

ABSTRACT

STANHOPE, DANIEL STERLING. Longitudinal Examination of the State-Like Motivational Processes Linking Ability and Dispositional Self-Efficacy to Training Effectiveness. (Under the direction of Samuel B. Pond III.)

Research on training effectiveness helps individuals, groups, and organizations benefit from this ubiquitous human resource development activity. Using longitudinal data ($N = 1459$) from a military training context, I employ multivariate latent growth modeling (LGM) to examine the impact of trait-like individual differences on learning outcomes through state-like intervening processes. Contrary to the common practice of collecting data on the mediator(s) on a single occasion, I measure mediators on multiple occasions, which allows for a more nuanced elucidation of the explanatory role played by motivational processes. I conduct a 3-step procedure that involves (a) modeling mediators (i.e., specific self-efficacy and self-set goals) as latent growth factors across 3 time points, (b) examining time-invariant predictors (i.e., ability and dispositional self-efficacy) of the latent growth factors, and (c) examining outcomes (i.e., cognitive, affective, and skill-based learning) of the latent growth factors. Results suggest the motivational process develops linearly and that interindividual variability exists in both starting values and growth rates for the process variables. Further, ability and dispositional self-efficacy relate differently to the latent growth factors and demonstrate both direct effects on learning and indirect effects on learning through the mediating motivational growth process. Results have scientific implications—for instance, examining intervening mechanisms with LGM allows one to better expose the “black-box” processes that occur between dispositional influence and training outcomes; results also have practical implications—for instance, better

understanding the growth process informs formative evaluation efforts, provides trainers with actionable diagnostic information, and may inform the utility of training interventions.

Longitudinal Examination of the State-Like Motivational Processes Linking Ability and
Dispositional Self-Efficacy to Training Effectiveness

by
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BIOGRAPHY

Daniel Sterling Stanhope was born and raised in Kansas. After graduating from a private high school, he attended the University of Kansas, at which he graduated cum laude with a Bachelor of Arts in Psychology. He then moved to Raleigh, North Carolina to study Industrial and Organizational Psychology at North Carolina State University. He has many research and professional interests, including training (broadly), measurement and psychometrics, research methodology, leadership (broadly), and learning and performance at the individual, group, and organizational levels. Daniel is passionate about the application of psychological science to various workplace settings; he has held multiple employment positions, including consultant at SWA Consulting Inc., graduate research assistant (and consultant) at the William and Ida Friday Institute for Educational Innovation, and Editor for the Meridian Online Journal. In addition, he has worked with numerous public, private, and non-profit organizations in various consulting capacities, and has published in multiple scholarly peer-reviewed journals (e.g., Journal of Applied Psychology, Journal of Research on Technology in Education). Beyond work and study, Daniel enjoys strategizing possible business ventures, exploring the world, experiencing new things, and nourishing the insatiable hunger pangs associated with being a tenacious competitor.

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Longitudinal Examination of the State-Like Motivational Processes Linking Ability and Dispositional Self-Efficacy to Training Effectiveness

A skilled and knowledgeable workforce is a strategic differentiator that provides a distinct competitive advantage (Bowen & Ostroff, 2004; Crook, Todd, Combs, Woehr, & Ketchen, 2011). Thus, leveraging and developing human capital through effective training and development creates discernible value for organizations (Huselid, 1995). One factor that influences training effectiveness is trainee characteristics (Goldstein & Ford, 2002; Tannenbaum & Yukl, 1992). However, there is a need to further our understanding of *how* trainee characteristics influence training effectiveness, including the need for research that investigates the intervening mechanisms that operate in the “black box” between trainee disposition and training outcomes (e.g., Gully & Chen, 2010).

In this study, I integrate several interrelated calls for research that suggest researchers should (a) look beyond main effects and focus on intervening mechanisms (e.g., Gully & Chen, 2010), (b) account for proximal state-like variables through which dispositional variables operate (e.g., Chen, Gully, Whiteman, & Kilcullen, 2000), and (c) include motivational processes when examining the influence of individual differences (e.g., Beier & Kanfer, 2010; Kanfer, 1990). To address these adjacent calls, I examine the extent to which individual differences influence training outcomes through influences on a motivational intervening mechanism. Further, I examine multiple measurement occasions, which allows me to study the intervening mechanism more appropriately as a latent growth process—thus, the purpose of this research is to examine an explanatory mechanism for learning where I

hypothesize that dispositional variables influence learning through their effects on dynamic change in motivational processes.

Training Effectiveness: Trainee Characteristics, Motivation, and Learning

Trainee characteristics display myriad linkages with training outcomes (Goldstein & Ford, 2002; Tannenbaum & Yukl, 1992). However, a paucity of research has examined the mechanisms that explain *how* they influence training outcomes. One tenable mechanism may be the motivational process (Gully & Chen, 2010; Kanfer, 1990). In a book devoted to training and development (i.e., Kozlowski & Salas, 2010), *person and process* emerged as a key theme, referring to the “central role of the person—the trainee—and the learning and motivational processes” (Salas & Kozlowski, 2010, p. 463). Multiple chapters (e.g., Beier & Kanfer, 2010; Gully & Chen, 2010) emphasized the need for research that elucidates how person and process influence learning. Herein I examine whether trainee characteristics (i.e., the person) operate through motivational processes (i.e., the process) to influence learning outcomes.

Trainee Characteristics: Trait-Like Individual Differences

Ability. General cognitive ability (GCA) refers to cognitive resource capacity or information processing capabilities (e.g., Ackerman, 1986)—or more simply as the ability to learn (Alvarez, Salas, & Garofano, 2004; Hunter, 1986). GCA has received consistent support as a dominant predictor of learning and performance (e.g., Hunter, 1986; Ree & Earles, 1991; Schmidt & Hunter, 1998); however, as noted by Gully and Chen (2010), “more research is needed to better establish why and when [GCA] promotes learning” (pp. 9-10).

Aptitude refers to more specific, process-oriented cognitive functioning (Thurstone, 1938).¹ Researchers have demonstrated that relevant aptitudes predict learning and performance (e.g., Petersen & Al-Haik, 1976; Silva & White, 1993), and have suggested aptitudes may be of import for training effectiveness research (Ackerman & Heggstad, 1997; Gully & Chen, 2010),

Dispositional self-efficacy. It is well documented that self-efficacy influences learning and training success (e.g., Mathieu, Martineau, & Tannenbaum, 1993; Stajkovic & Luthans, 1998). Whereas specific self-efficacy (S-SE) refers to specific tasks or activities and is malleable (e.g., Schwoerer, May, Hollensbe, & Mencl, 2005), dispositional self-efficacy (D-SE) spans a variety of activities and is a trait-like disposition (Sherer, 1982). Gully and Chen (2010) asserted that D-SE “is a useful self-evaluation construct for understanding learning and training effectiveness” (p. 27). Further, D-SE influences motivational processes such as task choice, effort intensity, and persistence (e.g., Bandura, 1977; Gist & Mitchell, 1992). Gully and Chen (2010) suggested that D-SE may relate to training outcomes through motivational intervening mechanisms such as S-SE and goal setting—Chen et al. (2000) provided empirical evidence for this mediated relationship. Despite support for the impact of D-SE on training, there is a need to further our understanding of the explanatory mechanisms through which it operates in learning contexts (Gully & Chen, 2010).

¹ I use *ability* to be inclusive of both general cognitive ability (GCA) and specific aptitude (aptitude).

Motivational Intervening Mechanisms

Gully and Chen (2010) called for an “increased focus on explanatory mechanisms that mediate the effects of individual differences on training outcomes” (p. 4). According to Salas and Kozlowski (2010), “to better understand the effects of individual differences...we must have a deeper understanding of learning and motivational processes” (p. 464). Thus, I examine an explanatory mechanism that involves the motivational process: *motivation and effort allocation* (MEA). MEA refers to effort, intensity, and persistence exhibited in achievement contexts (Gully & Chen, 2010; Kanfer, 1990). Research supports the importance of MEA process variables, including S-SE and goal setting (e.g., Colquitt, LePine, & Noe, 2000; Chen et al., 2000; Mathieu et al., 1993; Mento, Steel, & Karren, 1987; Phillips & Gully, 1997; Stanhope, Pond, & Surface, in press). In fact, researchers have called these two variables the primary motivational determinants of achievement outcomes (Bandura, 1997; Locke & Latham, 1990). Further, in a meta-analysis on self-regulated learning, Sitzmann and Ely (2011) reported that, of 16 self-regulation constructs, self-efficacy and goal level had the strongest effects on learning. They called for research that examines self-regulation over time, and noted that “limited research has examined differences in the effects of self-regulatory processes at the within- and between-subjects levels of analysis” (p. 436)—I address these calls herein, examining longitudinally the two self-regulation variables that they reported as having the strongest effects on learning.

MEA process variables. Locke (1991) referred to self-efficacy and goal setting as the *motivational hub* at which action occurs and asserted these variables “are considered to be the most direct and immediate motivational determinants of performance” (p. 293). S-SE

refers to one's perceived ability to "execute courses of action required to deal with prospective situations" (Bandura, 1982, p. 122). Self-set goals refer to specified levels of achievement or performance that an individual aims to accomplish (Locke & Latham, 1990). Ample research has demonstrated the impact of S-SE and self-set goals on behavior and performance (e.g., Dweck, 1986; Elliott & Dweck, 1988; Locke, Frederick, Lee, & Bobko, 1984), including training research that has included them as mediators (e.g., Chen et al., 2000; Stanhope et al., in press). Research examining explanatory mechanisms in learning contexts would benefit from including these process variables (Gully & Chen, 2010; Kanfer, 1990).

Training Criteria: Affective, Cognitive, and Skill-Based Learning

I categorize training criteria using a theory-driven learning classification (i.e., Kraiger, Ford, & Salas, 1993): affective, cognitive, and skill-based learning. The primary objective of this training is for trainees to acquire a minimum proficiency level in an assigned foreign language. Thus, I operationalize *skill-based learning* as end-of-course performance on a standardized proficiency test. One ancillary objective is adequate course grades. Thus, I operationalize *cognitive learning* as declarative knowledge, which is not only valuable in itself, but is also required for higher-order learning and transfer (Kraiger et al., 1993). Other ancillary objectives are confidence with language skills and motivation to maintain and use language skills. Thus, I operationalize *affective learning* as (a) posttraining self-efficacy and (b) motivation to transfer. Trainees should exit training feeling efficacious and they should be motivated to maintain and apply their learning (Gegenfurtner, Veermans, Festner, & Gruber, 2009; Noe, 1986). I examine longitudinally the extent to which objectives are met

(training evaluation), and I examine why and for whom objectives are met (training effectiveness).

Latent Growth Modeling and Training Effectiveness

Training effectiveness involves factors “that influence the training process before, during, and after training” (Alvarez et al., 2004, p. 389). “Snapshots” taken before and after training are incapable of capturing the intricate change processes that occur throughout training (Willett & Sayer, 1994, p. 363). A longitudinal examination with systematic measurement on multiple occasions is preferred. Conventional approaches to analyzing longitudinal data (e.g., repeated measures *t*-tests and analysis of variance) limit one’s ability to capture between-person differences in within-person change (Willett & Sayer, 1994). However, unlike the aforementioned methods, latent growth modeling (LGM) is a latent variable modeling technique that allows one to study patterns of change and individual differences in patterns of change by analyzing mean and covariance structures (Duncan, Duncan, & Strycker, 2006; Willett & Sayer, 1994). LGM allows one to test the adequacy of hypothesized models of growth², and to examine antecedents and consequents of growth. Hence, LGM is particularly appropriate for examining whether hypothesized growth processes (i.e., MEA) mediate the relationship between antecedents (i.e., ability and D-SE) and consequents (i.e., learning).

Proposed LGM: Trainee Characteristics Impact Learning through MEA

I examine a model in which dispositional predictors (i.e., ability and D-SE) operate through latent growth factors (i.e., intercept and slope) of motivational process variables (i.e.,

² *Growth* in latent growth modeling nomenclature denotes either incline or decline. The coefficient has a directional sign that indicates to the analyst whether the growth is incline or decline.

S-SE and self-set goals) to influence learning (see [Figure 1](#)). This LGM approach requires a sequential model-testing procedure in which adequacy of simpler models is required before proceeding to models of increasing complexity. I conduct the following steps in turn: (a) focus solely on the motivational process, (b) add predictors, and (c) add outcomes.

Step 1: The Longitudinal MEA Process

In Step 1 (see [Figure 2](#)), I examine the growth process for MEA variables (i.e., S-SE and self-set goals). First, I determine whether the average shape of growth in each process variable is linear. This provides interesting information about how the motivational process develops throughout training. I next examine variability in the latent growth factors; that is, I examine whether the motivational process differs nontrivially among trainees or whether all trainees follow the same trajectory. Variance indicates that individual differences exist, which may be accounted for by trainee disposition.

Learners are active participants in the learning process; as stated by Gully and Chen (2010), “Trainees actively regulate their motivation, emotion, and learning processes. They decide what to attend to, determine how much effort they will devote, and actively engage themselves in, or disengage themselves from, training” (pp. 4–5). Not all trainees engage in, exert effort toward, and persist with the learning process in the same manner. Trainees enter training with individual differences that influence the motivation and learning processes (Goldstein & Ford, 2002; Tannenbaum & Yukl, 1992). Research has demonstrated that individuals vary substantially in their levels of S-SE and in the difficulty of their self-set goals (e.g., Chen et al., 2000; Phillips & Gully, 1997; Stanhope et al., in press). I contend

that trainees will differ significantly in starting values and growth rates for both S-SE and self-set goals.

Hypothesis 1: Trainees exhibit interindividual variability in initial values and growth rates of (a) S-SE and (b) self-set goals.

Step 2: Trainee Characteristics and MEA

In Step 2 (see [Figure 3](#)), I examine whether individual differences account for variability in the MEA growth process. Specifically, I examine how ability and D-SE influence starting values and growth rates in the motivational process. Assuming there is evidence of variability, in Step 2 I attempt to predict that variance with individual differences.

GCA has received robust support as a predictor of learning and performance (e.g., Hunter, 1986; Schmidt & Hunter, 1998). Research suggests that GCA may operate at least partially through S-SE (e.g., Chen et al., 2000; Colquitt et al., 2000). GCA plausibly relates to growth in S-SE because “cognitive reiteration of efficacious courses of action strengthens self-percepts of efficacy” (Bandura, 1989, p. 729). I contend that trainees with higher GCA will enter training with higher perceived capability (i.e., higher starting values) and will thus engender the ability and motivation necessary to engage in and persist with behaviors that support learning and performance throughout training (i.e., higher growth rates). I contend aptitude will also foster higher initial confidence and greater increases in confidence as training progresses.

Past research has provided mixed findings regarding the relationship between GCA and self-set goals. Locke and Latham (1990) contended that GCA relates to learning and

performance through the motivational process of setting goals, which some research supports (e.g., Chen et al., 2000; Thomas & Mathieu, 1994). However, Phillips and Gully (1997) and Stanhope et al. (in press) found that GCA did not relate directly to self-set goals. Further, Barrick, Mount, and Strauss (1993) found that neither goal setting nor goal commitment mediated the relationship between GCA and performance; furthermore, Barrick and colleagues reported nonsignificant correlations between GCA and both goal setting ($r = .00$) and goal commitment ($r = .05$). I contend that GCA will not influence self-set goals at the beginning of training (i.e., starting values), nor will it influence changes in self-set goals throughout training (i.e., growth rates). Similarly, I contend that aptitude will be unrelated to self-set goals. However, due to the controvertible nature of past research, I will examine alternative models in which both GCA and aptitude operate through self-set goals to influence learning.

Hypothesis 2: GCA (a) accounts for variability in initial values and growth rates of S-SE, but (b) does not account for variability in initial values or rates of growth in self-set goals.

Hypothesis 3: Aptitude (a) accounts for variability in initial values and growth rates of S-SE, but (b) does not account for variability in initial values or rates of growth in self-set goals.

Those with high D-SE believe in their general capacity to perform well and summon the resources necessary to succeed in achievement situations (Sherer, 1982). Whether general conceptions of self-efficacy relate to specific conceptions of self-efficacy has been debated. Bandura (1997) cautioned against assuming a relationship between general efficacy

percepts and specific efficacy percepts—contrariwise, empirical evidence suggests the former positively influences the latter (e.g., Chen et al., 2000; Sherer, 1982). Research has also supported the influence of D-SE on self-set goals (e.g., Chen et al., 2000). I contend that trainees with high D-SE will enter training with higher S-SE (i.e., starting values) because of the general belief in their capacity to summon the resources necessary to succeed. These trainees will also set higher goals at the outset because the higher goals are concordant with their aspirations and with their agency beliefs (Luthans & Youssef, 2007; Sheldon & Elliot, 1999). However, because some debate exists, I will examine alternative models in which D-SE does not influence S-SE.

D-SE is one facet of an individual's core self-evaluations (CSE; Judge, Bono, Erez, & Locke, 2005). Research has demonstrated that CSE is related to goal self-concordance, and suggests individuals with high CSE are more likely to commit to and pursue goals for intrinsic, value-congruent reasons (Judge et al., 2005). Further, Stanhope et al. (in press) demonstrated that CSE influences learning, in part, through influences on midtraining S-SE and self-set goals. I contend that D-SE will influence one's S-SE and self-set goals throughout training because of self-concordance and because they may deal with training tribulations more effectively (Bandura, 1986). In sum, I expect that a general belief in one's competencies will influence initial ability conceptions (i.e., self-efficacy) and aspirations (i.e., goals), and this distal influence will continue to relate to these conceptions and aspirations as training progresses.

Hypothesis 4: D-SE accounts for variance in the initial values and growth rates of (a) S-SE and (b) self-set goals.

Step 3: Trainee Characteristics, MEA, and Learning

In Step 3 (see [Figure 4](#)), I examine whether the MEA process accounts for variability in learning, and ultimately whether the motivational process mediates the relationship between disposition and learning. Thus, I examine how starting values and growth rates in S-SE and self-set goals relate to learning. This comprehensive LGM addresses the extent to which the person-and-process theme (Salas & Kozlowski, 2010) accounts for variance in training effectiveness.

S-SE is an oft-studied variable and an important learning outcome to consider in training contexts (Kraiger et al., 1993; Salas & Cannon-Bowers, 2001). Research has demonstrated that pretraining and midtraining self-efficacy influence posttraining self-efficacy (e.g., Colquitt et al., 2000; Stanhope et al., in press), which occurs as efficacy percepts are strengthened and reinforced (Bandura, 1997). Additionally, past research has supported the influence of goals on posttraining self-efficacy (Bandura & Schunk, 1981; Seijts & Latham, 2001; Stanhope et al., in press). I expect that starting values and growth rates in S-SE will account for variability in posttraining self-efficacy. I also expect initial self-set goals and growth rates in self-set goals to account for variability in posttraining self-efficacy.

“People avoid activities that they believe exceed their coping capabilities, but they undertake and perform assuredly those that they judge themselves capable of managing” (Bandura, 1982, p. 123). Those who believe in their efficacy to maintain and use their KSAs will be more motivated to do so. This is consistent with theory on human agency (e.g., Bandura, 1982), intentional behavior (Fishbein, 1979), and planned behavior (Ajzen, 1991);

it is also consistent with empirical research that has demonstrated self-efficacy to directly or indirectly influence motivation to transfer (Chiaburu & Lindsay, 2008; Dierdorff, Surface, & Brown, 2010). I expect S-SE starting values and growth rates to account for variability in transfer motivation.

Research has supported the influence of goals on motivation to transfer (e.g., Smith, Jayasuriya, Caputi, & Hammer, 2008). Self-set goals represent performance levels that an individual aspires to attain (Locke & Latham, 1990); presumably, these aspirations align with the individual's interests and values—indeed, “goals can be viewed as applications of values to specific situations” (Locke, 1991, p. 292). Research on the self-concordance of goals—namely their consistency with interests and values—has demonstrated that pursuers of self-concordant goals exert greater effort toward achieving those goals, and are more motivated and likely to do so (e.g., Sheldon & Elliot, 1999). I expect trainees' initial self-set goals and growth rates in goal levels to account for variability in transfer motivation.

Hypothesis 5: Variability in affective learning is accounted for by initial values and growth rates for (a) S-SE and (b) self-set goals.

S-SE and goals govern how individuals approach, engage in, and persist with learning activities, and are important determinants of learning (Bandura, 1997; Locke, 1991).

Acquiring knowledge and skills requires sufficient motivation, and efficacy percepts “determine how much effort people will expend and how long they will persist in the face of obstacles or aversive experiences” (Bandura, 1982, p. 123). Those with high S-SE exert greater effort toward and persist longer with mastering challenges (Bandura & Schunk, 1981). Further, research has demonstrated that S-SE is malleable (e.g., Gist & Mitchell,

1992; Schwoerer et al., 2005), and that increases in S-SE lead to increases in learning (e.g., Gist, 1989; cf. Bandura, 2012; Vancouver, 2012). Similarly, goals affect learning via directed, concentrated, and persistent effort exertion (Locke & Latham, 1990). Those who set difficult goals demonstrate greater motivation and higher levels of learning (Locke & Latham, 1990). I hypothesize that both starting values and growth rates in S-SE and self-set goals will influence cognitive learning.

Hypothesis 6: Variability in cognitive learning is accounted for by initial values and growth rates for (a) S-SE and (b) self-set goals.

An individual's goals or aspirations, and his or her self-confidence, strongly influences training performance (Locke, 1991). S-SE and goals have shown utility as process variables in training contexts (e.g., Chen et al., 2000; Stanhope et al., in press), and both have consistently predicted performance in a variety of contexts (Locke & Latham, 2002; Salas & Cannon-Bowers, 2001). Gist (1989) asserted that S-SE is an important process variable for training effectiveness research and demonstrated empirically that enhancing S-SE during training leads to better training performance (cf. Bandura, 2012; Vancouver, 2012). Proximal goals set throughout the process have a particularly profound influence on performance and achievement behaviors (e.g., Bandura & Schunk, 1981). Further, Chen et al. (2000) and Stanhope et al. (in press) reported that S-SE and goals, operationalized as mediators, predicted training performance. I expect starting values and growth rates in both S-SE and self-set goals to influence skill-based learning.

Hypothesis 7: Variability in skill-based learning is accounted for by initial values and growth rates for (a) S-SE and (b) self-set goals.

The hypotheses in Step 3 assume that dispositional effects are fully mediated—this assumption is worth testing. To learn and perform in training, trainees must have the requisite ability and motivation (Noe, 1986). This suggests the possibility of partial mediation (i.e., both direct and indirect effects). Past research has demonstrated that dispositional variables exert both direct and indirect influences on learning and performance (e.g., Chen et al., 2000; Colquitt et al., 2000; Stanhope et al., in press), which also supports the tenability of a partially mediated model. To examine whether partial mediation is more appropriate than full mediation, I test multiple alternative models grounded in theory that specify both direct and indirect effects.

Methods

Sample

The sample consists of military personnel ($N = 1459$)—mostly males between the ages of 18 and 44 ($M = 26$)—from a job-mandated training program for foreign language acquisition. For these military personnel, foreign language proficiency is a critical competency (U.S. Department of Defense, 2006) and they must meet a minimum proficiency standard to attain certification requirements. Trainees who exceed the standard receive monetary incentives (i.e., skill-based pay; Dierdorff & Surface, 2008). Each trainee in this study was assigned to a foreign language, which included Spanish ($n = 577$, 40%), Indonesian ($n = 233$, 16%), and French ($n = 649$, 45%). According to a common government classification system, each language falls into similar categories of language difficulty, which is based on the difficulty for a native English speaker to learn the language due to linguistic

similarity or dissimilarity (Silva & White, 1993). All course structures and learning and performance objectives are standardized across languages.

Procedures

The duration of training was 18 weeks. The first measurement occasion (S_0^3) occurred pretraining; data were collected on time-invariant individual differences and on the initial status of each process variable. Trainees provided data pertaining to D-SE, S-SE, and self-set goals using self-report surveys. A third party provided scores for trainees on GCA and aptitude. For the second measurement occasion (S_1 ; after a 4-week interval) and third measurement occasion (S_2 ; after a 5-week interval), trainees provided data on process variables (i.e., S-SE and self-set goals) using self-report surveys. At the end of training, data were collected for the affective and cognitive learning outcomes. A third party provided data for the skill-based learning outcome.

Measures

Time-invariant covariates. I measured *GCA* using the Wonderlic Cognitive Ability Test. The Wonderlic consists of 50 multiple-choice items and subjects have 12 minutes to respond (Wonderlic, 1992). The Wonderlic has received evidence of reliability and validity as a measure of general intelligence in a diverse range of subjects (e.g., Dodrill, 1981, 1983; Dodrill & Warner, 1988). *Specific aptitude* in this study refers to foreign language learning aptitude; I measured it using the Defense Language Aptitude Battery (DLAB; Petersen & Al-Haik, 1976), a personnel selection tool developed for the Defense Language Institute (DLI).

³ Consistent with latent growth modeling nomenclature, I use S_0 to denote the first measurement occasion because it represents initial status. Successive measurement occasions are S_1, S_2, \dots, S_{t-1} , where t = total number of occasions.

Research has supported the validity of the DLAB in predicting training success (e.g., Petersen & Al-Haik, 1976), which includes listening and speaking proficiency (Silva & White, 1993).

I measured *D-SE* ($\alpha = .91$; see [Appendix A](#)) with eight items that assessed trainees' learning-related general efficacy percepts. Trainees rated each item on an 11-point confidence scale that ranged from 1 (0%) to 11 (100%), with 10% gradients. The instrument consisted of a stem ("Please indicate your confidence in your ability to perform each of the following activities..."), followed by items such as, "Master new material in learning situations," and, "Perform well in academic courses or training." This scale has structural validity evidence and sufficient internal consistency reliability (.91; Dierdorff et al., 2010).

Process variables. I measured the first process variable, *S-SE* ($\alpha = .96-.99$; see [Appendix A](#)), on three occasions (i.e., S0, S1, and S2) with eight items that assessed trainees' specific efficacy percepts regarding training-related knowledge and skills. Trainees rated each item using an 11-point confidence scale ranging from 1 (0%) to 11 (100%), with 10% gradients. The items were preceded by a stem ("Please indicate your confidence in your current ability to perform the following activities"), followed by items such as, "Use military-technical vocabulary."

I measured the second process variable, *self-set goals* ($\alpha = .96-.97$; see [Appendix A](#)), on three occasions (i.e., S0, S1, and S2) using three items. At each measurement occasion, trainees indicated their goals for (a) reading proficiency at the end of training, (b) listening proficiency at the end of training, and (c) speaking proficiency at the end of training. The scale mapped directly onto the metric of the skill-based learning outcome, which is the

ultimate criterion for trainees—namely, the Oral Proficiency Interview (i.e., 0, 0+, 1, 1+, 2, 2+, 3, 3+, 4, 4+, and 5). Trainees set personal goals for proficiency ranging from 1 (0) to 11 (5).

Criteria. I examined two affective learning outcomes. I assessed *posttraining self-efficacy* ($\alpha = .96$; see [Appendix A](#)) with eight items that trainees rated on an 11-point confidence scale ranging from 1 (0%) to 11 (100%), with 10% gradients. The instrument mapped onto the S-SE scale, but was assessed at the end of training. I assessed *motivation to transfer* ($\alpha = .97$; see [Appendix A](#)) with nine items where trainees reported their likelihood of engaging in activities that support maintenance and application of foreign language skills. Each item was on an 11-point likelihood scale ranging from 1 (0%) to 11 (100%), with 10% gradients. Trainees were given a stem (“Please estimate the likelihood that you will...”), followed by transfer activities such as, “Use your language skills when you have the opportunity on missions.”

I operationalized cognitive learning as declarative knowledge, and measured it using *course grades* that trainees merited based on performance on tests administered by the course instructors. The paper-and-pencil tests covered training-related content that trainees needed to learn in order to demonstrate training proficiency. The course instructors provided results from these objectively scored measures of cognitive learning.

I measured skill-based learning with scores from the *Oral Proficiency Interview (OPI)*. The ultimate training objective was for trainees to acquire foreign language proficiency that enabled them to meet a minimum proficiency level on the OPI. The OPI is a standardized instrument designed by DLI to assess foreign language proficiency and is used

in high-stakes testing by the United States Department of Defense (DoD). The OPI is also used to determine whether trainees meet minimum qualifications and determines their skill-based pay (Dierdorff & Surface, 2008). The scoring rubric for the OPI ranges from 1 to 11 (i.e., 0, 0+, 1, 1+, 2, 2+, 3, 3+, 4, 4+, and 5), with higher scores denoting higher proficiency.

Analysis

I conducted multivariate LGM in an iterative model-testing fashion to address the study hypotheses. I conducted LGM using *Mplus* Version 7.0 (Muthén & Muthén, 1998-2011). For each model, I used maximum-likelihood estimation, continuous variables, and included both mean and covariance structures. I evaluated each model using several criteria. First, to assess model fit, I drew from well-established recommendations (e.g., Hu & Bentler, 1999), and examined chi-square (χ^2), comparative fit index (CFI; Bentler, 1990), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA; Browne & Cudeck, 1993), and the standardized root mean square residual (SRMR). Second, I examined the magnitudes and significance of structural relations. Third, I judged interpretability by determining whether models made sense theoretically and whether parameter estimates fell within appropriate ranges and were concordant with past research. When comparing models, I compared the fit of a given model and theory-based alternative models with differing constraints using a χ^2 difference test for nested models (Satorra, 2000). If specification of a simpler model (i.e., fewer freely estimated parameters) did not lead to significant decrement in model fit (compared to the more complex model), then I retained the simpler model.

In Step 1, I examined unconditional growth models—namely, simple growth models with no covariates and no criteria—to determine whether linear growth best characterized the

longitudinal MEA process. Specifying the appropriate shape of growth in successive models is critical (Duncan et al., 2006). Then, to address Hypotheses 1a and 1b, I examined whether interindividual variability existed in the latent growth factors—that is, I determined whether individuals differed significantly in both initial values (intercepts) and rates of growth (slopes) for the MEA process variables. In Step 2, I addressed Hypotheses 2–4 by determining whether time-invariant predictors accounted for the variance in the latent growth factors. Specifically, I added to the model GCA, specific aptitude, and D-SE to determine the extent to which these predictors accounted for variance in both starting values and rates of growth in the MEA process variables. In Step 3, to address Hypotheses 5–7, I added learning criteria to determine whether the latent growth factors accounted for variability in learning outcomes.

Results

I included all constructs that had multiple indicators in a 10-factor, fully disaggregated confirmatory factor analysis (CFA) with maximum likelihood estimation. I modeled all items as effects indicators. I allowed the latent constructs to correlate, and specified no cross-loaders and no correlated residuals. The model demonstrated acceptable fit ($\chi^2 = 11433.02$, $n = 1457$, $df = 1665$, $p < .001$, CFI = .92, TLI = .91, RMSEA = .06, SRMR = .03), which provided structural validity evidence for the latent constructs and supported the viability of the measurement model.⁴

In [Table 1](#), I present scale reliabilities, descriptive statistics, and zero-order correlations. All measures had sufficient internal consistency reliability ($.91 < \alpha < .99$;

⁴ Author will provide results of the confirmatory factor analysis upon request.

Nunnally, 1978). As would be expected, average levels of S-SE increased from S0 ($M = 2.60, SD = 2.80$) to S1 ($M = 4.46, SD = 2.49$) to S2 ($M = 6.67, SD = 2.22$). On average, trainees gained confidence throughout training. Conversely, trainees generally set lower goals as training progressed. Goal levels were highest at Time 1 (S0; $M = 4.28, SD = 0.97$) and lowest at Time 3 (S2; $M = 3.97, SD = 0.95$). Thus, it appears that the latent slope factor will be positive for S-SE and negative for goal setting—the reason for the decline in goal setting, especially occurring contemporaneously with increases in confidence, presents an interesting avenue for further exploration.

Several bivariate correlations are worth noting. First, GCA and aptitude correlated moderately ($r = .46, p < .001$), which suggests they are related yet sufficiently distinct. D-SE was uncorrelated with both GCA and aptitude. D-SE had stronger correlations with affective learning— $r = .26$ ($p < .001$) for posttraining self-efficacy and $r = .29$ ($p < .001$) for motivation to transfer—than it did with course grades ($r = .09, p = .005$) and OPI ($r = .12, p < .001$). The patterns of results differed for GCA and aptitude. GCA correlated negatively with posttraining self-efficacy ($r = -.08, p = .015$) and motivation to transfer ($r = -.11, p = .001$), but correlated positively with course grades ($r = .27, p < .001$) and OPI ($r = .09, p = .006$). Aptitude, on the other hand, did not correlate with the affective learning outcomes, but was positively correlated with course grades ($r = .36, p < .001$) and OPI ($r = .18, p < .001$). Thus, it initially appears D-SE influences affective learning and ability influences cognitive and skill-based learning.

The relations between and among process variables and learning across time are also worth noting. The correlations for S-SE are highest between S1 and S2, second highest

between S0 and S1, and lowest between S0 and S2. This same pattern of correlations is present among self-set goals. This suggests self-efficacy percepts and goal-setting beliefs strengthen as training progresses. In general, the correlations among process variables and learning outcomes become stronger from S0 to S2—that is, S-SE and self-set goals are more predictive of learning outcomes at the final time point than they are at the initial time point.

Step 1: The Longitudinal MEA Process

The linear LGM for S-SE demonstrated good fit ($\chi^2 = 0.787$, $df = 1$, $p = .375$, CFI = 1.00, TLI = 1.00, RMSEA = .00, SRMR = .01). The linear LGM for self-set goals also demonstrated good fit ($\chi^2 = 4.835$, $df = 1$, $p = .028$, CFI = 1.00, TLI = .99, RMSEA = .05, SRMR = .01). After confirming linear growth for each process variable in isolation, I included both in the same model. This model, referred to as a growth model for parallel processes, allowed me to examine concomitantly the growth processes throughout training to examine the relations among their latent growth factors. This model demonstrated good fit ($\chi^2 = 17.902$, $df = 7$, $p = .012$, CFI = 1.00, TLI = .99, RMSEA = .03, SRMR = .01).

The relations among latent growth factors in the parallel processes growth model provide useful information (see [Table 2](#)). First, I examined within-factor relations to determine how starting values related to growth rates within each process variable. For S-SE, the intercept and slope correlated at $-.40$ ($p < .001$), which indicates that trainees with lower starting values had greater increases in self-efficacy as training unfolded. For self-set goals, the correlation between the intercept and slope was nonsignificant, which indicates that trainees' goal levels at the beginning of training were unrelated to increases or decreases in goal levels throughout training. Next, I examined between-factor relations to determine

how starting values and growth rates related between S-SE and self-set goals. The intercept factors ($r = .35, p < .001$) and the slope factors ($r = .14, p = .014$) were positively correlated. Thus, higher starting values in one process variable related to higher starting values in the other process variable; likewise, greater rates of growth throughout training in one process variable related to greater rates of growth in the other process variable. Conversely, between-factor slopes and intercepts were uncorrelated, indicating that starting values in one process variable did not relate to rates of growth in the other.

Also important to examine for each process variable was the arithmetic mean for the intercept and slope, which combine to represent the average true mean trajectory (see [Table 2](#)). For S-SE, the mean of the intercept ($M = 2.63, SE = .07, p < .001$) represents the average level at initial testing (S0) and the mean of the slope ($M = 2.25, SE = .04, p < .001$) represents the average rate of change from S0 to S1 to S2. Thus, the initial level of S-SE was 2.63 (out of 11) and this level increased linearly by 2.25 at both S1 and S2. Likewise, for self-set goals, the mean of the intercept ($M = 4.30, SE = .02, p < .001$) represents the average goal level at initial testing (S0) and the mean of the slope ($M = -0.18, SE = .01, p < .001$) represents the average rate of change from S0 to S1 to S2. Thus, the initial level of self-set goals was 4.30 (out of 6) and this level decreased linearly by 0.18 at both S1 and S2.

The average true mean trajectories provide information about averages but provide no information about individual differences. Thus, to address H1a and H1b, which concern interindividual variability in starting values and growth rates, I examined the estimated residuals (see [Table 2](#)). The residuals represent deviations from the average intercept and slope, which one intuitively can interpret as interindividual variability. For S-SE, residual

variances were significant for both the intercept ($p < .001$) and slope ($p < .001$), which indicates that there were individual differences among trainees in both starting values and rates of growth. Likewise, residual variances for both intercept ($p < .001$) and slope ($p < .001$) were significant for self-set goals, which indicates variability among trainees in both starting values and rates of growth. I can now examine in Step 2 whether ability and D-SE account for this variability.

Step 2: Trainee Characteristics and MEA

To address H2a-b, H3a-b, and H4a-b, I added GCA, aptitude, and D-SE to the parallel processes growth model to determine whether individual differences accounted for variance in the starting values and growth rates of MEA process variables. In accord with the proposed model, I specified paths from GCA and aptitude to the intercept and slope of S-SE, and I specified paths from D-SE to the intercepts and slopes of both S-SE and self-set goals (see [Figure 3](#)). Although this model demonstrated good fit ($\chi^2 = 43.117$, $df = 17$, $p = .001$, CFI = .99, TLI = .98, RMSEA = .03, SRMR = .02), I compared it to theoretical alternatives (see [Table 3](#)).

First, I compared the model to a more constrained model in which I removed the correlational paths between D-SE and both GCA and aptitude. The relation between GCA and aptitude is well grounded but research has reported trivial relations between ability and D-SE (cf. Ackerman & Heggestad, 1997; Chen et al., 2000). This more constrained model did not lead to significant decrement in model fit ($\Delta\chi^2 = 6.432$, $\Delta df = 2$, $p = .040$), which supports the additional constraints. Retaining this model, I then examined a less constrained model in which I added paths from GCA and aptitude to the intercept and slope of self-set

goals. I tested this model because of the mixed findings in past research regarding the relationship between ability and self-set goals. The less constrained model did not demonstrate significantly better fit ($\Delta\chi^2 = 9.980, \Delta df = 4, p = .041$), which supports the proposed lack of paths linking ability to self-set goals. Finally, I examined a more constrained model in which I removed paths from D-SE to S-SE. I tested this model because of the debate regarding the relationship between D-SE and S-SE. This more constrained model demonstrated significant decrement in model fit ($\Delta\chi^2 = 83.389, \Delta df = 2, p < .001$), which supports the proposed paths between D-SE and S-SE.

I then examined the structural portion. First, I examined the structural regression paths emanating from GCA and aptitude to the growth factors for S-SE. GCA had a significant path to the intercept ($\beta = -.21, p < .001$) but not to the slope ($\beta = .08, p = .096$). For aptitude, paths to the intercept and slope were nonsignificant. Interestingly, GCA related to lower starting values for S-SE but did not relate to growth rates (although it trended toward relating positively). Further, aptitude did not relate to either starting values or rates of growth in S-SE.

Next, I examined the structural regression paths emanating from D-SE to the growth factors of S-SE and self-set goals. For S-SE, D-SE had significant paths to both the intercept ($\beta = .12, p = .001$) and the slope ($\beta = .15, p < .001$). For self-set goals, only the path to the intercept was significant ($\beta = .38, p < .001$). Thus, D-SE related to higher starting values and growth rates for S-SE, and related to higher starting values for self-set goals.

Finally, it is worth noting the relations between the latent growth factors of S-SE and self-set goals. The intercepts for S-SE and self-set goals were significantly related ($r = .31, p$

< .001); in addition, their slopes were significantly related ($r = .13, p = .023$). However, the intercepts and slopes between process variables were unrelated. Thus, an individual's starting value in S-SE related to his or her starting goal level, but did not relate to growth rates in goal level. Further, an individual's starting value in self-set goals related to his or her starting level of S-SE, but did not relate to rates of growth in S-SE throughout training. Lastly, rates of growth in process variables seemed to mirror each other, such that individuals who demonstrated greater rates of growth in S-SE also demonstrated greater rates of growth in self-set goals.

Step 3: Trainee Characteristics, MEA, and Learning

To address H5a-b, H6a-b, and H7a-b, I examined how starting values and growth rates in MEA process variables influenced training outcomes. Building on the retained model from Step 2, I added criteria to determine whether the latent growth process influenced learning, and ultimately to determine whether the MEA process mediates the relationship between dispositional variables and learning outcomes. In accord with the proposed model, I specified paths from each of the growth factors to each of the learning criteria (see [Figure 4](#)). In this model, the effects of predictors on outcomes were fully mediated by latent change processes in the mediating variables. This model demonstrated mediocre fit ($\chi^2 = 304.420, df = 43, p < .001, CFI = .93, TLI = .88, RMSEA = .07, SRMR = .05$). I compared this model to partially mediated models that included theory-based direct effects from predictors to outcomes (see [Table 4](#)).

First, I tested a partially mediated model that included direct effects from GCA and aptitude to cognitive and skill-based learning. Research has supported these direct effects

(e.g., Chen et al., 2000; Stanhope et al., in press). This less constrained model fit the data significantly better than did the fully mediated model ($\Delta\chi^2 = 137.403$, $\Delta df = 4$, $p < .001$), which supports the additional paths. I then tested a model with less constraints in which I added paths from D-SE to affective learning. Research has documented direct effects from personality variables to affective learning (e.g., Stanhope et al., in press). This less constrained model fit the data significantly better than did the previous model ($\Delta\chi^2 = 39.407$, $\Delta df = 2$, $p < .001$), which supports the additional paths. Finally, I specified a model with fewer constraints in which I added paths from D-SE to cognitive and skill-based learning and paths from GCA and aptitude to affective learning—in essence, I included direct paths from all predictors to all outcomes. This least constrained model did not fit the data substantially better than did the previous model ($\Delta\chi^2 = 24.030$, $\Delta df = 6$, $p = .001$); further, the additional paths did not add theoretical value. Thus, based on model fit, interpretability, and theoretical soundness, I retained the partially mediated model (see [Figure 5](#)) with direct effects from GCA and aptitude to cognitive and skill-based learning and with direct effects from D-SE to affective learning.

After retaining the most appropriate model, I then examined the impact of individual differences and the latent growth process on affective learning by looking at direct, indirect, and total effects (see [Table 5](#)). Individual differences directly and indirectly influenced affective learning. For *posttraining self-efficacy*, there were both direct and indirect effects. Surprisingly, GCA had a negative impact overall on posttraining self-efficacy because of its negative influence on initial levels of S-SE at S0. Aptitude had no significant direct or indirect effects on S-SE. D-SE had a direct effect ($\beta = .10$, $p < .001$) on S-SE and indirect

effects through impacts on starting values and rates of growth in S-SE throughout training. For *motivation to transfer*, there were both direct and indirect effects, and all indirect effects flowed through change in self-set goals. Neither GCA nor aptitude had significant direct or indirect effects. However, D-SE had a direct effect ($\beta = .22, p < .001$) and an indirect effect through its influence on self-set goals at S0.

Next, I examined the impact of the individual differences and the latent growth process on cognitive learning. Individual differences influenced course grades both directly and indirectly, with indirect effects flowing through change in both S-SE and self-set goals. GCA had a positive direct effect ($\beta = .16, p < .001$) on course grades, but its positive impact was mitigated by its negative influence on starting values in S-SE—in total, GCA still had a positive overall influence on course grades. Aptitude had only a direct effect ($\beta = .33, p < .001$) on course grades. D-SE had a small positive indirect effect on course grades through its influence on initial levels of S-SE at S0. D-SE had a small negative indirect effect through its relationship with S-SE growth rates, which was due to the unexpected inverse relationship between S-SE growth rates and course grades (see Vancouver, 2012, for possible explanations, such as overconfidence). In total, D-SE's indirect effects essentially canceled out each other.

Finally, I examined the impact of the individual differences and the latent growth process on skill-based learning. Individual differences influenced OPI both directly and indirectly, with indirect effects flowing through latent change in both S-SE and self-set goals. GCA had a negative indirect effect on OPI through its inverse relationship with S-SE at S0; however, this effect was essentially counterbalanced by a positive direct relationship with

OPI that trended toward significance. Aptitude had a direct effect on OPI ($\beta = .18, p < .001$), but had no indirect effects. D-SE had no direct effect on OPI, but did have indirect effects through its impact on initial values of S-SE at S0 and initial values of self-set goals at S0.

Discussion

I proposed a model and tested it using multivariate LGM to examine the impact of trait-like individual differences (i.e., GCA, aptitude, and D-SE) on learning outcomes through a state-like intervening mechanism (i.e., MEA). Using a three-step process, I examined (a) the shape of growth in the motivational process, (b) whether dispositional variables influenced MEA process variables, and (c) whether MEA process variables influenced learning. Results supported a partially mediated model with linear growth in the motivational process and with both direct effects from dispositional variables to learning and indirect effects through MEA (see [Figure 5](#)).

Step 1: The Longitudinal MEA Process

Step 1 involved studying the growth process of the intervening mechanism (i.e., MEA). First, I addressed the functional shape of growth in the process variables—both evinced linearity. Positive growth in S-SE was expected. Trainees entered training with limited exposure to training content and they developed KSA-related confidence as training progressed. Self-set goals had negative growth (albeit small in magnitude). Perhaps trainees entered training with aggrandized goals and aspirations, but accurately revised goals during training. In support, the relationship between goals and the performance criterion (OPI) increased from S0 ($r = .18$) to S1 ($r = .27$) to S2 ($r = .34$). Research has shown that goal-performance discrepancies and S-SE impact goal revision (e.g., Donovan & Williams, 2003;

Tolli & Schmidt, 2008). Perhaps trainees used proxies of performance (e.g., course tests, class exercises) to revise goals. Further, intercepts and slopes were positively correlated in the parallel processes growth model, indicating that starting values and changes in S-SE accompanied increases in goal levels.

Next, I examined variability in the growth process. In support of both H1a and H1b, the data indicated significant individual differences in the starting values and rates of growth in S-SE and self-set goals. That is, trainees varied in their initial levels of S-SE and goals, and they varied in their intraindividual growth in each variable throughout training.

Step 2: Trainee Characteristics and MEA

Step 2 involved determining whether individual differences account for variability in the MEA process. In support of H2b and H3b, neither GCA nor aptitude related to starting values or growth rates in self-set goals. These results align with research that suggests ability impacts work outcomes through paths other than self-set goals (e.g., Stanhope et al., in press). Contrary to Hypotheses 2a and 3a, GCA and aptitude were unrelated to starting values and growth rates in S-SE, with one exception: GCA was negatively related to starting values in S-SE. It is possible that trainees with higher ability self-assessed with greater accuracy upon entering training, thus reporting lower S-SE. Research by Kruger, Dunning, and colleagues (e.g., Kruger & Dunning, 1999) has shown that individuals with *lower* ability tend to inflate their ability estimates. Exploring this effect in this context provides an interesting avenue for future research.

In support of H4a, D-SE related to starting values and growth rates in S-SE, which aligns with past research (e.g., Chen et al., 2000; Mathieu et al., 1993). As mentioned earlier,

the relationship between D-SE and S-SE has been a topic of debate—however, whereas Bandura cautioned against the use of *decontextualized* general efficacy measures (Bandura, 2012), D-SE herein is a *contextualized* general efficacy measure because it refers to efficacy percepts in training contexts, which possibly explains the relationship. In partial support of H4b, D-SE related to starting values in self-set goals, but did not relate to growth rates. Chen et al. (2000) found bivariate correlations between D-SE and goals to drop from Time 1 ($r = .24, p < .01$) to Time 2 ($r = .14, p < .05$). Similarly, D-SE related to starting values of self-set goals ($\beta = .38$), but did not relate to growth. Further, Chen et al. (2000) and Phillips and Gully (1997) showed dispositional variables operated through S-SE to influence goals; both reported correlations between S-SE and goals ranging from .37–.48. Thus, it appears that more distal, general efficacy percepts exert influence in training contexts at least partly through influences on more proximal, specific efficacy percepts. Further, the relationship between D-SE and self-set goals is likely explained in part by S-SE. The positive relationship between latent intercepts (starting values) and slopes (growth rates) of S-SE and self-set goals further corroborates these inferences.

Step 3: Trainee Characteristics, MEA, and Learning

In Step 3, I added outcomes to determine whether the MEA process influenced learning. The starting values and growth rates in MEA process variables related to affective learning (H5a and H5b partially supported), cognitive learning (H6a and H6b partially supported), and skill-based learning (H7a and H7b partially supported). Hypotheses were only partially supported for two reasons. First, for each learning outcome at least one of the four paths (i.e., paths emanating from the intercepts and slopes of S-SE and self-set goals)

was nonsignificant. Second, rather than full mediation, each of the outcomes also had direct effects emanating from at least one of the dispositional variables.

For affective learning (i.e., posttraining self-efficacy and motivation to transfer), the personality predictor (i.e., D-SE) provided direct influence and provided indirect influence through MEA. Ability predictors (i.e., GCA and aptitude) did not influence affective learning. For cognitive (i.e., course grades) and skill-based (i.e., OPI) learning, ability predictors provided direct influence but provided minimal indirect influence through MEA. The personality predictor had a small influence on skill-based learning through its influence on MEA. The finding that ability predicts cognitive and skill-based learning is consistent with past research (Gully & Chen, 2010; Salas & Cannon-Bowers, 2001). Further, the finding that personality predicts affective learning directly and skill-based learning indirectly through intervening mechanisms aligns with past research (e.g., Chen et al., 2000; Stanhope et al., in press). Ultimately, findings suggest that affective learning is influenced more by personality than by ability, and that cognitive and skill-based learning is influenced by both but through different explanatory routes. Future research should continue to explore this supposition.

Implications for Theory and Practice

Results suggest that dispositional variables operate both directly and indirectly to influence learning. Further, dispositional variables operate through unique mechanisms. Whereas personality may influence affective learning through direct routes, ability may influence cognitive and skill-based learning through direct routes. Beyond direct effects, personality may have indirect effects on affective, cognitive, and skill-based learning through

intervening mechanisms such as MEA. Understanding not only *which* individual differences impact learning but also *how* they impact learning is a rich source of knowledge for researchers and practitioners.

Results suggest that MEA is a useful explanatory mechanism in training effectiveness contexts. Research has demonstrated that MEA affects learning (e.g., Chen et al., 2000; Stanhope et al., in press); however, past research has typically operationalized the motivational process as a single measurement occasion. Having longitudinal data throughout training enabled me to model the dynamic learning process, which provided information on the motivational process and on the antecedents and consequents of it. I was able to examine antecedents of change (whether dispositional variables influenced MEA), change itself (shape and variability in MEA), and consequents of change (whether MEA affected outcomes). Operationalizing the intervening motivational process as a process rather than a snapshot enhanced the study's verisimilitude. Understanding explanatory mechanisms helps demystify the learning process, helps elucidate the "black-box" processes that occur between dispositional influence and learning, and helps delineate how individual differences are important in learning contexts.

Organizations spend billions of dollars annually on training and development (Green & McGill, 2011). Because training is expensive and pervasive, and because it offers individuals and organizations inimitable value, it is critical to identify factors that contribute to training effectiveness. First, selecting or promoting individuals who are likely to benefit from training ensures that organizations allocate resources strategically. Second, assessing the trainability of potential trainees informs decisions about whether to select or place

trainees into various training endeavors. Ultimately, it would behoove organizations to train and develop individuals likely to benefit, and to recruit and hire based on information that determines whether individuals will acquire and transfer the training that they will inevitably receive.

It is not always feasible to select into organizations or to select into training only individuals who appear trainable. However, another practical implication involves training interventions. A trainee's disposition (e.g., ability and D-SE) is difficult to manipulate and dispositional barriers—though surmountable—are often formidable. Thus, self-management training or training interventions that influence self-regulatory and motivational processes may be especially effective for helping trainees overcome dispositional barriers—or, alternatively, helping trainees accentuate dispositional proclivities. For example, trainees who set lower goals or who are predisposed to set lower goals may benefit from a goal-setting intervention. Setting specific, measurable, and difficult goals increases motivation and performance (Locke & Latham, 1990, 2002). Research has consistently supported this theory (e.g., Chen et al., 2000; Phillips & Gully, 1997). Another possible intervention is infusing S-SE by ensuring early successes. This intervention may be especially beneficial for those with low D-SE, as research has demonstrated that performance relates more strongly to S-SE for individuals with low D-SE (Chen et al., 2000), and that S-SE interventions are more effective for trainees with low D-SE (Eden & Aviram, 1993).

Limitations and Future Research

The ability to extrapolate results from a specific sample (i.e., military personnel) to the general population is limited by the extent to which characteristics of the sample deviate

from those of the population. However, nothing suggests that findings are attributable to sample idiosyncrasies, and the general implications that dispositional variables and intervening mechanisms have in the training context are important nonetheless. That said, future research should attempt to replicate these findings and should investigate the cross-situational validity and transportability of these findings with nonmilitary samples. In addition, I examined training effectiveness in the context of foreign language training; future research should study whether these results generalize to additional training contexts and additional KSAs.

Two potential methodological limitations are worth noting. First, I collected some same-source data. However, none of the self-report variables had high-stakes implications for the participants whose anonymity was assured; thus, respondents had no foreseeable motive for faking or false reporting. Further, deleterious effects of common-source bias were alleviated by including objective data for ability and for both cognitive and skill-based learning; by incorporating temporally spaced measurement occasions; and by including different response scales (Podsakoff, MacKenzie, & Podsakoff, 2012). Second, data were correlational, which limits one's ability to make strong causal inferences. However, the longitudinal study design was temporally aligned with theory and with the specification of the models. Furthermore, I examined multiple competing models with theory-based alternative specifications. Nonetheless, future research should explore and test additional models.

Future research should examine additional personality and ability predictors. Future research should also examine intervening mechanisms such as information-processing

capacity, attentional focus and metacognitive processing, and emotional regulation and control (Gully & Chen, 2010). Lastly, future research should examine how individual differences and intervening mechanisms influence other learning outcomes, transfer outcomes (i.e., maintenance and application of KSAs), and organizational outcomes (e.g., employee turnover, firm revenue).

Conclusion

A skilled and knowledgeable workforce is a distinct competitive advantage for organizations (Huselid, 1995). Hence, organizations invest immense resources annually into training and development (Green & McGill, 2011). To ensure that individuals learn, maintain, and use trained KSAs, researchers engage in research on training effectiveness. Factors that contribute to training effectiveness include distal dispositional variables and the proximal intervening mechanisms through which they operate. Analyzing multiple measurement occasions throughout the learning process is a valuable means of studying the dynamic processes through which dispositional variables and intervening mechanisms influence learning. Accordingly, I conducted multivariate LGM with multiple measurement occasions and found that (a) the motivational process unfolded linearly and varied across trainees, (b) the motivational process was influenced differently by ability and D-SE, and (c) disposition and MEA influenced cognitive, affective, and skill-based learning outcomes.

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Table 1
Descriptive Statistics, Zero-Order Correlations, and Scale Reliabilities

Variable	<i>n</i>	<i>M</i>	<i>SD</i>	1	2	3	4	5
1 Dispositional self-efficacy	1398	9.68	0.90	(.91)				
2 GCA	1078	51.77	26.02	.01	–			
3 DLAB	1047	80.94	17.47	.06	.46***	–		
4 Specific self-efficacy S0	1397	2.60	2.80	.07	-.16***	-.10**	(.99)	
5 Specific self-efficacy S1	1396	4.46	2.49	.17**	-.13***	-.06	.42***	(.97)
6 Specific self-efficacy S2	1348	6.67	2.22	.25***	-.09**	-.02	.32***	.61***
7 Self-set goals S0	1389	4.28	0.97	.30***	-.05	-.02	.17***	.16***
8 Self-set goals S1	1391	4.19	0.93	.25***	.04	.07*	.18***	.23***
9 Self-set goals S2	1349	3.97	0.95	.25***	.04	.08*	.16***	.19***
10 Posttraining self-efficacy	1309	8.11	1.90	.26***	-.08*	-.02	.22***	.44***
11 Motivation to transfer	1161	9.42	1.58	.29***	-.11**	.04	.07*	.07*
12 Course grades	1134	89.06	5.92	.09**	.27***	.36***	.04	.12***
13 Oral Proficiency Interview	1362	3.55	0.70	.12***	.09**	.18***	.13***	.14***

Note. *n* = 1047-1398 (pairwise). GCA = General cognitive ability. DLAB = Defense Language Aptitude Battery. S0 = Time point 1. S1 = Time point 2. S2 = Time point 3. Parenthetic values on the diagonal are internal consistency reliabilities (coefficient alpha).

p* < .05. *p* < .01. ****p* < .001.

Table 1 (*continued*)

Variable	6	7	8	9	10	11	12	13
Specific self-efficacy S2	(.96)							
Self-set goals S0	.21***	(.96)						
Self-set goals S1	.26***	.52***	(.96)					
Self-set goals S2	.26***	.48***	.66***	(.97)				
Posttraining self-efficacy	.66***	.18***	.21***	.26***	(.96)			
Motivation to transfer	.17***	.23***	.17***	.24***	.26***	(.97)		
Course grades	.08**	.06*	.19***	.29***	.12***	.11**	–	
Oral Proficiency Interview	.14***	.18***	.27***	.34***	.15***	.13***	.33***	–

Table 2

Parameter Estimates for Parallel Processes Growth Model

Variable					Factor Means		Factor Residuals	
	1	2	3	4	<i>Estimate</i>	<i>p-value</i>	<i>Estimate</i>	<i>p-value</i>
1 S-SE Intercept	–				2.63	< .001	3.71	< .001
2 S-SE Slope	-.40**	–			2.25	< .001	1.50	< .001
3 Goals Intercept	.35**	-.01	–		4.30	< .001	0.48	< .001
4 Goals Slope	-.06	.14*	-.08	–	-0.18	< .001	0.10	< .001

Note. $N = 1448$. Estimates for factor means and factor residuals are unstandardized. S-SE = Specific self-efficacy. Goals = Self-set goals.

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

Table 3
Model Comparisons for Step 2

Model	χ^2	<i>df</i>	CFI	TLI	RMSEA (90% CI)	SRMR
1: Least constrained	39.569	15	.99	.98	.03 (.02-.05)	.02
2: Proposed Model	43.117	17	.99	.98	.03 (.02-.05)	.02
3: More constrained ^a	49.549	19	.99	.98	.03 (.02-.05)	.02
4: Most constrained	132.938*	21	.96	.93	.06 (.05-.07)	.05

Note. $N = 1449$. Models presented based on increasing constraints (see text for information on model-testing sequence). CFI = Comparative fit index. TLI = Tucker-Lewis index. RMSEA = Root-mean-square error of approximation. CI = Confidence interval. SRMR = Standardized root-mean-square residual.

^a Retained model – this model is used as the base model in Step 3 (see Table 4).

* $p < .001$ (used method outlined by Satorra [2000] for nested-model χ^2 difference tests—if the simpler model [i.e., less freely estimated parameters] did not fit the model significantly worse than the more complex model [i.e., more freely estimated parameters], then I elected to retain the simpler model).

Table 4
Model Comparisons for Step 3

Model	χ^2	<i>df</i>	CFI	TLI	RMSEA (90% CI)	SRMR
1: Least constrained	103.58	31	.98	.96	.04 (.03-.05)	.03
2: More constrained 1 ^a	127.61	37	.98	.95	.04 (.03-.05)	.03
3: More constrained 2	167.017*	39	.97	.94	.05 (.04-.06)	.03
4: Proposed Model	304.42*	43	.93	.88	.07 (.06-.07)	.05

Note. $N = 1458$. Models presented based on increasing constraints (see text for information on model-testing sequence). CFI = Comparative fit index. TLI = Tucker-Lewis index. RMSEA = Root-mean-square error of approximation. CI = Confidence interval. SRMR = Standardized root-mean-square residual.

^a Retained model.

* $p < .001$ (used method outlined by Satorra [2000] for nested-model χ^2 difference tests—if the simpler model [i.e., less freely estimated parameters] did not fit the model significantly worse than the more complex model [i.e., more freely estimated parameters], then I elected to retain the simpler model).

Table 5
Direct Effects, Total Indirect Effects, and Total Effects of Dispositional Variables on Learning Outcomes

Outcome	General Cognitive Ability			Specific Aptitude			Dispositional Self-Efficacy		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Posttraining SE	–	-.07*	-.07*	–	–	–	.10**	.17**	.27**
Motivation to Transfer	–	–	–	–	–	–	.22**	.08**	.30**
Course Grades	.16**	-.07*	.09*	.33**	–	.30**	–	–	–
OPI	.07 [†]	-.05*	–	.18**	–	.16**	–	.10**	.10**

Note. $N = 1495$. SE = Self-efficacy. OPI = Oral Proficiency Interview.

* $p < .01$. ** $p < .001$. [†] $p < .10$.

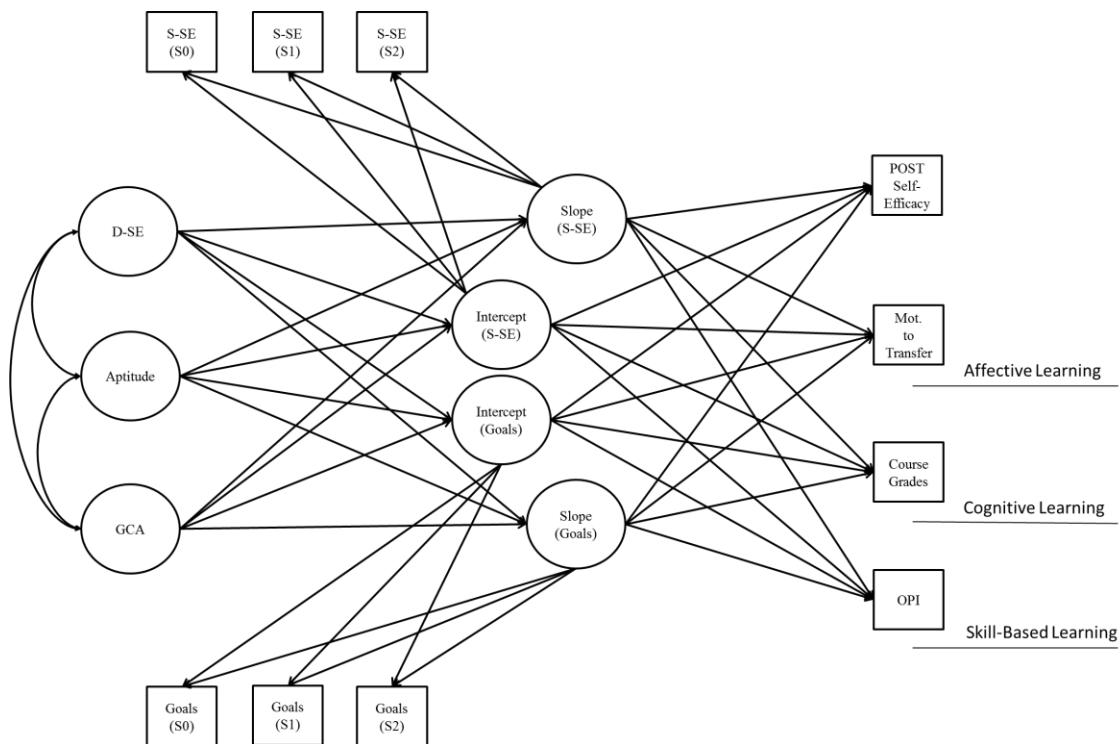


Figure 1. Latent growth model where individual differences influence training outcomes through longitudinal motivational intervening mechanisms. (Residuals and other paths omitted for visual simplicity.) D-SE = Dispositional self-efficacy. GCA = General cognitive ability. S-SE = Specific self-efficacy. Goals = Self-set goals. POST = Posttraining. Mot. = Motivation. S0 = Time 1. S1 = Time 2. S2 = Time 3.

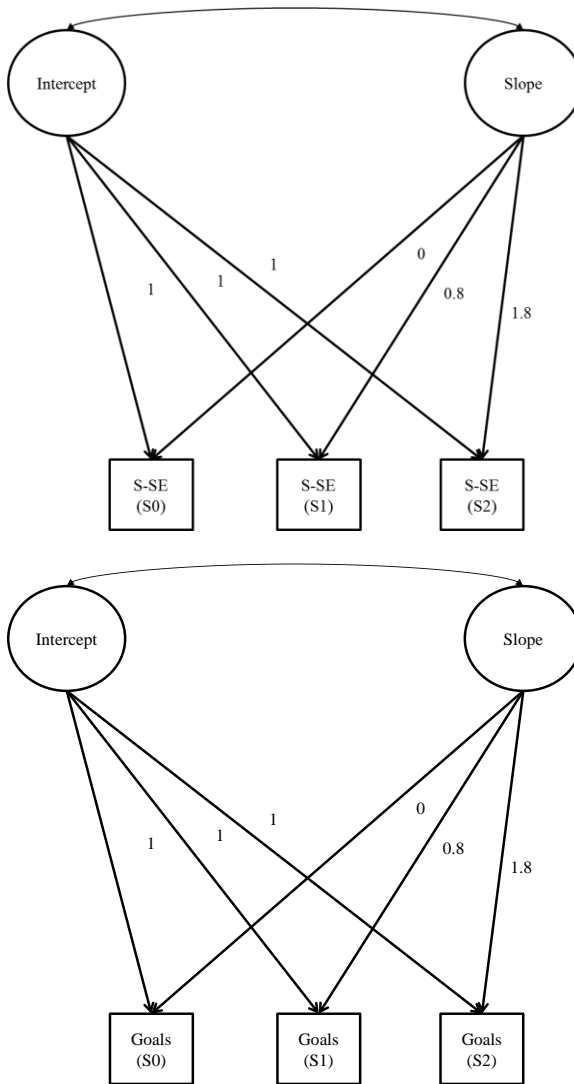


Figure 2. Latent growth models (LGM) for examining the functional shape of growth in mediating process variables. I conducted each LGM independently. After determining the shape of growth for each process variable, I combined the models to test the parallel processes LGM. (Residuals and other paths omitted for simplicity.) S-SE = Specific self-efficacy. Goals = Self-set goals. S0 = Time 1. S1 = Time 2. S2 = Time 3.

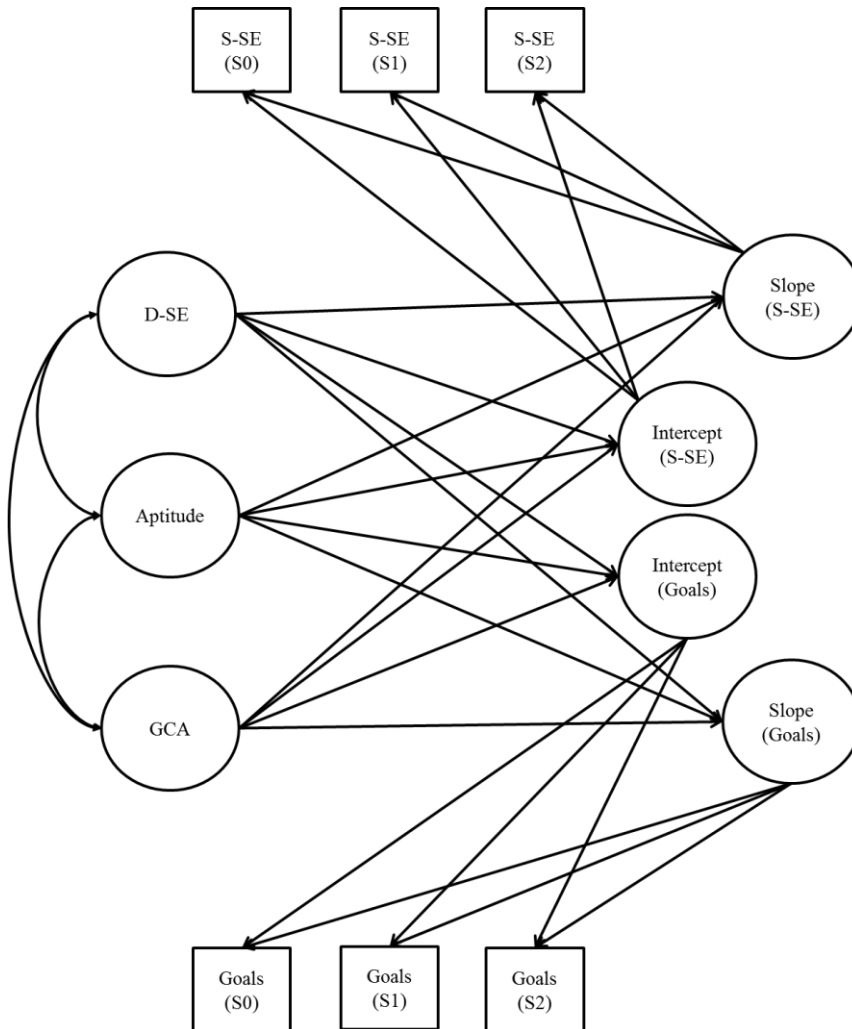


Figure 3. Latent growth model for examining the extent to which time-invariant covariates account for variability in latent growth factors of the mediating process variables. (Residuals and other paths omitted for simplicity.) D-SE = Dispositional self-efficacy. GCA = General cognitive ability. S-SE = Specific self-efficacy. Goals = Self-set goals. S0 = Time 1. S1 = Time 2. S2 = Time 3.

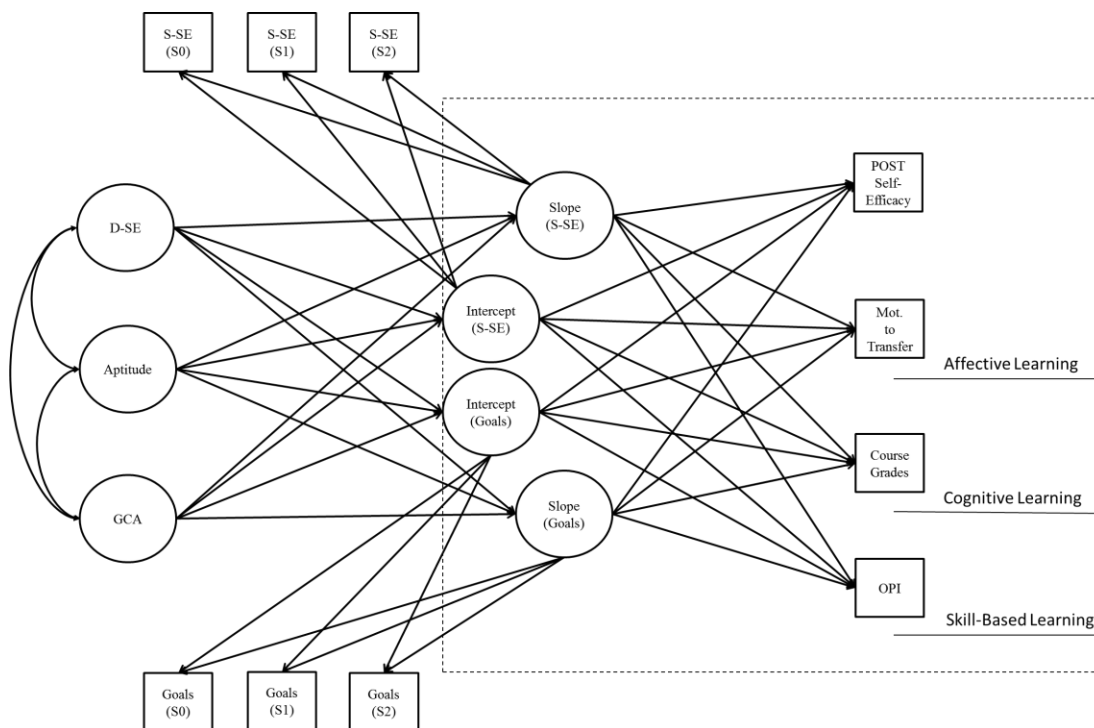


Figure 4. Latent growth model wherein trait-like individual differences influence training outcomes through longitudinal motivational intervening mechanisms. The portion of the structural model that I address is encapsulated in the perforated box. (Residuals and other paths omitted for visual simplicity.) D-SE = Dispositional self-efficacy. GCA = General cognitive ability. S-SE = Specific self-efficacy. Goals = Self-set goals. POST = Posttraining. Mot. = Motivation. OPI = Oral Proficiency Interview. S0 = Time 1. S1 = Time 2. S2 = Time 3.

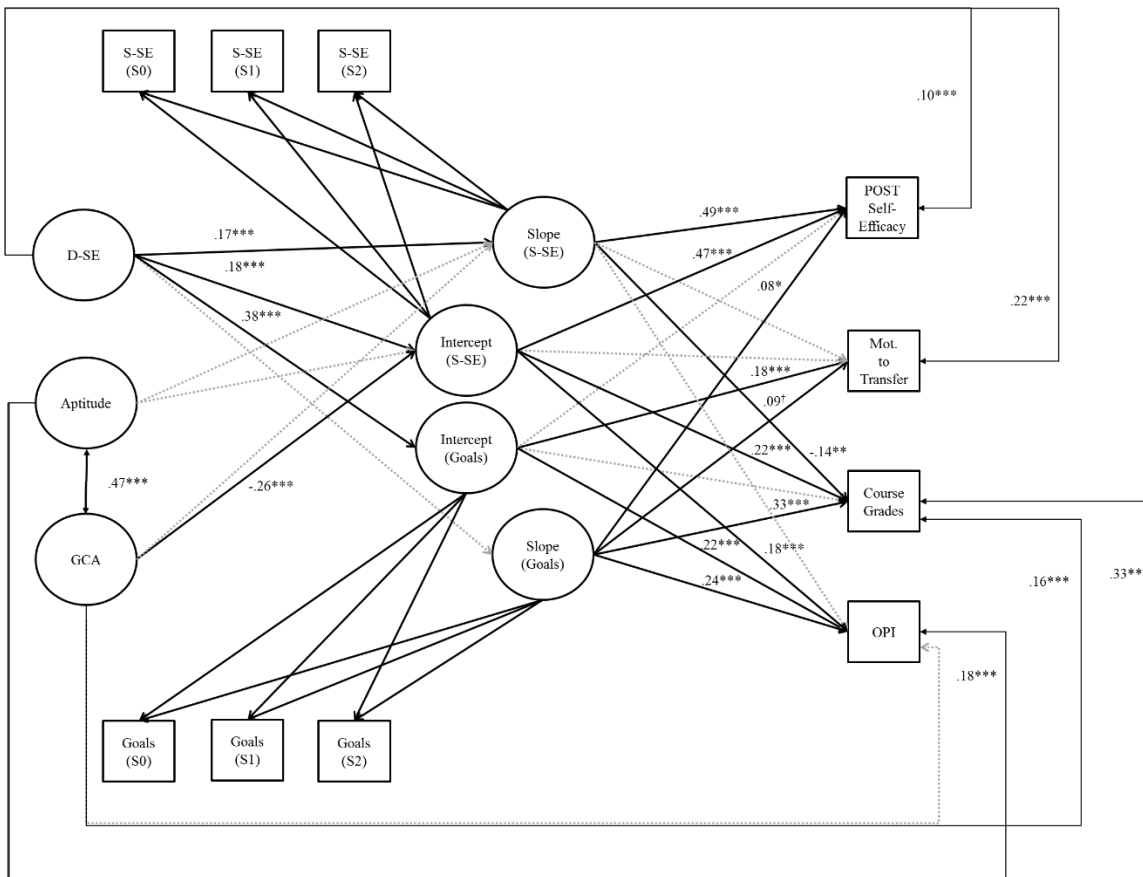


Figure 5. Latent growth modeling results for the effects of dispositional individual differences on learning outcomes through motivational intervening mechanisms. Residuals and disturbance terms are omitted for visual clarity. The diagrammed causal flow aligns with theory—namely, dispositional variables exert influence on process variables, which then exert influence on outcome variables—and denotes temporal precedence inherent in the study design. D-SE = Dispositional self-efficacy. GCA = General cognitive ability. S-SE = Specific self-efficacy. Goals = Self-set goals. POST = Posttraining. Mot. = Motivation. OPI = Oral Proficiency Interview. S0 = Time 1. S1 = Time 2. S2 = Time 3. All coefficients are standardized. All estimated paths are displayed; nonsignificant paths are denoted by a gray perforated arrow.

N = 1458. *p < .05. **p < .01. ***p < .001. †p < .10.

APPENDIX

DISSERTATION PROPOSAL:

Longitudinal Examination of the State-Like Motivational Processes Linking Ability and
Dispositional Self-Efficacy to Training Effectiveness

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Abstract

Understanding factors that contribute to training effectiveness helps both the individual and the organization benefit maximally from this pervasive human resource management activity. Using longitudinal data from a military training context, I propose to employ multivariate latent growth modeling (LGM) methodologies to examine the impact of trait-like individual differences on learning outcomes through state-like intervening mechanisms. Contrary to the more common practice of collecting data on the mediator at a single point in time, I will measure mediating variables at 4 time-structured measurement occasions, which will allow for a more nuanced elucidation of the explanatory mechanistic role played by motivational process variables. Thus, I propose to model (a) mediators (i.e., specific self-efficacy and goal setting) as latent growth factors across 4 equidistant time points, (b) trait-like individual differences (i.e., ability and dispositional self-efficacy) as time-invariant covariates that exert influence on the aforementioned mediating latent growth factors, and (c) training effectiveness criteria (i.e., cognitive, affective, and skill-based learning) as outcomes of the mediating latent growth factors. I propose to conduct an iterative model-testing procedure consisting of 3 focal inquiries: (a) whether there exists interindividual variability in trainees' starting values and rates of growth for each process variable, (b) whether ability and dispositional self-efficacy account for variability in the mediating latent growth factors, and (c) whether the mediating latent growth factors account for variance in posttraining measures of cognitive, affective, and skill-based learning. Results will have implications for and will help inform the science and practice of training and development efforts.

Longitudinal Examination of the State-Like Motivational Processes Linking Ability and Dispositional Self-Efficacy to Training Effectiveness

A knowledgeable and highly skilled workforce is a strategic differentiator that provides a competitive advantage for private, public, and non-profit organizations (Bowen & Ostroff, 2004; Crook, Todd, Combs, Woehr, & Ketchen, 2011; Hatch & Dyer, 2004; Huselid, 1995; Kogut & Zander, 1992; Subramony, Krause, Norton, & Burns, 2008). To build such a workforce, organizations offer organizational members numerous training and develop opportunities—both formal and informal. From a resource-based theory (RBT) perspective, training and development efforts that effectively develop human capital add discernible value to organizations (Acedo, 2006; Barney, 1991; Barney, Wright, & Ketchen, 2001; Carmeli & Schaubroeck, 2005; Hitt, Biermant, Shimizu, & Kochhar, 2001)—but not without cost. According to the American Society for Training and Development (ASTD; Green & McGill, 2011), U.S. organizations spent approximately \$171.5 billion on training and development in 2010, and spent an estimated \$1,228 per employee. In fact, despite the national recession and associated economic tribulations, ASTD (Green & McGill, 2011) reported that organizations have continued to invest in training at a greater rate than ever before—annual per-employee expenditures climbed 13.5% from 2010 to 2011 and is the highest it has ever been since ASTD began collecting these data. Because training efforts are expensive and increasingly pervasive (Green & McGill, 2011), and because they offer inimitable value to individuals and organizations (e.g., Huselid, 1995; Kogut & Zander, 1992), it is critically important to identify factors that contribute to the effectiveness of training endeavors and to understand the mechanisms through which these factors operate.

Research on training effectiveness has traditionally included the following factors: training design, organizational characteristics, and trainee characteristics (Alvarez, Salas, & Garofano, 2004; Goldstein & Ford, 2002). Whereas training design has received the most attention historically (Tannenbaum & Yukl, 1992), trainee characteristics have received considerable attention in recent decades (e.g., Baldwin & Ford, 1988; Colquitt, LePine, & Noe, 2000; Mathieu, Tannenbaum, & Salas, 1992; Noe, 1986). Past efforts to expand our understanding of the impact that trainee characteristics exert on learning factors have contributed substantially to training effectiveness research (Goldstein & Ford, 2002; Salas & Cannon-Bowers, 2001). Indeed, past research has demonstrated that individual differences exert considerable influence on important training criteria (e.g., Baldwin & Ford, 1988; Barrick & Mount, 1991; Colquitt et al., 2000; Martocchio & Judge, 1997). However, researchers have continued to emphasize the need to further our understanding of *how* trainee characteristics influence training effectiveness, including calls for research aimed at identifying and explicating the “black-box” processes occurring in the space between dispositional influence and purported criterion-related effects (e.g., Gully & Chen, 2010; Beier & Kanfer, 2010).

With this study, I set out to integrate and address several interrelated calls for research that, when juxtaposed, underscore the need for additional research that elucidates the processes by which individual differences influence training effectiveness. Firstly, moving beyond research that focuses on direct influence and main effects, researchers have called for additional research focusing on the intervening mechanisms through which trainee characteristics may operate to influence training outcomes (Gully & Chen, 2010). Relatedly,

researchers have called for additional studies that account for the proximal state-like variables through which distal dispositional variables operate to exert influence on training outcomes (e.g., Chen, Gully, Whiteman, & Kilcullen, 2000). Lastly, researchers have called for an increased emphasis on accounting for intervening motivational processes when examining the influence of individual differences on training outcomes (e.g., Beier & Kanfer, 2010; Campbell, 1989; Kanfer, 1990). Accordingly, drawing from these adjacent calls, I will examine the influence of trait-like individual differences (i.e., ability and dispositional self-efficacy) on intervening process variables (i.e., specific self-efficacy and goal setting), and I will examine the extent to which this intervening motivational process influences cognitive, affective, and skill-based learning criteria. Further, capitalizing on strengths of a longitudinal study design, I will operationalize the intervening motivational process as a latent growth process with multiple measurement occasions rather than the more traditional snapshot approach. Thus, the purpose of this research will be to examine intervening mechanisms in a longitudinal training program where I hypothesize that the effects of dispositional variables are achieved through their effects on latent change factors in intervening process variables.

Trainee Characteristics, Intervening Mechanisms, and Training Criteria

Training is a pervasive, multibillion-dollar-per-year human resource management (HRM) practice that organizations rely on to equip employees with the knowledge, skills, and abilities (KSAs) necessary to contribute to organizational performance. For this practice to have maximal organizational utility, trainees must effectually learn the training content and subsequently transfer KSAs from the training context to the workplace. Thus, training objectives often involve the acquisition and application of trained KSAs. Determining the

extent to which training programs meet training objectives is addressed systematically through *training evaluation* (e.g., Kraiger, Ford, & Salas, 1993). Not to be used interchangeably with training evaluation, *training effectiveness* research then aims to determine *why* and *how* training objectives were or were not successfully achieved (Alvarez et al., 2004; Salas & Cannon-Bowers, 2001). Training evaluation and effectiveness work that determines if and explains why various factors contribute to training success not only informs training research and science, but it also provides actionable information that informs efforts to aid individuals, groups, and organizations with maximizing their return on invested resources.

Trainee Characteristics: Trait-Like Individual Differences

Characteristics of the trainee contribute to training effectiveness and influence the extent to which trainees learn and perform in training contexts (Ackerman & Heggestad, 1997; Goldstein & Ford, 2002; Tannenbaum & Yukl, 1999). In the recent Society for Industrial and Organizational Psychology (SIOP) Organizational Frontiers publication (Kozlowski & Salas, 2010) devoted to training and development, *person and process* emerged as one of three key themes with consistent coverage throughout the edited book (Salas & Kozlowski, 2010). This theme refers to the “central role of the person—the trainee—and the learning and motivational processes that are inherent in the training enterprise” (Salas & Kozlowski, 2010, p. 463). There was unanimous support for the importance of the role played by the learner in the learning process; however, multiple chapters in the aforementioned book emphasized the need for additional research that

examines which and elucidates how the learner influences the learning process (e.g., Beier & Kanfer, 2010; Gully & Chen, 2010; Salas & Kozlowski, 2010).

Trainees bring into training unique dispositions, idiosyncrasies, and experiences (Campbell, 1989), and these individual differences influence the learning process (Goldstein & Ford, 2002; Salas & Cannon-Bowers, 2001; Tannenbaum & Yukl, 1992). Indeed, individual differences have displayed myriad linkages with salutary training variables, including training motivation (e.g., Colquitt et al., 2000; Fecteau, Dobbins, Russell, Ladd, & Kudisch 1995; Noe, 1986), training proficiency (e.g., Barrick, Mount, & Judge, 2001; Colquitt et al., 2000), and transfer of training (e.g., Baldwin & Ford, 1988; Blume, Ford, Baldwin, & Huang, 2010). Both ability and nonability characteristics of the trainee have consistently demonstrated utility in the training context (e.g., Campbell, 1988; Chen et al., 2000; Chen, Gully, & Eden, 2004; Kim, Oh, Chiaburu, & Brown, 2012; Salas & Cannon-Bowers, 2001; Tannenbaum & Yukl, 1992). However, a paucity of research has examined the explanatory mechanisms driving the impact of individual differences on training effectiveness. One such mechanism that may tenably carry out the influence actuated by individual differences is the intervening motivational process (Chen et al., 2004; Colquitt et al., 2000; Gully & Chen, 2010; Kanfer, 1990; Salas & Kozlowski, 2010). Thus, consistent with the aforementioned person-and-process theme (Salas & Kozlowski, 2010), I will examine the extent to which individual differences (i.e., *the person*; ability and dispositional self-efficacy), influence training effectiveness through influences on longitudinally operationalized motivational intervening mechanisms (i.e., *the process*; specific self-efficacy and goal setting).

Ability. Cognitive ability “involves the performance of higher mental processes including reasoning, remembering, understanding, and problem solving” and, further, “it is associated with the increased ability to acquire, process, and synthesize information, allowing for more rapid acquisition, application, and generalization of knowledge” (Gully & Chen, 2010, p. 9). Researchers typically explain cognitive ability in terms of cognitive resource capacity or information processing capabilities (e.g., Ackerman, 1986; Carroll, 1993; Kanfer & Ackerman, 1989)—or, more simply, as the ability to learn (Alvarez et al., 2004; Hunter, 1986). In their seminal meta-analysis, Schmidt and Hunter (1998) revealed convincing evidence in support of the validity of cognitive ability for predicting training performance. In fact, cognitive ability has received consistent support as a dominant predictor of learning and performance (e.g., Alvarez et al., 2004; Colquitt et al., 2000; Driskell, Hogan, Salas, & Hoskin, 1994; Hunter, 1986; Pintrich, Cross, Kozma, & McKeachie, 1986; Ree, Carretta, & Teachout, 1995; Ree & Earles, 1991; Schmidt & Hunter, 1998). Gully and Chen (2010) asserted the “general conclusion of both qualitative (Salas & Cannon-Bowers, 2001) and quantitative reviews (Colquitt et al., 2000) is that [cognitive ability] matters to training success”; however, they noted, “more research is needed to better establish why and when [cognitive ability] promotes learning” (pp. 9-10).

Whereas general cognitive ability refers to information processing or cognitive resource capacity in the broadest sense, specific mental ability (or specific cognitive aptitude) refers to more focused, task- or process-oriented cognitive functioning (Carroll, 1993; Spearman, 1904; Thurstone, 1938). Examples of specific cognitive aptitudes include mathematical comprehension and reading comprehension. Past research has demonstrated

that specific aptitudes predict learning and performance (e.g., Petersen & Al-Haik, 1976; Silva & White, 1993). It is reasonable to assume that, in general, individuals with high aptitude in a specific domain will demonstrate greater learning and performance outcomes when training covers that respective domain. For example, one would expect individuals with high mathematical aptitude to perform better than those with low mathematical aptitude in, say, a course on calculus. *Specific aptitude theory*, or *differential aptitude theory*, takes this supposition a step further, suggesting that specific aptitudes may predict variance in learning and performance above-and-beyond that of general cognitive ability; this supposition, however, is not without critics (e.g., Brown, Le, & Schmidt, 2006; Hunter, 1986; Ree, Earles, & Teachout, 1994). Critics suggest that specific aptitudes fail to predict learning and performance beyond that of general cognitive ability. Although the topic of general-versus-specific ability is outside the realm of this paper, including both cognitive ability and specific aptitude in the proposed structural model will allow me to examine their unique influences in this particular training context.

Dispositional Self-Efficacy. Individual differences other than ability are also important for learning and training effectiveness (e.g., Ackerman, Kanfer, & Goff, 1995; Cannon-Bowers, Salas, Tannenbaum, & Mathieu, 1995; Driskell et al., 1994; Pintrich et al., 1986; Tannenbaum & Yukl, 1992). It has been well documented that self-efficacy—that is, self-confidence in one’s competence to perform given tasks or activities (Bandura, 1977, 1986)—is a factor that influences learning outcomes and training success (e.g., Chen et al., 2000; Gully & Chen, 2010; Mathieu et al., 1993; Stajkovic & Luthans, 1998). Bandura (1977) asserted that efficacy percepts are the single greatest determinants of behavioral

change due to their impacts on an individual's decision to exert effort toward a given pursuit and persist through tribulations. In fact, according to Salas and Cannon-Bowers (2001), findings related to self-efficacy have been consistent: "Self-efficacy, whether one has it before or acquires it during training, leads to better learning and performance" (p. 478).

Researchers have conceptually mapped self-efficacy onto a continuum of specificity ranging from the very specific to the very general (e.g., Bandura, 1977; Schwoerer, May, Hollensbe, & Mencl, 2005; Sherer, 1982). Specific self-efficacy consists of percepts that are linked to specific tasks or activities, whereas general self-efficacy consists of percepts that span a variety of tasks or activities. Where specific self-efficacy is malleable (e.g., Schwoerer et al., 2005), general self-efficacy is cross-situational and is said to be a stable, trait-like disposition (Sherer, 1982). In accord, I will refer to dispositional self-efficacy as a stable, trait-like individual differences predictor and I will refer to specific self-efficacy as a state-like motivational process variable. Operationalizing self-efficacy in this manner aligns with my study design of examining the processes by which distal, trait-like individual differences influence training outcomes through more proximal, state-like motivational intervening mechanisms.

Gully and Chen (2010) asserted that a generalized conception of self-efficacy has shown predictive utility in the training context and that it "is a useful self-evaluation construct for understanding learning and training effectiveness" (p. 27). Further, Gully and Chen (2010) suggested that its influence on training outcomes may be mediated by motivational intervening mechanisms such as self-efficacy and self-set goals, which was evidenced empirically by Chen et al. (2000). Indeed, past research has provided evidence

that dispositional self-efficacy influences motivational processes such as task choice, effort intensity, and persistence (e.g., Gist & Mitchell, 1992). Despite consistent support for the impact of self-efficacy on training outcomes, there is a need to further our understanding of how it operates in training contexts (Gully & Chen, 2010).

Motivational Intervening Mechanisms

Referencing research from Ackerman and colleagues (e.g., Ackerman & Kanfer, 2004; Ackerman, Kanfer, & Goff, 1995), Gully and Chen (2010) noted, “Training outcomes are determined by a combination of mechanisms that influence how people process information, focus their attention, direct their effort, and manage their affect during learning” (p. 7). Thus, according to Gully and Chen, training research would benefit from an “increased focus on explanatory mechanisms that mediate the effects of individual differences on training outcomes” (p. 4). Cannon-Bowers et al. (1995) asserted, “Despite the centrality of motivation to most conceptions of learning performance, there has not been a great deal of empirical research that has examined the role of trainee motivation in training effectiveness” (p. 146). Further, Salas and Kozlowski (2010) suggested, “To better understand the effects of individual differences...we must have a deeper understanding of learning and motivational processes” (p. 464). They go on to aver the critical importance of understanding “that motivation is intimately entwined in the processes of learning, skill acquisition, and expertise development” (p. 464). Accordingly, I will examine *motivation and effort allocation* (MEA; see Gully & Chen, 2010) as an intervening mechanism that plausibly explains processes through which disposition impacts training effectiveness. Further, I contend that this rich explanatory process is best understood through a longitudinal

lens; I will therefore model the intervening motivational process with four measurement occasions and examine the extent to which disposition influences training outcomes through effects on latent change processes occurring in the process variables throughout training.

MEA refers to the direction, effort, intensity, and persistence trainees exhibit during training (Kanfer, 1990), and governs trainee engagement in, effort allocation toward, and persistence with achievement-oriented activities in learning contexts. Colquitt et al. (2000) provided empirical evidence that individual differences influence the motivational system in the training context and that this process influences training outcomes. In their meta-analytic path analysis, state-like motivational variables served as intervening process variables that mediated the relationship between dispositional variables and learning outcomes. Additional research has demonstrated the influence of motivational process variables on learning and performance (e.g., Chen et al., 2000; Ford et al., 1998; Mathieu, Martineau, & Tannenbaum, 1993; Phillips & Gully, 1997). Oft-studied process variables that serve as intervening mechanisms that influence learning and performance include self-efficacy (e.g., Chen et al., 2000; Gist, 1989; Mathieu et al., 1993; Salas & Cannon-Bowers, 2001) and goal setting (e.g., Chen et al., 2000; Locke & Latham, 2002; Mento, Steel, & Karren, 1987). In fact, several researchers have considered self-efficacy and goal setting to be the primary motivational constructs that influence achievement-related outcomes (e.g., Bandura, 1997; Locke & Latham, 1990).

Motivational process variables. Locke (1991) referred to the state-like motivational constructs of self-efficacy and goal setting as the *motivational hub* at which action occurs in the process to influence performance, asserting that these two variables “are considered to be

the most direct and immediate motivational determinants of performance” (p. 293). Specific self-efficacy refers to one’s perceived ability to “execute courses of action required to deal with prospective situations” (Bandura, 1982, p. 122). Self-set goals, or goal setting, refer to specified levels of achievement or performance that an individual aims to accomplish (Locke & Latham, 1990). Both specific self-efficacy and goal setting are well-documented motivational determinants of behavior (Stajkovic & Luthans, 1998) and behavior change (Bandura, 1977).

The positive influences of both self-efficacy and goal setting on learning, achievement, and task performance have received immense support in the motivation literature (e.g., Dweck, 1986; Elliott & Dweck, 1988; Kanfer & Ackerman, 1989; Locke, Frederick, Lee, & Bobko, 1984; Locke & Latham, 2002; Mento et al., 1987), as well as in the training literature (e.g., Chen et al., 2000; Colquitt et al., 2000; Gist & Mitchell, 1992; Mathieu et al., 1993; Stajkovic & Luthans, 1998). Past research has provided evidence that these variables influence the processes through which individuals engage in achievement-related behaviors (e.g., Bandura, 1989; Bandura & Locke, 2003; Bandura & Schunk, 1981; Kanfer, 1990). Additionally, research has demonstrated that these variables contribute to the prediction of training outcomes (e.g., Chen et al., 2000; Colquitt et al., 2000). In fact, Stajkovic and Luthans (1998) asserted that “few cognitive determinants of behavior...have received as ample and consistent empirical support” as self-efficacy and goal setting (p. 240). Hence, it is not surprising that multiple researchers have called for research that incorporates these motivational process variables into the study of potential explanatory mechanisms for learning and training effectiveness (e.g., Gully & Chen, 2010; Kanfer, 1990).

Training Criteria: Cognitive, Affective, and Skill-Based Learning

Evaluation is an integral piece of the instructional design process, and a fundamental concern when conducting training evaluation is the extent to which trainees learn the trained KSAs (Campbell, 1988). Learning is not only valuable in itself, but it is also a prerequisite for KSA maintenance and on-the-job application (Baldwin & Ford, 1988; Blume et al., 2010). A useful delineation of the complex, multifaceted learning process is the theory-driven classification scheme that trifurcates the learning criteria space into cognitive, affective, and skill-based outcomes (Ford, Kraiger, & Merritt, 2010; Kraiger et al., 1993). Cognitive learning involves acquisition of declarative knowledge, knowledge organization, and cognitive strategies; affective learning involves attitudinal and motivational changes that result from training; and skill-based learning refers to procedural knowledge, behavioral application, and such concepts as automaticity and compilation (Kraiger et al., 1993). This conceptually grounded framework informs “research in training that advances our understanding of training evaluation and training effectiveness” (Kraiger et al., 1993, p. 325). In this study, using this classification scheme of learning as a framework for delineating study outcomes, I will include a measure for each taxon in the learning criteria taxonomy.

I will operationalize cognitive learning as declarative knowledge and assess it with paper-and-pencil examinations administered by the instructor. Declarative knowledge about the training content is not only valuable in itself, but it is also required for higher-order learning and transfer (Kraiger et al., 1993). I will operationalize the affective learning outcome as trainees’ reported motivation to transfer trained KSAs. Of paramount concern in training research and practice is training transfer (Baldwin & Ford, 1988; Blume et al.,

2010); it is critical that trainees exit training with an enthusiasm to maintain and apply acquired KSAs from the training context to the work context (Gegenfurtner, Veermans, Festner, & Gruber, 2009; Noe, 1986). I will operationalize skill-based learning outcomes as end-of-course proficiency scores. One can measure these learning outcomes using scored examinations that elicit targeted performance samples from the trainees. Theoretically, these performance samples should differentiate trainees who are in the early stages of KSA acquisition from those trainees who are in the latter stages of KSA acquisition. Early stages include the acquisition and application of procedural knowledge, whereas later stages involve automaticity and compilation (Kraiger et al., 1993). Measuring cognitive, affective, and skill-based learning outcomes will allow me to get a comprehensive look at the criterion space and will allow me to determine how the motivational process influences each type of training outcome.

In the training program I will examine herein, the paramount objective is to acquire proficiency in an assigned foreign language and to demonstrate that acquisition by attaining an established proficiency rating on a standardized language proficiency examination. Thus, meeting the standard is the primary objective. Ancillary objectives include trainees' performance throughout the course (i.e., course grades) and posttraining motivation to transfer language skills to the work setting. Collecting data at multiple time points—including before, during, and after training—will allow me to determine the extent to which these objectives are met (training evaluation) and allow me to determine why and for whom these objectives are met (training effectiveness). Multivariate latent growth modeling (LGM) is a methodological technique that is particularly suitable for capitalizing on the utility of

analyzing the longitudinal intervening processes that potentially operate as explanatory mechanisms. LGM will allow me to examine whether time-invariant individual differences (i.e., ability and dispositional self-efficacy) influence learning outcomes through both starting values and growth trajectories in the intervening motivational process variables of specific self-efficacy and goal setting.

Latent Growth Modeling

Theoreticians and practitioners continuously benefit from advances in the analytic methodology of testing theoretical approximations of real-world phenomena via analysis of covariance structures using a structural equation modeling (SEM) framework. LGM is one such technique that has developed considerably in recent years. LGM from an SEM framework allows one to study patterns of change and individual differences in said patterns of change by analyzing mean and covariance structures (e.g., MacCallum, Kim, Malarkey, & Kiecolt-Glaser, 1997; McArdle & Epstein, 1987; Meredith & Tisak, 1990; Muthén & Khoo, 1998). The LGM framework allows for a multitude of flexible and innovative applications (e.g., Duncan, Duncan, & Strycker, 2006; Muthén, 1991, 2002; Muthén & Muthén, 2000; Nylund, Asparouhov, & Muthén, 2007). Perhaps most appealing for this study is the ability to test the adequacy of hypothesized models of growth⁵ empirically with real-world data, as well as the ability to examine antecedents and consequents of said growth models. Specifically, LGM will allow me to determine empirically the most suitable shape of growth for the intervening process variables studied herein; I will then be able to (a) add covariates

⁵ *Growth* in the latent growth modeling nomenclature can denote either incline or decline in the given outcome variable. The coefficient representing growth will have a directional sign (i.e., plus or minus) which informs the analyst whether growth should be interpreted as incline or decline—regardless, it is still labeled *growth*.

to examine their influence on both starting values and growth rates for the process variables and (b) add criteria to examine how both starting values and growth rates influence learning outcomes. Applying LGM techniques to longitudinal data collected from a complex training program will allow me to examine thoroughly the motivational process as it unfolds and investigate the explanatory mechanisms driving determinants of training effectiveness.

Recognizing the influence that trainee characteristics exert on the training process is important for training effectiveness research and practice (Goldstein & Ford, 2002; Matthieu, Tannenbaum, & Salas, 1992; Tannenbaum & Yukl, 1992). According to Alvarez et al. (2004), training effectiveness involves examining “the individual, training, and organizational characteristics that influence the training process before, during, and after training” (Alvarez et al., 2004, p. 389); hence, a particularly appropriate research design to study training effectiveness would be a longitudinal study with measurement before, during, and after training. The conventional pre-to-post approaches to investigating relations between individual differences and training outcomes are incapable of capturing the intricate change processes that occur throughout the training experience. As Willett and Sayer (1994) stated, “When true development follows an interesting trajectory over time, ‘snapshots’ of status taken before and after are unlikely to reveal the intricacies of individual change” (p. 363).

Thorough examination of the motivational intervening processes requires systematic measurement of trainees at multiple temporally spaced intervals—namely, a longitudinal approach. However, conventional analytic approaches to examining longitudinal data—including repeated measures *t* tests, analysis of variance (ANOVA), and analysis of

covariance (ANCOVA)—limit how well one can capture between-person differences in within-person change over time (Duncan, Duncan, & Strycker, 2006; Willett & Sayer, 1994). Fortunately, the emergence of LGM in the social and behavioral sciences has presented a set of promising methodologies for analyzing repeated measures that allow the analyst to examine both intraindividual change and interindividual differences in intraindividual temporal development. Indeed, “growth curve analysis is particularly useful when an attempt is made to explain the individual variation in initial status and growth rate using [time-invariant] variables for the individual” (Muthen & Khoo, 1998, p. 4). Herein, I will examine initial statuses and growth rates for motivational process variables and I will attempt to explain individual variation using time-invariant individual differences. Further, I will examine how the initial statuses and growth rates relate to learning outcomes. Because development is of paramount concern for training research and practice, LGM provides an applicative and flexible approach for empirically investigating how learning unfolds throughout the training process.

Proposed Model, Research Questions, and Hypotheses

Using longitudinal training effectiveness data, I propose to examine a comprehensive path model that includes multiple exogenous predictors, multiple process variables (through which the predictors operate), and multiple criteria. In the proposed model, I will test the contention that distal, trait-like individual differences influence training outcomes through their influence on more proximal, state-like process variables. Specifically, I hypothesize that dispositional variables (i.e., ability and dispositional self-efficacy) will work through

proximal process variables (i.e., specific self-efficacy and goal setting) to influence the motivational process and enhance cognitive, affective, and skill-based learning outcomes.

I will test the proposed model using LGM analytical techniques with a longitudinal study design—in addition to the proposed model, I will examine competing models when appropriate. The proposed LGM includes latent growth factors (i.e., intercept and slope) for two process variables, multiple time-invariant covariates, and multiple learning outcomes (see Appendix, Figure 1). Testing the proposed model will require an iterative approach, wherein less complex models are tested initially and more complex models are tested successively thereafter (see Proposed Analysis for further explanation). In short, I will conduct the following process in the order presented: (a) I will focus solely on the intervening motivational process; (b) I will examine potential dispositional predictors of the motivational process; and (c) I will examine potential criteria of the motivational process. The following research questions and hypotheses align with the sequential, iterative model-testing approach.

Research Question 1: Starting Values, Growth Rates, and Interindividual Variability

Research Question 1 (RQ1)—which has to do with the shape of growth for motivational process variables throughout a complex training event, including average starting values, average rates of growth, and trainee variability in both starting values and growth (see Appendix, Figure 2)—is two-pronged: *Is the motivational process, as operationalized by specific self-efficacy and goal setting, a generally linear (or continuous) process? Is there interindividual (between-trainee) variability in the growth factors (i.e., intercept and slope)?* First, I will explore whether trainees' growth rates for the process

variables follow a generally linear trajectory. In other words, does growth in the process variables occur in a continuous manner or do the trajectories follow a nonlinear pattern (e.g., quadratic, piecewise)? Accounting for the appropriate shape of growth in successive models is important for model specification and interpretation (Duncan et al., 2006; Meredith & Tisak, 1990); moreover, the shape of growth will provide interesting information concerning how the motivational process unfolds throughout the training event.

Second, I will examine whether trainees exhibit interindividual variability in the latent growth factors (i.e., intercept and slope). The first facet of RQ1 deals only with general trends in the data (e.g., *average* starting value and *average* growth rate) and conveys no information about individual differences. For the second facet, however, I will examine whether values for intercept and slope differ nontrivially among trainees, or conversely whether all trainees register statistically equivalent starting values and follow functionally the same growth trajectories throughout training. This latter facet of RQ1 will address the extent to which variability exists in the latent growth factors; in this context, variability can be interpreted as individual differences—lack of variability means absence of individual differences. Conversely, presence of variability in the latent growth factors indicates that predictable variance is present and I will then examine whether ability and dispositional self-efficacy account for said variance.

Learners are not passive recipients of trained KSAs; rather, they are active participants in the learning process (e.g., Bell & Kozlowski, 2008, 2010; Ford, Smith, Weissbein, Gully, & Salas, 1998; Kozlowski & Bell, 2008; Smith, Ford, & Kozlowski, 1997). As stated by Gully and Chen (2010), “Trainees actively regulate their motivation,

emotion, and learning processes. They decide what to attend to, determine how much effort they will devote, and actively engage themselves in, or disengage themselves from, training” (pp. 4-5). Not all trainees engage in, exert effort toward, and persist with the learning process in the same manner. Trainees enter training with individual differences (e.g., unique characteristics, idiosyncrasies, and experiences) that influence the motivation and learning processes (Campbell, 1989; Goldstein & Ford, 2002; Salas & Cannon-Bowers, 2001; Tannenbaum & Yukl, 1992). Past research has consistently demonstrated that individual differences play an important role in the learning process (e.g., Ackerman & Heggestad, 1997; Goldstein & Ford, 2002; Noe, 1986; Tannenbaum & Yukl, 1999). Furthermore, past research has demonstrated that trainees vary significantly in the extent to which they engage in mediating processes such as self-efficacy and goal setting (e.g., Bandura, 1989; Chen et al., 2000; Colquitt et al., 2000; Gist & Mitchell, 1992; Schwoerer et al., 2005). Accordingly, I contend that trainees will differ significantly in both starting values and rates of growth for both specific self-efficacy and goal setting.

Hypothesis 1: Trainees will exhibit significant interindividual variability in the latent growth factors (i.e., intercept and slope) for both (a) specific self-efficacy and (b) goal setting.

Research Question 2: Influence of Individual Differences

For Research Question 2 (RQ2), I will examine whether individual differences account for interindividual variability in the starting values and growth rates for the motivational process variables (see Appendix, Figure 3): *How do trait-like individual differences (i.e., ability and dispositional self-efficacy) influence starting values and growth*

in state-like motivational process variables (i.e., specific self-efficacy and goal setting)?

Assuming there is significant interindividual variability in the intercept and slope growth factors, RQ2 involves determining whether various dispositional individual differences account for said variance.

Cognitive ability has received unwavering support as a robust predictor of learning and performance (e.g., Alvarez et al., 2004; Hunter, 1986; Ree et al., 1995; Ree & Earles, 1991; Schmidt & Hunter, 1998). Research has demonstrated that ability relates to learning and performance at least partially through specific self-efficacy (e.g., Chen et al., 2000; Colquitt et al., 2000; Phillips & Gully, 1997). Not only does ability relate to pretraining self-efficacy (e.g., Colquitt et al., 2000) and midtraining self-efficacy (e.g., Phillips & Gully, 1997), but it plausibly relates to self-efficacy growth trajectories because, among other things, past performance positively influences self-efficacy (Bandura, 1977) and because “cognitive reiteration of efficacious courses of action strengthens self-percepts of efficacy” (Bandura, 1989, p. 729). I contend that those with higher ability will enter training with higher perceived capability to succeed in the complex training environment (i.e., higher starting values) and will thus engender the ability and motivation necessary to engage in and persist with behaviors that support learning and performance throughout training (i.e., higher growth rates). Training-related aptitude, I contend, will work through this same process of fostering higher initial confidence in trainees and greater rates of growth in confidence as they progress through training.

Researchers have contended that cognitive ability relates to learning and performance through the motivational process of setting goals (e.g., Locke & Latham, 1990), and

empirical research has provided support for this contention (e.g., Chen et al., 2000; Phillips & Gully, 1997; Thomas & Mathieu, 1994). I contend that those with higher ability will set higher goals at the beginning of training (i.e., higher starting values). Further, I contend that these individuals will engage in and persist with behaviors that support learning and performance throughout training, which will lead to greater increases in the difficulty of goals (i.e., higher growth rates). Further, I contend training-related aptitude will work through this same process of influencing higher initial goals for trainees and greater rates of growth in those goals as training progresses.

Hypothesis 2: Cognitive ability will account for variance in the initial values of (a) specific self-efficacy and (b) goal setting. Cognitive ability will account for variance in the rates of growth for (c) specific self-efficacy and (d) goal setting.

Hypothesis 3: Training-related aptitude will account for variance in the initial values of (a) specific self-efficacy and (b) goal setting. Training-related aptitude will account for variance in the rates of growth for (c) specific self-efficacy and (d) goal setting.

Those with high dispositional (or trait-like) self-efficacy believe in their general capacity to perform well and summon the resources necessary to succeed in achievement situations (Sherer, 1982). The question of whether general conceptions of self-efficacy relate to specific conceptions of self-efficacy has not gone without debate (see Bandura, 1997; Judge, Locke, & Durham, 1997). Bandura asserted that general conceptions of self-efficacy should not be considered to relate to specific efficacy percepts. Contrariwise, empirical evidence has supported the influence of dispositional self-efficacy on specific self-efficacy (e.g., Chen et al., 2000, 2004; Sherer et al., 1982). In addition, empirical evidence has

supported the influence of dispositional self-efficacy on self-set goals (e.g., Chen et al., 2000, 2004). I contend that those with high dispositional self-efficacy will enter training with higher specific self-efficacy (i.e., starting values) because of the general belief in their capacity to summon the cognitive and motivational resources necessary to succeed in achievement situations. These individuals, compared to those with low dispositional self-efficacy, will also set higher goals at the outset because they believe in their agency and because the higher goals are concordant with their aspirations and with their agency beliefs (Luthans & Youssef, 2007; Sheldon & Elliot, 1999).

Further, dispositional self-efficacy is one facet of an individual's core self-evaluations (CSE; see Judge et al., 1997) and past research demonstrated that CSE related positively to goal self-concordance, and that individuals with high CSE were more likely to commit to and pursue goals for intrinsic and value-congruent reasons (Judge, Bono, Erez, & Locke, 2005). Thus, even as training progresses, I contend that one's efficacy percepts and self-set goals will continue to be related to dispositional self-efficacy because of the aforementioned self-concordance and because those with high dispositional self-efficacy may deal with training tribulations more effectively (Bandura, 1986)—hence, dispositional self-efficacy will influence growth rates for both specific self-efficacy and goal setting. In sum, a general belief in one's competencies will influence initial ability conceptions (i.e., self-efficacy) and aspirations (i.e., goals), and this distal influence will continue to relate to these conceptions and aspirations as they become situated in the learning context.

Hypothesis 4: Dispositional self-efficacy will account for variance in the initial values of (a) specific self-efficacy and (b) goal setting. Dispositional self-efficacy will account for variance in the rates of growth for (c) specific self-efficacy and (d) goal setting.

Research Question 3: Motivational Process and Learning Outcomes

For Research Question 3 (RQ3), I will examine whether motivational process variables account for variability in learning outcomes (see criterion space in Appendix, Figure 4): *How do starting values and growth rates in motivational process variables (i.e., specific self-efficacy and goal setting) influence cognitive, affective, and skill-based learning outcomes?* To address RQ3, I will examine the complete multivariate LGM, which will include all time-invariant covariates, latent growth factors, and criteria. RQ3 ultimately addresses the extent to which the *person-and-process* theme (Salas & Kozlowski, 2010) accounts for variance in important training effectiveness outcomes.

Both self-efficacy and goal setting have accumulated large bodies of evidence in support of their utility as predictors of learning and performance (e.g., Locke, 1991; Locke et al., 1984; Locke & Latham, 1990; Salas & Cannon-Bowers, 2001; Stajkovic & Luthans, 1998; Zimmerman, Bandura, & Martinez-Pons, 1992). These efficacy percepts and self-set goals govern how individuals approach, engage in, and persist with learning-related activities, and thus represent important motivational factors in the acquisition of new knowledge and skills (Bandura, 1997; Locke & Latham, 1990). Acquiring new knowledge and skills during a complex training context will require sufficient motivation, and “judgments of self-efficacy...determine how much effort people will expend and how long they will persist in the face of obstacles or aversive experiences” (Bandura, 1982, p. 123).

Those with high self-efficacy exert greater effort toward and persist longer with mastering challenges (Bandura & Schunk, 1981). Further, Gist and colleagues have demonstrated with past research that specific self-efficacy is malleable (Gist & Mitchell, 1992; Schwoerer, May, Hollensbe, & Mencl, 2005), and that increases in self-efficacy lead to increases in performance (Gist, 1989; Gist, Schwoerer, & Rosen, 1989). Similar to self-efficacy, goal setting influences learning and performance through influencing effort exertion that is directed, concentrated, and persistent (Locke & Latham, 1990). Those who set more difficult goals demonstrate greater motivation and higher levels of learning and performance (Locke & Latham, 1990). I hypothesize that both starting values and growth rates in specific self-efficacy will influence cognitive learning—that is, those who start with higher self-efficacy and those who show greater gains in self-efficacy will perform better on the cognitive learning examination. Similarly for goal setting, I hypothesize that both initial levels and growth rates will account for variability in cognitive learning.

Hypothesis 5: Variability in cognitive learning will be accounted for by (a) both initial values and growth rates for specific self-efficacy and (b) both initial values and growth rates for goal setting.

“People avoid activities that they believe exceed their coping capabilities, but they undertake and perform assuredly those that they judge themselves capable of managing” (Bandura, 1982, p. 123); thus, those who believe in their efficacy to maintain and use the trained KSAs will be more motivated to do so. This presupposition is consistent with theory and past research on human agency (e.g., Bandura, 1982), intentional behavior (Fishbein, 1979), and planned behavior (Ajzen, 1991); it is also consistent with empirical research that

has demonstrated self-efficacy to directly or indirectly influence motivation to transfer (Chiaburu & Lindsay, 2008; Dierdorff, Surface, & Brown, 2010; Smith, Jayasuriya, Caputi, & Hammer, 2008). Thus, I expect that growth rates in self-efficacy will account for variability in transfer motivation; however, because the initial measurement of specific self-efficacy takes place prior to training, I do not expect the initial value to account for variability in transfer motivation.

Past empirical research has also provided support in favor of the influence of goals on motivation to transfer (e.g., Smith et al., 2008). Self-set goals represent performance levels that an individual aspires to attain (Locke & Latham, 1990); presumably, these aspirations align with the individual's interests and values—indeed, “Goals can be viewed as applications of values to specific situations” (Locke, 1991, p. 292). Research on the aforementioned self-concordance of goals—namely their consistency with the goal setter's interests and values—has demonstrated that pursuers of self-concordant goals exert greater effort toward achieving those goals, and are more motivated and likely to do so (e.g., Sheldon & Elliot, 1999; Sheldon & Houser-Marko, 2001). Thus, I expect trainees' initial self-set goals and their growth rates to account for variability in their transfer motivation.

Hypothesis 6: Variability in affective learning will be accounted for by (a) growth rates but not initial values for specific self-efficacy and (b) both initial values and growth rates for goal setting.

Regardless of having the requisite skills and abilities, trainees must have sufficient motivation in order to learn and perform in training (Noe, 1986). Performance is strongly influenced by individuals' goals or aspirations and by their perceived competence or

confidence in being able to perform (Locke, 1991). Though empirical research has demonstrated the importance of accounting for state-like motivational processes when examining the influence of distal dispositional variables (e.g., ability, personality) on learning and performance (e.g., Chen et al., 2000; Colquitt et al., 2000), researchers have continued to express the need for additional research that further elucidates these processes (e.g., Beier & Kanfer, 2010; Campbell, 1989; Chen et al., 2000; Gully & Chen, 2010).

With regard to specific self-efficacy, numerous past studies have conceived self-efficacy as a mediating variable between individual differences and training outcomes (e.g., Chen et al., 2000; Colquitt et al., 2000; Mathieu et al., 1993), and have consistently shown it to predict learning and training outcomes (Salas & Cannon-Bowers, 2001). Mathieu et al. (1993) provided evidence that self-efficacy operates as a process variable that positively related to knowledge and skill acquisition. Gist (1989) asserted that specific self-efficacy is an important process variable for understanding training effectiveness and demonstrated empirically that enhancing self-efficacy during training leads to better training outcomes. Salas and Cannon-Bowers (2001) noted that, “[s]elf-efficacy, whether one has it before or acquires it during training, leads to better learning and performance” (p. 478). Further, when examining distal and proximal influences of learning, Chen et al. (2000) found that cognitive ability and general self-efficacy influenced training performance through specific self-efficacy as a mediating process variable. Similarly, I expect that trait-like individual differences (i.e., ability and dispositional self-efficacy) will contribute to enhanced training outcomes through influences on the proximal state-like variable, self-efficacy.

Hypothesis 7: Variability in skill-based learning will be accounted for by (a) initial values for specific self-efficacy and (b) growth rates in specific self-efficacy.

With regard to goal setting, empirical research has demonstrated the influence of goal setting on task motivation, and has demonstrated that goal setting strongly relates to performance across a variety of contexts (e.g., Erez & Judge, 2001; Mento et al., 1987). Further, Mesmer-Magnus and Viswesvaran (2007) reported goal setting related to increased learning outcomes and training performance. Further, proximal goals in particular—namely, goals set throughout the process—have been shown to have a particularly profound influence on performance and achievement-related behaviors (e.g., Bandura & Schunk, 1981). Chen et al. (2000) found that cognitive ability and general self-efficacy influenced training performance through goal setting as a mediating process variable. Similarly, I expect that individual differences (i.e., ability and dispositional self-efficacy) will influence training outcomes through influences on the proximal state-like variable, goal setting. I contend that both initial values and growth rates will contribute to increased skill-based learning outcomes.

Hypothesis 8: Variability in skill-based learning will be accounted for by (a) initial values for goal setting and (b) growth rates in goal setting.

In sum, in RQ1, I will hone in on the motivational process and exclude any potential predictors or outcomes. In RQ2, I will add time-invariant covariates to the model, which will allow me to examine the extent to which various trait-like predictors (ability and dispositional self-efficacy) influence the motivational process. Finally, in RQ3, I will add criteria to the model, which will allow me to examine the extent to which the motivational

process influences important learning outcomes. In total, the comprehensive model will allow me to investigate the supposition that dispositional variables operate through more proximal state-like process variables to impact training outcomes. Furthermore, using LGM techniques with longitudinal data provides a unique approach to examining the aforementioned explanatory mechanism as an intervening process rather than a mediational snapshot.

Method

Sample

Participants will consist of approximately 4000 military personnel from a job-mandated training program for foreign language acquisition. For these military personnel, foreign language proficiency is a critical competency (U.S. Department of Defense, 2006) and they must meet or exceed a minimum proficiency level in order to attain standard certification requirements. Further, trainees who exceed the proficiency standard receive monetary incentives (i.e., skill-based pay; see Dierdorff & Surface, 2008). Each trainee is assigned to one foreign language, and each foreign language resides in one of four categories, with higher categories denoting higher difficulties (e.g., Category IV being the highest difficulty). Examples from each language category are Spanish (Category I), Indonesian (Category II), Russian (Category III), and Modern Standard Arabic (Category IV). According to rough estimates, the data will include approximately 2600 Category I and II trainees (65%) and approximately 1400 Category III and IV trainees (35%). All learning and performance outcomes are standardized across languages.

For this study, I will divide the data into two samples: Sample 1 and Sample 2. I will conduct the proposed analyses on each sample separately. Using two unique samples rather than one combined sample is necessary because of differences in training duration. Trainees assigned to training languages in Categories I and II (i.e., Sample 1) participated in an 18-week training design, whereas trainees assigned to training languages in Categories III and IV (i.e., Sample 2) participated in 24 weeks of training. Although the proposed analyses can handle time lags between measurement occasions to be unevenly spaced, one analytical assumption made by LGM methodologies is uniformity of spacing for all individuals included in the model. Said differently, time intervals between measurement occasions can be nonuniform, but each member of the sample must follow the same nonuniform pattern—hence the need to model separately Sample 1 and Sample 2. Although this will reduce the maximum possible sample size, the total sample size will be large enough to allow bifurcating into two samples that each consists of enough cases to adequately power the proposed analyses. Further, having two samples will (a) allow me to test the proposed model on two unique samples that differ only on language difficulty, (b) obviate the need to control for language difficulty in each sample, and (c) allow me to conduct a multigroup LGM to determine whether the model deviates based on training difficulty (i.e., language difficulty).

Procedures

In conducting this study, I will present results from a longitudinal training evaluation of a job-mandated foreign language acquisition training. The training lasted 18 weeks for Sample 1 and 24 weeks for Sample 2. There were four time-structured (i.e., equidistant) measurement occasions for the longitudinal process variables (5-week intervals for Sample 1

and 7-week intervals for Sample 2). The first measurement occasion (S_0^6) occurred prior to commencement of training, where data were collected on the time-invariant, trait-like individual differences and on the initial status of the state-like process variables. Using surveys, data were collected on dispositional self-efficacy, specific self-efficacy, and goal setting. Using extant data provided by a third party, scores were collected for each trainee on recently administered cognitive ability tests and training-related aptitude assessments. During the second measurement occasion (S_1 ; occurred after 5 weeks for Sample 1 and after 7 weeks for Sample 2) and the third measurement occasion (S_2 ; occurred after 10 weeks for Sample 1 and after 14 weeks for Sample 2), another wave of data were collected on the process variables. At the end of training, during the fourth (and final) measurement occasion (S_3 ; occurred after 15 weeks for Sample 1 and after 21 weeks for Sample 2), the final wave of data were collected on the process variables, and criteria data were collected for the cognitive learning outcome and the affective learning outcome. Additionally, data were collected from a third party on the skill-based learning outcome.

Strategically mapping a longitudinal research endeavor onto the training process as it unfolds will allow me to study how individual differences relate to motivational intervening mechanisms, how these relationships develop over time, and how both individual differences and motivational intervening mechanisms influence training outcomes. Furthermore, this will allow me to examine how these relationships develop within trainees (i.e., intraindividual), in addition to examining how these relationships differ across trainees (i.e.,

⁶ S_0 will be used to denote the first measurement occasion because it occurs pretraining and represents the initial status on the latent growth factors. This is consistent with the latent growth modeling nomenclature. The successive measurement occasions will be S_1, S_2, S_{t-1}, \dots , where t = total number of measurement occasions.

interindividual). Alternatively, examining pre- to posttraining relationships in lieu of multiple measurement occasions may obfuscate important in-training processes and mechanisms. Longitudinal study designs that capture data as the learning process unfolds allow researchers to capture more comprehensively the rich learning experience that takes place in training contexts. This comprehensive understanding of the processes through which trainee characteristics influence learning in training contexts should help researchers and practitioners identify and understand the mechanisms that drive training effectiveness.

Measures

Time-invariant covariates. I will measure three time-invariant covariates. Two covariates are indicators of trainee ability (i.e., cognitive ability and training-related aptitude) and the remaining covariate is a self-evaluative indicator of trainee disposition (i.e., dispositional self-efficacy). In this study, I conceptualize and operationalize all three covariates as temporally stable, trait-like individual differences.

I will measure *cognitive ability* using the Wonderlic Cognitive Ability Test (hereafter referred to as Wonderlic). The Wonderlic is an intelligence test that consists of 50 multiple-choice items (adapted from the Otis Test of Mental Ability) to which subjects must respond in 12 minutes (Wonderlic, 1992). Wonderlic test scores are determined by summing the total number of correct responses provided within the 12-minute timeframe, and a score of 20 is purportedly indicative of average intelligence (Wonderlic, 1992). In terms of reliability, past research has demonstrated that the Wonderlic consistently achieves between .82 and .94 for test-retest reliability (Dodrill, 1983; Wonderlic 1992), split-half reliability of .88 to .94 (Wonderlic, 1992), and alternate-forms reliability of .87 to .99 (Wonderlic, 1992). In terms

of validity evidence, past research reported Wonderlic scores correlated strongly ($r = .93$) with the Wechsler Adult Intelligence Scale Full Scale IQ (WAIS FSIQ; Dodrill, 1981); further, Dodrill and Warner (1988) found that the strong correlations ($.85 \geq r \geq .91$) generalized across a range of subjects, including hospitalized, nonpsychiatric, psychiatric, and control groups.

Because the training I propose to examine concerns the acquisition of a foreign language, I will operationalize *training-related aptitude* as language aptitude, and I will measure it using the Defense Language Aptitude Battery (DLAB; Petersen & Al-Haik, 1976). The DLAB (successor to the Defense Language Aptitude Test [DLAT]) was developed as a selection tool for the Defense Language Institute (DLI). DLI offers foreign language training to military personnel in more than 50 foreign languages. DLAB was developed, in part, because of the need for audiolingually-focused aptitude tests that could demonstrate discriminant validity with general intelligence (Silva & White, 1993). Past research has demonstrated the utility of the DLAB in predicting training success (e.g., Petersen & Al-Haik, 1976), and Silva and White (1993) reported that DLAB accounted for incremental validity in posttraining reading, listening, and speaking proficiency scores beyond that contributed by general intelligence and the Armed Services Vocational Aptitude Battery (ASVAB).

I will measure *dispositional self-efficacy* with an instrument developed to assess the trainees' general competency beliefs pertaining to learning in achievement-related situations. The instrument consists of eight items that trainees will rate on an 11-point confidence scale that ranges from 1 (0%) to 11 (100%), with 10% gradients. The instrument consists of a

stem (“Please indicate your confidence in your ability to perform each of the following activities...”), followed by items such as, “Master new material in learning situations,” and, “Perform well in academic courses or training.” This scale has shown to be unidimensional through factor analysis and has demonstrated internal consistency reliability evidence (.91; Dierdorff et al., 2010).

Process Variables. I will examine two motivational process variables. Both process variables studied herein will be measured on four occasions: S0 (pretraining), S1, S2, and S3 (posttraining). Two latent growth factors for each process variable are of interest: (a) intercept, or initial scores at S0 and (b) slope, or trainees’ growth trajectories from S0 to S3. First, I will examine referent levels (or initial scores); that is, I will determine trainees’ baseline standings on each process variable based on measurement at the first (of four) occasions. Second, I will examine trainees’ growth trajectories; that is, I will determine trainees’ rates of growth (or decline) in each process variable throughout training. I will examine intraindividual (within-person) growth trajectories in the process variables, as well as interindividual (between-person) differences in starting values and growth rates.

The first process variable, *specific self-efficacy*, will be measured on four measurement occasions (i.e., S0, S1, S2, and S3) using a scale developed to assess a trainee’s current confidence in his or her ability to perform specific, training-related tasks. The scale will consist of 8 items and will be rated on an 11-point confidence scale ranging from 1 (0%) to 11 (100%), with 10% gradients. The items are preceded by a stem (“Please indicate your confidence in your current ability to perform the following activities”), followed by items

including, “Use military-technical vocabulary,” and, “Exchange mission-related information with a counterpart in the host country.”

The second process variable, *goal setting*, will be measured on four measurement occasions (i.e., S0, S1, S2, and S3) using three items that capture trainees’ self-set goals. At each measurement occasion, trainees will indicate their (a) goals for reading proficiency at the end of training, (b) goals for listening proficiency at the end of training, and (c) goals for speaking proficiency at the end of training. The scale maps directly onto the metric of the ultimate criterion that trainees must pass—namely, the Oral Proficiency Interview (OPI; i.e., 0+, 1, 1+, 2, 2+, and 3; for additional details, see Silva & White, 1993). A 0+ is the lowest proficiency scoring and 3 is the highest proficiency scoring. Thus, trainees will be asked to set a personal goal for proficiency at or between 1 (0+) through 7 (3) for each measurement occasion.

Criteria. I will operationalize *cognitive learning* as course grades (GPA) that trainees merit based on performance on paper-and-pencil tests that the course instructor administers. The paper-and-pencil tests cover important training-related content that trainees must master in order to demonstrate training proficiency. The course instructors will provide these objectively scored measures of cognitive learning.

For the affective learning outcome, I will examine trainees’ scores on an instrument developed to measure *motivation to transfer*. The instrument was developed to assess the motivation that trainees had to maintain and apply their foreign language skills. The instrument consists of six items, each of which asks trainees to report their likelihood of engaging in various transfer-related activities. Each item is scaled on an 11-point likelihood

response format; response options range from 1 (0%) to 11 (100%), with 10% gradients. Trainees will be presented with a stem (“Please estimate the likelihood that you will...”), followed by transfer-related activities such as, “Improve your language proficiency,” and, “Use your language on missions when you have an opportunity.”

The skill-based learning outcome for this study will be scores from the *Oral Proficiency Interview (OPI)*. The ultimate objective for the trainees in this training program is to acquire a level of foreign language proficiency that enables them to reach a predetermined proficiency level, as measured by the OPI. The OPI is a standard instrument designed by DLI to assess foreign language proficiency, and is used in high-stakes testing by the United States Department of Defense (DoD). The OPI consists of three sections: reading, listening, and speaking. The scoring rubric for the OPI ranges from 1 to 7 (i.e., 0, 0+, 1, 1+, 2, 2+, and 3), with higher scores denoting higher proficiency. The OPI is the high-stakes examination that determines whether trainees qualify for selection and determines their skill-based pay (Dierdorff & Surface, 2008).

Proposed Analysis

Several assumptions must be met when using LGM techniques. First, a representative sample must be examined systematically over multiple temporally spaced measurement occasions (Willett & Sayer, 1994). Second, the spacing of measurement occasions must be the same for all individuals. As I mentioned previously, this requirement is the main reason for splitting the sample into Sample 1 and Sample 2. Third, data should be collected on at least three measurement occasions. In this study, I will have four measurement occasions, which allows for more flexible modeling of the growth process; for

instance, I can add quadratic effects or additional slopes if the data suggest nonlinearity. Fourth, the sample must be sufficiently large to power the detection of within-person and between-person effects (MacCallum, Browne, & Sugawara, 1996; Willett & Sayer, 1994). The estimated sample sizes for Sample 1 ($n = 2400$) and Sample 2 ($n = 1600$) are sufficiently large to power these analyses. (For additional information regarding assumptions and the theoretical underpinnings of LGM, see Duncan et al., 2006; Meredith & Tisak, 1990; Willett & Sayer, 1994.)

Preliminary analysis. Prior to substantive analyses, I will conduct preliminary analyses to check various assumptions (e.g., normality, linearity, heteroscedasticity). Then, I will conduct confirmatory factor analysis (CFA) to test the structural validity of the measurement model. A sound measurement model is a prerequisite for examining the structural portion of the model (Anderson & Gerbing, 1988). I will then compute and examine descriptive statistics, internal consistency reliabilities, and zero-order correlations among study variables. Finally, for an illustrative depiction, I will create longitudinal scatterplots of the observed score growth trajectories to display general patterns, or trends, in the data (see Appendix, Figure 5 for examples). These observed score trends provide a valuable look at the data and they provide useful information for determining how to specify the model in terms of the functional shape of growth present in the longitudinal process variables.

Following this preliminary analysis, I will conduct multivariate LGM in an iterative model-testing fashion to address the study's research questions and hypotheses. I will conduct the LGM analyses using *Mplus* Version 7.0 (Muthén & Muthén, 1998-2011).

Analyses based on SEM will use maximum-likelihood estimation, continuous variables, and inclusion of both mean and covariance structures. To assess model fit, I will use chi-square (χ^2), comparative fit index (CFI; Bentler, 1990), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA; Browne & Cudeck, 1993), and the standardized root mean square residual (SRMR). In determining the adequacy of model fit, I will draw from well-established recommendations and guidelines (e.g., Hu & Bentler, 1999; Marsh, Hau, & Wen, 2004; Mulaik, 2007).

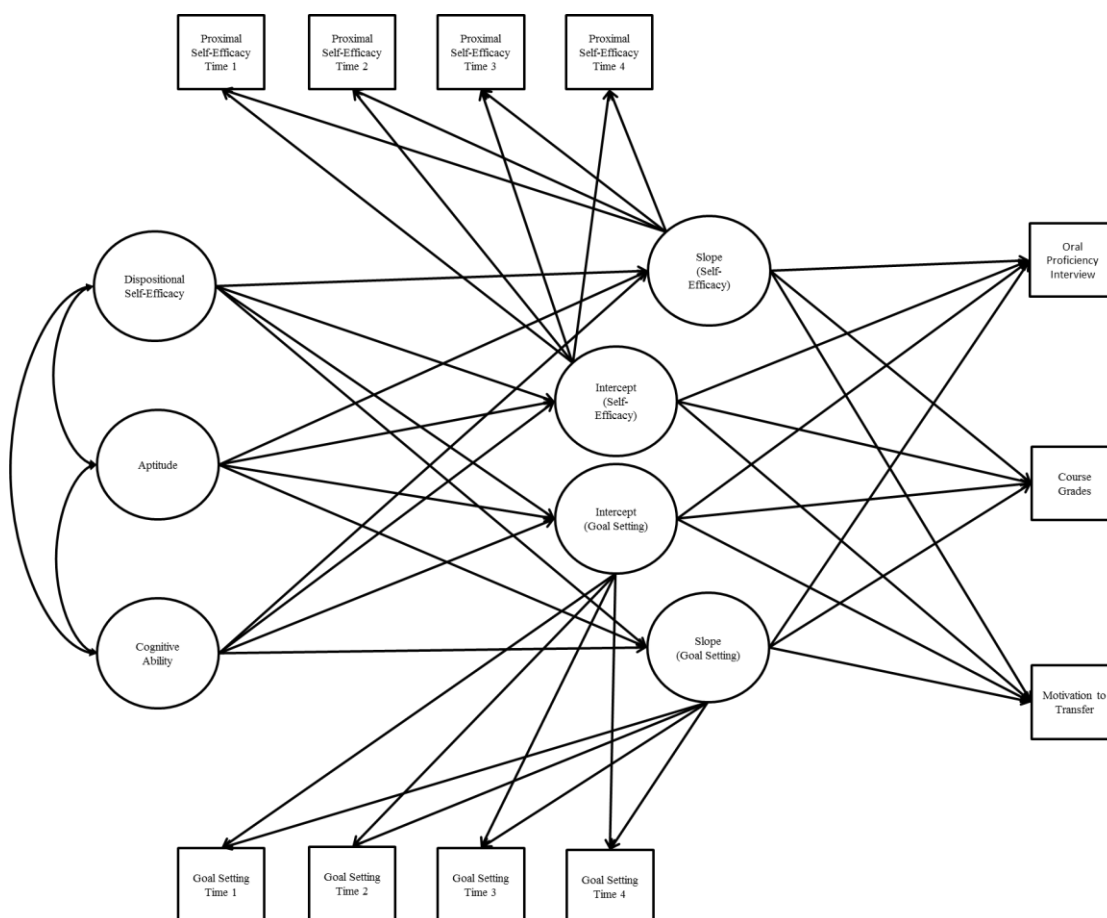
Primary Analysis. First, to address RQ1 (and H1a and H1b), I will compare multiple competing unconditional growth models—namely, simple growth models without covariates and criteria—to determine whether the longitudinal process variables are best represented by linear growth or nonlinear growth (e.g., quadratic or piecewise). Then, using the appropriate unconditional model identified in the previous step, I will determine whether there exists interindividual variability in the latent growth factors (i.e., intercept and slope)—that is, I will determine whether individuals differ significantly in initial values and whether they differ significantly in rates of growth. Second, assuming significant differences exist in the previous step, I will then address RQ2 (and H2a-d, H3a-d, and H4a-d) by determining whether various individual differences account for the variance in these latent growth factors. Specifically, I will add time-invariant covariates in order to determine whether cognitive ability, aptitude, or dispositional self-efficacy account for variance in both initial status and rates of growth in the mediating process variables. Thirdly, to address RQ3 (and H5a-b, H6a-b, H7a-b, and H8a-b), I will add learning criteria to determine whether the latent growth factors account for variability in trainees' scores on various learning outcomes. Ultimately,

using an innovative LGM approach to examining intervening mechanisms, I will evaluate mediational process variables in a longitudinal training program where I hypothesize that the effects of dispositional influence will be achieved through their effects on dynamic intervening process variables.

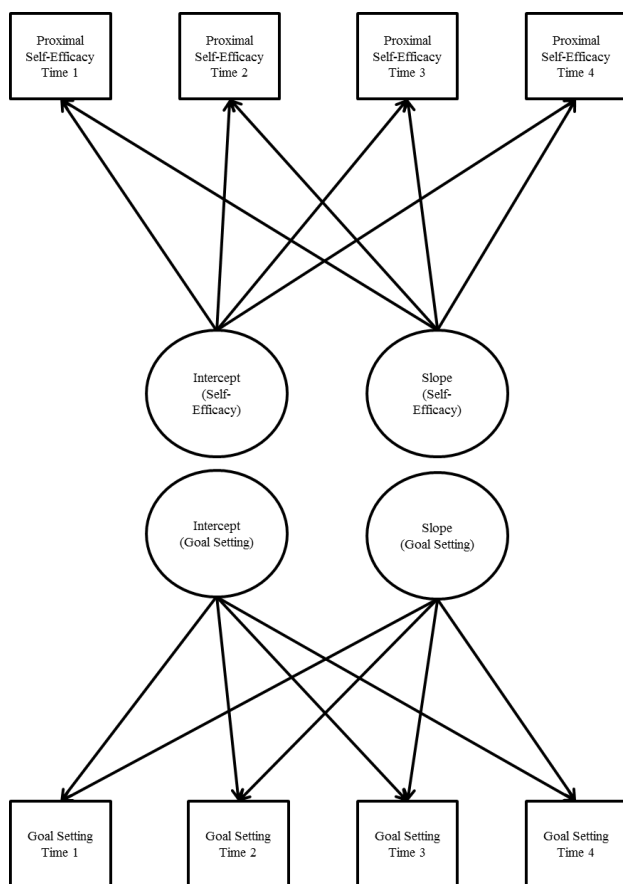
Proposal Conclusion

A skilled and knowledgeable workforce is a distinct competitive advantage for organizations (Huselid, 1995). Organizations invest immense resources into training and development efforts to maximize said advantage (Green & McGill, 2011). To optimize this endeavor, to ensure a return on this investment, and to ensure that individuals and organizations learn, maintain, and use that which is trained, researchers endeavor to understand why training events are (or are not) successful through training effectiveness research. This research has benefitted recently from studies examining the influence of dispositional variables on learning and training outcomes through more proximal state-like process variables (e.g., Chen et al., 2000, 2004). Oftentimes the learning process unfolds over time and these complex relationships (e.g., between individual differences and intervening mechanisms, between intervening mechanisms and training outcomes) are better understood when analyzing multiple measurement occasions. Accordingly, in this study I will conduct multivariate LGM with four measurement occasions to examine (a) how motivational intervening mechanisms unfold over time, (b) how individual differences (i.e., ability and dispositional self-efficacy) relate to motivational intervening mechanisms (i.e., specific self-efficacy and goal setting), and (c) how intervening mechanisms influence cognitive, affective, and skill-based learning outcomes. The main purpose, therefore, is to

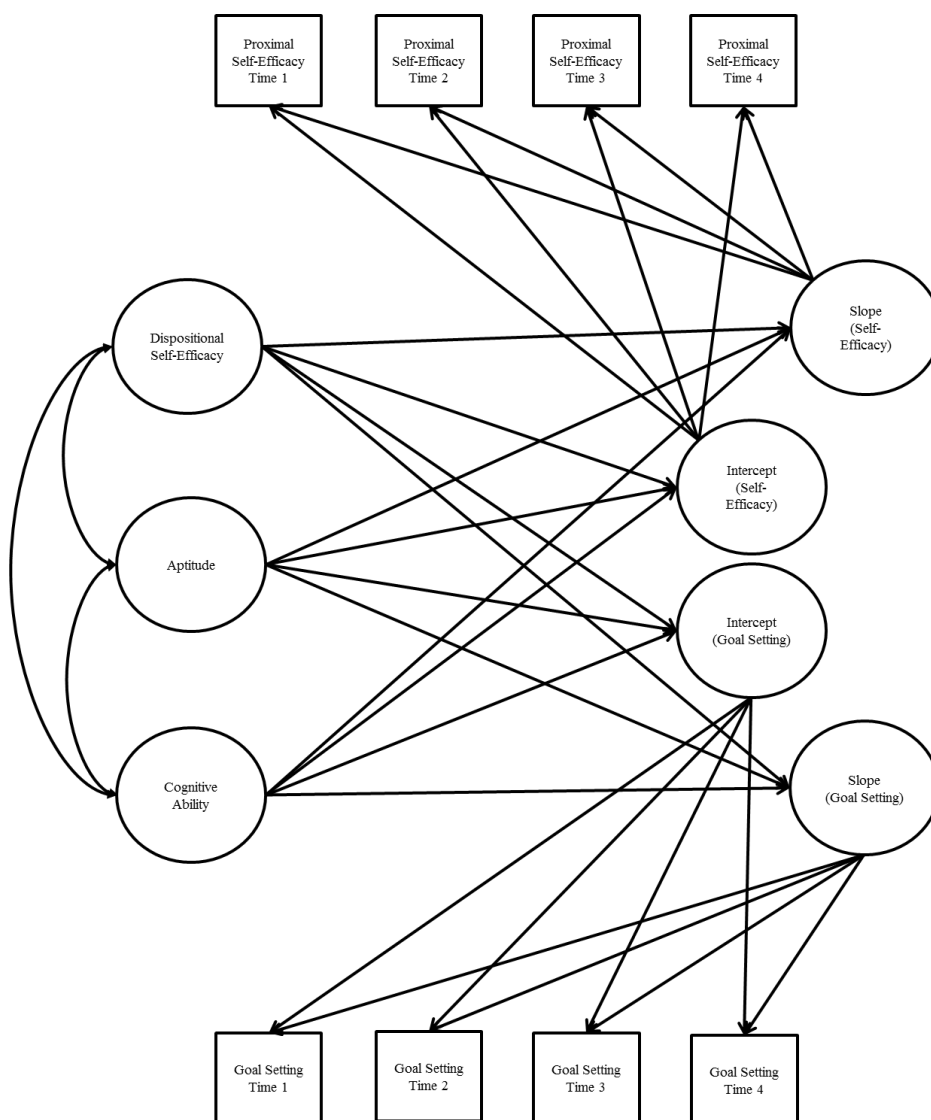
evaluate mediational mechanisms in a longitudinal training program where I hypothesize that the effects of dispositional variables are achieved through their effects on dynamic intervening process variables such as self-efficacy and goal setting.



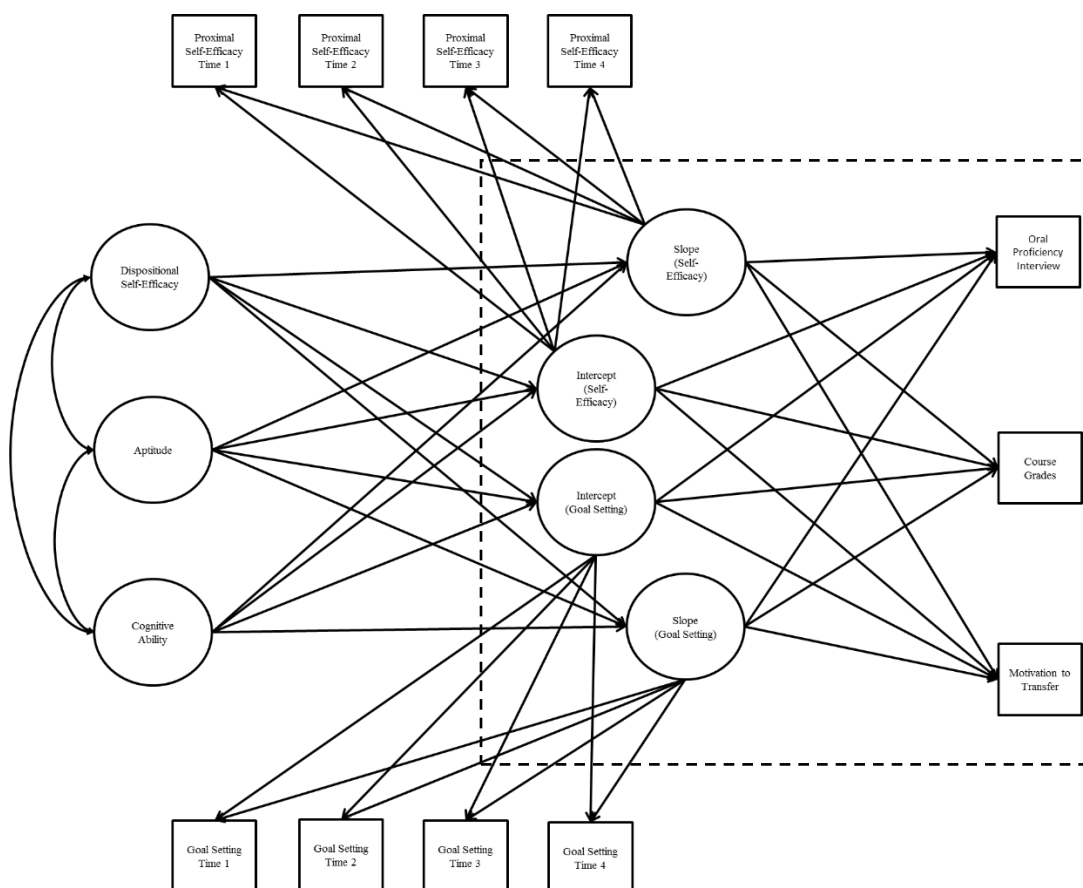
Appendix, Figure 1. Proposed latent growth model wherein trait-like individual differences influence training outcomes through longitudinal motivational intervening mechanisms. (Residuals and other paths omitted for visual simplicity.)



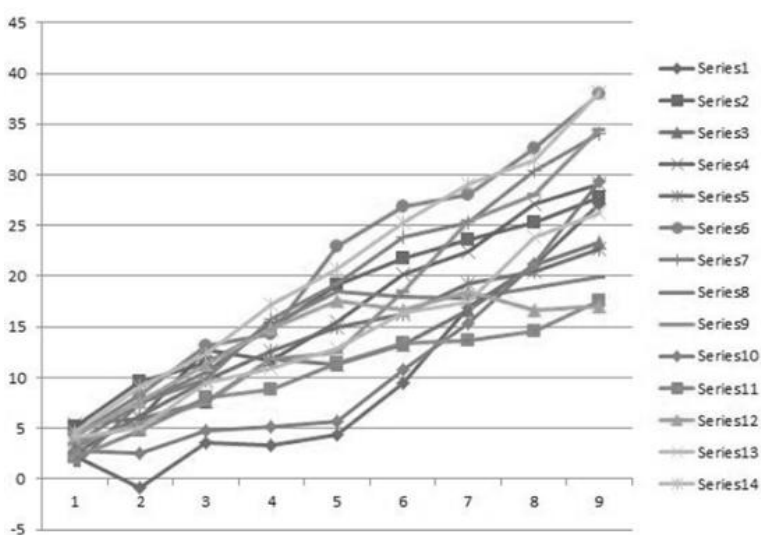
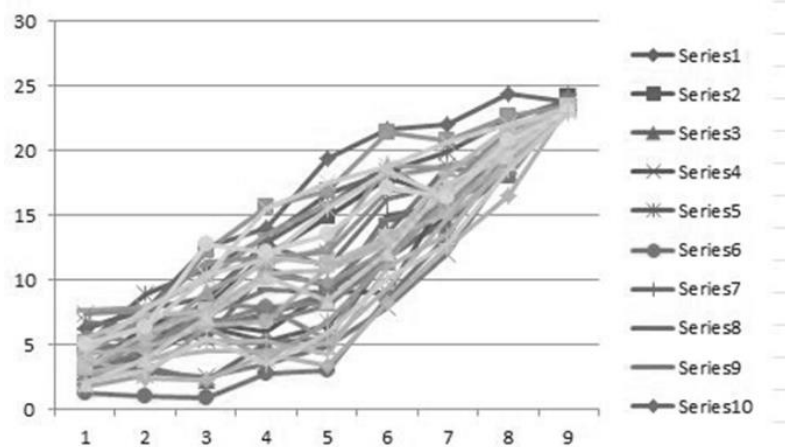
Appendix, Figure 2. Proposed latent growth model for examining functional shape of growth in mediating process variables. (Residuals and other paths omitted for simplicity.)



Appendix, Figure 3. Proposed latent growth model for examining the extent to which time-invariant covariates account for variability in latent growth factors of the mediating process variables. (Residuals and other paths omitted for simplicity.)



Appendix, Figure 4. Proposed latent growth model wherein trait-like individual differences influence training outcomes through longitudinal motivational intervening mechanisms. The portion of the structural model that I address with RQ 3 is encapsulated in the perforated box. (Residuals and other paths omitted for visual simplicity.)



Appendix, Figure 5. Example of observed score scatterplots that display trends in the data. To provide an example, these data were simulated for nine measurement occasions.

Dispositional Self-Efficacy

1. Master new material in learning situations.
2. Perform well in academic courses or training.
3. Participate in role-plays or simulations in front of the class.
4. Read course material and understand the content.
5. Perform a task or activity after receiving instruction on that task/activity.
6. Learn to speak this language very well.
7. Master the material in this language course.
8. Learn my assigned language.

Specific Self-Efficacy

1. Acquire supplies for my mission.
2. Use military-technical vocabulary.
3. Exchange mission-related information with a counterpart in the host country.
4. Describe features of the environment.
5. Conduct negotiations in the training language.
6. Use this language to train or teach others.
7. Use this language to maintain control in hostile confrontations.
8. Use this language to persuade people to provide sensitive information.

Self-Set Goals

1. Personal goal for proficiency at the end of training – Participatory Listening

2. Personal goal for proficiency at the end of training – Speaking
3. Personal goal for proficiency at the end of training – Reading

Motivation to Transfer

1. Volunteer for government-sponsored refresher training.
2. Seek out additional language training opportunities.
3. Participate in language self-study.
4. Attempt to improve your language proficiency.
5. Learn more about the cultures associated with your language.
6. Maintain your current language proficiency.
7. Volunteer for missions that require having language skills.
8. Use your language skills when you have the opportunity on missions.
9. Actively seek out opportunities to use your language skills.