation measures for Time 1, Time 2, Time 3, and Time 4 are located in Appendices V through X.

Because all scales were reduced to 4 items, the use of parcels in the measurement models used to test the hypotheses was omitted. Two 2-item parcels would have reduced the degrees of freedom and resulted in parametrically underidentified models making hypotheses testing impossible. As a solution, the measurement models used for hypothesis testing were identified at the item level and did not include parcels. Fortunately, this did not impair the ability to achieve proper model solutions and the covariance matrix of items did not exceed the limits of Amos 17.0.

Reliability Analysis

Cronbach's coefficient alpha was computed for all scales at all periods of measurement using Enders' (2004) recommended ML procedure for computing reliability with missing data. Appendices Y, Z and AA contain scale reliabilities and 95% confidence intervals (CI) for the general trait, domain-specific trait and state goal orientation scales, respectively. Reliability ranged from a low of 0.71 for the domain-specific trait performance-avoid scale at Time 2 to a high of 0.89 for the general trait learning, performance-prove, and performance-avoid scales at Time 1and the domain-specific trait learning scale at Time 1.

ME/I Results

Based on the tests of ME/I, most scales showed no evidence of beta or gamma change. For nearly all scales the $\Delta\chi^2$ tests were not statistically significant and ΔCFI values were less than 0.01. The sole exception was the scale for general trait learning goal orientation. The $\Delta\chi^2$ test of equality of factor variance-covariance matrices was significant, indicating that the learning scale displayed gamma change between occasions of measurement. However, the $\Delta\chi^2$ test is an excessively stringent test of invariance (Cudeck & Browne, 1983). The ΔCFI test is a more reasonable option (Cheung & Resvold, 2002). The ΔCFI value for the test of equality of factor variance-covariance matrices was less than 0.01, indicating equivalence. According to this test of ME/I, the general trait learning goal orientation scale was not affected by gamma change.

Appendices AB through JJ contain the goodness-of-fit indices and details of the ME/I tests for all goal orientation scales.

DESCRIPTIVE STATISTICS

Demographics

Of the 244 participants, 68.4% were female. Participant age ranged from 18 to 29 years with a mean of 18.96 years and a SD of 1.79 years. By academic year, 59.4% of participants were first-year students, 24.6% second-year, 8.2% third-year, 4.9% fourth year, and 2.9% other. By academic major, 20.4% of the participants were psychology majors, 19.2% undecided, and other majors each comprised less than 10% of the sample. Other participant majors were drawn from all of the university colleges, including fine and liberal arts, business and public administration, education, engineering and technology, health sciences, and sciences.

Study Variables

The estimated means, standard deviations, and intercorrelations for demographic variables, goal orientation general trait, domain-specific trait, and state measures at Times 1 through 4, learning outcomes at Times 1 through 4, and academic performance are in Appendix KK. Estimates were based on the implied covariance matrix using FIML estimation.

RESULTS OF HYPOTHESES TESTS

The $\chi 2$ values from all models included in testing Hypotheses 1a through 3c, as well as most models used in testing the remained of the hypotheses, were significant, indicating a poor fitting model. When implementing a longitudinal design, one would not expect the chi-square to be non-significant because of nonzero covariances among the error terms between items from different occasions of measurement. These covariances are explained by construct-irrelevant similarities in language among certain pairs of items. (Millsap, 2007; p. 879) As an alternative, Steiger (2007) suggests estimating the RMSEA 90% confidence interval as a test of not-close fit. This procedure was followed using the recommendations of MacCallum et al. (1996).

General Trait Goal Orientation (Hypothesis 1a through 1c)

Hypothesis 1a. It was hypothesized that a latent trait-state model would provide a better fit for general trait learning goal orientation than either a trait or state model. Seven models were tested. The goodness-of-fit indices for all seven models are displayed in Table 4. The solution for Model 7, the latent TSO model, was initially inadmissible due to a negative variance estimate (for the uniqueness factor associated with the occasion latent variable at Time 2), known as a Haywood case. This problem was remedied following the procedure recommended by Rindskopf (1984). A small starting value (0.08) was assigned to the uniqueness factor and the model was retested. The upper bounds of the RMSEA 90% CI values for Models 3 through 7 and CFI values for models 4 through 7 met cut-off criteria indicating a good fit.

The AIC, AIC_C and BIC values in Table 5 reveal that Model 7, the latent TSO model, provided the best fit. According to the model probabilities in Table 6, the latent TSO model had a probability of .66 of being the K-L best fitting model, given the candidate models and the data. Compared to the LTS-AR model, the model ranked as the next best fitting, the latent TSO model had an evidence ratio of 2.73 to one of being the best fitting model. Expressed as a normalized probability, the latent TSO model had a

.73 probability of being the K-L best fitting model compared to the LST-AR model.

Further and as illustrated in Figure 21, except for the regression coefficients from occasion 1 to occasion 2 and from occasion 2 to occasion 3, all other coefficients were statistically significant. The coefficients for latent trait decreased over time while the state coefficients for the occasion factors increased. These findings thus support Hypothesis 1a.

Table 4

Goodness-of-Fit Indices of Models for General Trait Learning Goal Orientation (N = 244)

Model	*df*	$\chi2$	*p*	RMSEA	RMSEA 90% CI	CFI	TLI
1. Trait	112	462.10	0.00	0.110	[0.102, 0.123]	0.82	0.78
2. State	109	561.70	0.00	0.130	[0.119, 0.140]	0.77	0.71
3. State-AR	106	220.90	0.00	0.070	[0.054, 0.078]	0.94	0.93
4. LTS	105	191.70	0.00	0.060	[0.044, 0.070]	0.96	0.94
5. LTS-EC	108	206.20	0.00	0.060	[0.048, 0.073]	0.95	0.94
6. LTS-AR	105	189.90	0.00	0.060	[0.044, 0.070]	0.96	0.94
7. Latent TSO	106	190.97	0.00	0.057	[0.044, 0.070]	0.96	0.94

Note. State-AR = state model with first-order autoregressive state factors, LTS = latent trait state model, LTS-EC = LTS model with equality constraints on latent trait factor loadings, LTS-AR = LTS model with first-order autoregressive latent state factors, Latent STO = latent state trait occasion model.

Table 5

Model Comparison Criteria of Models for General Trait Learning Goal Orientation (N = 244)

Model	AIC	AIC_C	BIC
1. Trait	542.118	558.276	557.614
2. State	647.661	666.581	664.319
3. State-AR	312.878	334.827	330.698
4. LTS	285.699	308.719	303.906
5. LTS-EC	294.216	314.115	311.261
6. LTS-AR	283.903	306.923	302.110
7. Latent TSO	**282.967**	**304.916**	**300.787**

Note. Boldface indicates best fitting model for criterion. See note to Table 1.

Table 6

Ranking, AIC_C, AIC_C Differences (Δ_i), and Probability (w_i) of Models for General Trait Learning Goal Orientation (N = 244)

Model	AICc	Δ_i	w_i
7. Latent TSO	304.916	0.000	0.655
6. LTS-AR	306.923	2.007	0.240
4. LTS	308.719	3.803	0.098
5. LTS-EC	314.115	9.199	0.007
3. State-AR	334.827	29.911	0.000
1. Trait	558.276	253.360	0.000
2. State	666.581	361.665	0.000

Note. See note to Table 1.

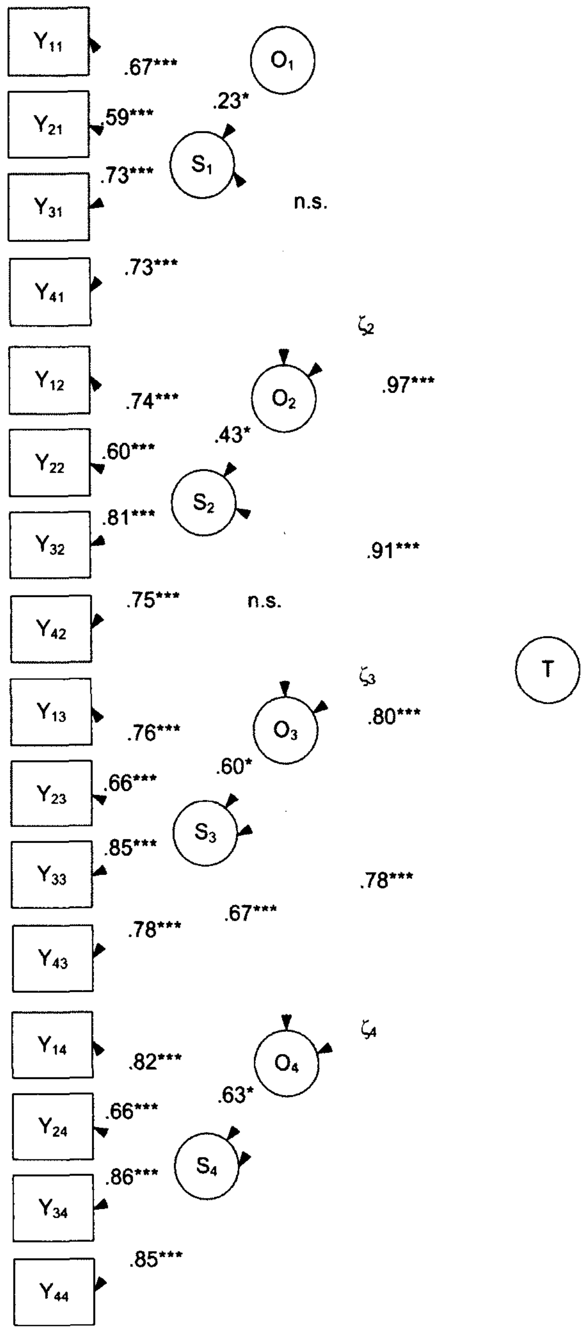

Figure 21. Standardized coefficients for Model 7: Latent TSO model for general trait learning goal orientation.

Note. T = trait, O_k = occasion for four points in time, S_k = state for four points in time, ζ_k = uniqueness factor for three occasions, and four manifest variables Y_{ik} for four points in time. n.s. = not significant. $*p < .05$. $***p < .001$.

Hypothesis 1b. It was hypothesized that a latent trait-state model would provide a better fit for general trait performance-prove goal orientation than either a trait or state model. Seven models were tested. The fit indices for all seven models are displayed in Table 7. RMSEA and CFI values for models 3 through 7 and TLI values for Models 3, 4, 6, and 7 indicate good fit. The AIC, AIC_C and BIC values in Table 8 indicate that Model 7, the latent TSO model, provided the K-L best fit, given the set of models and the data.

According to Table 9, the latent TSO model had a probability of .78 of being the K-L best fitting model, given the candidate models and the data. Compared to the state-AR model, the model ranked as the next best fitting, the latent TSO model had an evidence ratio of 4.95 to one of being the best fitting model. Expressed as a normalized probability, the latent TSO model had a .83 probability of being the K-L best fitting model compared to the state-AR model.

The regression coefficients for the best fitting model were similar to those found in the previous analysis. As illustrated in Figure 22, except for the regression coefficients from occasion 1 to occasion 2 and from occasion 2 to occasion 3, all other coefficients were statistically significant. The coefficients for latent trait decreased over time while the state coefficients for the occasion factors increased. These findings thus support Hypothesis 1b.

Table 7

Goodness-of-Fit Indices of the Models for General Trait Performance-Prove Goal Orientation (N = 244)

Model	*df*	$\chi2$	*p*	RMSEA	RMSEA 90% CI	CFI	TLI
1. Trait	112	345.90	0.00	0.090	[0.081, 0.103]	0.90	0.88
2. State	109	703.00	0.00	0.150	[0.138, 0.158]	0.74	0.64
3. State-AR	106	178.34	0.00	0.050	[0.039, 0.065]	0.97	0.96
4. LTS	105	179.20	0.00	0.050	[0.040, 0.066]	0.97	0.96
5. LTS-EC	108	206.20	0.00	0.060	[0.048, 0.073]	0.95	0.94
6. LTS-AR	105	178.10	0.00	0.050	[0.039, 0.066]	0.97	0.96
7. Latent TSO	105	172.07	0.00	0.050	[0.037, 0.064]	0.97	0.96

Note. See note to Table 1.

Table 8

Model Comparison Criteria of Models for General Trait Performance-Prove Goal Orientation (N = 244)

Model	AIC	AIC_C	BIC
1. Trait	425.915	442.073	441.411
2. State	788.957	807.877	805.615
3. State-AR	270.339	292.288	288.159
4. LTS	273.222	296.242	291.429
5. LTS-EC	294.216	314.115	311.261
6. LTS-AR	272.068	295.088	290.275
7. Latent TSO	**266.070**	**289.090**	**284.277**

Note. Boldface indicates best fitting model for criterion. See note to Table 1.

Table 9

Ranking, AIC_C, AIC_C Differences (Δ_i), and Probability (w_i) of Models for General Trait Performance-Prove Goal Orientation (N = 244)

Model	AICc	Δ_i	w_i
7. Latent TSO	289.090	0.000	0.781
3. State-AR	292.288	3.198	0.158
6. LTS-AR	295.088	5.998	0.039
4. LTS	296.242	7.152	0.022
5. LTS-EC	314.115	25.025	0.000
1. Trait	442.073	152.983	0.000
2. State	807.877	518.787	0.000

Note. See note to Table 1.

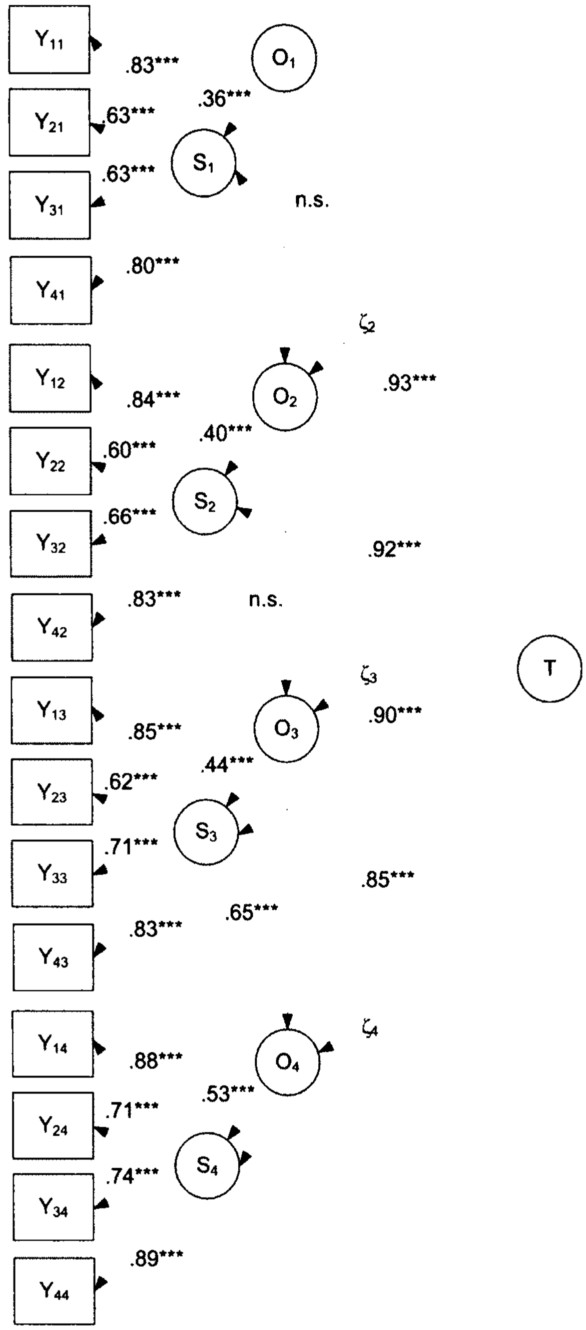

Figure 22. Standardized coefficients for Model 7: Latent TSO model for general trait performance-prove goal orientation.

Note. T = trait, O_k = occasion for four points in time, S_k = state for four points in time, ζ_k = uniqueness factor for three occasions, and four manifest variables Y_{ik} for four points in time. n.s. = not significant.

$^{***}p < .001$.

Hypothesis 1c. It was hypothesized that a latent trait-state model would provide a better fit for general trait performance-avoid goal orientation than either a trait or state model. Seven models were tested. The fit indices for all seven models are displayed in Table 6. The initial solution for Model 7 was a Haywood case, inadmissible due to a negative variance estimate (for the uniqueness factor associated with the occasion latent variable at Time 2). Like the solution for Model 7 in Hypothesis 1c, the problem was remedied following the procedure recommended by Rindskopf (1984). A small starting value (0.08) was assigned to the uniqueness factor and the model was retested.

RMSEA values and RMSEA 90% CI values for models 4 through 7, CFI values for models 3 through 7 and TLI values for models 4, 6 and 7 met cut-off criteria indicating good fit. The AIC, AIC_C and BIC values in Table 11 indicate that Model 7, the latent TSO model, provided the K-L best fit, given the set of models and the data. According to the results in Table 12, the latent TSO model had a probability of .95 of being the K-L best fitting model, given the candidate models and the data. Compared to the LTS model, the model ranked as the next best fitting, the latent TSO model had an evidence ratio of 22.75 to one of being the best fitting model. Expressed as a normalized probability, the latent TSO model had a .96 probability of being the K-L best fitting model compared to the LTS model.

The regression coefficients for the best fitting model were similar to those found in the previous analysis. As illustrated in Figure 23, except for the regression coefficients from occasion 2 to occasion 3, all other coefficients were statistically significant. The regression coefficient from occasion 1 to occasion 2 was negative and large (β = -.95). The coefficients for latent trait decreased over time while the state coefficients for the occasion factors increased. These findings thus support Hypothesis 1c.

Table 10

Goodness-of-Fit Indices of the Models for General Trait Performance-Avoid Goal Orientation (N = 244)

Model	*df*	$\chi2$	*p*	RMSEA	RMSEA 90% CI	CFI	TLI
1. Trait	112	456.37	0.00	0.110	[0.101, 0.122]	0.82	0.78
2. State	109	533.80	0.00	0.130	[0.115, 0.136]	0.78	0.72
3. State-AR	106	198.15	0.00	0.060	[0.046, 0.072]	0.95	0.94
4. LTS	105	176.50	0.00	0.050	[0.038, 0.065]	0.96	0.95
5. LTS-EC	108	210.70	0.00	0.050	[0.049, 0.074]	0.95	0.93
6. LTS-AR	105	179.90	0.00	0.050	[0.040, 0.067]	0.96	0.95
7. Latent TSO	106	173.30	0.00	0.050	[0.039, 0.066]	0.97	0.96

Note. See note to Table 1.

Table 11

Model Comparison Criteria of Models for General Trait Performance-Avoid Goal Orientation (N = 244)

Model	AIC	AIC_C	BIC
1. Trait	536.370	552.528	551.866
2. State	619.799	638.719	636.457
3. State-AR	290.145	312.094	307.965
4. LTS	270.476	293.496	288.683
5. LTS-EC	298.693	318.592	315.738
6. LTS-AR	273.914	296.934	292.121
7. Latent TSO	**265.298**	**287.247**	**283.118**

Note. Boldface indicates best fitting model for criterion. See note to Table 1.

Table 12

Ranking, AIC_C, AIC_C Differences (Δ_i), and Probability (w_i) of Models for General Trait Performance-Avoid Goal Orientation (N = 244)

Model	AICc	Δ_i	w_i
7. Latent TSO	287.247	0.000	0.951
4. LTS	293.496	6.249	0.042
6. LTS-AR	296.934	9.687	0.007
3. State-AR	312.094	24.847	0.000
5. LTS-EC	318.592	31.345	0.000
1. Trait	552.528	265.281	0.000
2. State	638.719	351.472	0.000

Note. See note to Table 1.

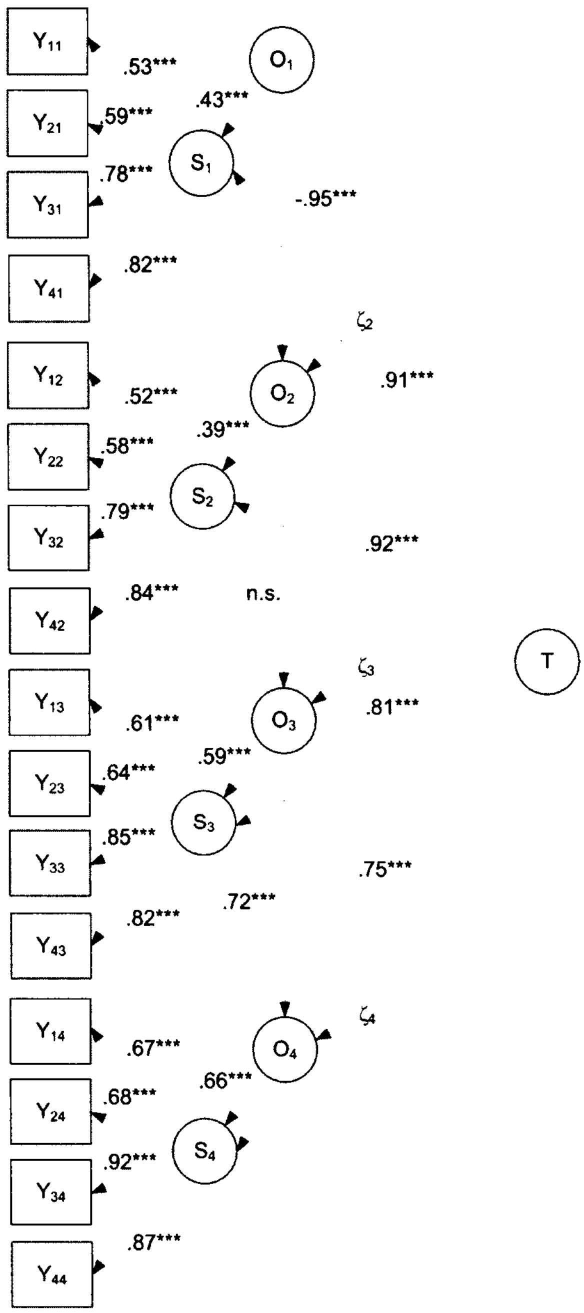

Figure 23. Standardized coefficients for Model 7: Latent TSO model for general trait performance-avoid goal orientation.

Note. T = trait, O_k = occasion for four points in time, S_k = state for four points in time, ζ_k = uniqueness factor for three occasions, and four manifest variables Y_{ik} for four points in time. n.s. = not significant.

$^{***}p < .001$.

Domain-Specific Goal Orientation (Hypothesis 2a through 2c)

Hypothesis 2a. It was hypothesized that a latent trait-state model would provide a better fit for domain-specific trait learning goal orientation than either a trait or state model. Seven models were tested. The fit indices for all seven models are displayed in Table 13. RMSEA, RMSEA 90% CI, CFI and TLI values for models 3 through 7 met cut-off criteria indicating good fit.

According to the AIC, AIC_C and BIC values in Table 14indicate that Model 7, the latent TSO model, was ranked as providing the best fit, given the candidate models and the data. However, values of Model 6, the LTS-AR model, and Model 7, the latent TSO model, were close. The AIC, AIC_C and BIC values for the two models were nearly equal. The AIC_C difference (Δ_i) between the two models is .29 and can be found in Table 15. The two models provided a similar expected K-L distance from reality. As mentioned previously, according to information-theoretic statistics, a true model does not exist. Therefore several models can approximate domain-specific learning goal orientation equally well. Based on the results in Table 15, the LTS-AR and latent TSO models had a combined probability of .87 of providing the K-L best fit, given the candidate models and the data. Compared to all other models, they had a combined evidence ratio of 6.38 to one of providing the best fit.

As illustrated in Figures 24 and 25, except for the regression coefficients from occasion 1 to occasion 2 and from occasion 2 to occasion 3, all other coefficients were statistically significant. The coefficients for latent trait decreased over time while the state coefficients for the occasion factors increased. These findings thus support Hypothesis 2a.

Table 13

Goodness-of-Fit Indices of the Models for Domain-Specific Trait Learning Goal Orientation (N = 244)

Model	*df*	χ2	*p*	RMSEA	RMSEA 90% CI	CFI	TLI
1. Trait	112	496.69	0.00	0.120	[0.107, 0.128]	0.81	0.77
2. State	109	556.51	0.00	0.130	[0.118, 0.139]	0.78	0.72
3. State-AR	106	181.52	0.00	0.050	[0.040, 0.067]	0.96	0.95
4. LTS	105	158.40	0.00	0.050	[0.030, 0.059]	0.97	0.97
5. LTS-EC	108	168.50	0.00	0.050	[0.033, 0.061]	0.97	0.96
6. LTS-AR	105	155.30	0.00	0.040	[0.028, 0.058]	0.98	0.97
7. Latent TSO	105	155.00	0.00	0.040	[0.028, 0.058]	0.98	0.97

Note. See note to Table 1.

Table 14

Model Comparison Criteria of Models for Domain-Specific Trait Learning Goal Orientation (N = 244)

Model	AIC	AIC_C	BIC
1. Trait	576.685	592.843	592.181
2. State	642.508	661.428	659.166
3. State-AR	273.523	295.472	291.343
4. LTS	252.401	275.421	270.608
5. LTS-EC	256.530	276.429	273.575
6. LTS-AR	249.287	272.307	267.494
7. Latent TSO	**248.997**	**272.017**	**267.204**

Note. Boldface indicates best fitting model for criterion. See note to Table 1.

Table 15

Ranking, AIC_C, AIC_C Differences (Δ_i), and Probability (w_i) of Models for Domain-Specific Trait Learning Goal Orientation (N = 244)

Model	AICc	Δ_i	w_i
7. Latent TSO	272.017	0.000	0.464
6. LTS-AR	272.307	0.290	0.401
4. LTS	275.421	3.404	0.084
5. LTS-EC	276.429	4.412	0.051
3. State-AR	295.472	23.455	0.000
1. Trait	592.843	320.826	0.000
2. State	661.428	389.411	0.000

Note. See note to Table 1.

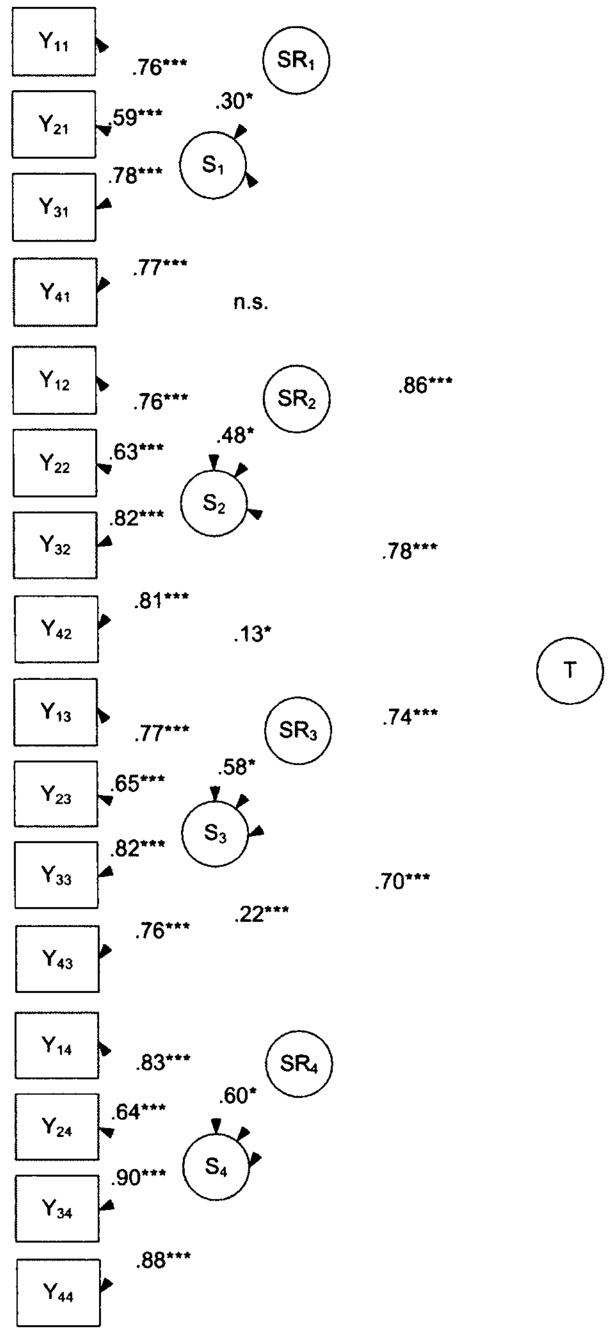

Figure 24. Standardized coefficients for Model 6: LTS-AR model for domain-specific trait learning goal orientation.

Note. T = trait, SR_k = state residual for four points in time, S_k = state for four points in time, and four manifest variables Y_{ik} for four points in time. n.s. = not significant.

$^{*}p < .05$. $^{***}p < .001$.

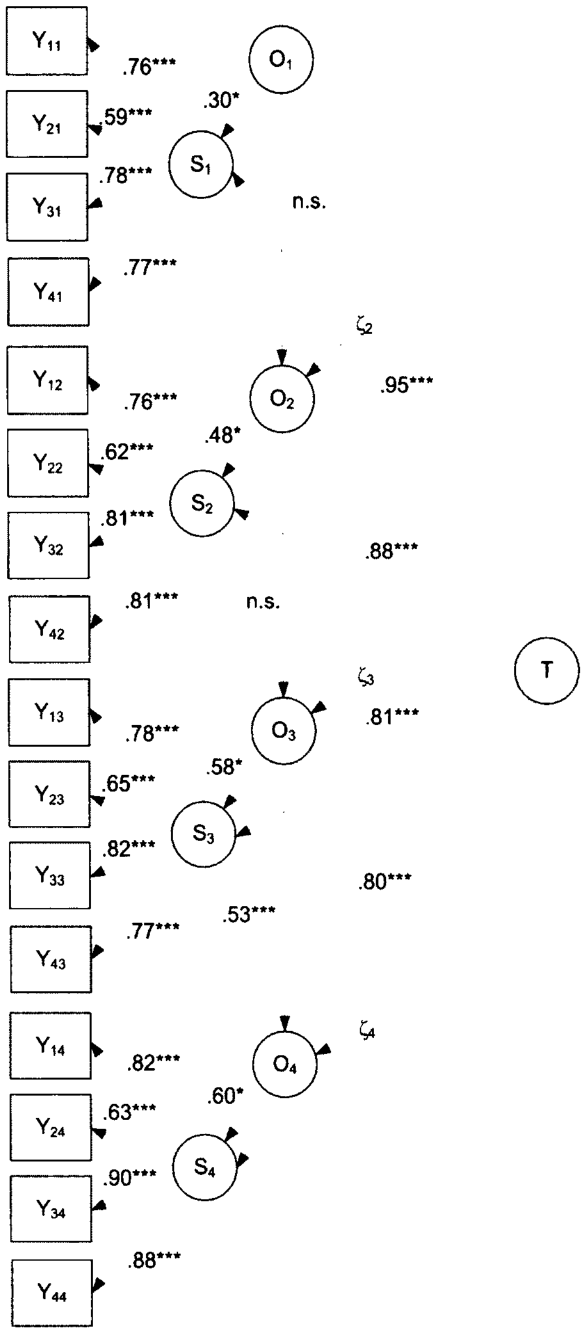

Figure 25. Standardized coefficients for Model 7: Latent TSO model for domain-specific trait learning goal orientation.

Note. T = trait, O_k = occasion for four points in time, S_k = state for four points in time, ζ_k = uniqueness factor for three occasions, and four manifest variables Y_{ik} for four points in time. n.s. = not significant. *p < .05. ***p < .001.

Hypothesis 2b. It was hypothesized that a latent trait-state model would provide a better fit for domain-specific trait performance-prove goal orientation than either a trait or state model. Seven models were tested. The fit indices for all seven models are displayed in Table 16. RMSEA, RMSEA 90% CI, CFI and TLI values for models 3 through 7 indicate good fit.

The AIC, AIC_C and BIC values in Table 17 suggest that Model 3, the state-AR model, provided the best fit. According to Table 18, the state-AR model had a probability of .65 of being the K-L best fitting model, given the candidate models and the data. However two other models had meaningful support: the LTS-AR and latent TSO models. The two models are reasonably plausible alternatives. Compared to the two, the state-AR model had an evidence ratio of 1.9 to one of being the best fitting model. Expressed as a normalized probability, the state-AR model had a .66 probability of being the K-L best fitting model when compared to the other two and given the data.

While two LTS models were plausible, the model with the strongest support was not one of them; it was a state model. These findings do not support Hypothesis 2b.

As illustrated in Figure 26, the regression weights between the occasions of measurement were significant and grew in strength over time.

Table 16

Goodness-of-Fit Indices of the Models for Domain-Specific Trait Performance-Prove Goal Orientation (N = 244)

Model	*df*	χ2	*p*	RMSEA	RMSEA 90% CI	CFI	TLI
1. Trait	112	363.53	0.00	0.100	[0.084, 0.106]	0.86	0.83
2. State	109	571.60	0.00	0.130	[0.120, 0.141]	0.74	0.68
3. State-AR	106	149.12	0.00	0.040	[0.024, 0.055]	0.98	0.97
4. LTS	105	157.70	0.00	0.050	[0.030, 0.059]	0.96	0.96
5. LTS-EC	108	184.70	0.00	0.050	[0.040, 0.066]	0.95	0.95
6. LTS-AR	105	148.70	0.00	0.040	[0.024, 0.055]	0.96	0.97
7. Latent TSO	105	148.75	0.00	0.040	[0.024, 0.055]	0.96	0.97

Note. See note to Table 1.

Table 17

Model Comparison Criteria of Models for Domain-Specific Trait Performance-Prove Goal Orientation (N = 244)

Model	AIC	AIC_C	BIC
1. Trait	443.530	459.688	459.026
2. State	657.596	676.516	674.254
3. State-AR	**241.123**	**263.072**	**258.943**
4. LTS	251.713	274.733	269.920
5. LTS-EC	272.663	292.562	289.708
6. LTS-AR	242.695	265.715	260.902
7. Latent TSO	242.754	265.774	260.961

Note. Boldface indicates best fitting model for criterion. See note to Table 1.

Table 18

Ranking, AIC_C, AIC_C Differences (Δ_i), and Probability (w_i) of Models for Domain-Specific Trait Performance-Prove Goal Orientation (N = 244)

Model	AICc	Δ_i	w_i
3. State-AR	263.072	0.000	0.654
6. LTS-AR	265.715	2.643	0.174
7. Latent TSO	265.774	2.702	0.169
4. LTS	274.733	11.661	0.002
5. LTS-EC	292.562	29.490	0.000
1. Trait	459.688	196.616	0.000
2. State	676.516	413.444	0.000

Note. See note to Table 1.

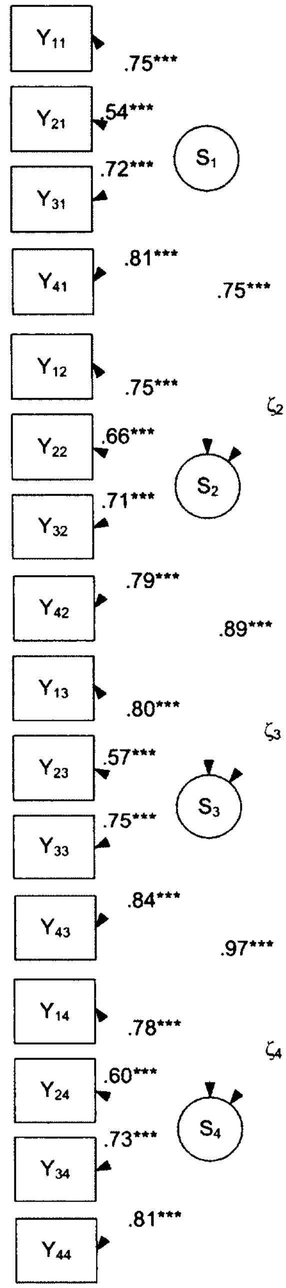

Figure 26. Standardized coefficients for Model 3: State-AR model for the domain-specific trait performance-prove goal orientation.

Note. S_k = state for four points in time, ζ_k = uniqueness factor for three occasions, and four manifest variables Y_{ik} for four points in time.

$^{***}p < .001$.

Hypothesis 2c. It was hypothesized that a latent trait-state model would provide a better fit for domain-specific trait performance-avoid goal orientation than either a trait or state model. Seven models were tested. The fit indices for all seven models are displayed in Table 9. RMSEA and RMSEA 90% CI values for models 3 through 7, CFI values for models 3 through 7, and TLI values for models 4, 6 and 7 met cut-off criteria indicating good fit.

The AIC, AIC_C and BIC values in Table 19indicate Model 7, the latent TSO model, provided the best fit. The latent TSO model had a probability of .72 of being the K-L best fitting model, given the candidate models and the data. Compared to the LTS model, the model ranked as the next best fitting, the latent TSO model had an evidence ratio of 3.94 to one of being the best fitting model. As a normalized probability, the latent TSO model had a .80 probability of being the K-L best fitting model compared to the LST model. As illustrated in Figure 27, the regression coefficients from occasion 1 to occasion 2 and from occasion2 to occasion 3 were not statistically significant. The coefficients for latent trait increased at Time 2 while the coefficients for occasion decreased. At Time 3 and 4, the coefficients for the latent trait decreased while the coefficients for occasion increased. These findings thus support Hypothesis 2c.

Table 19

Goodness-of-Fit Indices of the Models for Domain-Specific Trait Performance-Avoid Goal Orientation (N = 244)

Model	*df*	$\chi2$	*p*	RMSEA	RMSEA 90% CI	CFI	TLI
1. Trait	112	446.07	0.00	0.110	[0.099, 0.120]	0.80	0.76
2. State	109	465.13	0.00	0.120	[0.104, 0.125]	0.79	0.74
3. State-AR	106	187.55	0.00	0.060	[0.042, 0.068]	0.95	0.94
4. LTS	105	172.70	0.00	0.050	[0.037, 0.064]	0.96	0.95
5. LTS-EC	108	191.50	0.00	0.060	[0.043, 0.068]	0.95	0.94
6. LTS-AR	105	173.40	0.00	0.050	[0.037, 0.065]	0.96	0.95
7. Latent TSO	105	169.90	0.00	0.050	[0.036, 0.063]	0.96	0.95

Note. See note to Table 1.

Table 20

Model Comparison Criteria of Models for Domain-Specific Trait Performance-Avoid Goal Orientation (N = 244)

Model	AIC	AIC_C	BIC
1. Trait	526.067	542.225	541.563
2. State	551.129	570.049	567.787
3. State-AR	279.545	301.494	297.365
4. LTS	266.684	289.704	284.891
5. LTS-EC	279.469	299.368	296.514
6. LTS-AR	267.909	290.929	286.116
7. Latent TSO	**263.940**	**286.960**	**282.147**

Note. Boldface indicates best fitting model for criterion. See note to Table 1.

Table 21

Ranking, AIC_C, AIC_C Differences (Δ_i), and Probability (w_i) of Models for Domain-Specific Trait Performance-Avoid Goal Orientation (N = 244)

Model	AICc	Δ_i	w_i
7. Latent TSO	286.960	0.000	0.718
4. LTS	289.704	2.744	0.182
6. LTS-AR	290.929	3.969	0.099
5. LTS-EC	299.368	12.408	0.001
3. State-AR	301.494	14.534	0.001
1. Trait	542.225	255.265	0.000
2. State	570.049	283.089	0.000

Note. See note to Table 1.

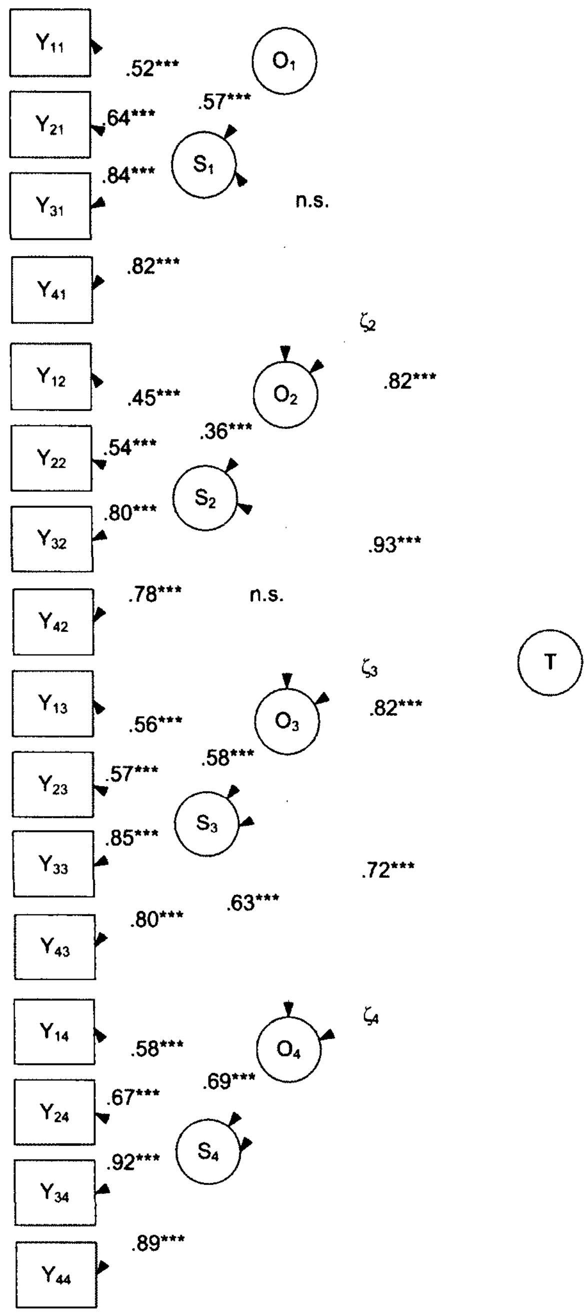

Figure 27. Standardized coefficients for Model 7: Latent TSO model for domain-specific trait performance-avoid goal orientation.

Note. T = trait, O_k = occasion for four points in time, S_k = state for four points in time, ζ_k = uniqueness factor for three occasions, and four manifest variables Y_{ik} for four points in time. n.s. = not significant.

$^{***}p < .001$.

State Goal Orientation (Hypothesis 3a through 3c)

Hypothesis 3a. It was hypothesized that a latent trait-state model would provide a better fit for state learning goal orientation than either a trait or state model. Seven models were tested. The fit indices for all seven models are displayed in Table 22. RMSEA, RMSEA 90% CI, and TLI values for models 4 through 7 and CFI values for models 3 through 7 met cut-off criteria indicating good fit.

The AIC, AIC_C and BIC values in Table 23 indicate that Model 7, the latent TSO model, provided the best fit. According to the model probabilities in Table 23, the latent TSO model had a probability of .81 of being the K-L best fitting model, given the candidate models and the data. According to the model probabilities in Table 23, the latent TSO model had a probability of .81 of being the K-L best fitting model, given the candidate models and the data. Compared to the LTS-AR model, the model ranked as the next best fitting, the latent TSO model had an evidence ratio of 5.97 to one of being the best fitting model. Expressed as a normalized probability, the latent TSO model had a .86 probability of being the K-L best fitting model compared to the LST-AR model. As illustrated in Figure 28, regression weights were similar to other goal orientation dimensions where the LTS model with regressed occasions provided the best fit. The regression paths from occasion 1 to occasion 2 and from occasion2 to occasion 3 were not statistically significant. The factor loadings for latent trait decreased over time while the loadings for occasion increased. These findings thus support Hypothesis 3a.

Table 22

Goodness-of-Fit Indices of the Models for State Learning Goal Orientation (N = 244)

Model	*df*	$\chi2$	*p*	RMSEA	RMSEA 90% CI	CFI	TLI
1. Trait	112	560.97	0.00	0.127	[0.117, 0.137]	0.78	0.74
2. State	109	559.43	0.00	0.129	[0.118, 0.139]	0.78	0.73
3. State-AR	106	196.62	0.00	0.060	[0.046, 0.071]	0.96	0.94
4. LTS	105	166.00	0.00	0.050	[0.034, 0.062]	0.97	0.96
5. LTS-EC	108	183.00	0.00	0.050	[0.039, 0.066]	0.96	0.95
6. LTS-AR	105	167.90	0.00	0.050	[0.035, 0.063]	0.97	0.96
7. Latent TSO	105	162.47	0.00	0.047	[0.032, 0.061]	0.97	0.96

Note. See note to Table 1.

Table 23

Model Comparison Criteria of Models for State Learning Goal Orientation (N = 244)

Model	AIC	AIC_C	BIC
1. Trait	640.970	657.128	656.466
2. State	645.429	664.349	662.087
3. State-AR	288.620	310.569	306.440
4. LTS	260.039	283.059	278.246
5. LTS-EC	271.200	291.099	288.245
6. LTS-AR	261.974	284.994	280.181
7. Latent TSO	**256.467**	**279.487**	**274.674**

Note. Boldface indicates best fitting model for criterion. See note to Table 1.

Table 24

Ranking, AIC_C, AIC_C Differences (Δ_i), and Probability (w_i) of Models for State Learning Goal Orientation (N = 244)

Model	AICc	Δ_i	w_i
7. Latent TSO	279.487	0.000	0.810
4. LTS	283.059	3.572	0.136
6. LTS-AR	284.994	5.507	0.052
5. LTS-EC	291.099	11.612	0.002
3. State-AR	310.569	31.082	0.000
1. Trait	657.128	377.641	0.000
2. State	664.349	384.862	0.000

Note. See note to Table 1.

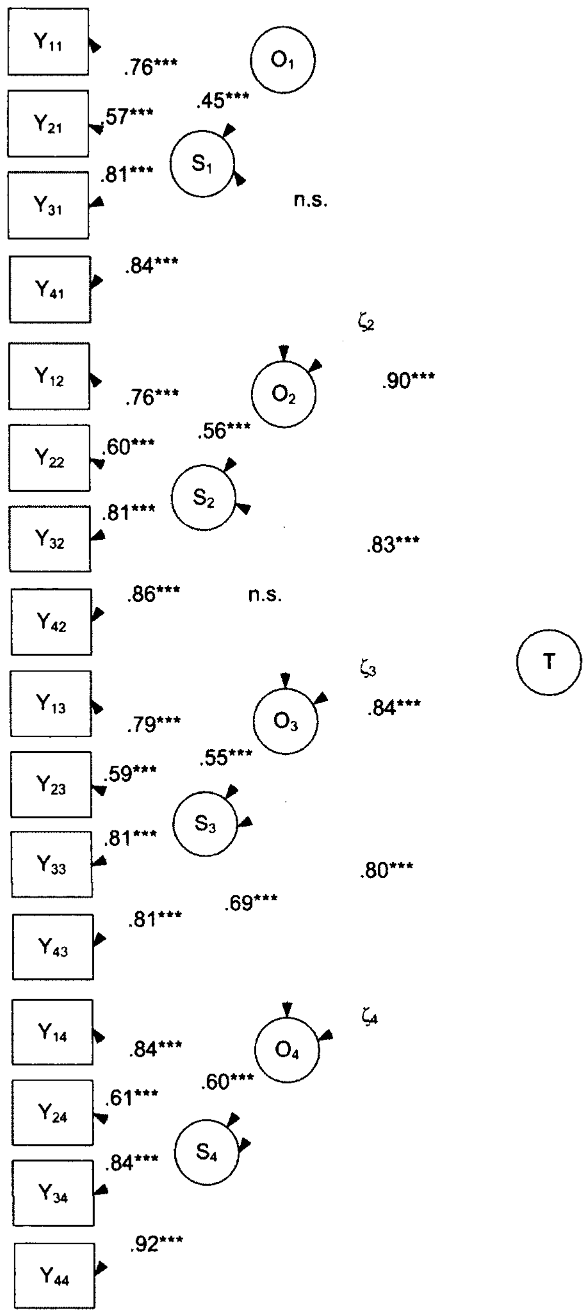

Figure 28. Standardized coefficients for Model 7: Latent TSO model for state learning goal orientation.

Note. T = trait, O_k = occasion for four points in time, S_k = state for four points in time, ζ_k = uniqueness factor for three occasions, and four manifest variables Y_{ik} for four points in time. n.s. = not significant.

$^{***}p < .001$.

Hypothesis 3b. It was hypothesized that a latent trait-state model would provide a better fit for state performance-prove goal orientation than either a trait or state model. Seven models were tested. The fit indices for all seven models are displayed in Table 25. RMSEA and RMSEA 90% CI values for models 4 through 7 and CFI and TLI values for models 3 through 7 indicate good fit.

The AIC, AIC_C and BIC values in Table 5 reveal that Model 26, the LTS-AR model, and Model 7, the latent TSO model, provided the best fit. According to the model probabilities in Table 27, the two models had a combined probability of .80 of being the K-L best fitting model, given the candidate models and the data. Compared to all the other models, the combination of the LTS-AR and latent TSO models had an evidence ratio of 4.31 to one of being the best fitting model. Expressed as a normalized probability, the models had a .81 probability of being the K-L best fitting compared to the LST-AR model.

Model 6 is depicted in Figure 29 while Model 7 is illustrated in Figure 30. The two models differed in three ways. First, in Model 6, the coefficient between Time 1 and Time 2 was statistically significant; in Model 7, however, it was not significant. Second, the coefficients for latent traits were larger in Model 7. Lastly, Model 7 provides a means by which to examine the influence of the occasion factor on the associated state, e.g., regression weights. While a single best fitting model was not identified given the data, the findings support Hypothesis 3b.

Table 25

Goodness-of-Fit Indices of the Models for State Performance-Prove Goal Orientation (N = 244)

Model	*df*	χ2	*p*	RMSEA	RMSEA 90% CI	CFI	TLI
1. Trait	112	427.43	0.00	0.110	[0.096, 0.117]	0.84	0.81
2. State	109	611.33	0.00	0.140	[0.126, 0.147]	0.75	0.69
3. State-AR	106	189.75	0.00	0.060	[0.043, 0.069]	0.96	0.95
4. LTS	105	164.60	0.00	0.050	[0.033, 0.061]	0.97	0.96
5. LTS-EC	108	176.40	0.00	0.050	[0.037, 0.064]	0.97	0.96
6. LTS-AR	105	162.40	0.00	0.050	[0.032, 0.061]	0.97	0.96
7. Latent TSO	105	162.70	0.00	0.050	[0.032, 0.061]	0.97	0.96

Note. See note to Table 1.

Table 26

Model Comparison Criteria of Models for State Performance-Prove Goal Orientation (N = 244)

Model	AIC	AIC_C	BIC
1. Trait	507.434	523.592	522.930
2. State	697.331	716.251	713.989
3. State-AR	281.748	303.697	299.568
4. LTS	258.554	281.574	276.761
5. LTS-EC	264.377	284.276	281.422
6. LTS-AR	**256.446**	**279.466**	**274.653**
7. Latent TSO	256.673	279.693	274.880

Note. Boldface indicates best fitting model for criterion. See note to Table 1.

Table 27

Ranking, AIC_C, AIC_C Differences (Δ_i), and Probability (w_i) of Models for State Performance-Prove Goal Orientation (N = 244)

Model	AICc	Δ_i	w_i
6. LTS-AR	279.466	0.000	0.429
7. Latent TSO	279.693	0.227	0.383
4. LTS	281.574	2.108	0.149
5. LTS-EC	284.276	4.810	0.039
3. State-AR	303.697	24.231	0.000
1. Trait	523.592	244.126	0.000
2. State	716.251	436.785	0.000

Note. See note to Table 1.

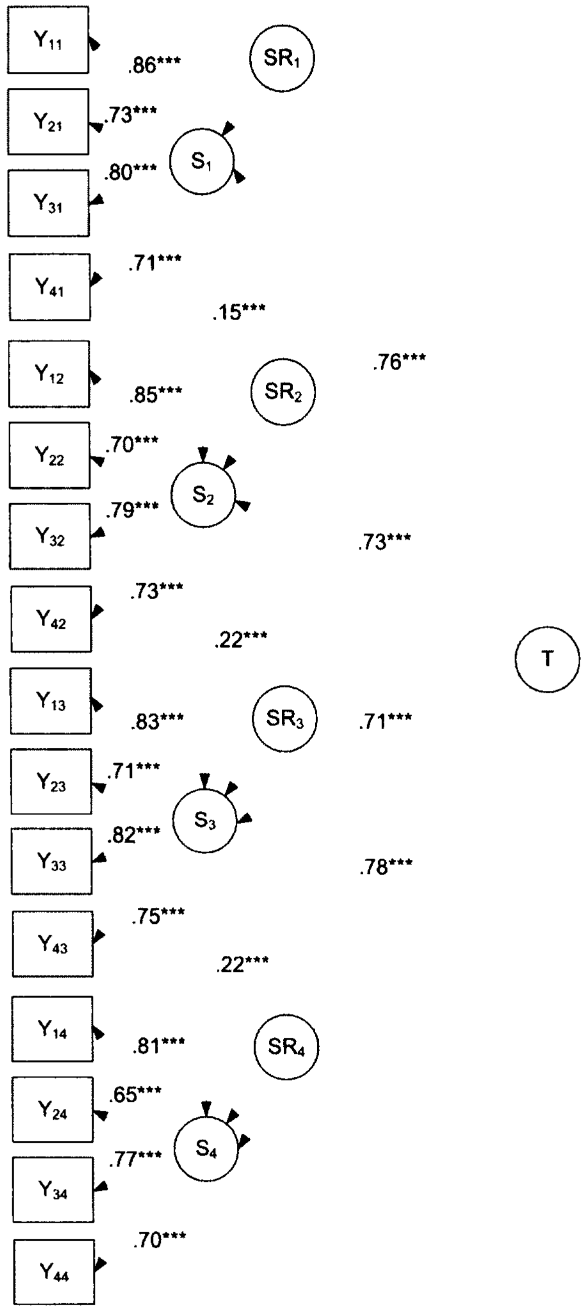

Figure 29. Standardized coefficients for Model 6: LTS-AR model for state performance-prove goal orientation measure.

Note. T = trait, O_k = occasion for four points in time, S_k = state for four points in time, ζ_k = uniqueness factor for three occasions, and four manifest variables Y_{ik} for four points in time. n.s. = not significant.

***$p < .001$.

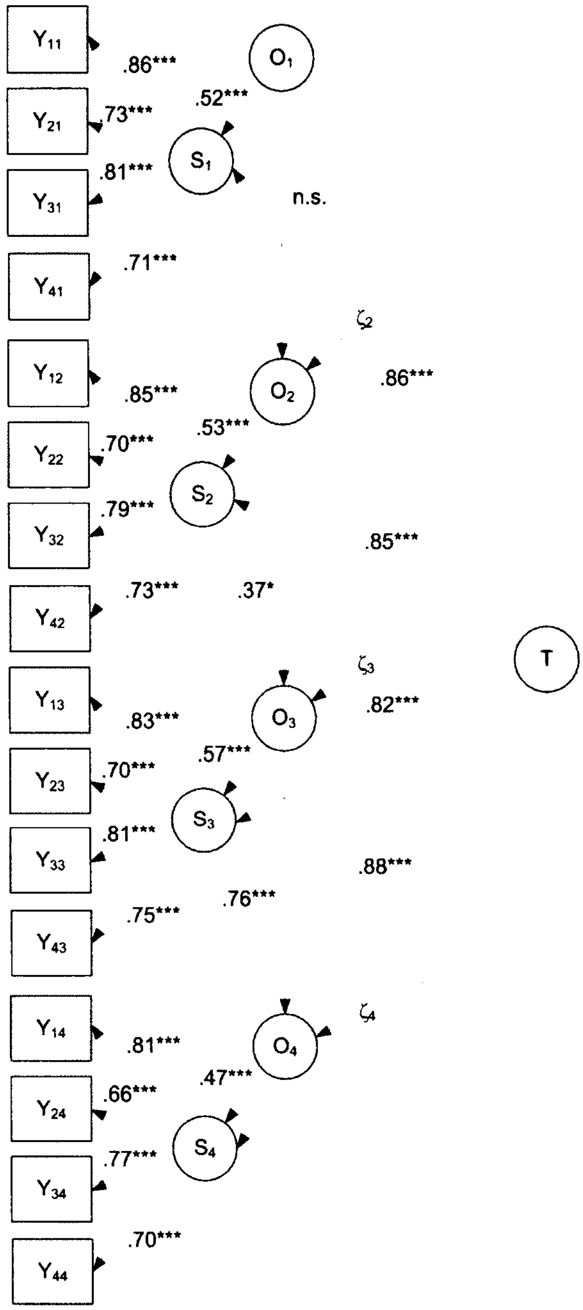

Figure 30. Standardized coefficients for Model 7: Latent TSO model for state performance-prove goal orientation.

Note. T = trait, O_k = occasion for four points in time, S_k = state for four points in time, ζ_k = uniqueness factor for three occasions, and four manifest variables Y_{ik} for four points in time. n.s. = not significant.

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

Hypothesis 3c. It was hypothesized that a latent trait-state model would provide a better fit for state performance-avoid goal orientation than either a trait or state model. Seven models were tested. The fit indices for all seven models are displayed in Table 28.

RMSEA, RMSEA 90% CI and CFI values for models 3 through 7 and the TLI value for model 7 met cut-off criteria indicating good fit. The AIC, AIC_C and BIC values in Table 29 indicate that Model 7, the latent TSO model, provided the best fit. The model probability for the latent TSO model was 1.00 and is located in Table 30. The evidence ratio for the latent TSO model to be the K-L best fitting model versus all the other candidate models is 4984.65 to one. As illustrated in Figure 31, regression weights were similar to TSO models of other goal orientation dimensions. The regression paths from occasion 1 to occasion 2 and from occasion2 to occasion 3 were not statistically significant. The factor loadings for latent trait decreased over time while the loadings for occasion increased. These findings thus support Hypothesis 3c.

Table 28

Goodness-of-Fit Indices of the Models for State Performance-Avoid Goal Orientation (N = 244)

Model	*df*	$\chi 2$	*p*	RMSEA	RMSEA 90% CI	CFI	TLI
1. Trait	112	484.26	0.00	0.120	[0.105, 0.126]	0.79	0.75
2. State	109	522.13	0.00	0.120	[0.113, 0.134]	0.77	0.71
3. State-AR	106	199.18	0.00	0.060	[0.047, 0.072]	0.95	0.93
4. LTS	105	194.70	0.00	0.060	[0.046, 0.071]	0.95	0.94
5. LTS-EC	108	210.50	0.00	0.060	[0.049, 0.074]	0.94	0.93
6. LTS-AR	105	192.70	0.00	0.060	[0.045, 0.071]	0.95	0.94
7. Latent TSO	105	174.13	0.00	0.051	[0.037, 0.065]	0.97	0.96

Note. See note to Table 1.

Table 29

Model Comparison Criteria of Models for State Performance-Avoid Goal Orientation (N = 244)

Model	AIC	AIC_C	BIC
1. Trait	564.255	580.413	579.751
2. State	608.129	627.049	624.787
3. State-AR	291.184	313.133	309.004
4. LTS	286.690	309.710	304.897
5. LTS-EC	296.463	316.362	313.508
6. LTS-AR	284.707	307.727	302.914
7. Latent TSO	**268.127**	**291.147**	**286.334**

Note. Boldface indicates best fitting model for criterion. See note to Table 1.

Table 30

Ranking, AIC_C, AIC_C Differences (Δ_i), and Probability (w_i) of Models for State Performance-Avoid Goal Orientation (N = 244)

Model	AICc	Δ_i	w_i
7. Latent TSO	291.147	0.000	1.000
6. LTS-AR	307.727	16.580	0.000
4. LTS	309.710	18.563	0.000
3. State-AR	313.133	21.986	0.000
5. LTS-EC	316.362	25.215	0.000
1. Trait	580.413	289.266	0.000
2. State	627.049	335.902	0.000

Note. See note to Table 1.

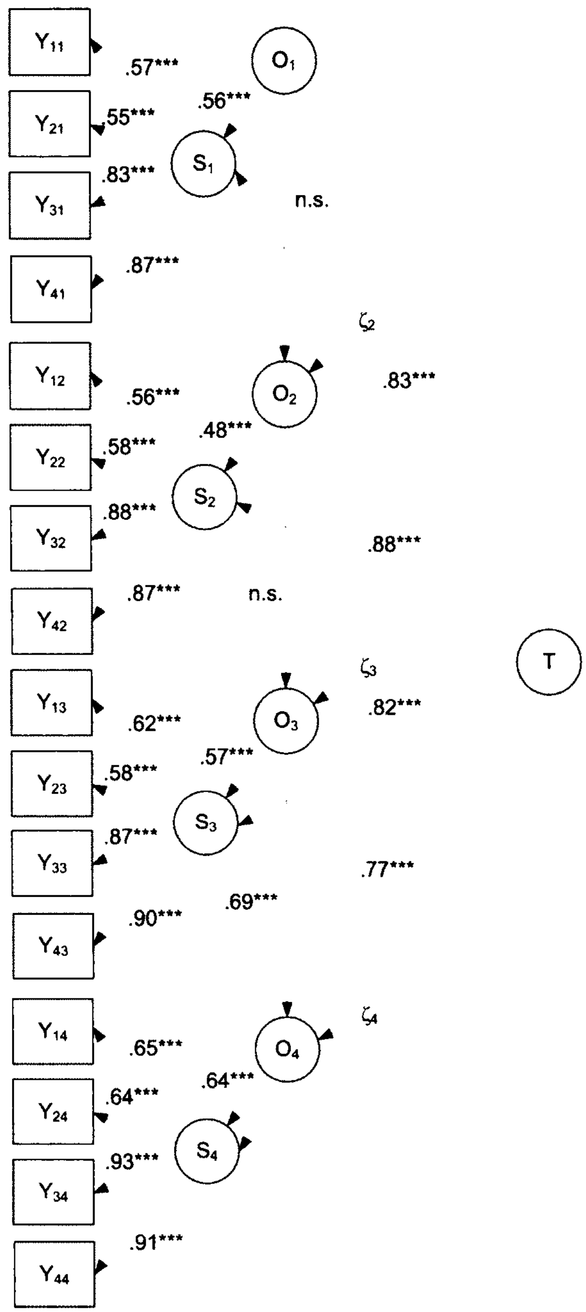

Figure 31. Standardized coefficients for Model 7: Latent TSO model for state performance-prove goal orientation.

Note. T = trait, O_k = occasion for four points in time, S_k = state for four points in time, ζ_k = uniqueness factor for three occasions, and four manifest variables Y_{ik} for four points in time. n.s. = not significant.

***$p < .001$.

Procedure for Testing Hypotheses 4a through 9c

To review, the best fitting model for testing Hypotheses 4a through 9c was selected using several criteria. The first criterion was identifying a single model that met or exceeded RMSEA, TLI, and CFI benchmarks while the alternative models fail to meet the benchmarks. Thus a model was identified as the best fitting when it met or exceeded goodness-of-fit indices cut-offs for good fit (RMSEA < 0.05, CFI > 0.95, and TLI > 0.95) and other models failed to meet the benchmark cut-offs. The second criterion for selecting the best fit was how well the model replicated or clarified the predictive relationship with learning and academic performance as noted in the Payne et al (2007) meta-analysis.

General Trait Goal Orientation and Learning in an Academic Setting (Hypothesis 4a through 4c)

Hypothesis 4a. It was hypothesized that a latent trait-state model would provide a better fit than a trait model when examining the relationship between general trait learning goal orientation and learning in an academic setting. Three models were tested; the fit indices for each of these models are displayed in Table 31.

Based on the RMSEA, CFI, and TLI benchmarks, Model 1, the latent trait model, provided the best fit. Model 1also detected a predictive relationship with learning outcome at Time 4. Model 2, the LTS model, did not meet the RMSEA and TLI cut-off values while Model 3, the latent TSO model, did not meet the TLI cut-off. Thus, these findings do not support Hypothesis 4a.

Table 31

Goodness-of-Fit Indices of the Models for General Trait Learning Goal Orientation Predicting Learning (N = 244)

Model	*df*	$\chi 2$	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	β
1. Latent Trait	14	19.83	0.14	0.041	[0.000, 0.079]	0.98	0.95	
Learning Time 1								0.05
Learning Time 2								0.07
Learning Time 3								0.07
Learning Time 4								0.15*
2. LTS	168	276.5	0.00	0.051	[0.040, 0.061]	0.95	0.93	
Learning Time 1								0.06
Learning Time 2								0.12
Learning Time 3								0.06
Learning Time 4								0.14*
3. Latent TSO	166	263.03	0.00	0.048	[0.037, 0.059]	0.95	0.94	
Learning Time 1								0.04
Learning Time 2								0.1
Learning Time 3								0.07
Learning Time 4								0.14

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index.

* $p < .05$.

Hypothesis 4b. It was hypothesized that a latent trait-state model would provide a better fit than a trait model when examining the relationship between general trait performance-prove goal orientation and learning in an academic setting. Three models were tested; the fit indices for each of these models are displayed in Table 32.

While the values for Model 1, the latent trait model, fit indices indicated a perfect fit, Models 2 and 3, the LTS and LTS-AR models respectively, met the benchmark cut-offs for good fit. None of the models, however, detected a relationship between performance-prove goal orientation and the learning outcome. Thus, the findings were inconclusive and did not support Hypothesis 4b.

Table 32

Goodness-of-Fit Indices of the Models for General Trait Performance-Prove Goal Orientation Predicting Learning (N = 244)

Model	*df*	χ2	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	*β*
1. Latent Trait	14	13.04	0.52	0.00	[0.000, 0.058]	1.00	1.01	
Learning Time 1								0.03
Learning Time 2								-0.05
Learning Time 3								0.01
Learning Time 4								-0.02
2. LTS	168	262.34	0.00	0.047	[0.036, 0.058]	0.96	0.95	
Learning Time 1								0.04
Learning Time 2								0.04
Learning Time 3								-0.04
Learning Time 4								0.01
3. Latent TSO	165	248.85	0.00	0.045	[0.033, 0.056]	0.96	0.95	
Learning Time 1								0.04
Learning Time 2								0.02
Learning Time 3								-0.03
Learning Time 4								-0.01

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index.

* $p < .05$.

Hypothesis 4c. It was hypothesized that a latent trait-state model would provide a better fit than a trait model when examining the relationship between general trait performance-avoid goal orientation and learning in an academic setting. Three models were tested; the fit indices for each of these models are displayed in Table 33.

Model 1, the latent trait model, fit indices indicated perfect fit. The relationship between the latent trait and learning was significant at Time 1. Model 3, the latent TSO model, met benchmark criteria. The significant relationship between the latent trait and learning at Time 4, however, was positive and contrary to what was reported by Payne et al. (2007): sample-weighted mean $r = -.13$ and $\rho = -.17$. These findings thus do not support Hypothesis 4c.

Table 33

Goodness-of-Fit Indices of the Models for General Trait Performance-Avoid Goal Orientation Predicting Learning (N = 244)

Model	*df*	χ2	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	*β*
1. Latent Trait	14	12.39	0.58	0.00	[0.000, 0.055]	1.00	1.01	
Learning Time 1								-0.18*
Learning Time 2								0.02
Learning Time 3								-0.06
Learning Time 4								0.14
2. LTS	168	279.48	0.00	0.052	[0.041, 0.062]	0.94	0.93	
Learning Time 1								-0.05
Learning Time 2								0.03
Learning Time 3								-0.02
Learning Time 4								0.14
3. Latent TSO	166	239.74	0.00	0.042	[0.030, 0.054]	0.96	0.95	
Learning Time 1								-0.06
Learning Time 2								0.04
Learning Time 3								-0.02
Learning Time 4								0.17*

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index.

General Trait Goal Orientation and Academic Performance (Hypothesis 5a through 5c)

Hypothesis 5a. It was hypothesized that a latent trait-state model would provide a better fit than a trait model for explaining the relationship between general trait learning goal orientation and academic performance. Three models were tested; the fit indices for these models are presented in Table 34.

All the models met the RMSEA criterion for reasonable fit and the CFI criterion for good fit. None of the models, however, met the benchmark for the TLI index. The relationship between the latent trait and academic performance was statistically significant in both Model 2, the LTS model, and Model 3, the latent TSO model. Unfortunately a clear choice of best model was not available as both models fit nearly as well. These findings do not support Hypothesis 5a.

Table 34

Goodness-of-Fit Indices of the Models for General Trait Learning Goal Orientation Predicting Academic Performance (N = 244)

Model	*df*	$\chi 2$	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	*β*
1. Latent Trait	5	9.35	0.1	0.059	[0.000, 0.117]	0.98	0.94	
AP								0.12
2. LTS	123	224.76	0.00	0.058	[0.046, 0.069]	0.95	0.94	
AP								0.16*
3. Latent TSO	121	209.8	0.00	0.054	[0.042, 0.066]	0.96	0.94	
AP								0.15*

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index; AP = academic performance.

* $p < .05$.

Hypothesis 5b. It was hypothesized that a latent trait-state model would provide a better fit than a trait model for explaining the relationship between general trait performance-prove goal orientation and academic performance. Three models were tested; the fit indices for each of the models are summarized in Table 35.

Although all models had good model fit, the relationship between latent trait and academic performance in all three models was not statistically significant. Thus, the findings were inconclusive and did not support Hypothesis 5b.

Table 35

Goodness-of-Fit Indices of the Models for General Trait Performance-Prove Goal Orientation Predicting Academic Performance (N = 244)

Model	*df*	χ2	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	*β*
1. Latent Trait	5	8.13	0.149	0.05	[0.000, 0.110]	0.99	0.97	
AP								-0.08
2. LTS	123	208.78	0.00	0.053	[0.040, 0.065]	0.96	0.95	
AP								-0.05
3. Latent TSO	121	195.68	0.00	0.05	[0.037, 0.062]	0.97	0.96	
AP								-0.06

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index; AP = academic performance.

Hypothesis 5c. It was hypothesized that a latent trait-state model would provide a better fit than a trait model for explaining the relationship between general trait performance-avoid goal orientation and academic performance. Three models were tested; the fit indices for the three models are presented in Table 36.

The findings in the table reveal that Model 3 met the RMSEA benchmark for close fit; it also met the TLI benchmark for good fit. Lastly, the relationship between latent trait and academic performance was statistically significant however in the opposite direction of that in the Payne et al. (2007) meta-analysis. T these findings do not support Hypothesis 5c.

Table 36

Goodness-of-Fit Indices of the Models for General Trait Performance-Avoid Goal Orientation Predicting Academic Performance (N = 244)

Model	*df*	$\chi2$	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	β
1. Latent Trait	5	10.2	0.07	0.065	[0.000, 0.122]	0.98	0.94	
AP								0.17*
2. LTS	123	234.38	0.00	0.06	[0.048, 0.072]	0.94	0.93	
AP								0.14
3. Latent TSO	121	195.32	0.00	0.05	[0.036, 0.062]	0.96	0.95	
AP								0.17*

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index.

* $p < .05$.

Domain-Specific Trait Goal Orientation and Learning in an Academic Setting (Hypothesis 6a through 6c)

Hypothesis 6a. It was hypothesized that a latent trait-state model would provide a better fit than a trait model for explaining the relationship between domain-specific trait learning goal orientation and academic performance. Three models were tested; the fit indices for these models are summarized in Table 37.

The findings in the table reveal that Model 2, the LTS model, and Model 3, the latent TSO model, met the benchmarks for RMSEA, TLI, and CFI. The relationship between latent trait and learning at Time 4 was statistically significant for the LTS model but not the other two models. When testing Hypothesis 6a, the LTS model detected a relationship between learning goal orientation and learning in an academic setting at Time 4 ($\beta = .14, p < .05$). The Time 4 β estimate for the trait model was not significant ($\beta = .10, p = .18$). The β estimates for the outcome measure at Times 1 through 3 were not significant for either model.

While the LTS model was superior to the trait model in this study, it did not improve the relationship between trait learning goal orientation and learning in an academic setting beyond that reported by Payne et al. (2007). The Payne et al. meta-analysis reported sample-weighted mean $r = .12$ and $\rho = .16$. These findings do not indicate support Hypothesis 6a.

Table 37

Goodness-of-Fit Indices of the Models for Domain-Specific Trait Learning Goal Orientation Predicting Learning (N = 244)

Model	*df*	$\chi 2$	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	β
1. Latent Trait	14	29.7	0.01	0.067	[0.033, 0.101]	0.96	0.89	
Learning Time 1								0.10
Learning Time 2								0.06
Learning Time 3								0.03
Learning Time 4								0.10
2. LTS	168	239.36	0.00	0.041	[0.029, 0.053]	0.97	0.96	
Learning Time 1								0.06
Learning Time 2								0.11
Learning Time 3								0.06
Learning Time 4								0.14*
3. Latent TSO	165	227.06	0.00	0.039	[0.025, 0.051]	0.97	0.96	
Learning Time 1								0.05
Learning Time 2								0.10
Learning Time 3								0.05
Learning Time 4								0.13

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index.

* $p < .05$.

Hypothesis 6b. It was hypothesized that a latent trait-state model would provide a better fit than a trait model for explaining the relationship between domain-specific trait performance-prove goal orientation and learning in an academic setting. Three models were tested; the fit indices for the models are displayed in Table 38.

All three models met the cut-off value for CFI. Model 2, the LTS model, and Model 3, the latent TSO model, met the fit benchmark for an RMSEA close fit while Model 1, the trait model, did not. Only the latent TSO model met the cut-off for TLI. Thus, Model 3 exhibited the best fit. Note, however, that the predictive relationship with learning outcome was not statistically significant with the latent TSO model. Altogether, these findings do not provide support for Hypothesis 6b.

Table 38

Goodness-of-Fit Indices of the Models for Domain-Specific Trait Performance-Prove Goal Orientation Predicting Learning (N = 244)

Model	*df*	χ2	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	*β*
1. Latent Trait	14	27.57	0.02	0.062	[0.026, 0.097]	0.96	0.9	
Learning Time 1								0.09
Learning Time 2								0.02
Learning Time 3								0.01
Learning Time 4								0.12
2. LTS	168	267.59	0.00	0.049	[0.038, 0.060]	0.95	0.93	
Learning Time 1								0.01
Learning Time 2								0.05
Learning Time 3								0.00
Learning Time 4								0.08
3. Latent TSO	165	231.27	0.00	0.04	[0.027, 0.052]	0.96	0.96	
Learning Time 1								0.04
Learning Time 2								0.06
Learning Time 3								0.01
Learning Time 4								0.14

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index.

Hypothesis 6c. It was hypothesized that a latent trait-state model would provide a better fit than a trait model for explaining the relationship between domain-specific trait performance-avoid goal orientation and learning in an academic setting. Three models were tested; the fit indices for the models are displayed in Table 39.

All three models met the cut-off value for CFI and the benchmark for an RMSEA close fit. However, the LTS model did not meet the cut-off for TLI. Although the latent TSO model exhibited the best fit, the predictive relationship with learning outcome was not statistically significant (nor was it significant in the other two models). Altogether, these findings do not provide support for Hypothesis 6c.

Table 39

Goodness-of-Fit Indices of the Models for Domain-Specific Trait Performance-Avoid Goal Orientation Predicting Learning (N = 244)

Model	*df*	χ2	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	*β*
1. Latent Trait	14	19.73	0.14	0.041	[0.000, 0.079]	0.98	0.96	
Learning Time 1								-0.13
Learning Time 2								0.02
Learning Time 3								-0.05
Learning Time 4								0.06
2. LTS	168	261.88	0.00	0.047	[0.036, 0.058]	0.95	0.93	
Learning Time 1								-0.09
Learning Time 2								0.00
Learning Time 3								-0.05
Learning Time 4								0.07
3. Latent TSO	165	239.88	0.00	0.043	[0.030, 0.054]	0.96	0.95	
Learning Time 1								-0.14
Learning Time 2								-0.04
Learning Time 3								-0.07
Learning Time 4								0.05

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index.

Domain-Specific Trait Learning Goal Orientation and Academic Performance (Hypothesis 7a through 7c)

Hypothesis 7a. It was hypothesized that a latent trait-state model for explaining the relationship between domain-specific trait learning goal orientation and academic performance. Three models were tested; the fit indices are summarized in Table 40.

Model 2, the LTS model, and Model 3, the latent TSO model, met the cut-off values for RMSEA, CFI, and TLI. Among the three models, only the LTS model was significantly related to academic performance ($\beta = .14, p < .05$). While this value was a slight improvement over the sample-weighted mean r reported by Payne et al. (2007; $r = .12$), it was less than the estimate true mean correlation ($\rho = .16$). Thus, these findings did not support Hypothesis 7a.

Table 40

Goodness-of-Fit Indices of the Models for Domain-Specific Trait Learning Goal Orientation Predicting Academic Performance (N = 244)

Model	*df*	χ2	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	*β*
1. Latent Trait	5	18.72	0.00	0.105	[0.057, 0.158]	0.96	0.87	
AP								0.06
2. LTS	123	224.76	0.00	0.058	[0.038, 0.063]	0.95	0.94	
AP								0.14*
3. Latent TSO	120	188.94	0.00	0.048	[0.034, 0.061]	0.97	0.96	
AP								0.12

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index.

* $p < .05$.

Hypothesis 7b. It was hypothesized that a latent trait-state model for explaining the relationship between domain-specific trait performance-prove goal orientation and academic performance. Three models were tested; the fit indices are summarized in Table 41.

Model 1, the trait model, only met the benchmark cut-off value for CFI while Model 2, the LTS model, met the RMSEA benchmark for close fit and CFI benchmark for good fit. Model 3, the latent TSO model, however, met all criteria. Further, this model included a statistically significant relationship between latent trait and academic performance ((β = .14, $p < .05$). this value was greater than the values reported by Payne et al. (2006), sample-weighted mean $r = .01$ and $\rho = .02$. Thus, Hypothesis 7b was supported.

Table 41

Goodness-of-Fit Indices of the Models for Domain-Specific Trait Performance-Prove Goal Orientation Predicting Academic Performance (N = 244)

Model	*df*	χ2	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	*β*
1. Latent Trait	5	17.21	0.00	0.099	[0.050, 0.152]	0.96	0.88	
AP								0.09
2. LTS	123	211.3	0.00	0.054	[0.041, 0.066]	0.95	0.94	
AP								0.06
3. Latent TSO	120	185.18	0.00	0.047	[0.033, 0.060]	0.96	0.95	
AP								0.14*

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index.

* $p < .05$.

Hypothesis 7c. It was hypothesized that a latent trait-state model for explaining the relationship between domain-specific trait performance-avoid goal orientation and academic performance. Three models were tested; the fit indices are presented in Table 42.

Only Model 3 met cut-off values for RMSEA, CFI and TLI. In addition, the path between the latent trait and academic performance was statistically significant ($\beta = .16$, $p < .01$). However, results were in the opposite direction to that reported by Payne et al. (2007), sample-weighted mean $r = -.05$ and $\rho = -.06$. Thus, Hypothesis 7c was not supported.

Table 42

Goodness-of-Fit Indices of the Models for Domain-Specific Trait Performance-Avoid Goal Orientation Predicting Academic Performance (N = 244)

Model	*df*	$\chi 2$	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	β
1. Latent Trait	5	12.79	0.03	0.079	[0.026, 0.134]	0.97	0.92	
AP								0.12
2. LTS	123	215.28	0.00	0.055	[0.043, 0.067]	0.95	0.93	
AP								0.12
3. Latent TSO	120	192.39	0.00	0.049	[0.036, 0.062]	0.96	0.95	
AP								0.16**

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index.

*p<.05.

State Goal Orientation and Learning in an Academic Setting (Hypothesis 8a through 8c)

Hypothesis 8a. It was hypothesized that a latent trait-state model would provide a better fit than a state model for explaining the relationship between situational influences on state learning goal orientation and learning in an academic setting. Three models were tested; the fit indices for the three models are presented in Table 43.

Models 2 and 3, the LTS and latent TSO models, met the cut-off criteria for RMSEA, CFI, and TLI. However, there were no statistically significant relationships between latent state and any of the learning outcomes. Thus, Hypothesis 8a was not supported.

Table 43

Goodness-of-Fit Indices of the Models for State Learning Goal Orientation Predicting Learning (N = 244)

Model	*df*	χ2	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	*β*
1. Latent State	166	275.81	0.00	0.052	[0.041, 0.062]	0.95	0.94	
Learning Time 1								0.04
Learning Time 2								0.06
Learning Time 3								0.08
Learning Time 4								0.09
2. LTS	168	261.85	0.00	0.047	[0.036, 0.058]	0.96	0.95	
Learning Time 1								0.06
Learning Time 2								0.06
Learning Time 3								0.08
Learning Time 4								0.09
3. Latent TSO	165	241.52	0.00	0.043	[0.031, 0.055]	0.96	0.95	
Learning Time 1								0.05
Learning Time 2								0.07
Learning Time 3								0.09
Learning Time 4								0.09

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index.

Hypothesis 8b. It was hypothesized that a latent trait-state model would provide a better fit than a state model for explaining the relationship between situational influences on state performance-prove goal orientation and learning in an academic setting. Three models were tested; the fit indices for the three models are displayed in Table 44.

All the models met benchmark values for RMSEA, CFI, and TLI. In addition, in all models, the relationship between latent state and learning in Time 4 was statistically significant. However, the size of all of model regression weights was nearly the same. These findings do not support Hypothesis 8b.

Table 44

Goodness-of-Fit Indices of the Models for State Performance-Prove Goal Orientation Predicting Learning (N = 244)

Model	*df*	χ2	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	*β*
1. Latent State	166	239.21	0.00	0.042	[0.030, 0.054]	0.96	0.96	
Learning Time 1								0.03
Learning Time 2								0.12
Learning Time 3								0.06
Learning Time 4								0.23***
2. LTS	168	233.27	0.00	0.04	[0.026, 0.051]	0.97	0.96	
Learning Time 1								0.03
Learning Time 2								0.13
Learning Time 3								0.06
Learning Time 4								0.22***
3. Latent TSO	165	222.39	0.00	0.037	[0.023, 0.049]	0.97	0.96	
Learning Time 1								0.03
Learning Time 2								0.13
Learning Time 3								0.07
Learning Time 4								0.23***

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index.

*** $p < .001$.

Hypothesis 8c. It was hypothesized that a latent trait-state model would provide a better fit than a state model for explaining the relationship between situational influences on state performance-avoid goal orientation and learning in an academic setting. Three models were tested; the fit indices for the three models are shown in Table 45.

Only Model 3, the latent TSO model, met the benchmark cut-off values for the RMSEA, CFI, and TLI. The path between the latent state construct and learning at Time 4 was statistically significant for all three models, however in the opposite direction to that found by Payne et al. (2007). Thus, Hypothesis 8c was not supported.

Table 45

Goodness-of-Fit Indices of the Models for State Performance-Avoid Goal Orientation Predicting Learning (N = 244)

Model	*df*	$\chi 2$	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	β
1. Latent State	166	271.82	0.00	0.05	[0.040, 0.061]	0.95	0.94	
Learning Time 1								-0.12
Learning Time 2								-0.01
Learning Time 3								0.01
Learning Time 4								0.16*
2. LTS	168	279.96	0.00	0.052	[0.041, 0.062]	0.95	0.93	
Learning Time 1								-0.12
Learning Time 2								0.00
Learning Time 3								0.00
Learning Time 4								0.13*
3. Latent TSO	165	254.3	0.00	0.047	[0.035, 0.058]	0.96	0.95	
Learning Time 1								-0.12
Learning Time 2								0.00
Learning Time 3								0.01
Learning Time 4								0.15*

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index.

* $p < .05$.

State Goal Orientation and Academic Performance (Hypothesis 9a through 9c)

It was hypothesized that a latent trait-state model would provide a better fit than a state model for explaining the relationship between situational influences of state learning (Hypothesis 9a), performance-prove (Hypothesis 9b), and performance-avoid (Hypothesis 9c) goal orientation with academic performance.

The solutions for tests of Hypotheses 9a, 9b, and 9c were inadmissible due to empirical underidentification (Kenny, 1979). No unique solution exists for an underidentified model. Underidentification occurs when parameters cannot be adequately estimated. There are two types of underidentification. The first type is parametric underidentification which happens when a model cannot be identified based on its structure. The second type is empirical underidentification which happens when a model is not identified based on the sample data being analyzed. It was this second type which affected the analyses for Hypothesis 9. Empirical underidentification results in unstable parameter estimates and large standard errors. According to Kenny, multicollinearity is an example of empirical underidentification.

Multicolinearity was not identified by tests for this problem during the data screening process. Once the issue was found during analysis, I followed Tabachnik and Fidell's (2001) recommendations to address multicolinearity and converted the state goal orientation variables into *z*-scores and reanalyzed the data. Unfortunately, this measure did not prevent empirical underidentification. Results were nearly identical. Tables 46 through 48 contain the reanalyzed values.

In Table 46, several of the standardized regression weights between the goal orientation scales and academic performance were in excess of 1.00, an indication of multicollinearity (Byrne, 2010). The results were inconclusive. Models were inadmissible due to empirical underidentification. For Model 1, the regression coefficient for state at Time 3 to academic performance was larger than the other weights but was not significant, suggesting multicolinearity. All of the models contained relatively large but non-significant regression coefficients (e.g., $\beta > 0.18$). Also, the size of the significant regression coefficient for state at Time 3 predicting academic performance was much larger than anticipated. The meta-analysis by Payne at el. (2007) did not find a statistically significant relationship between the dimensions of state goal orientation and academic performance. In the current study, a small modest relationship was expected. Findings were inconclusive and Hypothesis 9a was not supported.

Table 46

Goodness-of-Fit Indices of the Models for State Learning Goal Orientation Predicting Academic Performance (N = 244)

Model	*df*	χ2	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	*β*
1. Latent State	118	215.2	0.00	0.058	[0.045, 0.070]	0.95	0.94	
State at T1 to AP								-0.27*
State at T2 to AP								0.33*
State at T3 to AP								0.34
State at T4 to AP								-0.21
2. LTS	120	195.36	0.00	0.05	[0.037, 0.063]	0.96	0.95	
State at T1 to AP								-0.19
State at T2 to AP								0.47***
State at T3 to AP								0.05
State at T4 to AP								-0.10
3. Latent TSO	117	179.8	0.00	0.046	[0.032, 0.059]	0.97	0.96	
State at T1 to AP								-0.19
State at T2 to AP								0.41***
State at T3 to AP								0.19
State at T4 to AP								-0.20

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index; State1 = latent state at Time 1; State2 = latent state at Time 2; State3 = latent state at Time 3; State4 = latent state at Time 4; AP = academic performance.

$^{*}p < .05$. $^{***}p < .001$.

In Table 47, all model solutions were inadmissible due to empirical underidentification. Standardized regression coefficients greater than 1.00 indicate mutlicolinearity. The large yet non-significant regression weights for latent state at Time 3 for Models 1 (β = -0.95) and 4 (β = -0.74) also suggests multicolinearity. Tests yielded inconclusive findings. Thus Hypothesis 9b was not supported.

Table 47

Goodness-of-Fit Indices of the Models for State Performance-Prove Goal Orientation Predicting Academic Performance (N = 244)

Model	*df*	χ2	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	*β*
1. Latent State	118	196.8	0	0.052	[0.039, 0.064]	0.96	0.95	
State at T1 to AP								-0.02
State at T2 to AP								0.03
State at T3 to AP								-0.95
State at T4 to AP								1.16*
2. LTS	120	191.17	0	0.049	[0.035, 0.061]	0.97	0.96	
State at T1 to AP								-0.09
State at T2 to AP								-0.06
State at T3 to AP								-0.60*
State at T4 to AP								0.91**
3. Latent TSO	117	180.54	0	0.047	[0.033, 0.060]	0.97	0.96	
State at T1 to AP								-0.09
State at T2 to AP								-0.05
State at T3 to AP								-0.74
State at T4 to AP								1.05*

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index; State1 = latent state at Time 1; State2 = latent state at Time 2; State3 = latent state at Time 3; State4 = latent state at Time 4; AP = academic performance.

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

All models in Table 48 were inadmissible. Again, this was due to empirical underidentification. The large yet non-significant regression coefficient at Time 4 (β = 0.27 – 0.30) for all models is evidence of multicolinearity. Results were inconclusive. Therefore Hypotheses 9c were not supported.

Table 48

Goodness-of-Fit Indices of the Models for State Performance-Avoid Goal Orientation Predicting Academic Performance (N = 244)

Model	*df*	χ2	*p*	RMSEA	RMSEA 90% CI	CFI	TLI	*β*
1. Latent State	118	214.09	0	0.057	[0.045, 0.069]	0.95	0.94	
State at T1 to AP								0.26*
State at T2 to AP								0.09
State at T3 to AP								-0.52*
State at T4 to AP								0.3
2. LTS	120	223.69	0	0.059	[0.047, 0.071]	0.94	0.93	
State at T1 to AP								0.24*
State at T2 to AP								0.04
State at T3 to AP								-0.39*
State at T4 to AP								0.27
3. Latent TSO	117	205.62	0	0.055	[0.042, 0.067]	0.95	0.94	
State at T1 to AP								0.23*
State at T2 to AP								0.01
State at T3 to AP								-0.41*
State at T4 to AP								0.3

Note. RMSEA = root mean square error of approximation; RMSEA 90% CI = root mean square error of approximation 90% confidence interval; CFI = comparative fit index; TLI = Tucker-Lewis index; State1 = latent state at Time 1; State2 = latent state at Time 2; State3 = latent state at Time 3; State4 = latent state at Time 4; AP = academic performance.

* $p < .05$.

Summary of Findings

A summary of the results of all the model tests is presented in Table 49. Hypotheses 1a through 1c were supported. Thus, a LTS model provided a better fit for general trait goal orientation than either a trait or state model. Hypotheses 2a and 2c were supported. A LTS model provided a better fit for domain-specific trait learning and performance-avoid orientation than either a trait or state model. However, a LTS model did not provide a better fit for domain-specific performance-prove goal orientation than a state model (Hypothesis 2b). Hypotheses 3a through 3c were supported. A LTS model provided a better fit for state goal orientation than either a trait or state model.

None of the sub-hypotheses of Hypothesis 4 were supported. Accordingly, a LTS model did not provide a better fit than a trait model when examining the relationship between general trait goal orientation and learning in an academic setting. Hypotheses 5a through 5c were not supported. A LTS model did not provide a better fit for explaining the relationship of general trait learning, performance-prove and performance-avoid goal orientation with academic performance. Hypotheses 6a through 6 c were not supported. It thus appears that domain-specific trait goal orientation does not predict learning and academic performance. Hypotheses 7a and 7c were not supported. However, Hypothesis 7b, which examined the relationship between domain-specific trait performance-prove goal orientation and academic performance, was significant.

Hypotheses 8a through 8c were not supported. Thus, a LTS model did not provide a better fit than a state model for explaining the relationship between situational influences on state performance-prove and performance-avoid goal orientation and learning in an academic setting. Hypotheses 9a through 9c were not supported as all models were inadmissible due to empirical underestimation. Therefore, a LTS model did not provide a better fit than a state model for explaining the relationship between situational influences on state learning, performance-prove, and performance-avoid goal orientation and academic performance.

Table 49

Summary of Findings

Hypothesis	Finding
General trait goal orientation (H1)	
H1a: Learning	Supported
H1b: Performance-prove	Supported
H1c: Performance-avoid	Supported
Domain-specific goal orientation (H2)	
H2a: Learning	Supported
H2b: Performance-prove	Not supported
H2c: Performance-avoid	Supported
State goal orientation (H3)	
H3a: Learning	Supported
H3b: Performance-prove	Supported
H3c: Performance-avoid	Supported
General trait goal orientation and learning in academic setting (H4)	
H4a: Learning	Not supported
H4b: Performance-prove	Not supported
H4c: Performance-avoid	Not supported
General trait goal orientation and academic performance (H5)	
H5a: Learning	Not supported
H5b: Performance-prove	Not supported
H5c: Performance-avoid	Not supported

Continued Table 49

Hypothesis	Finding
Domain-specific goal orientation and learning in academic setting (H6)	
H6a: Learning	Not supported
H6b: Performance-prove	Not supported
H6c: Performance-avoid	Not supported
Domain-specific goal orientation and academic performance (H7)	
H7a: Learning	Not supported
H7b: Performance-prove	Supported
H7c: Performance-avoid	Not supported
State goal orientation and learning (H8)	
H8a: Learning	Not supported
H8b: Performance-prove	Not supported
H8c: Performance-avoid	Not supported
State goal orientation and academic performance (H9)	
H9a: Learning	Not supported
H9b: Performance-prove	Not supported
H9c: Performance-avoid	Not supported

Secondary Analysis: Variability in the Strength of Psychologically Active Characteristics of Situations

This study uncovered a trend in the latent TSO model parameter coefficients for nearly all of the goal orientation dimensions. The latent trait regression coefficients for latent states decreased over time, while the latent occasion coefficients for the latent states increased. This pattern was present in the estimates for general trait learning, performance-prove, and performance-avoid; domain-specific learning and performance-avoid; and finally state learning and performance-avoid goal orientation. The pattern was not present for two dimensions: domain-specific performance-prove and state performance-prove goal orientation.[1]

The standardized path (regression) coefficients from Figures 21 to 23, 25, 27, 28, 30, and 31 presented as line graphs in Figures 32 to 40, respectively. The latent trait standardized regression weights for general trait learning goal orientation (Figure 32) were .97 for the state factor at Time 1, .91 at Time 2, .80 at Time 3, and .78 at Time 4. The latent occasion regression weights for latent state are .23 at Time 1, .43 at Time 2, .60 at Time 3, and .63 at Time 4. The latent occasion coefficients for general trait performance-prove goal orientation (Figure 33) start at .36 at Time 1 and increase temporally to .53 at Time 4, while the regression coefficients for latent trait decrease from .93 at Time 1 to .75 at Time 4. The latent occasion and latent trait weights are closest to converging for general trait performance-avoid goal orientation (latent occasion β_4 = .66 and latent trait β_4 = .75) found in Figure 34 and domain-specific performance-avoid goal orientation (latent occasion β_4 = .69 and latent trait β_4 = .72) found in Figure 37. A possible explanation is the situation had a greater influence on goal orientation scores as time increased. Variability increased as individuals spent more time in the

[1] One possible explanation for the lack of the pattern may be because models other than the latent TSO provided a better fit for these two dimensions of goal orientation. In the case of domain-specific performance-prove goal orientation (Hypothesis 2b), the latent state model provided a better fit. For state performance-prove goal orientation (Hypothesis 3b), the LTS-AR model provided as good of a fit as the latent TSO model.

learning environment (i.e., classroom).

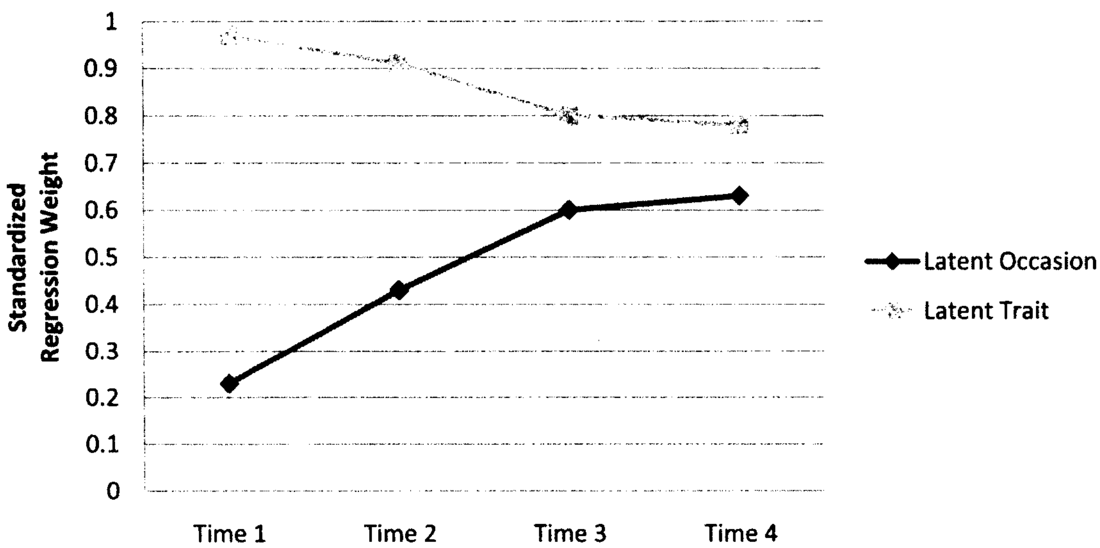

Figure 32. Latent trait and latent occasion standardized regression weights for the latent TSO model for general trait learning goal orientation.

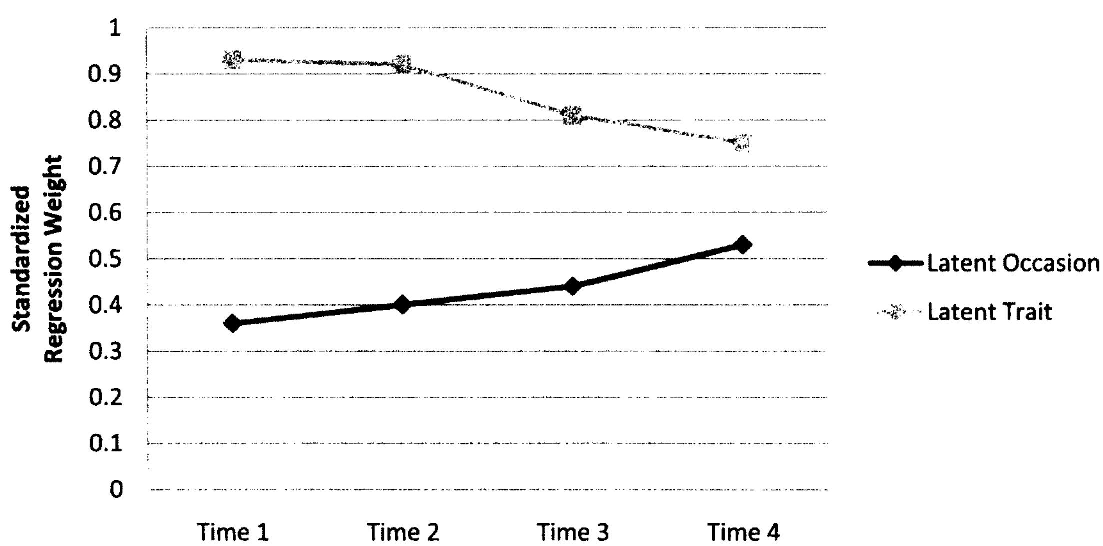

Figure 33. Latent trait and latent occasion standardized regression weights for the latent TSO model for general trait performance-prove goal orientation.

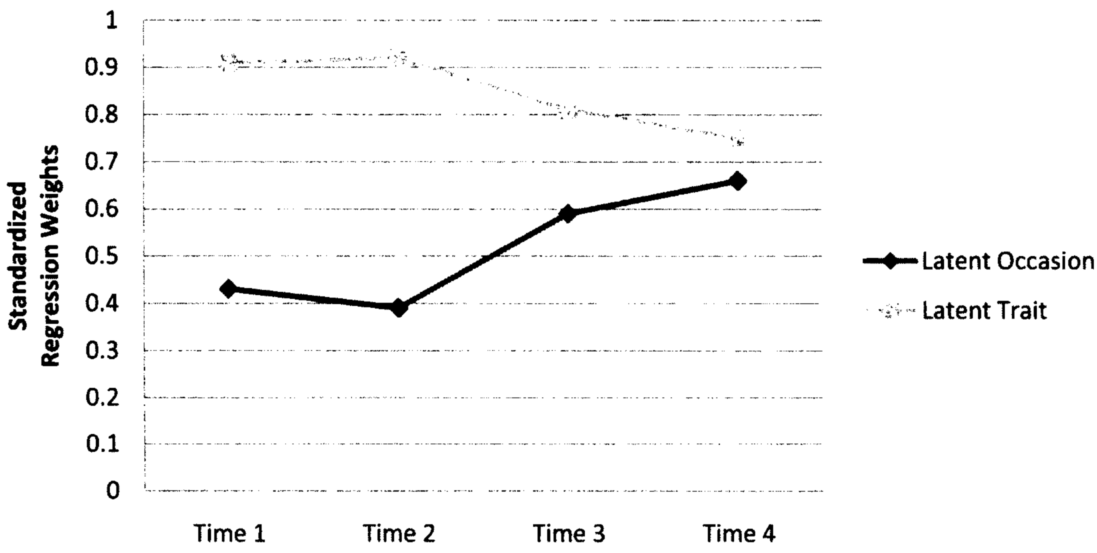

Figure 34. Latent trait and latent occasion standardized regression weights for the latent TSO model for general trait performance-avoid goal orientation.

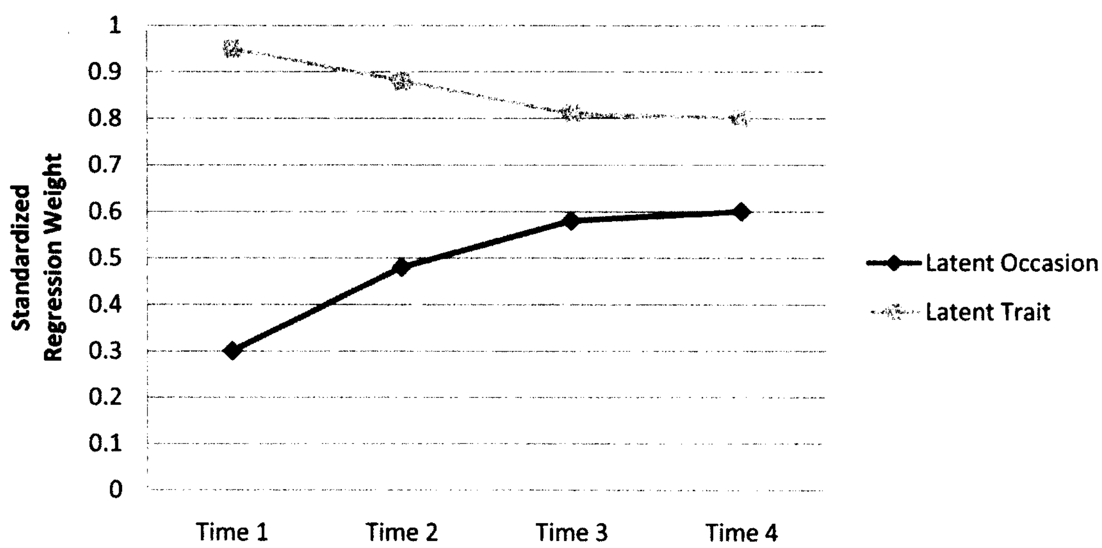

Figure 35. Latent trait and latent occasion standardized regression weights for the latent TSO model for domain-specific trait learning goal orientation.

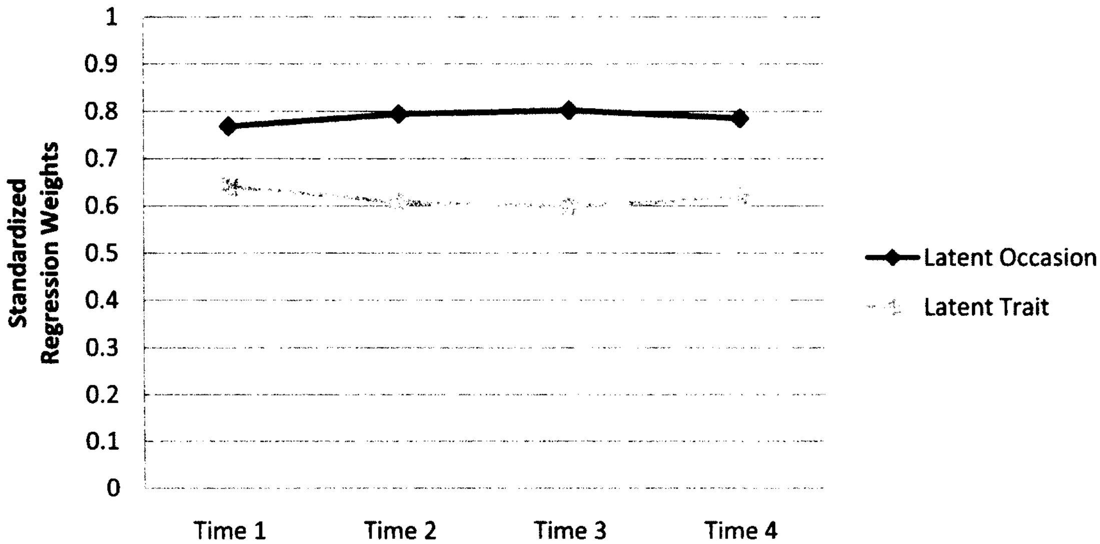

Figure 36. Latent trait and latent occasion standardized regression weights for the latent TSO model for domain-specific trait performance-prove goal orientation.

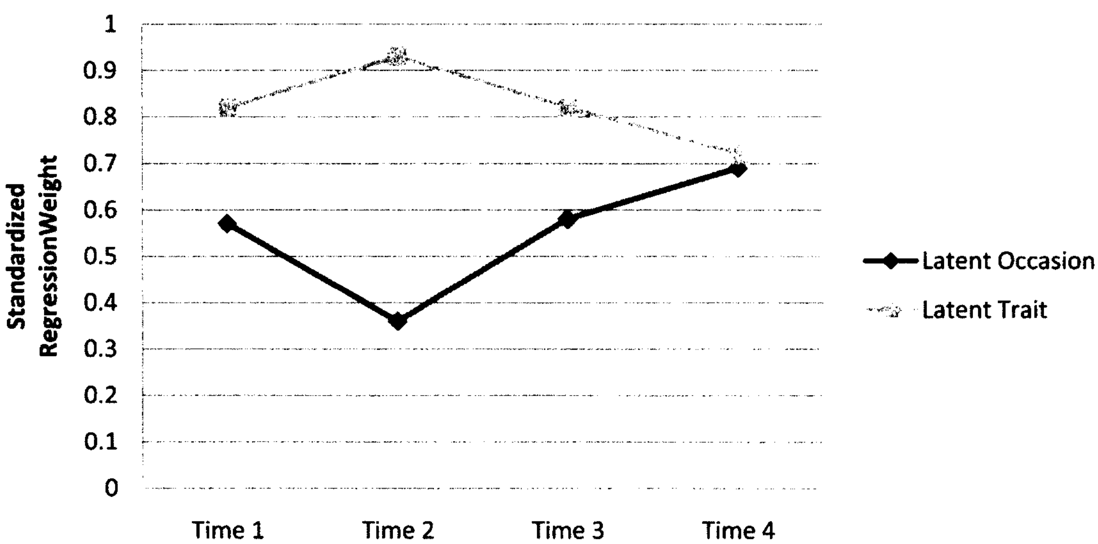

Figure 37. Latent trait and latent occasion standardized regression weights for the latent TSO model for domain-specific trait performance-avoid goal orientation.

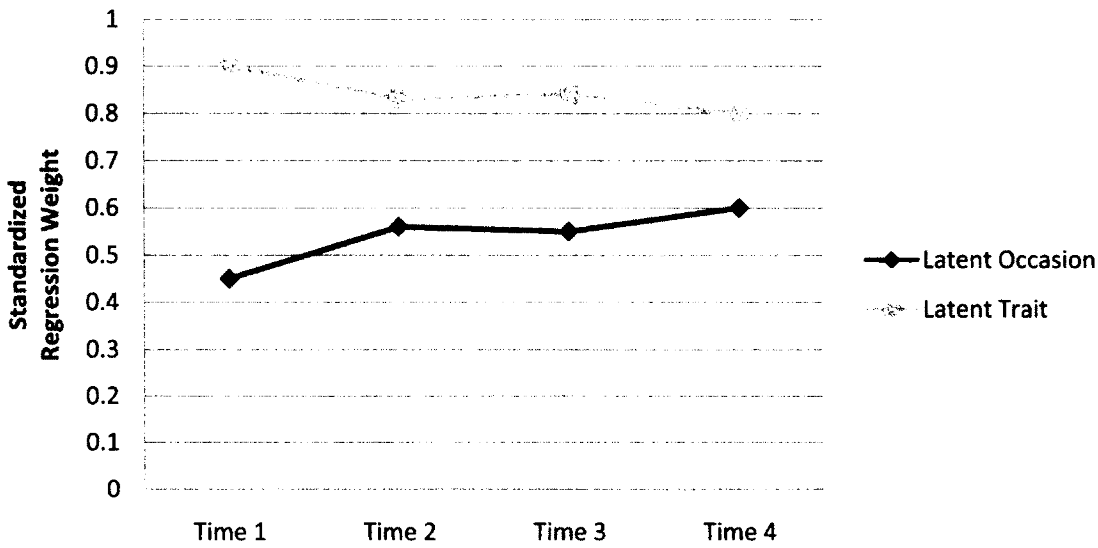

Figure 38. Latent trait and latent occasion standardized regression weights for the latent TSO model for state learning goal orientation.

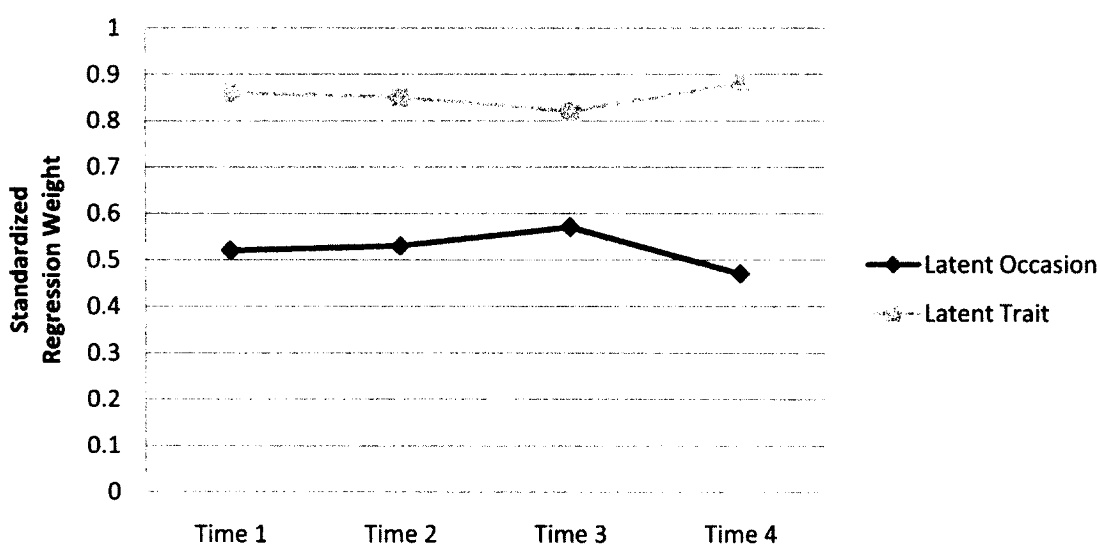

Figure 39. Latent trait and latent occasion standardized regression weights for the latent TSO model for state performance-prove goal orientation.

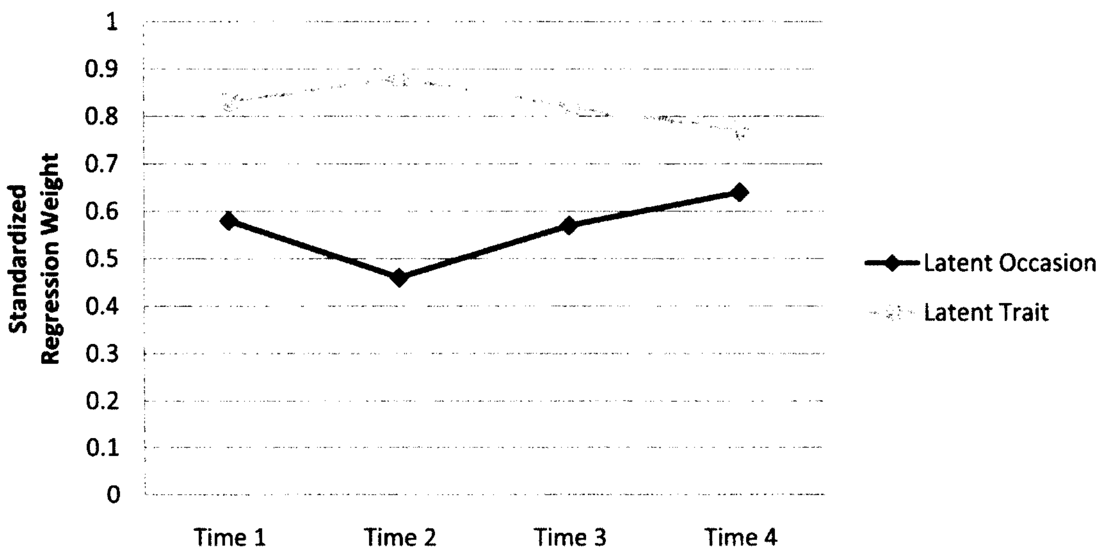

Figure 40. Latent trait and latent occasion standardized regression weights for the latent TSO model for state performance-avoid goal orientation.

Mischel (1977) suggested that the expression of psychological attributes is a function of the strength of situational cues or psychologically active characteristics of situations. This may describe only part of what is taking place. The influence of salient situational cues on the expression of goal orientation may also be a function of time. The strength of situational cues may grow as individuals spend more time in a setting. The strength of the situational may not be constant, but rather grow in influence as an individual acclimates to the setting. As an individual spends more time in a setting with psychologically active characteristics, the setting may have a greater influence on his or her behavior. The influence of important situational cues increases. Individuals regulate their behavior and over time gradually acclimate to the situation. Their responses to repeated exposure to psychologically active characteristics in a setting coalesce into a new pattern of behavior. The influence of trait on the behavioral expression of goal orientation diminishes as salient cues of the classroom (or possibly the broader academic setting) grow in strength and influence goal orientation expression to an increasing degree over time. Future research can test this assertion. One such possibility would be applying Tisak and Tisak's (2000) unified latent curve and latent state-trait model (LC-LSTM). Their approach allows a researcher to compute latent trait and state residual (i.e., latent occasion) variance components and then examine the growth trajectories of the two variance components independently.

CHAPTER IV

DISCUSSION AND CONCLUSION

The first purpose of this study was to investigate the temporal stability of goal orientation operationalized at multiple levels of specificity. More specifically I tested how well Fleeson's (2001) density distribution theory applies to goal orientation using LTS models. The second purpose of this study was to test whether LST modeling of density distributions provided additional value when examining the predictive relationship of goal orientation with achievement-oriented performance in an academic setting, specifically learning and academic performance. An interpretation of the results for each hypothesis, implications for research and applied settings, study limitations, and future research are discussed in more detail below.

HYPOTHESES 1a THROUGH 3c

According to Fleeson (2001), individuals express behavior episodically as states. Psychological states are influenced by salient psychological cues in the situation and an underlying trait that has the same content, breath and scale. The density distribution approach suggests that individuals' score on a trait may be better represented as a distribution of state levels rather than just one of the levels (Fleeson & Leicht, 2006).

Results supported all but one of the first nine hypotheses. The best fitting models extracted a variance component attributable to stability (i.e., latent trait) and components attributable to change (i.e., latent state residual or latent occasion). With the exception of domain-specific performance-prove goal orientation, LTS models fit better than trait or state models, no matter the level of specificity the goal orientation scale was intended to measure: general trait, domain-specific trait, or state. In all but one condition, goal orientation more closely resembled a distribution of states influenced by both an underlying trait and the situation than a trait or a state.

An LTS model, either the latent TSO or LTS-AR variant, provided the best fit among candidate models for all but one of the first nine hypotheses. The exception was Hypothesis 2b, which examined the performance-prove dimension of domain-specific trait goal orientation. For this dimension of goal orientation, the state-AR model provided the best fit. Domain-specific performance-prove goal orientation did not follow the assumptions of a density distribution. A possible explanation is the presence of trait change (Hertzog & Nesselroade, 1987). The participants' experience over the course of the semester may have changed their level of domain-specific trait performance-prove goal orientation. A number of previous studies have successfully induced changes in performance and performance-prove goal orientation (e.g., Chen & Mathieu, 2008; Kozlowski et al., 2001). The state-AR models and all LTS models share features that account for both stability (the stability β coefficients in the state-AR model and the latent trait variable in the LTS models as well as stability β coefficients in LTS models with an autoregressive component) and change (the latent state variables in both the state-AR and LTS models), albeit in differing degrees.

For several dimensions of goal orientation, notably domain-specific trait learning and state performance-prove, two LTS models fit equally well: the latent TSO and LTS-AR models. Based on the candidate models and the data, the two models provided equally as good a fit. For a number of hypotheses, the AIC_C Δ_i values for the second best fitting models were approximately 2 or 3. These "second string" models have meaningful empirical support with relative values of that size (Burnham and Anderson, 2010). Model 6 was a LTS model with autoregressive states. For Model 7, the autoregressive component was associated with latent occasions.

The difference between the models was the location of the autoregressive component, stability β coefficients. The placement of these coefficients influenced other parameter estimates. As an example, two sets of parameter coefficients found in the LTS-AR and latent TSO models used to test Hypothesis 3a (state learning goal orientation) differed by model: latent trait path estimates (γ_k) and stability β coefficients. For the LTS-AR model, the $\gamma_k$estimates for latent state at Times 1 through 4 were .76, .73, .71, and .78, respectively. For the latent TSO model, the corresponding coefficients were .86, .85, .82, and .88. The coefficients for the latent TSO model were higher at each time period. For the LTS-AR model, the values were .15 for β_1, .22 for β_2, and .22 for β_3. For the latent TSO model, the first β value was not significant, while the second and third values were .37 and .76, respectively. For the LTS-AR model, β values were generally smaller but more stable than the latent TSO variant. This may be because the autoregressive function (stability β coefficients) on the latent state variables (β_k) for the LTS-AR model is not independent of the effects of the latent trait variable (Cole et al., 2005). In this model, β_k is confounded with the latent trait variable. In Model 7, they are not confounded; the autoregressive function is associated with the latent occasion variable. This difference influences model interpretation. The latent TSO model constrains the latent trait and occasion variables to be uncorrelated. The model assumes no shared variance in the contributions of latent occasions and latent trait to the latent state variable. Stated differently, the latent TSO model assumes no interaction between occasion and trait. The LTS-AR model and other LTS models without stability β coefficients do not include this assumption. Therefore, an LTS model with autoregressive latent states would provide a better account for trait × situation interaction.

This explanation may explain why the LTS-AR model fit so well for domain-specific learning and state performance-avoid goal orientation. Features of a classroom environment, such as exams and norm-referenced feedback, can induce a performance goal orientation frame (Payne et al., 2007). Data for the current study was collected in a similar setting. The LTS-AR model may fit well because of a latent performance-avoid trait × performance-inducing situation interaction. As mentioned previously, the induction of a performance orientation may also account for the trait change in domain-specific performance-prove goal orientation.

In the LTS model without an autoregressive component, the latent state residuals include situation as well as trait × situation interactions. In the LTS model with autoregressive states, trait × situation interactions may be present in the latent state variables and latent state autoregression. In contrast, the latent TSO model may not be able to detect interactions. This assertion should be tested in future research.

Davey (2001) listed three alternative reasons to explain why LTS models with an autoregressive path coefficients (stability β's) provide a good fit, even after trait-like variability is partitioned out. First, nearly all social science measures contain residual variability due to systematic error. These sources contribute to correlated uniqueness over time. Including method factors (Steyer et al., 1992) would reduce the correlation of observations over occasions by controlling for method bias. Second, autoregression may be due to minimal change in the environment. The full variability of situations across time should be considered. Depending on the purpose of the research, the researcher may want occasions to be as independent as possible and include varying degrees and different types of psychologically active characteristics of situations. Finally, the autoregression may be due to the reciprocal relationship between individuals and the environment. While the environment may shape an individual's state, the individual may select and influence their environment. For example, individuals may avoid academic situations (i.e., academic majors and classes) that are incongruent with their levels of learning, performance-prove and performance-avoid goal orientations.

More than One Best Model

Burnham and Anderson (2010) anticipate researchers' possible frustration in not having "some value or cutoff point that provides a simple dichotomy to indicate what is *important* (i.e., 'significant' under the Neyman-Pearson null hypothesis testing procedure where a decision can be reached" (p. 78). Best model is not true model but rather an approximation. According to information-theoretic statistics, a true model does not exist. Full reality is infinitely dimensional and can only be approximated by models with finite numbers of parameters. The inability to identify a single best model is not a limitation of AIC_C or any other selection criterion. It is an indication that the data are inadequate to make a more precise inference. Follow up studies may help identify a single best model.

HYPOTHESES 4a THROUGH 9c

Only one of the performance prediction hypotheses was supported. In general, the LTS models did not provide a better explanation of the relationship between goal orientation and performance outcomes in an academic setting. The single exception was domain-specific trait performance-prove goal orientation. Removing the variance attributable to the state residual factors improved the relationship. However, the LTS model was not the best fitting model for an earlier hypothesis examining this dimension. For Hypothesis 2b, which tested the measurement model of domain-specific performance-prove goal orientation, the best fitting model was the state-AR model.

However, as a whole, the results suggest that LTS models do not increase the sensitivity of predictive analyses of goal orientation and performance in an academic setting. An alternative explanation for the failure to support the performance prediction hypotheses may be weak outcome measures. This is elaborated in the section discussing study limitations.

IMPLICATIONS FOR FUTURE RESEARCH

This study highlights a limitation of classical true-score theory (CTT; Allen & Yen, 1979). CTT was developed as a solution to solve the problem of measurement error. It does not tell us much about the nature of the construct other than the proportion of error and construct variance in observed scores. The ability to account for situational and trait × situation affects is limited. In CCT, discriminating a trait from a state measure is based on a coefficient of stability, also known as test-retest reliability (Allen & Yen, 1979). The method does not meet the level of sophistication that is often assumed when measures are applied in research. The inability of a state measure to discriminate between experimental conditions may be attributed to low sensitivity due to latent trait variance rather than a weak manipulation. Also, the inability of trait measure to predict outcomes may be due to situational influences that alter individuals' scores. In both situations, the coefficient of stability is of limited value. Poor understanding of the variance components in a measure impedes our understanding of the construct.

LTS models provide an extension of CTT to longitudinal data. Davey (2001) argues that this is the goal of LTS modeling. That is, the goal is to partition true score and other effects from observed scores and to further partition true score into person and person-in-situation components. According to Steyer et al. (1992), LST models are a generalization of CTT. In CTT, observed scores (Y_{ik}) are composed of a true score (τ), representing person, and measurement error (ε). In LST models, true score (τ_{ik}) represents person-in-situation, not person. As mentioned previously, this is called a latent state variable and can be noted as S_k rather than τ_{ik}. Also mentioned earlier, latent state variables (S_k) consists of two components: a latent trait variable (T), which is the person-across-situations, and latent state residuals (SR_k), which is the effect of the situation and person×situation interactions. Steyer et al. (1992) also defined LTS models that include method factors (M_i) to estimate the proportion of variance attributable to systematic error. In summary, LTS models can be used to address limitations in CTT true score.

Kanfer, Chen and Pritchard (2008) developed a thematic heuristic to organize work motivation research to better reflect current trends and anticipate future developments. They refer to it as the three C's framework. It includes three dimensions: content (or person), context, and change. Content is the internal forces that drive motivation and includes person-centered approaches to motivation, such as traits. Context is the external forces that influence motivation and includes different features of the setting. The final dimension allows for the examination of change in the internal and external forces that influence motivation. They speculate that future progress in content theories of work motivation will strongly depend on the extent to which we adequately consider the contextual and temporal affects.

The current study wedded density distribution theory and LTS modeling. Hopefully, this marriage will be fruitful in producing future research that examines both the underlying trait and situational influences in the behavioral expression of goal orientation as well as other motivation and psychological constructs. Several examples of how the types of questions that can be answered by this approach are discussed next.

The method used in this study can be applied to test a number of assertions researchers may make about a construct's density distribution and the nature of psychologically active characteristics of situations. Researchers could select a set of theoretically meaningful alternative LTS models to test a number of hypotheses about the nature of a density distribution. First, several of the SEM models used in the current study can be used to test for tested the stability of trait manifestations in states across time or setting. For this test, Models 4 and 5 from Figure 7 would be applied. The difference between the models is equality constraints on the latent trait variable path coefficients connected to the latent states. This comparison would test the null hypothesis $H_0: \gamma_1 = \gamma_2 = \gamma_k = \gamma$. Second, one could assess the stability of psychologically active characteristics of situations over time or assess if different settings share the psychologically active characteristics. In this example, Model 5 from Figure 7 would be compared to Models 6 from Figure 8 or Model 7 from Figure 9. The differences between the models are autoregressive parameter coefficients (β_k) between periods of measurement. This comparison would test the null hypothesis $H_0: \beta_k = 0$. Third, researchers could test how to model the stability of situational influences more accurately by comparing Model 6 from Figure 8 to Model 7 from Figure 9. In Model 6, the autoregressive β_k is associated with the latent state variables (S_k), while in Model 7 it is associated with the latent occasion variables (O_k). Fourth, a researcher could test whether the degree of stability changes across occasions (either time or setting) using two methods: either by comparing Model 6 from Figure 8 to a LTS model with equality constraints on the autoregressive path coefficients ($H_0: \beta_1 = \beta_2 = \beta_{k-1} = \beta$) or by comparing Model 7 from Figure 9 to a LTS model with equality constraints on latent occasion variance ($H_0: \sigma_{O_1} = \sigma_{O_2} = \sigma_{O_k} = \sigma_O$). Finally, one could test for the presence of Tett and Guterman's (2000) principle of trait activation or person×situation interactions by comparing LTS models that allow for the interactions to models that do not (i.e., a latent STO model). The last example could be used to investigate

These tests could be used to explore the influence of a number of situational features on goal orientation. A framework for organizing the features was proposed by Kaplan and Maehr (2007). They created a taxonomy of six situational cues relevant to goal orientation. Categories include the type of *task*, the *autonomy* in deciding how to complete the task, the type of *recognition* given for completing the task, the assignment of individuals to different *groups*, how task progress is *evaluated*, and *time* to complete the task (TARGET). Another option would be the types of feedback outlined by Park, et al. (2007). They found the three dimensions of goal orientation were related to different cost/value perceptions which predicted preferences in type of feedback. In a future study, the types of feedback could be manipulated to compliment or conflict with goal orientation. Density distributions of other dispositions can be investigated using Tett & Burnett's (2003) trait-relevant situational features or Meyer et al.'s (2010) facet structure of situational strength.

Steyer et al. (1992) described how to define several reliability indices using LTS model state, trait, method, and error variance components. Their LTS models permitted the estimation of reliability based on coefficients of common consistency (latent trait variance), occasion specificity (state residual variance) and method specificity (systematic error due to method effects). An estimate of consistency was created by combining common consistency and method specificity. Estimates of common reliability consist of common consistency and occasion specificity, while reliability was defined as the sum of common reliability plus method specificity. These estimates could be useful for assessing the psychometric properties during test development and take the place of using test-retest reliability as a coefficient of stability.

If a test is to be used to measure a trait, as in the case of general or domain-specific goal orientation, it should exhibit high consistency and low occasion specificity coefficients. If the goal is to measure a state, the test should have a low consistency and high occasion specificity. In both situations the reliability (common consistency + occasion specificity) should be high.

This approach has been used to estimate consistency, occasion specificity and derived reliability for a number of constructs, including organizational commitment (Tisak & Tisak, 2000), attitudes towards non-citizen workers (Steyer & Schmitt, 1990), family support and problem behavior (Dumenci & Windle, 1998), mood (Steyer & Riedl, 2004), personality scales from the Freiburg Personality Inventory (FPI), the NEO Five-

Factor Inventory (NEO-FFI), and the Eysenck Personality Inventory (EPI; Deinzer, et al., 1995), primary emotions, such as happiness, anger, fear, and sadness (Eid & Diener, 1999), psychopathology (Steyer, Krambeer & Hannöver, 2004), and test anxiety (Schermelleh, Keith, Moosbrugger, & Hodapp, 2004).

PRACTICAL IMPLICATIONS FOR APPLIED I-O PSYCHOLOGY SETTINGS

The current study provides several implications for I-O Psychology in applied settings. First, density distributions may help explain the weak predictive validity of non-cognitive selection tests such as personality measures. According to Oppler, Peterson, and Russell (1992), the predictive validities for personality measures were considerably lower when estimated using a longitudinal design rather than a concurrent design. That is, the relationship between personality and work-related performance was lower for newcomers than for job incumbents. The reason for the difference may be changes in density distributions attributable to the work setting and how newcomers' express personality. If the job candidate was measured later, after working in the position for a period of time, his or her score may change and alter the predictive validity. The proportion of variance attributable to situation may have increased over time reducing the accuracy of newcomers' initial personality scores. In the current study, the situation accounted for a progressively larger portion of the variance in goal orientation as a function of time. In addition, models that accounted for this were more sensitive to the relationship between goal orientation and performance outcomes. Longitudinal predicative validities may be weaker because they do not account for self-regulation in personality expression (i.e., personality test scores) due to the job setting. Newcomer levels of an expressed personality attribute change over time, thus reducing the validity of trait measures. Conversely, incumbents' personality scores may be more influenced by psychologically salient cues in the job setting. This would also help explain why concurrent validities are higher.

Second, the approach used in the current study could improve our understanding of the dynamic nature of work. The current study addresses Kanfer's (2009) call for work motivation research with practical implications that integrates context and change into content or person-centered formulations of motivation. The influence of training initiatives intended to induce changes in goal orientation (e.g., Chen & Mathieu, 2008) could be measured more accurately. Furthermore, the influence of organizational factors on other motivation-related individual differences could be assessed using this approach. For example, practitioners could more accurately determine the impact of training design and organizational climate for learning on self-efficacy (Chen, Gully, & Eden, 2001) and self-esteem (Chen, Gully, & Eden, 2004). It could also be used to assess the influence of job design, the use of teams, organizational restructuring or other organizational interventions on individual differences used in personnel selection, such as the Big Five Model of personality (i.e., Barrick & Mount, 1991; Mount & Barrick, 1995). Self-regulation factors, such as goal commitment (Klein,Wesson, Hollenbeck, Wright, & DeShon, 2001), could also be examined. As another example, it could be used to assess changes in employee engagement (Macy & Schneider, 2008), job satisfaction (Smith, Kendall, & Hulin, 1969) and job commitment (Meyer, Allen, & Smith, 1993) or emotions in the workplace, including emotional intelligence (Bar-On, 1997; Mayer, Caruso, & Salovey, 2000) and emotional affect (Watson, Clark, & Tellegen, 1988). Finally, the method could be adapted to model trait and situational factors in performance outcomes, such as job performance (Newman, Kinney, & Farr, 2004), organizational citizenship performance (Kaufman & Borman, 2004), and team performance (Salas, Burke, Fowlkes, & Priest, 2004).

POSSIBLE REASONS FOR THE LACK OF LTS MODELS IN RESEARCH

Several plausible reasons may explain the lack of LTS models in organizational research. The first reason is the perceived difficulty. A casual review of organizational journals may suggest an aversion of statistics more advanced than ANOVA or simple regression. The second reason may be the lack of exposure to LTS models. They are not mentioned in statistical texts on structural equation modeling. A third and related reason may be the lack of knowledge concerning how to test non-nested models. "Non-nested models appear infrequently in publications using SEM in the organizational sciences. One reason for this may be the lack of understanding of how one selects the "best" model (Vandenberg & Grell, 2009; p. 178)." A fourth possible reason is concern about how best to handle missing data due to attrition in the sample over time. There may also be concern about low statistical power due to small sample size or shrinking sample size due to attrition. A final reason may be the perceived effort. LTS models require large data sets and a minimum of 3 periods of data collection

LIMITATIONS OF CURRENT STUDY

The current study had several limitations. The first set of limitations was associated with the use of self-report measures. Several types of response distortion associated with self-report measures exist. The first type, socially desirable distortion

(SDD), can be intentional (impression management) or unintentional (self-deception; Paulhus, 1984; Paulhus & Reid, 1991). Intentional distortion is called impression management and is the deliberate over reporting of desirable behaviors and under reporting of undesirable behaviors. Unintentional distortion is called self-deception and represents overconfidence in one's ability. Self-deception is not a deliberate attempt to deceive, but rather inaccurate positive self-beliefs. Intentional distortion or impression management is typically more relevant in self-report measures due to the desire to look ones best in order to obtain the desired job. However, either type of SDD may result in attenuated observed variance in applicant responses. That is, participants who may be faking their responses are more likely to use less of the response scale than if they were honest. Further, due to genuine individual differences in goal orientation, there would be greater variance in response given a particular population.

A second type of response distortion associated with self-report measures is carelessness. When participants do not fully read the items, they introduce additional measurement error. Poor quality data may result from participants rushing to complete questionnaire, not reading the complete questions or providing superficial answers. The results of the CFA for the current study point to participant carelessness. Negatively worded items were cut from 8 out of 9 goal orientation scales due to poor factor loadings. Also, participants may have attempted to recall and record their answers from the previous time they completed the questionnaires rather than examine their current feelings towards goal orientation. Due to the redundant nature of the questionnaires, participants may have written the same answers for similar general trait, domain specific trait, and state items.

Issues related to self-report measures may be exasperated by the population examined in the current study: undergraduate students. The mean age was less than 19 years of age. In general, young adults have a limited understanding of themselves and their ability compared to older adults. This may have increased the likelihood of unintentional SDD. In addition, this is an active population who are trying to balance competing goals. The faster they completed the goal orientation questionnaire, the sooner they could start their next activity, such as take the final exam or join their friends at the student center. These limitations may have lowered the reliability of several goal orientation scales. Low scale reliabilities (e.g., 0.71 – 0.79) may have impeded the ability to find significant relationships with the performance measures.

Another limitation of the current study was how performance was operationalized. For the hypotheses investigating learning in an academic setting, goal orientation was a better predictor of learning at Time 4 than Times 1, 2 or 3. This may be due to how learning in an academic setting was operationalized. Learning at Time 4 was scores on the final exam. Learning at Times 1 through 3 was operationalized as quiz scores. The Time 4 measure was longer and more comprehensive than the other 3 learning measures. Future research should control for this limitation.

The last set of limitations concern the nature of the study setting. As mentioned previously, an academic setting provides a naturalistic performance-prove goal orientation manipulation (i.e., expectations about demonstrating performance and norm-based feedback). However, other features of the setting such as the weather, student course load, sports, clubs and other extracurricular activities, as well as a sense of urgency as the semester draws to a close, may have contributed to changes in goal orientation. Because the study did not include a true experimental design with a control group, one may not make the causal inference that changes in goal orientation were only due to basic features of the Introduction to Psychology classroom setting (Shadish, Cook, & Campbell, 2002). Measurement period was confounded with systematic changes in the learning environment. The study coincides with the beginning and end of the marking period. Knowledge about the end of the course may have contributed to a distinct sense of urgency as the time approached. This is unique to academic life and may not generalize to other settings. To summarize, changes in goal orientation may be due to situational factors other than those considered in the design of the study.

CONCLUSION

The current study demonstrated the value of density distribution theory and LTS modeling for understanding human behavior, in particular, how individuals perceive and act in achievement situations. The LTS models provided a better explanation of the underlying structure of goal orientation than traditional trait or state models. Whether measured as a state or a trait, goal orientation contains variance components attributable to both. This was interpreted as proof that goal orientation is best described as a density distribution rather than a trait or a state. Unfortunately, the ability to isolate variance components in LTS models did not improve the ability to detect relationships between goal orientation and performance outcomes not.

REFERENCES

Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle. In S. Kotz & N. L. Johnson (Eds.), *Breakthroughs in statistics* (pp. 599-624). New York: Singer.

Akaike, H. (1987). Factor analysis and AIC. *Psychometrika, 52*, 317-332.

Allen, M. J., & Yen, W. M. (1979). *Introduction to measurement theory.* Monterey, CA: Brooks/Cole.

Allport, G. W. (1937). *Personality: Characters and characteristics.* New York: Henry Holt.

Ames, C. (1984). Classrooms: Goals, structures, and student motivation. Journal of *Educational Psychology, 84*, 261-271.

Ames, C., & Archer, J. (1988). Achievement goals in the classroom: Students' learning strategies and motivation processes. *Journal of Educational Psychology, 80,* 260-267.

Ames, C., Ames, R., & Felker, D. W. (1977). Effects of competitive reward structure and valence of outcome on children's achievement attributions. *Journal of Educational Psychology, 69*, 1-8.

Anderson, D. R. (2008). *Model based inference in the life sciences: A primer on evidence.* New York: Springer.

Bagozzi, R. P., & Heatherton, T. F. (1994). A general approach to representing multifaceted personality constructs: Application to state self-esteem. *Structural Equation Modeling, 1*, 35-67.

Bandalos, D. L., & Finney, S. L. (2001). Item parceling issues in structural equation modeling. In G. A. Marcoulides (Ed.), *New developments and techniques in structural equation modeling* (pp. 269-296). Mahwah, NJ: Lawrence Erlbaum.

Bar-On, R. M. (1997). *BarOn Emotional Quotient Inventory (EQ-i): A test of emotional intelligence*. Toronto: Multi-Health Systems.

Barrick, M. R., & Mount, M. K. (1991). The Big Five personality dimensions and job performance: A meta-analysis. *Personnel Psychology, 44*, 1-26.

Bell, B., & Kozlowski, S. W. J. (2002). Goal orientation and ability: Interactive effects on self-efficacy, performance, and knowledge. *Journal of Applied Psychology, 87,* 497-505.

Bentler, P. M. (1985). *Theory and Implementation of EQS: A Structural Equations Program*, Manual for Program Version 2.0, Los Angeles: BMDP Statistical Software, Inc.

Bollen, K. A. (1989). *Structural equations with latent variables.* New York: Wiley.

Boyle, K. A., & Klimoski, R. J. (1995, May). *Toward an understanding of goal orientation in a training context.* Paper presented at the 10th annual meeting of the Society for Industrial and Organizational Psychology, Orlando, FL.

Breland, B. T., & Donovan, J. J. (2005). The role of state goal orientation in the goal establishment process. *Human Performance, 18*, 23-53.

Brett, J. F., & VandeWalle, D. (1999). Goal orientation and goal content as predictors of performance in a training program. *Journal of Applied Psychology, 84,* 863-873.

Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen & J. S. Long (Eds.), *Testing structural equation models* (pp. 136–162).

Newbury Park, CA: Sage.

Burnham, K. P., & Anderson, D. R. (2004). Multimodal inference: Understanding AIC and BIC in model selection. *Sociological Methods and Research, 33*, 261-304.

Burnham, K. P., & Anderson, D. R. (2010). *Model selection and multimodel inference: A practical information-theoretic approach* (2nd ed.). New York: Springer.

Button, S. B., Mathieu, J. E., & Zajac, D. M. (1996). Goal orientation in organizational research: A conceptual and empirical foundation. *Organizational Behavior and Human Decision Processes, 67*, 26-48.

Byrne, B. M. (2010). *Structural equation modeling with AMOS: Basic concepts, applications, and programming* (second edition). New York: Routledge.

Carver, C. S., & Scheier, M. F. (1981). Control theory: A useful conceptual framework for personality-social, clinical, and health psychology. *Psychological Bulletin, 92*, 111-135.

Cervone, D. (2005). Personality architecture: Within-person structures and processes. *Annual Review of Psychology, 56*, 423-452.

Chan, D. (1998). The conceptualization and analysis of change over time: An integrative approach incorporating longitudinal means and covariance structures analysis (LMACS) and multiple indicator latent growth modeling (MLGM). *Organizational Research Methods, 1*, 421-483.

Chen, G., Gully, S. M., & Eden, D. (2001). Validation of a new general self-efficacy scale, *Organizational Research Methods, 4*, 62-83.

Chen, G., Gully, S. M., & Eden, D. (2004). General self-efficacy and self-esteem: Toward theoretical and empirical distinction between correlated self-evaluations.

Journal of Organizational Behavior, 25, 375-395.

Chen, G., Gully, S. M., Whiteman, J.-A., & Kilcullen, R. N. (2000). Examination of relationships among trait-like individual differences, state-like individual differences, and learning performance. *Journal of Applied Psychology, 85*, 835-847.

Chen, G., & Mathieu, J. E. (2008). Goal orientation dispositions and performance trajectories: The roles of supplementary and complementary situational inducements. *Organizational Behavior and Human Decision Processes, 106*, 21-38.

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling, 9*, 233-255.

Cole, D. A. (2006). Coping with longitudinal data in research on developmental psychopathology. International Journal of Behavioral Development, 30, 20–25.

Cole, D. A., Martin, N. C., & Steiger, J. H. (2005). Empirical and conceptual problems with longitudinal trait-state models: Support for a trait-state-occasion model. *Psychological Methods*, *10*, 3–20.

Collins, L. M. (2006). Analysis of longitudinal data: The integration of theoretical model, temporal design, and statistical model. *Annual Review of Psychology, 57*, 505-528.

Cortina, J. M. (2002). Big things have small beginnings: An assortment of "minor" methodological misunderstandings. *Journal of Management, 28*, 339-362.

Cudeck, R., & Browne, M. W. (1983). Cross-validation of covariance structures. *Multivariate Behavioral Research, 18,* 147-167.

Davey, A. (2001). The trait-state distinction and its dialectic balance. In L. M. Collins & A. G. Sayer (Eds.), *New methods for the analysis of change* (pp. 265-269). Washington, D.C.: American Psychological Association.

Davey, A., Halverson, C. F., Zonderman, A. B., & Costa, P. T. (2004). Change in depressive symptoms in the Baltimore longitudinal study of aging. *The Journals of Gerontology: Series B, 59,* 270-277.

Day, E. A., Yeo, S., & Radosevich, D. J. (2003). *Comparing two- and three-factor models of goal orientation: A meta-analysis.* Paper presented at the annual meeting of the Society for Industrial and Organizational Psychology, Orlando, FL.

Deinzer, R. Steyer, R., Eid, M., Notz, P., & Schwenkmezger, P., Ostendorf, F., Neubauer, A. (1995). Situational effects in trait assessment: The FPI, NEOFFI, and EPI questionnaires. *European Journal of Personality, 9,* 1-23.

DeShon, R. P., & Gillespie, J. Z. (2005). A motivated action theory of goal orientation. *Journal of Applied Psychology, 90,* 1096-1127.

Dumenci, L., & Windle, M. (1998). A multitrait–multioccasion generalization of the latent trait-state model: Description and application. *Structural Equation Modeling, 5,* 391–410.

Dweck, C. S. (1986). Motivational processes affecting learning. *American Psychologist, 41,* 1040-1048.

Dweck, C. S. (2000). *Self-theories: Their role in motivation, personality, and development.* Philadelphia, PA: Taylor & Francis.

Eid, M., & Diener, E. (1999). Intraindividual variability in affect: Reliability, validity, and personality correlates. *Journal of Personality and Social Psychology, 76,* 662–676.

Eid, M., & Langeheine, R. (1999). The measurement of consistency and occasion specificity with latent class models: A new model and its application to the measurement of affect. *Psychological Methods, 4,* 100–116.

Elliot, A. J. (1999). Approach and avoidance motivation and achievement goals. *Educational Psychologist, 34,* 169–189.

Elliot, A. J., & Church, M. A. (1997). A hierarchical model of approach and avoidance achievement motivation. *Journal of Personality and Social Psychology, 72,* 218-232.

Elliot, A. J., & Dweck, C. S. (1988). Goals: An approach to motivation and achievement. *Journal of personality and Social Psychology, 70,* 461-475.

Elliot, A. J., & Harackiewicz, J. M. (1996). Approach and avoidance achievement goals and intrinsic motivation: A mediational analysis. *Journal of Personality and Social Psychology, 70,* 461-475.

Elliot, A. J., & McGregor, H. A. (2001). *A 2 X 2 achievement goal framework, 80,* 501-519.

Elliot, A. J., & Thrash, T. M. (2001). Achievement goals and the hierarchical model of achievement motivation. *Educational Psychology Review, 13,* 139–156.

Enders, C. K. (2004). The impact of missing data on sample reliability estimates: Implications for reliability reporting practices. *Educational and Psychological Measurement, 64,* 419-436.

Farr, J. L., Hofmann, D. A., & Ringenbach, K. L. (1993). Goal orientation and action control theory: Implications for industrial and organizational psychology. *International Review of Industrial and Organizational Psychology, 8*, 193-232.

Fisher, S. L., & Ford, J. K. (1998). Differential effects of learner effort and goal orientation on two learning outcomes. *Personnel Psychology, 51*, 397-420.

Fleeson, W. (2001). Towards a structure- and process-integrated view of personality: Traits as density distributions of states. *Journal of Personality and Social Psychology, 80*, 1011-1027.

Fleeson, W. (2007). Situation-based contingencies underlying trait-content manifestation in behavior. *Journal of Personality, 75*, 825-861.

Fleeson, W., & Leicht, C. (2006). On delineating the integrating the study of variability and stability in personality psychology: Interpersonal trust as illustration. *Journal of Research in Personality, 40*, 5-20.

Gist, M. E., & Stevens, C. K. (1998). Effects of practice conditions and supplemental training method on cognitive learning and interpersonal skill generalization. *Organizational Behavior and Human Decision Processes, 75*, 142-169.

Golembiewski, R. T., Billingsley, K., & Yeager, S. (1976). Measuring change and persistence in human affairs: Types of change generated by OD designs, *Journal of Applied Behavioral Science, 12*, 133-157.

Grant, H., & Dweck, C. S. (2003). Clarifying achievement goals and their impact. *Journal of Personality and Social Psychology, 85,* 541–553.

Hansberger, J. (1999). Varying levels of goal orientation specificity in a dynamic driving task. Paper presented at the 14th annual meeting of the Society for Industrial and Organizational Psychology, Atlanta, GA.

Heggestad, E. D. (1997). Motivation from a personality perspective: The development of a measure of motivational traits. *Dissertation Abstracts International, 58(9-B),* 5179. (UMI No. AAT 9808936)

Heggestad, E. D., & Kanfer, R. (2000). Individual differences in trait motivation: Development of the Motivational Trait Questionnaire. *International Journal of Educational Research, 33*, 751-776.

Hertzog, C., & Nesselroade, J. R. (1987). Beyond autoregressive models: Some implications of trait-state distinction for the structural modeling of developmental change. *Child Development,* 58, 93-109.

Horvath, M., Sheau, C. R., & DeShon, R. P. (2004, April). *The effects of domain specification the construct and predictive validity of goal orientation measures.* Paper presented at the 19th annual conference of the Society for Industrial and Organizational Psychology, Chicago, IL.

Hu, L.-T., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods, 3*, 424-453.

Hu, L.-T., & Bentler, P. M. (1999). Cutoff criteria for fit indices in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*, 1-55.

Joreskog, K. G. (1979). Statistical estimation of structural models in longitudinal investigations. In J. R. Nesselroade & P. B. Baltes (Eds.), *Longitudinal research in the study of behavior and development* (pp. 303-351). New York: Academic Press.

Judge, T. A., & Kammeyer-Mueller, J. D. (2008). Affect, satisfaction, and performance. In N. M. Ashkanasy & C. L. Cooper (Eds.), *Research companion to emotion in organizations* (pp. 136-151). Northampton, MA: Edward Elgar Publishing.

Kanfer, R. (1992). Work motivation: New directions in theory and research. In C. L. Cooper & I. T. Robertson (Eds.), *International Review of Industrial and Organizational Psychology* (Vol. 7, pp.1-53). London: John Wiley & Sons

Kanfer, R. (2009). Work motivation: Identifying use-inspired research directions. *Industrial and Organizational Psychology, 2*, 77-93.

Kanfer, R., Chen, G., & Pritchard, R. D. (2008). The three C's of work motivation: Content, context, and change. In R. Kanfer, G. Chen, R. D. Pritchard (Eds.), *Work motivation: Past, present, and future* (pp. 1-16). New York: Routledge.

Kanfer, R., & Heggestad, E. D. (1997). Motivational traits and skills: A person-centered approach to work motivation. *Research in Organizational Behavior, 19*, 1-56.

Kaplan, A., & Maehr, M. L. (2007). The contributions and prospects of goal orientation theory. *Educational Psychology Review, 12*, 63-83.

Kaufman, J. D., & Borman, W. C. (2004). Citizenship performance in organizations. In J. C. Thomas (Ed.), *Comprehensive handbook of psychological assessment: Volume 4, Industrial and Organizational Psychology* (pp. 412-424). Hoboken, NJ: John Wiley & Sons.

Kenny, D. A. (1979). *Correlation and causality*. New York: Wiley.

Kenny, D. A., & Zautra, A. (1995). The trait-state-error model for multiwave data. *Journal of Consulting and Clinical Psychology*, *63*, 52–59.

Kenny, D.A., & Zautra, A. (2001). Trait-state models for longitudinal data. In L.M.

Collins & A.G. Sayer (Eds.), *New methods for the analysis of change.* (pp. 243–263).Washington, DC: American Psychological Association.

Kishton, J. M., & Widaman, K. F. (1994). Unidimensional versus domain representative parceling of questionnaire items: An empirical example. *Educational and Psychological Measurement, 54*, 757-765.

Klein, H. J., Wesson, M. J., Hollenbeck, J. R., Wright, P. M., & DeShon, R. P. (2001). The assessment of goal commitment: A measurement model meta-analysis. *Organizational Behavior and Human Decision Processes, 85*, 32-55.

Kline, R. B. (1998). *Principles and practice of structural equation modeling.* New York: Guildford Press.

Kozlowski, S. W. J., Gully, S., Brown, K. G., Salas, E., Smith, E. M., & Nason, E. R. (2001). Effects of training goals and goal orientation traits on multidimensional training outcomes and performance adaptability. *Organizational behavior and human decision processes*, 85, 1-31.

Kraiger, K., Ford, J. K., & Salas, E. (1993). Application of cognitive, skill-based, and affective theories of learning outcomes to new methods of training evaluation, *Journal of Applied Psychology, 78*, 311-328.

Landis, R. S., Edwards, B. D., & Cortina, J. M. (2009). On the practice of allowing correlated residuals among indicators in structural equation models. In C. E. Lance & R. J. Vandenberg (Eds.), *Statistical and methodological myths and urban legends: Doctrine, verity and fable in the organizational and social sciences* (pp. 193-218). New York: Rutledge.

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods, 1*, 130-149.

MacCallum, R. C., Roznowski, M., & Necowitz, L. B. (1992). Model modification in covariance structure analysis: The problem of capitalization on chance. *Psychological Bulletin, 111*, 490-504.

Macy, W. H., & Schneider, B. (2008). The meaning of employee engagement. *Industrial and Organizational Psychology: Perspectives on Science and Practice, 1*, 3-30.

Marsh, H. W., Hau, K. T., Balla, J. R., & Grayson, D. (1998). Is more ever too much? The number of indicators per factor in confirmatory factor analysis. *Multivariate Behavioral Research, 33*, 181-220.

Martocchio, J. J. (1994). Effects of conceptions of ability on anxiety, self-efficacy, and learning in training. *Journal of Applied Psychology, 79*,819-825.

Mayer, J. D., Caruso, D. R., & Salovey, P. (2000). Selecting a measure of emotional intelligence: The case for ability scales. In R. Bar-On & J. D. A. parker (eds.), The handbook of emotional intelligence (pp. 320-342). San Francisco, CA: Josey-Bass.

McArdle, J. J., & Epstein, D. (1987). Latent growth curves within developmental structural equation models. *Child Development, 58,* 110-133.

Meredith, W., & Tisak, J. (1990). Latent curve analysis. *Psychometrika, 55,* 107-122.

Meyer, L. P., Allen, N. J., & Smith, C. A. (1993). Commitment to organizations and occupations: Extension and test of a three-component conceptualization. *Journal of Applied Psychology, 78*, 538-551.

Meyer, R. D., Dalal, R. S., & Hermida, R. (2010). A review and synthesis of situational strength in the organizational sciences. *Journal of Management, 36*, 121-140.

Millsap, R. E. (2007). Structural equation modeling made difficult. *Personality and Individual Differences, 42*, 875-881.

Mischel, W. (1968). *Personality and assessment*. New York: Wiley.

Mischel, W. (1977). On the future of personality measurement. *American Psychologist, 32*, 246-254.

Mount, M. K., & Barrick, M. R. (1995). The Big Five personality dimensions: Implications for research and practice in human resources management. In K. M. Rowland & G. Ferris (Eds.), *Research in personnel and human resources management* (pp. 153-200). Greenwich, CT: JAI Press.

Newman, A., Kinney, T., & Farr, J. L. (2004). Job performance ratings. In J. C. Thomas (Ed.), *Comprehensive handbook of psychological assessment: Volume 4 Industrial and Organizational Psychology* (pp. 373-389). Hoboken, NJ: John Wiley & Sons.

Oppler, S. H., Peterson, N. G., & Russell, T. (1992). Basic validation results for the LVI sample,. In J.P. Campbell & L. M. Zook (eds.), *Building and retaining the career force: New procedures for accessing and assigning Army enlisted personnel - Annual report 1991 fiscal year* (ARI Research Note 94-10) (pp. 155-194). Alexandria, VA: U.S. Army Research Institute for the Behavioral and Social Sciences.

Park, G., Schmidt, A. M., Scheu, C., & DeShon, R. P. (2007). A process model of goal orientation and feedback seeking. *Human Performance, 20*, 119-145.

Paulhus, D. L. (1984). Two-component models of socially desirable responding. *Journal* *of Personality and Social Psychology, 46*, 598-609.

Paulhus, D. L., & Reid, D. B. (1991). Enhancement and denial in socially desirable responding. *Journal of Personality and Social Psychology, 60*, 307-317.

Payne, S. C., Youngcourt, S. S., & Beaubien, J. M. (2007). A meta-analytic examination of the goal orientation nomological net. *Journal of Applied Psychology, 92*, 128-150.

Pedhazur, E. J. (1997). *Multiple regression in behavioral research: Explanation and prediction* (Third Edition). Forth Worth, TX: Harcourt Brace.

Phillips, J. M., & Gully, S. M. (1997). Role of goal orientation, ability, need for achievement, and locus of control in the self-efficacy and goal-setting process. *Journal of Applied Psychology, 82*, 792-802.

Rawsthorne, L. J., & Elliot, A. J. (1999). Achievement goals and intrinsic motivation: A meta-analytic review. *Personality and Social Psychology Review, 3*, 326–344.

Rindskopf, D. (1984). Structural equation models: Empirical identification, Haywood cases, and related problems. *Sociological Methods & Research, 13*, 109-119.

Rogers, W. M., & Schmitt, N. (2004). Parameter recovery and model fit using multidimensional composites: A comparison of four empirical parceling algorithms. *Multivariate Behavioral Research, 39*, 379-412.

Salas, E., Burke, C. S., Fowlkes, J. E., & Priest, H. A. (2004). On measuring teamwork skills. In J. C. Thomas (Ed.), *Comprehensive handbook of psychological assessment: Volume 4 Industrial and Organizational Psychology* (427-442). Hoboken, NJ: John Wiley & Sons.

Salas, E., & Cannon-Bowers, J. A. (2001). The science of training: A decade of progress.

Annual Review of Psychology, 52, 471-499.

Scafer, J. L., & Graham, J. W. (2002). Missing data: Our view of the state of the art. *Psychological Methods, 7*, 147-177.

Schermelleh-Engel, K., Keith, N., Moosbrugger, H., & Hodapp, V. (2004). Decomposing person and occasion-specific effects: An extension of latent state-trait (LST) Theory to hierarchical LST models. *Psychological Methods, 9*, 198-219.

Schmidt, A. M., & Ford, K. (2003). Learning within a learner control training environment: The interactive effects of goal orientation and metacognitive instruction on learning outcomes. *Personnel Psychology, 56*, 405–429.

Schmitt, N., Pulakos, E. D., & Lieblein, A. (1984). Comparison of three techniques to assess group-level beta and gamma change. *Applied Psychological Measurement, 8*, 249-260.

Schwartz, G. (1978). Estimating the dimension of a model. *Annals of Statistics, 6*, 461-464.

Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Boston: Houghton Mifflin.

Smith, P. C., Kendall, L. M., & Hulin, C. L. (1969). *The measurement of satisfaction in work and retirement*. Chicago: Rand McNally.

SPSS. (2009). Amos (Version 17.0) [Computer Software]. Chicago, IL: SPSS.

Steele-Johnson, D., Beauregard, R. S., Hoover, P. B., & Schmidt, A. M. (2000). Goal orientation and task demand effects on motivation, affect, and performance. *Journal of Applied Psychology, 85*, 724-738.

Steiger, J. H. (2007). Understanding the limitations of global fit assessment in structural equation modeling. *Personality and Individual Differences, 42*, 893-898.

Stevens, C. K., & Gist, M. E. (1997). Effects of self-efficacy and goal-orientation training on effective negotiation skills maintenance: What are the mechanisms? *Personnel Psychology, 50*, 955-978.

Steyer, R., Ferring, D., & Schmitt, M. J. (1992). States and Traits in Psychological Assessment. *European Journal of Psychological Assessment, 8*, 79-98.

Steyer, R., Krambeer, S., & Hannöver, W. (2004). Modeling latent trait-change. In K. van Montfort, J.H.L. Oud, & A. Satorra (Eds.), *Recent developments on structural equation models: Theory and applications* (pp. 337–357). Amsterdam: Kluwer Academic Press.

Steyer, R., & Riedl, K. (2004). Is it possible to feel good and bad at the same time? New evidence on the bipolarity of mood-state dimensions. In K. V. Montfort, H. Oud, & A. Satorra (Eds.), *Recent developments on structural equation modeling: Theory and applications* (pp. 197-220). Amsterdam: Kluwer Academic Press.

Steyer, R., & Schmitt, M. J. (1990). The effects of aggregation across and within occasions on consistency, specificity and reliability. *Methodika, 4*, 58-94.

Steyer, R., Schmitt, M., & Eid, M. (1999). Latent state-trait theory and research in personality and individual differences. *European Journal of Personality, 13*, 389-408.

Steyer, R., & Schmitt, T. (1994). The theory of confounding and its application in causal modeling with latent variables. In A. von Eye & C.C. Clogg (Eds.), *Latent variables analysis: Applications for developmental research* (pp. 36–67). Thousand Oaks, CA: SAGE Publications.

Tabachnick, B. G., & Fidell, L. S. (2001). *Using multivariate statistics, fourth edition.* Needham Heights, MA: Allyn and Bacon.

Tett, R. P., & Burnett, D. D. (2003). A personality trait-based interactionist model of job performance. *Journal of Applied Psychology, 88*, 500-517.

Tisak, J., & Tisask, M. S. (2000). Permanency and ephemerality of psychological measures with application to organizational commitment. *Psychological Methods, 5*, 175-198.

Utman, C. H. (1997). Performance effects of motivational state: A meta-analysis. *Personality and Social Psychology Review, 1*, 170-182.

Vandenberg, R. J., & Grelle, D. M. (2009). Alternative model specification in structural equation modeling: Facts, fictions, and truth. In C. E. Lance & R. J. Vandenberg (Eds.), *Statistical and methodological myths and urban legends: Doctrine, verity and fable in the organizational and social sciences* (pp. 165-192). New York: Rutledge.

Vandenberg, R. J., & Lance, C. E. (2000). A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational Research Methods, 3*, 4-69.

VandeWalle, D. (1996, August). *Are our students trying to prove or improve their ability? Development and validation of an instrument to measure academic goal orientation.* Paper presented at the annual meeting of the Academy of Management, Cincinnati, OH.

VandeWalle, D. (1997). Development and validation of a work domain goal orientation instrument. *Educational and Psychological Measurement, 57*, 995-1015.

VandeWalle, D., Cron, W. L., Slocum, J. W. (2001). The role of goal orientation following performance feedback. *Journal of Applied Psychology, 86*, 629-640.

VandeWalle, D., & Cummings (1997). A test of the influence of goal orientation on the feedback-seeking process. *Journal of Applied Psychology, 82,* 390-400.

Wagenmakers, E.-J., & Farrell, S. (2004). AIC model selection using Akaike weights. *Psychonomic Bulletin & Review, 11*, 192-196.

Ward, R., & Heggestad, E. (2004). *What is goal orientation anyway? Disentangling goals, traits, and situations.* Paper presented at the 19th annual conference of the society of Industrial and Organizational Psychology, Chicago, IL.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology, 54*, 1063-1070.

Yeo, G. B., & Neal, A. (2004). A multilevel analysis of effort, practice, and performance: Effects of ability, conscientiousness, and goal orientation. *Journal of Applied Psychology, 89*, 231-247.

Yuan, K. H., Bentler, P. M., & Kano, Y. (1997). On average variables in a confirmatory factor analysis model. *Behaviormetrika, 24*(1), 71-83.

APPENDIX A

THE ABBREVIATED MOTIVATIONAL TRAIT QUESTIONNAIRE

SELF-DESCRIPTION QUESTIONNAIRE

INSTRUCTIONS:

This questionnaire asks you to respond to statements about your attitudes, opinions, and behaviors. Read each statement carefully, and decide whether or not the statement describes you. Using the scale at the top of each page indicate the degree to which the **ENTIRE** statement is true of you. Give only one answer for each statement.

Some of the statements may refer to experiences you may not have had. Respond to these statements in terms of how true you think it **WOULD BE** of you.

Look at the sample statement below.

SAMPLE STATEMENT:

1	2	3	4	5	6
▪	▪	▪	▪	▪	▪
Very UNTRUE *of Me*	**UNTRUE *of Me***	**Somewhat UNTRUE of Me**	**Somewhat TRUE of Me**	***TRUE* of Me**	***Very* TRUE *of Me***

I like to go to parties.

MARK **1** ▪ *if you really dislike parties and you try to avoid them.*
2 ▪ *if you generally dislike parties and only go when you have to.*
3 ▪ *if you think parties are okay but generally prefer not to go.*
4 ▪ *if you think parties are okay and generally prefer to go.*
5 ▪ *if you generally like parties and go to most of the time.*
6 ▪ *if you really like parties and only miss one if you absolutely have to.*

PLEASE NOTE:

- There are no right or wrong answers. Simply describe yourself honestly and state your opinions accurately.
- Deciding on an answer may be difficult for some of the statements. If you have a hard time deciding, choose the answer that is **MOST** true of you.

- Some of the items will seem repetitive. These are not meant to be trick questions. Do not look back at your previous answers, simply answer each question honestly.

In deciding on your answer, consider your life in general and <u>not</u> only the last few weeks or months.

1	2	3	4	5	6
Very UNTRUE *of Me*	**UNTRUE *of Me***	**Somewhat UNTRUE of Me**	**Somewhat TRUE of Me**	***TRUE* of Me**	***Very* TRUE *of Me***

1. ____ Item 1.
2. ____ Item 2.
3. ____ Item 3.
4. ____ Item 4.
5. ____ Item 5.
6. ____ Item 6.
7. ____ Item 7.
8. ____ Item 8.
9. ____ Item 9.
10. ____ Item 10.
11. ____ Item 11.
12. ____ Item 12.
13. ____ Item 13.
14. ____ Item 14.
15. ____ Item 15.
16. ____ Item 16.
17. ____ Item 17.
18. ____ Item 18.

MOTIVATIONAL TRAIT QUESTIONNAIRE: SCORING KEY
18 ITEM FORM

Note: (R) indicates that the item is reverse scored.

Learning Goal Orientation (Personal Mastery)
6, 7, 8, 12, 13 (R), 16

Performance-Prove Goal Orientation (Competitive Excellence)
1, 2, (R), 4, 9, 10, 14

Performance-Avoid Goal Orientation (Motivation Anxiety)
3, 5, 11 (R), 15, 17, 18

APPENDIX B

ITEMS FROM THE ACADEMIC DOMAIN GOAL ORIENTATION MEASURE

The next set of questions includes statements about your attitudes, opinions, and behaviors within a classroom setting or academic environment. In deciding on your answer, consider your academic experiences in general.

1	2	3	4	5	6
Very UNTRUE *of Me*	**UNTRUE *of Me***	**Somewhat UNTRUE of Me**	**Somewhat TRUE of Me**	***TRUE* of Me**	***Very* TRUE *of Me***

19. ____ Item 19.
20. ____ Item 20.
21. ____ Item 21.
22. ____ Item 22.
23. ____ Item 23.
24. ____ Item 24.
25. ____ Item 25.
26. ____ Item 26.
27. ____ Item 27.
28. ____ Item 28.
29. ____ Item 29.
30. ____ Item 30.
31. ____ Item 31.
32. ____ Item 32.
33. ____ Item 33.
34. ____ Item 34.
35. ____ Item 35.
36. ____ Item 36.

ACADEMIC DOMAIN GOAL ORIENTATATION INSTRUMENT: SCORING KEY 18 ITEM FORM

Note: (R) indicates that the item is reverse scored.

Learning Goal Orientation (Personal Mastery)
24, 25, 26, 30, 31 (R), 34

Performance-Prove Goal Orientation (Competitive Excellence)
19, 20 (R), 22, 27, 28, 32

Performance-Avoid Goal Orientation (Motivation Anxiety)
21, 23, 29 (R), 33, 35, 36

APPENDIX C

ITEMS FROM THE STATE GOAL ORIENTATION MEASURE

The next set of questions also includes statements about your attitudes, opinions, and behaviors within a classroom setting or academic environment. In deciding on your answer for these questions, consider how you currently feel.

1	2	3	4	5	6
Very UNTRUE *of Me*	**UNTRUE *of Me***	**Somewhat UNTRUE of Me**	**Somewhat TRUE of Me**	***TRUE* of Me**	***Very* TRUE *of Me***

37. ____ Item 37.
38. ____ Item 38.
39. ____ Item 39.
40. ____ Item 40.
41. ____ Item 41.
42. ____ Item 42.
43. ____ Item 43.
44. ____ Item 44.
45. ____ Item 45.
46. ____ Item 46.
47. ____ Item 47.
48. ____ Item 48.
49. ____ Item 49.
50. ____ Item 50.
51. ____ Item 51.
52. ____ Item 52.
53. ____ Item 53.
54. ____ Item 54.

STATE GOAL ORIENTATATION INSTRUMENT: SCORING KEY
18 ITEM FORM

Note: (R) indicates that the item is reverse scored.

Learning Goal Orientation (Personal Mastery)
42, 43,44, 48, 49 (R), 52

Performance-Prove Goal Orientation (Competitive Excellence)
37, 38 (R), 40, 45, 46, 50

Performance-Avoid Goal Orientation (Motivation Anxiety)
39, 41, 47 (R), 51, 53, 54

APPENDIX D

AMOS GRAPHICS MODELS FOR HYPOTHESIS 1a

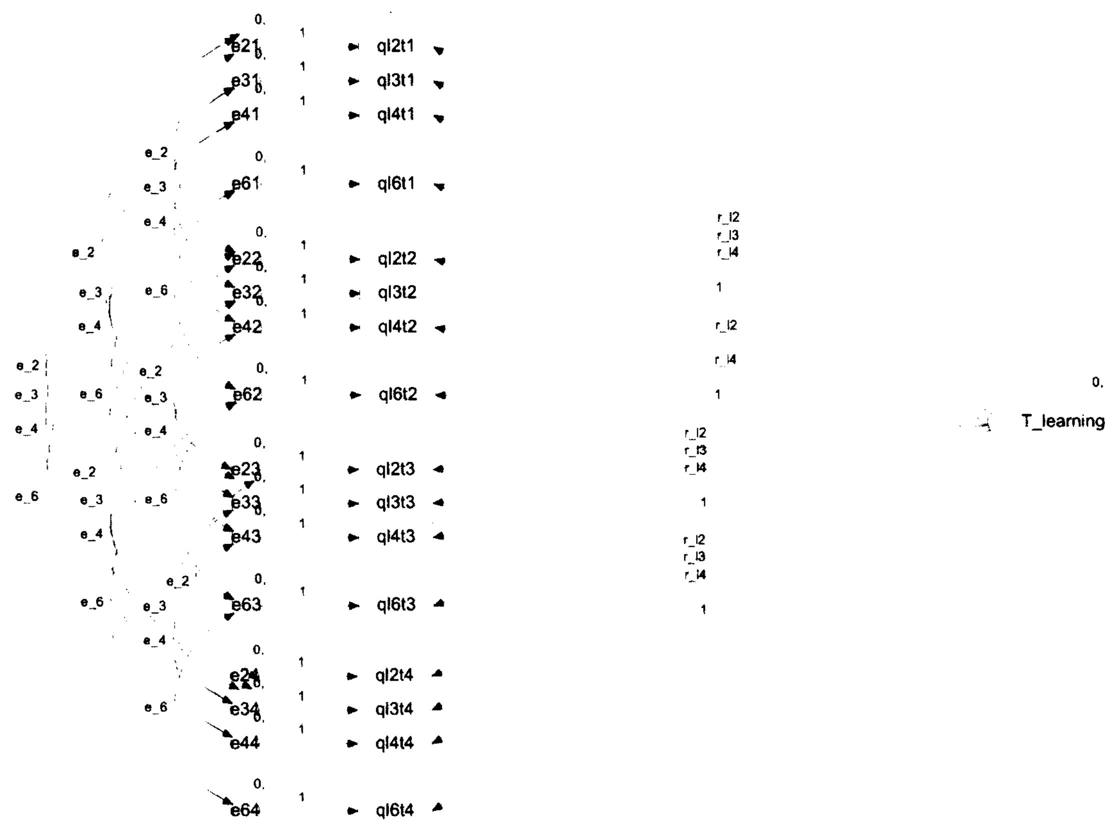

Figure D1. Model 1: Trait model for Hypothesis 1a.

Note. e_2 = error covariance between occasions of measurement for item 2; e_3 = error covariance between occasions of measurement for item 3; e_4 = error covariance between occasions of measurement for item 4; e_6 = error covariance between occasions of measurement for item 6; e21 = error for item 2 at time 1; e31 = error for item 3 at time 1; e41 = error for item 4 at time 1; e61 = error for item 6 at time 1; e22 = error for item 2 at time 2; e32 = error for item 3 at time 2; e42 = error for item 4 at time 2; e62 = error for item 6 at time 2; e23 = error for item 2 at time 3; e33 = error for item 3 at time 3; e43 = error for item 4 at time 3; e63 = error for item 6 at time 3; e24 = error for item 2 at time 4; e34 = error for item 3 at time 4; e44 = error for item 4 at time 4; e64 = error for item 6

at time 4; ql2t1 = learning item 2 at time 1; ql3t1 = learning item 3 at time 1; ql4t1 = learning item 4 at time 1; ql6t1 = learning item 6 at time 1; ql2t2 = learning item 2 at time 2; ql3t2 = learning item 3 at time 2; ql4t2 = learning item 4 at time 2; ql6t2 = learning item 6 at time 2; ql2t3 = learning item 2 at time 3; ql3t3 = learning item 3 at time 3; ql4t3 = learning item 4 at time 3; ql6t3 = learning item 6 at time 3; ql2t4 = learning item 2 at time 4; ql3t4 = learning item 3 at time 4; ql4t4 = learning item 4 at time 4; ql6t4 = learning item 6 at time 4; r_l2 = path coefficient for learning item 2; r_l3 = path coefficient for learning item 3; r_l4 = path coefficient for learning item 4; T_learning = trait learning.

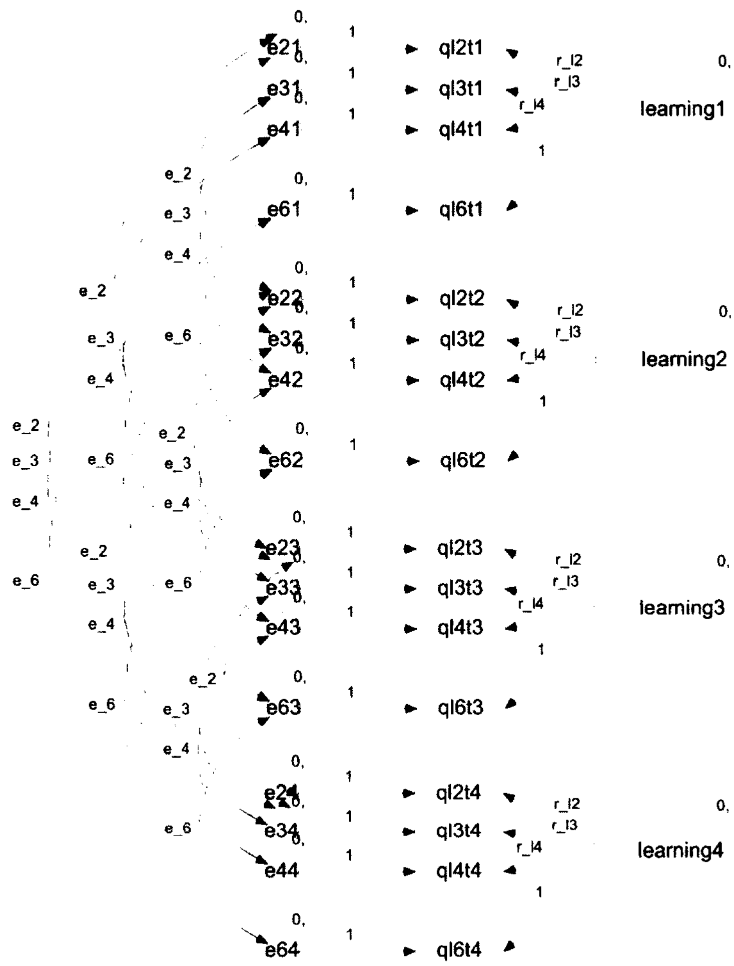

Figure D2. Model 2: State model for Hypothesis 1a.

Note. See note to Figure D1. learning1 = state learning at time 1; learning2 = state learning at time 2; learning3 = state learning at time 3; learning4 = state learning at time 4.

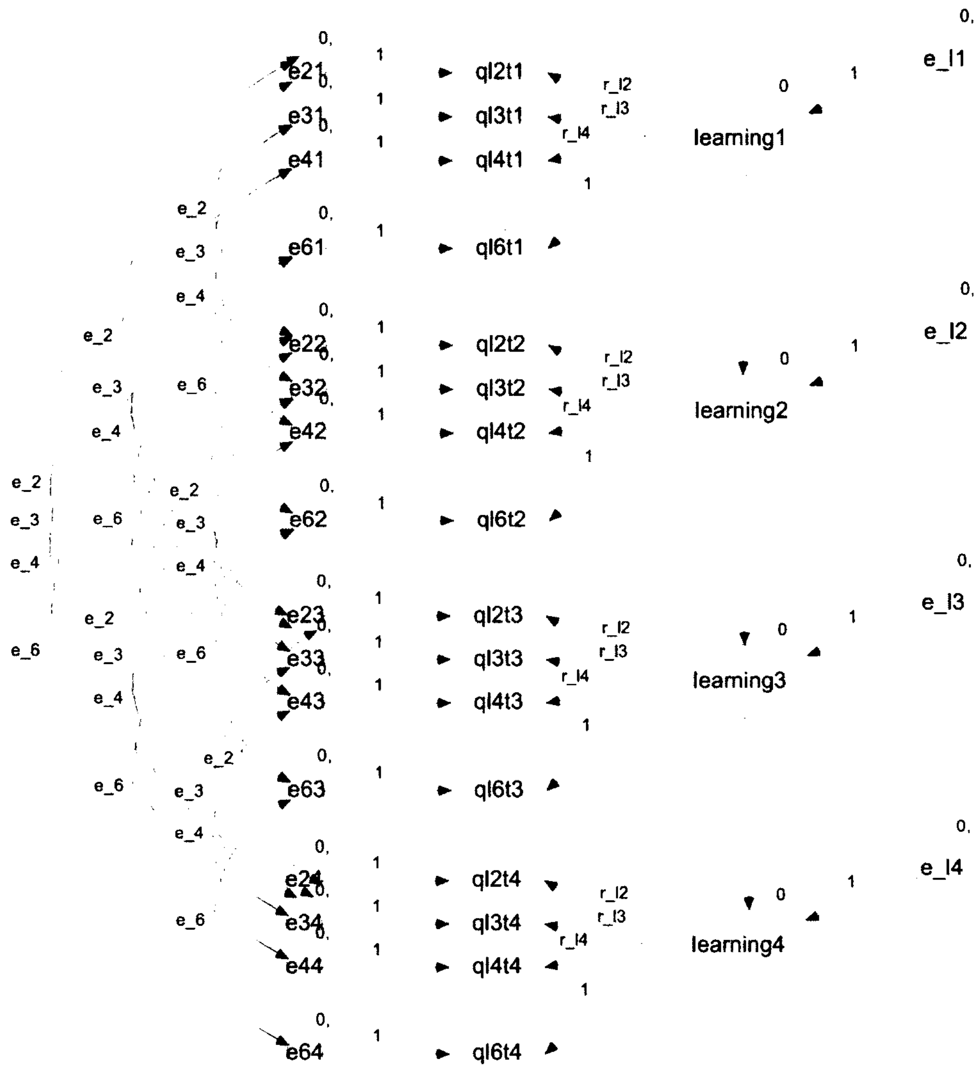

Figure D3. Model 3: State model with first-order autoregressive state factors for Hypothesis 1a.

Note. See note to Figures D1 and D2. e_l1 = error for latent state learning at time 1; e_l2 = error for latent state learning at time 2; e_l3 = error for latent state learning at time 3; e_l4 = error for latent state learning at time 4.

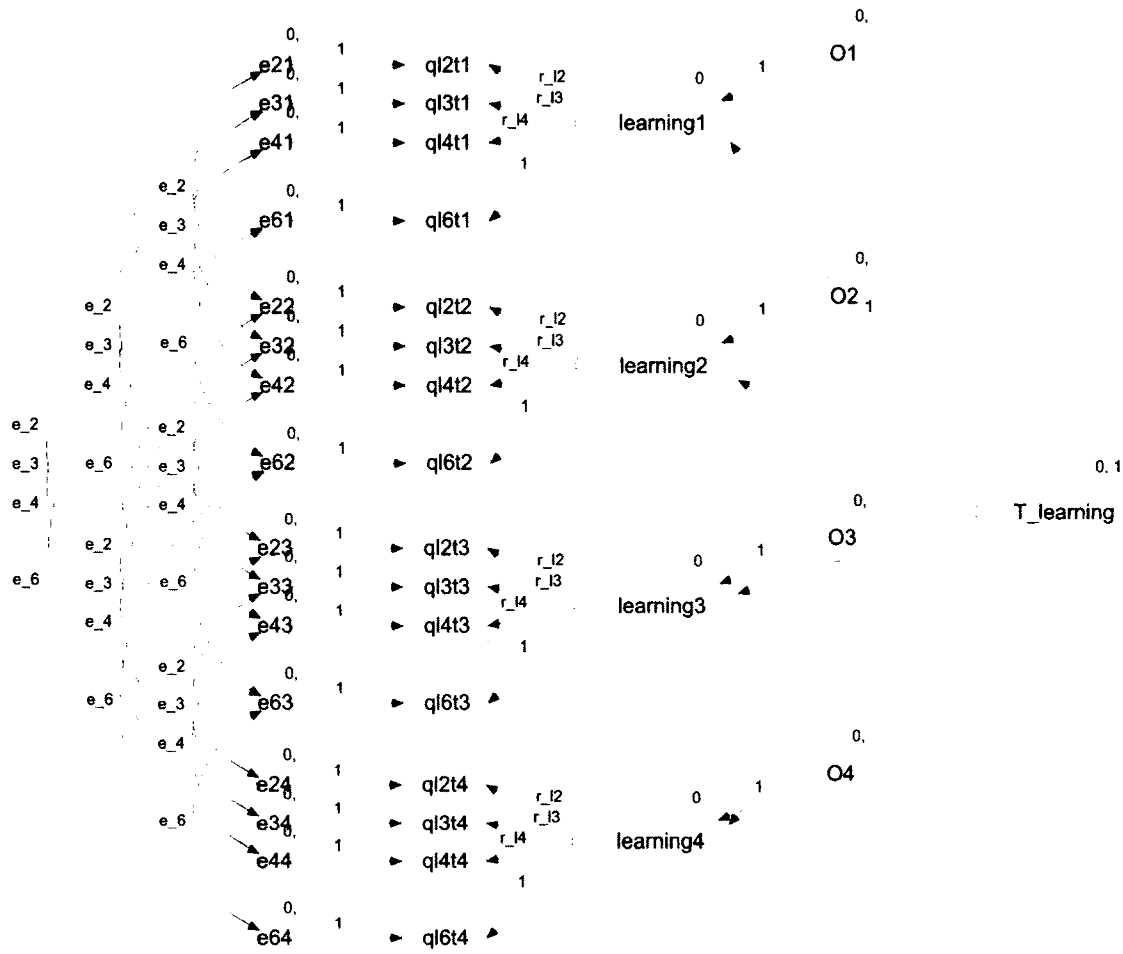

Figure D4. Model 4: LTS model for Hypothesis 1a.

Note. See note to Figures D1 and D2. O1 = latent occasion at time 1; O2 = latent occasion at time 2; O3 = latent occasion at time 3; O4 = latent occasion at time 4.

Figure D5. Model 5: LTS model with equality constraints on latent trait factor loadings for Hypothesis 1a.

Note. See note to Figures D1, D2 and D4. reg_t = path coefficient for latent trait.

Figure D6. Model 6: LTS model with first-order autoregressive latent state factors for Hypothesis 1a.

Note. See note for Figures D1, D2, D4, and D5.

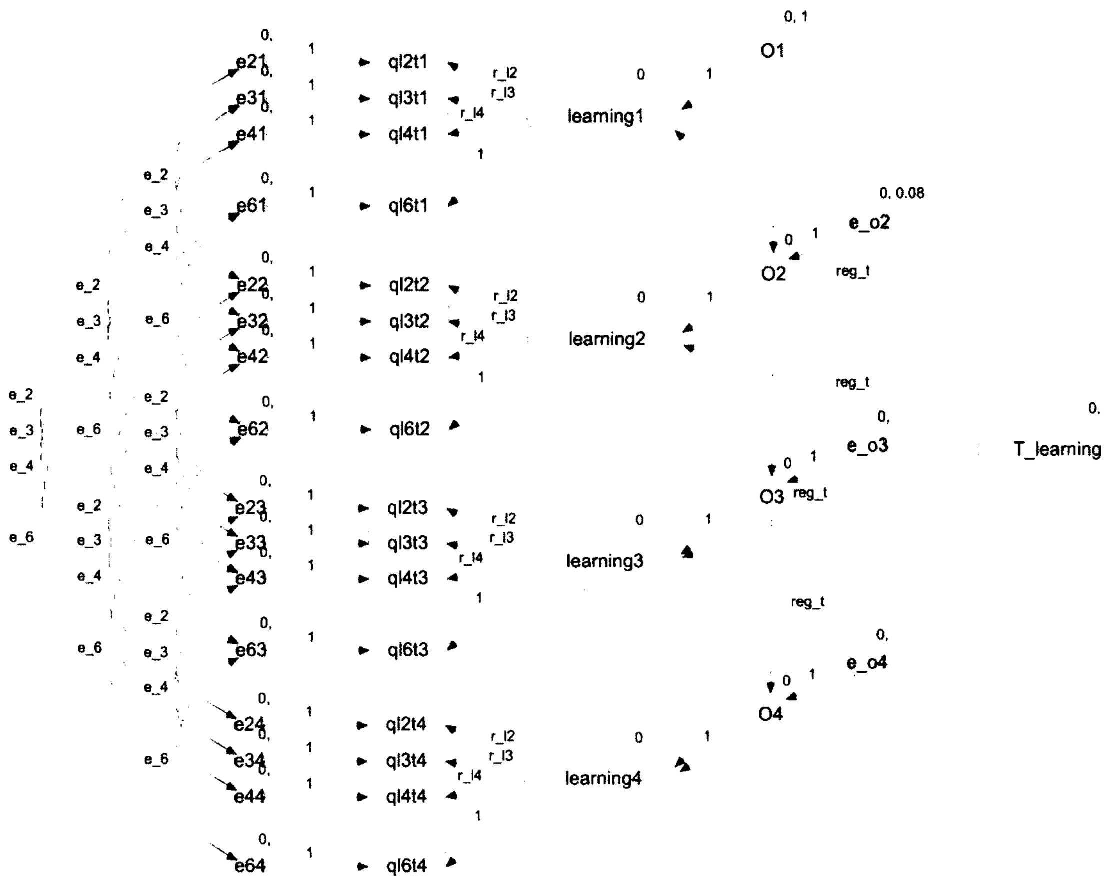

Figure D7. Model 7: LTS model with first-order autoregressive occasion factors for Hypothesis 1a.

Note. See note for Figures D1, D2, D4, and D5. e_o2 = error term for latent occasion at time 2; e_o3 = error term for latent occasion at time 3; e_o4 = error term for latent occasion at time 4.

APPENDIX E

AMOS GRAPHICS MODELS FOR HYPOTHESIS 1b

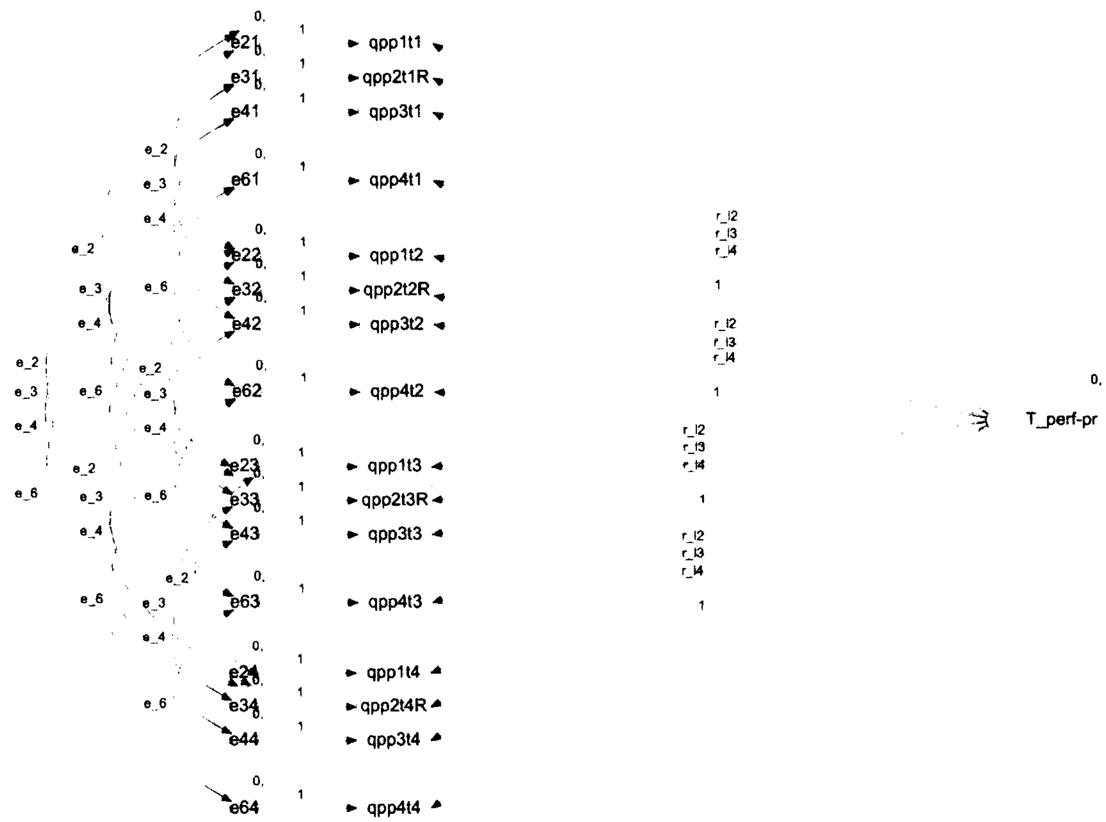

Figure E1. Model 1: Trait model for Hypothesis 1b.

Note. e_2 = error covariance between occasions of measurement for item 1; e_3 = error covariance between occasions of measurement for item 2; e_4 = error covariance between occasions of measurement for item 3; e_6 = error covariance between occasions of measurement for item 4; e21 = error for item 1 at time 1; e31 = error for item 2 at time 1; e41 = error for item 3 at time 1; e61 = error for item 4 at time 1; e22 = error for item 1 at time 2; e32 = error for item 2 at time 2; e42 = error for item 3 at time 2; e62 = error for item 4 at time 2; e23 = error for item 1 at time 3; e33 = error for item 2 at time 3; e43 = error for item 3 at time 3; e63 = error for item 4 at time 3; e24 = error for item 1 at time 4; e34 = error for item 2 at time 4; e44 = error for item 3 at time 4; e64 = error for item 4

at time 4; qpp1t1 = performance-prove item 1 at time 1; qpp2t1R = performance-prove item 2 (reverse scored) at time 1; qpp3t1 = performance-prove item 3 at time 1; qpp4t1 = performance-prove item 4 at time 1; qpp1t2 = performance-prove item 1 at time 2; qpp2t2R = performance-prove item 2 (reverse scored) at time 2; qpp3t2 = performance-prove item 3 at time 2; qpp4t2 = performance-prove item 4 at time 2; qpp1t3 = performance-prove item 1 at time 3; qpp2t3R = performance-prove item 2 (reverse scored) at time 3; qpp3t3 = performance-prove item 3 at time 3; qpp4t3 = performance-prove item 4 at time 3; qpp1t4 = performance-prove item 1 at time 4; qpp2t4R = performance-prove item 2 (reverse scored) at time 4; qpp3t4 = performance-prove item 3 at time 4; qpp4t4 = performance-prove item 4 at time 4; r_l2 = path coefficient for performance-prove item 1; r_l3 = path coefficient for performance-prove item 2; r_l4 = path coefficient for performance-prove item 3; T_perf-pr = trait performance-prove.

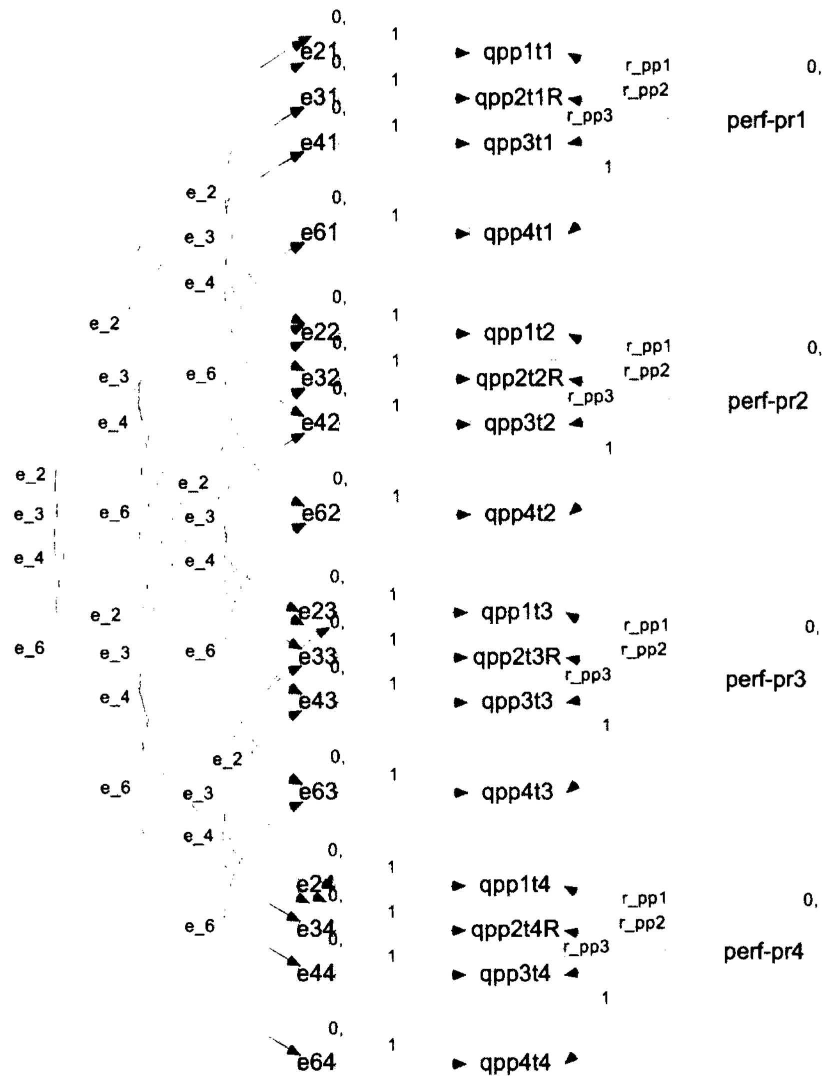

Figure E2. Model 2: State model for Hypothesis 1b.

Note. See note to Figure E1. r_pp1 = path coefficient for performance-prove item 1; r_pp2 = path coefficient for performance-prove item 2; r_pp3 = path coefficient for performance-prove item 3; perf-pr1 = state performance-prove at time 1; perf-pr2 = state performance-prove at time 2; perf-pr3 = state performance-prove at time 3; perf-pr4 = state performance-prove at time 4.

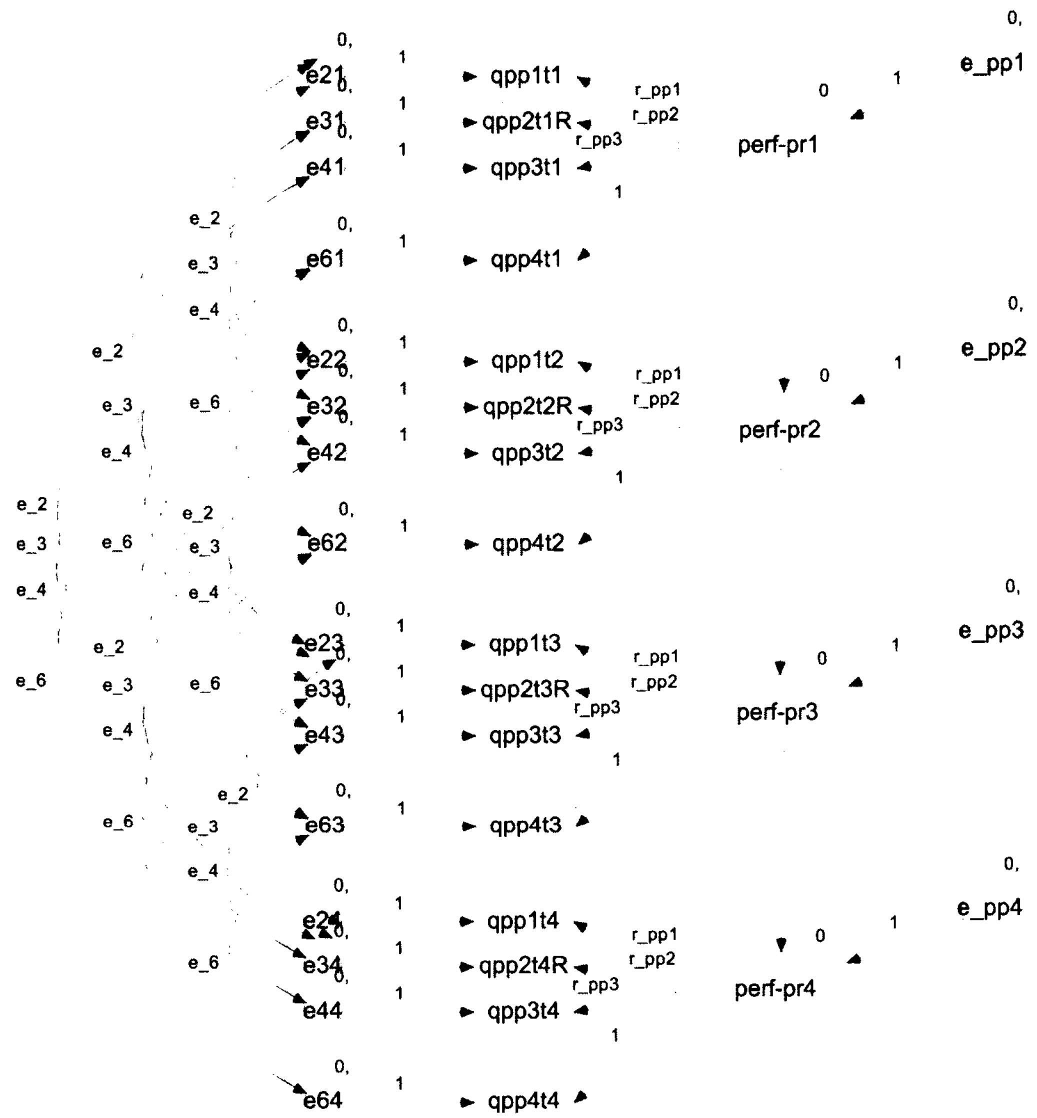

Figure E3. Model 3: State model with first-order autoregressive state factors for Hypothesis 1b.

Note. See note to Figures E1 and E2. e_pp1 = error for latent state performance-prove at time 1; e_pp2 = error for latent state performance-prove at time 2; e_pp3 = error for latent state performance-prove at time 3; e_pp4 = error for latent state performance-prove at time 4.

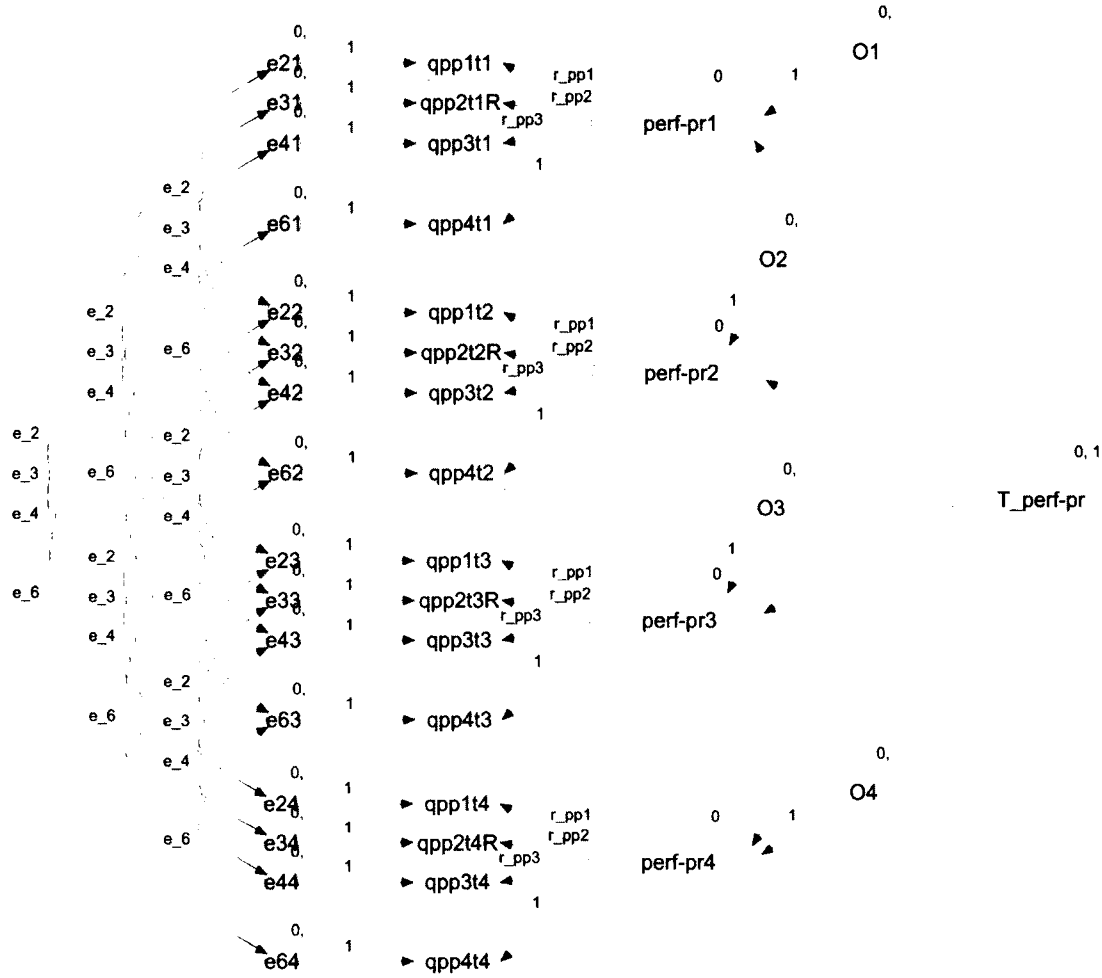

Figure E4. Model 4: LTS model for Hypothesis 1b.

Note. See note to Figures E1 and E2. O1 = latent occasion at time 1; O2 = latent occasion at time 2; O3 = latent occasion at time 3; O4 = latent occasion at time 4.

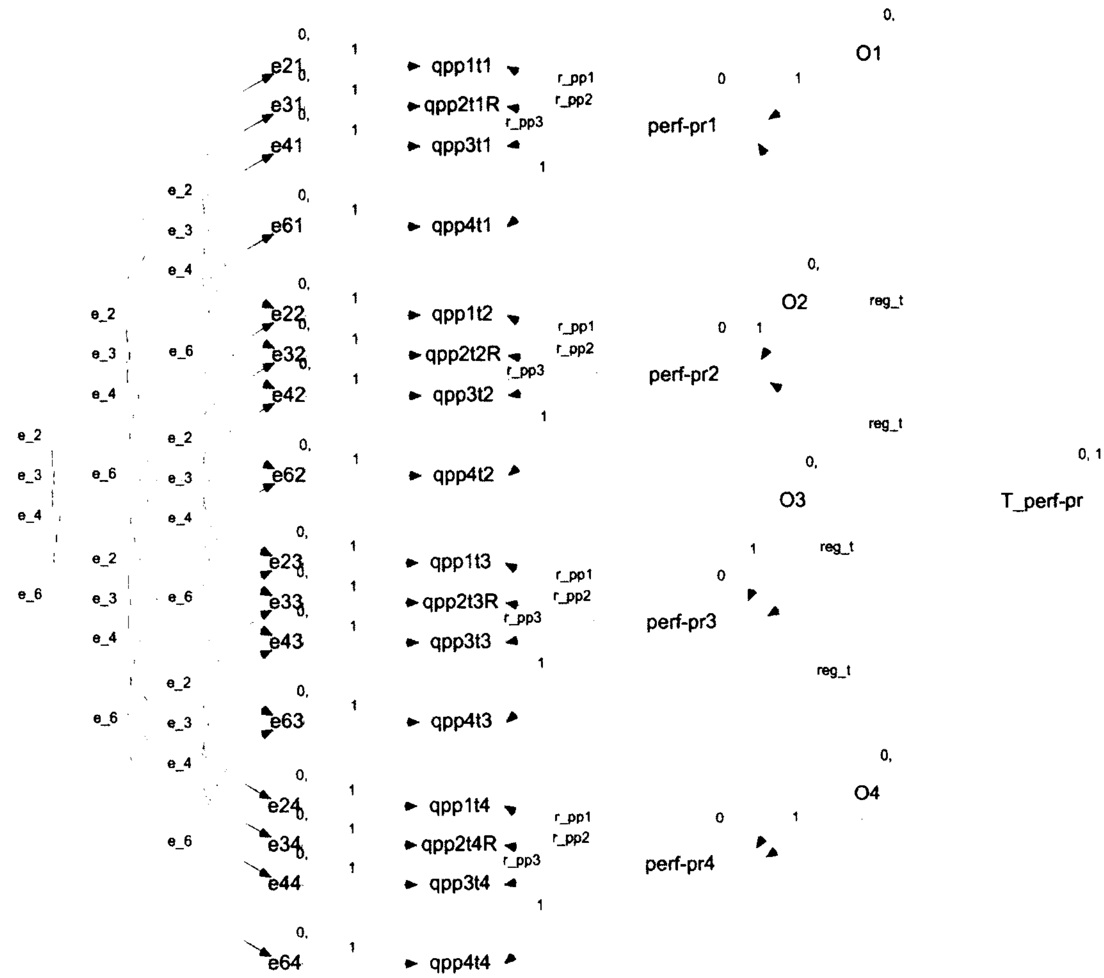

Figure E5. Model 5: LTS model with equality constraints on latent trait factor loadings for Hypothesis 1b.

Note. See note to Figures E1, E2 and E4. reg_t = path coefficient for latent trait.

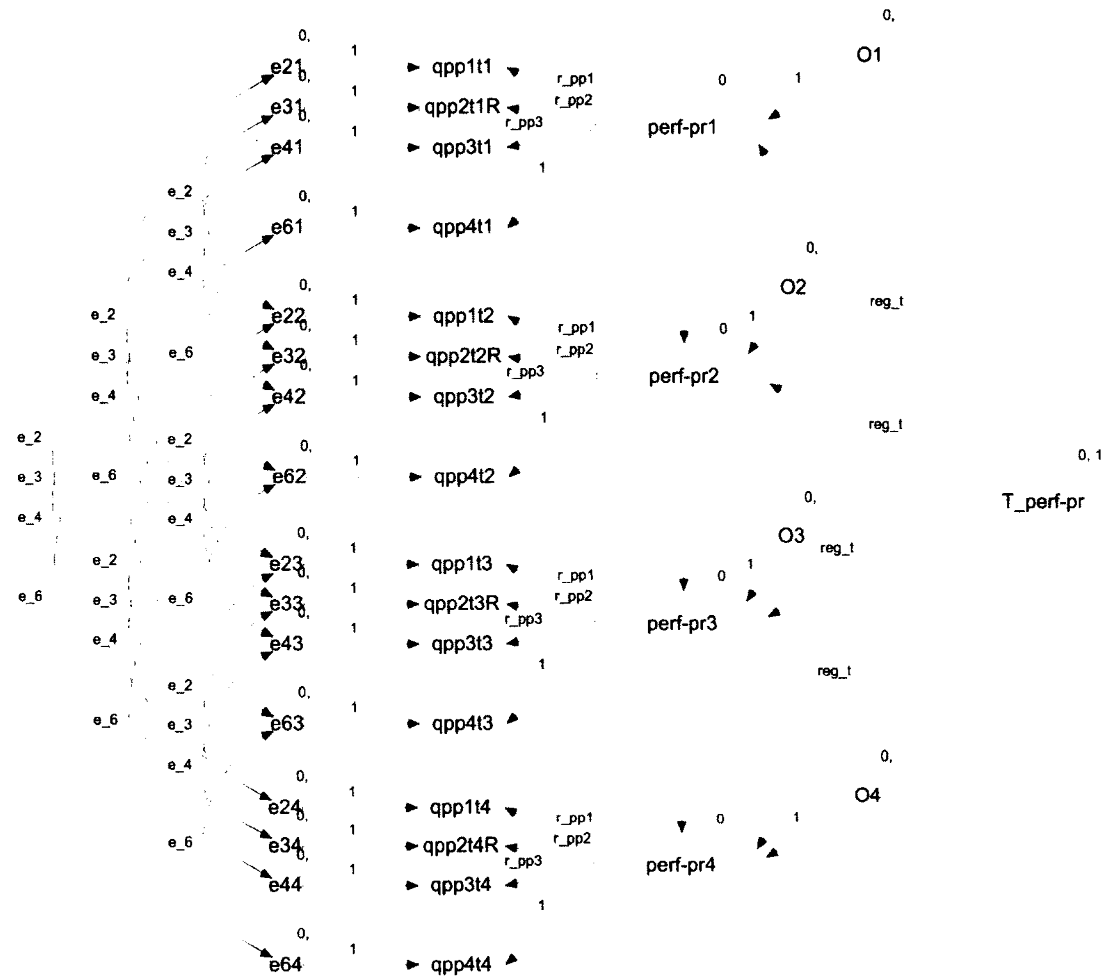

Figure E6. Model 6: LTS model with first-order autoregressive latent state factors for Hypothesis 1b.

Note. See note for Figures E1, E2, E4, and E5.

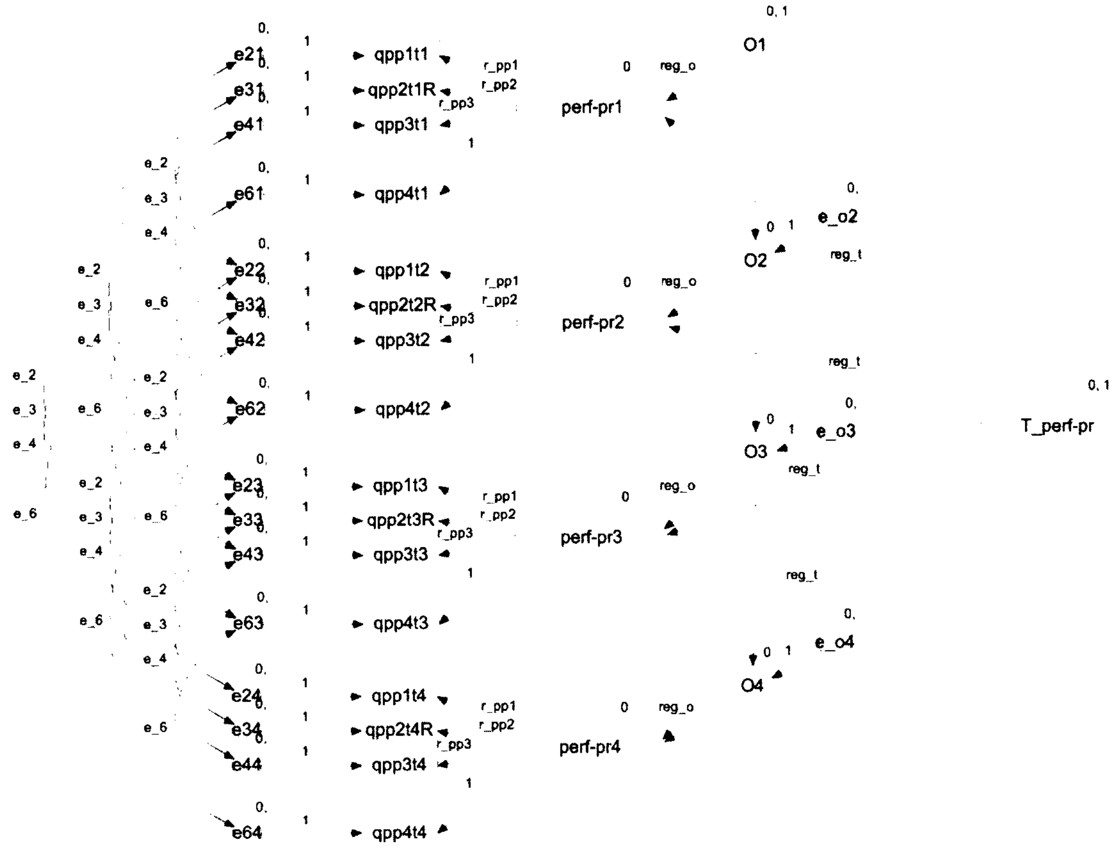

Figure E7. Model 7: LTS model with first-order autoregressive occasion factors for Hypothesis 1b.

Note. See note for Figures E1, E2, E4, and E5. e_o2 = error term for latent occasion at time 2; e_o3 = error term for latent occasion at time 3; e_o4 = error term for latent occasion at time 4.

APPENDIX F

AMOS GRAPHICS MODELS FOR HYPOTHESIS 1c

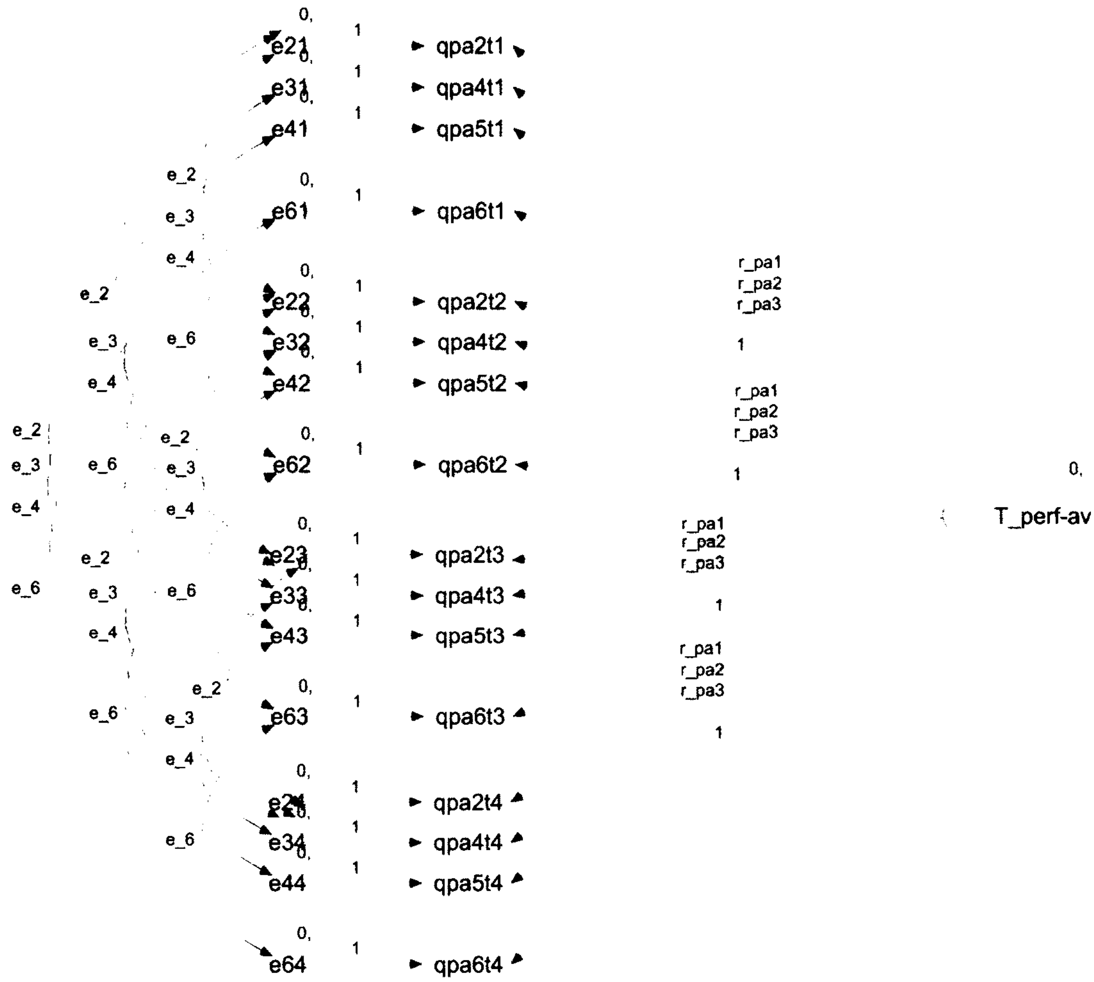

Figure F1. Model 1: Trait model for Hypothesis 1c.

Note. e_2 = error covariance between occasions of measurement for item 2; e_3 = error covariance between occasions of measurement for item 4; e_4 = error covariance between occasions of measurement for item 5; e_6 = error covariance between occasions of measurement for item 6; e21 = error for item 2 at time 1; e31 = error for item 4 at time 1; e41 = error for item 5 at time 1; e61 = error for item 6 at time 1; e22 = error for item 2 at time 2; e32 = error for item 4 at time 2; e42 = error for item 5 at time 2; e62 = error for

item 6 at time 2; e23 = error for item 2 at time 3; e33 = error for item 4 at time 3; e43 = error for item 5 at time 3; e63 = error for item 6 at time 3; e24 = error for item 2 at time 4; e34 = error for item 4 at time 4; e44 = error for item 5 at time 4; e64 = error for item 6 at time 4; qpa2t1 = performance-avoid item 2 at time 1; qpa4t1 = performance-avoid item 4 at time 1; qpa5t1 = performance-avoid item 5 at time 1; qpa6t1 = performance-avoid item 6 at time 1; qpa2t2 = performance-avoid item 2 at time 2; qpa4t2 = performance-avoid item 4 at time 2; qpa5t2 = performance-avoid item 5 at time 2; qpa6t2 = performance-avoid item 6 at time 2; qpa2t3 = performance-avoid item 2 at time 3; qpa4t3 = performance-avoid item 4 at time 3; qpa5t3 = performance-avoid item 5 at time 3; qpa6t3 = performance-avoid item 6 at time 3; qpa2t4 = performance-avoid item 2 at time 4; qpa4t4 = performance-avoid item 4 at time 4; qpa5t4 = performance-avoid item 5 at time 4; qpa6t4 = performance-avoid item 6 at time 4; r_pa1 = path coefficient for performance-avoid item 2; r_pa2 = path coefficient for performance-avoid item 4; r_pa3 = path coefficient for performance-avoid item 5; T_Perf-Av = trait performance-avoid.

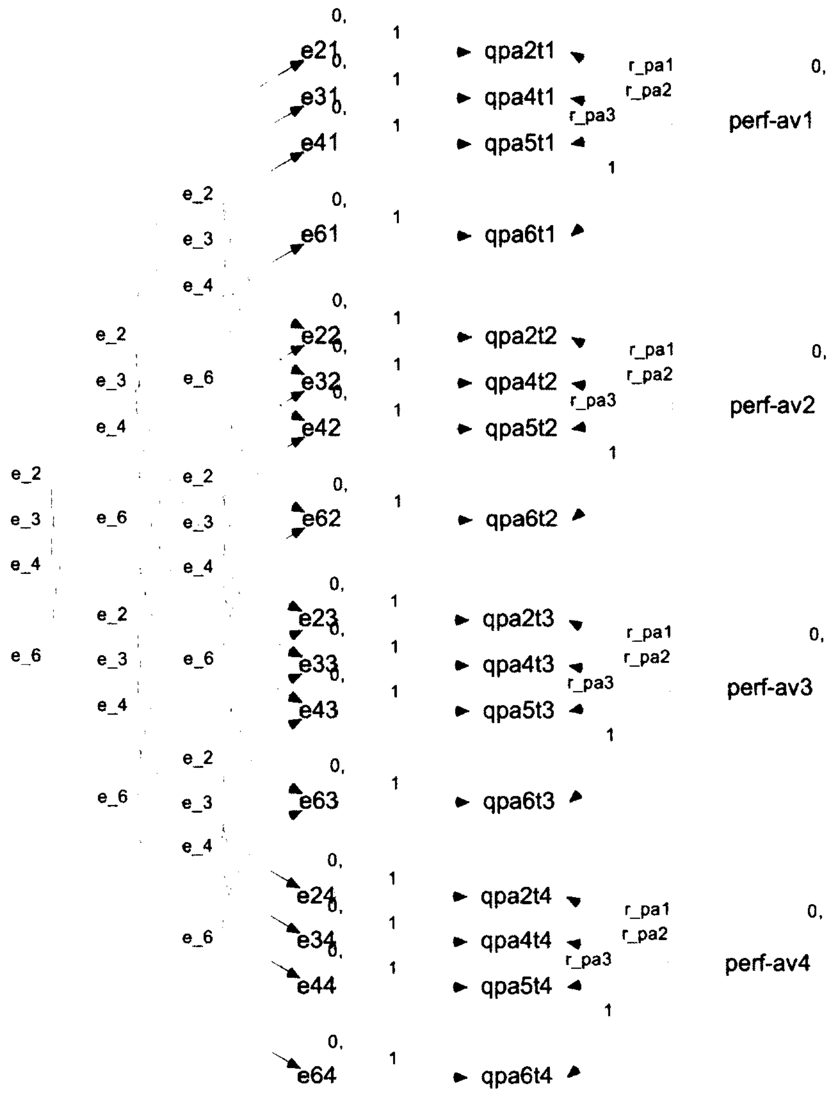

Figure F2. Model 2: State model for Hypothesis 1c.

Note. See note to Figure F1. performance-avoid1 = state performance-avoid at time 1; performance-avoid2 = state performance-avoid at time 2; performance-avoid3 = state performance-avoid at time 3; performance-avoid4 = state performance-avoid at time 4.

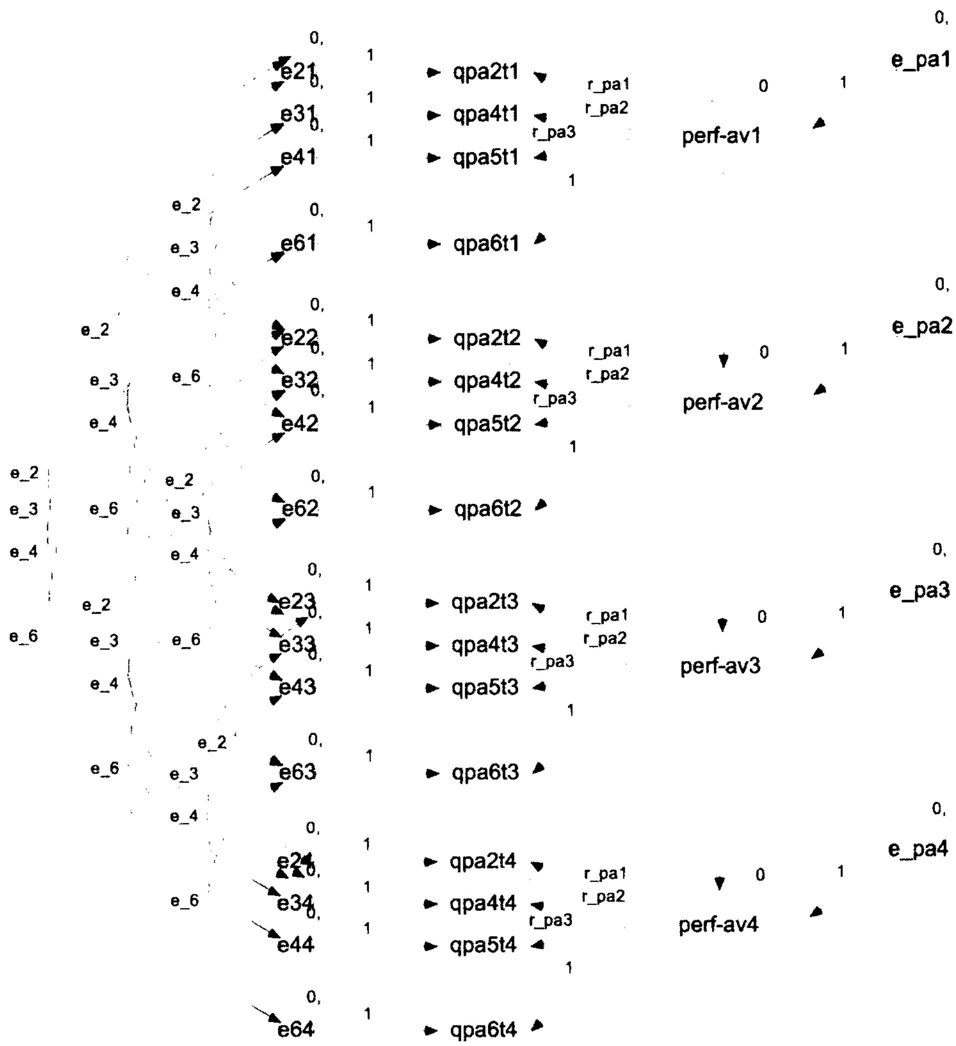

Figure F3. Model 3: State model with first-order autoregressive state factors for Hypothesis 1c.

Note. See note to Figures E1 and E2. e_l1 = error for latent state performance-avoid at time 1; e_l2 = error for latent state performance-avoid at time 2; e_l3 = error for latent state performance-avoid at time 3; e_l4 = error for latent state performance-avoid at time 4.

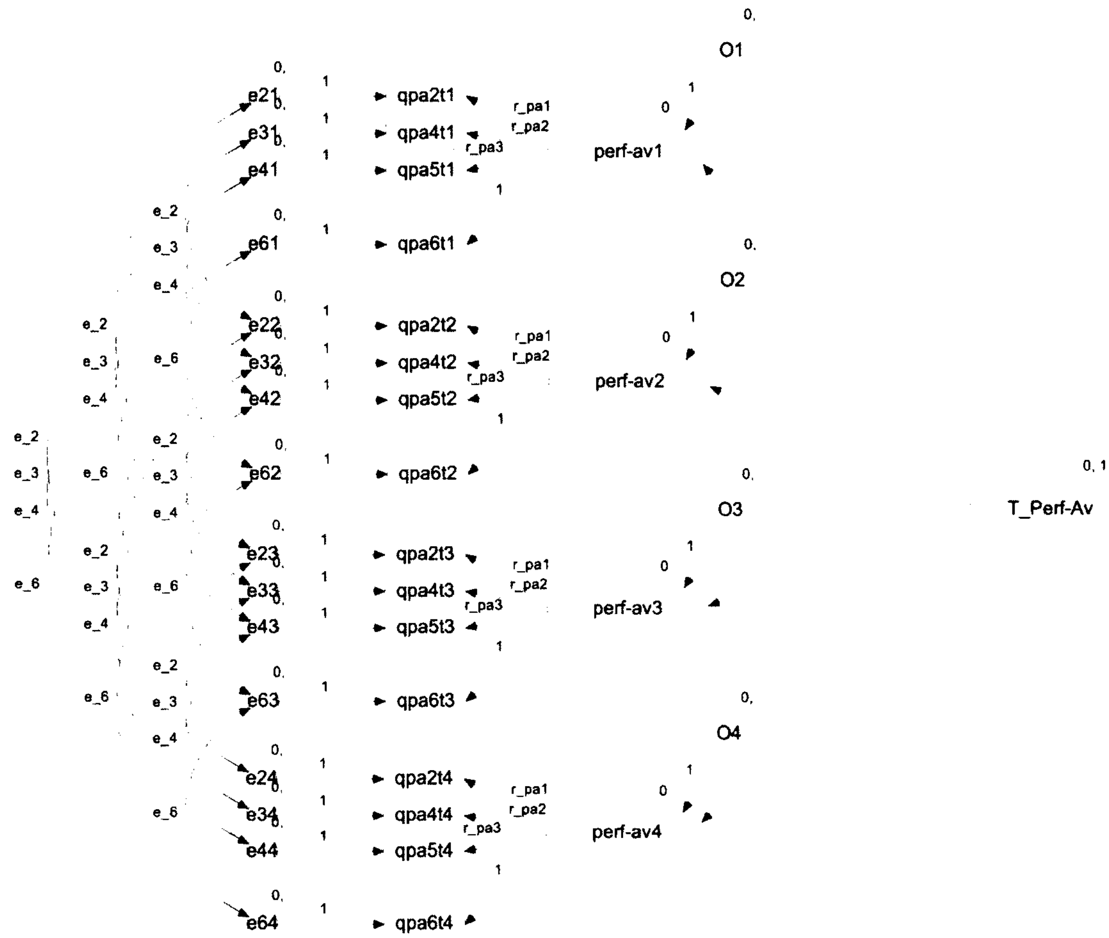

Figure F4. Model 4: LTS model for Hypothesis 1c.

Note. See note to Figures E1 and E2. O1 = latent occasion at time 1; O2 = latent occasion at time 2; O3 = latent occasion at time 3; O4 = latent occasion at time 4.

Figure F5. Model 5: LTS model with equality constraints on latent trait factor loadings for Hypothesis 1c.

Note. See note to Figures E1, E2 and E4. reg_t = path coefficient for latent trait.

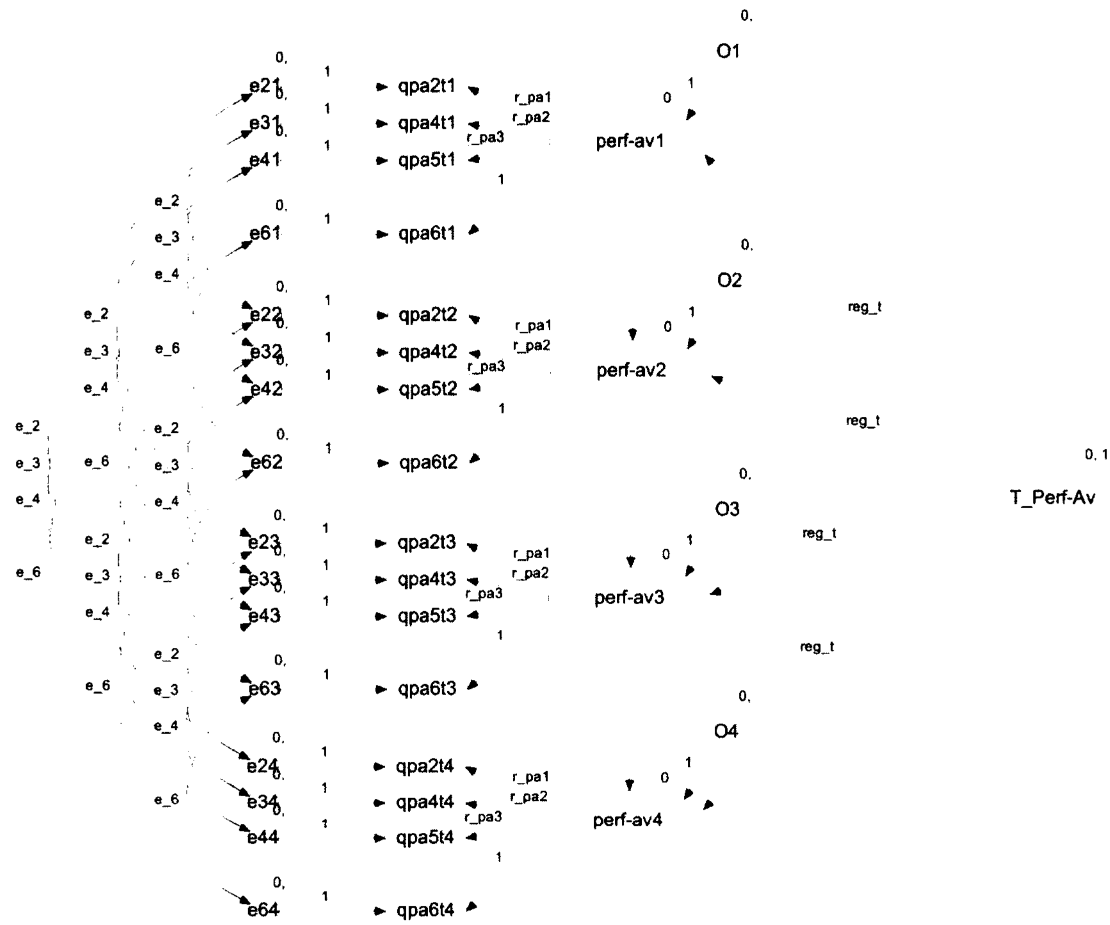

Figure F6. Model 6: LTS model with first-order autoregressive latent state factors for Hypothesis 1c.

Note. See note for Figures E1, E2, E4, and E5.

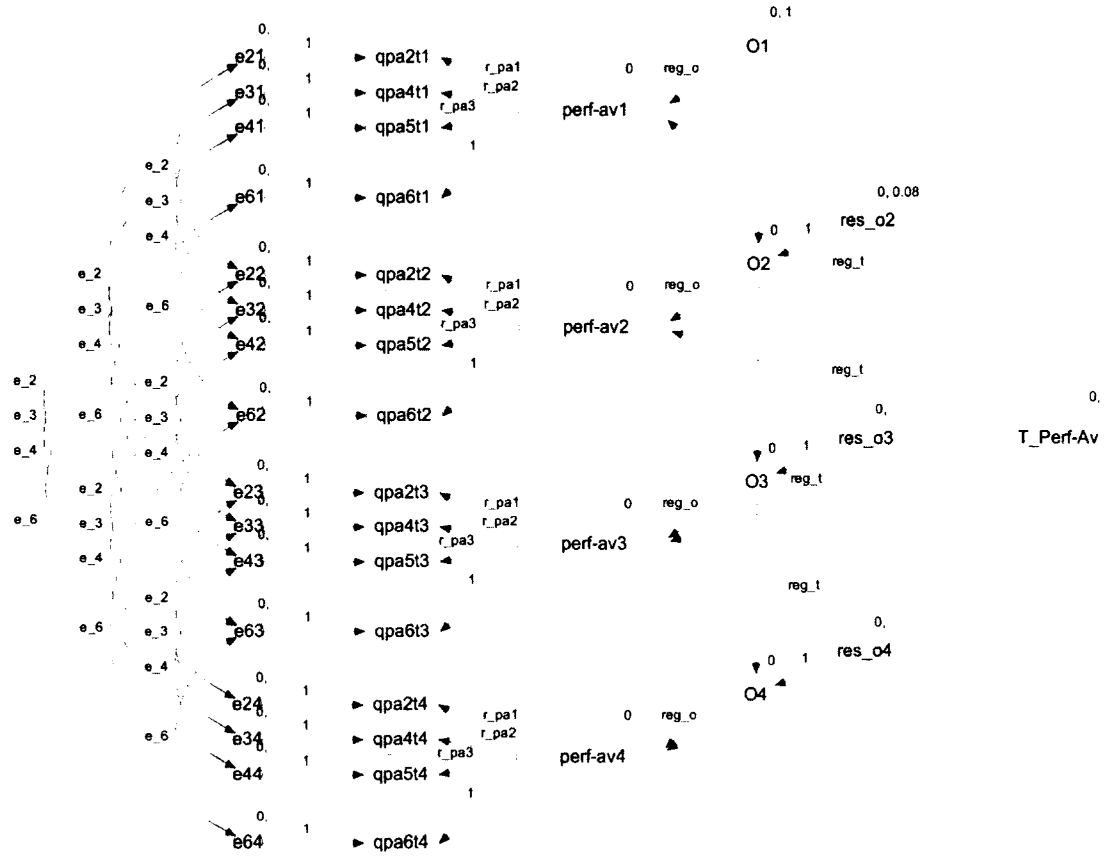

Figure F7. Model 7: LTS model with first-order autoregressive occasion factors for Hypothesis 1c.

Note. See note for Figures E1, E2, E4, and E5. e_o2 = error term for latent occasion at time 2; e_o3 = error term for latent occasion at time 3; e_o4 = error term for latent occasion at time 4.

APPENDIX G

AMOS GRAPHICS MODELS FOR HYPOTHESIS 2a

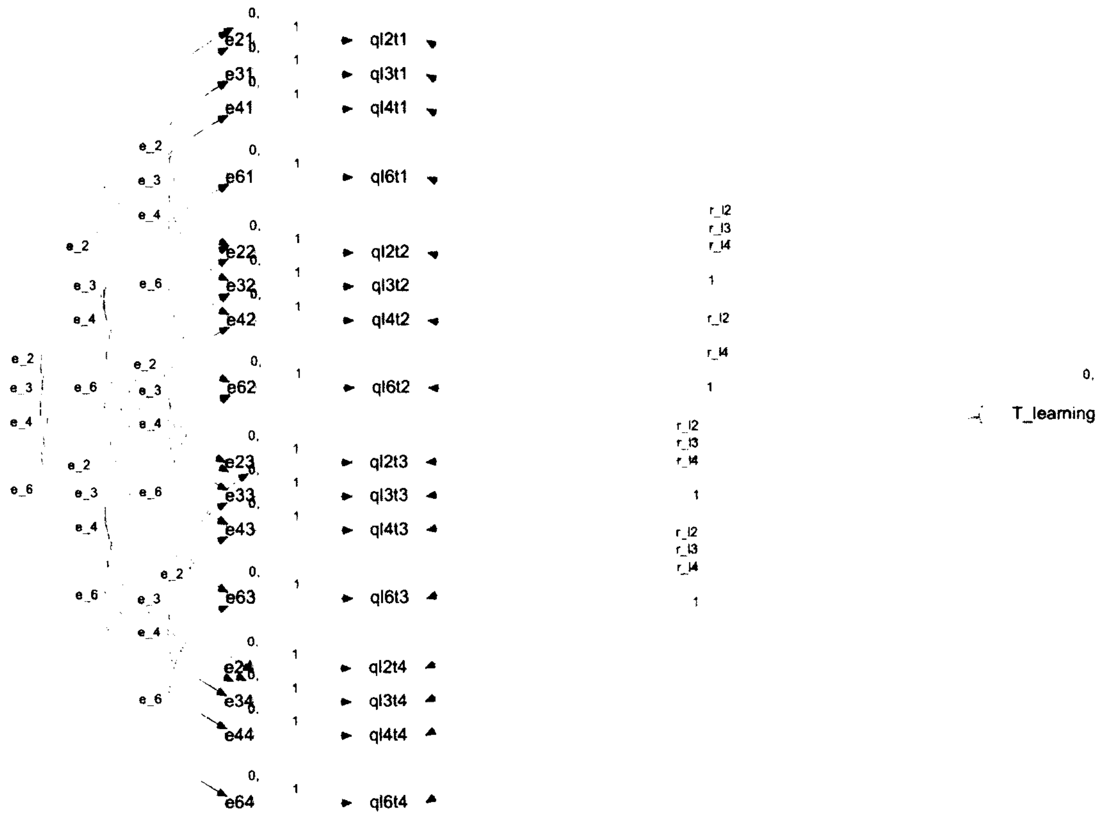

Figure G1. Model 1: Trait model for Hypothesis 2a.

Note. e_2 = error covariance between occasions of measurement for item 2; e_3 = error covariance between occasions of measurement for item 3; e_4 = error covariance between occasions of measurement for item 4; e_6 = error covariance between occasions of measurement for item 6; e21 = error for item 2 at time 1; e31 = error for item 3 at time 1; e41 = error for item 4 at time 1; e61 = error for item 6 at time 1; e22 = error for item 2 at time 2; e32 = error for item 3 at time 2; e42 = error for item 4 at time 2; e62 = error for item 6 at time 2; e23 = error for item 2 at time 3; e33 = error for item 3 at time 3; e43 = error for item 4 at time 3; e63 = error for item 6 at time 3; e24 = error for item 2 at time 4; e34 = error for item 3 at time 4; e44 = error for item 4 at time 4; e64 = error for item 6

at time 4; ql2t1 = learning item 2 at time 1; ql3t1 = learning item 3 at time 1; ql4t1 = learning item 4 at time 1; ql6t1 = learning item 6 at time 1; ql2t2 = learning item 2 at time 2; ql3t2 = learning item 3 at time 2; ql4t2 = learning item 4 at time 2; ql6t2 = learning item 6 at time 2; ql2t3 = learning item 2 at time 3; ql3t3 = learning item 3 at time 3; ql4t3 = learning item 4 at time 3; ql6t3 = learning item 6 at time 3; ql2t4 = learning item 2 at time 4; ql3t4 = learning item 3 at time 4; ql4t4 = learning item 4 at time 4; ql6t4 = learning item 6 at time 4; r_l2 = path coefficient for learning item 2; r_l3 = path coefficient for learning item 3; r_l4 = path coefficient for learning item 4; T_learning = trait learning.

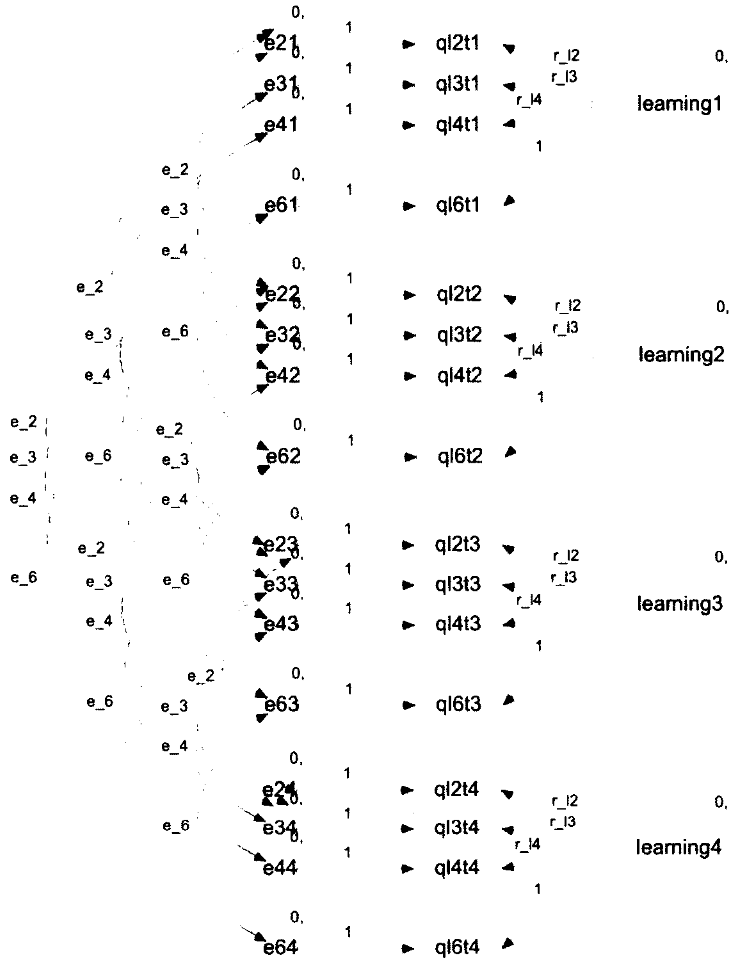

Figure G2. Model 2: State model for Hypothesis 2a.

Note. See note to Figure G1. learning1 = state learning at time 1; learning2 = state learning at time 2; learning3 = state learning at time 3; learning4 = state learning at time 4.

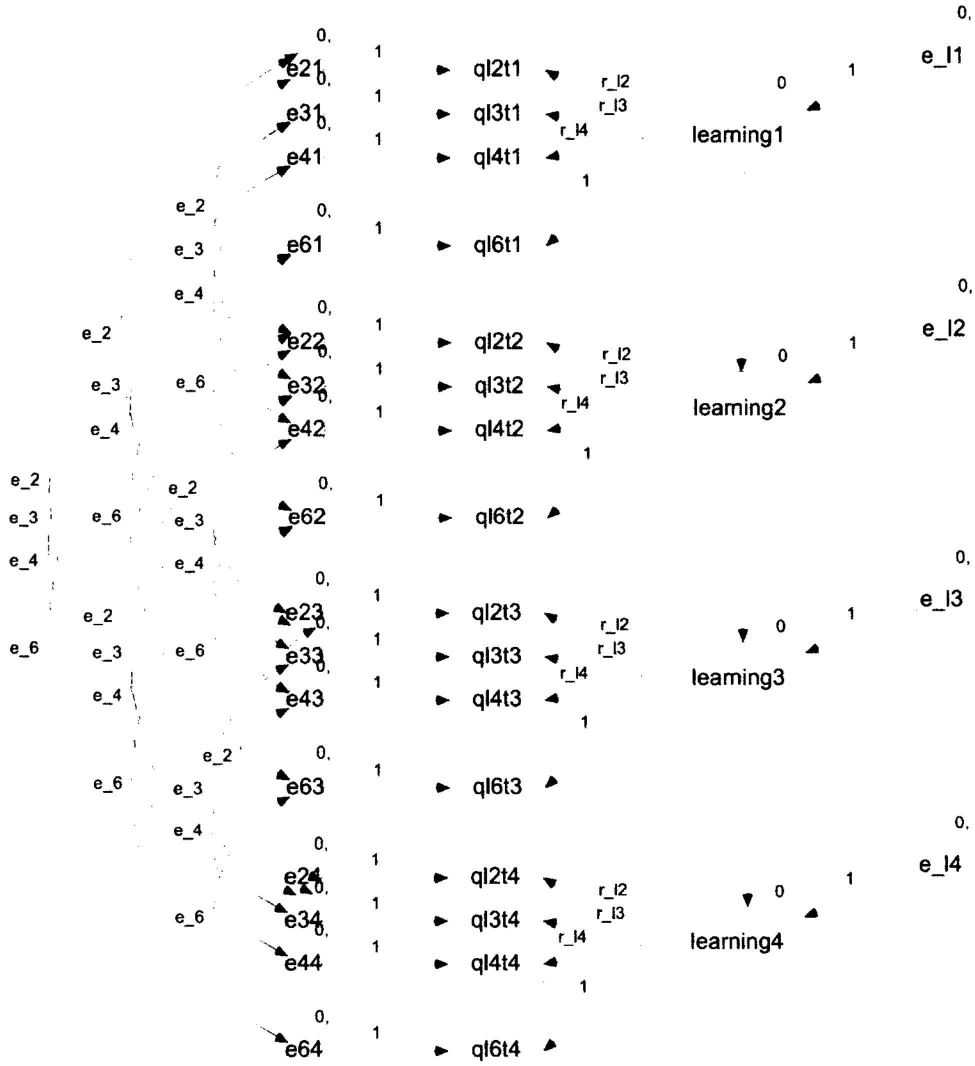

Figure G3. Model 3: State model with first-order autoregressive state factors for Hypothesis 2a.

Note. See note to Figures G1 and G2. e_l1 = error for latent state learning at time 1; e_l2 = error for latent state learning at time 2; e_l3 = error for latent state learning at time 3; e_l4 = error for latent state learning at time 4.

Figure G4. Model 4: LTS model for Hypothesis 2a.

Note. See note to Figures G1 and G2. O1 = latent occasion at time 1; O2 = latent occasion at time 2; O3 = latent occasion at time 3; O4 = latent occasion at time 4.

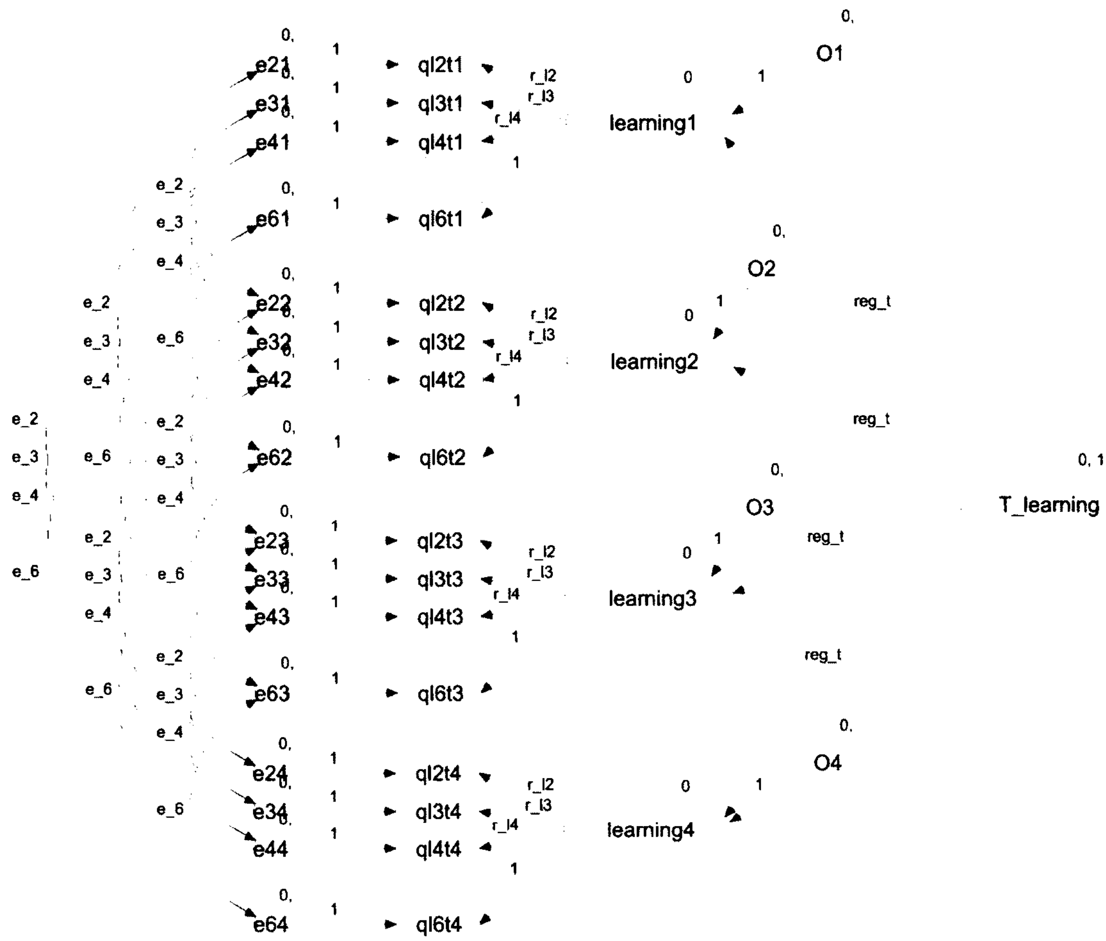

Figure G5. Model 5: LTS model with equality constraints on latent trait factor loadings for Hypothesis 2a.

Note. See note to Figures G1, G2 and G4. reg_t = path coefficient for latent trait.

Figure G6. Model 6: LTS model with first-order autoregressive latent state factors for Hypothesis 2a.

Note. See note for Figures G1, G2, G4, and G5.

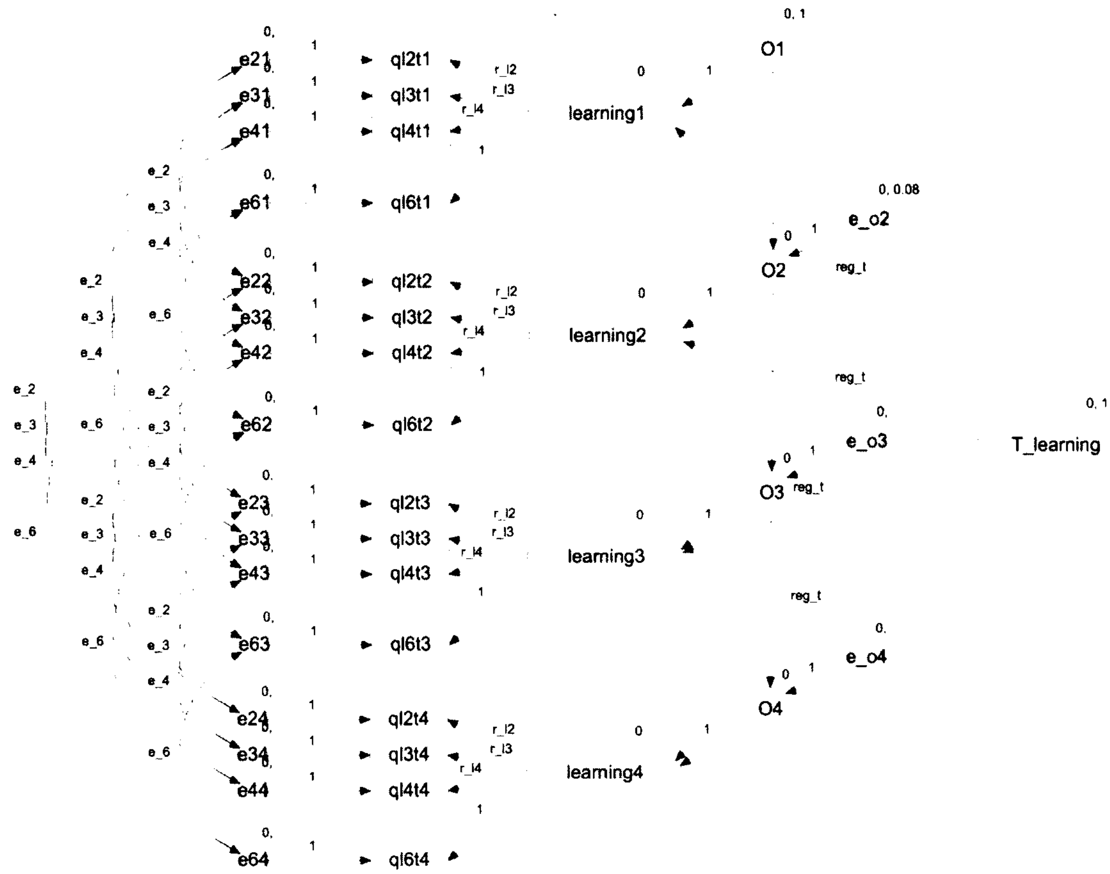

Figure G7. Model 7: LTS model with first-order autoregressive occasion factors for Hypothesis 2a.

Note. See note for Figures G1, G2, G4, and G5. e_o2 = error term for latent occasion at time 2; e_o3 = error term for latent occasion at time 3; e_o4 = error term for latent occasion at time 4.

APPENDIX H

AMOS GRAPHICS MODELS FOR HYPOTHESIS 2b

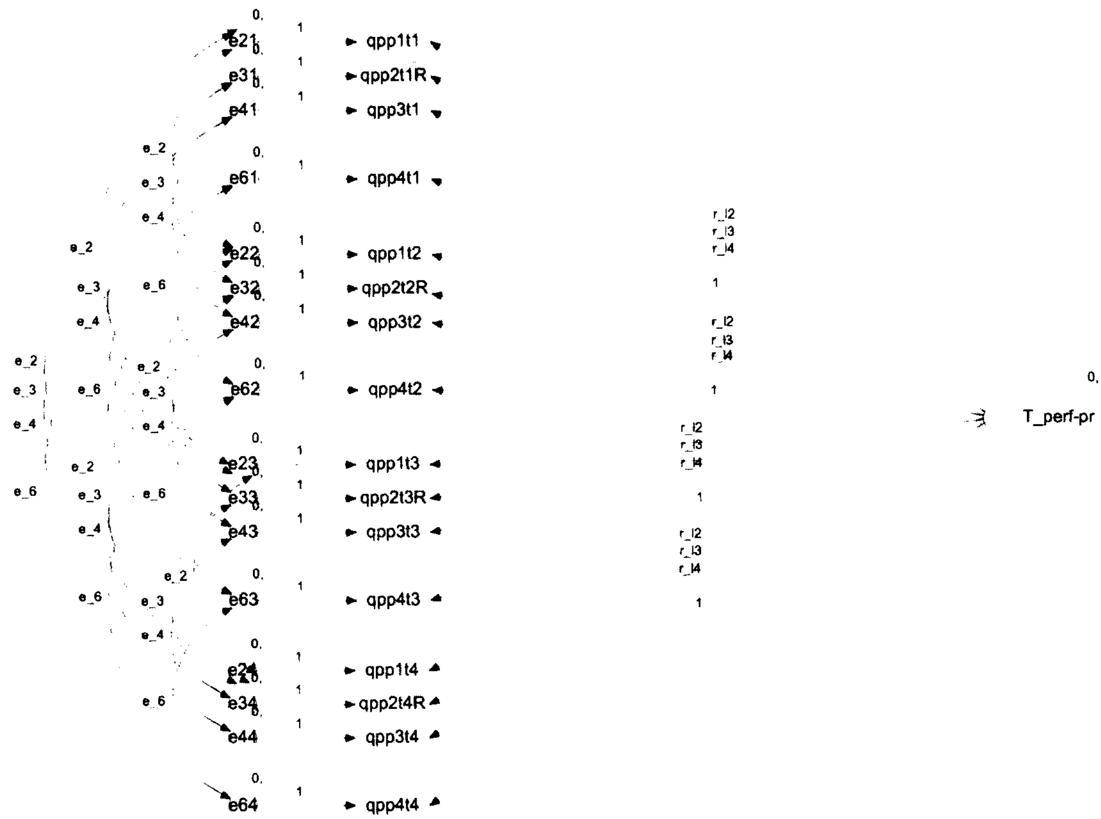

Figure H1. Model 1: Trait model for Hypothesis 2b.

Note. e_2 = error covariance between occasions of measurement for item 1; e_3 = error covariance between occasions of measurement for item 2; e_4 = error covariance between occasions of measurement for item 3; e_6 = error covariance between occasions of measurement for item 4; e21 = error for item 1 at time 1; e31 = error for item 2 at time 1; e41 = error for item 3 at time 1; e61 = error for item 4 at time 1; e22 = error for item 1 at time 2; e32 = error for item 2 at time 2; e42 = error for item 3 at time 2; e62 = error for item 4 at time 2; e23 = error for item 1 at time 3; e33 = error for item 2 at time 3; e43 = error for item 3 at time 3; e63 = error for item 4 at time 3; e24 = error for item 1 at time 4; e34 = error for item 2 at time 4; e44 = error for item 3 at time 4; e64 = error for item 4

at time 4; qpp1t1 = performance-prove item 1 at time 1; qpp2t1R = performance-prove item 2 (reverse scored) at time 1; qpp3t1 = performance-prove item 3 at time 1; qpp4t1 = performance-prove item 4 at time 1; qpp1t2 = performance-prove item 1 at time 2; qpp2t2R = performance-prove item 2 (reverse scored) at time 2; qpp3t2 = performance-prove item 3 at time 2; qpp4t2 = performance-prove item 4 at time 2; qpp1t3 = performance-prove item 1 at time 3; qpp2t3R = performance-prove item 2 (reverse scored) at time 3; qpp3t3 = performance-prove item 3 at time 3; qpp4t3 = performance-prove item 4 at time 3; qpp1t4 = performance-prove item 1 at time 4; qpp2t4R = performance-prove item 2 (reverse scored) at time 4; qpp3t4 = performance-prove item 3 at time 4; qpp4t4 = performance-prove item 4 at time 4; r_l2 = path coefficient for performance-prove item 1; r_l3 = path coefficient for performance-prove item 2; r_l4 = path coefficient for performance-prove item 3; T_perf-pr = trait performance-prove.

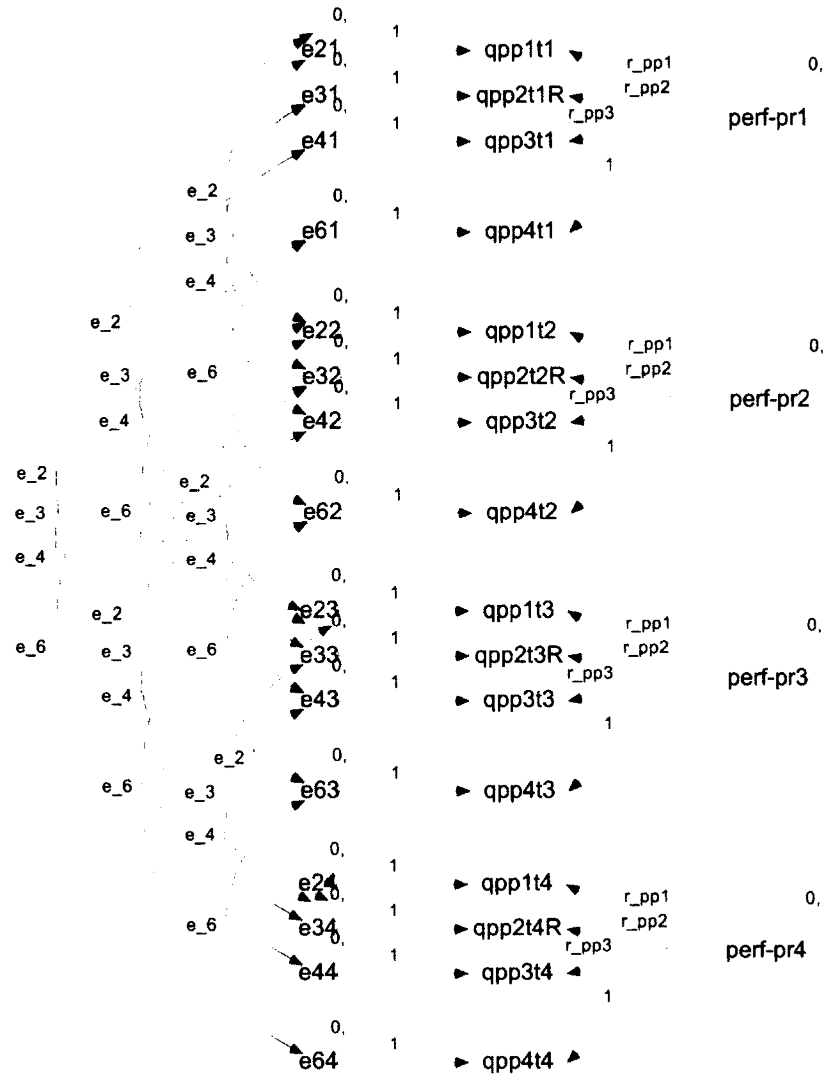

Figure H2. Model 2: State model for Hypothesis 2b.

Note. See note to Figure H1. r_pp1 = path coefficient for performance-prove item 1; r_pp2 = path coefficient for performance-prove item 2; r_pp3 = path coefficient for performance-prove item 3; perf-pr1 = state performance-prove at time 1; perf-pr2 = state performance-prove at time 2; perf-pr3 = state performance-prove at time 3; perf-pr4 = state performance-prove at time 4.

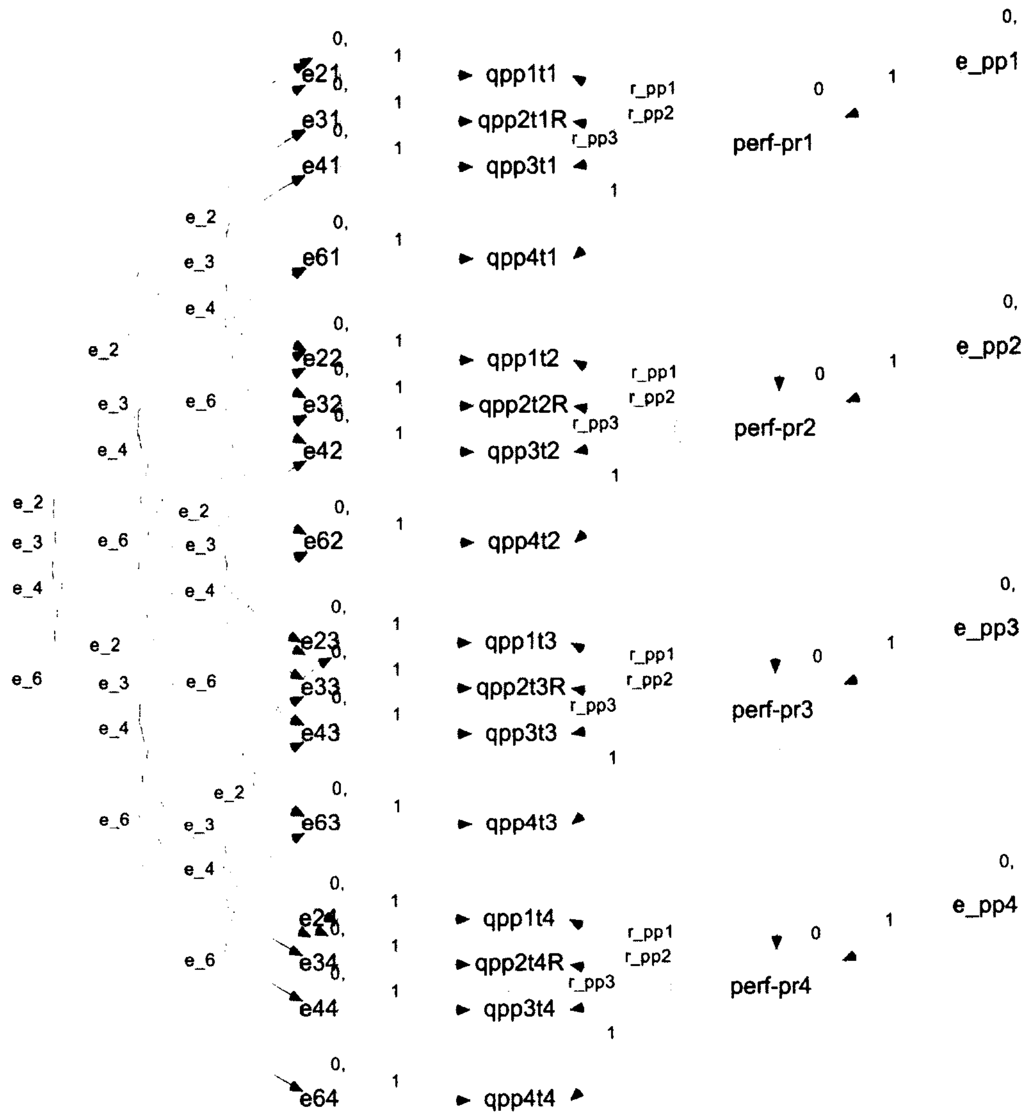

Figure H3. Model 3: State model with first-order autoregressive state factors for Hypothesis 2b.

Note. See note to Figures H1 and H2. e_pp1 = error for latent state performance-prove at time 1; e_pp2 = error for latent state performance-prove at time 2; e_pp3 = error for latent state performance-prove at time 3; e_pp4 = error for latent state performance-prove at time 4.

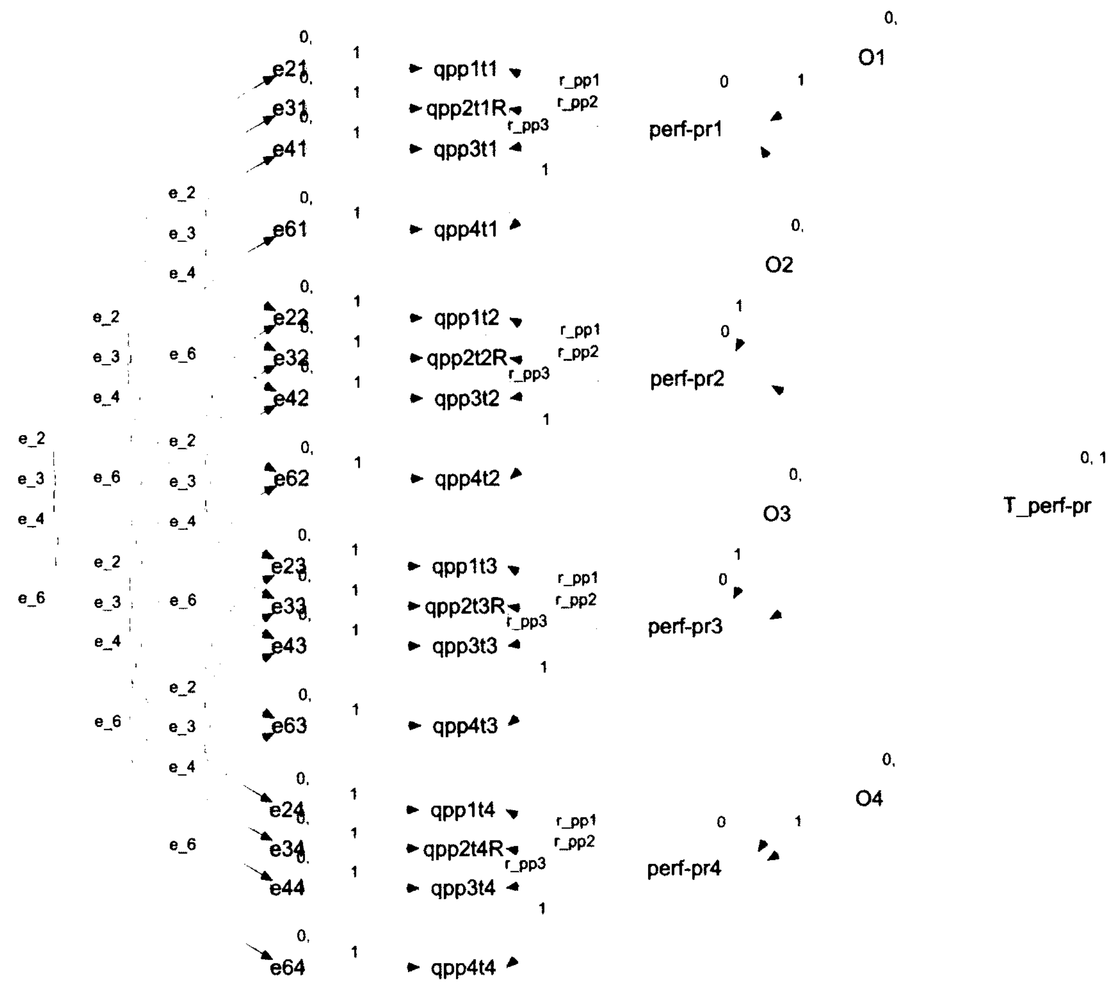

Figure H4. Model 4: LTS model for Hypothesis 2b.

Note. See note to Figures H1 and H2. O1 = latent occasion at time 1; O2 = latent occasion at time 2; O3 = latent occasion at time 3; O4 = latent occasion at time 4.

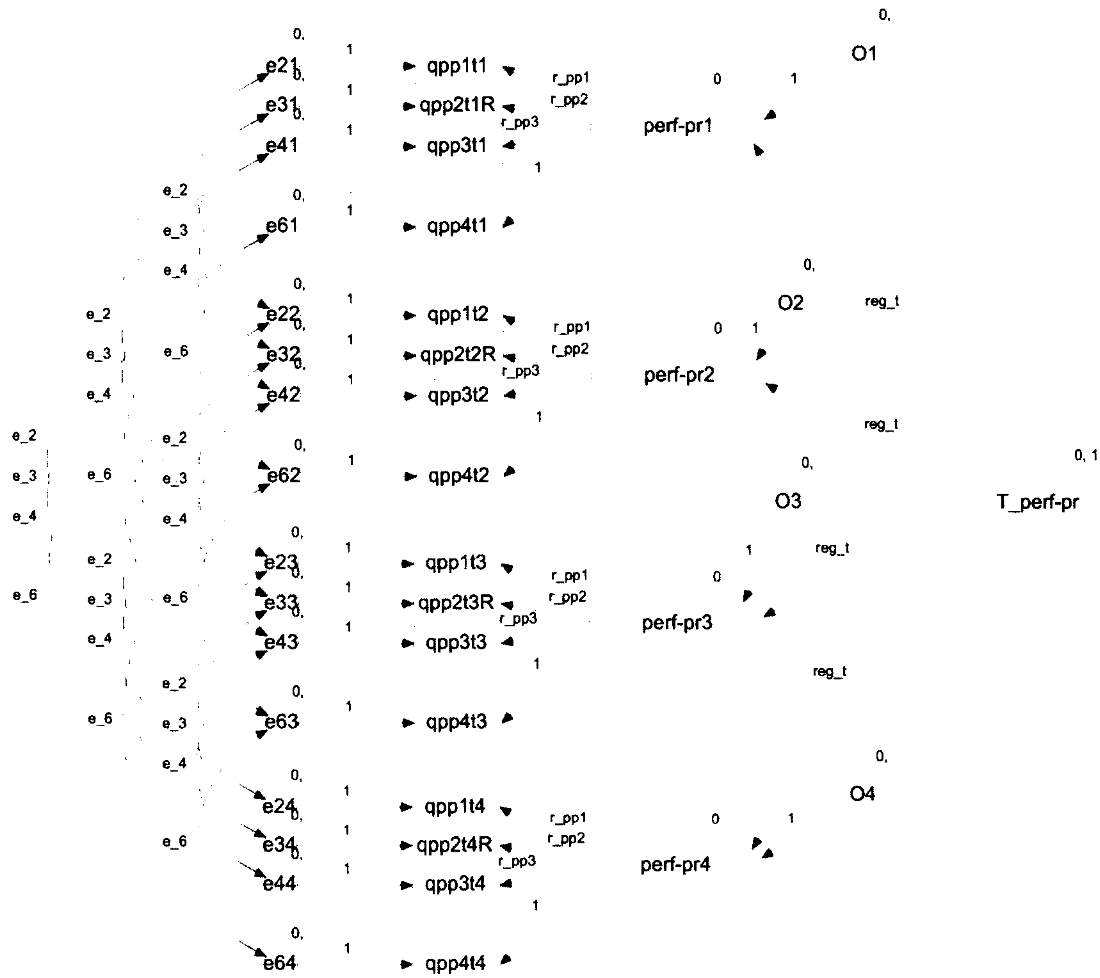

Figure H5. Model 5: LTS model with equality constraints on latent trait factor loadings for Hypothesis 2b.

Note. See note to Figures H1, H2 and H4. reg_t = path coefficient for latent trait.

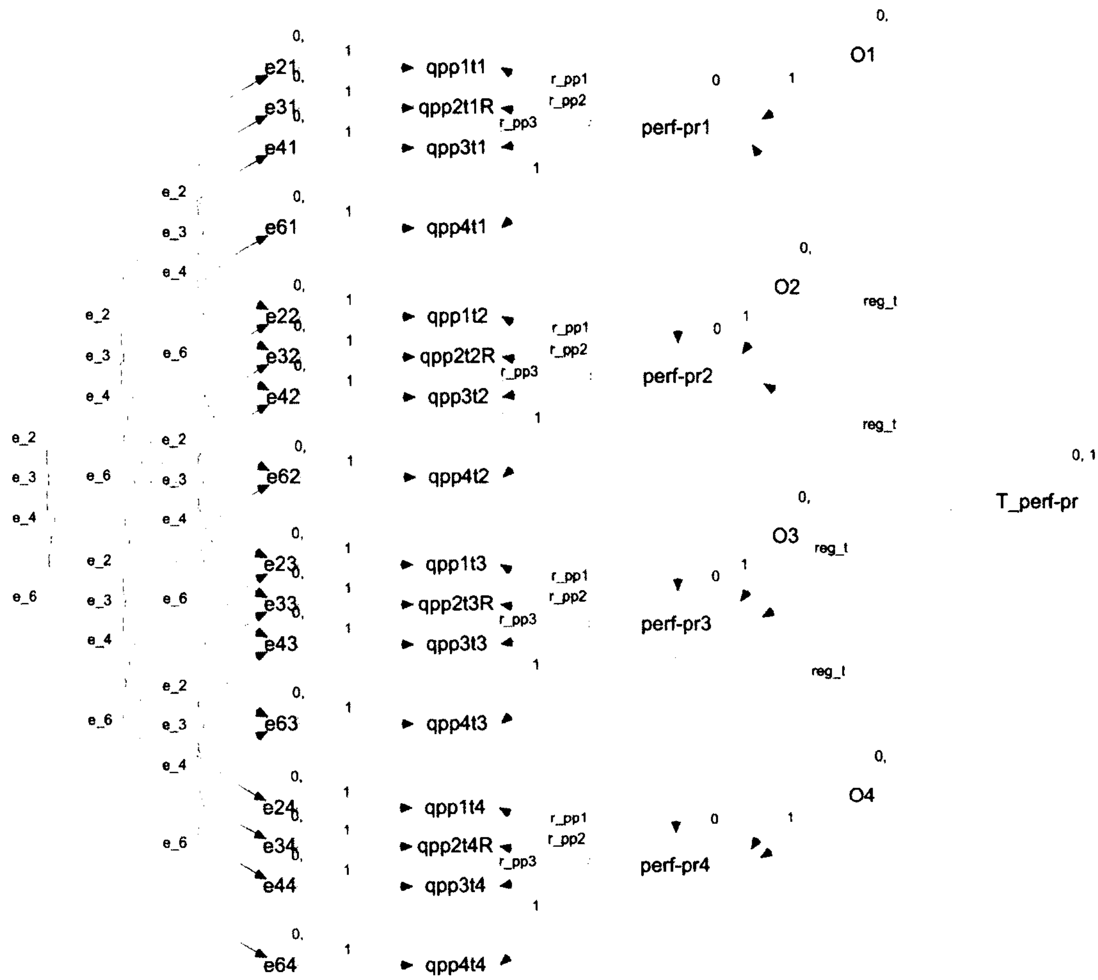

Figure H6. Model 6: LTS model with first-order autoregressive latent state factors for Hypothesis 2b.

Note. See note for Figures H1, H2, H4, and H5.

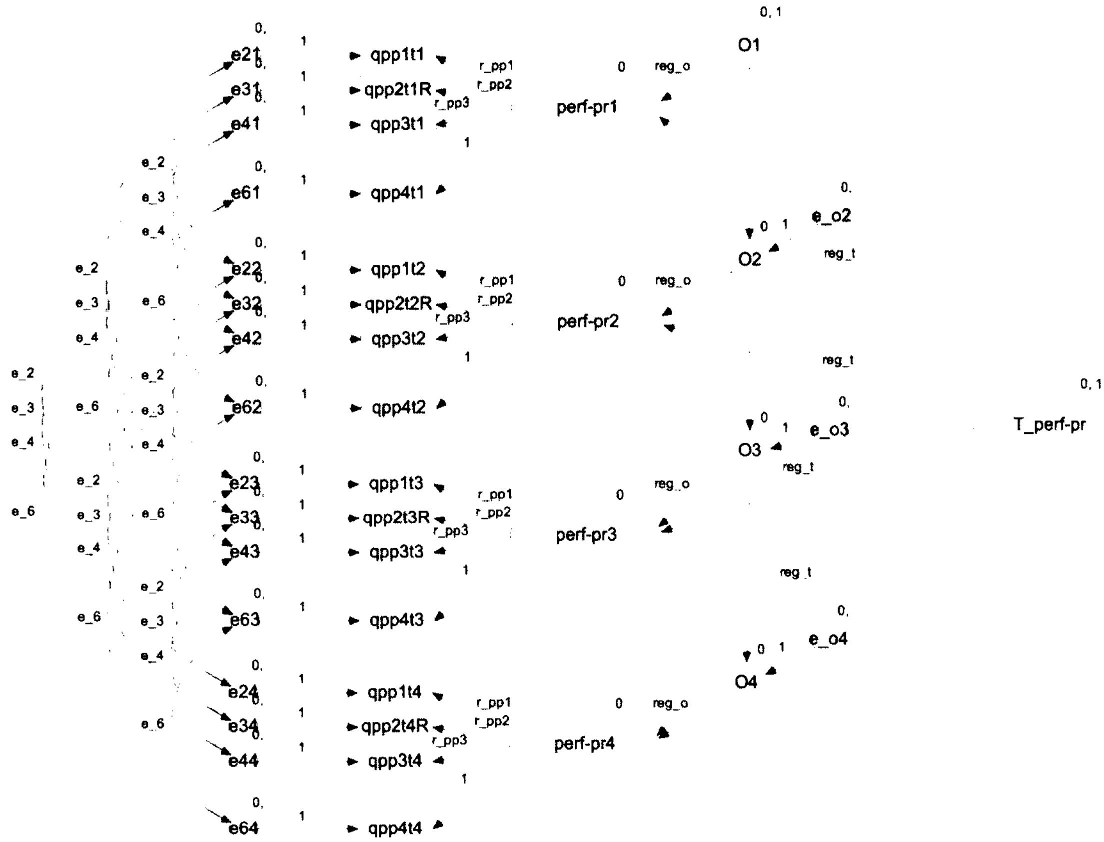

Figure H7. Model 7: LTS model with first-order autoregressive occasion factors for Hypothesis 2b.

Note. See note for Figures H1, H2, H4, and H5. e_o2 = error term for latent occasion at time 2; e_o3 = error term for latent occasion at time 3; e_o4 = error term for latent occasion at time 4.

APPENDIX I

AMOS GRAPHICS MODELS FOR HYPOTHESIS 2c

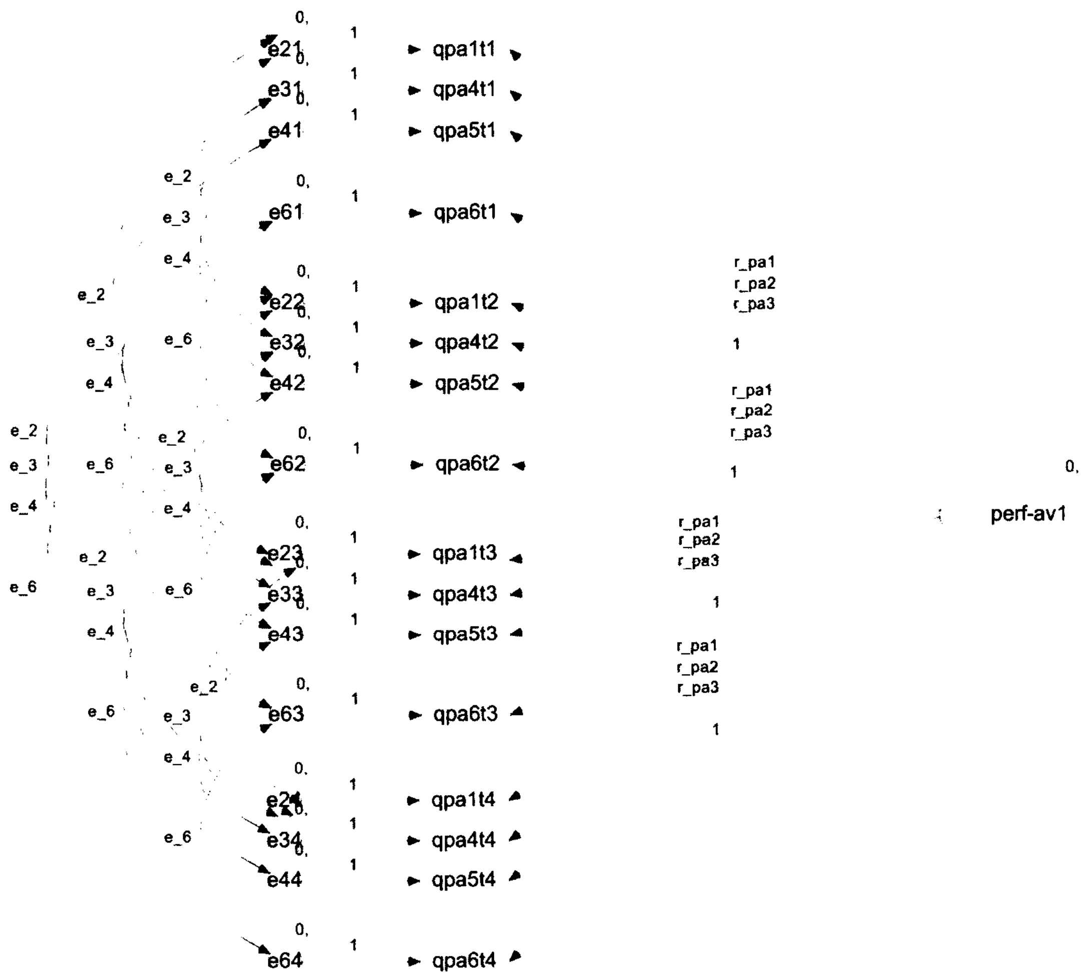

Figure I1. Model 1: Trait model for Hypothesis 2c.

Note. e_2 = error covariance between occasions of measurement for item 1; e_3 = error covariance between occasions of measurement for item 4; e_4 = error covariance between occasions of measurement for item 5; e_6 = error covariance between occasions of measurement for item 6; e21 = error for item 1 at time 1; e31 = error for item 4 at time 1; e41 = error for item 5 at time 1; e61 = error for item 6 at time 1; e22 = error for item 1 at time 2; e32 = error for item 4 at time 2; e42 = error for item 5 at time 2; e62 = error for

item 6 at time 2; e23 = error for item 1 at time 3; e33 = error for item 4 at time 3; e43 = error for item 5 at time 3; e63 = error for item 6 at time 3; e24 = error for item 1 at time 4; e34 = error for item 4 at time 4; e44 = error for item 5 at time 4; e64 = error for item 6 at time 4; qpa1t1 = performance-avoid item 1 at time 1; qpa4t1 = performance-avoid item 4 at time 1; qpa5t1 = performance-avoid item 5 at time 1; qpa6t1 = performance-avoid item 6 at time 1; qpa1t2 = performance-avoid item 1 at time 2; qpa4t2 = performance-avoid item 4 at time 2; qpa5t2 = performance-avoid item 5 at time 2; qpa6t2 = performance-avoid item 6 at time 2; qpa1t3 = performance-avoid item 1 at time 3; qpa4t3 = performance-avoid item 4 at time 3; qpa5t3 = performance-avoid item 5 at time 3; qpa6t3 = performance-avoid item 6 at time 3; qpa1t4 = performance-avoid item 1 at time 4; qpa4t4 = performance-avoid item 4 at time 4; qpa5t4 = performance-avoid item 5 at time 4; qpa6t4 = performance-avoid item 6 at time 4; r_pa1 = path coefficient for performance-avoid item 1; r_pa2 = path coefficient for performance-avoid item 4; r_pa3 = path coefficient for performance-avoid item 5; T_Perf-Av = trait performance-avoid.

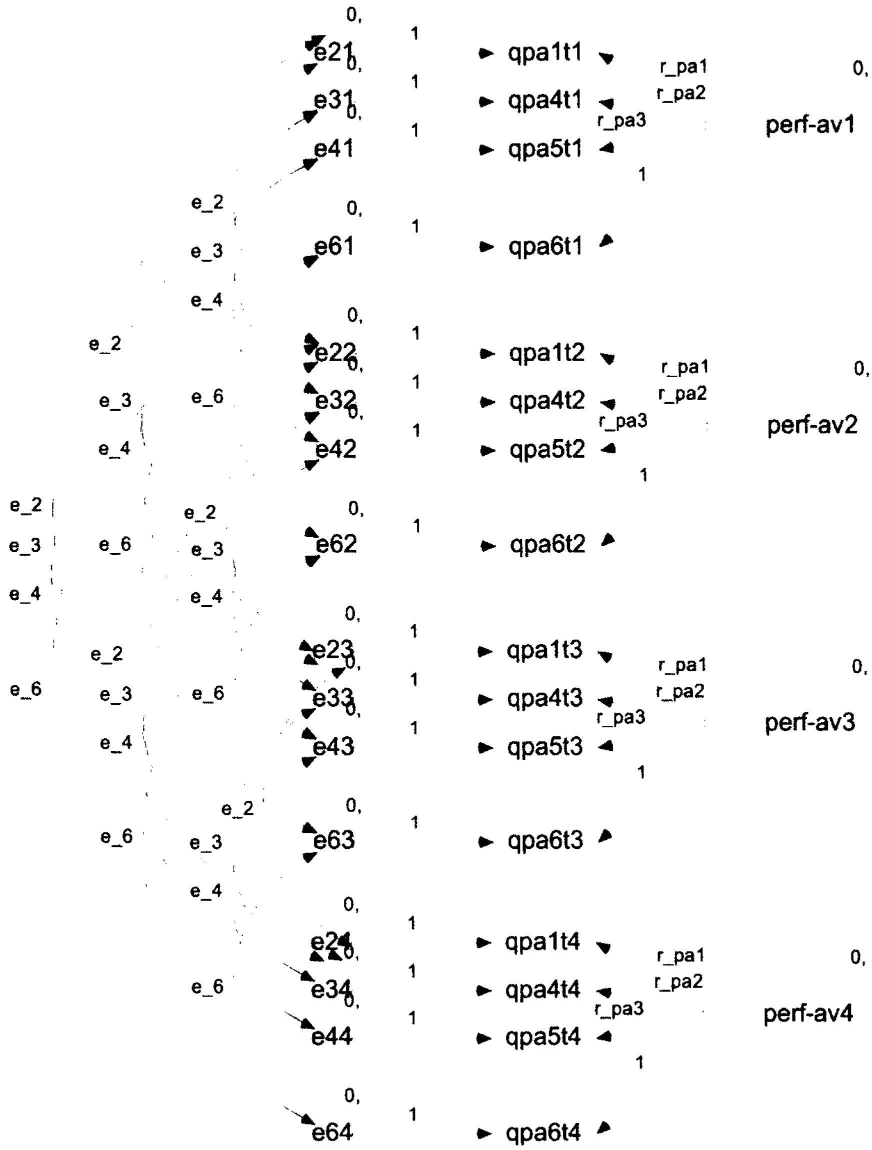

Figure I2. Model 2: State model for Hypothesis 2c.

Note. See note to Figure I1. performance-avoid1 = state performance-avoid at time 1; performance-avoid2 = state performance-avoid at time 2; performance-avoid3 = state performance-avoid at time 3; performance-avoid4 = state performance-avoid at time 4.

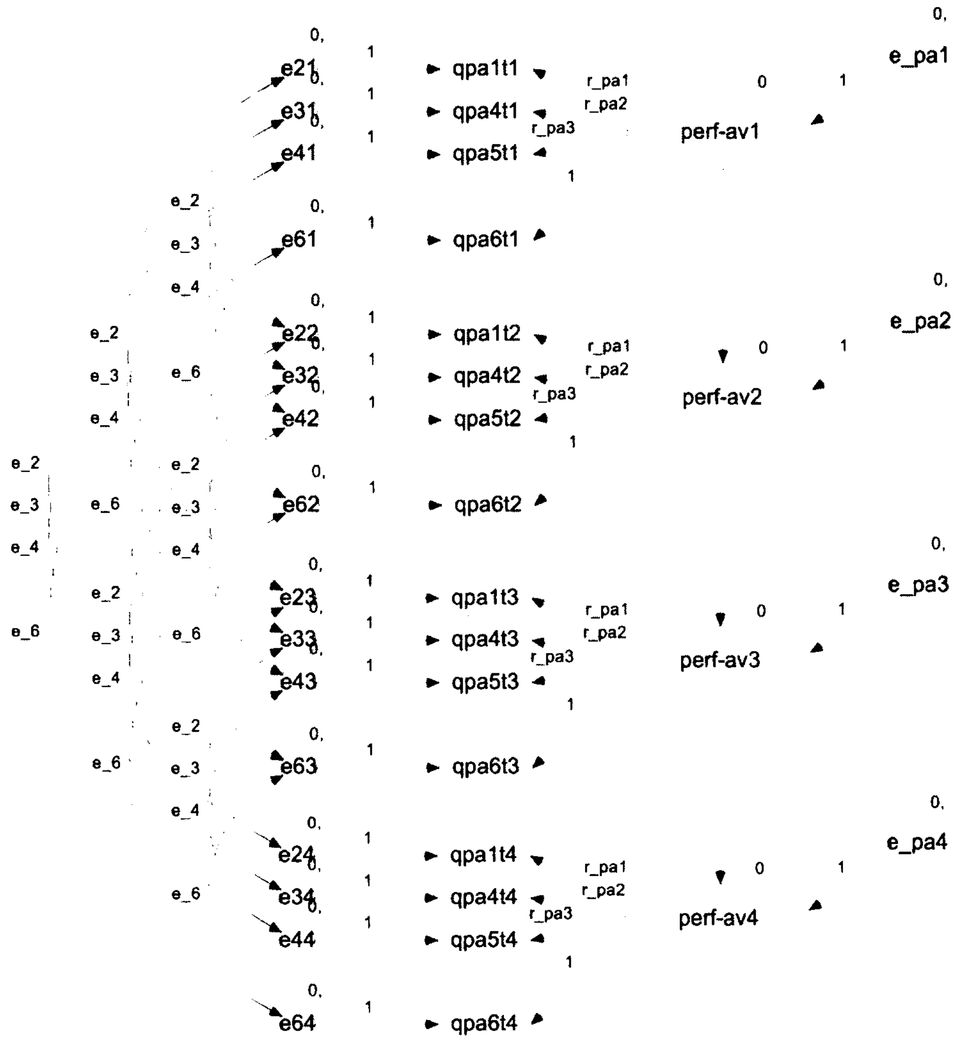

Figure I3. Model 3: State model with first-order autoregressive state factors for Hypothesis 2c.

Note. See note to Figures I1 and I2. e_l1 = error for latent state performance-avoid at time 1; e_l2 = error for latent state performance-avoid at time 2; e_l3 = error for latent state performance-avoid at time 3; e_l4 = error for latent state performance-avoid at time 4.

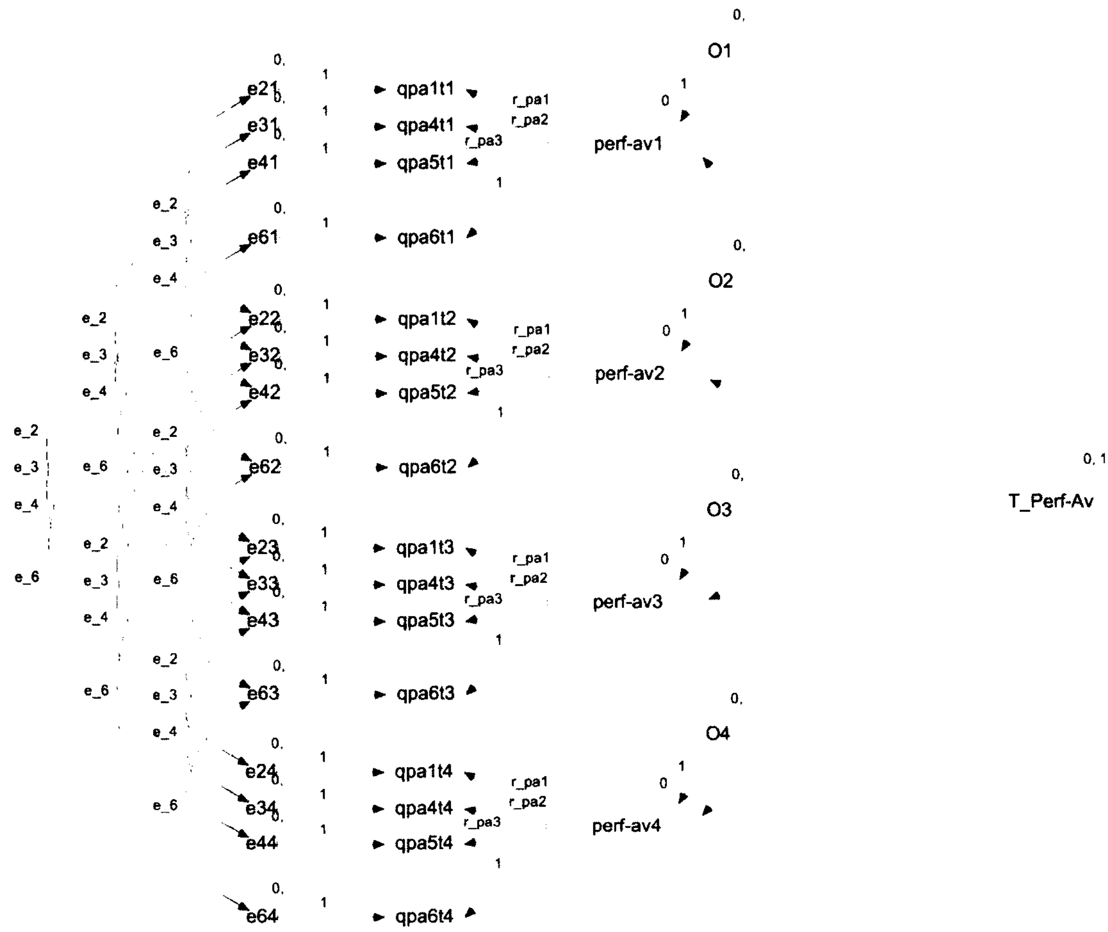

Figure I4. Model 4: LTS model for Hypothesis 2c.

Note. See note to Figures I1 and I2. O1 = latent occasion at time 1; O2 = latent occasion at time 2; O3 = latent occasion at time 3; O4 = latent occasion at time 4.

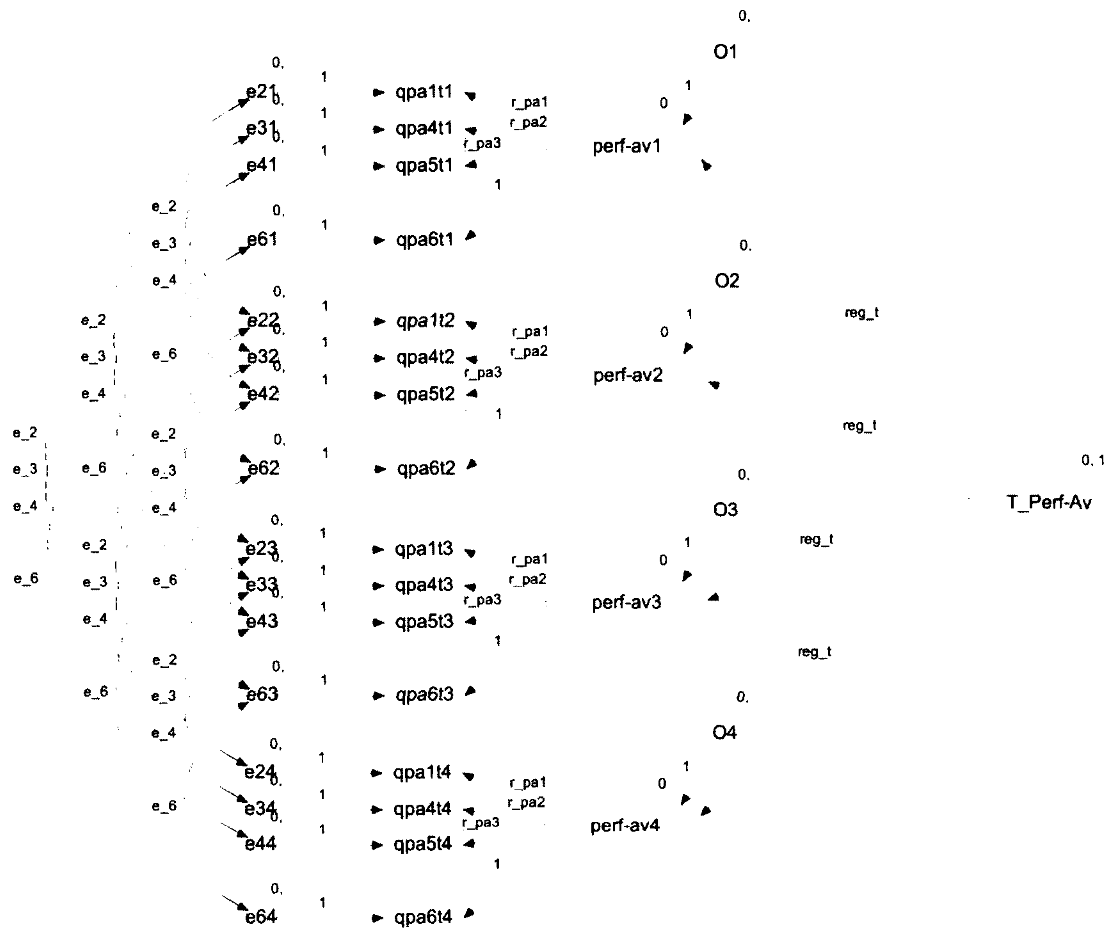

Figure I5. Model 5: LTS model with equality constraints on latent trait factor loadings for Hypothesis 2c.

Note. See note to Figures I1 and I2. reg_t = path coefficient for latent trait.

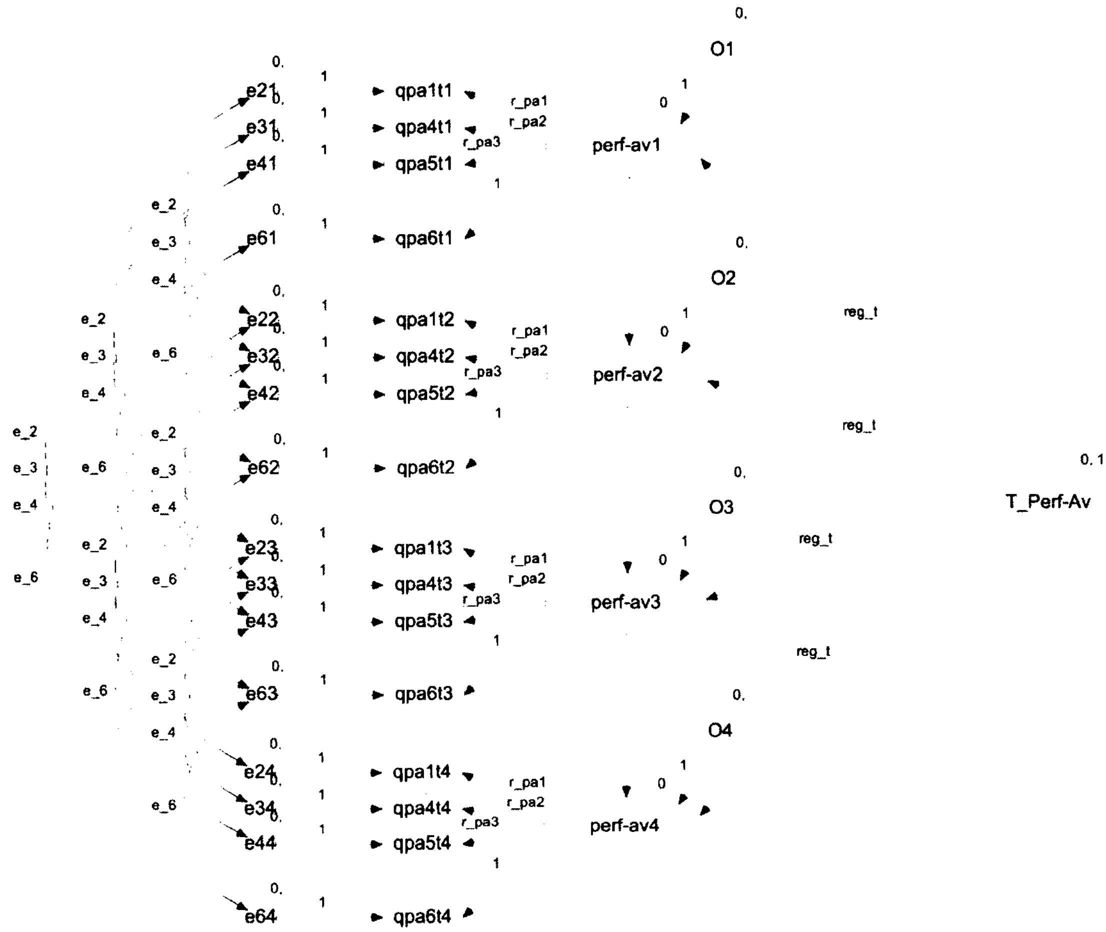

Figure I6. Model 6: LTS model with first-order autoregressive latent state factors for Hypothesis 2c.

Note. See note for Figures I1, I2, I4, and I5.

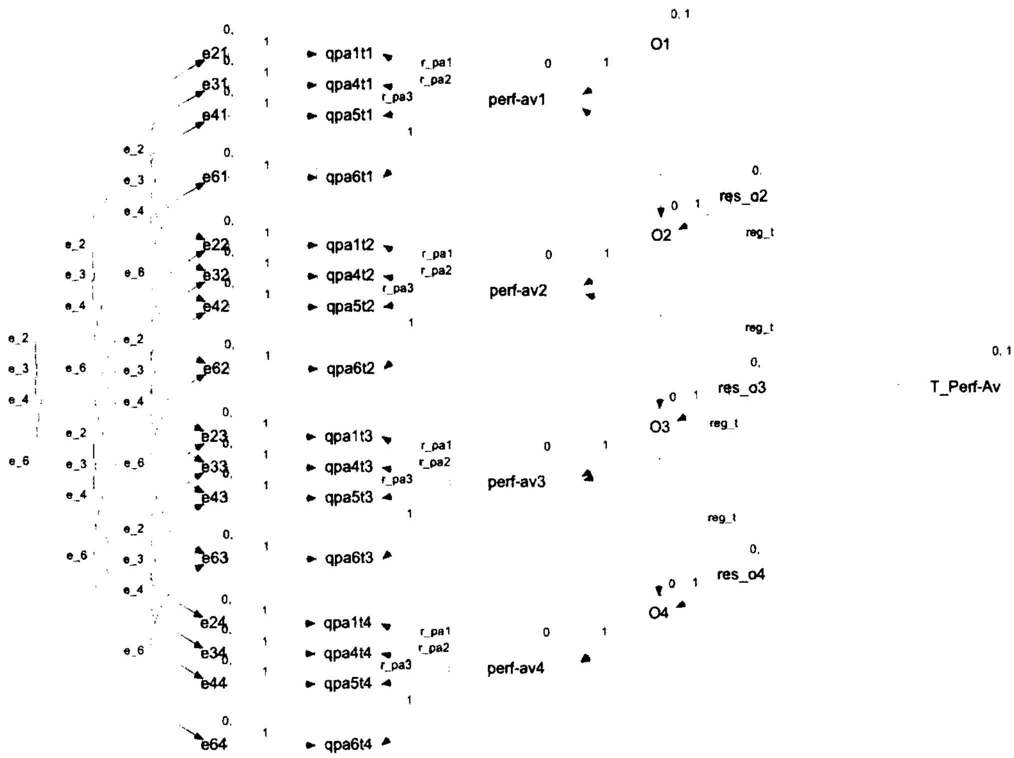

Figure I7. Model 7: LTS model with first-order autoregressive occasion factors for Hypothesis 2c.

Note. See note for Figures I1, I2, I4, and I5. e_o2 = error term for latent occasion at time 2; e_o3 = error term for latent occasion at time 3; e_o4 = error term for latent occasion at time 4.

APPENDIX J

AMOS GRAPHICS MODELS FOR HYPOTHESIS 3a

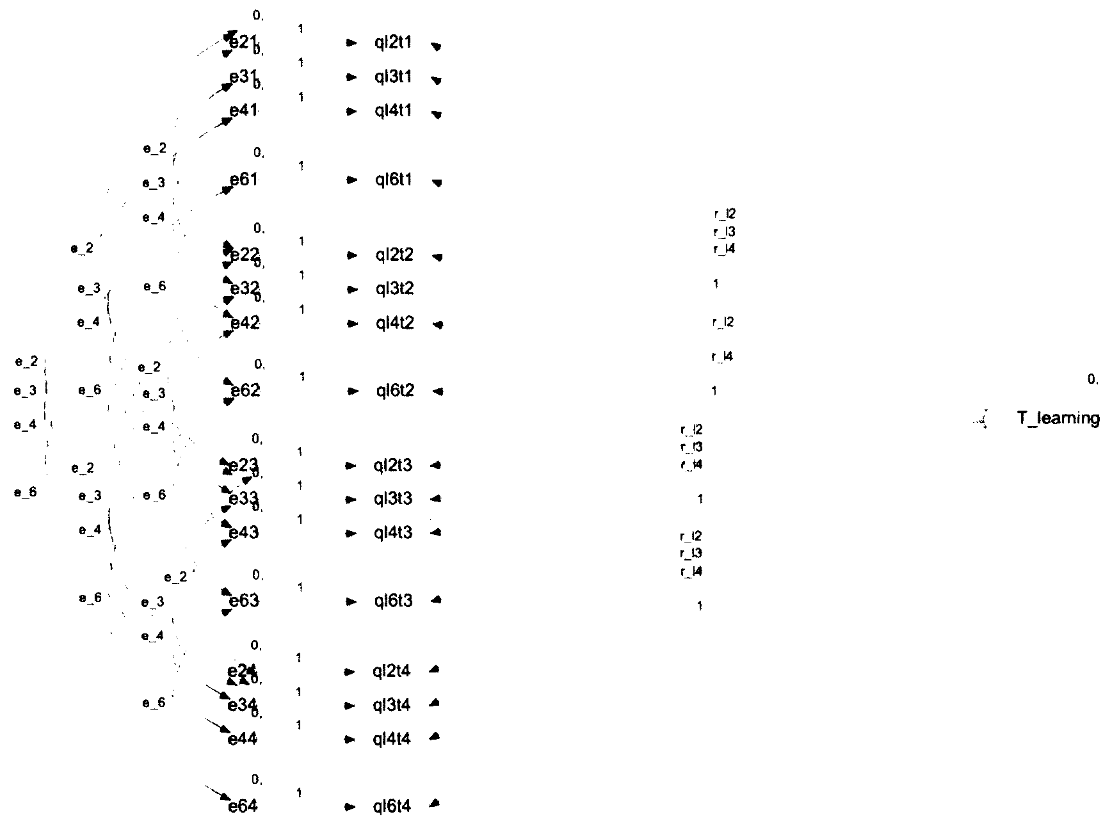

Figure J1. Model 1: Trait model for Hypothesis 3a.

Note. e_2 = error covariance between occasions of measurement for item 2; e_3 = error covariance between occasions of measurement for item 3; e_4 = error covariance between occasions of measurement for item 4; e_6 = error covariance between occasions of measurement for item 6; e21 = error for item 2 at time 1; e31 = error for item 3 at time 1; e41 = error for item 4 at time 1; e61 = error for item 6 at time 1; e22 = error for item 2 at time 2; e32 = error for item 3 at time 2; e42 = error for item 4 at time 2; e62 = error for item 6 at time 2; e23 = error for item 2 at time 3; e33 = error for item 3 at time 3; e43 = error for item 4 at time 3; e63 = error for item 6 at time 3; e24 = error for item 2 at time 4; e34 = error for item 3 at time 4; e44 = error for item 4 at time 4; e64 = error for item 6

at time 4; ql2t1 = learning item 2 at time 1; ql3t1 = learning item 3 at time 1; ql4t1 = learning item 4 at time 1; ql6t1 = learning item 6 at time 1; ql2t2 = learning item 2 at time 2; ql3t2 = learning item 3 at time 2; ql4t2 = learning item 4 at time 2; ql6t2 = learning item 6 at time 2; ql2t3 = learning item 2 at time 3; ql3t3 = learning item 3 at time 3; ql4t3 = learning item 4 at time 3; ql6t3 = learning item 6 at time 3; ql2t4 = learning item 2 at time 4; ql3t4 = learning item 3 at time 4; ql4t4 = learning item 4 at time 4; ql6t4 = learning item 6 at time 4; r_l2 = path coefficient for learning item 2; r_l3 = path coefficient for learning item 3; r_l4 = path coefficient for learning item 4; T_learning = trait learning.

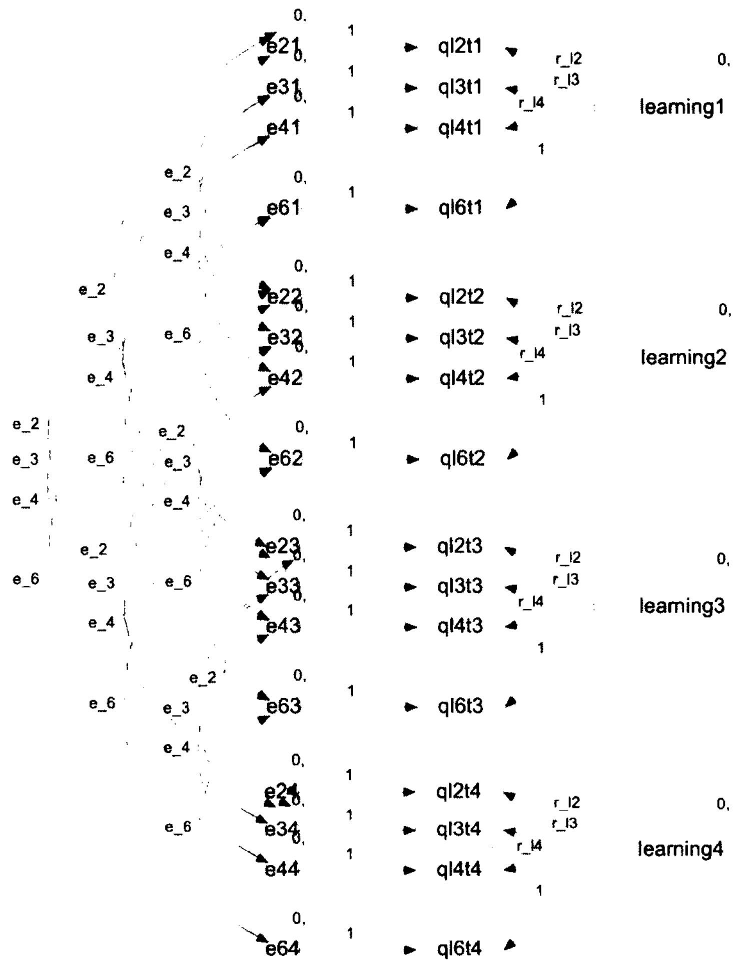

Figure J2. Model 2: State model for Hypothesis 3a.

Note. See note to Figure J1. learning1 = state learning at time 1; learning2 = state learning at time 2; learning3 = state learning at time 3; learning4 = state learning at time 4.

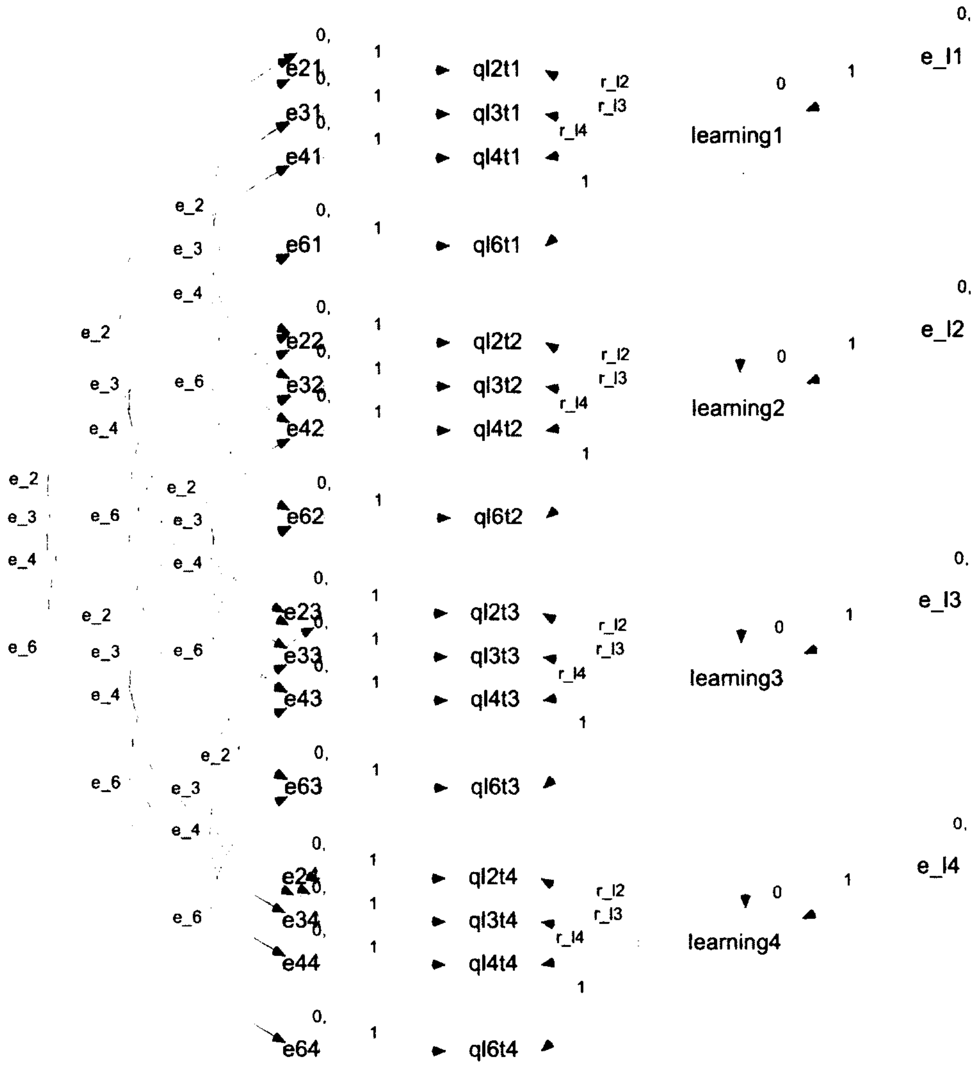

Figure J3. Model 3: State model with first-order autoregressive state factors for Hypothesis 3a.

Note. See note to Figures J1 and J2. e_l1 = error for latent state learning at time 1; e_l2 = error for latent state learning at time 2; e_l3 = error for latent state learning at time 3; e_l4 = error for latent state learning at time 4.

Figure J4. Model 4: LTS model for Hypothesis 3a.

Note. See note to Figures J1 and J2. O1 = latent occasion at time 1; O2 = latent occasion at time 2; O3 = latent occasion at time 3; O4 = latent occasion at time 4.

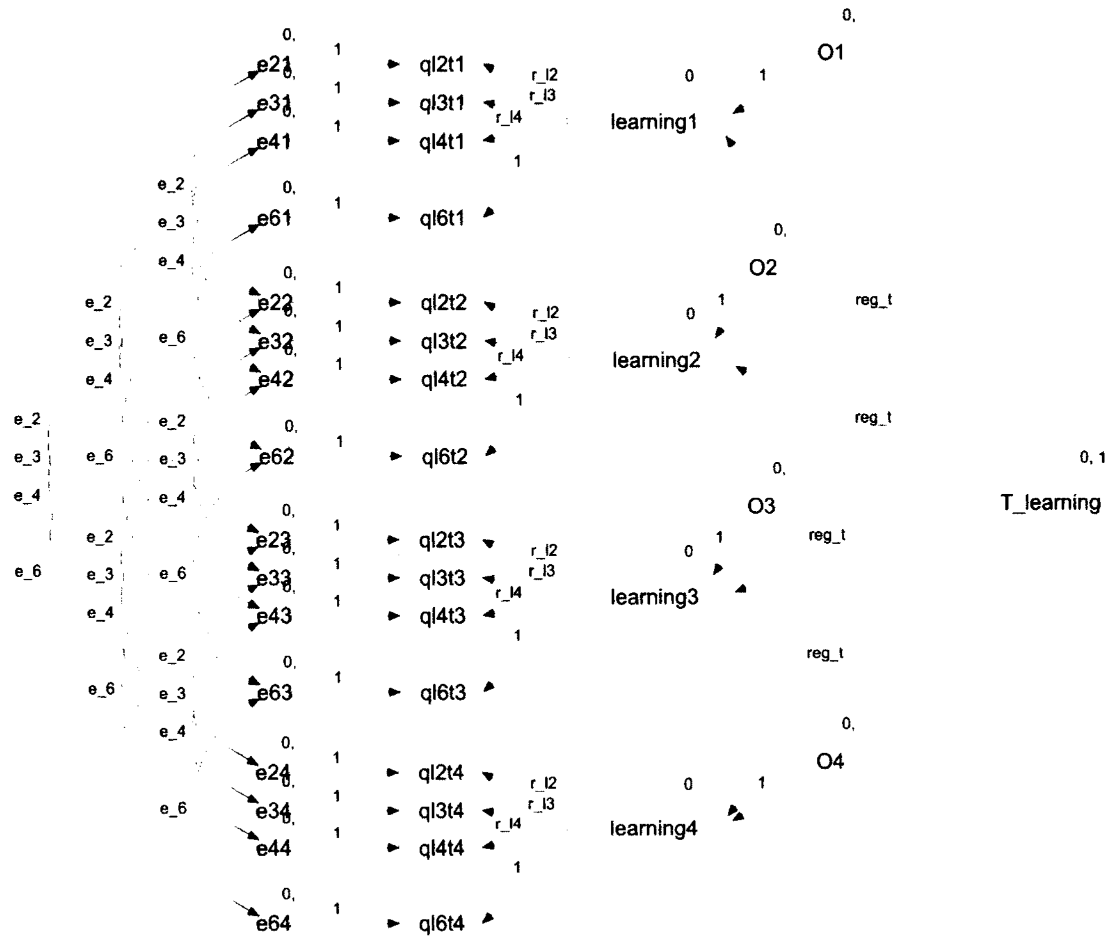

Figure J5. Model 5: LTS model with equality constraints on latent trait factor loadings for Hypothesis 3a.

Note. See note to Figures J1, J2 and J4. reg_t = path coefficient for latent trait.

Figure J6. Model 6: LTS model with first-order autoregressive latent state factors for Hypothesis 3a.

Note. See note for Figures J1, J2, J4, and J5.

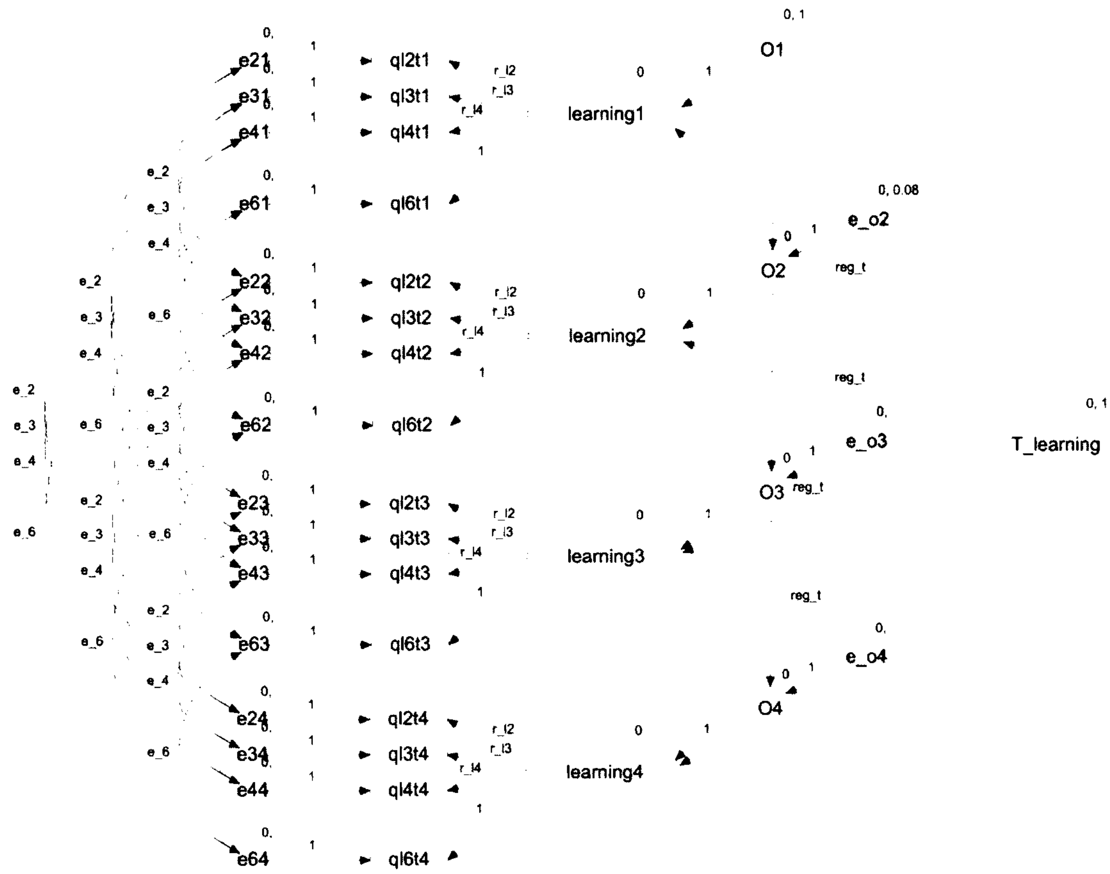

Figure J7. Model 7: LTS model with first-order autoregressive occasion factors for Hypothesis 3a.

Note. See note for Figures J1, J2, J4, and J5. e_o2 = error term for latent occasion at time 2; e_o3 = error term for latent occasion at time 3; e_o4 = error term for latent occasion at time 4.

APPENDIX K

AMOS GRAPHICS MODELS FOR HYPOTHESIS 3b

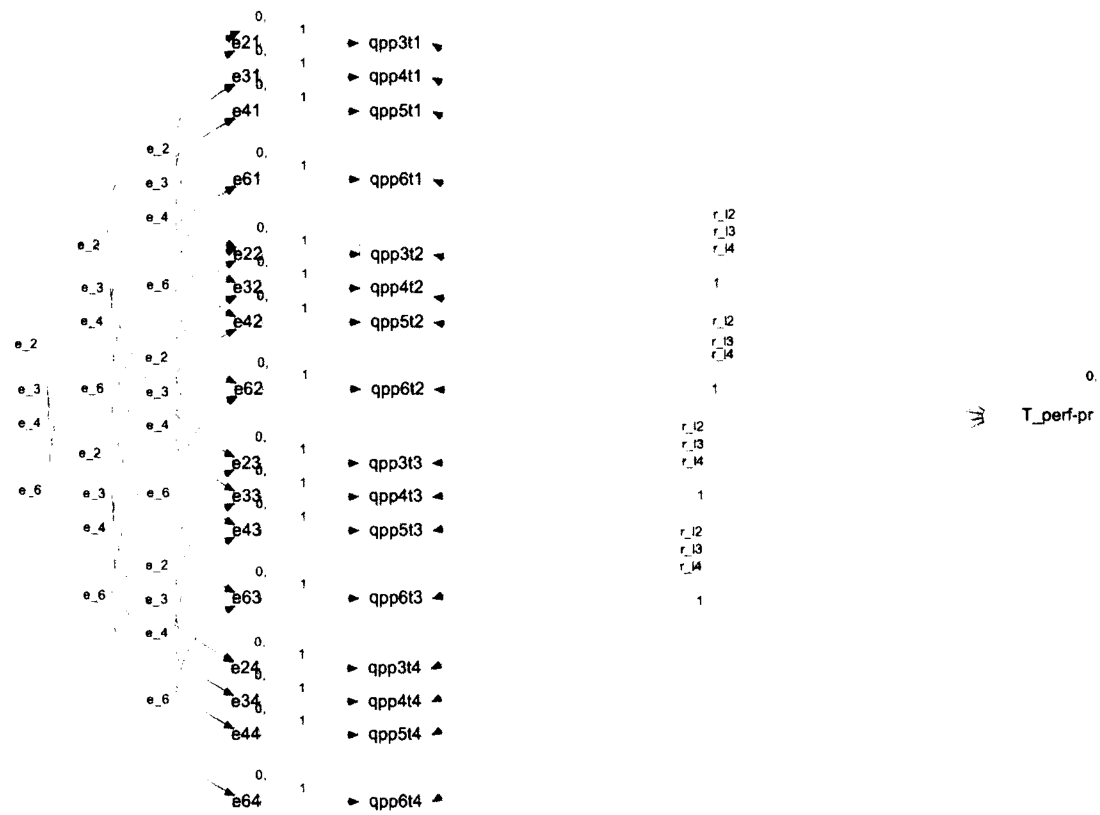

Figure K1. Model 1: Trait model for Hypothesis 3b.

Note. e_2 = error covariance between occasions of measurement for item 3; e_3 = error covariance between occasions of measurement for item 4; e_4 = error covariance between occasions of measurement for item 5; e_6 = error covariance between occasions of measurement for item 6; e21 = error for item 3 at time 1; e31 = error for item 4 at time 1; e41 = error for item 5 at time 1; e61 = error for item 6 at time 1; e22 = error for item 3 at time 2; e32 = error for item 4 at time 2; e42 = error for item 5 at time 2; e62 = error for item 6 at time 2; e23 = error for item 3 at time 3; e33 = error for item 4 at time 3; e43 = error for item 5 at time 3; e63 = error for item 6 at time 3; e24 = error for item 3 at time 4; e34 = error for item 4 at time 4; e44 = error for item 5 at time 4; e64 = error for item 6

at time 4; qpp3t1 = performance-prove item 3 at time 1; qpp4t1 = performance-prove item 4 at time 1; qpp5t1 = performance-prove item 5 at time 1; qpp6t1 = performance-prove item 6 at time 1; qpp3t2 = performance-prove item 3 at time 2; qpp4t2 = performance-prove item 4 at time 2; qpp5t2 = performance-prove item 5 at time 2; qpp6t2 = performance-prove item 6 at time 2; qpp3t3 = performance-prove item 3 at time 3; qpp4t3 = performance-prove item 4 at time 3; qpp5t3 = performance-prove item 5 at time 3; qpp6t3 = performance-prove item 6 at time 3; qpp3t4 = performance-prove item 3 at time 4; qpp4t4 = performance-prove item 4 at time 4; qpp5t4 = performance-prove item 5 at time 4; qpp6t4 = performance-prove item 6 at time 4; r_l2 = path coefficient for performance-prove item 3; r_l3 = path coefficient for performance-prove item 4; r_l4 = path coefficient for performance-prove item 5; T_perf-pr = trait performance-prove.

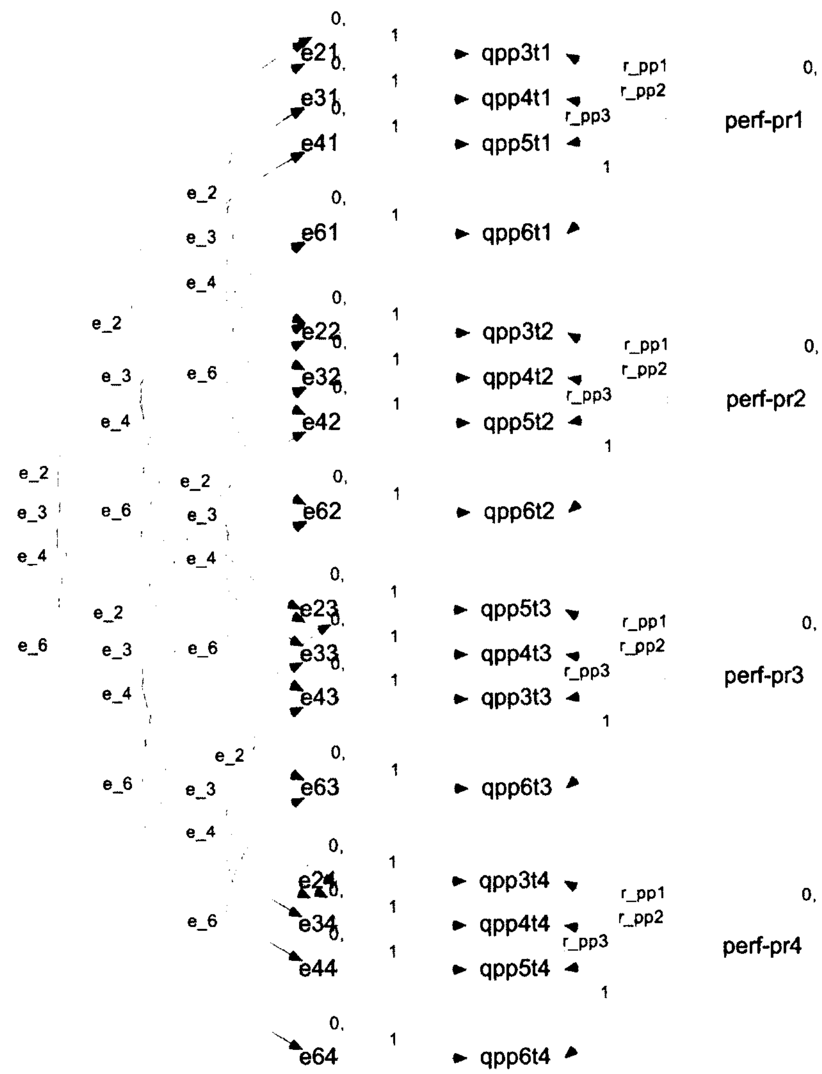

Figure K2. Model 2: State model for Hypothesis 3b.

Note. See note to Figure K1. r_pp1 = path coefficient for performance-prove item 3; r_pp2 = path coefficient for performance-prove item 4; r_pp3 = path coefficient for performance-prove item 5; perf-pr1 = state performance-prove at time 1; perf-pr2 = state performance-prove at time 2; perf-pr3 = state performance-prove at time 3; perf-pr4 = state performance-prove at time 4.

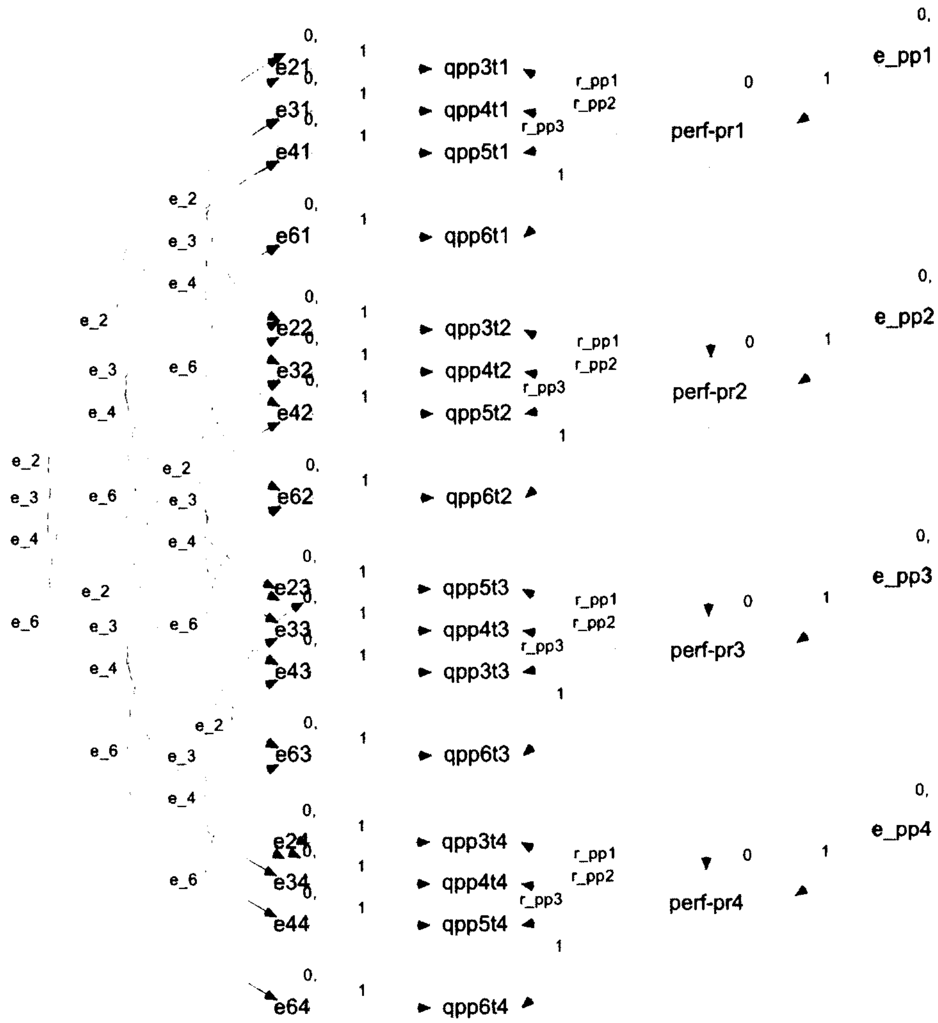

Figure K3. Model 3: State model with first-order autoregressive state factors for Hypothesis 3b.

Note. See note to Figures K1 and K2. e_pp1 = error for latent state performance-prove at time 1; e_pp2 = error for latent state performance-prove at time 2; e_pp3 = error for latent state performance-prove at time 3; e_pp4 = error for latent state performance-prove at time 4.

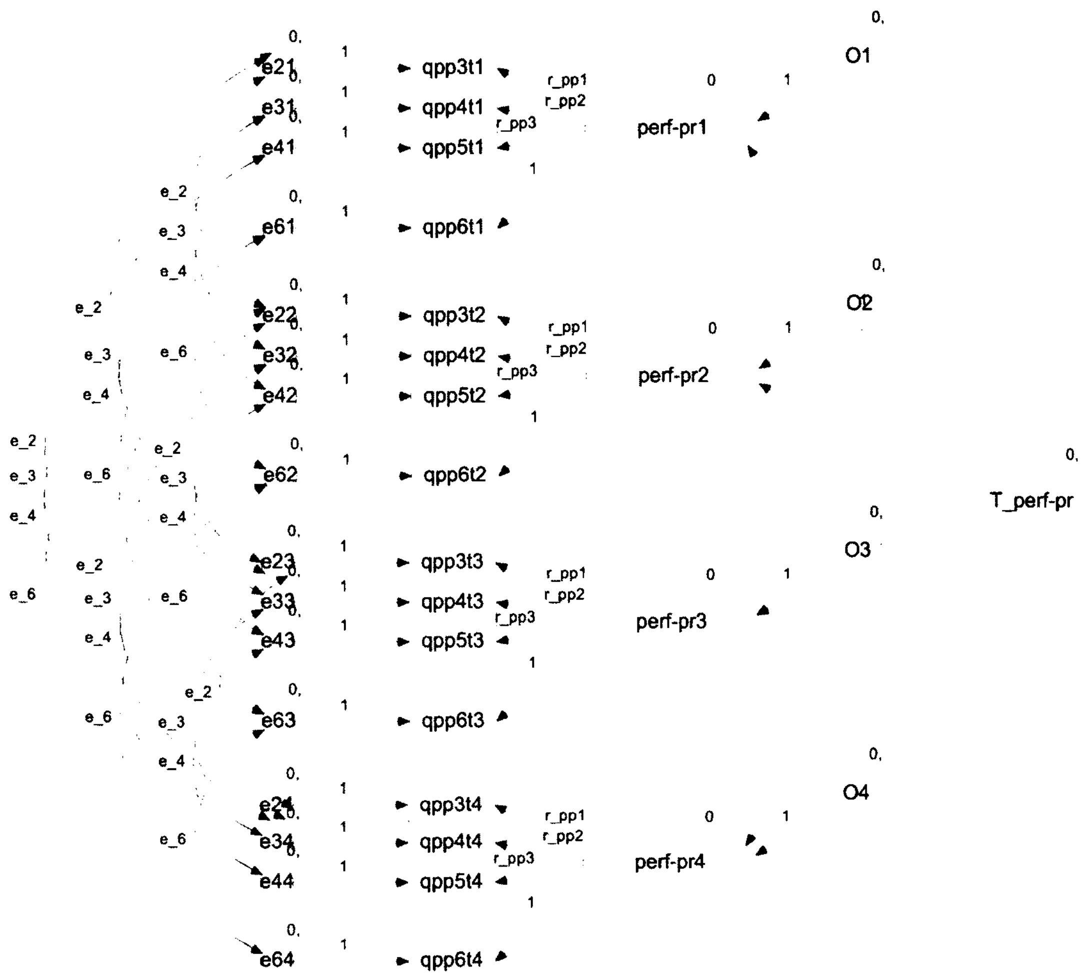

Figure K4. Model 4: LTS model for Hypothesis 3b.

Note. See note to Figures K1 and K2. O1 = latent occasion at time 1; O2 = latent occasion at time 2; O3 = latent occasion at time 3; O4 = latent occasion at time 4.

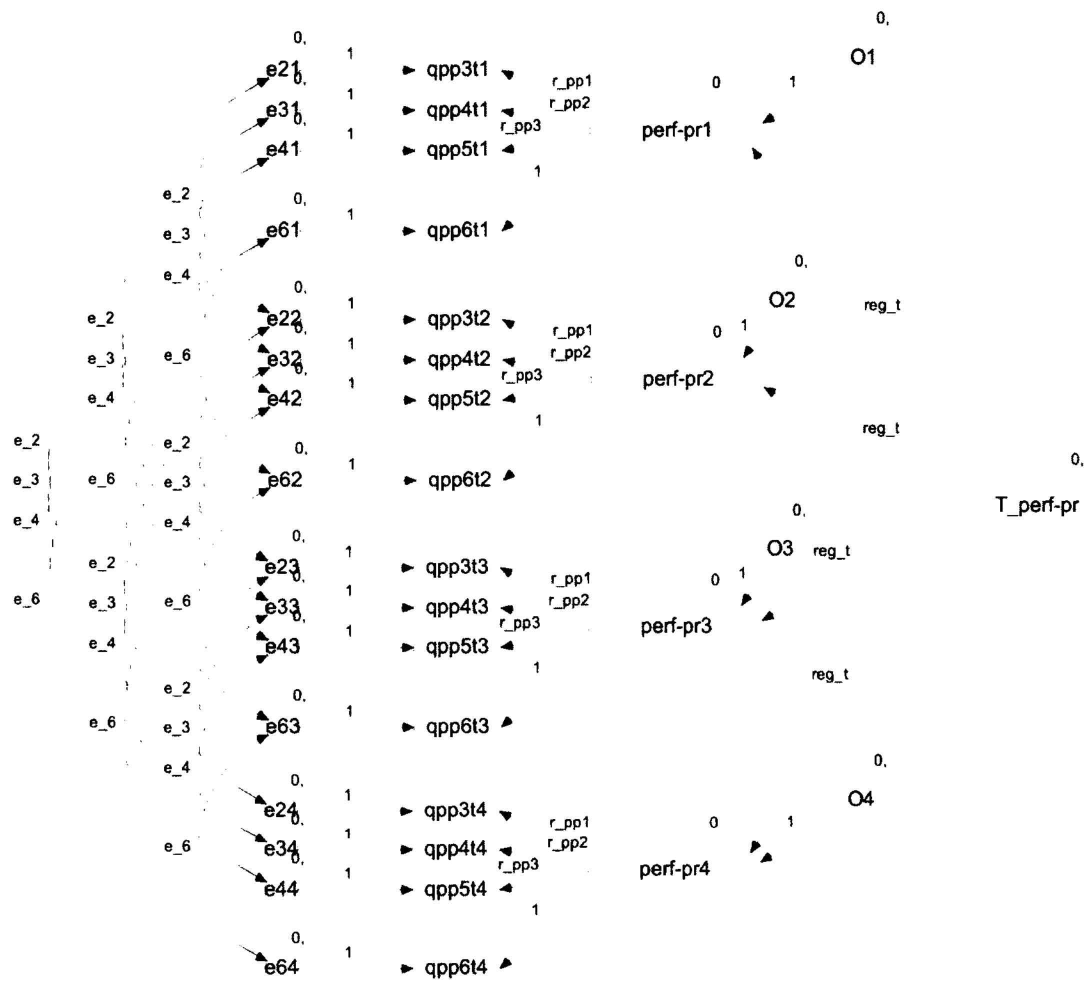

Figure K5. Model 5: LTS model with equality constraints on latent trait factor loadings for Hypothesis 3b.

Note. See note to Figures K1, K2 and K4. reg_t = path coefficient for latent trait.

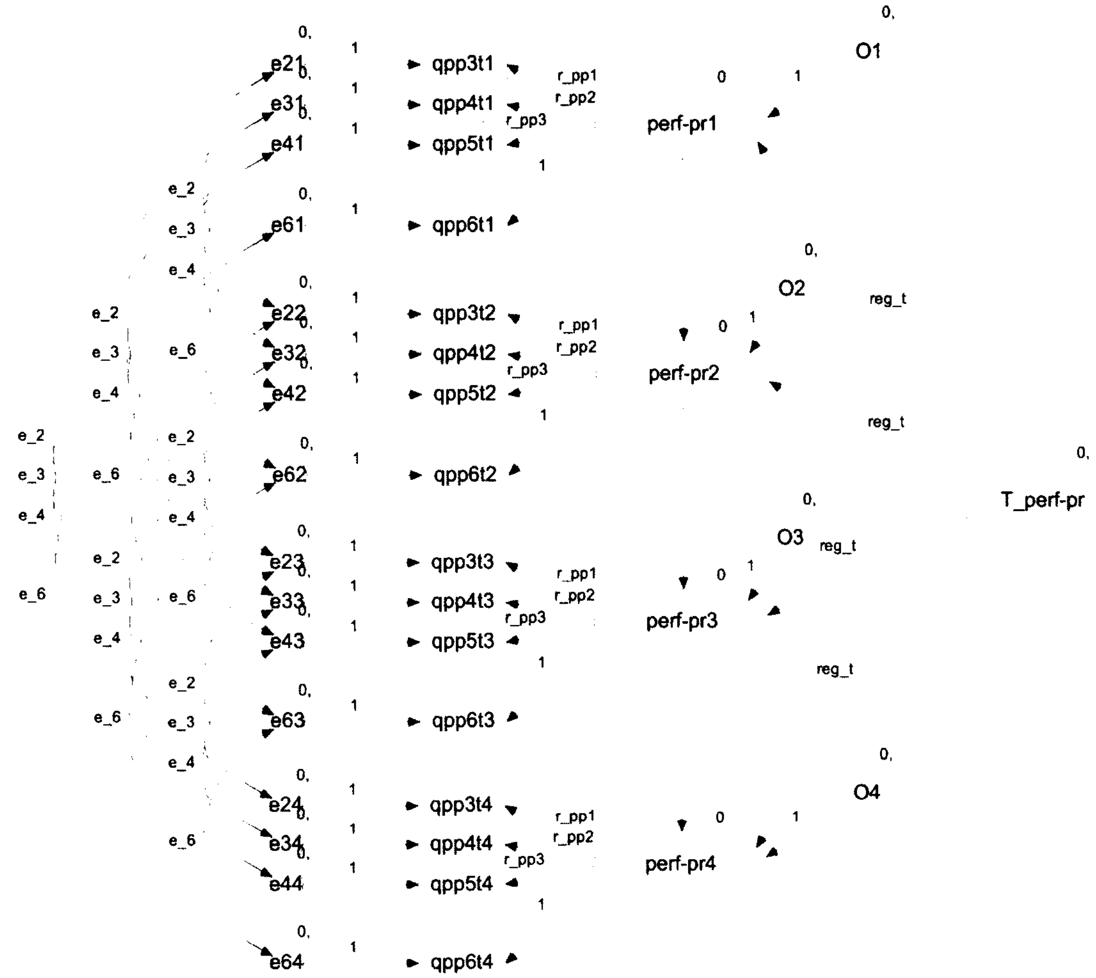

Figure K6. Model 6: LTS model with first-order autoregressive latent state factors for Hypothesis 3b.

Note. See note for Figures K1, K2, K4, and K5.

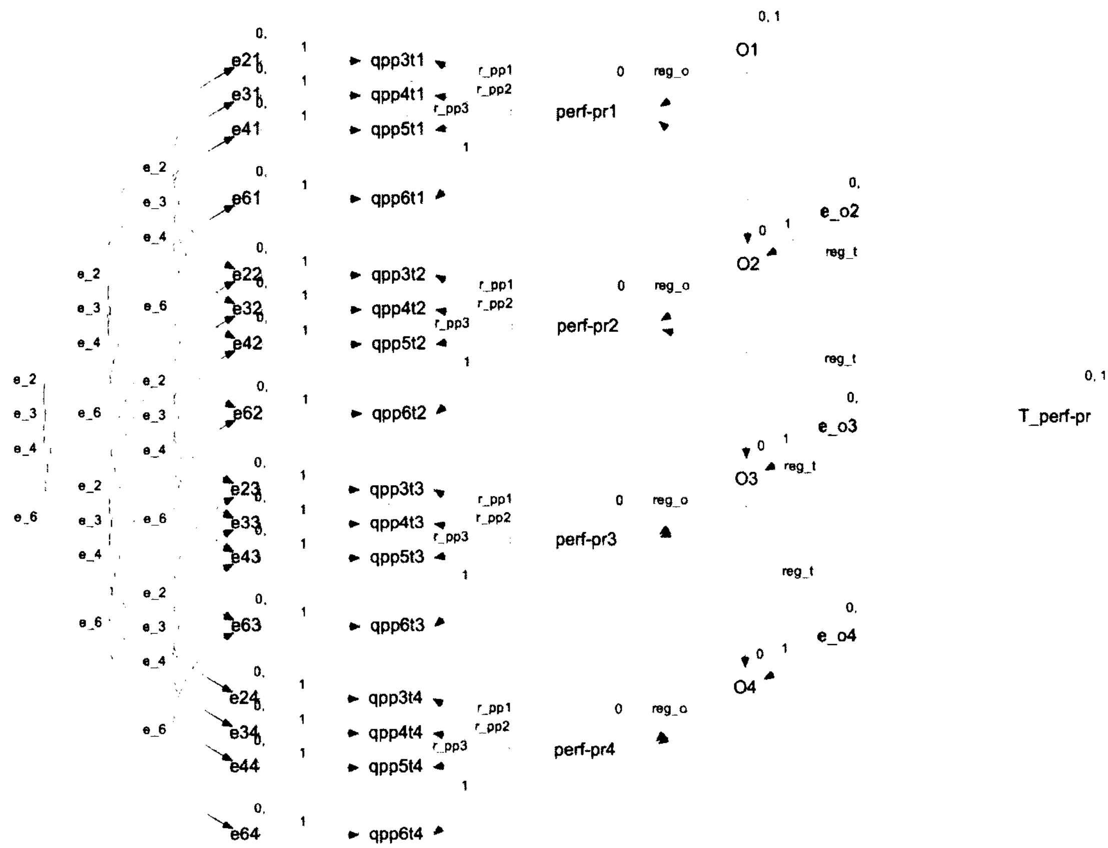

Figure K7. Model 7: LTS model with first-order autoregressive occasion factors for Hypothesis 3b.

Note. See note for Figures K1, K2, K4, and K5. e_o2 = error term for latent occasion at time 2; e_o3 = error term for latent occasion at time 3; e_o4 = error term for latent occasion at time 4.

APPENDIX L

AMOS GRAPHICS MODELS FOR HYPOTHESIS 3c

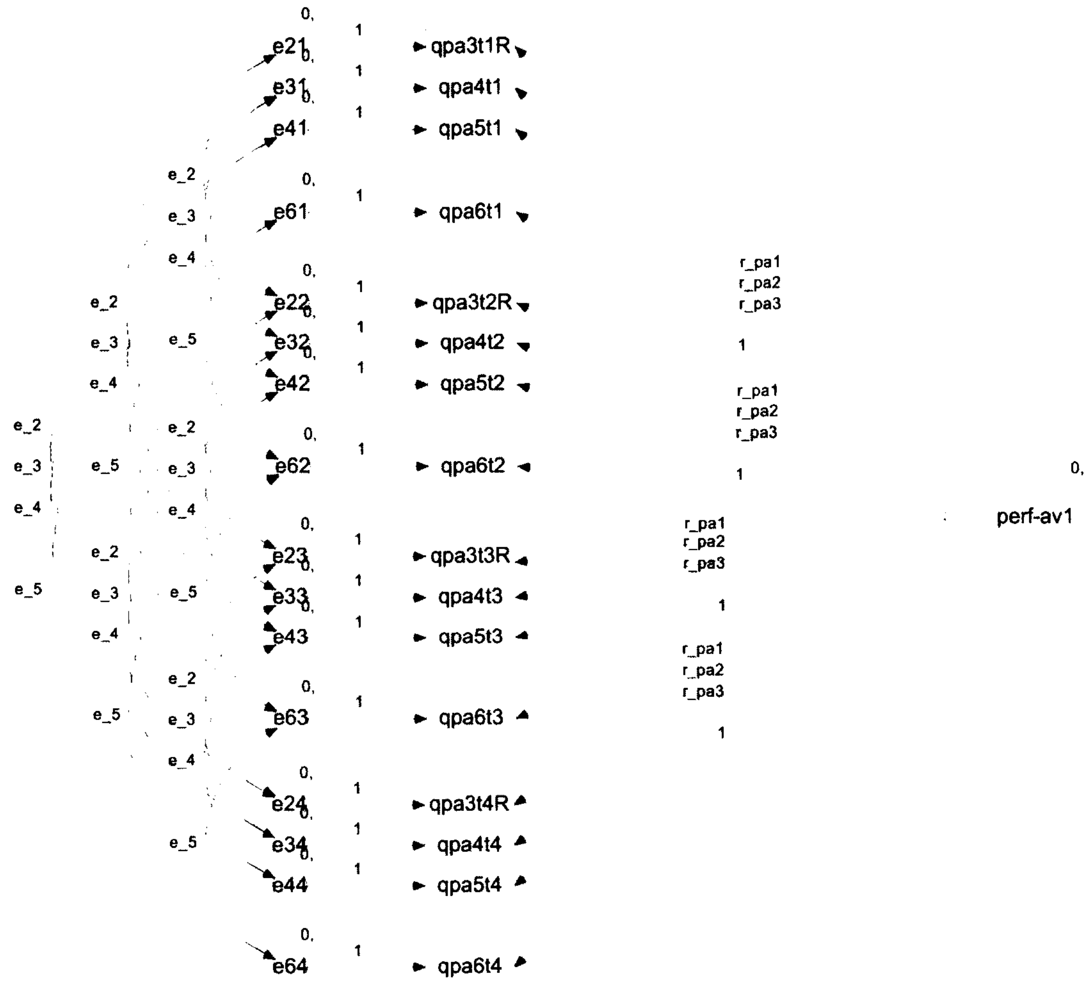

Figure L1. Model 1: Trait model for Hypothesis 3c.

Note. e_2 = error covariance between occasions of measurement for item 1; e_3 = error covariance between occasions of measurement for item 4; e_4 = error covariance between occasions of measurement for item 5; e_6 = error covariance between occasions of measurement for item 6; e21 = error for item 1 at time 1; e31 = error for item 4 at time 1; e41 = error for item 5 at time 1; e61 = error for item 6 at time 1; e22 = error for item 1 at time 2; e32 = error for item 4 at time 2; e42 = error for item 5 at time 2; e62 = error for

item 6 at time 2; e23 = error for item 1 at time 3; e33 = error for item 4 at time 3; e43 = error for item 5 at time 3; e63 = error for item 6 at time 3; e24 = error for item 1 at time 4; e34 = error for item 4 at time 4; e44 = error for item 5 at time 4; e64 = error for item 6 at time 4; qpa1t1R = performance-avoid item 1 (reverse scored) at time 1; qpa4t1 = performance-avoid item 4 at time 1; qpa5t1 = performance-avoid item 5 at time 1; qpa6t1 = performance-avoid item 6 at time 1; qpa1t2R = performance-avoid item 1 (reverse scored) at time 2; qpa4t2 = performance-avoid item 4 at time 2; qpa5t2 = performance-avoid item 5 at time 2; qpa6t2 = performance-avoid item 6 at time 2; qpa1t3R = performance-avoid item 1 (reverse scored) at time 3; qpa4t3 = performance-avoid item 4 at time 3; qpa5t3 = performance-avoid item 5 at time 3; qpa6t3 = performance-avoid item 6 at time 3; qpa1t4R = performance-avoid item 1 (reverse scored) at time 4; qpa4t4 = performance-avoid item 4 at time 4; qpa5t4 = performance-avoid item 5 at time 4; qpa6t4 = performance-avoid item 6 at time 4; r_pa1 = path coefficient for performance-avoid item 1; r_pa2 = path coefficient for performance-avoid item 4; r_pa3 = path coefficient for performance-avoid item 5; T_Perf-Av = trait performance-avoid.

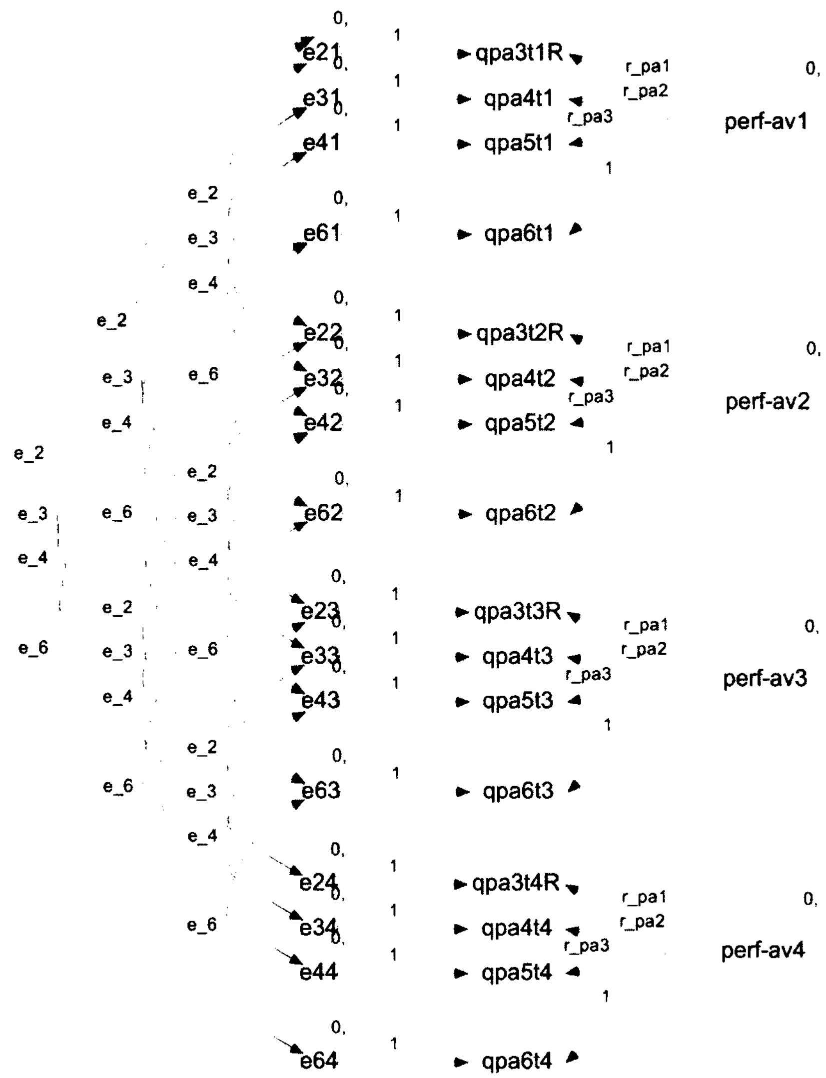

Figure L2. Model 2: State model for Hypothesis 3c.

Note. See note to Figure L1. performance-avoid1 = state performance-avoid at time 1; performance-avoid2 = state performance-avoid at time 2; performance-avoid3 = state performance-avoid at time 3; performance-avoid4 = state performance-avoid at time 4.

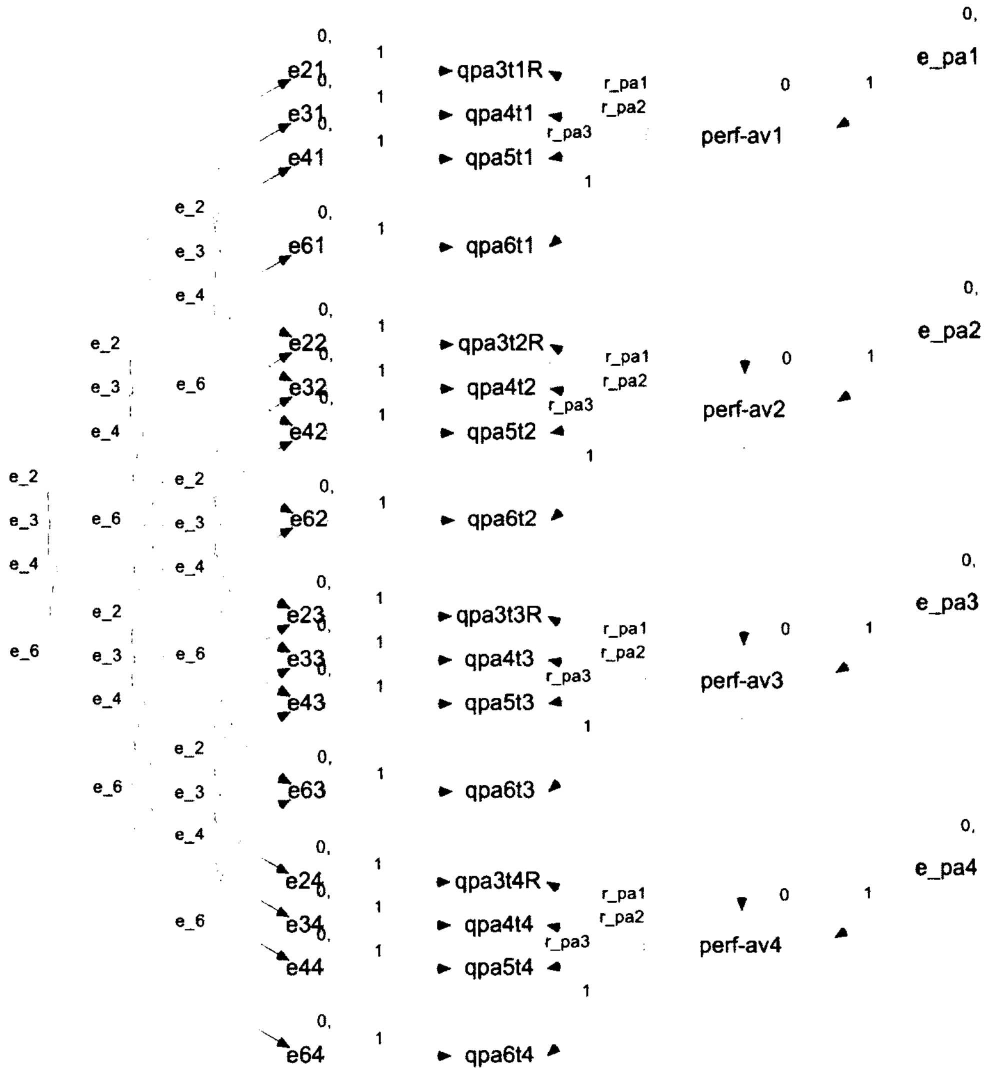

Figure L3. Model 3: State model with first-order autoregressive state factors for Hypothesis 3c.

Note. See note to Figures L1 and L2. e_l1 = error for latent state performance-avoid at time 1; e_l2 = error for latent state performance-avoid at time 2; e_l3 = error for latent state performance-avoid at time 3; e_l4 = error for latent state performance-avoid at time 4.

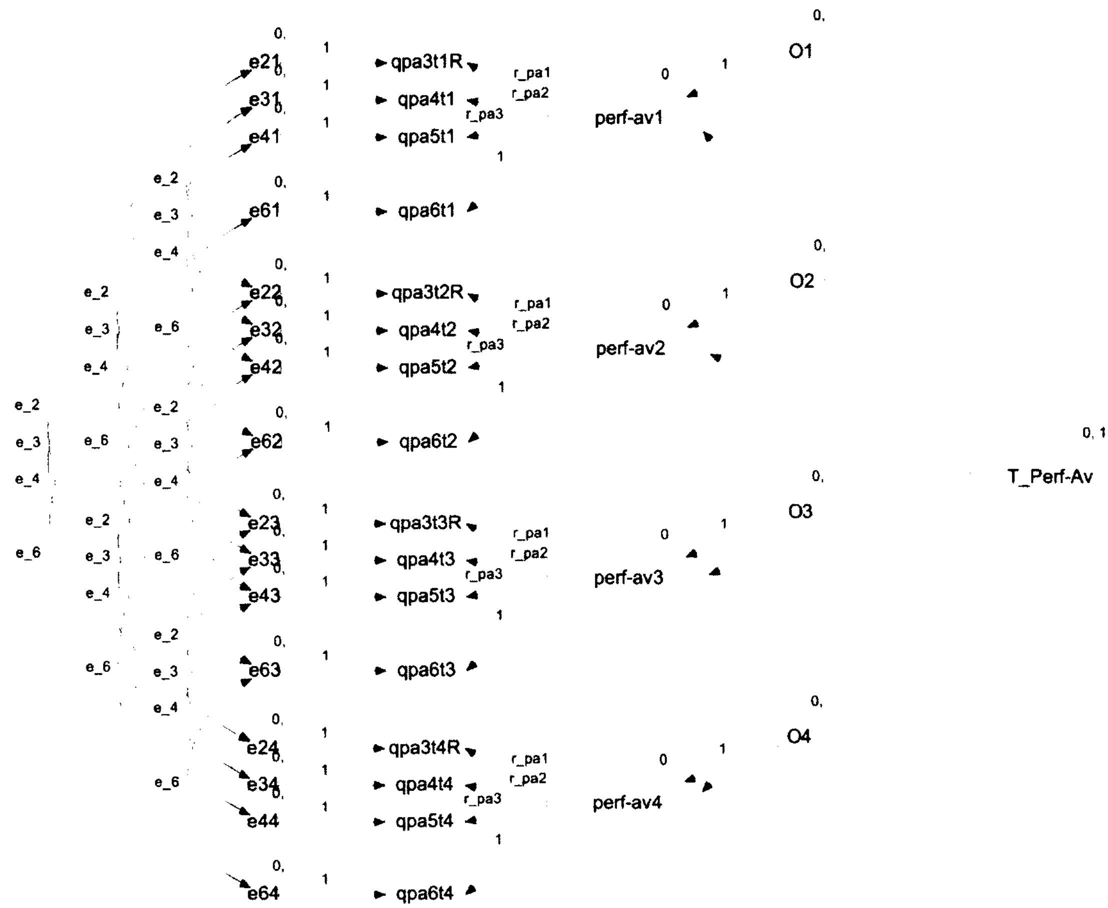

Figure L4. Model 4: LTS model for Hypothesis 3c.

Note. See note to Figures L1 and L2. O1 = latent occasion at time 1; O2 = latent occasion at time 2; O3 = latent occasion at time 3; O4 = latent occasion at time 4.

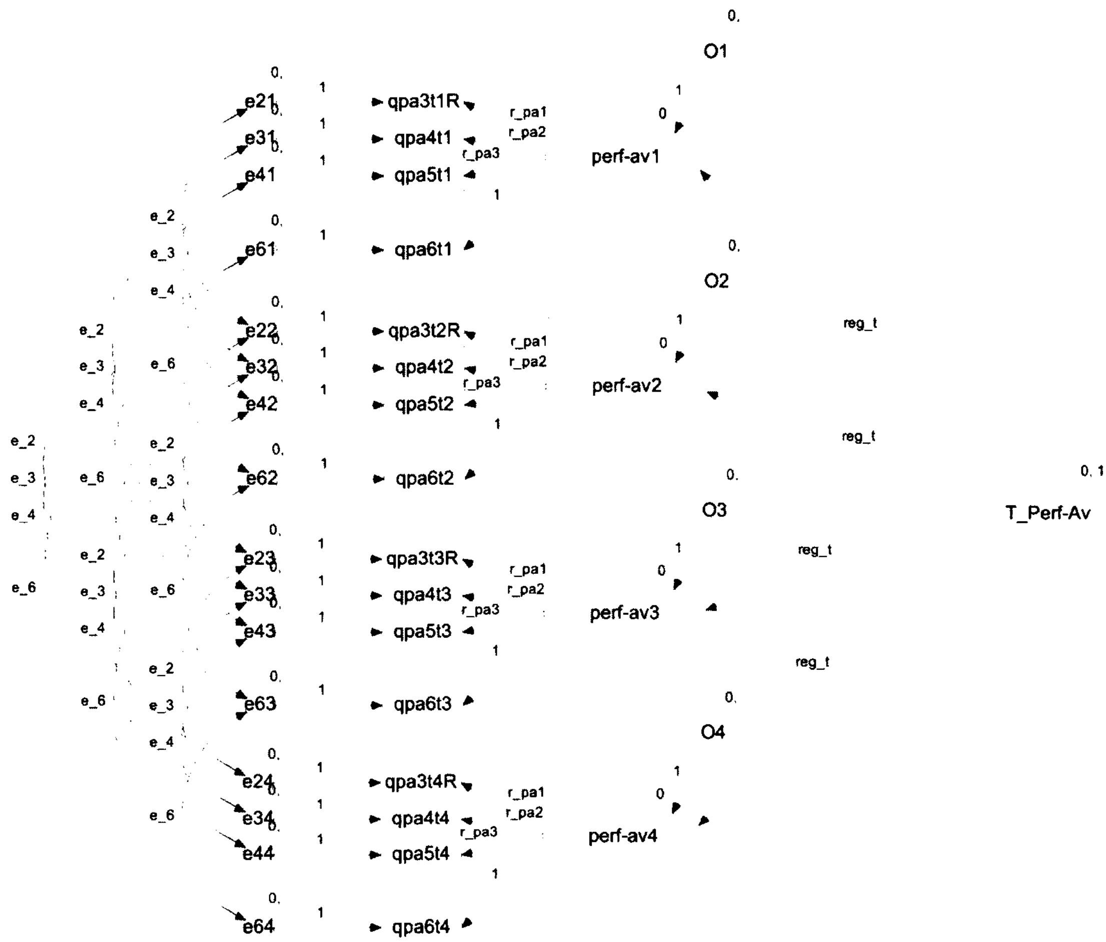

Figure L5. Model 5: LTS model with equality constraints on latent trait factor loadings for Hypothesis 3c.

Note. See note to Figures L1, L2 and L4. reg_t = path coefficient for latent trait.

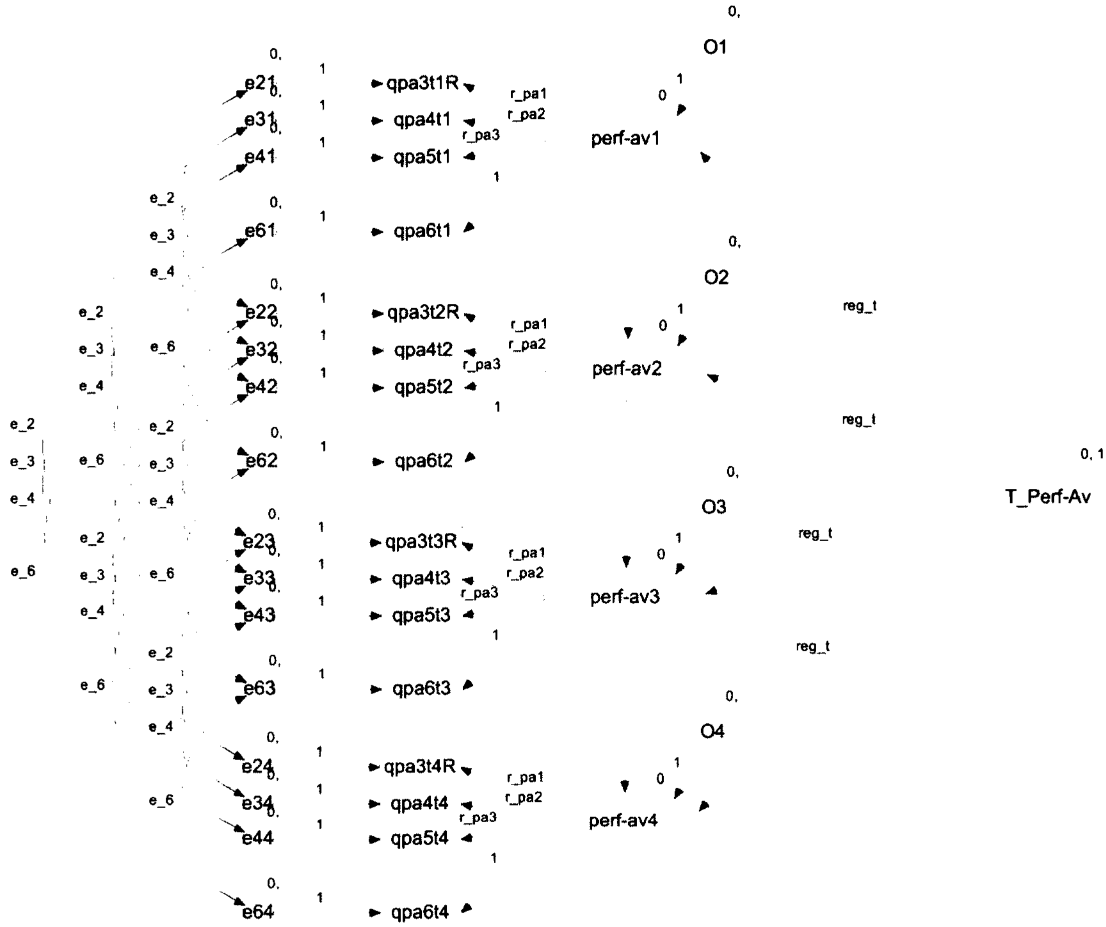

Figure L6. Model 6: LTS model with first-order autoregressive latent state factors for Hypothesis 3c.

Note. See note for Figures L1, L2, L4, and L5.

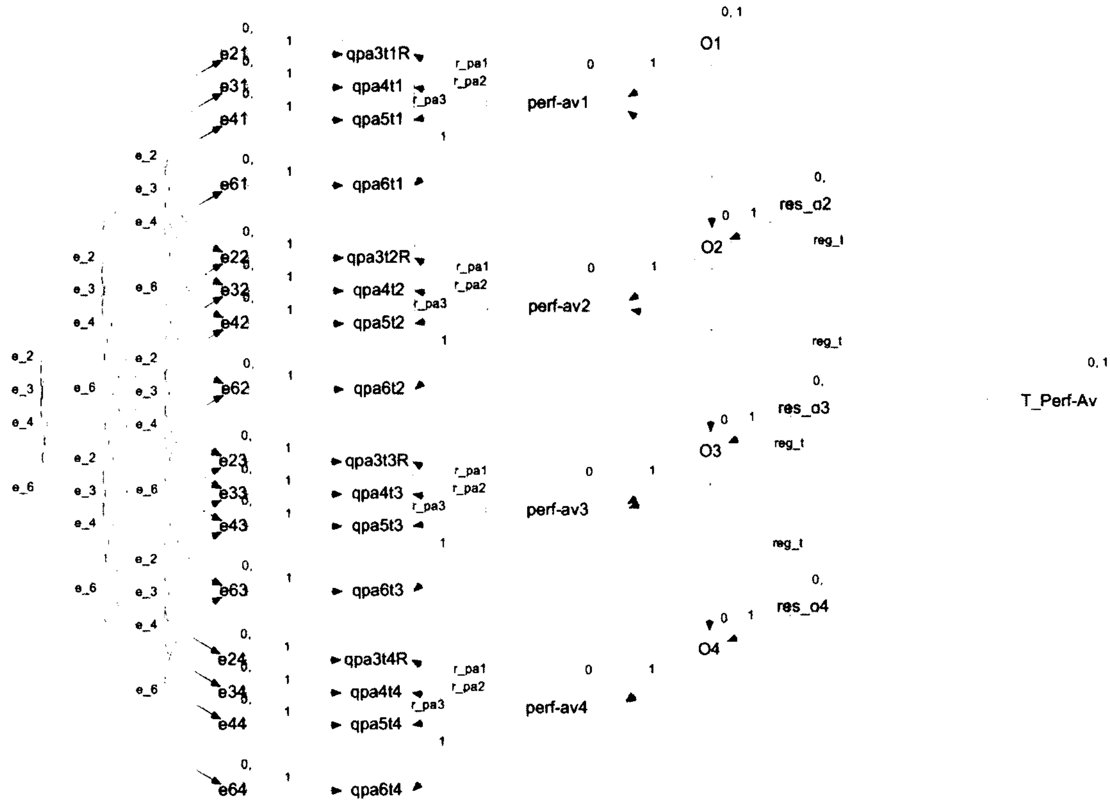

Figure L7. Model 7: LTS model with first-order autoregressive occasion factors for Hypothesis 3c.

Note. See note for Figures L1, L2, L4, and L5. e_o2 = error term for latent occasion at time 2; e_o3 = error term for latent occasion at time 3; e_o4 = error term for latent occasion at time 4.

APPENDIX M

CONFIRMATORY FACTOR ANALYSIS GOODNESS-OF-FIT INDICATORS OF MODELS FOR THE GENERAL TRAIT LEARNING GOAL ORIENTATION SCALE FOR FOUR OCCASIONS *(N = 244)*

Model	χ^2	*df*	*p*	RMSEA	CFI	TLI
			Time 1			
1. 6-item	92.90	9	<0.001	0.193	0.83	0.61
2. 5-item	60.39	5	<0.001	0.211	0.88	0.63
3. 4-item	2.44	2	0.30	0.030	1.00	0.99
			Time 2			
1. 6-item	70.71	9	<0.001	0.166	0.83	0.60
2. 5-item	37.08	5	<0.001	0.161	0.90	0.70
3. 4-item	2.27	2	0.32	0.023	1.00	1.00
			Time 3			
1. 6-item	86.12	9	<0.001	0.186	0.85	0.66
2. 5-item	49.88	5	<0.001	0.190	0.90	0.70
3. 4-item	28.35	2	<0.001	0.230	0.93	0.65
			Time 4			
1. 6-item	66.05	9	<0.001	0.160	0.90	0.77
2. 5-item	23.96	5	<0.001	0.123	0.96	0.89
3. 4-item	0.83	2	0.66	0.000	1.00	1.01

Note. RMSEA = root mean square error of approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index.

APPENDIX N

CONFIRMATORY FACTOR ANALYSIS GOODNESS-OF-FIT INDICATORS OF MODELS FOR THE GENERAL TRAIT PERFORMANCE-PROVE GOAL ORIENTATION SCALE FOR FOUR OCCASIONS *(N = 244)*

Model	χ^2	*df*	*p*	RMSEA	CFI	TLI
			Time 1			
1. 6-item	44.60	9	<0.001	0.126	0.93	0.83
2. 5-item	35.44	5	<0.001	0.156	0.93	0.80
3. 4-item	3.79	2	0.15	0.060	1.00	0.97
			Time 2			
1. 6-item	41.96	9	<0.001	0.121	0.92	0.81
2. 5-item	19.69	5	<0.001	0.109	0.96	0.87
3. 4-item	0.60	2	0.74	0.000	1.00	1.03
			Time 3			
1. 6-item	52.81	9	<0.001	0.140	0.92	0.82
2. 5-item	39.11	5	<0.001	0.166	0.93	0.78
3. 4-item	5.30	2	0.07	0.081	0.99	0.95
			Time 4			
1. 6-item	84.28	9	<0.001	0.183	0.88	0.72
2. 5-item	39.18	5	<0.001	0.166	0.93	0.80
3. 4-item	5.25	2	0.07	0.081	0.99	0.96

Note. RMSEA = root mean square error of approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index.

APPENDIX O

CONFIRMATORY FACTOR ANALYSIS GOODNESS-OF-FIT INDICATORS OF MODELS FOR THE GENERAL TRAIT PERFORMANCE-AVOID GOAL ORIENTATION SCALE FOR FOUR OCCASIONS *(N = 244)*

Model	χ^2	*df*	*p*	RMSEA	CFI	TLI
			Time 1			
1. 6-item	16.54	9	0.06	0.058	0.98	0.94
2. 5-item	10.09	5	0.07	0.064	0.98	0.95
3. 4-item	2.96	2	0.23	0.044	1.00	0.98
			Time 2			
1. 6-item	20.90	9	0.01	0.073	0.96	0.91
2. 5-item	5.02	5	0.41	0.004	1.00	1.00
3. 4-item	0.37	2	0.83	0.000	1.00	1.04
			Time 3			
1. 6-item	24.00	9	0.00	0.082	0.96	0.92
2. 5-item	12.90	5	0.02	0.080	0.98	0.94
3. 4-item	2.96	2	0.23	0.044	1.00	0.99
			Time 4			
1. 6-item	15.15	9	0.09	0.052	0.99	0.97
2. 5-item	10.19	5	0.07	0.065	0.99	0.97
3. 4-item	0.96	2	0.62	0.000	1.00	1.01

Note. RMSEA = root mean square error of approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index.

APPENDIX P

CONFIRMATORY FACTOR ANALYSIS GOODNESS-OF-FIT INDICATORS OF MODELS FOR THE DOMAIN-SPECIFIC TRAIT LEARNING GOAL ORIENTATION SCALE FOR FOUR OCCASIONS *(N = 244)*

Model	χ^2	*df*	*p*	RMSEA	CFI	TLI
			Time 1			
1. 6-item	69.56	9	<0.001	0.164	0.88	0.72
2. 5-item	39.07	5	<0.001	0.165	0.92	0.76
3. 4-item	2.06	2	0.36	0.011	1.00	1.00
			Time 2			
1. 6-item	60.50	9	<0.001	0.152	0.88	0.72
2. 5-item	43.87	5	<0.001	0.177	0.90	0.70
3. 4-item	0.83	2	0.66	0.000	1.00	1.02
			Time 3			
1. 6-item	48.18	9	<0.001	0.132	0.92	0.81
2. 5-item	29.38	5	<0.001	0.140	0.94	0.82
3. 4-item	3.00	2	0.22	0.045	1.00	0.98
			Time 4			
1. 6-item	86.35	9	<0.001	0.186	0.87	0.69
2. 5-item	54.34	5	<0.001	0.199	0.90	0.71
3. 4-item	6.26	2	0.04	0.092	0.99	0.95

Note. RMSEA = root mean square error of approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index.

APPENDIX Q

CONFIRMATORY FACTOR ANALYSIS GOODNESS-OF-FIT INDICATORS OF MODELS FOR THE DOMAIN-SPECIFIC TRAIT PERFORMANCE-PROVE GOAL ORIENTATION SCALE FOR FOUR OCCASIONS *(N = 244)*

Model	χ^2	*df*	*p*	RMSEA	CFI	TLI
			Time 1			
1. 6-item	22.16	9	0.01	0.077	0.97	0.94
2. 5-item	19.37	5	0.002	0.107	0.90	0.90
3. 4-item	2.14	2	0.34	0.017	1.00	1.00
			Time 2			
1. 6-item	40.17	9	<0.001	0.118	0.93	0.83
2. 5-item	22.19	5	<0.001	0.118	0.95	0.85
3. 4-item	13.76	2	0.001	0.154	0.95	0.77
			Time 3			
1. 6-item	55.80	9	<0.001	0.145	0.92	0.81
2. 5-item	18.42	5	0.002	0.104	0.97	0.91
3. 4-item	6.42	2	0.04	0.094	0.99	0.93
			Time 4			
1. 6-item	43.50	9	<0.001	0.124	0.92	0.81
2. 5-item	19.24	5	0.002	0.107	0.96	0.87
3. 4-item	1.63	2	0.44	0.000	1.00	1.01

Note. RMSEA = root mean square error of approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index.

APPENDIX R

CONFIRMATORY FACTOR ANALYSIS GOODNESS-OF-FIT INDICATORS OF MODELS FOR THE DOMAIN-SPECIFIC TRAIT PERFORMANCE-AVOID GOAL ORIENTATION SCALE FOR FOUR OCCASIONS *(N = 244)*

Model	χ^2	*df*	*p*	RMSEA	CFI	TLI
			Time 1			
1. 6-item	45.08	9	<0.001	0.127	0.92	0.81
2. 5-item	24.64	5	<0.001	0.126	0.95	0.85
3. 4-item	3.86	2	0.15	0.061	0.99	0.97
			Time 2			
1. 6-item	53.51	9	<0.001	0.141	0.86	0.66
2. 5-item	25.99	5	<0.001	0.130	0.92	0.75
3. 4-item	0.43	2	0.81	0.000	1.00	1.05
			Time 3			
1. 6-item	43.77	9	<0.001	0.125	0.92	0.81
2. 5-item	13.11	5	0.02	0.081	0.98	0.93
3. 4-item	7.58	2	0.20	0.106	0.98	0.89
			Time 4			
1. 6-item	13.51	9	0.14	0.045	0.99	0.98
2. 5-item	3.84	5	0.57	0.000	1.00	1.01
3. 4-item	0.16	2	0.92	0.000	1.00	1.03

Note. RMSEA = root mean square error of approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index.

APPENDIX S

CONFIRMATORY FACTOR ANALYSIS GOODNESS-OF-FIT INDICATORS OF MODELS FOR THE STATE LEARNING GOAL ORIENTATION SCALE FOR FOUR OCCASIONS *(N = 244)*

Model	χ^2	*df*	*p*	RMSEA	CFI	TLI
			Time 1			
1. 6-item	92.90	9	<0.001	0.193	0.83	0.61
2. 5-item	60.39	5	<0.001	0.211	0.88	0.63
3. 4-item	2.44	2	0.30	0.030	1.00	0.99
			Time 2			
1. 6-item	105.83	9	<0.001	0.208	0.81	0.55
2. 5-item	69.91	5	<0.001	0.228	0.86	0.57
3. 4-item	6.00	2	0.05	0.090	0.99	0.94
			Time 3			
1. 6-item	67.23	9	<0.001	0.161	0.88	0.72
2. 5-item	45.97	5	<0.001	0.181	0.91	0.72
3. 4-item	2.68	2	0.26	0.037	1.00	0.99
			Time 4			
1. 6-item	104.78	9	<0.001	0.207	0.84	0.62
2. 5-item	62.97	5	<0.001	0.216	0.89	0.66
3. 4-item	14.15	2	0.001	0.156	0.97	0.86

Note. RMSEA = root mean square error of approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index.

APPENDIX T

CONFIRMATORY FACTOR ANALYSIS GOODNESS-OF-FIT INDICATORS OF MODELS FOR THE STATE PERFORMANCE-PROVE GOAL ORIENTATION SCALE FOR FOUR OCCASIONS *(N = 244)*

Model	χ^2	*df*	*p*	RMSEA	CFI	TLI
			Time 1			
1. 6-item	42.68	9	<0.001	0.123	0.94	0.86
2. 5-item	31.44	5	<0.001	0.146	0.95	0.85
3. 4-item	1.22	2	0.54	0.000	1.00	1.01
			Time 2			
1. 6-item	62.25	9	<0.001	0.154	0.89	0.75
2. 5-item	47.25	5	<0.001	0.184	0.91	0.72
3. 4-item	0.36	2	0.84	0.000	1.00	1.03
			Time 3			
1. 6-item	56.16	9	<0.001	0.145	0.92	0.80
2. 5-item	52.15	5	<0.001	0.195	0.91	0.74
3. 4-item	4.11	2	0.13	0.065	0.99	0.97
			Time 4			
1. 6-item	37.85	9	<0.001	0.113	0.93	0.83
2. 5-item	25.31	5	<0.001	0.128	0.94	0.83
3. 4-item	7.11	2	0.03	0.101	0.98	0.89

Note. RMSEA = root mean square error of approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index.

APPENDIX U

CONFIRMATORY FACTOR ANALYSIS GOODNESS-OF-FIT INDICATORS

OF MODELS FOR THE STATE PERFORMANCE-AVOID

GOAL ORIENTATION SCALE FOR FOUR OCCASIONS *(N = 244)*

Model	χ^2	*df*	*p*	RMSEA	CFI	TLI
			Time 1			
1. 6-item	78.56	9	<0.001	0.176	0.87	0.70
2. 5-item	35.13	5	<0.001	0.156	0.93	0.80
3. 4-item	2.78	2	0.25	0.040	1.00	0.99
			Time 2			
1. 6-item	46.65	9	<0.001	0.130	0.91	0.79
2. 5-item	19.23	5	0.002	0.107	0.96	0.88
3. 4-item	1.86	2	0.84	0.000	1.00	1.00
			Time 3			
1. 6-item	35.61	9	<0.001	0.109	0.95	0.87
2. 5-item	21.84	5	0.001	0.116	0.96	0.89
3. 4-item	6.24	2	0.13	0.092	0.99	0.94
			Time 4			
1. 6-item	47.41	9	<0.001	0.131	0.93	0.83
2. 5-item	24.03	5	<0.001	0.124	0.96	0.89
3. 4-item	3.11	2	0.03	0.047	1.00	0.99

Note. RMSEA = root mean square error of approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index.

APPENDIX V

FACTOR LOADINGS FOR THE 4-ITEM GENERAL TRAIT

GOAL ORIENTATION SCALES FOR FOUR OCCASIONS OF MEASUREMENT

Item number	Time 1	Time 2	Time 3	Time 4
		Learning		
2	0.77	0.67	0.81	0.87
3	0.61	0.50	0.72	0.70
4	0.81	0.84	0.81	0.87
6	0.83	0.81	0.75	0.85
		Performance-Prove		
1	0.85	0.84	0.88	0.86
2	0.69	0.60	0.50	0.74
3	0.65	0.63	0.72	0.75
4	0.80	0.84	0.83	0.90
		Performance-Avoid		
2	0.57	0.52	0.61	0.75
4	0.55	0.50	0.63	0.74
5	0.78	0.78	0.85	0.95
6	0.81	0.88	0.87	0.85

Note. All coefficients are significant at $p < .001$.

APPENDIX W

FACTOR LOADINGS FOR THE 4-ITEM DOMAIN-SPECIFIC TRAIT GOAL ORIENTATION SCALES FOR FOUR OCCASIONS OF MEASUREMENT

Item number	Time 1	Time 2	Time 3	Time 4
		Learning		
2	0.74	0.73	0.82	0.83
3	0.58	0.65	0.63	0.65
4	0.78	0.81	0.83	0.90
6	0.80	0.82	0.70	0.90
		Performance-Prove		
1	0.74	0.75	0.84	0.78
2	0.56	0.61	0.53	0.64
3	0.74	0.70	0.76	0.72
4	0.81	0.80	0.81	0.80
		Performance-Avoid		
1	0.58	0.40	0.58	0.63
4	0.52	0.47	0.53	0.77
5	0.87	0.78	0.87	0.91
6	0.82	0.85	0.82	0.88

Note. All coefficients are significant at $p < .001$.

APPENDIX X

FACTOR LOADINGS FOR THE 4-ITEM STATE

GOAL ORIENTATION SCALES FOR FOUR OCCASIONS OF MEASUREMENT

Item number	Time 1	Time 2	Time 3	Time 4
		Learning		
2	0.77	0.71	0.80	0.85
3	0.61	0.56	0.66	0.61
4	0.81	0.80	0.82	0.85
6	0.83	0.93	0.78	0.93
		Performance-Prove		
3	0.87	0.84	0.82	0.76
4	0.75	0.65	0.71	0.67
5	0.80	0.80	0.81	0.79
6	0.68	0.75	0.76	0.74
		Performance-Avoid		
1	0.63	0.50	0.54	0.55
4	0.52	0.53	0.53	0.74
5	0.84	0.90	0.90	0.94
6	0.90	0.86	0.89	0.89

Note. All coefficients are significant at $p < .001$.

APPENDIX Y

CRONBACH'S COEFFICIENT ALPHA FOR GENERAL TRAIT GOAL ORIENTATION SCALES AT FOUR OCCASIONS OF MEASUREMENT

Scale	α	95 % CI
Learning, Time 1	0.84	[0.80, 0.87]
Learning, Time 2	0.79	[0.75, 0.83]
Learning, Time 3	0.85	[0.82, 0.88]
Learning, Time 4	0.89	[0.87, 0.91]
Performance-Prove, Time 1	0.83	[0.79, 0.86]
Performance-Prove, Time 2	0.82	[0.76, 0.85]
Performance-Prove, Time 3	0.82	[0.78, 0.85]
Performance-Prove, Time 4	0.89	[0.86, 0.91]
Performance-Avoid, Time 1	0.77	[0.71, 0.81]
Performance-Avoid, Time 2	0.75	[0.70, 0.80]
Performance-Avoid, Time 3	0.82	[0.78, 0.86]
Performance-Avoid, Time 4	0.89	[0.86, 0.91]

Note. CI = confidence interval.

APPENDIX Z

CRONBACH'S COEFFICIENT ALPHA FOR DOMAIN-SPECIFIC TRAIT GOAL ORIENTATION SCALES AT FOUR OCCASIONS OF MEASUREMENT

Scale	α	95 % CI
Learning, Time 1	0.81	[0.77, 0.85]
Learning, Time 2	0.83	[0.80, 0.87]
Learning, Time 3	0.83	[0.80, 0.87]
Learning, Time 4	0.89	[0.86, 0.91]
Performance-Prove, Time 1	0.80	[0.76, 0.84]
Performance-Prove, Time 2	0.81	[0.77, 0.84]
Performance-Prove, Time 3	0.82	[0.79, 0.86]
Performance-Prove, Time 4	0.82	[0.78, 0.86]
Performance-Avoid, Time 1	0.78	[0.73, 0.82]
Performance-Avoid, Time 2	0.71	[0.64, 0.76]
Performance-Avoid, Time 3	0.79	[0.74, 0.83]
Performance-Avoid, Time 4	0.87	[0.84, 0.89]

Note. CI = confidence interval.

APPENDIX AA

CRONBACH'S COEFFICIENT ALPHA FOR STATE GOAL ORIENTATION SCALES AT FOUR OCCASIONS OF MEASUREMENT

Scale	α	95 % CI
Learning, Time 1	0.84	[0.80, 0.87]
Learning, Time 2	0.84	[0.80, 0.87]
Learning, Time 3	0.85	[0.82, 0.88]
Learning, Time 4	0.88	[0.86, 0.90]
Performance-Prove, Time 1	0.85	[0.82, 0.88]
Performance-Prove, Time 2	0.84	[0.81, 0.87]
Performance-Prove, Time 3	0.86	[0.83, 0.89]
Performance-Prove, Time 4	0.83	[0.79, 0.86]
Performance-Avoid, Time 1	0.81	[0.76, 0.84]
Performance-Avoid, Time 2	0.78	[0.73, 0.82]
Performance-Avoid, Time 3	0.80	[0.76, 0.84]
Performance-Avoid, Time 4	0.86	[0.83, 0.88]

Note. CI = confidence interval.

APPENDIX AB

GOODNESS-OF-FIT STATISTICS FOR TESTS OF MEASUREMENT EQUIVALENCE/INVARIANCE: GENERAL TRAIT LEARNING GOAL ORIENTATION SCALE

Model description	Comparative model	χ^2	*df*	$\Delta\chi^2$	Δdf	CFI	ΔCFI
1. Configural model - equal factor structure	--	48.369	14	--	--	0.973	--
2. Equality of factor loadings	2 versus 1	54.449	17	6.080	3	0.970	-0.003
3. Equality of factor variance-covariance matrices	3 versus 1	69.446	20	21.077**	6	0.965	-0.008

Note. $\Delta\chi^2$ = difference in χ^2 values between models; Δdf = difference in number of degrees of freedom between models; ΔCFI = difference in CFI values between models.

**$p < 0.01$.

APPENDIX AC

GOODNESS-OF-FIT STATISTICS FOR TESTS

OF MEASUREMENT EQUIVALENCE/INVARIANCE:

GENERAL TRAIT PERFORMANCE-PROVE GOAL ORIENTATION SCALE

Model description	Comparative model	χ^2	*df*	$\Delta\chi^2$	Δdf	CFI	ΔCFI
1. Configural model - equal factor structure	--	23.338	14	--	--	0.993	--
2. Equality of factor loadings	2 versus 1	27.122	17	3.784	3	0.993	0
3. Equality of factor variance-covariance matrices	3 versus 1	28.184	20	4.846	6	0.993	0

Note. $\Delta\chi^2$ = difference in χ^2 values between models; Δdf = difference in number of degrees of freedom between models; ΔCFI = difference in CFI values between models.

APPENDIX AD

GOODNESS-OF-FIT STATISTICS FOR TESTS OF MEASUREMENT EQUIVALENCE/INVARIANCE: GENERAL TRAIT PERFORMANCE-AVOID GOAL ORIENTATION SCALE

Model description	Comparative model	χ^2	*df*	$\Delta\chi^2$	Δdf	CFI	ΔCFI
1. Configural model - equal factor structure	--	16.342	14	--	--	0.998	--
2. Equality of factor loadings	2 versus 1	16.888	17	0.546	3	1.000	0.002
3. Equality of factor variance-covariance matrices	3 versus 1	27.916	20	11.574	6	0.993	-0.005

Note. $\Delta\chi^2$ = difference in χ^2 values between models; Δdf = difference in number of degrees of freedom between models; ΔCFI = difference in CFI values between models.

APPENDIX AE

GOODNESS-OF-FIT STATISTICS FOR TESTS

OF MEASUREMENT EQUIVALENCE/INVARIANCE:

DOMAIN-SPECIFIC TRAIT LEARNING GOAL ORIENTATION SCALE

Model description	Comparative model	χ^2	*df*	$\Delta\chi^2$	Δdf	CFI	ΔCFI
1. Configural model - equal factor structure	--	10.125	14	--	--	1.000	--
2. Equality of factor loadings	2 versus 1	10.370	17	0.245	3	1.000	0
3. Equality of factor variance-covariance matrices	3 versus 1	17.765	20	7.640	6	1.000	0

Note. $\Delta\chi^2$ = difference in χ^2 values between models; Δdf = difference in number of degrees of freedom between models; ΔCFI = difference in CFI values between models.

APPENDIX AF

GOODNESS-OF-FIT STATISTICS FOR TESTS OF MEASUREMENT EQUIVALENCE/INVARIANCE: DOMAIN-SPECIFIC TRAIT PERFORMANCE-PROVE GOAL ORIENTATION SCALE

Model description	Comparative model	χ^2	*df*	$\Delta\chi^2$	Δdf	CFI	ΔCFI
1. Configural model - equal factor structure	--	40.379	14	--	--	0.975	--
2. Equality of factor loadings	2 versus 1	40.699	17	0.320	3	0.977	0.002
3. Equality of factor variance-covariance matrices	3 versus 1	41.664	20	1.285	6	0.979	0.004

Note. $\Delta\chi^2$ = difference in χ^2 values between models; Δdf = difference in number of degrees of freedom between models; ΔCFI = difference in CFI values between models.

APPENDIX AG

GOODNESS-OF-FIT STATISTICS FOR TESTS OF MEASUREMENT EQUIVALENCE/INVARIANCE: DOMAIN-SPECIFIC TRAIT PERFORMANCE-AVOID GOAL ORIENTATION SCALE

Model description	Comparative model	χ^2	*df*	$\Delta\chi^2$	Δdf	CFI	ΔCFI
1. Configural model - equal factor structure	--	20.255	14	--	--	0.994	--
2. Equality of factor loadings	2 versus 1	21.029	17	0.774	3	0.996	0.002
3. Equality of factor variance-covariance matrices	3 versus 1	30.761	20	10.506	6	0.989	-0.005

Note. $\Delta\chi^2$ = difference in χ^2 values between models; Δdf = difference in number of degrees of freedom between models; ΔCFI = difference in CFI values between models.

APPENDIX AH

GOODNESS-OF-FIT STATISTICS FOR TESTS OF MEASUREMENT EQUIVALENCE/INVARIANCE: STATE LEARNING GOAL ORIENTATION SCALE

Model description	Comparative model	χ^2	*df*	$\Delta\chi^2$	Δdf	CFI	ΔCFI
1. Configural model - equal factor structure	--	32.295	14	--	--	0.987	--
2. Equality of factor loadings	2 versus 1	32.790	17	0.495	3	0.988	0.001
3. Equality of factor variance-covariance matrices	3 versus 1	34.038	20	1.743	6	0.990	0.003

Note. $\Delta\chi^2$ = difference in χ^2 values between models; Δdf = difference in number of degrees of freedom between models; ΔCFI = difference in CFI values between models.

APPENDIX AI

GOODNESS-OF-FIT STATISTICS FOR TESTS OF MEASUREMENT EQUIVALENCE/INVARIANCE: STATE PERFORMANCE-PROVE GOAL ORIENTATION SCALE

Model description	Comparative model	χ^2	*df*	$\Delta\chi^2$	Δdf	CFI	ΔCFI
1. Configural model - equal factor structure	--	10.281	14	--	--	1.000	--
2. Equality of factor loadings	2 versus 1	11.659	17	1.378	3	1.000	0
3. Equality of factor variance-covariance matrices	3 versus 1	15.573	20	5.292	6	1.000	0

Note. $\Delta\chi^2$ = difference in χ^2 values between models; Δdf = difference in number of degrees of freedom between models; ΔCFI = difference in CFI values between models.

APPENDIX AJ

GOODNESS-OF-FIT STATISTICS FOR TESTS

OF MEASUREMENT EQUIVALENCE/INVARIANCE:

STATE PERFORMANCE-AVOID GOAL ORIENTATION SCALE

Model description	Comparative model	χ^2	*df*	$\Delta\chi^2$	Δdf	CFI	ΔCFI
1. Configural model - equal factor structure	--	22.628	14	--	--	0.992	--
2. Equality of factor loadings	2 versus 1	25.515	17	2.887	3	0.992	0
3. Equality of factor variance-covariance matrices	3 versus 1	30.461	20	7.833	6	0.991	-0.001

Note. $\Delta\chi^2$ = difference in χ^2 values between models; Δdf = difference in number of degrees of freedom between models; ΔCFI = difference in CFI values between models.

APPENDIX AK

ESTIMATED MEANS, STANDARD DEVIATIONS,

AND INTERCORRELATIONS FOR THE STUDY VARIABLES

	1	2	3	4	5	6	7
1. Sex	--						
2. Age	.11	--					
3. Year	.09	.72***	--				
4. GTL1	.00	.17**	.11	--			
5. GTL2	.04	.14*	.12	.66***	--		
6. GTL3	.07	.02	.04	.66***	.68***	--	
7. GTL4	.08	.18**	.15*	.67***	.67***	.73***	--
8. GTPP1	.24***	.09	.06	.10	.08	.05	.09
9. GTPP2	.25***	.05	.04	.13	.10	.06	.10
10. GTPP3	.24***	-.04	-.02	.14*	.06	.14*	.18**
11. GTPP4	.13	-.05	.00	.15*	.10	.15*	.12
12. GTPA1	-.22***	-.05	.04	-.01	-.09	-.10	-.19**
13. GTPA2	-.24***	-.04	.07	-.02	.08	.00	-.05
14. GTPA3	-.28***	-.05	.04	.04	-.01	.06	-.01
15. GTPA4	-.28***	-.07	.00	-.03	-.07	-.03	-.02
16. DSTL1	-.04	.14*	.11	.83***	.61***	.65***	.67***
17. DSTL2	.01	.11	.07	.68***	.81***	.70	.69***
18. DSTL3	.05	.03	.04	.58***	.65***	.88***	.66***
19. DSTL4	.05	.15*	.11	.65***	.67***	.75***	.90***
20. DSTPP1	.16*	.04	.09	.14*	.08	.07	.10
21. DSTPP2	.10	-.01	.04	.25***	.24***	.16*	.21**
22. DSTPP3	.14*	-.03	.02	.19**	.18**	.20**	.22**
23. DSTPP4	.16*	-.05	.04	.19**	.14*	.20**	.19**
24. DSTPA1	-.33***	-.08	.05	-.04	-.05	-.12	-.17*
25. DSTPA2	-.20**	-.01	.04	.07	.10	.12	.00
26. DSTPA3	-.25***	.02	.03	.14*	.12	.16*	.07
27. DSTPA4	-.32***	.02	.01	.03	.00	-.04	.09
28. SL1	-.10	.11	.08	.78***	.58***	.64***	.68***
29. SL2	-.05	.05	-.02	.54***	.70	.61***	.50***
30. SL3	.03	.05	.03	.64***	.55***	.80***	.77***
31. SL4	-.02	.17*	.09	.66***	.63***	.70	.86***
32. SPP1	.02	-.04	.04	.09	.07	.04	.02
33. SPP2	.07	-.05	.07	.21**	.20**	.16*	.14*
34. SPP3	.07	-.05	.00	.17*	.15*	.15*	.18**
35. SPP4	.04	-.10	-.04	.15*	.09	.14*	.17*

	8	9	10	11	12	13	14	15
1.								
2.								
3.								
4.								
5.								
6.								
7.								
8.	--							
9.	.77***	--						
10.	.77***	.80***	--					
11.	.73***	.75***	.84***	--				
12.	-.04	-.11	-.12	-.04	--			
13.	-.04	-.05	-.09	-.01	.62***	--		
14.	.05	.02	-.02	.06	.68***	.65***	--	
15.	-.04	-.06	-.03	.00	.62***	.63***	.82***	--
16.	.02	.06	.14*	.20**	-.06	.04	.04	-.01
17.	.03	.07	.07	.12	-.02	.09	.02	-.09
18.	.03	.09	.07	.14	-.03	.07	.14	-.01
19.	.05	.07	.13	.13	-.16*	-.03	-.02	-.06
20.	.73***	.61***	.62***	.61***	.01	-.02	.03	-.01
21.	.60***	.77***	.71***	.68***	-.01	.01	.04	-.02
22.	.58***	.66***	.76***	.76***	-.09	-.03	.00	-.07
23.	.57***	.62***	.71***	.80***	-.01	-.02	.01	.02
24.	-.05	-.09	-.11	.00	.78***	.55***	.64***	.66***
25.	-.01	-.02	-.01	.03	.55***	.74***	.63***	.62***
26.	.05	-.01	.03	.11	.54***	.57***	.81***	.77***
27.	.01	-.02	.01	-.01	.54***	.56***	.73***	.88***
28.	.02	.05	.14*	.20**	-.08	.01	.04	.04
29.	.02	.14	.01	.09	-.02	.16*	.07	.00
30.	.03	.07	.09	.09	-.09	-.09	.07	-.06
31.	.01	.03	.07	.09	-.09	-.03	.01	-.04
32.	.58***	.48***	.53***	.57***	.22	.12	.23***	.16*
33.	.57***	.66***	.65***	.69***	.10	.14*	.17*	.10
34.	.50***	.52***	.67***	.65***	.08	.11	.19**	.16*
35.	.46***	.49***	.63***	.70	.11	.11	.19**	.21**

	16	17	18	19	20	21	22	23
1.								
2.								
3.								
4.								
5.								
6.								
7.								
8.								
9.								
10.								
11.								
12.								
13.								
14.								
15.								
16.	--							
17.	.65***	--						
18.	.58***	.67***	--					
19.	.64***	.71***	.74***	--				
20.	.15*	.14	.01	.07	--			
21.	.19**	.26***	.21**	.28***	.62***	--		
22.	.26***	.19**	.20**	.22***	.59***	.73***	--	
23.	.29***	.18*	.17*	.22**	.57***	.68***	.84***	--
24.	-.05	-.02	-.04	-.14*	.09	.02	-.04	.05
25.	.11	.20**	.17*	.01	.06	.08	.06	.06
26.	.14*	.11	.19**	.10	.09	.07	.04	.09
27.	.03	-.05	-.01	.05	.03	.06	-.04	-.03
28.	.92***	.62***	.55***	.62***	.14*	.13	.19**	.27***
29.	.52***	.72***	.65***	.53***	-.01	.28***	.13	.15*
30.	.63***	.69***	.80***	.77***	.07	.20**	.20**	.21**
31.	.65***	.73***	.67***	.90***	.07	.22**	.18*	.19**
32.	.11	.09	.02	-.02	.75***	.50***	.55***	.57***
33.	.27***	.24***	.17*	.17*	.59***	.75***	.69***	.67***
34.	.21**	.12	.14*	.16*	.55***	.64***	.81***	.78***
35.	.21**	.16*	.17*	.20**	.53***	.59***	.72***	.82***

	24	25	26	27	28	29	30	31
1.								
2.								
3.								
4.								
5.								
6.								
7.								
8.								
9.								
10.								
11.								
12.								
13.								
14.								
15.								
16.								
17.								
18.								
19.								
20.								
21.								
22.								
23.								
24.	--							
25.	.57***	--						
26.	.63***	.66***	--					
27.	.66***	.58***	.76***	--				
28.	-.04	.12	.13	.08	--			
29.	.01	.25***	.12	.11	.54***	--		
30.	-.08	.07	.16*	.01	.67***	.62***	--	
31.	-.05	.04	.11	.08	.66***	.57***	.81***	--
32.	.27***	.21**	.24***	.15*	.18*	.09	.04	.00
33.	.13	.21**	.17*	.12	.24***	.28***	.13	.13
34.	.11	.17*	.18**	.13	.20**	.09	.14*	.14*
35.	.19**	.17*	.24***	.19**	.25***	.18*	.17*	.21**

	32	33	34	35	36	37	38	39
1.								
2.								
3.								
4.								
5.								
6.								
7.								
8.								
9.								
10.								
11.								
12.								
13.								
14.								
15.								
16.								
17.								
18.								
19.								
20.								
21.								
22.								
23.								
24.								
25.								
26.								
27.								
28.								
29.								
30.								
31.								
32.	--							
33.	.63***	--						
34.	.65***	.73***	--					
35.	.66***	.71***	.82***	--				

	40	41	42	43	44
1.					
2.					
3.					
4.					
5.					
6.					
7.					
8.					
9.					
10.					
11.					
12.					
13.					
14.					
15.					
16.					
17.					
18.					
19.					
20.					
21.					
22.					
23.					
24.					
25.					
26.					
27.					
28.					
29.					
30.					
31.					
32.					
33.					
34.					
35.					

	1	2	3	4	5	6	7
36. SPA1	-.30***	-.10	-.02	-.07	-.11	-.12	-.17*
37. SPA2	-.25***	-.04	-.01	-.08	-.02	-.06	-.12
38. SPA3	-.24***	-.05	-.03	-.04	-.05	-.03	-.04
39. SPA4	-.31***	.03	-.01	-.03	-.04	-.06	.03
40. Learning1	.02	.01	.07	.01	-.02	.09	.09
41. Learning2	.09	-.07	-.04	.07	.08	.17*	.13
42. Learning3	.09	-.05	.03	.04	.10	.04	.06
43. Learning4	.01	-.01	.08	.12	.16*	.14*	.15*
44. AP	.04	-.02	.09	.11	.20**	.15*	.20**
M	.32	18.96	1.67	4.65	4.60	4.50	4.46
SD	.46	1.79	1.01	.74	.75	.87	.92

	8	9	10	11	12	13	14	15
36.	-.06	-.12	-.10	.03	.75***	.55***	.62***	.66***
37.	-.03	-.04	-.06	.01	.51***	.68***	.61***	.61***
38.	.01	-.03	-.04	.02	.60***	.60***	.82***	.80***
39.	-.02	-.05	.02	-.02	.45***	.47***	.65***	.78***
40.	.02	.02	.00	.11	-.14*	.03	-.03	-.10
41.	-.03	.08	.07	.10	.01	-.01	.02	.00
42.	-.01	-.03	-.07	-.05	-.02	.10	-.03	-.01
43.	-.02	-.06	.04	.06	.14*	.22***	.04	.05
44.	-.04	-.07	-.02	.03	.16*	.20**	.06	.05
M	3.77	3.89	3.80	3.79	4.00	4.03	3.96	4.02
SD	1.04	1.02	1.03	1.07	.95	.91	1.04	1.11

	16	17	18	19	20	21	22	23
36.	-.05	-.04	-.02	-.14*	.03	-.05	-.03	.05
37.	-.01	.04	.03	-.06	.03	.06	.02	.01
38.	-.03	.00	.06	-.01	.02	.03	-.03	.03
39.	.01	-.02	-.06	.04	.04	.03	-.01	.02
40.	.04	-.06	.12	.12	.09	-.01	.05	-.01
41.	.02	.11	.07	.11	.02	.03	.05	.11
42.	.02	.16*	.07	.05	-.02	-.03	.03	.10
43.	.08	.18**	.12	.11	.07	.00	.05	.19**
44.	.06	.28***	.14*	.16*	.07	.03	.04	.18**
M	4.52	4.45	4.45	4.40	3.39	3.64	3.59	3.57
SD	.80	.85	.85	.91	.94	.98	.98	.95
	24	25	26	27	28	29	30	31
36.	.86***	.59***	.57***	.63***	-.03	.04	-.09	-.08
37.	.57***	.77***	.63***	.61***	-.05	.08	-.07	-.03
38.	.66***	.63***	.82***	.78***	-.02	.06	.02	.01
39.	.58***	.58***	.73***	.85***	.07	.03	.00	.10
40.	-.09	-.02	-.04	-.09	.04	.01	.03	.10
41.	.01	.04	-.01	-.08	.07	.06	.10	.07
42.	-.02	.07	-.08	-.07	.04	.16*	.06	.04
43.	.09	.19**	.00	-.01	.09	.17*	-.02	.03
44.	.12	.21**	.00	-.01	.09	.23**	.06	.11
M	4.07	4.18	4.02	4.07	4.54	4.53	4.46	4.45
SD	1.01	.88	.99	1.11	.90	.93	.92	.92

	32	33	34	35	36	37	38	39
36.	.23***	.11	.08	.20**	--			
37.	.13	.23***	.11	.13	.61***	--		
38.	.24***	.18**	.20**	.22**	.64***	.69***	--	
39.	.20**	.17*	.17*	.24***	.59***	.67***	.79***	--
40.	.01	-.01	.02	.00	-.09	-.09	-.01	-.07
41.	.07	.09	.10	.15*	.04	-.02	-.02	-.11
42.	-.02	-.02	.05	.01	.05	-.03	.00	-.02
43.	.13	.09	.14*	.22***	.17**	.03	.04	.05
44.	.12	.06	.12	.20**	.17**	-.01	.03	.03
M	3.45	3.69	3.59	3.64	3.84	3.91	3.72	3.74
SD	1.01	1.04	1.07	1.01	1.06	.97	1.02	1.09

	40	41	42	43	44
36.					
37.					
38.					
39.					
40.	--				
41.	-.07	--			
42.	.04	-.10	--		
43.	.13*	.18**	.41***	--	
44.	.12	.22***	.46***	.89***	--
M	.00	.00	.00	-.03	.00
SD	1.00	1.00	1.00	1.07	1.00

Note. $N = 244$. GTL = general trait learning goal orientation; GTPP = general trait performance-prove goal orientation; GTPA = general trait performance-avoid goal orientation; DTL = domain-specific trait learning goal orientation; DSTPP = domain-specific trait performance-prove goal orientation; DSTPA = domain-specific trait performance-avoid goal orientation; SL = state learning goal orientation; SPP = state performance-prove goal orientation; SPA = state performance-avoid goal orientation; Learning = learning outcome; AP = academic performance.

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

VITA

Michael Charles Mihalecz

Old Dominion University
Department of Psychology
Mills Godwin Building, Room 250
Norfolk, VA 23529-0267

EDUCATION

Ph.D., Industrial/Organizational Psychology, Old Dominion University, 2011
M.S., Industrial/Organizational Psychology, Old Dominion University, 2003
M.A., Psychology, The Catholic University of America, 1998
B.A., Psychology, Rutgers University,1993

EXPERIENCE

- Senior Scientist, Klein Associates Division of ARA (12/2007–present)
- Project Scientist, Virginia Modeling, Analysis, & Simulation Center, (07/2001-9/2006)
- Consultant, Tidewater AIDS Crisis Taskforce (TACT), (7/00 – 9/05)
- Researcher, Graduate Student Researcher Program (GSRP), NASA-Langley, (6/00 – 4/03)
- Researcher, National Telework Study, International Telework Association and Council, (6/99 – 4/03)
- Consultant, Leadership at a distance: Managing distributed work teams in Asia and Europe, (6/00 – 10/02)
- Consultant, Eastern Virginia Medical School, Office for Women's Affairs, (9/00 – 1/01)
- Project Manager/Survey Specialist, Mathematica Policy Research, Inc., (8/98 – 8/99)

PUBLICATIONS AND PRESENTATIONS

Eshelman-Haynes, C., & Mihalecz, M. C. (2008). *Sensemaking in the Merchant Shipping Picture.* Human Interaction with Complex Systems (HICS) 2008 Conference, Norfolk, VA.

Mihalecz, M. C., & Eshelman-Haynes, C. (2008). Sensemaking in the maritime domain. *ARA Technology Review, 4,* 27-32.

Mihalecz, M. C., Bailey, W. R., & Bustamante, E. A. (2006). *Crewmember trust in the Trident Submarine internal communication subsystems during normal and emergency operating conditions.* Proceedings of the 50th Annual Meeting of the Human Factors and Ergonomics Society in San Francisco, CA.

Mihalecz, M. C., Bailey N. R., & Robinson, C. W. (2005, December). *Applying macroergonomics principles to enhance technology implementation effectiveness.* Proceedings of the 2005 Interservice/Industry Training, Simulation and Education Conference (I/ITSEC). Honorary mention for best conference paper.

Mihalecz, M. C., Fitzgibbons, A., Schutte, P., Burt, J. L, & Davis, D. D. (2004). *Pilot personality, decision-making and error management in commercial aviation.* NASA technical report. Norfolk, VA: Old Dominion University.

Davis, D. D., Mihalecz, M., Bryant, J., Tedrow, L., Liu, Y., & Say, R. (2003, April). *Leadership in global virtual teams.* Paper presented at the Society for Industrial and Organizational Psychology 2003 National Conference, Orlando, FL.

Mihalecz, M. C., Emery, N. P., Liu, Y., McFarlin, S. K., Major, D. A., and Heyl, A. R. (2001, August) *Formal and Informal Mentoring Among Men and Women in Medical School.* Paper presented at the Academy of Management 2001 National Conference, Washington, D.C.