THE ROLE OF TRAIT ACHIEVEMENT MOTIVATION AND ABILITY IN PREDICTING ACADEMIC PERFORMANCE TRAJECTORIES

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ABSTRACT

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In the organizational and educational domains, student and employee performance are central outcomes to applied psychologists, practitioners, and policymakers alike. In each of these domains, sizable literatures have been devoted to research on individual differences in cognitive ability and motivation as performance determinants, that is, how between-persons variability in ability and motivational characteristics contributes to between-persons variability in performance measured at a given point in time. However, it is commonly acknowledged that performance is not a static phenomenon; rather, how an individual performs varies in systematic and substantively meaningful ways over time. One method of describing these patterns of change in performance over time is through the analysis of performance trajectories. In two studies, the influence of ability and trait-like motivational characteristics on undergraduate academic performance trajectories was examined. Results suggest that individuals high in ability and need for achievement tend to perform better initially. However, relationships between change over time and both ability and need for achievement were not consistent across samples.

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INTRODUCTION

It is intuitive to conceive that indicators of performance, whether at the level of the individual, the team, or the firm, should display the characteristic of varying in a systematic manner with the passage of time. To imagine otherwise, that performance is indefinitely stable or even highly resistant to change, seems conceptually illogical, antithetical to many of the interventions commonly employed in organizational practice to influence performance (e.g., training, strategy intervention), and counter to everyday observation (e.g., financial reports indicating firm performance varying over time as a function of dynamics in macroeconomic conditions). Consequently, the study of variability in performance over time, and the determinants of such variability, has long interested researchers in a variety of fields across various levels of analysis.

One infamous example in the history of statistics pertains to Secrist's analysis of firm performance over time throughout the 1920s (Secrist, 1933, as cited in Stigler, 2002). Secrist believed he had discovered a fundamental law in economic activity, namely that competitive pressures lead to mediocrity, or an averaging out, in firm financial performance over the course of time. Unbeknownst to him, Secrist had (unwittingly) re-discovered the principle of regression toward the mean, first observed by Galton more than 45 years earlier (Galton, 1886). More recent, and perhaps less unfortunate, examples of research investigating determinants of organizational performance or productivity over time have focused on a variety of factors, with human resource management (HRM) practices receiving a sizable amount of attention (Birdi, Clegg, Patterson, et al., 2008; Collins & Smith, 2006; Wang & Shyu, 2009).

In addition to the examples cited above, applied researchers have not ignored temporal dynamics in performance at the individual level of analysis. Indeed, as noted more than 40 years ago by MacKinney (1967) in a discussion of temporal variability in individual-level job performance, “change is fashionable” (p. 9). Evidence of the popularity surrounding the study of temporal variability in human performance is reflected in the body of research on the topic of dynamic criteria, which amassed steadily throughout the latter half of the twentieth century. Defined broadly, the concept of dynamic criteria refers to the relative variability or instability of measures of performance over the course of time (Deadrick & Madigan, 1990; Steele-Johnson, Osburn, & Pieper, 2000). Dating to the 1950s (e.g., Worbois, 1951), the dynamic nature of criterion measures employed in organizational psychology and related fields has been the subject of much theoretical conceptualizing, empirical testing, and heated debate in light of ongoing research pertaining to the more general issue of the criterion problem acknowledged in applied psychology (Austin & Villanova, 1992; Barrett, Caldwell, & Alexander, 1985; Ghiselli, 1956). That the topic of dynamic criteria has been the center of a great deal of research activity is not surprising, given the potential implications of temporal variability in performance and performance measures for domains such as personnel psychology (e.g., personnel selection: choice of predictor constructs, validation study design and need to continually validate predictor measures, estimation of utility; training: aptitude-by-treatment interactions), organizational behavior (e.g., the role of state-like and trait-like motivational determinants of performance, employee socialization), educational psychology (e.g., similar concerns as those expressed above regarding personnel selection), and other areas within the general auspices of the applied social sciences.

Researchers investigating the dynamic nature of performance have posited a number of theoretical explanations for the phenomenon. Many of these perspectives focus on the temporally-varying importance of performance determinants in the ability and motivational individual difference domains (e.g., Ackerman, 1988; Alvares & Hulin, 1973; Helmreich, Sawin, & Carsrud, 1986; Kanfer & Ackerman, 1989; Murphy, 1989). In brief, these explanations postulate that constructs important for the prediction of initial or early performance may not be the same constructs important for the prediction of later performance. This shift in importance is often attributed to factors such as skill acquisition and dissipating task novelty, changes which alter the means by which ability and motivational constructs contribute to task performance. Researchers incorporating both ability and motivational constructs into theories of dynamic performance have generally postulated that, while individual differences in general cognitive ability may be more predictive of performance initially (early in the performance period or in one's tenure), ability-performance correlations should dissipate over time as the core job tasks become well learned. Conversely, correlations between individual difference motivational constructs and performance are expected to rise over time as the initial novelty of the task and job dissipates (e.g., Helmreich et al., 1986; Murphy, 1989).

Much of the empirical research from which these models and theories are drawn has focused on how predictor-criterion correlations change over time. However, research dating to the early 1990s has largely shifted to a focus on examining individual differences in performance trajectories over time, an approach that focuses on how performance develops across a period of time and what factors account for differences between persons in developmental trajectories. This body of research has examined how between-persons variability in trajectories can be accounted for by both stable, trait-like constructs (e.g., Ployhart & Hakel, 1998; Thoresen, Bradley, Bliese, & Thoresen, 2004; Voelkle, Wittmann, & Ackerman, 2006; Zyphur, Bradley, Landis, & Thoresen, 2008), as well as more proximal or situationally-specific constructs (Chen & Mathieu, 2008; Yeo & Neal, 2006, 2008).

Another line of research with a roughly parallel chronological lineage to that of dynamic criteria has developed around what has been referred to as the interaction hypothesis (Mount, Barrick, & Strauss, 1999), or the notion that job performance can be viewed as a multiplicative function of constructs in the domains of task-relevant ability and motivation. The interaction hypothesis, often attributed to Maier (1955), has been integrated into models of both work motivation (e.g., Dachler & Mobley, 1973) and static models of job performance (McCloy, Campbell, & Cudeck, 1994; Vroom, 1964). Traditional research on the interaction hypothesis, which has been conducted in both applied settings (e.g., Lawler & Suttle, 1973; Sackett, Gruys, & Ellingson, 1998; Wright, Kacmar, McMahan, & Deleeuw, 1995) and lab settings (e.g., Fleishman, 1958; French, 1958; Locke, Mento, & Katcher, 1976), seeks to address whether interactions between constructs in the ability and motivational domains add incrementally to the prediction of performance at a given time beyond the main effects attributed to either ability and motivation.

Despite the similar chronological paths of these two streams of research (viz., dynamic criteria and the interaction hypothesis) and the debate and research that each has generated, it is noteworthy that there has been little attempt at formally integrating the two into a single, coherent theoretical framework applicable to performance in applied domains. For the dynamic criteria literature, ability and motivation have both been jointly evoked in predominant theories put forth to account for the existence of dynamic criteria (e.g., Helmreich et al., 1986; Murphy, 1989). However, such treatments have generally focused on additive main effects of individual differences in ability and motivation, without much consideration for the form of the relationship between these determinants and performance in a time-varying context. With respect to the literature focusing on the interaction hypothesis, performance (albeit in a static perspective) has been the primary criterion utilized in empirical research. In addition, as previously mentioned, the interaction hypothesis has been incorporated into models of job performance utilized within the field of organizational psychology. Thus, while a connection between these two literatures seems a logical next step, it remains a step yet to be taken.

As such, the purpose of the present study is to integrate the literature on dynamic performance with prior theorizing and empirical research on the interaction hypothesis. The intention underlying this integration is to arrive at a formal analysis of the functional form of the relationships between performance trajectories and individual differences in the ability and motivational domains, so as to derive hypotheses about such relationships that can be tested empirically. To this end, the report is outlined as follows. First, prior research on individual difference determinants of performance and the interaction hypothesis will be reviewed in order to (a) explicate the primary implications derived from the interaction hypothesis; (b) summarize empirical research that has been conducted to test the feasibility of the interaction hypothesis, and; (c) elucidate theoretical justifications put forth for the interaction hypothesis with the aim of noting how such justifications may be extended from a focus on performance as a static concept to performance as a dynamic construct. Second, prior research on dynamic criteria will be reviewed in order to (a) derive its primary implications from both practical and theoretical perspectives; (b) examine relevant theoretical perspectives as they relate to individual difference predictor constructs in the ability and motivational domains, and; (c) highlight empirical research that has investigated relationships between individual difference predictor constructs and performance trajectories. Third, stemming from the literature in these two domains, a model describing determinants of performance trajectories will be put forth that attempts to explain how ability and motivation might account for inter-individual variation in such trajectories within a given applied context, with a specific focus on comparing additive versus multiplicative models. Fourth, results from a study conducted in order to test the aforementioned model will be presented. Finally, results from the present study will be discussed in light of (a) theoretical implications for the dynamic criteria and interaction hypothesis literatures, separately, as well as for how these two bodies of research may be more fully integrated into a model of determinants of performance trajectories; (b) practical implications stemming from the present findings, and; (c) limitations of the present study and suggestions for future research.

ABILITY AND MOTIVATION AS INDIVIDUAL DIFFERENCE DETERMINANTS OF PERFORMANCE

Historically, conceptualizations of human performance within industrial/organizational psychology have treated constructs in both the ability and motivational domains as fundamental determinants of performance. Examples include Kanfer and Ackerman's resource allocation model (Kanfer & Ackerman, 1989), Campbell and colleagues' model of job performance (Campbell, McCloy, Oppler,& Sager, 1993; McCloy et al., 1994), the task performance/contextual performance distinction proffered by Borman and Motowidlo (Borman & Motowidlo, 1993; Motowidlo, Borman, & Schmit, 1997), and variants of expectancy models of motivation (e.g., Lawler & Suttle, 1973). One issue that predates most current models of performance, however, is the recurrent question of how ability and motivation work in tandem to influence performance, that is, the functional form of the relationship between performance, on the one hand, and ability and motivation on the other. In order to understand how this question has been addressed in the literature, previous research on ability and motivation as separate predictors of performance is first reviewed. Consideration is then given to prior theoretical and empirical treatments of ability and motivation as joint determinants of performance.

Ability

Ability has been defined as interindividual variability in the maximum levels of task difficulty at which individuals exhibit successful performance on a given class of tasks, where tasks are differentiated according to the modalities or resources required for performance (e.g., cognitive, psychomotor, perceptual; Carroll, 1993). Within the differential psychology literature, one of the most widely accepted frameworks of the structure of human cognitive abilities is the Cattell-Horn-Carroll (CHC) model. In the CHC model, the domain of human cognitive abilities is structured hierarchically into three strata: stratum-I narrow abilities, stratum-II broad content abilities, and stratum-III general ability, or *g* (Carroll, 1993). Each higher-order stratum reflects an increasing degree of generality within the domain of cognitive ability. Stratum I is characterized by specialized abilities reflecting experience and the acquisition of task-specific strategies relevant to performance. Stratum-I factors load onto stratum-II factors similar to those suggested by Cattell and Horn (e.g., Cattell, 1963; Horn & Cattell, 1966), characterized by broad content abilities indicative of general domains of behavioral performance (e.g., fluid intelligence, crystallized intelligence, general visual perception, cognitive speed, memory and learning). These stratum-II factors, in turn, load on stratum-III *g*, indicating the general factor common to performance across the various cognitive subdomains. Stratum-III *g* has also been interpreted as general mental ability (Schmidt & Hunter, 1998) or general intelligence (Sheppard & Vernon, 2007).

Differential psychologists and applied measurement researchers have speculated as to the conceptual interpretation of *g* within the structure of human abilities. These considerations have resulted in three nonexclusive perspectives: *psychometric g*, pertaining to general intelligence and its foundation within the factor-analytic tradition in psychological measurement, primarily among researchers espousing simple structure; *physiological/biological g*, pertaining to the neurological, physiological, and biological substrates of general intelligence and its relation to various genetic phenomena (e.g., inbreeding depression, hybrid vigor), and; *psychological/behavioral g*, pertaining to the relation between general intelligence and performance in various domains of everyday life, including both academic and employment (e.g., Gottfredson, 1997, 2002; Jensen, 1986, 1998; Ree & Carretta, 2002; Schmidt, 2002). This third perspective would also encompass relationships between *g* and performance on basic information-processing components tasks employed in differential psychology (e.g., Kyllonen, 1993; Kyllonen & Christal, 1990; Sheppard & Vernon, 2007). Although there is no generally agreed upon definition of *g* (Jensen, 1986) and new perspectives continue to emerge (e.g., Van der Maas, Dolan, Raoul, Grasman, Wicherts, Huizenga, & Raijmakers, 2006), researchers have emphasized the importance of general intelligence as a determinant of performance in situations calling for complex information processing, fast and efficient learning, and adaptability in responding to novel environmental stimuli across situations.

Ability and performance. The vast majority of research in applied psychology examining human abilities as predictors of performance, particularly large-scale reviews and meta-analyses, has focused on general cognitive ability. The present review on ability correlates of performance summarizes these findings, while not discounting the potential importance of specific abilities in certain situations. A large body of literature speaks to the predictive efficacy of general cognitive ability in both the work and academic domains (Kuncel, Hezlett, & Ones, 2004). In the work domain, *g* is hypothesized to be a stronger predictor of core technical components of task performance, as opposed to behaviors categorized as contextual performance or citizenship behavior where weaker relationships are hypothesized (Gottfredson, 2002; Motowidlo et al., 1997). Supporting this hypothesis, research in personnel psychology has consistently shown general cognitive ability to be a moderate to strong predictor of job knowledge (Colquitt, LePine, & Noe, 2000; Hunter, 1983; Schmidt, Hunter, & Outerbridge, 1986), training performance and skill acquisition (Colquitt et al., 2000; Hunter, 1986; Hunter & Hunter, 1984; Olea & Ree, 1994; Ree & Earles, 1991, 1992), and various measures of job performance (Hunter, 1986; Hunter & Hunter, 1984; Kuncel et al., 2004; Ree, Earles & Teachout, 1994; Schmidt & Hunter, 1998). Collectively, these findings indicate that general intelligence is a robust, pervasive determinant of technical aspects of task performance; as Olea and Ree (1994) note, “from jelly rolls to aileron rolls, *g* predicts occupational criteria” (p. 848).

Recent meta-analyses and large-scale studies have explored the relationship between academic performance and general intelligence, often measured as a composite score derived from standardized examinations used in college admissions (e.g., ACT, SAT). Mirroring the results found in the personnel domain, results suggest that *g* is a moderate to strong predictor of student performance for both the undergraduate (Robbins, Lauver, Le, Davis, Langley, & Carlstrom, 2004; Sackett, Kuncel, Arneson, Cooper, & Waters, 2009; Tracey & Robbin, 2006) and graduate (Kuncel et al., 2004) populations. In the undergraduate domain, these studies have yielded validities in the range of .35 to .53, depending on the measurement and statistical artifacts corrected for. Kuncel and colleagues’ (2004) meta-analysis revealed that the validity for general intelligence may be slightly weaker in the graduate domain than in the undergraduate domain ($\bar{r}$ = .27, $\bar{r}_{\text{operational}}$ = .36 following corrections for restriction and criterion measurement error).

Theoretical explanations for the role of ability in performance. A number of theories have been put forth in the industrial/organizational psychology literature to account for the observed relationship between stable individual difference constructs and job performance. These theories vary in both the level of detail used to describe the role of ability, as well as the extent to which the propositions set forth have been empirically tested. Two prominent perspectives that have received a great deal of empirical examination are Hunter's theory (e.g., Hunter, 1983, 1986; Schmidt et al., 1986) and Ackerman's theory (e.g., Ackerman, 1987, 1988; Ackerman & Ciancolo, 2000; Kanfer & Ackerman, 1989; Voelkle et al., 2006).

Hunter (1986) presented a theory describing the role of ability as a determinant of performance that was influenced by the classic learning perspective of E. L. Thorndike (see also Hunter, 1983). As described by Hunter (1986), the classic learning perspective postulates that performance on complex tasks is strongly determined by prior learning and that learning is strongly determined by general intelligence. Therefore, performance on complex tasks is determined by general intelligence mediated through learning and the accumulation of knowledge. Hunter (1986) noted two types of learning relevant for performance within the workplace, formal training and on-the-job learning. Both types of learning lead to the accumulation of declarative and procedural knowledge, each of which yields increases in task performance (Hunter, 1983). Within a given learning situation, those high in general intelligence are believed to acquire more job knowledge and acquire it faster than those low in general intelligence (e.g., Schmidt, 2002). In addition, Hunter (1986) suggested that although performance is bounded by the amount of task-relevant knowledge held by the employee, performance may also require the employee to extend beyond the amount of knowledge already held. This state of affairs arises in situations where effective performance places demands on the worker requiring the allocation of higher-order cognitive processing to the task (e.g., problem solving, planning, memory, etc.; see Hunter, 1983). Because of these demands for higher-order cognitive processing, general intelligence will not only predict performance as mediated by learning (knowledge), but it will also have a direct effect on performance (Hunter, 1983).

Hunter (1983) meta-analyzed correlations among measures of cognitive ability, job knowledge, work sample performance, and supervisor performance ratings from both military and civilian samples. The meta-analytic correlations were used to create path models to test the aforementioned propositions regarding the influence of ability on performance. As hypothesized by Hunter, ability exhibited an indirect effect on performance through job knowledge, such that individuals with greater ability tended to have greater job knowledge, and those with greater job knowledge also exhibited higher performance on the work sample measure. Furthermore, ability demonstrated a direct effect on work sample performance beyond the mediated effect through job knowledge; however, the indirect effect was almost twice as large as the direct effect (.34 versus .19). Schmidt and colleagues (1986) extended upon Hunter's (1983) study by incorporating job experience as an antecedent to job knowledge, with experience exhibiting effects parallel to those of general intelligence. Finally, Borman, White, Pulakos, and Oppler (1991) tested Hunter's theory using a sample of first-term soldiers in nine military occupations derived from the Project A dataset. Borman and colleagues (1991) confirmed the theorized indirect effect of ability on work sample performance through job knowledge; however, no evidence was found for a direct effect between ability and work sample performance in this study. Similar findings were reported by Borman, White, and Dorsey (1995).

Ackerman (e.g., 1987, 1988; Kanfer & Ackerman, 1989; Voelkle et al., 2006) presented a theory of skill acquisition integrating perspectives from the differential psychology, human information-processing, and skilled performance literatures. Ackerman's theory suggests that, as an individual acquires experience on a task that permits for consistent information processing, he or she passes through three qualitatively distinct stages of skill acquisition that correspond to the manner in which knowledge is acquired or used at a given stage. These stages are labeled declarative knowledge, knowledge compilation, and procedural knowledge, respectively (Kanfer & Ackerman, 1989; see also Anderson, 1982). These stages correspond largely to Schneider and Shiffrin's controlled-automatic processing distinction (Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977; see also Schneider & Chein, 2003). During the declarative knowledge stage, the individual attempts to understand the task environment and specifications, store rules for effective performance, and derive effective performance strategies. Because of the novelty imposed on the leaner by the task environment at this stage, substantial demands are made on the individual's attentional resources, resulting in slow and error-prone performance. During the knowledge compilation stage, sequences of cognitive and motor processes are integrated, resulting in performance that is faster, more accurate, and less resource-intensive. Finally, during the procedural knowledge stage, the skill has been automatized and can be performed largely outside the individual's attention; attentional demands are reduced sharply, with performance being fast, efficient, and accurate.

Ackerman's theory suggests that the types of ability relevant for performance during skill acquisition can be mapped onto the three stages described above (Ackerman, 1988; Kanfer & Ackerman, 1989). At the declarative knowledge stage, general intelligence and content abilities corresponding roughly to Carroll's stratum-II broad factors are the primary determinants of performance, with demands on general intelligence being invoked by the high attentional requirements confronting the learner and task content determining the relevance of the broad content abilities. As the individual progress to knowledge compilation, demands on perceptual speed ability increase as the learner attempts to compile production rules into fast, efficient performance sequences; concurrently, the demand on general intelligence wanes as attentional load decreases. Finally, as the individual progresses in the procedural knowledge stage, performance is determined largely by individual differences in psychomotor ability that influences task execution and speed; demands on general intelligence and perceptual speed reduce. Together, both of the theories described above provide largely complimentary and congruent treatments of the role of general intelligence in performance. Both theories suggest that general intelligence leads to the accumulation of procedural and declarative knowledge that leads to subsequent increases in performance. The one area where the two theories would likely diverge pertains to the type of abilities involved (i.e., the exclusive focus on general intelligence in Hunter's theory versus the differential importance of abilities at varying levels of generality in Ackerman's theory).

The separate models of Hunter and Ackerman provide useful and unique perspectives on the determinants of human performance in work settings, although both have certain limitations relevant to the present study. Hunter's model has largely received support in the various empirical examinations of it as reported by both Hunter and colleagues and Borman and colleagues. However, the model contains an inherent time precedence that has been thus far neglected; no true longitudinal examinations of the model exist in the published literature that test key propositions (e.g., tests of the proposition that learning mediates the ability-knowledge relationship). Furthermore, the direct effect of ability on performance remains uncertain, as results have not been entirely consistent across studies. Ackerman's theory focuses explicitly on the skill learning process. It was not intended to be a theory of higher-order task performance measured over long-run time sequences as is the case in much of the job and academic performance research referred to elsewhere herein, a point that Ackerman acknowledges (Kanfer & Ackerman, 1989). Furthermore, the theory's propositions regarding the differential importance of various ability constructs throughout skill acquisition have not always found clear support in empirical examinations (e.g., Voelkle et al., 2006). However, the theory is useful for present purposes due to its specification of the role of cognitive abilities in determining performance at a level of detail that is lacking in other individual difference models of job performance.

Motivation

The present focus restricts the domain of motivational constructs in two ways. First, consideration is restricted to constructs relevant to the domain of achievement motivation. The achievement domain includes settings within which behavior is evaluated in light of some standard of excellence and where motivation serves the purpose of energizing and directing affect, behavior, and cognition tied to one's competence in meeting such standards (Cooper, 1983; Elliot, 1999). Broadly speaking, the domain of interest (e.g., interpersonal, achievement, etc.) can be viewed as reflecting those specific affective, behavioral, and cognitive manifestations that are adaptive for performance within that domain; motivational processes, both internal and external to the individual, undergird these manifestations. Using an academic setting as a specific instance of an achievement setting, such manifestations include being ambitious in establishing one's goals, being highly involved in and maintaining control of one's performance and progress, and being persistent and hard working (e.g., Nonis &Wright, 2003). In this sense, achievement motivation is viewed as being an appetitive construct (Kanfer & Heggestad, 1997).

Second, the present focus is on stable individual difference constructs in the domain of achievement motivation. State-like or malleable constructs are relevant insofar as they can be considered manifestations tied to distal individual difference attributes or that represent characteristic responses (cognitive, affective, or otherwise) to an environmental stimulus or set of stimuli. Such malleable constructs can be viewed as the means by which distal, stable characteristics ultimately influence behavior in a given context. Individual difference characteristics associated with achievement motivation become relevant only in the presence of appropriate environmental incentives and when goal choice and pursuit is not constrained (Kanfer & Heggestad, 1997).

The growth and decline of need for achievement. One construct that has played a central role in achievement motivation research over the past 60 years is need for achievement (also commonly referred to as nAch, the achievement motive, achievement motivation, or achievement orientation). The concept of need for achievement has historical roots in early psychological thinking, including William James, Narziss Ach, and Henry Murray (Fineman, 1977). McClelland and colleagues (e.g., Atkinson, 1957; McClelland, 1985; McClelland, Atkinson, Clark, & Lowell, 1953; McClelland, Koestner, & Weinberger, 1989) developed the conceptual domain of achievement motivation around the need for achievement construct by describing the construct's developmental origins, the role of environmental stimuli in causing it to become manifest in a given setting, and the construct's basis in affective arousal.

Atkinson (1957) defined need for achievement as a stable, trait-like disposition associated with strivings for achievement and success. This trait was assumed to be latent or dormant until activated by environmental or contextual cues indicating the instrumentality associated with high achievement (Atkinson, 1953, 1957). Murray (1938, as cited in Fineman, 1977) emphasized a number of characteristics associated with high need for achievement: the tendency to do things quickly and as well as possible, the desire to accomplish difficult tasks, to overcome challenges, and to improve oneself and to surpass others. High standing on need for achievement is associated with competition against standards of excellence, preferences for difficult or challenging tasks, striving to attain high levels of competence, and preferences for feedback information about competence levels (Puca & Schmalt, 1999). These characteristics share in common an adaptive, appetitive form of motivation that is hypothesized to be beneficial in achievement contexts.

Early theorizing from the program of research initiated by McClelland and Atkinson highlighted a number of cognitive manifestations believed to be associated with high standing on need for achievement, including initial selection of moderately difficult tasks (Atkinson, 1957; Cooper, 1983; DeCharms & Davé, 1965; Karabenick & Youssef, 1968), selection of novel and more difficult tasks as previous tasks are mastered (Atkinson, 1957), heightened subjective probabilities of success (Atkinson, 1957), recall of incomplete tasks when performance is interrupted (Atkinson, 1953), choice behavior leading to patterns of persistence when confronted with failure (Cooper, 1983; Feather, 1961), and tendencies toward the delay of gratification (Mehrabian, 1968). Furthermore, affect was posited as the primary driver underlying need for achievement (McClelland et al., 1953). High standing on need for achievement is associated with feelings of positive affect or satisfaction derived from striving and the anticipation of success in achievement-related endeavors; conversely, low standing on need for achievement is associated with feelings of defensiveness and a fear of failure stemming from the anticipation of poor performance (McClelland et al., 1953). Rooted in the hedonic principle, this distinction between approach and avoidance motivation has been adopted by psychologists as diverse as E. L. Thorndike, Tolman, Hebb, Maslow, and Eysenck (Elliot, 1999) and remains a central premise in many contemporary theories of motivational psychology (Higgins, 1997).

Atkinson (1957, 1974) integrated the construct of need for achievement into a model of achievement motivation that attempted to account for action selection, exertion, and persistence in achievement settings. This model was, in essence, an integration of trait-based and cognitive-motivational perspectives, viewing the tendency to achieve success (T_S) as multiplicative function of need for achievement (M_S), the strength of the individual's expectancy, or subjective probability, for achieving success (P_S), and the attractiveness, or valence, associated with achieving success (I_S; Atkinson, 1974). Based on this formulation, Atkinson hypothesized many of the cognitive manifestations associated with need for achievement listed previously. Subsequent researchers sought to verify and extend upon the propositions laid out in Atkinson's theory (e.g., DeCharms & Davé, 1965; Feather, 1961; Karabenick & Youssef, 1965; Raynor, 1969, 1970).

Over the years, the predominant stream of research in the domain of achievement motivation has shifted (Elliot, 1999). With the introduction of cognitive and social-learning perspectives into achievement motivation research between the 1950's and 1970's, interest in trait-based perspectives declined. The shift was evident early on among researchers studying need for achievement, as the construct was merged into models comprising constructs derived from the cognitively-oriented perspectives. Subsequent researchers in the social psychological and educational disciplines redirected their efforts to the study of attributional processes (e.g., Kukla, 1972a, 1972b; Weiner & Kukla, 1970), self-perceptions of ability and beliefs regarding the determinants of outcomes in achievement situations (e.g., Bandura, 1977; Dweck & Leggett, 1988; Rotter, 1990), and goals in achievement environments (e.g., Duda & Nicholls, 1992; Dweck, 1986; Harackiewicz & Elliot, 1993). Over the same time period, cognitive perspectives were pervasive in many theories of work motivation, as reflected in research on goals and intentions (e.g., Locke, 1968; Locke, Shaw, Saari, & Latham, 1981) and expectancy theory (e.g., Lawler & Suttle, 1973; Vroom, 1964).

While a number of factors likely lead to the declining interest in need for achievement, one area that has caused considerable controversy has been the measurement of the construct. Over the years, need for achievement has been operationalized using projective measures (e.g., the Thematic Apperception Test [TAT], Iowa Picture Interpretation Test, Test of Insight), self-report measures (e.g., Mehrabian, 1968; Steers & Braunstein, 1976), and hybrid measurement systems incorporating projective and self-report components (e.g., Puca, 2005; Puca & Schmalt, 1999). Until the 1970s, projective measures were the most widely used means of operationalizing need for achievement (Hermans, 1970; Klinger, 1966), with McClelland, Atkinson, and colleagues relying primarily on the TAT.

Early research and reviews of the literature suggested that projective measures exhibited poor internal-consistency and test-retest reliability, a near-absence of convergence between projective measures of need for achievement, and low criterion-related validity (e.g., Entwisle, 1972; Klinger, 1966). Fineman (1977) concluded that there can be little “confidence that the TAT is measuring any unitary psychological construct, let alone nAch,” (p. 8; see also Hermans, 1970). Other criticisms levied against projective measures of need for achievement included concerns regarding the impact of the motive-arousing instructions used to activate latent motives prior to administration of the TAT (Klinger, 1966), arguments that scores on projective measures are likely contaminated by ability (Entwisle, 1972), and suggestions that projective measurement is not amenable to applied settings due to the difficulty associated with administration and the likely elicitation of poor test-taker reactions (Fineman, 1977).

Due to the logistical and measurement problems discussed with respect to projective measurement, a large number of self-report measures of need for achievement have proliferated throughout the literature (Fineman, 1977). These scales exist as components of larger personality inventories (e.g., CPI, PRF, NEO PI-R), as well as stand-alone measures developed explicitly to assess need for achievement (Kanfer & Heggestad, 1997). Estimates of internal-consistency have often been quite low (e.g., Geiger & Cooper, 1995; Slade & Rush, 1991; Williams & Woodward, 1980; Yukl & Latham, 1978). However, convergent validities among self-report measures of nAch and similar constructs have been stronger than those obtained with projective measures (e.g., Mehrabian, 1969; Miller, Woehr, & Hudspeth, 2002; Steers & Braunstein, 1976; Steinmayr & Spinath, 2009; although see Entwisle, 1972; Fineman, 1977; Wotruba & Price, 1975). Researchers have lamented the lack of similarity between various self-report measures of need for achievement with regard to item content (Fineman, 1977), suggesting that these measures may be tapping distinct constructs or subfacets of the higher-order need for achievement construct (Cassidy & Lynn, 1989).

Given the concerns listed above, it is not surprising that projective and self-report measures of need for achievement have failed to exhibit convergence with one another (e.g., Klinger, 1966), with large-scale studies and meta-analyses yielding estimated correlations between projective and self-report of .08 and .15 (Fineman, 1977; Spangler, 1992). The lack of convergence between projective and self-report measures of need for achievement has long been acknowledged. Throughout much of his career, McClelland

(1985; McClelland et al., 1953; McClelland et al., 1989) argued for the use of projective measurement in research on need for achievement (ironically, proponents of projective measurement for assessing need for achievement have frequently used self-report measures to assess fear of failure, the avoidance component of achievement motivation).

McClelland's arguments were based on several grounds, often tied to the level of conscious accessibility associated with motives and the theoretical foundation of need for achievement in affect. These included: (1) projective measures assess unconscious motives, while self-report measures assess conscious motives; (2) projective measures assess affective bases of need for achievement, while self-report measures tap cognitive aspects of the construct; (3) many people are not capable of accurately reporting their motives or will distort their responses, and; (4) implicit motives reflect a general orientation toward certain types of goals, while explicit motives combine with explicit goals associated with doing well in a particular achievement domain (e.g., academics, employment; McClelland, 1985; McClelland et al., 1989). These arguments have not always been met with acceptance (e.g., Fineman, 1977; Locke & Latham, 2004). However, the implicit-explicit motive distinction is one that still carries use in current research and theorizing on achievement motivation (e.g., Kehr, 2004; Thrash & Elliot, 2002).

Renewed interest in trait conceptualizations of achievement motivation. During the same period that interest in need for achievement waned in social psychological and educational circles, researchers within social/organizational psychology attempted to integrate the construct into various theoretical and empirical frameworks. Thus, researchers interested in job design (Orpen, 1985; Steers & Spencer, 1977), leadership

(Arvey & Dewhirst, 1976), organizational attraction (Turban & Keon, 1993), and entrepreneurial behavior (e.g., Collins, Hanges, & Locke, 2004) have examined the construct in an attempt to highlight the role of individual differences in various social processes within organizations. Similarly, goal-setting researchers have long viewed need for achievement as a potentially important individual difference construct (e.g., Locke, Shaw, Saari, & Latham, 1981; Matsui, Okada, & Kakuyama, 1982; Steers, 1975; Wofford, Goodwin, & Premack, 1992; Yukl & Latham, 1978).

In addition to growing interest in organizational psychology, recent attempts to develop trait-based perspectives of achievement motivation have been influenced greatly by classic conceptualizations of need for achievement. For example, Cassidy and Lynn (1989) developed a 49-item scale based on a faceted perspective of need for achievement incorporating seven lower-order constructs: work ethic, pursuit of excellence, mastery, status aspiration, competitiveness, acquisitiveness for money and material wealth, and dominance. Story, Hart, Stasson and Mahoney (2009) presented a two-factor theory extending upon the Cassidy and Lynn (1989) structure, with the facets divided into intrinsic motivation (work ethic, pursuit of excellence, and mastery) and extrinsic motivation (acquisitiveness for money and wealth, dominance, competitiveness, and status aspiration). Story and colleagues' perspective is particularly useful, in that it distinguishes between aspects of trait-based need for achievement arising from both internal and external cues and stimuli.

In the industrial/organizational psychology literature, Kanfer and Heggestad's (2000; Kanfer & Ackerman, 2000) conceptualization of motivational traits illustrates a recent example of a modern trait-based perspective of achievement motivation. Based on a review of the need for achievement and avoidance motivation/test anxiety literature and several empirical studies, Kanfer and Heggestad (2000) developed the Motivational Trait Questionnaire (MTQ), a multidimensional measure of trait motivation comprising three distinct higher-order factors: Personal Mastery, Competitive Excellence, and Achievement Anxiety. Kanfer and Ackerman (2000) described Personal Mastery as an appetitive motivational trait based on the facets Desire to Learn and Mastery. Competitive Excellence includes both Other Referenced Goals (a combination of approach and avoidance-related characteristics) and Competitiveness (approach-oriented). Achievement Anxiety was described as including both two avoidance-related tendencies, Worry and Emotionality, associated with negative cognition and emotionality in evaluative contexts.

Finally, recent theoretical frameworks in motivational psychology often include need for achievement as a key distal individual difference trait. For example, Elliot and colleagues' (e.g., Elliot, 1999; Elliot & Church, 1997; Elliot & Thrash, 2001; Thrash & Elliot, 2002) hierarchical model of achievement motivation positions trait achievement motivation as a distal predictor of achievement goals (i.e., performance-approach, mastery-approach, performance-avoid, mastery-avoid). Payne, Youngcourt, & Beaubien (2007) also view need for achievement as an antecedent to goal orientation along with several other individual difference characteristics (e.g., cognitive ability, general self-efficacy, self-esteem). Steel and König's (2006) temporal motivational theory includes needs broadly, and need for achievement in particular, as dispositional characteristics impacting upon people's perceptions of outcome evaluation. In the training literature, Colquitt and colleagues' (2000) model of training motivation views achievement motivation as a dispositional antecedent to several proximal characteristics, including pre-training self-efficacy, valence, and job/career constructs. Finally, more recent models associated with goal-setting constructs have also included need for achievement as a stable antecedent (e.g., Campbell, 1982; Phillips & Gully, 1997).

Validity of need for achievement/trait achievement motivation. Need for achievement has been examined as an antecedent of many proximal mediating constructs in both applied and basic motivational research. This research highlights a number of outcomes associated with high standing on need for achievement likely to be beneficial for task performance. The most consistent outcomes of need for achievement that have been recently examined are individuals' achievement goals. Need for achievement, or facets of it, has been found to be a consistent positive predictor of mastery goals (Bipp, Steinmayr, & Spinath, 2008; Durik, Lovejoy, & Johnson, 2009; Elliot & Church, 1997; Elliot & Murayama, 2008; Harackiewicz, Barron, Tauer, & Elliot, 2002; Payne et al., 2007; Steinmayr & Spinath, 2009; Thrash & Elliot, 2002; VandeWalle, 1997), with uncorrected correlations commonly in the upper .30s for global need for achievement scales and evidence of stronger correlations for facet scales. Although somewhat weaker in magnitude, consistent positive correlations have also been found with performance-approach goals (Bipp et al., 2008; Durik et al., 2009; Elliot & Church, 1997; Elliot & Murayama, 2008; Steinmayr & Spinath, 2009; Thrash & Elliot, 2002; VandeWalle, 1997; however, see Payne et al., 2007). Need for achievement also appears to be a negative predictor of both work avoidance and performance avoidance goals (Bipp et al., 2008; Harackiewicz et al., 2002; Payne et al., 2007; Steinmayr & Spinath, 2009; VandeWalle, 1997).

In addition, need for achievement has been found to predict self-efficacy and similar constructs (e.g., subjective probabilities of success, generalized expectancy for success, self-reported competence; Elliot & Church, 1997; Kirk & Brown, 2003; Puca, 2005; Steel, Mento, Davis, & Wilson, 1989; Steinmayr & Spinath, 2009; Story et al., 2009), goal and task difficulty (Matsui et al., 1982; Puca & Schmalt, 1999; Yukl & Latham, 1978), behavioral, physiological, and self-report measures of effort allocation (Capa, Audiffren, & Ragot, 2008a, 2008b; Geiger & Cooper, 1995), and learning strategies and academic-related skills (Busato, Prins, Elshout, & Hamaker, 1999, 2000; Robbins et al., 2004). Finally, need for achievement has been found to be positively related to interest and task-relevant positive affect (Barron & Harackiewicz, 2001; Harackiewicz et al., 2002; Puca & Schmalt, 1999) and self-reported feedback seeking behavior (VandeWalle, 1997) and negatively related to procrastination (Steel, 2007). Although many of these studies were conducted more than 50 years after McClelland and colleagues' initial theorizing on need for achievement (and Murray's theorizing before that), the pattern of results conforms quite well to early descriptions of characteristics associated with high standing on the trait.

With regard to behavioral outcomes, a large number of studies have examined need for achievement as a predictor of performance in both educational and work environments. Early research on the relationship between need for achievement and ratings or objective measures of job performance produced inconsistent results, often resulting in nonsignificant relationships and correlations that appeared to vary greatly between studies (e.g., Fineman, 1975; Steers, 1975; Steers & Braunstein, 1976; Steers & Spencer, 1977; Tziner & Elizur, 1985; Yukl & Latham, 1978). However, much of this research was characterized by small sample sizes and measures of need for achievement with questionable psychometric characteristics. Recent results from large-scale studies and meta-analyses indicate that measures of need for achievement/achievement motivation have yielded relatively weak correlations with measures of job and task performance (in the mid .10s; Dudley, Orvis, Lebiecki & Cortina, 2006), although estimates for training performance have been more favorable (r = .33; Hough, Eaton, Dunnette, Kamp, & McCloy, 1990).

Recent large-scale studies and meta-analyses on the relationship between achievement motivation and performance have also been conducted in the academic domain. Robbins and colleagues (2004) reported a mean uncorrected correlation of .257 between achievement motivation and performance (90% CI = .221,.292, 90% CV = .136,.471). The researchers also found a weaker non-zero relationship with retention (mean r = .105; 90% CI = .042,.168), although the 90% credibility interval overlapped with zero (-.083–.214). Lievens, Ones, and Dilchert (2009) reported increasing operational validities for achievement motivation in predicting medical school GPA across seven years. Aside from the first year (.14), estimates were .31 or higher, reaching a maximum of .48 during the sixth year of school. Durik and colleagues (2009) reported a negative correlation between the Work Mastery subscale of Spence and Helmreich's (1983) achievement motivation measure and diversity in course selection. Durik and colleagues hypothesized that the negative relationship was due to a tendency for highly motivated students to either direct their interests into specific areas of study or to enter into college with plans that were more solidified than those who were less motivated.

*Summary. R*esearch has shown need for achievement to be associated with a number of beneficial outcomes likely to result in strong performance in work and educational environments. Validities for need for achievement in predicting training and academic performance have been promising, although relationships with job and task performance have been relatively weak. Given recent advances with regard to conceptual models of performance (e.g., Borman & Motowidlo, 1993; Campbell et al., 1993) and the measurement of individual differences in trait motivation (e.g., Cassidy & Lynn, 1989; Kanfer & Heggestad, 2000), additional research is warranted to examine whether these estimates still hold.

Thus far, the discussion has focused on ability and trait motivation as isolated predictors of performance in applied settings. Both domains stem from a relatively long theoretical tradition and, for each, empirical research has demonstrated outcomes (affective, behavioral, or cognitive) beneficial for task performance in educational and work settings. However, in many cases, theorizing and research has tended to emphasize one domain (e.g., ability) to the relative exclusion of the other, despite the commonly-held position that both ability and motivation are both fundamental determinants of performance. The next section transitions to a review of research that has attempted to explain how individual differences in ability and motivation function together to explain inter-individual variability in performance in applied contexts.

The Interaction Hypothesis: M + A or M × A?

Among researchers interested in ability- and motivation-based determinants of performance, one issue that has let to persistent controversy pertains to the functional form of the relationship between performance on the one hand, and ability and motivation on the other (Locke et al., 1978). Two opposing viewpoints have been prominent in this debate (Mount et al., 1999), namely an *additive-model perspective* and a *multiplicative-model perspective*. Those subscribing to an additive-model perspective suggest that motivation and ability contribute to performance in an isolated manner, with each determinant having positive, independent effects upon performance (Mount et al., 1999). This perspective implies that the influence of one domain (e.g., motivation) on performance is constant across varying levels of the other domain (e.g., ability).

Those subscribing to a *multiplicative-model perspective* suggest that motivation and ability function interactively in determining performance, such that constructs in one domain (ability) are expected to exert a stronger effect on performance among individuals who are higher in the other domain (motivation; Lawler, 1966; Sackett et al., 1998; Wright et al., 1995). Dating to researchers in the 1950s and 1960s (e.g., Gagné & Fleishman, 1959; Maier, 1955; Vroom, 1964), the multiplicative-model perspective implies the notion that, regardless of one's standing on the latent ability construct(s) relevant to the performance on the task at hand, one cannot exhibit high performance if one does not also put forth effort in applying his or her ability to that task (e.g., French, 1958). The concept can be framed with motivation as the referent construct, as well; regardless of one's level of motivation to perform, high levels of performance cannot be expected if one does not have the requisite ability needed to perform at a certain level. These additive and multiplicative perspectives jointly form what Mount and colleagues (1999) referred to as the interaction hypothesis, with the multiplicative-model perspective referring to the alternative hypothesis and the additive-model perspective referring to the null hypothesis.

Theoretical perspectives relevant to the interaction hypothesis. A number of explanations have been put forth to explain why a multiplicative model should be a valid account of how ability and motivation influence performance. Unfortunately, many applied researchers have posited “person-on-the-street” accounts, much like those described in the previous paragraph, for why such an interaction should exist. Although these descriptions provide a lay-oriented heuristic that is easy to communicate and grasp, they carry no theoretical utility, as there is no attempt to describe the intervening processes that explain why such explanations would hold true. This has often been the case for researchers who attempt to integrate ability into expectancy-theory models (e.g., Dachler & Mobley, 1973). As noted by Campbell and Pritchard (1976), the lack of detail provided in explanations for such an ability-motivation interaction in expectancy models was likely a primary cause for the recurrent nonsignificant findings observed for interactive effects, as will be discussed below.

Kanfer and Ackerman (1989) went beyond a simplistic description and justification for why ability and motivation should interact to influence task performance. Kanfer and Ackerman’s (1989) resource allocation theory relates the concepts of ability and effort to attentional resources (see also Humphreys & Revelle, 1984 for a similar perspective). According to this perspective, ability denotes inter-individual variability in the total amount of attentional capacity that is available to be allocated to a given task. Effort denotes the proportion of attentional resources allocated. During the declarative stage of skill acquisition, the task taxes the individual’s attentional resources by confronting him or her with a novel task environment within which task strategies, rules, and instructions for performance must be learned. Thus, on a moderately difficult task, the declarative stage is both ability- and effort-intensive. From a within-persons perspective, the individual then progresses through the remaining stages of skill acquisition, assuming a task with consistent information-processing demands, which subsequently leads to a reduction in the amount of effort that must be invested toward the task to achieve a given level of performance. However, from a between-persons perspective, individual differences in ability explain the rate at which different people progress through these stages. Other factors held constant, individuals high in ability will proceed at a faster rate than those who are low in ability. Therefore, for those high in ability, the relationship between effort and performance should decrease at a faster rate than for those low in ability.

Other researchers have provided explanations of the joint role of ability and motivation in determining performance, although these have generally been less formalized than that posited by Kanfer and Ackerman's resource allocation theory. For instance, Bell and Kozlowski (2002) suggested that ability moderates the relationship between goal orientation and both performance and knowledge. According to this perspective, learning goal orientation should be positively related to both performance and knowledge among high-ability individuals, but negatively related to performance and knowledge among low-ability individuals. The rationale for this hypothesis was that individuals who adopt learning goals tend to use complex learning strategies and engage in more effortful information processing when confronting a novel task. Individuals high in ability should have the necessary resources needed to apply and benefit from such learning strategies. Conversely, those who are low in ability may be impeded by attempting to use strategies that are difficult to implement. Bell and Kozlowski further hypothesized that performance goal orientation should be negatively related to performance and knowledge among high-ability individuals, but positively related to performance and knowledge for low-ability individuals. High-ability individuals who adopt performance goals constrain their development by utilizing simpler task strategies, while low-ability individuals may benefit from applying less complex strategies by reducing the extent to difficulty associated with learning.

Empirical evidence pertaining to the interaction hypothesis. Results from field studies in work settings testing the interaction hypothesis have been quite inconsistent. Several studies have found evidence for a significant interaction between ability and motivation in predicting performance (e.g., Hollenbeck, Brief, Whitener & Pauli, 1988; Lawler, 1966; Wright et al., 1995). For example, Hollenbeck and colleagues (1988) tested the significance of ability-motivation interactions involving measures of both self-esteem and locus of control in one sample of employees and self-esteem in a second sample. In the first sample, a significant interaction was found between locus of control and ability (SAT); no evidence was found for an interaction with self-esteem. In the second sample, a significant interaction was found between self-esteem and ability (the Aptitude Index Battery).

Lawler (1966) divided a sample of state employees into high- and low-contingency groups, where contingency was defined with respect to the degree to which pay was perceived as being contingent upon job performance. Lawler found support for an interactive effect between the two variables. For those low in ability, perceptions of pay-performance contingency were not related to performance, with reported correlations in the low .10s. For those high in ability, contingency did correlate with performance.

Those who perceived a high pay-performance contingency had stronger performance, with observed correlations reported at .35 and .30 for self- and supervisor ratings, respectively.

Wright and colleagues (1995) investigated the significance of interactive effects between cognitive ability (a four-test composite that included the Wonderlic) and the need for achievement scale from the PRF for a sample of warehouse employees. Zero-order correlations between performance and both ability and need for achievement were not significant; however, the interaction between ability and need for achievement was, accounting for an additional nine percent of performance variance beyond the main effects. The form of the interaction was such that need for achievement was positively related to performance among those high in ability, but negatively related to performance among those low in ability.

In addition to the studies cited above, there are also a number of other field studies failing to find evidence for interactive effects. Several of these studies were in the expectancy theory stream of research (e.g., Dachler & Mobley, 1973; Galbraith & Cummings, 1967; Lawler & Suttle, 1973; for reviews, see Campbell & Pritchard, 1976; Heneman & Schwab, 1972); others were not, focusing on interactions between self-report personality scales and ability measures (e.g., Mount et al., 1999; Sackett et al., 1998). It should be noted that several of the expectancy theory studies did not actually test the interaction hypothesis as intended. For example, Dachler and Mobley (1973) did not examine the hypothesis in either of their samples; ability scores were available for only a subset of employees in one sample and ability was uncorrelated with performance for the second sample. Galbraith and Cummings (1967) set out to test the interaction between ability and motivation in predicting performance; however, they operationalized ability using tenure. Because a host of other factors likely serve to influence tenure, it would seem unlikely that this variable would provide a construct valid measure of ability. These examples characterize the quality of research on the interaction hypothesis within the expectancy-theory stream of research. In many cases, hypotheses were tested on small samples using crude methods employed on unreliable measures or questionable proxies for the constructs of interest.

Mount and colleagues (1999) and Sackett and colleagues (1998) each conducted multiple-sample studies to assess the feasibility of the interaction hypothesis. In each case, results were largely disconfirmatory. In three studies, Mount and colleagues (1999) found no evidence of interactive effects between PCI Conscientiousness and scores on the Wonderlic, with negligible incremental variance in performance explained by the interaction. In four studies, Sackett and colleagues (1998) reported largely disconfirmatory evidence for the interaction hypothesis using different measures of ability and two personality characteristics (dependability, need for achievement) and various criteria.

In addition to the field studies cited above, a number of researchers have tested the interaction hypothesis in lab and educational settings. Compared to field research in organizational contexts, studies conducted in academic settings have often resulted in findings supporting the interaction hypothesis (e.g., Edwards & Waters, 1981; Ganzach, Saporta, & Weber, 2000; Hirschfeld, Lawson, & Mossholder, 2004; Nonis & Wright, 2003; Rosopa & Schroeder, 2009). Semester, yearly, or cumulative GPA has generally served as the criterion measure, with self-report measures of personality and ability tests serving as predictor measures. In most cases, the form of the relationship has been such that high standing on trait motivational characteristics increases the validity of ability for predicting performance (e.g., Edwards & Waters, 1981; Hirschfeld et al., 2004; Nonis & Wright, 2003; Rosopa & Schroeder, 2009) or that high standing on ability increases the validity of motivational attributes for predicting performance (e.g., Hollenbeck et al., 1988; Nonis & Wright, 2003).

Likewise, studies conducted in laboratory settings, often employing psychomotor tasks or simulations to operationalize performance, have provided more consistent evidence for the interaction hypothesis than have field samples in work settings (e.g., Bell & Kozlowski, 2002; Fleishman, 1958; French, 1958; Kanfer & Ackerman, 1989; Locke et al., 1978; Yeo & Neal, 2004), although there are exceptions (Terborg, 1977). The types of ability-performance interactions hypothesized and observed have also differed across lab studies. Many researchers have focused on examining the incremental validity of a cross-product term above a set of first-order predictors in a standard fixed-effects OLS regression. Others have examined cross-level interactions between ability and motivational variables, where levels differentiate within- and between-persons effects, so as to better understand how stable individual differences and proximal characteristics function together to influence how performance unfolds over time (e.g., Kanfer & Ackerman, 1989; Yeo & Neal, 2004).

Critique of extant research relating to the interaction hypothesis. Looking at the set of studies reviewed above as a whole, two patterns emerge. First, tests of the interaction hypothesis in laboratory and academic settings do not necessarily converge with those found in organizational contexts. Second, tests of the interaction hypothesis conducted within organizational settings have been somewhat contradictory, with some researchers finding support (e.g., Hollenbeck et al., 1988; Wright et al., 1995) and others not (e.g., Lawler & Suttle, 1973; Mount et al., 1999; Sackett et al., 1998). A number of potential reasons can be put forth to explain the variability in findings that have emerged.

First, much of the research on the interaction hypothesis is characterized by poor measurement of the predictor domain, as reflected in varying definitions of attributes in the motivational and abilities domains. With regard to motivational characteristics, a host of constructs have been examined: expectancy-theory characteristics (e.g., Lawler & Suttle, 1973), goal orientation (Bell & Kozlowski, 2002), need for achievement/achievement motivation (French, 1958; Hirschfeld et al., 2004; Sackett et al., 1998), dependability (Sackett et al., 1998), effort (Terborg, 1977; Yeo & Neal, 2004), broad or complex personality characteristics (Mount et al., 1999; Rosopa & Schroeder, 2009), manipulations intended to influence goal characteristics or other state-like motivational attributes (e.g., Kanfer & Ackerman, 1989; Locke et al., 1978), trait self-esteem (e.g., Hollenbeck et al., 1988), attitudinal variables (e.g., Lawler, 1966), and role perceptions (Lawler & Suttle, 1973).

In many cases, a rationale for examining a given motivational characteristic is not explicated by the researcher. This amounts to the implicit assumption that motivation, whether trait-like or state-like in nature, can be treated as an undifferentiated construct that should yield comparable results regardless of how it is theoretically or operationally defined. In addition, questions have been raised about the use of between-subjects designs to study propositions derived from expectancy theory (Campbell & Pritchard, 1973) and about the predictive utility of expectancy theory in general (Heneman &

Schwab, 1972). To the extent that such arguments are true, one must question whether the general pattern of disconfirming findings from studies using expectancy-value constructs and operationalizations is of any use at all with regard to the validity of the interaction hypothesis.

The measurement of ability characteristics in research on the interaction hypothesis has not always fared much better than has been the case for motivation. Many researchers have operationalized ability constructs using traditional psychometric ability tests (e.g., Hirschfeld et al., 2004; Mount et al., 1999; Sackett et al., 1998; Terborg, 1977). However, ability has also been operationalized using measures of questionable construct validity, including tenure (Galbraith & Cummings, 1967), tests for which no description of validity or reliability is provided (Dachler & Mobley, 1973), supervisor rankings (e.g., Lawler, 1966), and performance during early or practice trials of the same measure used to define criterion performance (Fleishman, 1958; Locke et al., 1978). Heneman and Schwab (1972) criticized the use of tenure and super rankings as measures of ability, calling instead for researchers to use standardized tests. Ackerman (1989) questioned the use of early-trial or practice performance on the same task used to define criterion performance as a measure of ability.

Questions regarding measurement also arise when examining how researchers have operationalized the performance side of the equation. Much of the research has examined traditional measures of performance used in the personnel and education domains, including supervisory judgments (Lawler, 1966; Mount et al., 1999; Sackett et al., 1998), objective measures of employee output (Dachler & Mobley, 1973; Galbraith & Cummings, 1967; Hollenbeck et al., 1988), GPA (Hirschfeld et al., 2003; Hollenbeck et al., 1988; Nonis & Wright, 2003), and graduation (Ganzach et al., 2000). Others have examined performance on psychomotor or perceptual speed tasks (Fleishman, 1958; French, 1958; Locke et al., 1978), self-ratings of performance (Lawler & Suttle, 1973), judgments of performance from the same supervisor providing judgments of ability (Lawler, 1966), performance on air traffic control or decision-making simulations (Bell & Kozlowski, 2002; Kanfer & Ackerman, 1989; Yeo & Neal, 2004), managerial level attained (Sackett et al., 1998), and time spent working on proficiency tests (Terborg, 1977).

Judgments of the appropriateness of a given performance measure will vary depending on the interests of the researcher; those interested in predicting employee performance will likely choose different criterion measures from those interested in skill acquisition. However, it has long been acknowledged that applied psychologists are often predictor-centric (Ford, Kraiger, & Schechtman, 1986; James, 1973; Jenkins, 1946; Toops, 1944), placing greater emphasis on the quality of predictor measures while accepting whatever criterion that happens to be available (Thayer, 1992). This situation is problematic, given that it is not feasible to design or select appropriate predictor measures without some clarity as to what performance means in a given context (Kane, 1986).

The present purpose is not to question the reliability or construct validity of specific criterion measures employed in research on the interaction hypothesis, but to make explicit the implications that follow from the choices made with regard to adequately testing the interaction hypothesis. For instance, researchers have examined distal, trait-like measures of motivation as predictors of both broad, long-run performance measures (e.g., supervisor ratings) and specific, short-term performance measures (e.g., simulation performance, performance on psychomotor tasks). However, these same researchers have not always explicated the rationale for why a given motivational construct should be relevant to performance at different levels of bandwidth or timeframe in the performance domain, nor how that construct is theoretically expected to operate in the context at hand. It is feasible that this mixing of criteria has resulted in the pattern of inconsistent results observed, given that aggregating measures of behavior over situations often yields different patterns of results than those obtained on single or short-run measures of behavior (e.g., Epstein, 1979, 1980).

Finally, Hirschfeld and colleagues (2003) have suggested that one reason for past inconsistency in research on the interaction hypothesis pertains to the manner in which trait motivation has been operationalized, specifically with respect to self-report measures. Researchers interested in trait motivation have often used global, context-free measures in research on the interaction hypothesis. As Hirshfeld et al. (2003) note, the theory underlying the interaction hypothesis implies that motivation determines or reflects the amount of resources allocated to tasks in a given context (e.g., school, work). Because global trait measures do not provide a frame of reference for respondents to use in evaluating item content, these respondents may generate responses that reflect a different frame of reference that does not reflect how the individual behaves or thinks in the intended context. In support of this argument, Hirschfeld and colleagues found that a contextualized measure of achievement motivation had higher criterion-related validity and explained variance above and beyond that of a context-free measure of the same trait for predicting student GPA. They also found support for the interaction hypothesis with the contextualized measure, but not the context-free measure.

Summary. Theorizing on the interaction hypothesis began with general, unspecified explanations for why constructs in the ability and motivational domains should interact in accounting for between-persons variation in performance. Perhaps unsurprisingly, results from subsequent studies investigating the interaction hypothesis were largely inconsistent. However, much of the empirical research in this area has suffered from measurement and conceptual limitations that may account for variability in results across studies (e.g., operational definitions with questionable reliability and construct validity, lack of specification or explanation for the relevance of the motivation construct studied, lack of specification or explanation for the relevance of the predictor constructs studied with regard to the type of performance in question). More recently, detailed accounts and explanations of the interaction hypothesis have been put forth and tested (e.g., Kanfer & Ackerman, 1989). Furthermore, in spite of the unsupportive evidence discussed above, supportive findings have been reported in various contexts. The pattern of results has yielded somewhat of a controversy. Some researchers have concluded that the interaction hypothesis is an unlikely explanation for how ability and motivation influence performance; others have highlighted the limitations of prior research and suggest that the interaction hypothesis may still hold in certain situations. Therefore, a tentative conclusion would be that, although much of the research on the interactive hypothesis has been unsupportive, an outright rejection of the interaction hypothesis may be premature at this juncture.

To this point, the review has focused on individual difference determinants of performance in the ability and motivational domains, considered both in isolation and together. However, less attention has been placed on the performance domain in question.

One perspective particularly relevant for the present paper pertains to the temporally varying nature of performance, as is often observed when measures of the same performance construct are collected for the same individuals over several points in time. Very little research linking the interaction hypothesis to current perspectives of performance over time has been conducted; the research that has been conducted carries with it limitations that question its generalizability to long-run performance in educational and work contexts. So as to provide background for the integration of theory and research on the interaction hypothesis and performance in a time-varying context, the next section reviews prior research on dynamic criteria and correlates of performance trajectories.

DYNAMIC CRITERIA AND THE STUDY OF TRAJECTORIES IN PERFORMANCE

Dynamic Criteria: Initial Research, Theory, and Debate

Broadly speaking, the concept of dynamic criteria refers to the relative variability or instability of worker performance measures over time (Deadrick & Madigan, 1990; Steele-Johnson et al., 2000). For more than fifty years, questions regarding the existence of dynamic criteria, the nature of the phenomenon, and the concept's implications for applied measurement practice have appeared in the personnel selection literature. The notion of dynamic criteria is a component of the larger "criterion problem" in applied psychology (Ghiselli, 1956), which recognizes that performance measures are not only temporally dynamic, but also factorially complex, situationally specific, and employed to serve multiple (sometimes competing) organizational goals and functions (Austin & Villanova, 1992). This state of affairs arises from the fact that the latent construct space underlying performance can be measured in multiple ways, but that without a means of direct comparison among measurement methods, difficulties arise as to ascertaining the most appropriate method or operationalization to use (Gottfredson, 1991).

Despite recognition that the criterion problem in applied psychology reflects a measurement problem in large part, it has often been lamented that applied researchers have neglected or ignored issues associated with performance measurement at the expense of developing and validating measures of predictor constructs, as noted above (e.g., Ford et al., 1986; Ghiselli, 1956; Gottfredson, 1991; James, 1973; Jenkins, 1946; Toops, 1944). Although this may be true, it would be a mistake to conclude that the notion of dynamic criteria has been ignored by selection researchers; quite the opposite, the topic has been the source of a great deal of controversy and debate (Ackerman, 1989; Austin, Humphreys, & Hulin, 1989; Barrett & Alexander, 1989; Barrett, Alexander, & Doverspike, 1992; Barrett, Caldwell, & Alexander, 1985, 1989; Henry & Noon, 1987, 1989).

Evidence for dynamic criteria. Barrett and colleagues (1985) discuss three means by which dynamic criteria have been operationally defined (a fourth method of examining dynamic criteria involving exploratory factor analysis of predictor measures and criterion data gathered over time was also discussed, although this approach has long been criticized on both methodological and conceptual grounds; Corballis, 1965; Humphreys, 1960). The first definition pertains to changes in average level of group performance over time. Barrett and colleagues (1985) dismissed this definition as being conceptually and operationally weak, primarily due to the obscuring of individual-level information that results from using mean curves.

The second definition entails changes in the rank-ordering of individuals on a given criterion measure over time. A frequent observation in examinations of intercorrelations among measures of a criterion over time is a simplex (Humphreys, 1960) or superdiagonal (Adams, 1987) pattern, characterized by large positive correlations between measures at adjacent trials (e.g., time t and time $t + 1$) that become progressively weaker in magnitude as the size of the interval between measurements increases. Research addressing this definition has been conducted in both organizational (e.g., Bass, 1962; Deadrick & Madigan, 1990; Ghiselli & Haire, 1956; Rambo, Chomiak, & Price, 1983) and educational settings (e.g., Humphreys, 1968; Humphreys & Taber, 1973; Lin & Humphreys, 1977). The existence of declining between-trial intercorrelations appears to be a standard observation; however, results from several field studies (e.g., Butler & McCauley, 1987) question claims of the phenomenon's ubiquity (Henry and Hulin, 1987).

The third operational definition of dynamic criteria discussed by Barrett et al. (1985) relates to changes in validity coefficients between a predictor measured at one point in time and a criterion measured at several points in time. Of the various operational definitions of dynamic criteria explored in the selection literature, this definition appears to result in the greatest disagreement and debate, likely due to its direct implications for selection and admissions practice. Similar to the second definition described above, the changing-validities phenomenon has been examined extensively in both organizational (e.g., Bass, 1962; Deadrick & Madigan, 1990; Ghiselli & Haire, 1960; Helmreich et al., 1986) and educational settings (e.g., Butler & McCauley, 1987; Lin & Humphreys, 1977; Lunneborg & Lunneborg, 1970); large cross-domain summaries also exist (Barrett, Alexander, & Doverspike, 1990; Hulin, Henry, & Noon 1990).

Several studies examining test-predictor correlations over time provide evidence for declining validities (Bass, 1962; Humphreys & Taber, 1973; Lin & Humphreys, 1977; Lunneborg & Lunneborg, 1970). Other studies provide mixed evidence, indicating that validities for certain predictor measures appear to decline over time while others remain consistent or increase as the time between predictor measurement and criterion measurement increases (Butler & McCauley, 1987; Deadrick & Madigan, 1990; Ghiselli & Haire, 1960; Helmreich et al., 1986). Mirroring findings obtained from the primary studies, Hulin and colleagues' (1990) summary indicated that validities appeared to decline over time; however, Barrett, Alexander, and Doverspike's (1992) reanalyzed Hulin and colleagues' data and questioned the generalizability of the findings on methodological grounds. Thus, in spite of more than 30 years of research effort invested into the examination of test-predictor correlations over time in industrial and educational settings, the picture was as unclear as it was at the outset.

Theoretical perspectives on dynamic criteria. Researchers investigating dynamic criteria have posited a number of theoretical accounts of the phenomenon in an attempt to explain empirical findings observed in field and laboratory settings. Broadly speaking, these theories fall into three categories distinguishable on the basis of the underlying factor believed to account for performance dynamism: changing persons, changing tasks, or changing environments. Changing-persons theories postulate that, with practice, the underlying person characteristics believed to account for performance change; however, these characteristics' relative contribution to performance remains temporally invariant (Alvares & Hulin, 1973). Alvares and Hulin (1973) frame the prediction of performance on a given trial using a common-factor model of the form, $x_{ij} = \sum(a_{jk}y_{ik}) + e_{ij} + s_j$ (subscripts denoting the i^{th} person measured on the j^{th} trial with contributions from the k^{th} common ability factor). The changing-persons perspective thus suggests that experience results in increases in ability y_{ik} with constant loading a_{jk}.

Empirical tests of Alvares and Hulin's changing-persons model have yielded mixed findings. In an early study investigating predictors of aviation training, Alvares and Hulin (1973) administered pretest and posttest measures of various abilities, some believed to be relevant for performance and impacted by the type of training in question and others believed to be irrelevant and unaffected by training. Comparisons were made between an experimental group enrolled in an aviation class and a control group comprising participants not enrolled in the class. Gain scores, representing change from pretest to posttest, were examined based on the prediction that gains should be larger for the experimental group due to transfer effects, but only for relevant abilities likely to be influenced by training. In addition, correlations between performance and each of the pretest and posttest batteries were examined based on the prediction that pretest measures should predict early performance while posttest measures would predict late performance. Analyses of the gain scores provided some evidence for differential transfer effects on the posttest ability measures; however, hypotheses regarding the validities were largely not supported. Other empirical tests bearing on Alvares and Hulin's changing-persons theory have also cast doubt on aspects of the theory (Dunham 1974; Humphreys & Taber, 1973). The theory is also somewhat at odds with basic assumptions regarding the stability of individual differences in the cognitive and personality domains observed over relatively long time periods (e.g., Conley, 1984; Vaidya, Gray, Haig, & Watson, 2002). However, it may be tenable for relatively specific, lower-order characteristics that resemble malleable state-like constructs in the personality domain or trainable skills or knowledge in the abilities domain, although Alvares and Hulin (1973) explicitly suggested that the distinction between abilities and skills should be abandoned entirely.

Changing-tasks theories postulate that factors associated with increasing task-relevant experience (e.g., practice, the accumulation of task-relevant knowledge and skills, reduction in novelty associated with the task, automaticity) change the fundamental nature of the task itself for the individual. This view suggests that, although the individual difference characteristics underlying performance may remain relatively constant over time, those characteristics important for initial performance may not be the same characteristics that are required for later performance. Alvares and Hulin (1973) depict the changing-task model as one with temporally dynamic loadings a_{jk} and constant latent abilities y_{ik}. Over time, a large number of changing-task theories have been postulated by researchers interested in work performance. In addition, many of these models share quite a bit of commonality. The present treatment focuses largely on those models developed over the past 30 years. Although not discussed herein, the theory postulated by Fleishman arising from his program of research (e.g., Fleishman, 1953, 1960; Fleishman & Hempel, 1954, 1955; Fleishman & Parker, 1962; Fleishman & Rich, 1963) shares similarity with several recent frameworks, including Ackerman's theory of skill acquisition.

As previously discussed, Kanfer and Ackerman's (1989) theory posits three primary stages of skill acquisition (declarative knowledge, knowledge compilation, and procedural knowledge) that differ with regard to the type of knowledge being acquired or used, the degree of attentional load placed on the individual, and the speed and quality of performance exhibited by the individual. Because the abilities relevant for performance during each of these stages varies as a function of the demands placed on the individual (i.e., declarative knowledge: general intelligence and broad content abilities; knowledge compilation: perceptual speed; procedural knowledge: psychomotor ability), ability-performance correlations are also expected to vary across stages.

Kanfer and Ackerman's (1989) theory does not explicitly address stable individual differences in the motivational domain, which is somewhat of a limitation of the theory for the present study. Rather, distal motivational processes in their model focus on cognitive-motivational decision processes influencing goal choice and intended effort allocation, while proximal motivational processes pertain primarily to on-task self-regulatory behavior. However, two perspectives put forth in the literature around the same time as Kanfer and Ackerman's theory do take into consideration trait-like motivational constructs. Helmreich et al. (1986) noted that much of the prior research examining causes of dynamic criteria as relevant to individual differences focused almost exclusively on the domain of human cognitive ability. Helmreich and colleagues (1986) suggested that although predictive validities for measures of ability constructs may decrease over time, there are several reasons to believe that measures of personality attributes should increase in predictive validity as experience on the job accrues.

The primary rationale for the temporally increasing validities expected for personality attributes stems from what Helmreich and colleagues referred to as the "honeymoon effect," or the idea that, as the novelty and initial challenge associated with a job fades with experience, individual differences in task-relevant personality should subsequently increase in importance. Using subscales derived from measures of achievement motivation and interpersonal orientation to predict performance measured at three points in time for a sample of telephone reservation representative incumbents, Helmreich and colleagues found that three of the subscales (achievement motivation: work; interpersonal orientation: expressivity, verbal aggression, and submissiveness) showed significant increases in validity from initial performance to performance on a second performance measurement, with validities appearing to stabilize by the third performance measurement. Two of the achievement motivation measures (mastery and competitiveness) did not predict performance, although the researchers noted that mastery was likely not a relevant predictor for performance in the type of position examined.

The central premise of Murphy's (1989) theory pertains to the distinction between transition stages and maintenance stages of tenure. Transition stages occur early on in the individual's job tenure or during periods of large change to task-relevant duties or responsibilities. During transition stages, performance is largely dependent upon cognitive ability because of the need for the employee to acquire knowledge and because of the need to make accurate decisions in the absence of task-relevant experience. Maintenance stages (see also Rambo and colleagues' [1983] discussion of maintenance behaviors) correspond to periods of relative stability where tasks are relatively well-learned and do not impose strong attentional demands on the employee. At this stage, employees understand how to perform the job's primary tasks; in addition, situations confronting the individual with ambiguous or novel stimuli or demands become less common. As a result, performance becomes less sensitive to variability in cognitive ability and more sensitive to variability constructs in the domains of motivation and personality. Murphy's theory has been influential on empirical research examining cognitive and motivational predictors of job performance, although it seems relatively difficult to operationalize and measure transitional and maintenance phases of employee tenure in an unambiguous manner (Thoresen et al., 2004).

Finally, changing-environments perspectives highlight the role of dynamic contextual processes both internal and external to the organization as a causal factor underlying dynamic criteria. Collectively, these ideas supplement changing-persons and changing-tasks perspectives by highlighting contextual factors that may also result in criterion instability. Examples include changes in work-role requirements, tasks, and the design of jobs (Deadrick & Madigan, 1990; Murphy, 1989), organizational objectives and goals (Prien, 1966), incentive systems (Rambo et al., 1983), and opportunities and constraints afforded by co-workers and parties external to the organization (Stewart & Nandkeolyar, 2007). Hanges, Schneider, and Niles (1990 extended Murphy's (1989) concept of maintenance stages by incorporating ideas derived from interactional psychology. As previously mentioned, the notion of maintenance stages implies that performance is likely to stabilize once work tasks are well learned and when changes in work-relevant tasks and technology are not observed. Hanges and colleagues suggested that this proposition holds only in the case when employees' perceptions of situational characteristics also remain constant over time.

From Dynamic Criteria to Individual Differences in Performance Trajectories

As of the late 1980s and early 1990s, researchers interested in human performance had posited various theories and informal frameworks to account for phenomena associated with performance dynamism. As discussed above, these perspectives highlighted the roles of changing persons, tasks, and environments. Most theories attempted to account for change in one of these three areas; few integrative treatments existed that sought to explain dynamic criteria from all three perspectives in any type of detailed, comprehensive manner. In spite of the theoretical advancements made in the dynamic criteria literature, however, researchers were still in a state of disaccord regarding the relevance, interpretation, and implications of empirical research findings pertaining to dynamic criteria.

Around the same time, Hofmann and colleagues (Hofmann, Jacobs, & Baratta, 1993; Hofmann, Jacobs, & Gerras, 1992) introduced a new perspective into the dynamic criteria literature by demonstrating the utility of modeling interindividual differences in performance trajectories over time. Hofmann et al. (1993) noted that an exclusive focus on the interpretation of correlations and aggregated results fails to adequately describe the nature of individual change over time (see also Estes, 1956). Although the idea of examining rate of change over time was not novel within the dynamic criteria literature (see Ghiselli & Haire, 1960 for an early examination of correlates of linear change in performance), Hofmann and colleagues solidified the notion by providing a more detailed treatment of the theoretical significance of examining change over time, by demonstrating the application of specific analytic methods (e.g., hierarchical linear modeling) as a means to modeling individual differences in performance trajectories, and by providing initial evidence that such trajectories are both systematic and capable of being predicted. Thus, it appeared that the dynamic criteria debate had been largely resolved (Chen & Mathieu, 2008; Stewart & Nandkeolyar, 2007).

Hofmann and colleagues (1993) acknowledged that both organizational factors and individual differences would likely influence the rate at which employees would learn job-relevant tasks and that the importance of various attributes would likely wax and wane over time. Several studies have examined the influence of contextual and organizational characteristics on performance trajectories, including organizational socialization (Chan & Schmitt, 2000; Lance, Vandenberg, & Self, 2000) and opportunities and constraints afforded by other individuals (Stewart & Nandkeolyar, 2007). The present discussion examines the role of person characteristics as correlates of performance trajectories.

Cognitive predictors of performance trajectories. Subsequent to Hofmann and colleagues' work, researchers began to investigate correlates of individual differences in performance trajectories. Skill acquisition researchers have examined cognitive predictors of performance trajectories, although results have not been consistent. Voelkle and colleagues (2006) found that spatial-numerical ability and perceptual speed were significant predictors of both initial performance and linear growth on the TRACON air traffic controller situation. In support of Ackerman's theory of skill acquisition, results suggested that spatial-numerical ability was the stronger predictor of initial performance, while perceptual speed was the stronger predictor of performance growth. Chen and Mathieu (2008) examined general cognitive ability (self-reported SAT scores) and working memory capacity as predictors of trajectories on a computer-based logic game. Both general ability and working memory significantly predicted initial performance; however, neither was a significant predictor of linear change in performance over time.

Eyring, Johnson, and Francis (1993) examined general cognitive ability, derived from scores on the Wonderlic, as a predictor of learning rate on an air traffic control simulation comparable to that of Kanfer and Ackerman (1989). In this case, within-subjects variability in performance was modeled using a negative exponential model, resulting in parameters denoting asymptotic performance and learning rate. Results suggested that those high in ability began task practice at a higher level of performance, but paradoxically increased at a slower rate compared to those lower in ability. Eyring and colleagues interpreted this finding as indicating that subsequent increases in performance are harder to attain for those high in ability because of initial high performance (i.e., a ceiling effect on performance); therefore, controlling for initial performance should result in a reversal of the ability-learning rate relationship. After controlling for initial performance, however, the relationship between ability and learning rate became nonsignificant. Finally, Yeo and Neal (2004) examined general cognitive ability (Raven's APM) and a self-developed measure of dynamic spatial ability as predictors of learning on an air traffic control task. Results suggested that although dynamic spatial ability was significantly related to learning, general cognitive ability was not.

Cognitive predictors of performance trajectories have also been examined over time frames longer than that observed in a typical skill acquisition study; again, however, results have not been entirely consistent. Deadrick, Bennett, and Russell (1997) examined general cognitive ability and psychomotor ability (both computed from relevant GATB aptitude scales) as predictors of performance trajectories for a sample of sewing machine operators over 24 weeks. Results suggested that psychomotor ability predicted initial performance, while cognitive ability did not; conversely, cognitive ability was a significant predictor of linear change in performance, while psychomotor ability was not. Collectively, the ability measures accounted for 12% and 5% in initial performance and linear change, respectively.

Zyphur et al. (2008) examined general cognitive ability (SAT and ACT scores obtained from university transcripts) as a predictor of trajectories of students' academic performance during their college careers. Results suggested that ability was related to students' initial performance, although the relationship between ability and linear change was only marginally significant ($p < .08$). Zyphur and colleagues further hypothesized that academic performance, as measured by GPA, imposes a limit on the amount that performance can increase over time. Because high-ability students begin college performing strongly, initial performance should therefore mediate the relationship between ability and learning rate, resulting in a negative indirect effect between ability and the individual-level slope parameters. Results from a mediated model tested by Zyphur et al. supported this hypothesis. Similar findings regarding the direct effects of cognitive ability in predicting student performance were reported by Shivpuri, Schmitt, Oswald, and Kim (2006), with cognitive ability predicting initial performance but not linear change.

Non-ability predictors of performance trajectories. Researchers interested in skill acquisition and personnel selection have investigated numerous non-ability predictors of performance trajectories. Generally, selection researchers have focused more so on stable, distal individual difference attributes, while skill acquisition researchers have examined both distal and proximal non-ability attributes. With regard to distal characteristics, several researchers have examined the role of the Big Five broad personality traits as predictors of performance trajectories (Thoresen et al., 2004; Yeo & Neal, 2004; Zyphur et al., 2008).

Thoresen and colleagues (2004) investigated the relationship between the Big Five and performance trajectories for two samples of sales representatives, one believed to be in a transitional stage of tenure and the other believed to be in a maintenance stage of tenure. Measures of performance were derived from results-oriented sales criterion measures (i.e., quarterly territory sales for the maintenance sample, quarterly product market share for the transition sample). For the maintenance sample, extraversion emerged as a significant predictor of incumbents' initial performance; conscientiousness was marginally related to initial performance. However, none of the Big Five measures significantly predicted linear change in performance.

For the transition sample, Thoresen and colleagues found that openness and agreeableness were both significant predictors of incumbents' initial performance. In addition, emotional stability was marginally related to initial performance, although the relationship was negative (i.e., those higher in emotional stability had lower initial performance). With regard to linear change, emotional stability and agreeableness emerged as significant predictors; however, the relationship between linear change and emotional stability was again negative. Finally, openness also exhibited a significant negative relationship with the individual-level quadratic parameter (in the transition sample, evidence was found for significant individual-level variability in the quadratic parameter, unlike in the maintenance sample), indicating that those higher in openness were less likely to experience a plateau in performance during the time period observed.

Zyphur and colleagues (2008) examined the Big Five as predictors of performance trajectories in a sample of college students using four-year grade point average as the criterion on which trajectories were modeled. Conscientiousness and openness both exhibited significant relationships with initial performance, although the relationship for openness was negative. Neuroticism exhibited a marginally significant relationship with initial performance ($p = .05$); however, the relationship in this case was positive. In addition, Zyphur et al. found that conscientious was significantly related to linear change; the relationship between linear change and neuroticism was marginally significant ($p < .08$), although it was also positive in direction. As was the case for cognitive ability described above, Zyphur and colleagues also found that conscientiousness had a negative indirect relationship with linear change through initial performance. Finally, Yeo and Neal (2004) examined the relationship between learning on an air traffic control task and conscientiousness. Results suggested those higher in conscientiousness learned at a significantly lower rate compared with those lower in conscientiousness. This result was hypothesized based on prior researchers in certain employment and learning contexts.

Several noncognitive constructs outside of the Big Five have also been examined as predictors of performance trajectories. Two studies (Chen & Mathieu, 2008; Yeo & Neal, 2004) have examined learning and performance goal orientation in the context of skill acquisition. Chen and Mathieu (2008) found no evidence that either learning or performance goal orientation was related to performance intercepts or linear change, although they did find evidence that goal orientations interacted with type of feedback and situational goal orientation. Yeo and Neal (2004) found that performance orientation was negatively related to learning rate, although learning orientation was not.

Ployhart and Hakel (1998) examined three biodata predictors (past sales commission and salary potential, persuasion, and empathy) of performance trajectories modeled from gross sales commissions over eight quarters for a sample of national securities brokerage incumbents. Time was coded such that the intercept parameter for the trajectories represented performance at one year (four quarters). Results suggested that all three biodata predictors were related to performance at one year, while both persuasion and empathy were positively related to linear change. Furthermore, persuasion and empathy were both significant predictors of the individual-level quadratic estimates, although in opposing directions; those high in persuasion were more likely to decrease in performance over time, while those high in empathy were less likely to decrease in performance over time.

Finally, Shivpuri and colleagues (2006) investigated the role of six characteristics (knowledge of general principles, continuous learning, interpersonal skills, perseverance, and adaptability) measured via a biodata inventory as predictors of academic performance trajectories over four semesters for a sample of undergraduates. Knowledge of general principles was found to be a significant predictor of initial performance. Adaptability and continuous learning were significantly related to linear change; however, the relationships were both negative in direction.

Summary. As shown from the studies described above, researchers interested in human performance have explored a variety of individual difference characteristics as predictors of performance in numerous settings (laboratory-based skilled performance, work, education). This body of research affords a number of conclusions regarding the nature of performance trajectories and predictors of them. First, as has been suggested by others, we can conclude that performance truly varies over time. Although this conclusion is intuitive, it was not until researchers began modeling performance trajectories before agreement existed that performance dynamism reflected more than unsystematic measurement error. Starting with Hofmann and colleagues' research in the early 1990s, a consistent finding has been that individuals exhibit performance trajectories over time and that between-subjects variability in the parameters underlying these trajectories has a sizeable systematic component. Second, between-subjects variability in performance trajectories can be partly accounted for by both distal individual difference constructs and proximal, malleable characteristics. At present, greater specificity regarding the particular constructs is not possible; results have not been entirely consistent across studies and additional replications are needed. Differences in findings across studies may stem from methodological and contextual differences (e.g., differences in how performance is modeled within subjects, the varying nature of the tasks used in the across laboratory studies, differences in the time frame over which performance is measured, the potential influence of extraneous characteristics on performance trajectories, etc.).

Third, constructs that correlate with initial performance are not necessarily the same constructs that account for variance in change over time. Numerous studies described above provide examples highlighting this point. In several cases, however, constructs hypothesized to be significant predictors of change parameters have not emerged as such on a consistent basis. For instance, with regard to cognitive ability, several studies show marginal or significant relationships with linear or higher-order trajectory parameters, while other studies fail to find an effect. Why this is so is not entirely clear.

At this juncture, research on individual difference determinants of performance and dynamic criteria has been reviewed. The next section discusses aspects of educational contexts that highlight the need to modify extant theoretical perspectives on individual difference determinants of performance trajectories when making predictions regarding correlates of performance over time. Theory and prior research are then integrated to derive predictions regarding ability and trait motivation as predictors of college student performance trajectories.

Integrating the Interaction Hypothesis into the Study of Trajectories in Performance

The streams of research reviewed above provide two assumptions that undergird the present study: (1) human performance in organizational and educational contexts varies over time, and between-subjects variance in performance trajectories is partly accounted for by stable individual differences; (2) individual differences in the domains of human ability and trait motivation are theoretically fundamental to understanding variation in performance-relevant behavior in organizational and education contexts. The theoretical issue addressed in the present study pertains to the manner in which individual differences in ability and motivation contribute to human performance over an extended time period, that is, during a student's undergraduate career. However, although the literature on individual difference predictors of performance trajectories has grown over time, there are concerns with respect to generalizing from much of the research that has been conducted to the issues and questions addressed in the present study.

Zyphur and colleagues (2008) note several aspects of academic performance and the academic context that make performance in educational contexts a somewhat unique criterion. First, the shift from high school to life in college, which is initially quite unstructured, marks a major life transition in the lives of students. This disruption may lead to difficulties associated with students' performance upon entry in college. Although theoretical accounts exist regarding performance in novel environments (e.g., Ackerman's research on skill acquisition, Murphy's discussion of transition stages), these concepts do not explicitly take into consideration the major life changes that occur during college students' entry into post-secondary education.

Second, because time in college is structured on the basis of semesters (or other similar demarcation), performance periods span several months. The end of each performance period (semester) brings changes in course content as students enroll in new classes. Zyphur and colleagues (2008) suggest that because the primary job of students is to learn information, and because this information is constantly changing across semesters, this aspect of student performance is similar to Murphy's transition stage. At the same time, many aspects of students' skill-based performance (e.g., writing reports) are relevant across semesters and generally do not change, making this aspect of student performance comparable to Murphy's maintenance stage. As Zyphur and colleagues note, this state of affairs (i.e., recurrent transition stages undergirded by a constant underlying maintenance component) results in uncertainty regarding the extent to which models like those presented by Murphy and Ackerman are accurate descriptions of performance over time in a college environment.

A third aspect that makes generalization from much of the prior research on performance trajectories questionable pertains to the level of contingency that is inherent in college student performance. Unlike much of the research conducted in organizational or laboratory settings, future academic performance is often dependent on how much the student has learned in the past because future coursework often builds or extends upon information learned in more basic courses. This state of affairs provides one reason for why many post-secondary institutions use prior achievement (high school grade point average) as a predictor in the admissions process; students who enter college having performed well in the past are presumed to have a larger knowledge base that will aid them in introductory coursework upon entry into college. This situation also means that students who perform poorly at one time period (e.g., during the second year of college) are at risk of even poorer performance the following year if the knowledge missed during the earlier time period is to serve as a foundation for the information to be learned in the future.

Individual Difference Determinants of Academic Performance Trajectories

Predictors of initial performance. Dating to the theoretical foundations of need for achievement initially developed by Murray, McClelland, and Atkinson, the construct has been viewed as a central component in a framework of adaptive tendencies and characteristics associated with approach motivation that are likely to be of benefit to students' initial performance in college. The first year of college provides both opportunities and challenges to new students that implicate individual differences in achievement motivation as a predictor of initial performance. From an opportunities standpoint, the new student finds him or herself embedded in a novel academic and social environment that contains features likely to appeal to those who are high in academic achievement motivation. Examples include clubs and organizations relevant to one's major that provide students the opportunity to meet like-minded individuals who share similar interests and the availability of faculty members pursuing research in an area that a student might be interested in learning about. On an even simpler level, college course scheduling allows students the opportunity to plan what courses they can take over the course of their college careers. This future oriented activity is likely to cause students to think more about where they see themselves over the course of their college career and to develop academically-relevant goals, likely to have both short-run and long-run benefits, to ensure that they meet their milestones. Because need for achievement is related to the adoption of goals that are both challenging (e.g., Matsui et al., 1982; Yukl & Latham, 1978) and are inclusive of both approach-oriented performance and mastery characteristics (e.g., Elliot & Murayama, 2008), such activities are likely to be beneficial to those who are initially proactive.

From a challenges perspective, the first year of college is also associated with a difficult transition period for many students (e.g., Zyphur et al., 2008). Because students high in achievement motivation are more likely to be both efficacious (e.g., Kirk & Brown, 2003) and perseverant (e.g., Cooper 1983) and to employ problem-focused coping strategies (Halamandaris & Power, 1999), such individuals should be well-equipped to deal with the new challenges they face. Conversely, those low in achievement motivation are more likely to display maladaptive patterns that hinder academic performance, such as the adoption of avoidance performance goals (Payne et al., 2007) and an adverse reaction to failure experiences (e.g., Elliot & Church, 1997; Halamandaris & Power, 1999).

Similarly, the transition to college requires the need to adapt to an unstructured environment that affords one opportunities to engage activities likely to detract from time otherwise invested in academic pursuits. First-year students find themselves in a new location, surrounded by a new social environment, and without any degree of close supervision to ensure that time is allocated efficiently and focus is maintained on one’s coursework. Such circumstances may increase the importance of certain behaviors related to achievement motivation (e.g., delaying gratification, avoiding behaviors related to procrastination; Mehrabian, 1968; Steel, 2007) that are important for ensuring that adequate attention is paid to one's academic performance. Therefore, Hypothesis 1 states:

Hypothesis 1: Individual differences in achievement motivation will be positively related to initial performance.

Individual differences in cognitive ability are likely to influence initial performance in at least three ways. First, as noted by Zyphur and colleagues (2008) and as stated above, the change to college from high school marks a major life change transition into an unstructured environment that is novel and requires adaptation. Students who are low in cognitive ability will likely experience greater difficulty adjusting to the new environment in an adaptive manner; therefore, these students are also more likely to experience initially poor academic performance than students high in cognitive ability. Second, cognitive ability will be reflected in the gross amount of knowledge that students carry with them from high school into college. That is, students high in cognitive ability have likely learned more in their prior academic endeavors. This greater knowledge base will afford such students an advantage at the beginning of their college careers. This is largely the case because students' initial course loads are often composed of general, introductory classes that share greater content similarity with students' high school courses than is the case with courses taken later in college. Third, cognitive ability will be reflected in the gross amount of knowledge that students learn in their coursework during the initial time period (i.e., the first year of college); individuals who are higher in cognitive ability gain a larger amount knowledge during their first year of college compared to individuals lower in cognitive ability. Thus, Hypothesis 2 states:

> *Hypothesis 2: Individual differences in cognitive ability will be positively related to initial performance.*

Predictors of performance trajectories. Prior research implicates achievement motivation and its facets as determinants of students' use of learning strategies (Elliot & McGregor, 2001), adaptive learning styles (Busato et al., 1999, 2000), and study behaviors (Robbins et al., 2004). Relatedly, conscientiousness, of which achievement motivation is a component, has been found to be related to the amount of time that students allocate toward studying (Biderman, Nguyen, & Sebren, 2008). This finding concurs with Zyphur and colleagues' (2008) point that individual differences in conscientiousness, as indicative of motivation, are predictive of performance trajectories because they reflect characteristics that obtain meaning in the context of time (e.g., persistence and striving). When applied to the present study, the findings of Biderman and colleagues suggest that the skills that undergird students' learning strategies and behaviors are likely to improve over time through experience and application, particularly for those who are high in achievement motivation. In other words, highly motivated students' use of such strategies and behaviors are likely to strengthen over time, becoming more efficient and effective, as they experiment with and learn how to better utilize the skills underlying these strategies and behaviors.

As students' study skills increase with application and experience, performance should increase over time, as well, given that study behaviors and strategies are related to performance in academic contexts (Credé & Kuncel, 2008). Therefore, the present argument suggests the following: (1) students who are high in achievement motivation utilize learning strategies and study behaviors to a greater extent than students who are low in achievement motivation; (2) therefore, the skills underlying these strategies and behaviors should increase over time with application and experience, particularly for highly-motivated students that invest greater time on task, and; (3) because these skill increases should lead to subsequent increases in performance over time, it is thus the case that grades for high achievement motivation students should increase over time to a greater extent than is the case for low achievement motivation students.

It should be noted that if achievement motivation is related to higher levels of initial performance, it may exhibit a negative indirect relationship with linear performance change if initial performance and performance change are negatively correlated (Zyphur et al., 2008). This state of affairs would be expected in the present situation, given that academic performance (GPA) has an upper limit; students who perform well initially have less room to continue improving compared to students who initially perform poorly. Therefore, the positive relationship expected between achievement motivation and linear change should be evident after controlling for initial performance, as found by Zyphur and colleagues (2008). As such, Hypothesis 3 states:

Hypothesis 3: Individual differences in achievement motivation will be positively related to linear change in performance over time after controlling for initial performance.

Increases in the skills underlying learning strategies and study behaviors are not likely to impact performance trajectories in the same way for all individuals, however. As Bell and Kozlowski (2002) suggest, the use of learning strategies and effortful processing should result in larger gains for individuals who are high in ability than those who are low in ability, because individuals who are high in ability have greater resources to invest when employing such strategies. Therefore, individual differences in cognitive ability should moderate the relationship between achievement motivation and increases in grades over time. Again, this relationship is expected to hold only after controlling for initial performance, for the reasons noted above. Hypothesis 4 states:

Hypothesis 4: Individual differences in cognitive ability will moderate the relationship between achievement motivation and linear change in academic performance over time after controlling for initial performance, such that the relationship will be stronger for individuals high in cognitive ability.

With regard to the role of cognitive ability in predicting linear change in performance, there are both reasons to expect a positive relationship and reasons to expect no relationship. Each viewpoint merits further consideration. On the one hand, the notions of learning and knowledge acquisition are central to the construct of cognitive ability, as reflected in classical definitions of *g* and in models of job performance determinants (e.g., Borman & Motowidlo, 1993; Campbell et al., 1993; Hunter, 1983, 1986). Because learning is the primary task for students in an academic context and because *g* is theoretically central to learning, one might hypothesize that ability should be related to linear change in performance over time. This argument is further bolstered by the fact that advanced-level college courses are often grounded in content learned in basic or introductory college courses as a foundation, particularly in areas that are strongly cumulative in nature (e.g., mathematics, physics, medicine). Students who acquire knowledge in basic or introductory courses are likely to perform more strongly in advanced-level courses because they have the basic knowledge on which future courses extend. Those who do not acquire such knowledge are at risk of performing even more poorly once they reach advanced-level courses because they are deficient in basic knowledge areas.

On the other hand, it could be argued that, instead of contributing to intra-individual variation in performance, cognitive ability may play a stronger role in determining individuals' mean level of performance throughout college. In other words, all else held constant, students whose high level of cognitive ability affords them the advantage of efficient and effective learning during the first year of college are likely to be those same high-ability students that learn efficiently and effectively during their final year of college.

This argument stems in part from a closer examination of the nature of GPA as a measure of performance in academic contexts. In this case, performance is being assessed using a molar criterion, namely semester or yearly GPA, designed to reflect *gross* *knowledge obtained* at the end of a time period, as opposed to the amount, or rate, of *knowledge growth*. An example illustrates the difference between these two concepts. Assume that several tests are administered for a course over the period of a semester on a bi-weekly basis, starting with the first day of class. Assume also that each test contains a representative sampling of the *entirety* of the knowledge domain relevant to that course for the semester. Each test score for a student reflects the total amount of course-relevant knowledge that the student holds at a given point in time. Initially, we would expect poor performance and low variance because students have not yet been exposed to the material covered later in the course. Ignoring the role of retest effects, as the term progresses, test score means and variances should increase over time as students are further exposed to the course's knowledge domain and have the opportunity to learn relevant concepts and skills. If cognitive ability is indeed central to learning, it should be reflected in increases in students' test scores across tests. Thus, if one were to model trajectories from the test scores, theory would suggest that cognitive ability *should* be positively related to the rate of knowledge growth, or the slope of performance regressed on time. This is because the performance measures themselves allow one to model trajectories that can be interpreted as a measure of knowledge growth, or learning, in a relatively unambiguous manner.

This, however, is not the nature of semester or yearly GPA as a measure of academic performance. Even if tests in college courses were similar to the type described in the example above (imagine how the professor's ratings would look if one tried this), academic scheduling in most U.S. institutions of higher learning is not structured such that students must take progressively more difficult courses in the same exact content domain that extend directly upon the courses taken in the previous term. Rather, students are afforded some degree of flexibility regarding whether they take certain classes and if they take them in a sequential order or not. Therefore, course content is subject to great variability from semester to semester. This lack of structure precludes the interpretation of linear trajectories as rates of cumulative knowledge gain, because the content domain varies. Therefore, cognitive ability is instead reflected in the rate at which students learn within a semester, which is likely to result in similarly high (low) levels of performance for individuals high (low) in ability at the end of each semester, as reflected in GPA. For this reason, cognitive ability should be largely reflected in mean performance (which, in the present case, will be largely reflected in initial performance), as opposed to linear change.

This argument is not in conflict with either the theoretical role of *g* in learning (e.g., Hunter, 1986) nor the interpretation of *g* as individual differences in attentional resources that can be allocated to learning performance (e.g., Ackerman, 1988) or any other interpretation of the construct. Rather, the argument suggests that the criterion in question is not a pure measure of (or, perhaps more importantly for the present discussion, does not allow one to model trajectories that are a pure measure of) the outcomes to which cognitive ability should be related or the manner in which cognitive ability should be relevant theoretically. This argument is also not in conflict with the notion that cognitive ability is an important determinant of both learning and academic performance in later periods of college tenure. Quite the opposite, learning capacity should be just as important later in college as it is earlier in college; although the correlations attenuate somewhat with time, research from the dynamic criteria literature supports this statement (e.g., Butler & McCauley, 1987; Humphreys, 1968).

Finally, this argument is not in conflict with Hypothesis 4, which addressed the interactive relationship between achievement motivation and ability in predicting linear performance increases. The role of ability in moderating the motivation-performance relationship pertains to how ability alters the relationship between strategies and behaviors and performance over time. Recall that the effective application of such skills should increase over time because the skills underlying these strategies and behaviors are also changing over time and because increases in such skills should be reflected in concomitant increases in performance. Rather, the present argument merely states that the role of cognitive ability, in isolation, plays a constant, invariant role in students' performance over time, as reflected in GPA, because GPA does not allow for the modeling of trajectories that represent knowledge growth, or rate of learning, over molar time periods.

In summary, because of the reasons stated above, any relationship between cognitive ability and linear performance change likely results from factors that are substantially less salient than those which were used in hypothesizing the role of ability in predicting initial performance. A strong perspective would be to hypothesize that cognitive ability should not be related to linear change in performance over time. However, given that only two studies have examined this relationship in the past in a college student population (i.e., Shivpuri et al., 2006; Zyphur et al., 2008) and a lack of pre-existing theoretical evidence to buttress the arguments described above, it is merely hypothesized that the relationship between cognitive ability and linear performance change will be weaker than that observed between cognitive ability and initial performance. Thus, Hypothesis 5 states:

Hypothesis 5: The relationship between cognitive ability and linear change in performance over time will be weaker than the relationship between cognitive ability and initial performance.

The hypotheses stated above integrate the literature streams pertaining to job performance, dynamic criteria, and performance trajectories with prior research on the interactive hypotheses to result in a theoretical account of academic performance relevant to the college student population. The present study tests these hypotheses on two samples of college students. The first sample comprised students from a single university, with performance measures representing semester GPA for the first four semesters of a student's tenure. The second sample comprised students from several institutions, with performance measures representing yearly GPA for the first four years of a student's tenure.

METHOD

Two samples were included in the primary analyses discussed in the report herein. For the remainder of the report, these samples will be referred to as 'Sample 1: MSU-Only' (comprised of Michigan State University undergraduate students) and 'Sample 2: Multi Institution' (comprised of undergraduate students from several college and universities from around the United States).

Sample and Procedures

Sample 1: MSU-Only. Data for participants in Sample 1, referred to hereafter as the MSU-Only sample, were drawn from a dataset containing predictor and criterion data on 644 respondents from Michigan State University. Inclusion criteria were limited to the restriction that respondents must be in their freshman year of college at the time of data collection. Missing data was addressed via the missing values imputation procedure in PRELIS. This procedure entails substituting missing values from cases matched on similar non-missing background variables, where similarity is evaluated with respect to user-specified variance ratio (the value .5 was chosen for present purposes). In the event that a case with missing data is not deemed similar to another case in the dataset, imputation is not performed.

This approach was taken in the present study because of heterogeneity in the mechanisms underlying missing data for participants, including institutional non-response, student attrition from college altogether, or students transferring to other institutions. Because there was no way to identify the mechanism leading to missingness for any given case, no assumptions can be made regarding the type of missingness present (e,g., MAR, MCAR) and, thus, the appropriateness of common strategies for dealing with missing data cannot be evaluated. The matching procedure in PRELIS makes no assumptions regarding the type of mechanism leading to missing data. Implementation of the inclusion restriction and subsequent imputation resulted in an operational sample size of 568 participants (88.2% of the original data file).

Participants in the MSU-Only sample were predominantly female (72.2%). Average age for participants in the MSU-Only sample was 18.48 (*SD*=.57). Racioethnic composition of participants in the MSU-Only sample was as follows: Mexican/Latino (1.3%), Other Hispanic (.5%), American Indian or Alaskan Native (.2%), Asian (4.9%), Black/African American (9.2%), White/Caucasian (80.2%), Native Hawaiian or other Pacific Islander (.5%), and Two or More Races (3.2%). Of the MSU-Only sample participant, the vast majority (97.3%) were United States citizens, with 98.0% of participants endorsing English as their primary language. Finally, academic major composition for participants in the MSU-Only sample was as follows: Business (20.7%), Engineering (6.4%), Fine Arts/Humanities (6.6%), Social Science (20.5%), Natural or Physical Science (34.6%), and Other (11.3%).

In order to assess whether there were systematic differences with regard to background or demographic variables between respondents included in the study and those not, Table 5 lists proportions and frequencies with regard to gender, racioethnic status, citizenship status, English speaking status, and academic major for both the analysis sample (MSU-Only) and excluded cases. As indicated by the χ^2 values in Table 5, there was little evidence of differences between those retained and those excluded with regard to gender, $\chi^2(1) = .019$, $p = .809$, citizenship status, $\chi^2(2) = .740$, $p = .691$, and English speaking status, $\chi^2(5) = 2.481$, $p = .115$.

Although differences were not significant, there was some evidence of differences between the two samples with respect to racioethnic composition, $\chi^2(7) = 13.152$, $p = .068$, and academic major, $\chi^2(5) = 9.447$, $p = .093$. Compared to respondents who were excluded, respondents included in the analysis sample were significantly more likely to identify as being White (80.2% in the analysis subset, 69.4% in the excluded subset; $p = .030$) and were significantly less likely to identify as being Mexican / Latino (1.3% in the analysis subset, 5.9% in the excluded subset; $p = .003$). In addition, respondents included in the analysis sample were significantly more likely to be in an academic major affiliated with the natural or physical sciences (34.6% in the analysis subset, 22.2% in the excluded subset; $p = .030$) and were significantly less likely to be in an academic major affiliated with the social sciences (20.5% in the analysis subset, 33.3% in the excluded subset; $p = .010$). As shown in Table 7, the difference in age between the analysis sample and excluded cases was small and not significant ($d = -.163$, 95% CI = -.394, .067).

Sample 2: Multi-Institution. Data on participants in Sample 2, hereafter referred to as the Multi-Institution sample, were drawn from a file containing data on 2,787 respondents from ten public and private institutions across various regions of the continental United States. Inclusion criteria were limited to the restrictions that respondents must be in their freshman year of college at the time of data collection and that the institution they attended agreed to report GPA data for research purposes.

Imputation was handled in the same manner as that described for the MSU-Only sample. Following imputation, implementing these restrictions resulted in an operational sample size of 1,279 participants (45.9% of the original data file) from five institutions.

Participants in the Multi-Institution sample were predominantly female (61.8%). Average age of participants in the Multi-Institution sample was 18.12 (*SD*=.39). Racioethnic composition of participants in the Multi-Institution sample was as follows: Mexican/Latino (1.3%), Puerto Rican (.2%), Other Hispanic (.9%), American Indian or Alaskan Native (.1%), Asian (5.7%), Black/African American (8.4%), White/Caucasian (78.8%), Native Hawaiian or other Pacific Islander (.5%), and Two or More Races (2.8%). Of the Multi-Institution sample participants, the vast majority (97.5%) had United States citizenship, with 96.8% of participants endorsing English as their primary language. Academic major composition for participants in the Multi-Institution sample was as follows: Business (16.3%), Engineering (11.3%), Fine Arts/Humanities (9.0%), Social Science (14.3%), Natural or Physical Science (20.2%), Other (14.6%), and Undeclared (14.3%). University affiliation among participants in the Multi-Institution sample was as follows: Michigan State University (30.5%), Ohio State University (20.0%), University of Indiana (7.9%), University of Iowa (20.2%), and University of Michigan (21.4%).

In order to assess whether there were systematic differences with regard to background or demographic variables between respondents included in the study and those not, Table 6 lists proportions and frequencies with regard to gender, racioethnic status, citizenship status, English speaking status, and academic major for both the analysis sample (Multi-Institution) and excluded cases. It should be kept in mind while interpreting the χ^2 values and associated significance levels that the effective sample for these analyses was quite large (N = 2,787); thus, differences of a relatively small magnitude are likely to be identified as significant due to the power afford by the large sample size. Indeed, as shown in Table 6, significant differences were found between the analysis sample and excluded cases with respect to gender, $\chi^2(1) = 4.864$, $p = .027$, racioethnic status, $\chi^2(9) = 564.985$, $p < .001$, citizenship status, $\chi^2(2) = 6.853$, $p = .032$, English speaking status, $\chi^2(1) = 17.980$, $p < .001$, and academic major, $\chi^2(6) = 43.019$, $p < .001$.

Relative to respondents whose data was retained for analysis, excluded cases were more likely to be female (61.8% in the analysis subset, 65.9% in the excluded subset; $p = .027$). With regard to racioethnic status, respondents included in the analysis sample were significantly more likely to identify as White (78.8% in the analysis subset, 35.3% in the excluded subset, $p < .001$) and were significantly less likely to identify as Mexican/Latino (1.3% in the analysis subset, 5.8% in the excluded subset; $p < .001$), Other Hispanic (.9% in the analysis subset, 2.7% in the excluded subset; $p < .001$), and Black/African American (8.4% in the analysis subset, 40.2% in the excluded subset; $p < .001$).

Respondents included in the analysis sample were significantly more likely than excluded cases to have U.S. citizenship (97.5% in the analysis subset, 95.7% in the excluded subset; $p < .001$), while excluded cases were significantly more likely than those in the analysis sample to have non-U.S. citizenship within a country other than

Canada (2.3% in the analysis subset, 4.0% in the excluded subset; $p = .021$). Finally, respondents in the analysis sample were significantly more likely than excluded cases to have an academic major in the areas of business (16.3% in the analysis subset, 13.9% in the excluded subset, $p = .019$) or the natural or physical sciences (20.2% in the analysis subset, 14.9% in the excluded subset; $p < .001$). Respondents included in the analysis sample were also more likely than excluded cases to be undeclared with respect to academic major (14.3% in the analysis subset, 10.2% in the excluded subset; $p < .001$). Conversely, excluded cases were significantly more likely to be in an academic major within the social sciences (14.3% in the analysis subset, 18.9% in the excluded subset; $p = .012$) or within an academic domain other than those listed (14.6% in the analysis subset, 19.9% in the excluded subset, $p = .003$). As shown in Table 8, the difference in age between the analysis sample and excluded cases was small and not significant ($d = -.064$, 95% CI = -.140, .012).

Measures: MSU-Only Sample

Predictor measures. Need for achievement was measured in the MSU-Only sample via a 10-item composite (hereafter referred to as AM SBF-10; α=.784) comprising five items taken from the need for achievement scale used by Steers and Braunstein (1976) and five items taken from the Work Preference Questionnaire used by Fineman (1975). Where necessary, items were adapted to an academic context in order to make the content relevant for the sample and purposes at hand. Both of the scales comprising the AM SBF-10 have been employed in applied research examining achievement motivation in the work domain (e.g., Steers & Spencer, 1977). The AM

SBF-10 was administered to respondents during their first year of college. Items were rated on 5-point Likert-type scales. Items used in the AM SBF-10 are reported in Table 1.

Ability was measured in the MSU-Only sample via respondents' standardized examination scores. Prior research examining correlates of student performance have often used standardized examination scores as a measure of student ability (e.g., Harackiewicz et al., 2002; Hollenbeck et al., 1988; Kuncel et al., 2004; Nonis & Wright, 2003). Similarly, previous research has demonstrated that such measures are strongly correlated with general cognitive ability (e.g., Carroll, 1997; Coyle & Pillow, 2008; Gottfredson, 2002; Jensen, 1998; Koenig, Frey, & Detterman, 2008).

For instance, Koenig and colleagues (2008) reported an uncorrected correlation of .77 between total ACT and the first factor derived from a principle axis factor analysis of the 10 ASVAB subtests in the National Longitudinal Survey of Youth 1979 dataset. In addition, they reported a correlation (corrected for restriction of range) of .75 between total ACT and scores on the Raven's APM in a separate sample of undergraduate college students. Coyle and Pillow (2008) estimated *g*-loadings using hierarchical confirmatory factor analysis for both the SAT and ACT in two samples. In each sample, both the SAT and ACT exhibited relatively large *g*-loadings compared to the other indicators included in the models (for the SAT, .90 and .78; for the ACT, .92 and .75). The large correlations and path coefficients observed in these studies indicate that both the SAT and ACT appears to be a relatively good measure of general cognitive ability within the college-aged population.

In the present study, data on standardized examination scores were collected during the application process prior to the respondents' first year in college. During the informed consent process, participants signed optional data release forms permitting the researchers to access standardized exam scores from the respondents' records stored by the institutional registrars. All participants included in the MSU-only sample had taken either the SAT or ACT, with some participants having taken both tests in the process of applying to different institutions.

To compute the measure of ability used in the present study, either ACT or SAT scores were used if respondents had completed only one of the two tests; in situations where respondents had completed both tests, scores were averaged to derive a single index of ability. Prior to computing the final ability variable, raw ACT composite test scores were first converted to equivalent SAT scores using a conversion table from www.collegeboard.com (see also Dorans, Lyu, Pommerich, & Houston, 1997). Among participants in the MSU-Only sample who had taken both the ACT and SAT (n=123), the uncorrected correlation between the two measures was .853. Because overall scores were obtained from the institutional registrars, reliability estimates for ACT and SAT could not be computed. The interaction term was the cross-product obtained from multiplying the respondents' need for achievement scores with their ability scores. Both predictors were mean-centered prior to computation of the interaction term; these mean-centered variables were also used in all analyses examining ability and need for achievement as predictors.

Table 7 shows mean scores for ability and achievement motivation for both the analysis sample and cases excluded from analysis. Although respondents in the analysis sample had higher scores on ability compared to excluded cases by slightly more than one-fifth of a standard deviation, the difference was not significant (d = .220, 95% CI = -

.016, .456). Similarly, there was no evidence for a significant difference with regard to achievement motivation between the analysis subsample and cases excluded from analysis (d = .040, 95% CI = -.189, .296).

Criterion measures. During the informed consent process, participants signed optional data release forms permitting the researchers to access grade point average (GPA) data from the respondents' records stored by the institutional registrars. For participants in the MSU-only sample, respondents' GPAs were obtained for each of the first four semesters of college (Fall-01, Spring-02, Fall-02, and Spring-03), thus yielding measures of performance at each of four points in time.

Table 7 shows mean GPA for each time point for both the analysis sample and cases excluded from analysis. At Times 1 and 2 (i.e., Fall-01 and Spring-02), cases included in the analysis sample had significantly higher GPA compared with cases excluded from analysis (GPA_1: d = .685, 95% CI = .426, .942; GPA_2: d = .787, 95% CI = .522, 1.050). The number of cases excluded from analysis with GPA data available at Times 3 and 4 was too small for comparison purposes (8 and 6 cases at Times 3 and 4, respectively). However, the tendency for mean GPA to continue declining among excluded cases at Times 3 and 4 (1.84 and .72, respectively) suggests that differences between the analysis sample and excluded cases remains large.

Measures: Multi-Institution Sample

Predictor measures. Need for achievement was measured in the Multi-Institution sample using a 15-item biographical data (biodata) inventory (α = .757 within the analysis sub-sample [n = 1,325]; α = .736 within the entire multi-institution dataset [N = 2,787]), referred to hereafter as the Achievement Motivation Biodata Inventory (AM

BIO-15). This measure utilized a multiple-choice, self-report format whereby participants were asked questions regarding their prior experiences or history in the academic domain and were then presented with either four or five options from which to choose a response. Items included in the AM BIO-15 were drawn from a pre-existing pool of biodata items which has been used extensively in prior selection research using college samples (e.g., Oswald, Schmitt, Kim, Ramsay, & Gillespie, 2004; Ramsay, Schmitt, Oswald, Kim, & Gillespie, 2006; Schmitt, Oswald, Kim, Gillespie, Ramsay, & Yoo, 2003; Schmitt, Oswald, Kim, Imus, Merritt, Friede, & Shivpuri, 2007).

Items from the AM BIO-15 are shown in Table 2. Items were chosen so as to match, to the extent possible, the item content found in the achievement motivation scale utilized for the MSU-Only sample and to reflect current conceptualizations of trait achievement motivation. In doing so, items were drawn from certain motivational constructs theoretically mapping onto dimensions of college student performance (Oswald, Friede, Schmitt, Kim, & Ramsay, 2005), namely *Perseverance, Knowledge,* and *Continuous Learning.* Oswald and colleagues (2005) define Perseverance as "[c]ommitting oneself to goals and priorities set, regardless of the difficulties that stand in the way," (p. 155) where goals refer to both short-term (e.g., attending class on a daily basis) and long-term (e.g., college graduation) outcomes. Knowledge refers to "[g]aining knowledge and mastering facts, ideas, and theories and how they interrelate and understanding the relevant contexts in which knowledge is developed and applied," (Oswald et al., 2005; p. 154). Although this definition does not explicitly delineate any specific motivational mechanisms or processes pertaining to the acquisition of knowledge, content for the Knowledge items included in the AM BIO-15 covers a number of motivational concepts relevant to the academic domain, including self-established and external standards for performance and effort invested to master relevant course content and material. Finally, Continuous Learning refers to "[b]eing intellectually curious and interested in continuous learning," (p.154), with a specific emphasis placed on active, self-driven behavior guided towards seeking knowledge in both the declarative and procedural domains in core and peripheral areas of study.

Ability was measured using scores obtained from standardized examinations administered as part of the college application process. The procedures used for obtaining the data and computing the final Ability composite score were identical to those described for the MSU-Only sample. As was the case in the MSU-Only sample, the interaction term was the cross-product obtained from multiplying the respondents' need for achievement scores with their ability scores. As above, both predictors were mean-centered prior to computation of the interaction term; these mean-centered variables were also used in all analyses examining ability and need for achievement as predictors.

Table 8 shows mean scores for ability and achievement motivation for both the analysis sample and cases excluded from analysis. Contrary to the results obtain with respect to ability differences between cases included for and excluded from analysis in the MSU-Only sample, the difference favoring the analysis sample with regard to ability was quite large in the Multi-Institution sample (d = .659, 95% CI = .578, .738). Although not as large, the analysis sample also had significantly higher scores with respect to achievement motivation compared to excluded cases (d = .095, 95% CI = .020, .171).

Criterion measures. During the informed consent process, participants signed optional data release forms permitting the researchers to access grade point average

(GPA) data from the respondents' records stored by the institutional registrars. For the Multi-Institution sample, respondents' GPAs were obtained for each of the first four academic years of college (2004-2005, 2005-2006, 2006-2007, and 2007-2008). Thus, as was the case for the MSU-Only sample, measures of performance were obtained for each participant at each of four points in time. Unlike the MSU-Only sample, each time point represented each participant's cumulative yearly GPA, encompassing grades from all institutional time periods (e.g., semesters, trimesters, quarters).

The fact that GPAs were obtained from various institutions in the Multi-Institution sample also resulted in procedural differences pertaining to how GPA was computed at each time point compared to the MSU-Only sample, where all GPA data were obtained from the same institution. More specifically, admissions policies at the various institutions included in the Multi-Institution sample resulted in differential selectivity on various student characteristics (e.g., high school grade point average, standardized examination scores). In order to correct for these differences, which are irrelevant for the present study, GPA was corrected using a procedure employed by the College Board in conducting validation studies of the SAT in similar situations. The procedure for correction was as follows. First, a within-institution standardization on GPA to *z*-scores was employed. Standardized GPA was then regressed, using the entire sample, on the measure of ability (i.e., the ACT/SAT composite) along with a set of dummy variables corresponding to each institution. In this case, the regression coefficients for the dummy variables indicate variability in GPA that would be expected for students with comparability ability levels at the various institutions. Finally, GPAs for students at each institution were adjusted by that institution's regression coefficient, such that students at institutions with higher average standardized examination scores received a relatively higher adjusted GPA and, conversely, students at institutions with lower average standardized examination scores received a relatively lower adjusted college GPA.

Table 8 shows mean GPA for each time point for both the analysis sample and cases excluded from analysis. At Times 1 and 2 (i.e., Year 1 and Year2), cases included in the analysis sample had significantly higher GPA compared with cases excluded from analysis (GPA_1: d = 1.286, 95% CI = 1.134, 1.436; GPA_2: d = 1.545, 95% CI = 1.310, 1.777). The number of cases excluded from analysis with GPA data available at Times 3 and 4 was too small for comparison purposes (8 and 5 cases at Times 3 and 4, respectively). However, the tendency for mean GPA to remain relatively low among excluded cases at Times 3 and 4 (1.43 and 2.88, respectively) suggests that differences between the analysis sample and excluded cases remains large.

Convergent validity of achievement motivation measures. Because two different measures of trait achievement motivation were employed in the two samples included in the present study, efforts were taken to ensure comparability across the measures with regard to construct measurement and item content. The items used in the AM SBF-10 scale examined in the MSU-Only sample were adapted from previously established need for achievement scales with a relatively long track record in the organizational psychology literature. With respect to the AM BIO-15 scale utilized in the Multi-Institution sample, items were taken from a pre-existing pool of biodata items that have been used extensively in prior selection research with samples that are similar to those used in the present study. In addition, care was taken to ensure that the content included in the AM BIO-15 items was comparable to that used in the 10-item scale in the MSU-Only sample, while still mapping onto current conceptualizations of trait achievement motivation. Finally, in line with previous recommendations (Hirschfeld et al., 2004), item content was contextualized to refer specifically to the academic setting.

However, it is necessary to demonstrate an acceptable degree of convergent validity between the two measures to ensure that results obtained using one scale are likely to generalize to those obtained using the other. To this end, a pilot study was conducted whereby the following measures were administered via an Internet-based platform to 128 undergraduate college students at Michigan State University: (1) the AM SBF-10 administered to the MSU-Only sample; (2) the AM BIO-15 administered to the Multi-Institution sample, and; (3) a 21-item scale comprising the Achievement Motivation facets of Work Ethic, Excellence, and Mastery from Cassidy and Lynn (1989). The Cassidy and Lynn (1989) measure, hereafter referred to as AM CL-21, was administered so as to have data on a more recent conceptualization of need for achievement that has tended toward a facet-based perspective of the construct.

The initial sample of 128 participants in the pilot sample was reduced to 110 participants after 18 participants were removed for exhibiting careless responding, as detected by items inserted into the questionnaires designed to assess carelessness (e.g., “For this item, please mark ‘Strongly Disagree.’”). For the reduced sample, 95.4% of participants were 21 years of age or younger; 81.5% were female. Year in college was distributed as follows: freshman (32.1%), sophomore (28.4%), junior (23.9%), senior (13.8%), and fifth year or later (1.8%). Racioethnic composition of participants in the pilot sample was as follows: American Indian or Alaska Native (1.0%), Asian (7.6%), Black (1.9%), White (81.9%), Two or More Races (3.8%), and Other (3.8%). Of the pilot study participants, 99.1% endorsed English as their primary language. Academic major composition for the pilot study participants was as follows: Undecided (9.2%), Business (5.5%), Fine Arts/Humanities (4.6%), Social Science (34.9%), Natural/Physical Science (22.9%), and Other (22.9%).

Table 3 provides correlations between 15 items from the AM BIO-15 with the AM SBF-10 and Cassidy and Lynn's (1989) need for achievement scale (AM CL-21). All correlations are corrected for unreliability (Cronbach's α was .684 and .826 for the AM SBF-10 and AM CL-21, respectively). For the Cassidy and Lynn facet scales, Cronbach's α was .722, .752, and .715 for Work Ethic, Excellence, and Mastery, respectively. As originally developed, Cassidy and Lynn's (1989) scale is broader than what is shown in Table 3 and includes facets tied to extrinsic motivation that are not as relevant for the study of achievement motivation as a determinant of performance among college students (e.g., dominance, acquisitiveness for money and wealth). The scales chosen (i.e., Work Ethic, Pursuit of Excellence, and Mastery) correspond to the intrinsic motivation factor that Story and colleagues (2009) derived from Cassidy and Lynn's (1989) scale.

Most of the AM BIO-15 items correlate at least .15 with AM SBF-10 and AM CL-21 scales; 12 of the 15 items exhibit correlations of at least .25 with one of the two scales. Two of the items (e.g., 11 and 12) show correlations below .15 in magnitude with both scales; however, removal of either item subsequently reduces internal consistency for the AM BIO-15. Furthermore, despite yielding somewhat low correlations with the global achievement motivation scales, items 11 and 12 correlate at a level higher than .15

with relevant facets of Need for Achievement from the Cassidy and Lynn scale (r = .190 and .235, respectively, for Cassidy and Lynn's Mastery facet). Therefore, both 11 and 12 were retained for inclusion in the AM BIO-15 scale.

The strongest (dominant) correlation between each AM BIO-15 item and the three intrinsic motivation facet scales from Cassidy and Lynn is highlighted in bold italicized font. Dominant correlations ranged from .184 (item 14 with Learning) to .609 (item 2 with Excellence). Many of the AM BIO-15 items had one correlation that was distinctly higher on a given facet. In several cases, an AM BIO-15 item exhibited correlations that were comparable in magnitude with two of the Cassidy and Lynn scales (e.g., items 4, 5, 14). That an item might be correlated with multiple facets is not surprising, given findings from Cassidy and Lynn (1989) showing that the facets are not orthogonal. These results were replicated in the pilot sample, with positive correlations between Work Ethic and Excellence (.396), Work Ethic and Mastery (.505), and Excellence and Mastery (.295.). Corresponding estimates corrected for unreliability were .537, .703, and .402, respectively.

Table 4 provides descriptive statistics for and intercorrelations among the AM BIO-15, AM SBF-10, and AM CL-21. Uncorrected correlations between the AM BIO-15 and both of the pre-existing Achievement Motivation measures were .570 for the AM SBF-10 (95% CI = .443–.697) and .568 for the AM CL-21 (95% CI = .442–695). The point estimates for the correlations involving the AM BIO-15 are somewhat lower than the observed correlation between the AM SBF-10 and the AM CL-21 (.637, 95% CI = .525–.748), although the 95% confidence intervals overlap considerably. Corrected correlations between the AM BIO-15 and the pre-existing need for achievement measures were .835 for the AM SBF-10 (95% CI = .649–1.000) and .758 for the AM CL-21 (95% CI = .589–.927). The corrected correlation between the AM SBF-10 and the AM CL-21 was .847 (95% CI = .698–.995). These correlations highlight two points. First, the correlation between the two scales of primary interest to the present study (the AM BIO-15 and the AM SBF-10) are sufficiently strong to suggest that both scales share considerable overlap with regard to the underlying construct measured. Second, both the AM BIO-15 and the AM SBF-10 demonstrate comparable correlations with a relatively recent measure of achievement motivation (the AM CL-21) that is based on a modern perspective of trait achievement motivation as a multidimensional construct comprising several lower-order facets.

Analytic Strategy

The aim of the present research is to test the interaction hypothesis with academic performance trajectories across both semesters (the MSU-Only sample) and academic years (the Multi-Institution sample) as the outcome of interest. In order to achieve this outcome, the present analytic strategy can be decomposed into two primary phases: *Descriptive and Static Analyses* (Phase 1) and *Model Building and Model Testing* (Phase 2). As discussed in greater detail below, Phase 1 includes traditional descriptive analyses of relevant predictor and outcome measures (e.g., description of distributional characteristics, zero-order correlations). Phase 2 entails analyses subsumed under the framework of latent growth modeling (LGM) so as to construct an adequate model of individual difference determinants of performance trajectories and to test hypotheses concerning relationships within this model.

Phase 1: Descriptive and static analyses. As mentioned above, Phase 1 entails a basic descriptive analysis of the predictor and outcome measures central to the present study (i.e., ability, achievement motivation, GPA across relevant time periods), including description of the measures' distribution characteristics (e.g., means, standard deviations) and zero-order correlations among the measures. Phase 1 analyses will also include testing of relationships for both the primary predictor and outcome measures with relevant student characteristics (e.g., gender, racioethnic status) and academic context characteristics (e.g., major area, university). Although such student and academic context characteristics are not a central concern of the present study, results pertaining to such analyses may provide guidance on potential ancillary variables to be included in the Phase 2 and Phase 3 analyses described below.

Phase 2: Model building and model testing. Although concern with individual differences in ability and motivation entails a between-subjects perspective, individual differences in growth or change in performance is a longitudinal issue. Adopting a multilevel paradigm, time of performance measurement (time) in this sense can be viewed as nested within subjects (students). Parameters describing the relationship between time and performance for each subject depend upon parameters at the between-subjects level that can, in turn, incorporate subject characteristics (Raudenbush, 2001). The analytic approach described above has been termed hierarchical linear modeling (HLM; Bryk & Raudenbush, 1992) and can also be handled flexibly within a structural equation modeling (SEM) framework, commonly referred to as latent growth modeling (LGM), latent curve analysis (LCA), or otherwise (Singer & Willett, 2003). Because LGM encompasses HLM (Bauer, 2003; Curran, 2003) and includes analytic advantages over HLM (e.g., the estimation of global model fit indices in common SEM software), the present research focuses on growth modeling in an SEM framework.

Modeling the relationship between individual-difference constructs, conceived of here as time-invariant covariates whose values vary across individuals but are measured only once, and latent trajectories entails three models: (1) the y-measurement model that relates the observed outcome measures (in the present case, GPA over four points in time) to the trajectory parameters used to characterize the form of change over time; (2) the x-measurement model that relates the observed predictor variables (in the present case, ability, achievement motivation, and their interaction) to latent factors that presumably account for variance between subjects in predictor scores, and; (3) the structural model that represents the hypothesized relationships between the exogenous predictor factors and the endogenous latent trajectory parameters (Singer & Willett, 2003). The following sections describe each of these models in detail, with equations borrowed from Singer and Willett (2003). Equations are presented in Figure 1. Elements in bold typeface are matrices.

Eq. (1) represents the y-measurement model. This model relates the latent trajectory parameters, $\boldsymbol{\eta}$, to the observed outcome measures, $\mathbf{Y}$, via the factor loading matrix, $\mathbf{\Lambda_y}$. In Eq. (1), primary interest with regard to trajectory parameters is on the intercept, denoting true initial performance (π_{0i}), and the linear slope, denoting the amount of linear change in GPA associated with a one-unit change in time (i.e., one semester, one year), represented by π_{1i}. This is illustrated by the inclusion of these two parameters as elements within $\boldsymbol{\eta}$ in Eq. (2). These elements can be modified to test hypotheses regarding the form of change over time; this point will be elaborated upon briefly as it relates to the present study.

The elements in the $\boldsymbol{\tau}_{\mathbf{y}}$ matrix correspond to mean parameters for the observed indicators in Eq. (1); for present purposes, this matrix is not of interest. The elements contained in the $\boldsymbol{\Lambda}_{\mathbf{y}}$ matrix are fixed factor loadings that represent the relationship between the underlying latent trajectory parameters, π_{0i} and π_{1i}, and the observed indicators contained in $\mathbf{Y}$. The first column of $\boldsymbol{\Lambda}_{\mathbf{y}}$, with all elements fixed to unity, contains the loadings of the indicators onto the latent intercept trajectory parameter (π_{0i}). The second column $\boldsymbol{\Lambda}_{\mathbf{y}}$ contains loadings of the four indicators onto the latent linear slope trajectory parameter (π_{1i}). Finally, the elements within the diagonal $\boldsymbol{\theta}_{\boldsymbol{\varepsilon}}$ matrix are the estimated residual variances in the observed outcome measures within the y-measurement model. The form of the $\boldsymbol{\theta}_{\boldsymbol{\varepsilon}}$ matrix can be altered to accommodate tests of hypotheses concerning the error structure underlying the observed indicators with respect to heterogeneity and autocorrelation. This point is returned to briefly.

As shown in Eq. (3), the trajectory parameters themselves are assumed to be distributed normally over subjects, with variances $\sigma^2_{\pi_0}$ and $\sigma^2_{\pi_1}$, and covariance $\sigma_{\pi_0\pi_1}$. This equation corresponds to the unconditional model for interindividual differences in change (Singer & Willett, 2003), permitting individuals (i) to have different estimates for true initial performance and the degree of linear change over time. The mean parameters, $\mu\pi_0$ and $\mu\pi_1$, correspond to the average unconditional intercept and linear slope across subjects.

The structural model in Eq. (4) decomposes the latent intercept and slope parameters in Eq. (3) into average ($\mu\pi_0$ and $\mu\pi_1$) and residual (ζ_{0i} and ζ_{1i}) components. In matrix form, this decomposition can be expressed as per Eq. (5), which introduces the terms $\mathbf{B}\boldsymbol{\eta}$ and $\boldsymbol{\Gamma\xi}$. This equation expresses the latent trajectory parameters, $\boldsymbol{\eta}$, as a function of $\boldsymbol{\alpha}$ (trajectory parameter averages; $\mu\pi_0$ and $\mu\pi_1$), $\mathbf{B}\boldsymbol{\eta}$ (relationships between the latent trajectory parameters, $\boldsymbol{\eta}$, with coefficients $\mathbf{B}$), $\boldsymbol{\Gamma\xi}$ (regressions of the latent trajectory parameters on exogenous latent factors, $\boldsymbol{\xi}$, via elements in the $\boldsymbol{\Gamma}$ matrix), and $\boldsymbol{\zeta}$ (a residual matrix). Because exogenous predictors have yet to be introduced, $\boldsymbol{\Gamma}$ is set to zero in Eq. (6). For illustration purposes, the latent trajectory parameters are assumed to be orthogonal (per the zero elements shown in the $\mathbf{B}$ matrix in Eq. [6]). However, elements in $\mathbf{B}$ can also be estimated if there exists an empirical, logical, or theoretical reason to believe that trajectory parameters are correlated with one another.

As mentioned above, the elements of the $\boldsymbol{\zeta}$ matrix (ζ_{0i} and ζ_{1i}) are residuals, specifically, person-specific deviations of the values $\pi_{.i}$ about their respective means, $\mu\pi_{.}$. These residuals, contained in the $\boldsymbol{\Psi}$ matrix shown in Eq. (7), represent individual differences in (variances) and relationships among (covariances) the latent trajectory parameters. Significant variance estimates are a prerequisite for examining predictors of these parameters; if there is no variance in the trajectory parameters, there is no variance available to be accounted for. The off-diagonal elements of $\mathbf{\Psi}$ in Eq. (7) are covariances among the latent trajectory parameters. In the two-parameter case (intercept and slope), a positive relationship suggests that individuals with higher initial status exhibit steeper increasing slopes in change over time, while a negative relationship suggests that individuals with higher initial status exhibit steeper declining slopes in change over time.

Collectively, the first seven equations are of interest during the initial process of constructing the y-measurement model that characterizes change over time. With regard to the present research, the selection of a y-measurement model to capture change in GPA over time was conducted in the following manner. For both datasets, 12 models were tested in an attempt to identify the model that best satisfied relevant criteria (e.g., model convergence, acceptable fit to the data as indicated by global fit indices, logical parameter estimates, and parsimony). The 12 models varied in the following characteristics: the latent trajectory parameters included (i.e., intercept, linear, quadratic), the assumption of fixed versus random trajectory components (i.e., intercepts or slopes that are constant across subjects or are permitted to vary between subjects), the coding of time (linear and higher-order transformations to capture nonlinear change versus logarithmic change), and the use of fixed factor loadings versus freely estimated loadings for the third and fourth performance observations (discussed in greater detail shortly). These models are listed in Table 9 and discussed in greater detail below.

Model 1 was a random-intercept model. This model assumes that within-subjects variability in GPA over time can be captured by a person-specific grand average that varies across subjects (thus, there is no change over time). The next four models (models

2-5) assumed that a linear slope parameter was also necessary to characterize change over time in GPA. Model 2 was a fixed-intercept, fixed-slope model. This model assumes that a single estimate for the slope and linear change parameter holds for all subjects (i.e., all subjects follow the same trajectory with regard to change over time). Model 3 was a random-intercept, fixed-slope model, which assumes that individuals vary in initial performance, but change over time can be characterized using a global estimate appropriate for all subjects. Model 4 was a fixed-intercept,-random-slope model, which assumes no variance across individuals with regard to initial performance, but permits for varying degrees of linear change over time across individuals. Finally, model 5 was a random-intercept, random-slope model, which assumes that individuals vary with respect to both initial performance and the degree of linear change over time.

The remaining seven models (models 6-12) allowed for the possibility of nonlinear change in performance over time. Across these models, nonlinearity was tested using several different approaches. Models 6 and 7 attempted to accommodate nonlinear change via the inclusion of a latent quadratic parameter in addition to the intercept and linear slope parameters. Model 6 was a random-intercept, random-slope, fixed-quadratic model. This model assumes that individuals vary with respect to both initial performance and linear change, but that all subjects exhibit the same degree of nonlinear change characterized by the higher-order quadratic parameter. Model 7, the random-intercept, random-slope, random-quadratic model, extended model 6 by permitting the quadratic trajectory parameter to also vary between subjects, thus permitting varying degrees of inflection in the trajectories across subjects.

Models 8 and 9 attempted to capture nonlinear change via an intercept parameter and a slope parameter with the linear elements being transformed into their natural logs to accommodate logarithmic change. Models incorporating the logarithmic slope parameter were tested in a manner parallel to that described above with regard to the linear slope models; thus, model 8 was a fixed-intercept, fixed-slope model, model 9 was a random-intercept, fixed-slope model, and model 10 was a random-intercept, random-slope model.

Finally, models 11 and 12 attempted to capture nonlinearity by relaxing constraints on the factor loadings between the outcome measures and the latent slope parameter. Specifically, constraining the loadings to the order [0 1 2 3] forces the latent slope parameter to assume a linear interpretation. Permitting the estimation of loadings at certain time points allows for some degree of nonlinearity in the slopes, with the form of nonlinear change determined empirically. In order for the y-measurement model to be identified, the first and second loadings are set to 0 and 1, respectively; thus, the estimated loadings correspond to the third and fourth performance observations. In other words, nonlinear change was modeled by allowing the vector of loadings on the latent slope parameter to take the form [0 1 *x x*], with *x* denoting estimated loadings. Models 11 and 12 were random-intercept, fixed-slope and random-intercept, random-slope models, respectively.

For each of the 12 models above, three submodels were evaluated in an attempted to test hypotheses with regard to the error structure underlying the observed outcome measures. Submodel 1 made the assumption that the residuals for the outcome measures, contained in the matrix $\boldsymbol{\theta}_{\boldsymbol{\varepsilon}}$, were homogeneous across measures (i.e., $\sigma_{\varepsilon 1}^2 = \cdots =$

$\sigma^2_{\varepsilon 4}$) and uncorrelated with one another. Submodel 2 permitted residuals to be heterogeneous; however, residuals were assumed to be uncorrelated. Submodel 3 permitted residuals to be heterogeneous and permitted residuals between time-adjacent measures to be correlated, with all correlations constrained to equality (i.e., $\sigma_{\varepsilon 1 \varepsilon 2} = \sigma_{\varepsilon 2 \varepsilon 3} = \sigma_{\varepsilon 3 \varepsilon 4}$).

Crossing the 12 y-measurement models with the three submodels described above resulted in 36 models evaluated for each sample. The process for selecting a y-measurement model will begin by comparing global fit indices across all models for submodel 1. Models that meet criteria for global fit, discussed shortly, are retained for examination with respect to local parameter estimates and error structure (comparisons among submodels 1, 2, and 3). Because the samples differed with regard to the temporal specificity of the criterion examined (i.e., semester GPA in the MSU-Only sample versus yearly GPA in the Multi-Institution sample) and the time over which measures were obtained (two years of college for the MSU-Only sample versus four years for the Multi-Institution sample), it was not assumed that the y-measurement model chosen for one sample would be the same as that chosen for the other.

The second model of relevance to the present study was the x-measurement model, which contains the exogenous individual-difference predictors (in this case, ability, achievement motivation, and their interaction). As shown in Eq. (8), the x-measurement model parallels the y-measurement model described by Eq. (1) with regard to form. Composites for ability, achievement motivation, and the cross-product term were used in the present research. In order for the model to be identified when single-indicator latent factors are introduced, elements of the vector-matrices $\boldsymbol{\delta}$ (the residual matrix for the predictor measures) and $\boldsymbol{\tau}_{\mathbf{X}}$ (the intercepts, or means, for the observed predictor measures) were constrained to zero (Singer & Willett, 2003). Estimates for the predictor means and variance-covariance matrix were modeled as characteristics of the factors, ξ, via the $\boldsymbol{\kappa}$ and $\boldsymbol{\Phi}$ matrices, as shown in Eq. (10).

Eqs. (11.a) and (11.b) show cognitive ability (*cog*), achievement motivation (*ach*), and the interaction (*int*) term as predictors of two latent trajectory parameters, π_{0i} and π_{1i}. The structural path coefficients, γ, are examined in testing hypotheses concerning relationships between predictors and trajectory parameters. Eqs. (11.a) and (11.b) are represented in matrix form in Eq. (5); however, the elements within the matrices now appear as in (12). The $\boldsymbol{\alpha}$ matrix contains conditional means for the trajectory parameters adjusting for the influence of the exogenous predictors, $\boldsymbol{\Gamma}$ contains structural path coefficients, γ, between the exogenous predictor factors, ξ, and the endogenous latent trajectory parameters, π. As before, the elements of $\mathbf{B}$ in Eq. (12) are set to zero, based on the assumption that parameter trajectories are uncorrelated for purposes of simplification. Finally, the $\boldsymbol{\Psi}$ matrix in (13) contains the variances and covariances of the latent trajectory parameters controlling for the influence of the exogenous predictors. Assuming that the predictors account for a nonzero amount of variance in the trajectory parameters, the elements of this matrix will be smaller in magnitude than those in (7).

Hypothesis evaluation. Figure 2 is a conceptual representation of the present research in path diagrammatic form. In the figure, solid black paths with one-way arrows correspond to structural paths, dotted black paths with one-way arrows correspond to fixed loadings, and grey paths with two-way arrows correspond to latent variances or covariances. Given the analytic strategy described above, Hypotheses 1through 5 will be evaluated as follows. Hypotheses 1 and 2 stated that achievement motivation and cognitive ability would be positively related to initial performance. With respect to Figure 2, tests of Hypotheses 1 and 2 would entail evaluating the magnitude of the structural paths γ_1 and γ_2 relative to their respective standard errors. Positive, nonzero estimates for γ_1 and γ_2 would provide support for Hypotheses 1 and 2. Hypothesis 3 stated that achievement motivation would be positively related to linear change in performance over time. Testing Hypothesis 3 would entail evaluating the magnitude of the structural path γ_5 relative to its standard error. A positive, nonzero estimate for γ_5 would provide support for Hypothesis 3. In addition to evaluating the main effects as described above for Hypotheses 1 through 3, latent trajectories were plotted at low (-1 *SD*) and high (+1 *SD*) values of each predictor (see Curran, Bauer, & Willoughby, 2006 for a description of this process), thus permitting visual inspection of the manner in which each predictor influences performance trajectories.

Hypothesis 4 stated that cognitive ability and achievement motivation would interact in predicting the linear slope. The hypothesized form of the interaction was such that the relationship between achievement motivation and linear change would increase as cognitive ability increases (i.e., the relationship between achievement motivation and linear change in performance will be stronger in magnitude among high-ability compared to low-ability students). The evaluation of Hypothesis 4 entails a two-step process. First, the magnitude of the structural coefficient γ_6 is evaluated; a nonzero coefficient would provide evidence for an interaction between cognitive ability and achievement motivation in predicting linear change. Second, simple intercepts and simple slopes were computed to assess the form of the interaction (Curran et al., 2004; Preacher, Curran, & Bauer, 2006). Simple intercepts and simple slopes were evaluated for low- and high-motivation students at two levels of ability: low ability and high ability. As before, conditional values correspond to low and high are -1 *SD* and +1 *SD* from each variable's respective mean.

Finally, Hypothesis 5 suggested that the relationship between ability and initial performance, γ_1, would be stronger in magnitude than the relationship between ability and linear change in performance, γ_4. In order to evaluate Hypothesis 5, 95% confidence intervals were estimated about the structural path estimates γ_1 and γ_4. Evidence that the estimate for γ_1 was stronger in magnitude than γ_4 and the confidence intervals did not overlap would support Hypothesis 5.

Analyses were conducted in Mplus version 3.01 using maximum likelihood estimation (MLE). Global model fit was assessed using the model χ^2, the comparative fit index (CFI; Bentler, 1990), the Tucker-Lewis nonnormed index (TLI; Tucker & Lewis, 1973), the root mean squared residual (SRMR; Bentler, 1995) and the root mean square error of approximation (RMSEA; Steiger, 1990). Because of the relatively large sample sizes employed in the present research, the model χ^2 will be overpowered and, hence, should be interpreted cautiously. Hu and Bentler (1999) suggested the following cutoff criteria under MLE for the incremental (TLI, CFI) and absolute (SRMR, RMSEA) fit indices examined herein: CFI $\geq$ .95, TLI $\geq$ .95, SRMR $\leq$ .08, and RMSEA $\leq$ .06. Browne & Cudeck (1993) suggested that values for the RMSEA between .05 and .08 indicate reasonable model fit, and values less than .05 indicate close fit. 90% confidence intervals about the RMSEA point estimate are reported for interpretation.

Nested models were compared using the difference in χ^2 between the two models ($\Delta\chi^2$), which was evaluated against the difference in degrees of freedom between the two models (Δdf). Nested and non-nested models were also compared by examining change in the incremental and absolute fit indices listed above.

RESULTS: MSU-ONLY SAMPLE

Descriptive and Static Analyses

Table 10 provides descriptive statistics (means, standard deviations, and zero-order correlations) for the study measures. As mentioned above, ability and achievement motivation were centered about their respective means ($\bar{X}_{cent}$ = 0.00, $SD_{\text{x.cent}}$ = SD_{X}, where x.cent = $[x - \bar{X}]$) prior to computing the cross-product term for interpretative purposes in the subsequent regression analyses. In the MSU-Only sample, ability and achievement motivation were significantly and negatively related to one another; however, the magnitude of the correlation was weak (r = -.084, p = .047). With regard to academic performance, mean GPA increased slightly from the first to second time point (3.08 to 3.11), and then remained near 3.00 during the final two time points (3.01 and 3.03, respectively). The pattern of standard deviations exhibited for GPA suggested variance in academic performance was similar for the first and second performance observations (.65 and .65 at Times 1 and 2) and for the third and fourth performance observations (.72 and .74 at Times 3 and 4).

Intercorrelations among the four GPA measures yielded some evidence of a simplex pattern, with intercorrelations being moderate in strength (.600s among time-adjacent elements; .500s and .400s among elements further separate in time). Criterion-related validities for both predictors showed a decreasing pattern over time, although the reduction was more severe for achievement motivation (ability: .290, .261, .273, and .266; achievement motivation: .235, .264, .119, and .132). All predictor-criterion correlations remained significant through Time 4.

Latent Trajectory Models

Y-measurement model. Table 11 provides global model fit indices for the measurement model in the MSU-Only sample. A browsing of the fit indices in Table 11 suggests that all models with fixed intercepts (models 2, 4, 8) yielded an unacceptably poor fit to the data according to all fit indices. Therefore, any model retained for consideration would allow for between-subjects variability in initial performance. In addition, the fit indices suggest that models with variable intercepts, but either no estimated slopes (i.e., the intercept-only model, model 1) or fixed slope components (models 3 and 9), yielded CFI values below the .95 cutoff and RMSEA and SRMR values at or above .08.

Therefore, five models that also permitted random slope parameters were retained for further consideration: 5 (Random-Intercept, Random-Slope), 6 (Random-Intercept, Random-Slope, Fixed-Quadratic), 7 (Random-Intercept, Random-Slope, Random-Quadratic), 10 (Random-Intercept, Random-Slope [Logarithmic]), and 12 (Random-Intercept, Random-Slope [Loadings Estimated at Times 3 and 4]). For each of these models, CFI and TLI values met the .95 cutoff and SRMR values met the .08 cutoff. However, RMSEA values were above.08 for model 6 (.083), model 7 (.101), model 10 (.089), and model 12 (.086). The only model producing an RMSEA value under .08 was model 5, the random-intercept, random-slope model (RMSEA = .077, 90% CI = .051, .104). The remaining fit indices all met relevant criteria (CFI = .973, TLI = .979, SRMR = .040).

Table 12 provides the local parameter estimates for model 5, submodel 1 (referred to hereafter as model 5.1). The mean estimated true intercept was 3.090 (*SE* = .026, 95%

CI = 3.038, 3.142), which is similar to the observed value for GPA during participants' first semester at Time 1 (3.08). Similarly, the mean estimated linear change parameter was -.023 (*SE* = .010, 95% CI = -.042, -.004), indicating that GPA decreased by approximately .02 grade points per semester. Figure 3 provides a plot of the unconditional mean performance trajectory for the MSU-Only sample including 95% confidence bands (Curran et al., 2004).

The variances for the latent intercept and slope parameters are both significant ($\psi_{\text{Intercept}\leftrightarrow\text{Intercept}}$ = .272, *SE* = .024, 95 CI = .225, .319; $\psi_{\text{Slope}\leftrightarrow\text{Slope}}$ = .019, *SE* = .003, 95% CI = .013, .026), indicating meaningful between-subjects variability in the parameters underlying latent change. The covariance between the latent intercept and slope parameters was negative, although there was no evidence that the relationship differed from zero ($\psi_{\text{Intercept}\leftrightarrow\text{Slope}}$ = -.010, *SE* = .007, 95% CI = -.023, .004). The standardized covariance between the latent intercept and slope parameters was -.131, suggesting little between-subjects variance shared between the two trajectory parameters. Finally, the unstandardized residual variance (θ_{ε}) estimated for the four performance measures was .168 (*SE* = .007, 95% CI = .154, .0182). Standardizing these estimates and subtracting them from 1.00 yields R^2 estimates for each indicator, which ranged from .618 to .698.

Submodel 5.2 relaxes the equality constraint placed on the error variances, thus permitting heterogeneous error variances for the performance indicators. The nested model χ^2 estimate comparing the fit of 5.2 against 5.1 was significant, $\chi^2(3) = 15.24$, p =

.001, indicating that a model permitting the error variances to vary over indicators provides a better fit to the data than a model assuming homogeneous variances. Referring back to Table 11, the mean intercept and linear slope parameters are similar to those estimated under submodel 5.1 (specifically, 3.092 and -.023, respectively). In addition, the variances for the latent intercept and slope parameters were again significant ($\psi_{\text{Intercept}\leftrightarrow\text{Intercept}}$ = .286, *SE* = .025, 95% CI = .237, .335; $\psi_{\text{Slope}\leftrightarrow\text{Slope}}$ = .019, *SE* = .004, 95% CI = .011, .027). Similar to model 5.1, the covariance between the latent intercept and slope parameters was nonsignificant and negative ($\psi_{\text{Intercept}\leftrightarrow\text{Slope}}$ = -.014, *SE* = .008, 95% CI = -.029, .001; unstandardized ψ: -.190).

Submodel 5.3 permits both heterogeneous and correlated error variances between time-adjacent indicators, with the time-adjacent correlations constrained to equality over indicator pairs (i.e., $\theta_{\varepsilon(t)} \leftrightarrow \theta_{\varepsilon(t+1)} = \theta_{\varepsilon(t+1)} \leftrightarrow \theta_{\varepsilon(t+2)}$). Introducing the time-adjacent correlations in submodel 5.3 significantly improved model fit over 5.2, $\Delta\chi^2(1) = 6.42$, $p = .011$. Despite the significant χ^2 estimate, the improvement in the other global model fit indices was small (changes in the CFI, TLI, RMSEA, and SRMR were all less than .01 in magnitude). In addition, introducing the constrained time-adjacent correlation, variability in the latent slope parameter was no longer significant ($\psi_{\text{Slope}\leftrightarrow\text{Slope}}$ = .010, *SE* = .006, 95% CI = -.001, .022). Because the less-parsimonious 5.3 did not appear to yield an appreciable increase in model fit and because of the nonsignificant variance estimate for the linear slope, 5.2 (random-intercept, random-slope with heterogeneous error variances) was retained to model change in performance over time.

Structural model. In order to examine the contribution of ability and achievement motivation as predictors of the performance trajectories, the indicator variables corresponding to ability, achievement motivation, and their interaction were introduced with structural paths estimated between each of the three predictors and the two latent trajectory parameters (the intercept and linear change over time). This model will be referred to as structural model 5.2 from here on. Table 13 provides global model fit statistics for the structural model described above. All fit indices met cutoff criteria and indicated reasonable to good fit, $\chi^2(11) = 30.93$, CFI = .982, TLI = .970, RMSEA = .057 (90% CI = .034, .081).

Table 14 provides parameter estimates for structural model 5.2. Hypotheses 1 and 2 stated that achievement motivation and ability would be positively related to initial performance. The structural path between ability and the latent intercept parameter was .291 (*SE* = .036, 95% CI = .220, .362, standardized γ = .363); the structural path between achievement motivation and the latent intercept parameter was .363 (*SE* = .048, 95% CI = .270, .457, standardized γ = .347). Both achievement motivation and ability were positively related to initial performance; thus, Hypotheses 1 and 2 were both supported.

Hypothesis 3 suggested that achievement motivation would be positively related to linear change over time, that is, individuals who are higher in achievement motivation would have steeper, positive increases in GPA across the four time points. The estimated structural path between achievement motivation and the latent slope parameter was -.053 (*SE* = .019, 95% CI = -.091, -.016, standardized γ = -.197). Although achievement motivation was significantly related to the linear change parameter, the relationship was negative in sign; thus, Hypothesis 3 is not supported. Parenthetically, the path between ability and the latent linear change parameter was nonsignificant (γ = .006, *SE* = .015, 95% CI = -.022, .034, standardized γ = .029).

To further illustrate the influence of ability and achievement motivation on latent trajectories, Figure 4 shows plots of estimated latent performance trajectories at both low (-1 *SD*) and high (+1 *SD*) ability and motivation. Figure 4(a) shows estimated trajectories for individuals at both low and high ability. In line with the results above, estimated initial performance for high-ability individuals was much higher than that for low-ability individuals (low-ability: 2.897, 95% CI = 2.830, 2.964; high-ability: 3.285, 95% CI = 3.218, 3.352). However, the estimated latent slope parameters were negative and similar in magnitude at low and high ability (low-ability: -.017, 95% CI = -.044, .010; high-ability: -.025, 95% CI = -.052, .002), as reflected in the roughly parallel trajectories shown in Figure 4(a). Although the negative linear slope parameter was stronger in magnitude for high-ability students than for low-ability students, the 95% confidence bands about the trajectories shown in Figure 2(a) did not overlap. Therefore, there is no evidence that the estimated latent trajectory at high ability converges with the trajectory estimated at low ability.

Figure 4(b) shows estimated trajectories at both low and high achievement motivation. Estimated initial performance was higher at high-motivation compared to low-motivation (low-motivation: 2.906, 95% CI = 2.839, 2.973; high-motivation: 3.277, 95% CI = 3.210, 3.344). The negative structural coefficient reported above between achievement motivation and the latent linear slope parameter is reflected in negative estimated conditional slope at high-motivation (-.048, 95% CI = -.075, -.021) compared to the slight positive estimated conditional slope at low-motivation (.006, 95% CI = -.021, .033). Figure 4(b) shows that the estimated latent trajectories at low- and high-motivation appear to be approaching convergence over time as indicated by the 95% confidence bands about the estimated trajectories. Specifically, the lower band for the high-motivation students intersects the upper band for the low-motivation and slightly beyond time point 3 (i.e., the third semester in school).

Hypothesis 4 suggested that there would be a significant interaction between ability and achievement motivation in predicting linear change over time, such that the relationship between motivation and linear change would be stronger among high-ability individuals than for low-ability individuals. As shown in Table 14, the structural path between the interaction term and the latent linear slope parameter was positive and significant (γ = .062, *SE* = .027, 95% CI = .009, .115, standardized γ = .162). In order to assess whether the significant interaction was of the form hypothesized, simple intercepts and slopes were estimated at low- and high-motivation at both low and high conditional values for ability.

At low-ability, low-motivation, the estimated simple intercept was 2.693 (*SE* = .051, 95% CI = 2.593, 2.793) and the estimated simple slope was .023 (*SE* = .020, 95% CI = -.016, .062). At low-ability, high-motivation, the estimated simple intercept was 3.101 (*SE* = .047, 95% CI = 3.009, 3.193) and the estimated simple slope was -.073 (*SE* = .019, 95% CI = -.110, -.036). Thus, at low ability, increases in motivation were associated with higher estimated initial performance and more negative linear change over time. At high-ability, low-motivation, the estimated simple intercept was 3.119 (*SE*

= .044, 95% CI = 3.033, 3.205) and the estimated simple slope was -.011 (*SE* = .018, 95% CI = -.046, .024). Finally, at high-ability, high-motivation, the estimated simple intercept was 3.452 (*SE* = .049, 95% CI = 3.356, 3.548) and the estimated simple slope was -.023 (*SE* = .020, 95% CI = -.062, .016). Thus, at high ability, there was a tendency for initial performance to increase and for the linear slope to become more negative as achievement motivation increased.

Estimated trajectories for low- and high-motivation at low- and high-ability are plotted in Figure 5(a) and 5(b). The hypothesized form of the interaction, that the relationship between achievement motivation and linear change would become more positive as ability increased, is not at all evident in the plots. Indeed, the only situation where a positive slope is found is at low-ability, low-motivation. Thus, hypothesis 4 was not supported.

Finally, Hypothesis 5 suggested that the relationship between ability and initial performance would be significantly stronger in magnitude compared to the structural path between ability and linear change. The 95% confidence interval about the unstandardized path coefficients were as follows: $\gamma_{\text{Ability}\rightarrow\text{Intercept}}$ = .291(95% CI = .220, .362), $\gamma_{\text{Ability}\rightarrow\text{Slope}}$ = .006 (95% CI = -.023, .035). These results suggest that, in the MSU-Only sample, ability was more strongly related to initial performance than linear change overtime; thus, Hypothesis 5 is supported.

RESULTS: MULTI-INSTITUTION SAMPLE

Descriptive and Static Analyses

Table 10 provides descriptive statistics (means, standard deviations, and zero-order correlations) among the study measures. As was done in the MSU-Only sample, ability and achievement motivation were centered about their respective means ($\bar{X}_{cent}$ = 0.00, $SD_{\text{X.cent}} = SD_{\text{X}}$, where x.cent = $[x - \bar{X}]$) prior to computing the cross-product term for interpretative purposes in the subsequent regression analyses.

In the Multi-Institution sample, ability and achievement motivation were positively and significantly related to one another, although the relationship was weak in magnitude (r = .109, p < .001). With regard to academic performance, mean GPA decreased across all four time periods at a relatively steady rate (3.45, 3.42, 3.40, and 3.38 for Times 1 through 4, respectively). The pattern of standard deviations exhibited for GPA suggested a slight tendency for variability in the GPA measures to increase over time, although the increase was small (standard deviations increasing from .60 to .63 for Times 1 through 4, respectively).

Intercorrelations among the four GPA measures again yielded evidence of a simplex pattern, with intercorrelations being stronger in magnitude than that observed within the MSU-Only sample (.900s among time-adjacent elements; .800s and upper .700s among elements further separate in time). Criterion-related validities for both predictors showed a decreasing pattern over time, although the reduction was not overly large for either predictor (ability: .546, .546, .514, and .461; achievement motivation:

.191, .185, .180, and .148). All predictor-criterion correlations remained significant through Time 4.

Latent Trajectory Models

Y-measurement model. Table 15 provides global model fit indices for the measurement model in the Multi-Institution sample. A browsing of the fit indices in Table 15 suggests that all models with fixed intercepts (models 2, 4, 8) yielded a poor fit to the data; thus, any model retained for consideration would allow for between-subjects variability in initial performance. In addition, a browsing of the fit indices suggests that models with variable intercepts, but either no estimated slopes (the intercept-only model, model 1) or fixed slope components (models 3 and 9), yielded values below the cutoff criteria for CFI, TLI, and RMSEA.

Therefore, five models were thus retained for further consideration: 5 (Random-Intercept, Random-Slope), 6 (Random-Intercept, Random-Slope, Fixed-Quadratic), 7 (Random-Intercept, Random-Slope, Random-Quadratic), 10 (Random-Intercept, Random-Slope [Logarithmic]), and 12 (Random-Intercept, Random-Slope [Loadings Estimated at Times 3 and 4]). Note that these are the same five models as those retained within the MSU-Only sample at this stage of the analysis. For models 5, 6, 10, and 12, the CFI value was marginal with respect to the .95 cutoff criteria, with values ranging from .94 to .95; the CFI for model 7 was well above the cutoff (.993). TLI values for all models were higher than the .95 cutoff. Furthermore, SRMR values across all models were well below the .08 cutoff. The RMSEA values for all five models were all above the .08 value suggested by Browne and Cudeck (1993) as indicating reasonable model fit. For four of the five models (5, 6, 10, and 12), the RMSEA value was greater than .200, while the RMSEA value for model 7 was .109. In addition, model 7 was the only model where the RMSEA value fell below .08 when various submodels were tested, as shown in Table 15, with RMSEA values falling to less than .001 for models 7.2 and 7.3. Thus, model 7 (random-intercept, random-slope, random-quadratic) was retained for further examination. Aside from the RMSEA value, all other fit indices suggested excellent fit for model 7 (CFI = .993, TLI = .989, RMSEA = .109, SRMR = .005).

Examining the parameter estimates for model 7.1 under Table 16, the average trajectory is represented by the following estimates for average change parameters: intercept = 3.447 (*SE* = .017, 95% CI = 3.414, 3.479), slope = -.023 (*SE* = .008, 95% CI = -.039, -.007), quadratic = .001 (*SE* = .002, 95% CI = -.004, .005). The estimate for initial performance was comparable to the observed value for GPA at Time 1 (3.45 under Table 10). The negative slope in tandem with the relatively small mean estimate for the quadratic change parameter suggests that, on average, GPA tends to decrease over time at a slightly decreasing rate, as reflected in the change in observed GPA over the four time points in Table 10 (3.45, 3.42, 3.40, and 3.38 from Time 1 to Time 4). The mean unconditional academic performance trajectory for the Multi-Institution sample is shown in Figure 6.

The variance estimates for the latent intercept, slope, and quadratic parameters were as follows: $\psi_{\text{Intercept}\leftrightarrow\text{Intercept}}$ = .342 (*SE* = .014, 95% CI = .315, .369), $\psi_{\text{Slope}\leftrightarrow\text{Slope}}$ = .060 (*SE* = .004, 95% CI = .053, .067), $\psi_{\text{Quadratic}\leftrightarrow\text{Quadratic}}$ = .005 (*SE* < .001, 95% CI = .004, .005). Relative to each estimate's standard error, the observed estimates are large enough to infer meaningful between-subjects variability in each of the latent trajectory parameters. The estimated covariances among the latent trajectory parameters were as followes: $\psi_{\text{Intercept}\leftrightarrow\text{Slope}}$ = -.004 (*SE* = .005, 95% CI = -.014, .005, standardized ψ = -.029), $\psi_{\text{Intercept}\leftrightarrow\text{Quadratic}}$ = -.004 (*SE* = .001, 95% CI = -.007, -.001, standardized ψ = -.098), $\psi_{\text{Slope}\leftrightarrow\text{Quadratic}}$ = -.015 (*SE* = .001, 95% CI = -.017, -.013, standardized ψ = -.863). Similar to the results obtained with the MSU-Only sample, initial performance was not significantly related to linear change in performance. However, both initial performance and linear change in performance were related to the latent quadratic change parameter, with a particularly strong relationship observed between linear and quadratic change.

Despite the high intercorrelation between the linear and quadratic parameters, the random quadratic component was retained in the measurement model. Compared to model 6 (random-intercept, random-slope, fixed-quadratic), the fit estimates for all global fit indices were superior when the quadratic component was permitted to vary over subjects as opposed to when it was constrained to be invariant. Similar conclusions were reached when comparing model 7 to model 5 (random-intercept, random-slope), where no latent quadratic parameter was estimated at all. As shown under submodel 7.1, the estimated residual variance for the GPA indicators was significant (θ_{ε} = .011, *SE* < .001, 95% CI = .010, .012). Across the four GPA indicators, the measurement model specified in 7.1 accounted for approximately 97% of the observed variance in the GPA indicators.

Submodel 7.2 permitted the residual variances (θ_{ε}) to vary across indicators. Relaxing the equality constraint resulted in a significant improvement in model fit for submodel 7.2 compared to submodel 7.1, $\Delta\chi^2(3) = 63.71$, $p < .001$, suggesting that a measurement model permitting heterogeneous residual variances provided a better fit than that observed for a model constraining the residual variances to equality. Furthermore, Table 16 shows that permitting heterogeneous residual variances across GPA indicators did not substantially alter the local parameter estimates (i.e., latent variances and covariances, latent means) in the y-measurement model from what was observed when variances were homogeneous (compare parameter estimates for the columns corresponding to Submodels 7.1 and 7.2).

Submodel 7.3 (heterogeneous residual variances with correlations among time-adjacent indicators constrained to equality) failed to converge during estimation and, thus, was not further considered. Therefore, because Submodel 7.2 provided a better fit compared to Submodel 7.1 without resulting in large changes in the model's parameter estimates, Submodel 7.2 was retained as the model used to capture the latent structure of performance trajectories for subsequent hypothesis testing.

Structural model. Table 17 illustrates global model fit statistics for structural model 7.2 with ability, achievement motivation, and their interaction included as exogenous predictors of the latent change parameters. The estimates for the global fit indices suggested a reasonable fit to the data, $\chi^2(4) = 5.65$, CFI = 1.000, TLI = .999, RMSEA = .018, SRMR = .002. Table 18 provides parameter estimates for the structural model permitting structural paths between ability, achievement motivation, and their interactions with the latent trajectory parameters.

Hypotheses 1 and 2 suggested that there would be positive, significant relationships between both ability and motivation and initial performance. The estimates for the paths were as follows: $\gamma_{\text{Ability}\rightarrow\text{Intercept}}$ = .393 (*SE* = .017, 95% CI = .359, .426, standardized γ = .549), $\gamma_{\text{Motivation}\rightarrow\text{Intercept}}$ = .176 (*SE* = .032, 95% CI = .114, .239, standardized γ = .133). In support of Hypotheses 1 and 2, both ability and motivation were significantly related to initial performance, such that predicted initial performance increased as either ability or motivation increased.

Hypothesis 3 suggested that achievement motivation would be positively related to linear change in performance. The estimated structural path between motivation and linear change in performance was .012 (*SE* = .019, 95% CI = -.025, .049, standardized γ = .024). Although the relationship was in the expected direction, the estimated coefficient did not reach significance; thus, Hypothesis 3 is not supported. Parenthetically, the estimated structural path between ability and linear change was .019 (*SE* = .010, 95% CI = -.001, .039, standardized γ = .072). In addition, ability was significantly and negatively related to the latent quadratic parameter ($\gamma_{\text{Ability}\rightarrow\text{Quadratic}}$ = -.011, *SE* = .003, 95% CI = -.017, -.005, standardized γ = -.156), while the relationship between achievement motivation and quadratic change was not significant ($\gamma_{\text{Motivation}\rightarrow\text{Quadratic}}$ = -.007, *SE* = .005, 95% CI = -.018, .004, standardized γ = -.052).

To illustrate the main effects of ability and motivation on performance trajectories, simple intercepts and simple slopes were estimated for students both low (-1 *SD*) and high (+1 *SD*) in each construct. With regard to the ability, the strong effect on initial performance discussed above is reflected in the large difference between estimated initial performance at low and high ability (low-ability: intercept = 3.130, *SE* = .019, 95% CI = 3.093, 3.167; high-ability: intercept = 3.763, *SE* = .019, 95% CI = 3.726, 3.800). The linear slope parameter was negative in sign for at both low and high ability (low-ability: -.037, *SE* = .012, 95% CI = -.061, -.013; high-ability: -.006, *SE* = -.006, 95% CI = -.030, .018). The quadratic parameter was significant and positive at low ability, but significant and negative at high ability (low-ability: .009, *SE* = .003, 95% CI = .003, .015; high-ability: -.008, *SE* = .003, 95% CI = -.014, -.002).

The estimates reported above are plotted in Figure 7. As shown in Figure 5(a), estimated initial performance is much higher at high compared to low ability. However, estimated GPA for both low and high ability shows a tendency toward linear decline. The positive quadratic parameter at the low ability is reflected in the very slight positive inflection that appears around Year 3. Conversely, the negative quadratic parameter observed at high ability is reflected in the increasing rate of GPA decline over time. Despite the slight trend toward convergence in GPA over time, the 95% confidence bands suggest that the two groups remain far separated in performance at Year 4. In other words, there is no evidence that performance trajectories for low- and high-ability students converge by the final time observed (Year 4).

A somewhat different conclusion is reached with regard to the main effect of achievement motivation on performance trajectories. Estimated initial performance at high motivation is higher than that observed at low motivation (low-motivation: 3.369, *SE* = .019, 95% CI = 3.332, 3.406; high-motivation: 3.523, *SE* = .019, 95% CI = 3.484, 3.562). Furthermore, the slopes at both low- and high-motivation show a slight trend toward decrease over time, with the magnitude of the negative slope being relatively similar, albeit weak, at low and high motivation (low-motivation: -.027, *SE* = .012, 95% CI = -.051, -003; high-motivation: -.017, *SE* = .012, 95% CI = -.041, .007). Although the estimates for the quadratic parameters were not significant (in line with the nonsignificant effect of motivation on quadratic change noted above), the magnitude of the performance decline appeared to decrease over time at low motivation, as reflected in the positive quadratic parameter (.003, *SE* = .003, 95% CI = -.003, .009). Conversely, the rate of decline at high motivation appeared to increase over time, as reflected in the slight negative quadratic estimate (high-motivation: -.002, *SE* = .003, 95% CI = -.008, .004). Again, it should be noted that the estimates for the quadratic parameters were relatively weak, and thus should be interpreted with caution.

Figure 7(b) illustrates the results discussed above with regard to the main effect of motivation on performance trajectories. Highly motivated students begin college with relatively higher initial performance compared to low-motivation students. However, the advantage conferred to highly-motivated students dissipates rather quickly, as reflected in the overlap in the 95% confidence bands about the estimated trajectories for low- and high-motivation students slightly after Year 2. In conclusion, although the pattern of main effects exerted by ability and motivation were similar in form, the magnitude of the effects for ability resulted in an advantage conferred to high-ability students that continued on until the fourth year of college. The same could not be said with regard to motivation, as discussed above with respect to the overlapping confidence bands about the estimated trajectories for low- and high-motivation students.

Hypothesis 4 suggested a significant interaction between ability and motivation with regard to linear change in performance, such that the relationship between motivation and linear change would be stronger among high-ability students. As shown in Table 18, the interaction term was not significantly related to the linear change parameter (-.042, *SE* = .023, 95% CI = -.087, .004, standardized γ = -.069). Although the interaction term was not significant, plots of estimated trajectories for low- and high-motivation individuals at both low and high conditional values of ability are shown in Figure 8(a) and 8(b) for illustrative purposes.

At low ability, the estimates for the simple intercepts and slopes are as follows: low-motivation: intercept = 3.053 (*SE* = .026, 95% CI = 3.002, 3.104), slope = -.057 (*SE* = .015, 95% CI = -.088, -.026), quadratic = .016 (*SE* = .005, 95% CI = .006, .026); high-motivation: intercept = 3.207 (*SE* = .029, 95% CI = 3.150, 3.264), slope = -.017 (*SE* = .017, 95% CI = -.050, .016), quadratic = .003 (*SE* = .005, 95% CI = -.007, .013). Figure 8(a) compares the estimated trajectories at low ability across both low and high motivation. At low ability, trajectories at low motivation reach an inflection in their trajectory at around Year 3, after which performance begins to improve. Conversely, at high motivation, the decrease in performance appears to be sustained over time. Although the 95% confidence bands suggest that the trajectories do not overlap in initial performance, substantial overlap is observed beginning slightly prior to Year 2, suggesting that, among low-ability students, performance trajectories cannot be distinguished on the basis of motivation.

At high ability, the estimates for the simple intercepts and slopes are as follows: low-motivation: intercept = 3.686 (*SE* = .029, 95% CI = 3.629, 3.743), slope = .003 (*SE* = .017, 95% CI = -.030, .036), quadratic = -.009 (*SE* = .005, 95% CI = -.019, .001); high-motivation: intercept = 3.839 (*SE* = .026, 95% CI = 3.788, 3.890), slope = -.016 (*SE* = .015, 95% CI = -.045, .013), quadratic = -.008 (*SE* = .004, 95% CI = -.016, .000). Figure 8(b) shows the estimated trajectories at high ability across both low and high achievement motivation. As was the case at low ability, the two trajectories shown in Figure 8(b) do not overlap at Year 1; high motivation is associated with significantly higher initial performance compared to low standing on motivation. However, overlap is observed in the 95% confidence bands starting at about halfway between the Year 1 and Year 2 mark and convergence in the two estimated trajectories increases over the four years. Therefore, similar to what was described above at low ability, the trajectories associated with low and high standing on achievement motivation are not well distinguished at high ability. Therefore, even had the interaction been significant, the form of the interaction was not as hypothesized; thus, Hypothesis 4 is not supported.

Finally, Hypothesis 5 suggested that the structural path between ability and initial performance would be significantly stronger in magnitude compared to the structural path between ability and linear change. The 95% confidence interval about the unstandardized path coefficients were as follows: $\gamma_{\text{Ability}\rightarrow\text{Intercept}}$ = .393 (95% CI = .360, .426); $\gamma_{\text{Ability}\rightarrow\text{Slope}}$ = .019 (95% CI = -.001, .039). These results suggest that, in the Multi-Institution sample, ability was more strongly related to initial performance than linear change overtime; thus, Hypothesis 5 is supported.

DISCUSSION

The final section concludes by recapitulating and integrating findings from the two studies as they relate to the theory and hypotheses proposed above. Strengths and limitations of the present study are then discussed, and the paper concludes by addressing several potential avenues for future research.

Study Findings

In both studies reported above, ability and achievement motivation had a significant and positive relationship with initial academic performance. Thus, students who were higher in either ability or achievement motivation generally obtained higher initial performance compared to students low in ability or achievement motivation. Although both predictors were significantly related to initial performance, there was some evidence that ability was a stronger predictor of true initial performance compared to achievement motivation, primarily in the Multi-Institution sample. In the MSU-Only sample, the standardized path estimate for ability and initial performance was .363, while the standardized path estimate for motivation and initial performance was .347. In the Multi-Institution sample, the standardized path estimate for ability and initial performance was .549, while the standardized path estimate for motivation and initial performance was .133. Somewhat discrepant among these results is the relatively weak relationship observed between motivation and initial performance in the Multi-Institution sample. Two possible explanations for the difference in results with regard to the effect of motivation on initial performance are immediately evident.

First, the measures of achievement motivation differed between the two studies. In the MSU-Only sample, the 10-item composite derived from the Steers and Braunstein (1976) and Fineman (1975) scales was used to operationalize achievement motivation, while the 15-item biodata measure was used in the Multi-Institution sample. The relatively weak effect of motivation on initial performance in the Multi-Institution sample may have been attributable to some aspect related to the measurement of achievement motivation in this sample. Given the relatively high degree of convergence observed in the pilot study between the Steers & Braunstein/Fineman scale and the achievement motivation biodata scale, however, it is not clear how differences in measurement between the two studies may have produced the pattern of results observed.

A second potential explanation for the discrepant results observed with regard to the effect of achievement motivation on initial performance pertains to the varying time frames over which performance was measured in the two studies (GPA measured at the semester level in the MSU-Only sample, GPA measured yearly in the Multi-Institution sample, aggregated over semesters within a given year). It is possible that the differential magnitude of the relationships observed between motivation and initial performance is related to the temporal specificity of the criterion used. Because GPA was measured at the yearly level in the Multi-Institution sample, the relationship between achievement motivation and initial performance may have been attenuated if there exists some factor specific to first-semester GPA (e.g., being temporally closer to the transition between high school and college) that is obscured when GPA data is aggregated over semesters to derive a yearly composite.

In neither sample was achievement motivation found to be positively related to linear change in performance over time, although a significant negative relationship was observed in the MSU-Only sample. Zyphur and colleagues (2008) suggested that negative relationships between predictors and change parameters may occur if the predictor is related to initial performance and if initial performance is strongly and negatively related to performance change. The substantive explanation for this state of affairs is a ceiling effect inherent in GPA as a criterion: if highly-motivated students perform very well initially (e.g., 3.8 on a 4.0 scale), those students have less room on the scale to increase over time compared to individuals who may have obtained a lower GPA during the initial time period (e.g., a 3.3). In this case, a negative relationship between motivation and linear change would be expected because low-motivation students, on average, have more room to increase, while it is more likely that highly motivated students would either maintain a high GPA or exhibit some degree of decline.

However, evidence provided in the MSU-Only sample does not support a ceiling-effect argument. First, the relationship between initial performance and linear change in the MSU-Only sample was weak in magnitude (standardized γ = -.132), suggesting only a slight tendency for those who performed well initially to hit a ceiling on performance. Second, although motivation was positively related to initial performance in the MSU-Only sample, the relationship was not so strong as to preclude further increases in performance for highly-motivated students after the first semester. For instance, among high-motivation students (+1 *SD*), the estimated intercept was 3.28, which is quite far from the 4.0 ceiling. Based on these arguments, the negative relationship between motivation and linear change appears not to be an artifact caused by ceiling effects. An alternative explanation is touched upon later when study strengths and limitations are addressed.

Although no obvious explanation exists for the negative relationship between achievement motivation and the linear slope trajectory parameter in the MSU-Only sample, negative relationships have been reported in the past between nonability characteristics and linear change over time (e.g., conscientiousness and performance orientation, Yeo & Neal, 2004; emotional stability, Thoresen et al., 2004; motivation to learn, adaptability, Shivpuri et al., 2006). Whether these findings lend themselves to a substantive explanation or are simply attributable to methodological artifacts (e.g., sampling error, ill-fitted measurement models resulting in latent trajectory parameters that do not adequately represent change) remains unresolved.

One of the primary purposes of the present research was to test for interactive effects between ability and achievement motivation, particularly with regard to linear change in performance over time. The magnitude of the path coefficient between the interaction term and the latent slope parameter in the Multi-Institutuion sample failed to reach significance. A significant interaction term was observed in the MSU-Only sample; however, the form of the interaction was not as predicted. Estimated simple slopes for low- and high-motivation students at both low and high levels of ability suggested a tendency for the linear slope to become more negative as motivation increased among low-ability subjects. Among high-ability subjects, slopes did not appear to differ significantly between low- and high-motivation students. These findings contradict the hypothesized form of the interaction, which suggested that achievement motivation would be more strongly and positively related to linear change in performance among high-ability students. A potential explanation for this effect is discussed under study strengths and limitations below.

Finally, in both samples, support was found for the hypothesis that the relationship between ability and initial performance would be stronger in magnitude than the relationship between ability and linear change in performance, evidence was found for this hypothesis. This hypothesis was predicated on the argument that, due to the nature of the criterion measure from which trajectories were modeled in the present research, the primary influence of ability would be to differentiate students in a relatively constant manner throughout the duration of college, as opposed to influencing how students' performance may change over time. In both samples, it was further found that performance trajectories for low- and high-ability students never approached convergence, further supporting the idea that the advantage conveyed by ability is retained over the course of a student's undergraduate career.

Strengths and Limitations

The research reported herein contains a number of strengths in light of the questions addressed. First and foremost, the repeated measures of performance allowed for a test of the interaction hypothesis in a manner that has yet to be conducted in an applied setting. Given the field's acknowledgment that performance is not stable over time and the longstanding nature of the debate on the interaction hypothesis, this design allows a relatively novel means by which to address the independent and joint effects of ability and motivation on performance.

Similarly, the present study also represents, to the author's knowledge, the first test of trait achievement motivation as a predictor of performance trajectories. Given the recent resurgence of interest in trait-based perspectives on achievement motivation (e.g., Cassidy & Lynn, 1989; Kanfer & Heggestad, 2000), as well as arguments highlighting approach and avoidance temperament as a basic approach to the structure of human personality (e.g., Elliot & Thrash, 2010; Read, Monroe, Brownstein, Yang, Chopra, & Miller, 2010), it would appear that research on trait achievement motivation as a predictor of performance trajectories in applied settings is relatively timely. Second, the two-study design permitted replication of findings across the two studies. In addition to providing evidence for generalizability, attempts at replication also highlight potential boundary conditions (e.g., predictor operationalization, temporal specificity of the criterion) that may otherwise go unnoticed if a single-study design were to be employed. Third, the relatively large sample sizes in both studies (599 in the MSU-Only sample, 1,279 in the Multi-Institution sample) allowed for relatively precise parameter estimation.

In addition to the strengths noted above, the present research also contains several important limitations that should be mentioned. First, the two studies reported herein focused on predictors of performance trajectories within a relatively broad population (i.e., college undergraduates). It is quite possible that closer examination would reveal factors that may systematically alter either the form of performance trajectories or the relationships observed between trajectory parameters and the individual-difference constructs examined. One such factor may be college major. To date, no research that the author is aware of has examined systematic differences in academic performance trajectories across college majors. Given the large number of majors offered by post-secondary institutions, such an investigation would be challenging from both a logistical and methodological standpoint. One potential idea may be to explore systematic variation in trajectories across major clusters (e.g., natural sciences, social sciences, business, etc.). However, even within such clusters, majors are often quite different (e.g., within the social sciences, the course content for economics, psychology, and political science likely vary with regard to a number of characteristics). Although this issue is important and substantively interesting, the present study, and the results reported herein, cannot speak to it.

A second limitation of the present study pertained to the lack of information regarding choice behavior underlying course selection on the part of the participants. Beyond general common beliefs regarding course choice behavior for undergraduate students (e.g., enrollment in introductory classes tends to occur more frequently early in one's collegiate career), no information was available to aid the in the interpretation of trajectories or to employ as controls for factors such as course difficulty or other course characteristics. A recent study by Durik and colleagues (2009) found a negative relationship between the work-mastery facet measured in the Cassidy and Lynn (1989) achievement motivation scale and diversity in course selection within a sample of undergraduate students. If these results generalize beyond the sample examined by Durik et al. (2009), they suggest that students higher in achievement motivation tend to focus their efforts in a relatively narrow set of courses geared toward their academic interests.

If highly-motivated students exhibit a tendency to enroll in and complete a larger number of courses within their academic major compared to low-motivation students, they are also likely to progress more quickly through their major requirements and, hence, to enroll in a larger number of upper-level courses that are more challenging and demanding, relative to the courses taught at lower levels. If true, this state of affairs may be reflected in a greater tendency for highly-motivated students' GPAs to level off, or even decrease, over time due to the heightened demand and difficulty associated with the course material they are exposed to. In other words, over their undergraduate careers, the trajectories for students high in achievement motivation maybe more susceptible to some decrease over time because such students tend to enroll in more difficult courses compared to their low-motivation counterparts. This may provide a partial explanation for the negative relationship observed in the MSU-Only sample between achievement motivation and linear change in performance over time.

Furthermore, if highly-motivated students exhibit a tendency to focus on classes within their own major and, hence, enroll in more difficult upper-level courses, they may be at greater risk for failure if they do not have levels of academic ability commensurate to the difficulty associated with the course material they are exposed to. If so, then highly-motivated, low-ability students may exhibit a greater tendency toward a negative linear change in performance over time, relative to either low-ability, low-motivation or high-ability, low-motivation students (who presumably enroll in courses that are less demanding) or high-ability, high-motivation students (who presumably have the necessary levels of ability needed to excel when presented with challenging course content). This provides a potential explanation for the form of the significant ability-motivation interaction observed in the MSU-Only sample, wherein low-ability, high-motivation students exhibited the greatest tendency to decrease in performance over time (refer to Figure 5[a] and 5[b]).

A third limitation is the inability to explain several discrepant effects observed between the MSU-Only and Multi-Institution samples. Although the MSU-Only sample had lower power to detect significant effects due to the smaller sample size compared to the Multi-Institution sample, several significant relationships were found in this sample that were not found in the Multi-Institution sample (e.g., the significant negative relationship between achievement motivation and linear change and the significant interaction, as discussed above). Due to the nature of the differences between the samples (e.g., varying temporal specificity of the criterion measure, the inclusion of one institution in the MSU-Only sample versus five institutions in the Multi-Institution sample, differences in the operationalization of motivation between the two samples, the examination of performance over two years in one sample versus four years in the second), it is not possible to isolate the cause of the differences in results. That said, knowledge of these differences provides a potential avenue for future research in an attempt to systematically delineate potential boundary effects with respect to the effect of ability and achievement motivation on performance trajectories in academic settings.

A final limitation pertains to the differences observed between the subset of cases retained for analysis and those cases that were excluded. There was relatively little evidence for meaningful differences between those cases retained for analysis and cases that were excluded in the MSU-Only sample. However, the same could not be said for the Multi-Institution sample, where rather large differences were observed on demographic, background, and study variables. Although it is difficult to ascertain the specific implications associated with the attrition effects apparent in the Multi-Institution sample, it is possible that such effects may have contributed to differences in results observed compared to the MSU-Only sample. Furthermore, effects due to attrition in the

MSU-Only and Multi-Institution samples may also reduce the extent to which results obtained in the present research can be expected to generalize to other samples.

Future Research

With changing views on the dynamic nature of performance as well as increased understanding of methods for examining change in applied psychology, research on predictors of performance trajectories has increased greatly over the past twenty years. However, many topics remain to be examined. In the educational context, only two other studies known to the author have examined performance trajectories within undergraduate samples (i.e., Shivpuri et al., 2006; Zyphur et al., 2008). Results from three studies do not provide sufficient basis to make definitive, generalizable conclusions regarding individual difference correlates of trajectories. Thus, although the knowledge base on predictors of trajectories appears to be increasing, additional research is clearly needed.

Furthermore, no research on performance trajectories in educational settings has examined the effects of contextual or environmental influences. At a relatively proximal level, one concept that has been examined with regard to static measures of performance pertains to the idea of situational constraints introduced Peters and O'Connor (e.g., Peters, Chassie, Lindholm, O'Connor, & Kline, 1982; Peters, Fisher, & O'Connor, 1982; Peters & O'Connor, 1980) and extended to the academic context (Villanova, 1996). From a macro perspective, research has also provided support for the influence of various classes of institutional characteristics found to impact upon academic growth, achievement, and degree completion in college (e.g., Kim, 2002; Kim & Conrad, 2006). Again, however, research on institutional characteristics has tended to focus on static outcomes, as opposed to development or change in student achievement over time. Therefore, additional research on proximal and global influences on performance trajectories originating in the academic context and environment is greatly needed.

A second area for further research pertains to mediators between trait-like characteristics and performance trajectories. Pitariu and Ployhart (2010) discuss the value of examining dynamic mediated relationships, wherein both mediating and performance measures vary over time within subjects. The introduction of theoretically-relevant time-varying mediators into models of predictors of performance trajectories offers the opportunity to explore how stable characteristics may influence the form of performance trajectories via state-like or malleable characteristics. For instance, with regard to achievement motivation in an academic context, examples of potential mediating constructs of interest might include academic self-efficacy, choice behavior and the exertion of effort toward task-relevant endeavors, or study habits and learning strategies employed both in classroom and non-classroom settings.

A similar idea to the situational constraints notion mentioned above would be to measure students' perceptions of events that occur throughout the duration of their undergraduate careers (e.g., challenges, obstacles, or difficulties of life) that may have a proximal effect on academic performance. One hypothesis would be that students higher in approach-oriented forms of motivation and lower in avoidance-oriented forms of motivation would be better prepared to rebound from challenging circumstances, perhaps because such individuals employ more adaptive problem-focused coping strategies (Halamandaris & Power, 1999) compared to individuals higher in avoidance motivation. Thus, the deleterious effects of difficult events in one's life on academic performance at various points in time might in part be affected by one's standing on characteristics related to approach- or avoidance-oriented constructs.

Finally, a number of additional approaches could be taken to further the field's understanding of how constructs in the domains of ability and motivation contribute to trajectories of academic performance. The present study focused on a trait-based perspective of achievement motivation; therefore, the interaction occurred between two invariant, between-subjects characteristics. As noted above with regard to dynamic mediated relationships, a number of more proximal and situationally-responsive characteristics could also be examined (e.g., self-efficacy, achievement goals, constructs tied to task-relevant effort, etc.). Cross-level interactions between ability, conceptualized as a stable trait-like characteristic, and motivational characteristics, conceptualized as time-varying attributes, could then be examined. Skill acquisition research conducted in laboratory-based settings has provided evidence supporting the existence of cross-level ability-motivation interactions of this sort (e.g., Kanfer & Ackerman, 1989; Yeo & Neal, 2004). However, it remains to be seen whether such results generalize to field settings where principles from skill acquisition may not be expected to function as observed in controlled lab settings.

Conclusion

The present study extended ideas concerning the interaction hypothesis suggesting that ability and motivation interact with one another in determining performance, with more recent perspectives on performance trajectories. Based on the results reported herein, definitive conclusions cannot yet be reached with regard to the potential existence or substantive meaningfulness of ability-motivation interactions in the prediction of performance trajectories. However, given that research addressing the joint effect of ability and achievement motivation on performance trajectories has yet to be conducted in an applied setting, the present study provides an initial start in this direction. More broadly, it is suggested that researchers continue to examine correlates of performance trajectories, including characteristics of persons, as well as situations, contexts, or environments.

Table 1.

Listing of Achievement Motivation Items employed in MSU-Only Sample.

Items adapted from Steers and Braunstein (1976)

1. I do my best work when my tasks or homework is fairly difficult.
2. I try very hard to improve on my past performance in school work.
3. I sometimes take moderate risks and stick my neck out in volunteering for class projects to get better grades or learn more.
4. I try to avoid any added responsibilities or projects in my classwork.
5. I try to perform better than my classmates.

Items adapted from Fineman (1975)

6. I often put in more hours than required to get good grades in the courses I take.
7. I appreciate an instructor who gives me difficult homework assignments that lead to better understanding the material being taught.
8. I don't mind working extra hard if it means that I master an interesting subject.
9. I will often work hard to master course material even when my extra work will have no impact on my grades.
10. I think it is extremely important to do the best I can in all my courses.

Table 2.

Achievement Motivation Biodata Inventory (AM BIO-15) items.

1	How often have you accomplished something you initially thought was very difficult or almost impossible?
2	To what extent has it been important to you to do your very best whenever you take on a project?
3	How often have you finished a project when faced with difficult circumstances?
4	How often do others tend to compliment you on your determination to continue with a project under difficult circumstances?
5	How often do you tend to give up on a task after being told that you were not doing well?
6	Generally, whenever you lean about a topic or how to perform a task, how often do you learn all the details as well as the general principles?
7	How often have you studied for tests by trying to memorize just the basic factors and not much more?
8	How do you compare your standards for learning to those of your high school teachers?
9	In general, what is the lowest grade that you find acceptable for yourself?
10	In your last year of high school, on how many tests did you "settle" for a passing grade, rather than spend significant amounts of time learning material well?
11	How often do you ask a teacher or classmate questions that go beyond the material but are still relevant to the topic (either in or out of class)?
12	In the past month, how many times have you looked for more information about something that you found interesting?
13	How often do you spend extra time on school assignments, even after they are turned in, so that you can gain a better understanding of the material or principles?
14	When a textbook or instructor mentions another source of information on a topic, how likely are you to find it and learn more on your own?
15	How important is it to you to succeed in whatever task you are engaged in?

Table 3.

Listing of Achievement Motivation Biodata Inventory (AM BIO-15) items, College Board biodata dimensions, and convergent validities with achievement motivation scales in pilot sample.

	CB Dimension	AM SBF-10	AM CL-21	CL WE	CL EXC	CL MAS
1	Perseverance	.365	.172	.088	.165	***.199***
2	Perseverance	.559	.554	.444	***.609***	.371
3	Perseverance	.398	.220	.076	***.285***	.173
4	Perseverance	.322	.310	***.339***	.109	***.335***
5	Perseverance	.165	.470	***.406***	.352	***.418***
6	Knowledge	.458	.417	.322	.299	***.379***
7	Knowledge	.344	.320	.271	***.385***	.150
8	Knowledge	.240	.171	.115	***.220***	.075
9	Knowledge	.146	.261	.168	.193	***.302***
10	Knowledge	.424	.256	.158	.148	***.324***
11	Learning	.085	.128	.055	.077	***.190***
12	Learning	.118	.096	-.002	-.002	***.235***
13	Knowledge	.302	.172	.118	.072	***.267***
14	Learning	.255	.183	***.184***	.028	***.185***
15	Perseverance	.495	.588	***.563***	***.559***	.385

Note. AM SBF-10 = 10-item composite of Steers & Braunstein (1976) 5-item and Fineman (1975) 5-item scales. AM CL-21 = Cassidy & Lynn (1989) 21-item scale. CL WE = Cassidy & Lynn (1989): Work Ethic (7-item). CL EXC = Cassidy & Lynn (1989): Pursuit of Excellence (7-item). CL MAS = Cassidy & Lynn (1989): Mastery (7-item). CB Dimension = construct assessed in College Board biodata inventory. All correlations disattenuated for unreliability. *N* ranges from 107 to 110.

Table 4.

Descriptive statistics and intercorrelations for achievement motivation measures.

	N	*Mean*	*SD*	*Skew*	*Kurt*	1	2	3
1. AM BIO-15	110	3.39	.38	.354	.836	*.680*	.835	.758
2. AM SBF-10	109	3.55	.47	.115	.115	.570	*.684*	.847
3. AM CL-21	110	3.60	.43	-.224	-.084	.568	.637	*.826*

Note. AMBIO-15 = Achievement Motivation Biodata Inventory (15-item), SBF = 10-item composite of Steers & Braunstein (1976) 5-item and Fineman (1975) 5-item scales, CL = Cassidy & Lynn (1989) 21-item scale. Internal-consistency estimates shown along the diagonal in italicized typeface. Correlations below the diagonal are uncorrected; correlations above the diagonal corrected for unreliability.

Table 5.

Differences between analysis sample and excluded subjects on demographic and background categorical variables (MSU-Only Sample).

		Analysis	Excluded
$\chi^2(1)$ = .019, *p* = .890	Male	27.8% (155)	27.1% (23)
	Female	72.2% (403)	72.9% (62)
$\chi^2(7)$ = 13.152, *p* = .068	Other	0.0% (0)	0.0% (0)
	Mexican / Latino	1.3% (7)	5.9% (5)
	Puerto Rican	0.0% (0)	0.0% (0)
	Other Hispanic	0.5% (3)	0.0% (0)
	American Indian or Alaskan Native	0.2% (1)	0.0% (0)
	Asian	4.9% (27)	8.2% (7)
	Black/African American	9.2% (51)	11.8% (10)
	White/Caucasian	80.2% (446)	69.4% (59)
	Native Hawaiian or other Pacific Islander	0.5% (3)	0.0% (0)
	Two or More Races	3.2% (18)	4.7% (4)
$\chi^2(2)$ = .740, *p* = .691	U.S. Citizen	97.3% (544)	96.5% (82)
	Non-U.S. Citizen - Canada	0.4% (2)	0.0% (0)
	Non-U.S. Citizen - Other	2.3% (13)	3.5% (3)
$\chi^2(1)$ = 2.481, *p* < .115	English as Primary Language	98.0% (546)	95.2% (80)
	English as Secondary Language	2.0% (11)	4.8% (4)
$\chi^2(5)$ = 9.447, *p* = .093	Undeclared	0.0% (0)	0.0% (0)
	Business	20.7% (110)	21.0% (17)
	Engineering	6.4% (34)	8.6% (7)
	Fine Arts/ Humanities	6.6% (35)	4.9% (4)
	Social Science	20.5% (109)	33.3% (27)
	Natural or Physical Science	34.6% (184)	22.2% (18)
	Other	11.3% (60)	9.9% (8)

Note. Values reported are cell proportions (counts in parentheses). Total sample size is 644 (analysis *n* = 559; excluded *n* = 85).

Table 6.

Differences between analysis sample and excluded subjects on demographic and background categorical variables (Multi-Institution Sample).

		Analysis	Excluded
$\chi^2(1) =$ 4.864, $p = .027$	Male	38.2% (488)	34.1% (487)
	Female	61.8% (791)	65.9% (942)
$\chi^2(9) =$ 564.985, $p < .001$	Other	1.3% (17)	2.0% (28)
	Mexican / Latino	1.3% (16)	5.8% (82)
	Puerto Rican	0.2% (3)	0.7% (10)
	Other Hispanic	0.9% (11)	2.7% (39)
	American Indian or Alaska Native	0.1% (1)	0.2% (3)
	Asian	5.7% (73)	8.0% (114)
	Black/African American	8.4% (107)	40.2% (571)
	White/Caucasian	78.8% (1,005)	35.3% (501)
	Native Hawaiian or other Pacific Islander	0.5% (6)	0.8% (12)
	Two or More Races	2.8% (36)	4.3% (61)
$\chi^2(2) =$ 6.853, $p = .032$	U.S. Citizen	97.5% (1,246)	95.7% (1,365)
	Non-U.S. Citizen - Canada	0.2% (3)	0.4% (5)
	Non-U.S. Citizen - Other	2.3% (29)	4.0% (57)
$\chi^2(1) =$ 17.980, $p < .001$	English as Primary Language	96.8% (1,238)	93.2% (1,330)
	English as Secondary Language	3.2% (41)	6.8% (97)
$\chi^2(6) =$ 43.019, $p < .001$	Undeclared	14.3% (183)	10.2% (146)
	Business	16.3% (208)	13.9% (198)
	Engineering	11.3% (145)	12.4% (177)
	Fine Arts/ Humanities	9.0% (115)	9.8% (140)
	Social Science	14.3% (183)	18.9% (269)
	Natural or Physical Science	20.2% (258)	14.9% (212)
	Other	14.6% (187)	19.9% (284)

Note. Values reported are cell proportions (counts in parentheses). Total sample size is 2,787 (analysis n = 1,279; excluded n = 1,508).

Table 7.

Differences between analysis sample and excluded subjects on continuous variables (MSU-Only Sample).

	Analysis			Excluded			Standardized Difference		
	Mean	*SD*	*n*	*Mean*	*SD*	*n*	*d*	95% L	95% U
Age	18.48	.57	559	18.58	.72	83	-.163	-.394	.067
Ability	.57	.67	559	.42	.73	79	.220	-.016	.456
Achievement Motivation	3.42	.51	559	3.40	.45	84	.040	-.189	.269
GPA_1	3.08	.65	559	2.59	1.11	66	.685	.426	.942
GPA_2	3.11	.65	559	2.55	1.14	63	.787	.522	1.050
GPA_3	3.01	.72	554	1.84	1.77	8	1.582	.876	2.284
GPA_4	3.04	.74	544	.72	1.36	6	3.113	2.283	3.934

Note. 95% L = Lower 95% confidence interval. 95% U = Upper 95% confidence interval. Estimates for analysis sample based on observed values prior to imputation and mean-centering.

Table 8.

Differences between analysis sample and excluded subjects on continuous variables (Multi-Institution Sample).

	Analysis			Excluded			Standardized Difference		
	Mean	*SD*	*n*	*Mean*	*SD*	*n*	*d*	95% L	95% U
Age	18.12	.39	1,278	18.15	.56	1,421	-.064	-.140	.012
Ability	.90	.80	1,236	.32	.94	1,305	.659	.578	.738
Achievement Motivation	3.41	.44	1,279	3.37	.43	1,435	.095	.020	.171
GPA_1	3.45	.60	1,273	2.60	.95	217	1.286	1.134	1.436
GPA_2	3.43	.61	1,264	2.47	.78	80	1.545	1.310	1.777
GPA_3	3.41	.62	1,271	1.43	.78	8	3.202	2.494	3.906
GPA_4	3.43	.60	1,180	2.88	.81	5	.926	.046	1.804

Note. 95% L = Lower 95% confidence interval. 95% U = Upper 95% confidence interval. Estimates for analysis sample based on observed values prior to imputation and mean-centering.

Table 9.

Summary of y-measurement models evaluated in MSU-Only and Multi-Institution Samples.

1. Random-Intercept Only
2. Fixed-Intercept, Fixed-Slope
3. Random-Intercept, Fixed-Slope
4. Fixed-Intercept, Random-Slope
5. Random-Intercept, Random-Slope
6. Random-Intercept, Random-Slope, Fixed-Quadratic
7. Random-Intercept, Random-Slope, Random-Quadratic
8. Fixed-Intercept, Fixed-Slope (Logarithmic Slope)
9. Random-Intercept, Fixed-Slope (Logarithmic Slope)
10. Random-Intercept, Random-Slope (Logarithmic Slope)
11. Random-Intercept, Fixed-Slope (Loadings Estimated at Times 3 and 4)
12. Random-Intercept, Random-Slope (Loadings Estimated at Times 3 and 4)

Table 10.

Descriptive statistics and intercorrelations among study measures.

	MSU-Only		Multi-Institution								
	Mean	*SD*	*Mean*	*SD*	1	2	3	4	5	6	7
1. Ability	.00	.67	.00	.81		.109	.008	.546	.546	.514	.461
2. Achievement Motivation	.00	.51	.00	.44	-.084		.042	.191	.185	.180	.148
3. Interaction	-.03	.36	.04	.35	-.044	.116		.013	-.012	-.010	-.018
4. GPA_1	3.08	.65	3.45	.60	.290	.235	.005		.923	.863	.781
5. GPA_2	3.11	.65	3.42	.61	.261	.264	-.004	.647		.959	.878
6. GPA_3	3.01	.72	3.40	.62	.273	.119	.047	.536	.650		.919
7. GPA_4	3.03	.74	3.38	.63	.266	.132	.074	.494	.568	.624	

Note. MSU-Only sample n = 559; Multi-Institution sample n = 1,279. Correlations below diagonal from MSU-Only sample ($r \geq |.083|$ significant at $p < .05$); correlations above diagonal from Multi-Institution sample ($r \geq |.055|$ significant at $p < .05$).

Table 11.

Global model fit statistics for measurement model (MSU-Only Sample).

Model Description	Submodel (df)	χ^2	χ^2/df	$\Delta\chi^2$	Δdf	Δp	CFI	TLI	RMSEA	Lower 90%	Upper 90%	SRMR
1. Random Intercept Only	1 (11)	94.48	8.59	–	–	–	.913	.952	.117	.096	.139	.085
	2 (8)	54.83	6.85	39.65	3	.000	.951	.963	.102	.078	.129	.060
	3 (7)	26.72	3.82	28.11	1	.000	.979	.982	.071	.044	.100	.050
2. Fixed-Intercept, Fixed-Slope	1 (11)	983.42	89.40	–	–	–	.000	.446	.398	.377	.419	.392
	2 (8)	966.43	120.80	16.98	3	.001	.000	.249	.463	.439	.488	.387
	3 (7)	384.15	54.88	582.28	1	.000	.606	.662	.310	.284	.337	.278
3. Random-Intercept, Fixed-Slope	1 (10)	84.03	8.40	–	–	–	.919	.952	.117	.095	.141	.082
	2 (7)	46.93	6.70	37.09	3	.000	.958	.964	.101	.075	.129	.058
	3 (6)	21.90	3.65	25.04	1	.000	.983	.983	.069	.039	.101	.047
4. Fixed-Intercept, Random-Slope	1 (10)	608.76	60.88	–	–	–	.374	.624	.327	.305	.350	.323
	2 (7)	496.34	70.91	112.41	3	.000	.489	.562	.354	.328	.380	.293
	3 (6)	282.47	47.08	213.88	1	.000	.711	.711	.287	.259	.316	.255
5. Random-Intercept, Random-Slope	1 (8)	34.23	4.28	–	–	–	.973	.979	.077	.051	.104	.040
	2 (5)	18.98	3.80	15.24	3	.002	.985	.982	.071	.039	.106	.030
	3 (4)	12.56	3.14	6.42	1	.011	.991	.987	.062	.025	.102	.024
6. Random-Intercept, Random-Slope, Fixed-Quadratic	1 (7)	34.13	4.88	–	–	–	.972	.976	.083	.057	.112	.039
	2 (4)	18.33	4.58	15.80	3	.001	.985	.978	.080	.045	.119	.029
	3 (3)	11.89	3.96	6.45	1	.011	.991	.981	.073	.033	.118	.024
7. Random-Intercept, Random-Slope, Random-Quadratic	1 (4)	26.95	6.74	–	–	–	.976	.964	.101	.067	.139	.036
	2 (1)	11.15	11.15	15.80	3	.001	.989	.936	.135	.072	.211	.022
8. Fixed-Intercept, Fixed-Slope (Logarithmic)	1 (11)	983.89	89.44	–	–	–	.000	.445	.398	.377	.419	.393
	2 (8)	967.03	120.88	16.86	3	.001	.000	.248	.463	.439	.488	.387
	3 (7)	384.54	54.93	582.49	1	.000	.605	.662	.311	.285	.337	.278
9. Random-Intercept, Fixed-Slope (Logarithmic)	1 (10)	88.15	8.81	–	–	–	.918	.951	.118	.096	.142	.083
	2 (7)	48.94	6.99	39.21	3	.000	.956	.962	.104	.077	.132	.058
	3 (6)	23.52	3.92	25.42	1	.000	.982	.982	.072	.043	.104	.048
10. Random-Intercept, Random-Slope (Logarithmic)	1 (8)	43.09	5.39	–	–	–	.963	.972	.089	.064	.115	.043
	2 (5)	20.53	4.11	22.56	3	.000	.984	.981	.075	.043	.109	.031
	3 (4)	14.29	3.57	6.23	1	.013	.989	.984	.068	.032	.107	.026
11. Random-Intercept, Fixed Slope (Loadings Estimated at Times 3 & 4)												
12. Random-Intercept, Random-Slope (Loadings Estimated at Times 3 & 4)	1 (6)	30.81	5.14	–	–	–	.974	.974	.086	.057	.117	.034
	2 (3)	8.79	2.93	22.02	3	.000	.994	.988	.059	.059	.106	.029

Note. n = 559. Lower 90% and Upper 90% refer to 90% confidence intervals about the RMSEA estimate. Model highlighted in bold typeface selected as measurement model. Submodel 1: homogeneous, uncorrelated error variances for GPA indicators. Submodel 2: heterogeneous, uncorrelated error variances for GPA indicators. Submodel 3: heterogeneous error variances for GPA indicators with correlations permitted between time-adjacent indicators constrained to equality over indicator pairs. Rows highlighted in dark grey indicate models that failed to converge during estimation.

Table 12.

Unstandardized model parameters for unconditional measurement model (MSU-Only Sample).

	Parameter	Submodel 1 Est.	Submodel 2 Est.	Submodel 3 Est.
5. Random-Intercept, Random-Slope	$\psi_{\text{Intercept}\leftrightarrow\text{Slope}}$	-.010	-.014	-.001
	$\psi_{\text{Intercept}\leftrightarrow\text{Intercept}}$	***.272***	***.286***	***.248***
	$\psi_{\text{Slope}\leftrightarrow\text{Slope}}$	***.019***	***.019***	.010
	$\mu_{\text{Intercept}}$	***3.090***	***3.092***	***3.090***
	μ_{Slope}	***-.023***	***-.023***	***-.021***
	$\theta\varepsilon$ GPA_1	***.168***	***.146***	***.179***
	$\theta\varepsilon$ GPA_2	***.168***	***.137***	***.161***
	$\theta\varepsilon$ GPA_3	***.168***	***.198***	***.224***
	$\theta\varepsilon$ GPA_4	***.168***	***.195***	***.223***
	$\theta\varepsilon$ $\text{GPA}_{(t)}\leftrightarrow\text{GPA}_{(t+1)}$	–	–	***.027***
	R^2 GPA_1	.618	.662	.581
	R^2 GPA_2	.618	.669	.615
	R^2 GPA_3	.649	.607	.561
	R^2 GPA_4	.698	.657	.603

Note. n = 559. Est. = parameter estimate. Entries in bold, italicized typeface significant at $p < .05$. Submodel 1: homogeneous, uncorrelated error variances for GPA indicators. Submodel 2: heterogeneous, uncorrelated error variances for GPA indicators. Submodel 3: heterogeneous error variances for GPA indicators with correlations permitted between time-adjacent indicators constrained to equality over indicator pairs. Columns highlighted in dark grey indicate models that failed to converge during estimation. Columns highlighted in black indicate submodels not considered for a given model.

Table 13.

Global model fit statistics for structural model (MSU-Only Sample).

Model Description	Submodel (*df*)	χ^2	χ^2/df	$\Delta\chi^2$	Δdf	Δp	CFI	TLI	RMSEA	Lower 90%	Upper 90%	SRMR
5. Random-Intercept, Random-Slope	2 (11)	30.93	2.81	15.98	3	.001	.982	.970	.057	.034	.081	.023

Note. n = 559. Lower 90% and Upper 90% refer to 90% confidence intervals about the RMSEA estimate. Submodel 2: heterogeneous, uncorrelated error variances for GPA indicators.

Table 14.

Local model fit statistics for structural model (MSU-Only Sample).

	Parameter	Submodel 2 Est.
5. Random-Intercept, Random-Slope	$\psi_{Intercept \leftrightarrow Slope}$	-.010
	$\psi_{Intercept \leftrightarrow Intercept}$	***.220***
	$\psi_{Slope \leftrightarrow Slope}$	***.018***
	$\gamma_{Ability \rightarrow Intercept}$	***.291***
	$\gamma_{Ability \rightarrow Slope}$	.006
	$\gamma_{Motivation \rightarrow Intercept}$	***.363***
	$\gamma_{Motivation \rightarrow Slope}$	***-.053***
	$\gamma_{Interaction \rightarrow Intercept}$	-.055
	$\gamma_{Interaction \rightarrow Slope}$	***.062***
	$\alpha_{Intercept}$	***3.091***
	α_{Slope}	***-.021***
	$\theta\varepsilon$ GPA_1	***.149***
	$\theta\varepsilon$ GPA_2	***.135***
	$\theta\varepsilon$ GPA_3	***.199***
	$\theta\varepsilon$ GPA_4	***.195***
	$\theta\varepsilon$ $GPA_{(t)} \leftrightarrow GPA_{(t+1)}$	–
	R^2 GPA_1	.657
	R^2 GPA_2	.672
	R^2 GPA_3	.606
	R^2 GPA_4	.657
	R^2 Intercept	.230
	R^2 Slope	.059

Note. n = 559. Est. = parameter estimate. Entries in bold, italicized typeface significant at $p < .05$. Submodel 2: heterogeneous, uncorrelated error variances for GPA indicators.

Table 15.

Global model fit statistics for measurement model (Multi-Institution Sample).

Model Description	Submodel (df)	χ^2	χ^2/df	$\Delta\chi^2$	Δdf	Δp	CFI	TLI	RMSEA	Lower 90%	Upper 90%	SRMR
1. Random Intercept Only	1 (11)	1482.30	134.75	–	–	–	.818	.901	.323	.310	.337	.052
	2 (8)	661.13	82.64	821.17	3	.000	.919	.940	.253	.237	.269	.077
	3 (7)	197.74	28.25	463.39	1	.000	.976	.980	.146	.129	.164	.055
2. Fixed-Intercept, Fixed-Slope	1 (11)	8116.46	737.86	–	–	–	.000	.455	.759	.745	.773	.583
	2 (8)	8111.44	1013.93	5.03	3	.170	.000	.250	.890	.874	.906	.582
	3 (7)	3560.33	508.62	4551.10	1	.000	.562	.624	.630	.613	.647	.484
3. Random-Intercept, Fixed-Slope	1 (10)	1415.39	141.54	–	–	–	.827	.896	.331	.317	.346	.048
	2 (7)	608.34	86.91	807.06	3	.000	.926	.936	.259	.242	.277	.073
	3 (6)	158.01	26.33	450.33	1	.000	.981	.981	.141	.122	.160	.051
4. Fixed-Intercept, Random-Slope	1 (10)	6592.82	659.28	–	–	–	.188	.513	.717	.703	.732	.515
	2 (7)	5063.44	723.35	1529.37	3	.000	.376	.465	.752	.734	.769	.478
	3 (6)	2446.87	407.81	2616.58	1	.000	.699	.699	.564	.545	.583	.568
5. Random-Intercept, Random-Slope	1 (8)	425.78	53.22	–	–	–	.948	.961	.202	.186	.219	.031
	2 (5)	144.55	28.91	281.23	3	.000	.983	.979	.148	.128	.169	.062
	3 (4)	68.13	17.03	76.42	1	.000	.992	.988	.112	.090	.136	.042
6. Random-Intercept, Random-Slope, Fixed-Quadratic	1 (7)	425.97	60.85	–	–	–	.948	.956	.216	.199	.234	.031
	2 (4)	144.43	36.11	281.54	3	.000	.983	.974	.166	.143	.189	.062
	3 (3)	68.01	22.67	76.42	1	.000	.992	.984	.130	.104	.158	.042
7. Random-Intercept, Random-Slope, Random-Quadratic	1 (4)	64.27	16.07	–	–	–	.993	.989	.109	.086	.133	.005
	2 (1)	.57	.57	63.71	3	.000	1.000	1.000	.000	.000	.067	.001
	[redacted]											
8. Fixed-Intercept, Fixed-Slope (Logarithmic)	1 (11)	8116.67	737.88	–	–	–	.000	.455	.759	.745	.773	.583
	2 (8)	8111.64	1013.95	5.03	3	.169	.000	.250	.890	.874	.906	.582
	3 (7)	3560.27	508.61	4551.36	1	.000	.562	.624	.630	.613	.647	.484
9. Random-Intercept, Fixed-Slope (Logarithmic)	1 (10)	1417.21	141.72	–	–	–	.826	.896	.332	.317	.346	.048
	2 (7)	609.99	87.14	807.22	3	.000	.926	.936	.260	.242	.277	.073
	3 (6)	159.37	26.56	450.62	1	.000	.981	.981	.141	.123	.161	.051
10. Random-Intercept, Random-Slope (Logarithmic)	1 (8)	498.17	62.27	–	–	–	.940	.955	.219	.203	.235	.026
	2 (5)	111.11	22.22	387.06	3	.000	.987	.984	.129	.109	.150	.055
	3 (4)	46.43	11.61	64.68	1	.000	.995	.992	.091	.069	.115	.036
11. Random-Intercept, Fixed Slope (Loadings Estimated at Times 3 & 4)	1 (8)	1415.21	176.90	–	–	–	.826	.870	.371	.355	.387	.048
	2 (5)	607.92	121.58	807.30	3	.000	.926	.911	.307	.287	.328	.073
	3 (4)	157.32	39.33	450.60	1	.000	.981	.972	.173	.151	.197	.051
12. Random-Intercept, Random-Slope (Loadings Estimated at Times 3 & 4)	1 (6)	409.62	68.27	–	–	–	.950	.950	.229	.211	.248	.031
	2 (3)	54.61	18.20	355.00	3	.000	.994	.987	.116	.090	.144	.050
	3 (2)	23.70	11.85	30.91	1	.000	.997	.992	.092	.061	.127	.016

Note. n = 1,279. Lower 90% and Upper 90% refer to 90% confidence intervals about the RMSEA estimate. Model highlighted in bold typeface selected as measurement model. Submodel 1: homogeneous, uncorrelated error variances for GPA indicators. Submodel 2: heterogeneous, uncorrelated error variances for GPA indicators. Submodel 3: heterogeneous error variances for GPA indicators with correlations permitted between time-adjacent indicators constrained to equality over indicator pairs. Rows highlighted in dark grey indicate models that failed to converge during estimation.

Table 16.

Local model fit statistics for unconditional measurement model (Multi-Institution Sample).

	Parameter	Submodel 1 Est.	Submodel 2 Est.	Submodel 3 Est.
7. Random-Intercept, Random-Slope, Random Quadratic	$\psi_{Intercept \leftrightarrow Slope}$	-.004	.010	
	$\psi_{Intercept \leftrightarrow Quadratic}$	***-.004***	***-.008***	
	$\psi_{Slope \leftrightarrow Quadratic}$	***-.015***	***-.010***	
	$\psi_{Intercept \leftrightarrow Intercept}$	***.342***	***.330***	
	$\psi_{Slope \leftrightarrow Slope}$	***.060***	***.043***	
	$\psi_{Quadratic \leftrightarrow Quadratic}$	***.005***	***.003***	
	$\mu_{Intercept}$	***3.447***	***3.446***	
	μ_{Slope}	***-.023***	***-.023***	
	$\mu_{Quadratic}$	.001	.001	
	$\theta\varepsilon$ GPA_1	***.011***	***.024***	
	$\theta\varepsilon$ GPA_2	***.011***	***.006***	
	$\theta\varepsilon$ GPA_3	***.011***	***.013***	
	$\theta\varepsilon$ GPA_4	***.011***	***.027***	
	$\theta\varepsilon$ $GPA_{(t)} \leftrightarrow GPA_{(t+1)}$	–	–	
	R^2 GPA_1	.970	.932	
	R^2 GPA_2	.971	.985	
	R^2 GPA_3	.972	.967	
	R^2 GPA_4	.973	.933	

Note. n = 1,279. Est. = parameter estimate. Entries in bold, italicized typeface significant at $p < .05$. Submodel 1: homogeneous, uncorrelated error variances for GPA indicators. Submodel 2: heterogeneous, uncorrelated error variances for GPA indicators. Submodel 3: heterogeneous error variances for GPA indicators with correlations permitted between time-adjacent indicators constrained to equality over indicator pairs. Columns highlighted in dark grey indicate models that failed to converge during estimation.

Table 17.

Global model fit statistics for structural model (Multi-Institution Sample).

Model Description	Submodel (df)	χ^2	χ^2/df	$\Delta\chi^2$	Δdf	Δp	CFI	TLI	RMSEA	Lower 90%	Upper 90%	SRMR
7. Random-Intercept, Random-Slope, Random-Quadratic	2 (4)	5.65	1.41	61.82	3	.000	1.000	.999	.018	.000	.049	.002

Note. n = 1,279. Lower 90% and Upper 90% refer to confidence intervals about the RMSEA estimate. Submodel 2: heterogeneous, uncorrelated error variances for GPA indicators.

Table 18.

Local model fit statistics for structural model (Multi-Institution Sample).

	Parameter	Submodel 1 Est.	Submodel 2 Est.	Submodel 3 Est.
7. Random-Intercept, Random-Slope, Random-Quadratic	$\psi_{\text{Intercept}\leftrightarrow\text{Slope}}$	***-.010***	.002	
	$\psi_{\text{Intercept}\leftrightarrow\text{Quadratic}}$	-.001	-.004	
	$\psi_{\text{Slope}\leftrightarrow\text{Quadratic}}$	***-.014***	***-.010***	
	$\psi_{\text{Intercept}\leftrightarrow\text{Intercept}}$	***.230***	***.221***	
	$\psi_{\text{Slope}\leftrightarrow\text{Slope}}$	***.059***	***.045***	
	$\psi_{\text{Quadratic}\leftrightarrow\text{Quadratic}}$	***.005***	***.003***	
	$\gamma_{\text{Ability}\rightarrow\text{Intercept}}$	***.393***	***.393***	
	$\gamma_{\text{Ability}\rightarrow\text{Slope}}$	.019	.019	
	$\gamma_{\text{Ability}\rightarrow\text{Quadratic}}$	***-.011***	***-.011***	
	$\gamma_{\text{Motivation}\rightarrow\text{Intercept}}$	***.179***	***.176***	
	$\gamma_{\text{Motivation}\rightarrow\text{Slope}}$	.013	.012	
	$\gamma_{\text{Motivation}\rightarrow\text{Quadratic}}$	-.008	-.007	
	$\gamma_{\text{Interaction}\rightarrow\text{Intercept}}$	.003	.000	
	$\gamma_{\text{Interaction}\rightarrow\text{Slope}}$	-.039	-.042	
	$\gamma_{\text{Interaction}\rightarrow\text{Quadratic}}$	.008	.010	
	$\alpha_{\text{Intercept}}$	***3.447***	***3.446***	
	α_{Slope}	***-.021***	***-.022***	
	$\alpha_{\text{Quadratic}}$	.000	.000	
	$\theta\varepsilon$ GPA_1	***.011***	***.022***	
	$\theta\varepsilon$ GPA_2	***.011***	***.006***	
	$\theta\varepsilon$ GPA_3	***.011***	***.012***	
	$\theta\varepsilon$ GPA_4	***.011***	***.028***	
	$\theta\varepsilon$ $\text{GPA}_{(t)}\leftrightarrow\text{GPA}_{(t+1)}$	–	–	
	R^2 GPA_1	.970	.939	
	R^2 GPA_2	.971	.983	
	R^2 GPA_3	.972	.969	
	R^2 GPA_4	.973	.928	

Table 18 (cont'd).

	Parameter	Submodel 1 Est.	Submodel 2 Est.	Submodel 3 Est.
7. Random-Intercept, Random-Slope, Random-Quadratic	R^2 Intercept	.326	.335	
	R^2 Slope	.008	.011	
	R^2 Quadratic	.022	.032	

Note. n = 1,279. Est. = parameter estimate. Entries in bold, italicized typeface significant at $p < .05$. Submodel 1: homogeneous, uncorrelated error variances for GPA indicators. Submodel 2: heterogeneous, uncorrelated error variances for GPA indicators. Submodel 3: heterogeneous error variances for GPA indicators with correlations permitted between time-adjacent indicators constrained to equality over indicator pairs. Columns highlighted in dark grey indicate models that failed to converge during estimation.

Figure 1. Equations describing relationship between performance and time (within-subjects) and person-specific change parameters to subject characteristics (between-subjects).

$$\mathbf{Y} = \boldsymbol{\tau}_{\boldsymbol{y}} + \boldsymbol{\Lambda}_{\boldsymbol{y}}\boldsymbol{\eta} + \boldsymbol{\varepsilon} \tag{1}$$

$$\mathbf{Y} = \begin{bmatrix} \mathrm{gpa}_1 \\ \mathrm{gpa}_2 \\ \mathrm{gpa}_3 \\ \mathrm{gpa}_4 \end{bmatrix}, \boldsymbol{\eta} = \begin{bmatrix} \pi_{0i} \\ \pi_{1i} \end{bmatrix}, \boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_{\mathrm{i}1} \\ \varepsilon_{\mathrm{i}2} \\ \varepsilon_{\mathrm{i}3} \\ \varepsilon_{\mathrm{i}4} \end{bmatrix}, \boldsymbol{\tau}_{\boldsymbol{y}} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix},$$

$$\boldsymbol{\Lambda}_{\boldsymbol{y}} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \\ 1 & 3 \end{bmatrix}, \boldsymbol{\theta}_{\boldsymbol{\varepsilon}} = \begin{bmatrix} \sigma^2_{\varepsilon_1} & 0 & 0 & 0 \\ 0 & \sigma^2_{\varepsilon_2} & 0 & 0 \\ 0 & 0 & \sigma^2_{\varepsilon_3} & 0 \\ 0 & 0 & 0 & \sigma^2_{\varepsilon_4} \end{bmatrix} \tag{2}$$

$$\begin{bmatrix} \pi_{0i} \\ \pi_{1i} \end{bmatrix} \sim N\left(\begin{bmatrix} \mu_{\pi_0} \\ \mu_{\pi_1} \end{bmatrix}, \begin{bmatrix} \sigma^2_{\pi_0} & \sigma_{\pi_0\pi_1} \\ \sigma_{\pi_1\pi_0} & \sigma^2_{\pi_1} \end{bmatrix} \right) \tag{3}$$

$$\begin{bmatrix} \pi_{0i} \\ \pi_{1i} \end{bmatrix} = \begin{bmatrix} \mu_{\pi_0} \\ \mu_{\pi_1} \end{bmatrix} + \begin{bmatrix} \zeta_{0i} \\ \zeta_{1i} \end{bmatrix} \tag{4}$$

$$\boldsymbol{\eta} = \boldsymbol{\alpha} + \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta} \tag{5}$$

$$\boldsymbol{\alpha} = \begin{bmatrix} \mu_{\pi_0} \\ \mu_{\pi_1} \end{bmatrix}, \boldsymbol{\Gamma} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, \mathbf{B} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \tag{6}$$

Figure 1(cont'd).

$$\boldsymbol{\Psi} = \mathrm{COV}[\boldsymbol{\zeta}] = \begin{bmatrix} \sigma^2_{\pi_0} & \sigma_{\pi_0\pi_1} \\ \sigma_{\pi_1\pi_0} & \sigma^2_{\pi_1} \end{bmatrix} \tag{7}$$

$$\mathbf{X} = \boldsymbol{\tau_x} + \boldsymbol{\Lambda_x}\boldsymbol{\xi} + \boldsymbol{\delta} \tag{8}$$

$$\mathbf{X} = \begin{bmatrix} COG_i \\ ACH_i \\ INT_i \end{bmatrix}, \boldsymbol{\delta} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \boldsymbol{\tau_x} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \boldsymbol{\Lambda_x} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \tag{9}$$

$$\boldsymbol{\kappa} = \mathrm{Mean}[\boldsymbol{\xi}] = \begin{bmatrix} \mu_{COG} \\ \mu_{ACH} \\ \mu_{INT} \end{bmatrix}, \boldsymbol{\Phi} = \mathrm{COV}[\xi]$$
$$= \begin{bmatrix} \sigma^2_{COG} & \sigma_{COG.ACH} & \sigma_{COG.INT} \\ \sigma_{ACH.COG} & \sigma^2_{ACH} & \sigma_{ACH.INT} \\ \sigma_{INT.COG} & \sigma_{INT.ACH} & \sigma^2_{INT} \end{bmatrix} \tag{10}$$

$$\pi_{0i} = \alpha_0 + \gamma_1 COG_i + \gamma_2 ACH_i + \gamma_3 INT_i + \zeta_{0i} \tag{11.a}$$
$$\pi_{1i} = \alpha_1 + \gamma_4 COG_i + \gamma_5 ACH_i + \gamma_6 INT_i + \zeta_{1i} \tag{11.b}$$

$$\boldsymbol{\alpha} = \begin{bmatrix} \alpha_0 \\ \alpha_1 \end{bmatrix}, \boldsymbol{\Gamma} = \begin{bmatrix} \gamma_1 COG_i & \gamma_4 COG_i \\ \gamma_2 ACH_i & \gamma_5 ACH_i \\ \gamma_3 INT_i & \gamma_6 INT_i \end{bmatrix}, \mathbf{B} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \tag{12}$$

Figure 1(cont'd).

$$\mathbf{\Psi} = \mathrm{COV}[\boldsymbol{\zeta}] = \begin{bmatrix} \sigma^2_{\pi_0|COG,ACH,INT} & \sigma_{\pi_0\pi_1|COG,ACH,INT} \\ \sigma_{\pi_1\pi_0|COG,ACH,INT} & \sigma^2_{\pi_1|COG,ACH,INT} \end{bmatrix} \quad (13)$$

Figure 2. Conceptual path diagram of predictors of latent trajectory parameters (intercept, slope).

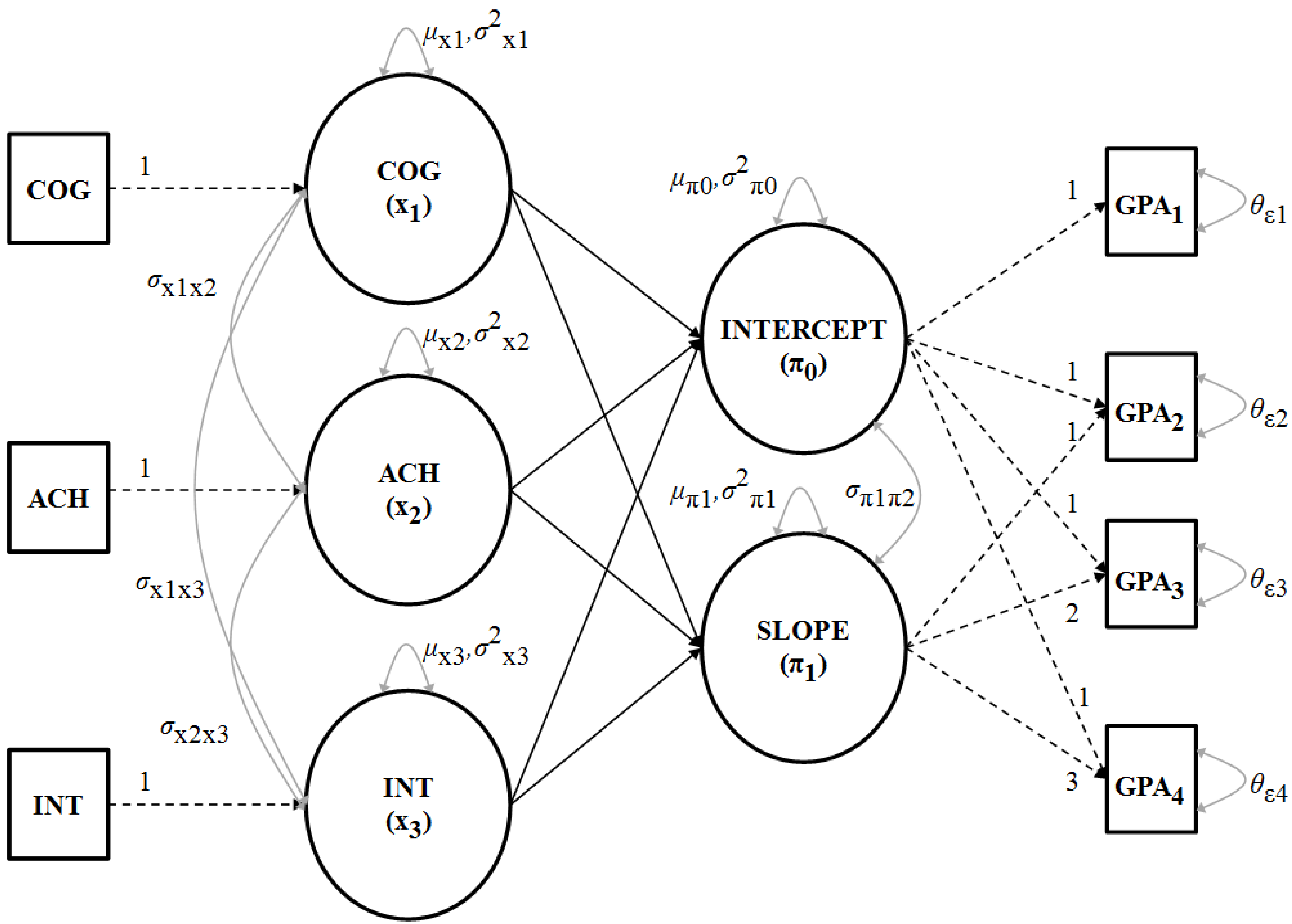


Figure 3. Plot of unconditional performance trajectory for MSU-Only Sample.

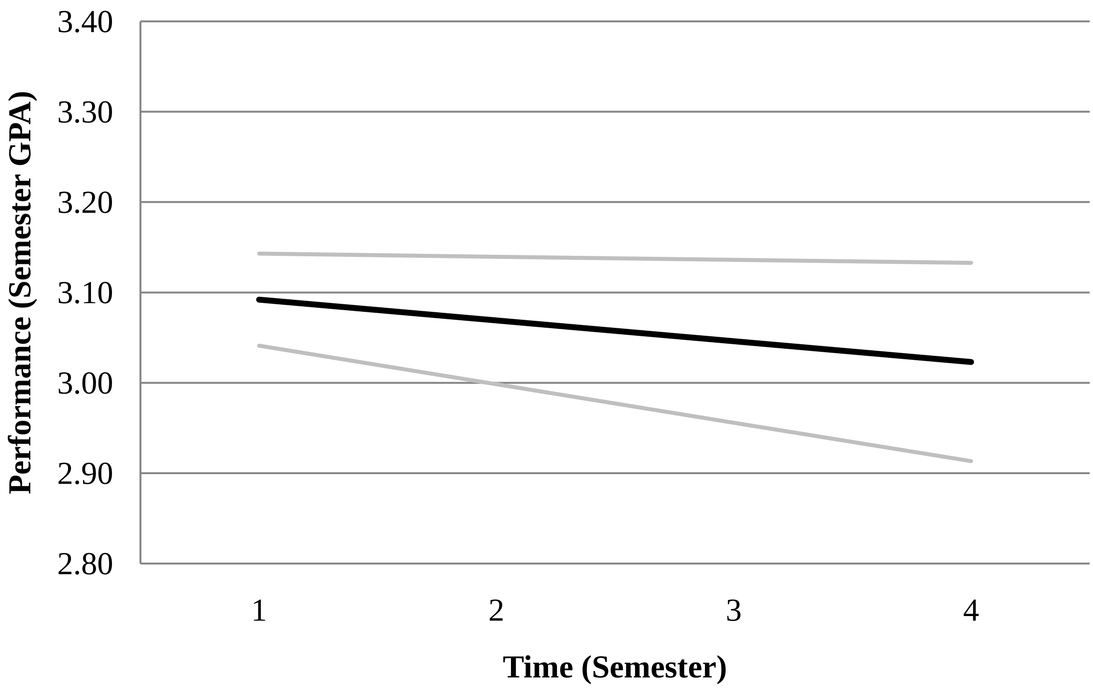


Figure 4. Plots of ability main effects (low: -1 *SD*, high: +1 *SD*) on latent performance trajectories (MSU-Only Sample).

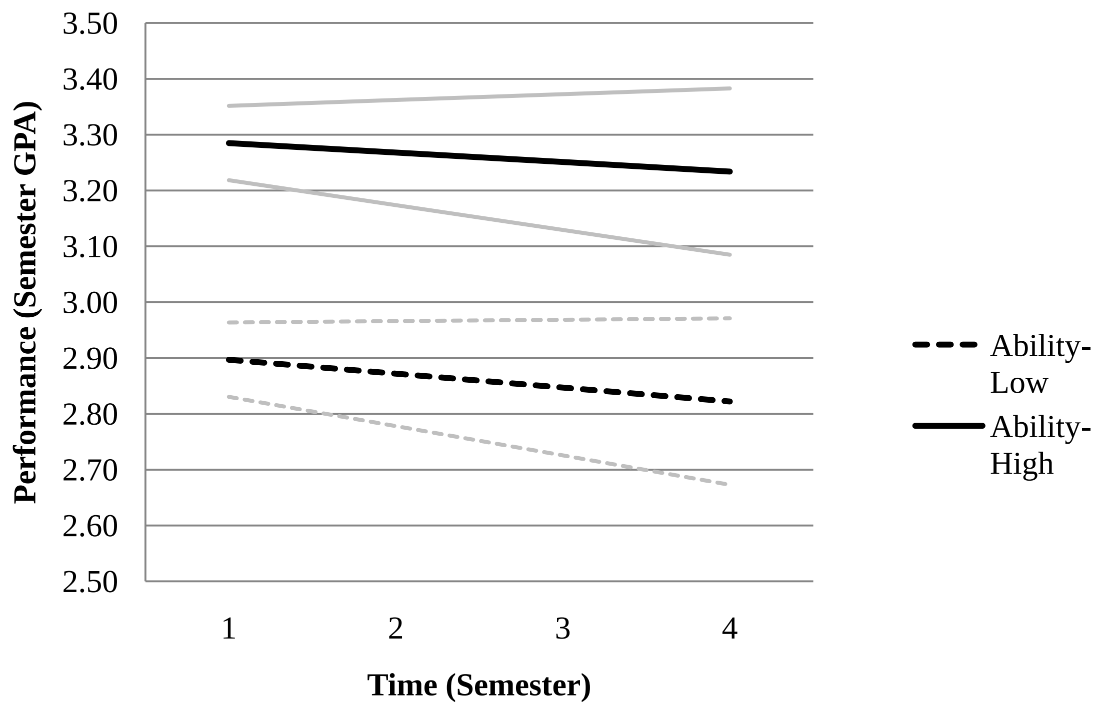


Figure 5. Plots of motivation main effects (low: -1 *SD*, high: +1 *SD*) on latent performance trajectories (MSU-Only Sample).

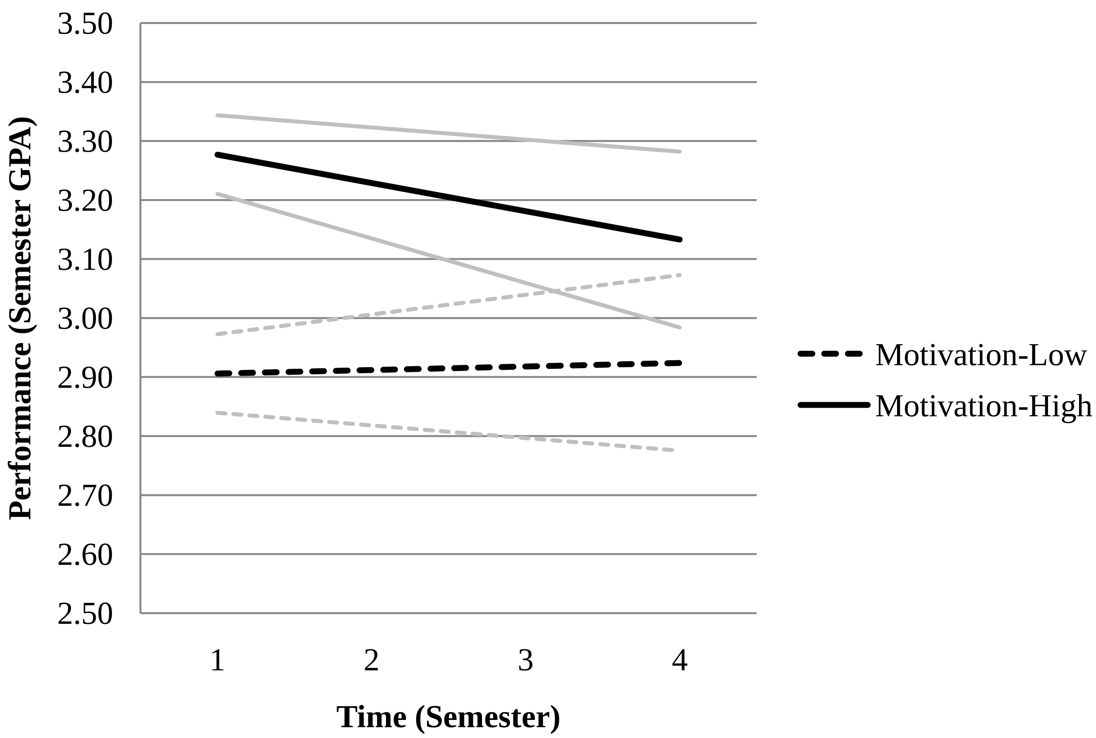


Figure 6. Plots of motivation conditional effects on latent performance trajectories at low ability (MSU-Only Sample).

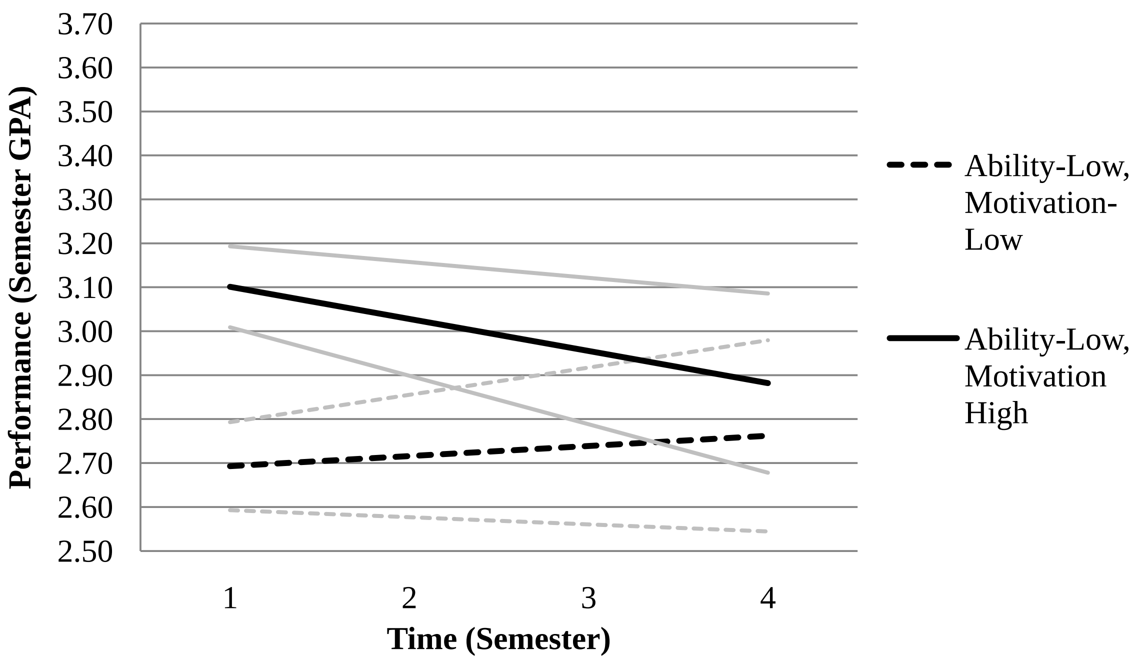


Figure 7. Plots of motivation conditional effects on latent performance trajectories at high ability (MSU-Only Sample).

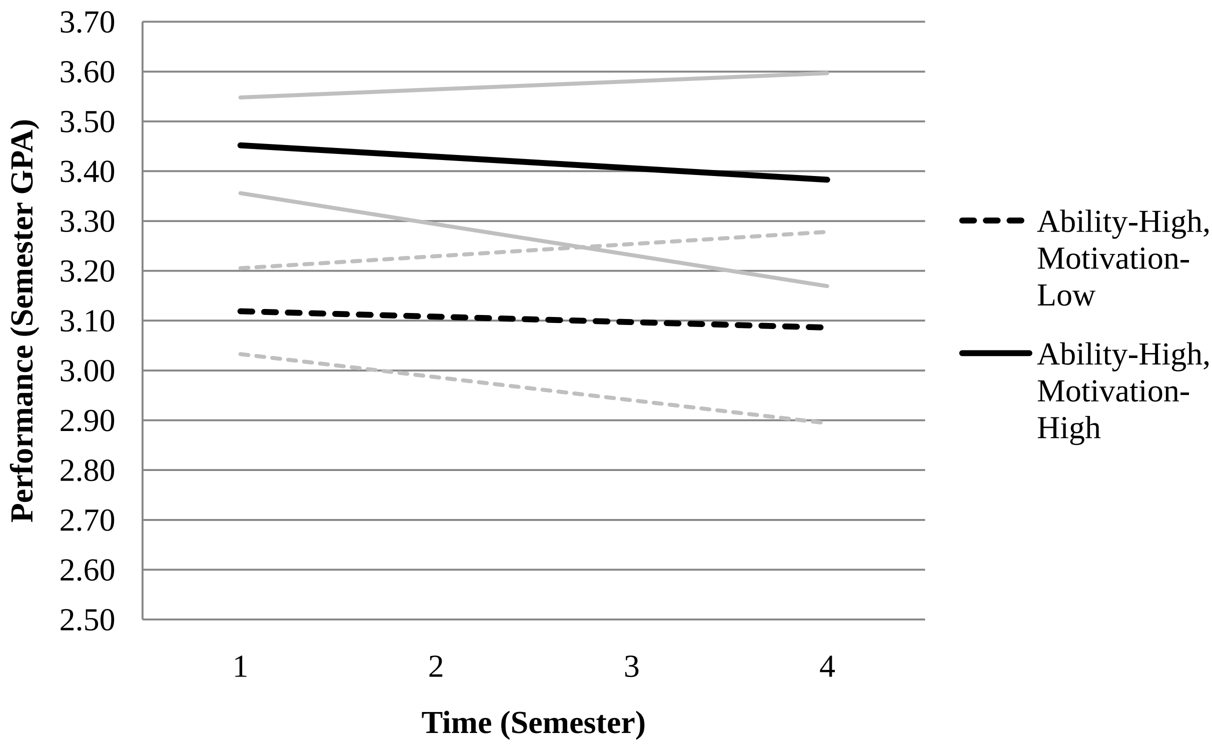


Figure 8. Plot of unconditional performance trajectory for Multi-Institution sample.

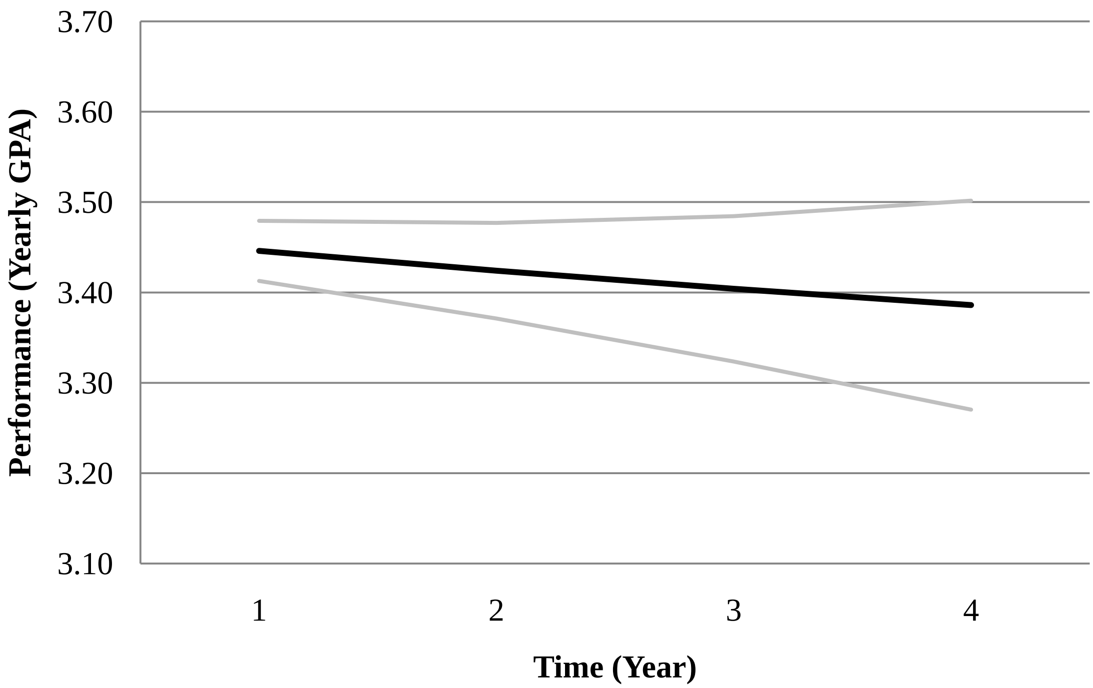


Figure 9. Plots of ability main effects (low: -1 *SD*, high: +1 *SD*) on latent performance trajectories (Multi-Institution Sample).

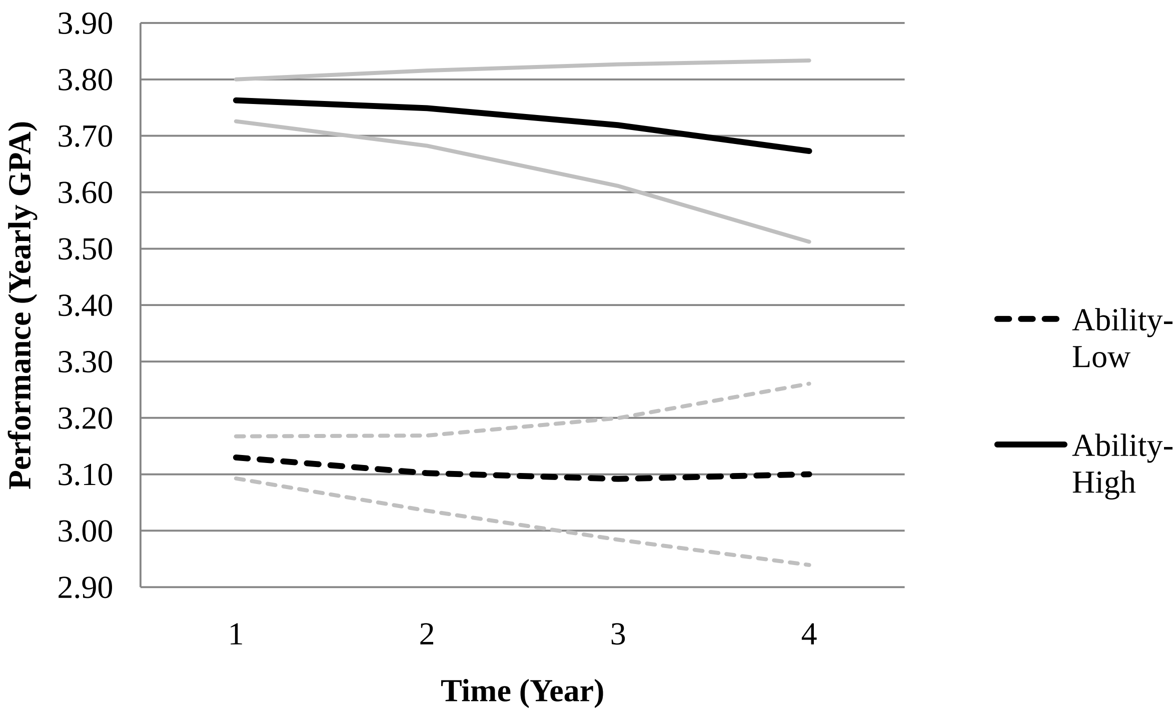


Figure 10. Plots of motivation main effects (low: -1 *SD*, high: +1 *SD*) on latent performance trajectories (Multi-Institution Sample).

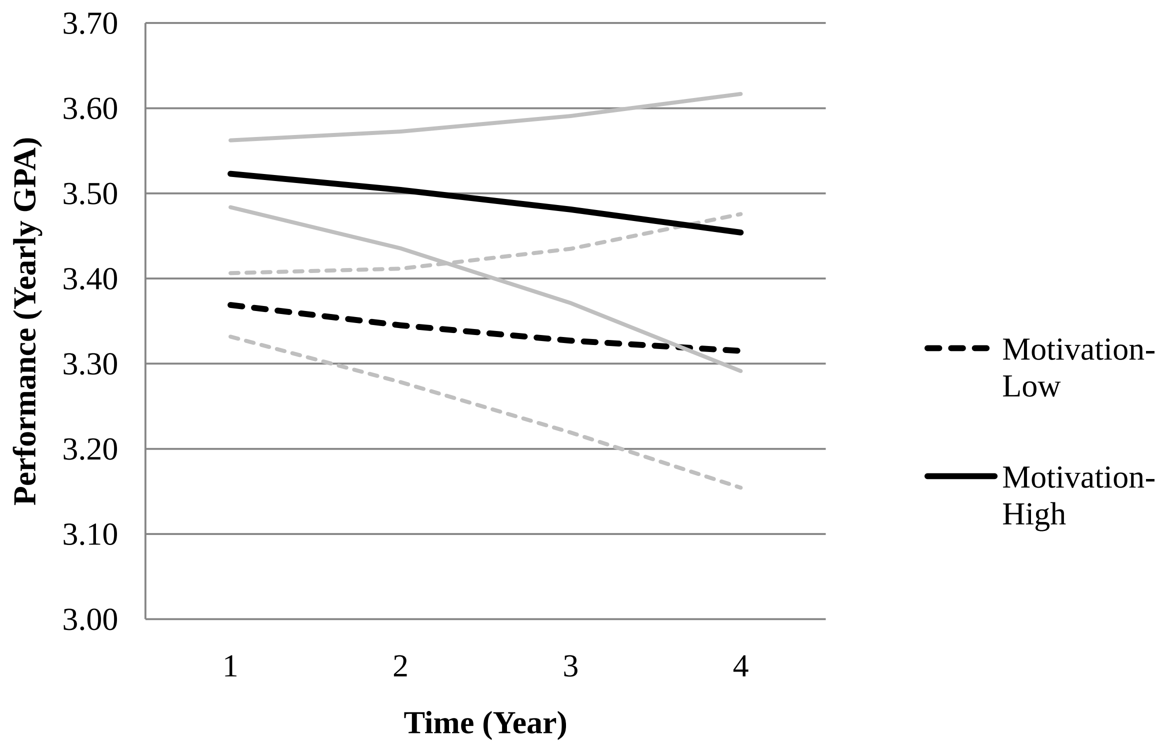


Figure 11. Plots of motivation conditional effects on latent performance trajectories at low ability (Multi-Institution Sample).

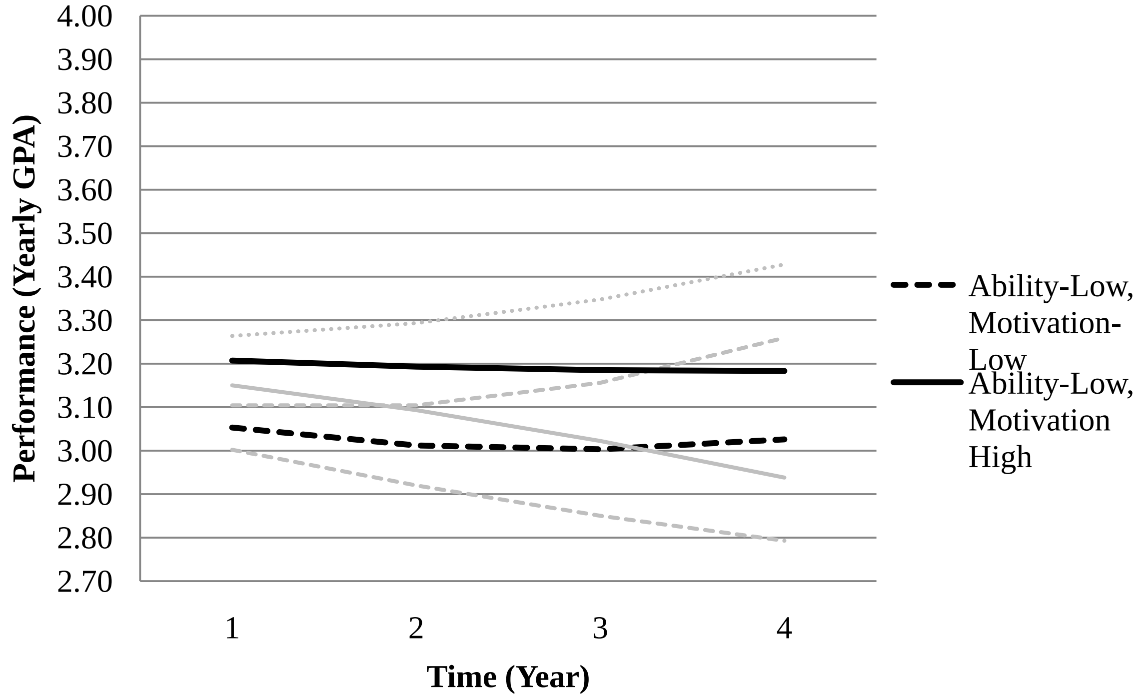
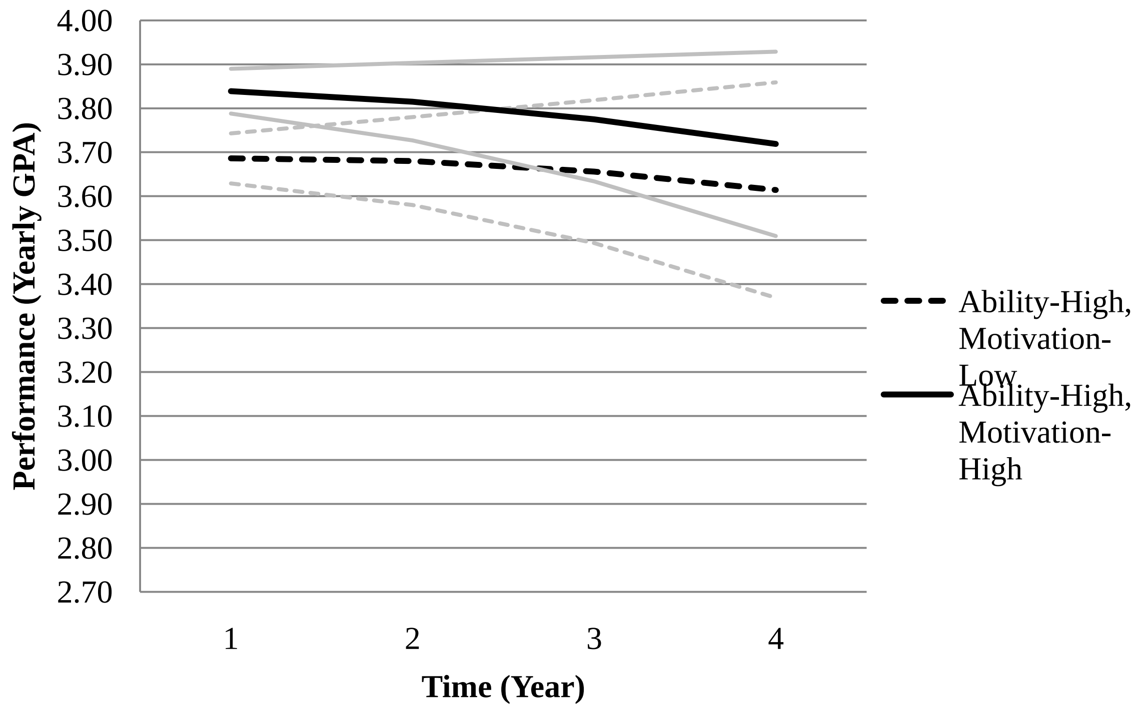


Figure 12. Plots of motivation conditional effects on latent performance trajectories at high ability (Multi-Institution Sample).



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