

ABSTRACT

WATSON, AARON MICHAEL. Cognitive and Motivational Influences on Performance during Training: A Longitudinal Field Study. (Under the direction of Lori Foster Thompson.)

The purpose of the current study is to investigate how individual factors and early training performance interact to influence subsequent performance in long-term training. Specifically, this longitudinal study sought to identify how motivation and cognitive ability relate to learners' ability to recover from early difficulties during training and demonstrate skill acquisition at the conclusion of training. The sample consisted of 578 military personnel participating in a four to six month foreign language training course required as a part of a broader job training and certification program. Though cognitive ability positively predicted who performed well early in training, motivation to learn did not. Both cognitive ability and motivation to learn predicted the absolute level of skill learners demonstrated after training. However, the influence of cognitive ability and motivation to learn on post-training test performance was not straightforward. A three-way interaction revealed a synergistic influence of cognitive ability and motivation to train, which depended on initial levels of training performance. Among trainees who struggled early on, motivation partially offset the detrimental effects of low cognitive ability on skill acquisition. Among those who began with high performance, motivation in the absence of sufficient cognitive resources appeared to impede skill acquisition. Implications for training research and practice, as well as limitations and directions for future research, are discussed.

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Cognitive and Motivational Influences on Performance during Training: A Longitudinal
Field Study

by
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Introduction

Employee training is both a vital and resource-intensive process in organizations. The changing nature of work, characterized by the increased necessity to adapt to changes both within and outside one's organization, has heightened the need for ongoing training and personnel development in today's organizations. Training represents a necessary function for organizations to be successful in meeting the demands of a dynamic market environment (Goldstein & Ford, 2002), adapting to technological change, and accommodating the expansion of knowledge and human capital within organizations (Preskill, 1994). These conditions have increased the rate with which job roles change, requiring workers and their employers to continue to develop their knowledge, skills, and competencies (i.e., intellectual capital) (Mayo, 2000). In 2007, organizations in the United States spent approximately \$58.5 billion for training, which was an increase of 9.6% from the \$53.4 billion spent just five years earlier in 2002 (Training, 2007). With such high levels of investment in training and development, it is important for organizations to understand factors shaping the success of training on human capital and organizational capability.

Training effectiveness research has enhanced our understanding of the inputs, processes, results, and organizational impact of training initiatives (Salas & Cannon-Bowers, 2001). This line of research has identified a number of individual and situational characteristics that influence training outcomes such as learning and transfer of training. While theory in this area continues to grow, there are certain areas in need of greater research to support, develop, and refine available theory. One such area pertains to the processes through which people learn and acquire new skills during training, particularly when faced

with challenges early in training. There remain unanswered questions regarding the trainee characteristics that impact how likely people are to recover from initial deficiencies during training. This area of research is particularly needed in long-term, cognitively demanding training contexts. Such training contexts are becoming increasingly prevalent in organizations, with corporate university courses providing an example of employee training which may take weeks or even months to complete (Prince & Stewart, 2002).

Practically speaking, it would be useful for organizations and learners to understand when and through which mechanisms people who struggle early in training subsequently recover and achieve acceptable results (Bandura, 1997; Schmidt & DeShon, 2009). There is limited empirical research addressing this issue, particularly in field settings. The purpose of the current study is to investigate how individual factors and early training performance interact to influence subsequent performance in long-term training. Specifically, this study seeks to identify how motivation and cognitive ability relate to learners' ability to recover from early difficulties during training and achieve greater subsequent skill acquisition at the conclusion of training. The research proposal upon which this study is based is provided in Appendix A.

Learners as Active Agents

The training effectiveness research field examines factors contributing to the success of training in organizational settings. This area of research seeks to better understand variables that impact "training outcomes at different stages (i.e., before, during, and after) of the training process" (Alvarez, Salas, & Garofano, 2004, p. 387). Several influential models of training effectiveness have emerged summarizing and integrating the state of knowledge

in the field (e.g., Alvarez et al., 2004; Baldwin & Ford, 1988; Cannon-Bowers, Salas, Tannenbaum, & Mathieu, 1995; Holton, 2005). For instance, Alvarez et al. (2004) reviewed 10 years of research in the training effectiveness and evaluation domain and, based on the consistency of available research findings, proposed an integrated model of training evaluation and effectiveness. This model posits how individual, training, and other characteristics impact changes in learners (i.e., learning) and organizational results.

In early training research, the predominant view of the learner was one of a “passive recipient, rather than an active participant, in training interventions” (Bell & Kozlowski, 2008, p. 296). That is, there was a strong emphasis placed on rigid structuring and sequencing of training content to produce a standardized experience with little or no learner control (Smith, Ford, & Kozlowski, 1997). Less emphasis was placed on understanding more learner-centered processes, such as self-regulation and information processing. This resulted in a notable gap in the literature.

More recent theory and research have emphasized the view of learners as active agents in the learning context (e.g., Beier & Kanfer, 2010; Bell & Kozlowski, 2008; Gully & Chen, 2010). Gully and Chen (2010) assert that learners “decide what to attend to, determine how much effort they will devote, and actively engage themselves, or disengage themselves” (p. 4-5). Increases in the availability and adoption of computer-based and other learner-driven training solutions have shifted much of the responsibility onto individual learners (as opposed to trainers or instructors) to engage and develop their skills (Beier & Kanfer, 2010). As learner control increases, individuals’ behavioral tendencies, cognitive capabilities, and

attitudes are likely to exert more influence on the direction, intensity, and persistence of effort and, ultimately, training outcomes (Ford & Kraiger, 1995).

Examining Individual Differences in Performance Improvement

Although research evidence illuminating the mechanisms through which individual differences shape learning outcomes is limited, empirical research into active learning has enhanced our understanding of how distal and proximal learner characteristics impact learner choices and goals and, in turn, training outcomes (e.g., Bell & Kozlowski, 2008). There is virtual consensus that the success of training depends on both learner characteristics and contextual factors. However, a debate exists concerning the extent to which the contributions of each are additive or dependent on one another (e.g., Sackett, Gruys, & Ellingson, 1998). Training outcomes are thought to depend on the configuration of individual and contextual factors involved in the learning and organizational environment. The question is to what extent does the impact of specific individual differences vary as a function of contextual factors (and vice versa). The possibility of such interactions renders broad claims of direct (i.e., main effect) relationships difficult to endorse without sufficient evidence ruling out more complex relationships (Alvarez et al., 2004). It is clear that additional research is needed to better understand potential complex interactive relationships to move the training effectiveness literature forward (Aguinis & Kraiger, 2009; Alvarez et al., 2004).

One particular interaction which warrants investigation pertains to the manner in which individual differences interact with early training performance (and feedback) to predict subsequent skill acquisition. Do initial performance problems forecast later deficiencies for all trainees, or are certain types of trainees more likely than others to recover

from difficulties encountered early in training? Past researchers have emphasized the benefits that may be gained from a clearer understanding of how individuals cope with and respond to difficulties encountered in learning contexts. For instance, Bandura (1997) states that understanding how individuals cope with challenges in the learning process can advance theory, as well as lead to practical interventions enabling learners to more adaptively respond to such challenges.

To address this issue, empirical studies have investigated the mechanisms through which early training performance relates to later training performance (e.g., Herold, Davis, Fedor, & Parsons, 2002; Schmidt & DeShon, 2009). Some research (e.g., Chen & Mathieu, 2008; Herold et al., 2002) suggests dispositional characteristics may play a role in determining whether individuals will recover from poor performance early in training. In their field study of a two-phase aviation training program, Herold et al. (2002) found that trainee personality characteristics interacted with training performance in the initial phase in the prediction of performance in the second stage. Specifically, these authors showed that highly conscientious learners were able to improve upon initially low training performance to a much greater extent than learners low in conscientiousness (Herold et al., 2002).

Schmidt and DeShon (2009) examined the interaction between goal-performance discrepancies and self-efficacy in the prediction of subsequent performance on a computer-based problem solving task. Results indicated that the nature of the relationship between self-efficacy and later task performance depended, in part, on initial task performance (Schmidt & DeShon, 2009). While Schmidt and DeShon's (2009) work substantially contributes to what is known about training dynamics, a key limitation to their study is the artificial nature of the

training task, which was a computerized analytical game involving identifying visual patterns in a color-coded display.

The current study adds to the existing empirical evidence in this area by examining previously unstudied interactions and doing so in a long-term, real-world training context. As discussed next, general cognitive ability and motivation to learn are two individual differences which are likely to affect not only pre- and post-training outcomes, but also the degree to which trainees rebound after initial failures. I consider the direct effects of each individual difference variable on early training performance and post-training skill acquisition. In addition, I develop hypotheses addressing the manner in which cognitive ability and motivation to learn should interact with early training performance to predict subsequent skill acquisition.

General cognitive ability. General cognitive ability (hereafter referred to as cognitive ability) is defined as the knowledge and capacities needed to acquire, encode, retrieve, actively process, and use information and concepts in novel situations (Humphreys, 1979). Cognitive ability has been linked to a variety of learning outcomes by many influential models of training effectiveness (e.g., Alvarez et al., 2004; Baldwin & Ford, 1988; Cannon-Bowers et al., 1995; Mathieu, Tannenbaum, & Salas, 1992). Meta-analyses summarizing numerous primary studies have supported the linkage between cognitive ability, learning, and job performance (Colquitt, Lepine, & Noe, 2000; Hunter & Hunter, 1984). To replicate previous findings in the context of a cognitively complex training task, I therefore hypothesized the following.

H1: Trainees higher in cognitive ability will show greater (H1a) initial performance and (H1b) end-of-training skill acquisition compared to those who are lower in cognitive ability.

Cognitive ability may not only impact early and late learning outcomes, as suggested by Hypothesis 1. It should also influence the *relationship* between early and late outcomes. That is, cognitive ability should help explain the degree to which people recover from early difficulties in training. Adapted from Herold et al. (2002), Figure 1 presents this conceptual relationship. As indicated in this conceptual model, early training outcomes (e.g., training performance, skills test scores) can serve as predictors of later training outcomes. That is, trainees' performance early on may be indicative of how they will perform during later phases of training. However, this may be truer for some trainees than others, which emphasizes the need for empirical work investigating who does and does not recover from early training performance problems.

While cognitive ability has been frequently studied in the training domain, relatively little is known about the way in which cognitive capabilities interact with early training performance to influence learning trends *during* long-term training. Scholars (e.g., Aguinis & Kraiger, 2009; Gully & Chen, 2010; Herold et al., 2002) have called for more research into the dynamics of the learning process during training as they relate to characteristics of the learner (e.g., cognitive ability). Aguinis and Kraiger (2009) specifically call for more research into how cognitive ability influences the “rate and depth of learning during training” (p. 467).

Past research suggests the complexity of the ability-acquisition relationship may be obscured with the cross-sectional designs so often employed in training research (Yeo & Neal, 2004). In a longitudinal laboratory study, Yeo and Neal (2004) found evidence of a complex ability-acquisition relationship. These authors demonstrated that cognitive ability moderated the relationship between effort and performance improvement over time in undergraduate students learning an air-traffic control task (Yeo & Neal, 2004). Specifically, effort became more strongly predictive of task performance over time for learners higher in cognitive ability compared to lower ability learners.

Previous theoretical development provides a solid foundation from which to hypothesize the role of cognitive ability in skill acquisition. Kanfer and Ackerman's (1989) resource allocation framework is an influential and well-supported model positing the roles of learner ability and motivation in the acquisition of new skills. This framework indicates that learner attention (or effort) is a limited resource, which can be directed toward on-task, off-task, or self-regulatory processes (Kanfer & Ackerman, 1989). Cognitive ability represents the amount of attentional resources available at any given time. When attentional demands are high (e.g., for challenging or novel tasks), trainees' cognitive ability will strongly relate to the acquisition of new skills (Kanfer & Ackerman, 1989). This relationship is expected to diminish in magnitude as resource demands of the training task decrease (Kanfer & Ackerman, 1989). That is, for cognitively demanding learning environments, people with greater cognitive resources (i.e., cognitive ability) should be more capable of acquiring and maintaining new knowledge and skills compared to those with fewer cognitive resources (e.g., Kanfer and Ackerman, 1989). Early training performance can serve as an

indicator of the demands of training for individuals. That is, lower initial training performance is likely indicative of training that is more challenging to a given individual. Thus, under conditions in which the demands of training are higher (as indicated, for example, by lower initial training performance), people with greater cognitive ability will likely be able to subsequently outperform those with lower cognitive ability.

Said another way, cognitive ability is likely an important factor determining learners' ability to adapt to difficulties experienced in training. In their conceptual model of training effectiveness, Gully and Chen (2010) consider information processing capacity (i.e., cognitive ability), along with trainee motivation, metacognitive processing, and emotional regulation, to be an important intervening mechanism through which dispositional individual differences (e.g., personality) and initial training performance interact to influence later learning outcomes. Higher cognitive ability should allow for greater attentional resources to be dedicated to the on-task and self-regulatory processes (Kanfer & Ackerman, 1989) needed to "catch up" to those with higher initial performance. Therefore, the following hypothesis is evaluated in this study.

H2: Cognitive ability will moderate the relationship between initial training performance and end-of-training skill acquisition. Initial training performance will be more positively predictive for learners lower in cognitive ability than it is for learners higher in cognitive ability.

Pre-training motivation to learn. In addition to cognitive ability, pre-training motivation to learn (hereafter referred to as motivation to learn) is also considered a key antecedent of learning. In the learning context, motivation has been characterized as

governing one's choice of direction, level, and persistence of effort (Campbell, 1990; Kanfer & Ackerman, 1989). The relationships between learner motivation and training outcomes have been well-documented both theoretically (e.g., Beier & Kanfer, 2010) and empirically (e.g., Colquitt et al., 2000). In their meta-analysis, Colquitt et al. (2000) showed that motivation to learn predicts cognitive-based, skill-based, and affective-based learning outcomes. In addition, the impact of motivation on actual learning was independent of cognitive ability (Colquitt et al., 2000). Thus, as a replication of prior research, I hypothesize the following.

H3: Trainees higher in motivation to learn will show greater (H3a) initial performance and (H3b) end-of-training learning outcomes compared to those who are lower in motivation to learn.

Motivation to learn may not only impact early and late learning outcomes, as suggested by Hypothesis 3. It is also expected to influence the *relationship* between early and late outcomes. As depicted in Figure 1, trainees' performance early in training is likely indicative of how they will perform during later phases of training—but more so for some trainees than for others. As with cognitive ability, motivation to train should help account for the degree to which people recover from early training performance deficits.

Learner motivation is expected to influence the allocation of attentional resources during the learning process, which are limited in capacity (Kanfer & Ackerman, 1989). As noted, effort may be directed toward on-task, off-task, or self-regulatory processes (Kanfer & Ackerman, 1989). More highly motivated learners are expected to devote greater effort toward on-task and self-regulatory process (necessary for effective learning), rather than

toward off-task processes and behaviors. This efficient allocation of learner resources should result in greater skill acquisition, particularly with difficult training tasks (Kanfer & Ackerman, 1989).

Motivation upon entering training should play an especially important role in learning dynamics by influencing how trainees deal with early failures, thus affecting the likelihood that trainees will overcome challenges encountered early on. Goal setting theory speaks to this assertion. People who enter training with higher levels of motivation are likely to set higher goals, which in turn foster subsequent motivation. Goal-setting is a specific self-regulatory process linked to increased learning over time (Locke & Latham, 2002). The learning goals one sets during training can be both an antecedent of learning, as well as an outcome of learning. For example, research suggests achievement during training is partially a function of learning goals (Locke & Latham, 2002) such that trainees who set and strive for higher goals are expected to show greater achievement. Achievement, in turn, predicts future learning goals, which in turn predict future achievement (Locke & Latham, 2002).

Early training successes and failures represent important forms of feedback shaping learners' subsequent goals (e.g., Schmidt & DeShon, 2007). Feedback provides diagnostic information with which trainees can gauge progress towards their goals. When feedback indicates low performance, learners with higher goals will experience greater goal-performance discrepancies than will their counterparts with more modest goals. In other words, when initial performance is lower, trainees whose higher levels of motivation have prompted them to set higher goals will be especially prone to goal-performance discrepancies.

Self-regulation theories suggest goal-performance discrepancies derived from performance feedback are particularly important in determining subsequent effort of trainees (e.g., Schmidt, Dolis, & Tolli, 2009). Discrepancies between one's performance goals and actual performance result in either reallocating attentional resources or revising goals downward. Individual differences can influence which of these strategies is chosen (DeShon & Gillespie, 2005). Highly motivated trainees are unlikely to revise goals downward. Instead, motivated trainees with sub-standard performance are expected to reallocate attentional resources (e.g., increased effort level, decreased off-task time) due to the goal-performance discrepancy. In this manner, the degree to which initially lower performing trainees remain "stuck" in a cycle of lower performance should in part depend on motivation.

Motivation to learn could also impact how trainees respond to initial performance deficiencies by influencing the interpretation of feedback received early in training. Higher motivation to learn or master a trained skill may be considered analogous to the adoption of a mastery goal orientation, as described by Dweck and Leggett (1988). These authors state that trainees who are more highly motivated interpret performance outcomes (e.g., training assessments) as feedback on their learning strategies and effort. These types of trainees tend to view critical feedback as a challenge to be overcome (DeShon & Gillespie, 2005). Negative feedback (e.g., poor task performance) thus results in shifts in learning strategies or increased effort for these trainees (Dweck & Leggett, 1988). Therefore, it is expected that trainees with higher motivation to learn will respond more constructively to initial performance deficiencies compared to those for less motivated trainees.

Some researchers have examined how motivation to learn relates to outcomes across multiple training events. Sitzmann, Brown, Ely, Kraiger, and Wisher (2009) examined the longitudinal impact of motivation to train on learning over the course of several training programs (i.e., multi-phase training). Results were mixed and did not conclusively indicate higher motivation resulted in greater learning (Sitzmann et al., 2009). However, these authors did find that motivation positively related to reactions at the end of each training phase, which, in turn, led to higher motivation and expectations for subsequent phases (Sitzmann et al., 2009).

The role of motivation during training warrants further investigation. In accordance with training theory, the potential benefits of motivation (e.g., increased on-task effort, reduced off-task attention) are expected to be more fully realized in those who encounter initial difficulties in training (i.e., poor performance). Compared to their less motivated counterparts, highly motivated trainees should be less likely to get “stuck” in a cycle of low performance. The present study tests this hypothesis.

H4: Motivation to learn will moderate the relationship between initial training performance and end-of-training skill acquisition. Initial training performance will be more positively predictive for learners lower in motivation than it is for learners higher in motivation.

Exploring Higher-order Interactions among Ability, Motivation, and Initial Performance

The aforementioned hypotheses *independently* consider how cognitive ability and motivation to learn interact with early training performance in the prediction of subsequent

training success. However, theory suggests both are necessary but not sufficient for maximizing skill acquisition. According to Kanfer and Ackerman's (1989) resource allocation framework, cognitive ability represents the upper limit of attentional resources available to dedicate to the on-task and self-regulatory processes necessary to acquire new skills. Motivation is expected to lead to the appropriate and efficient allocation of those cognitive resources, which will result in maximal learning and performance for challenging tasks (Kanfer & Ackerman, 1989). For a demanding task, maximum performance requires both a higher level and efficient allocation of available attentional resources. This is consistent with the notion learner *trainability* (Noe & Schmitt, 1986; Wexley & Latham, 1981), which varies as a function of both learner ability and motivation.

In short, theory suggests the possibility of a higher-order interaction among the variables investigated in this study. Trainees' ability to improve upon initially lower performance may depend on the joint impact of cognitive ability and motivation to learn. As the research literature is arguably too young to support a specific prediction regarding the precise nature of the potential interaction, I examine this prospect in the form of a research question.

RQ: Will there be a three-way interaction among cognitive ability, motivation to learn, and initial training performance when predicting end-of-training skill acquisition?

Method

Sample

The sample consisted of 578 military personnel participating in foreign language training at a large military installation in the southeastern United States. Approximately 99% of trainees were native English speakers. Trainees varied with regard to their highest level of education achieved. Fifty-three percent had completed some college, followed by 29% with a high school diploma or GED, 15% with a BA/BS, 1% with a Master's degree, and less than 1% with a Ph.D. Two percent of the sample indicated "Other" and 1% did not indicate their highest education. While age was not measured in this study, the typical age range of this trainee population falls between ages 22 and 31.

Training Context

The training context was a foreign language course participants were required to complete as a part of a broader job training and certification program. Trainees completed the course between July 2005 and July 2007. Training took place in a classroom setting, consisting of one instructor and between five and 12 trainees. The content of the training consisted of a basic introduction to the language (e.g., sounds, alphabet, etc.) followed by training modules centered around job-related topic areas such as formal and informal greetings and social interactions, conversing about personal backgrounds, regional and national geography, and job-specific (e.g., military-technical) tasks.

The total length of training was four to six months depending on the specific language to which participants were assigned. Languages considered to be easier for native English speakers to learn (e.g., Spanish, French), as determined by the Foreign Services Institute of the U.S. Department of State, received less training time compared to more difficult languages (e.g., Modern Standard Arabic, Korean). While total training time (i.e., in-class

hours) varied across languages, the training content was standardized across languages. That is, regardless of the language to which trainees were assigned, the program-of-instruction was designed to teach trainees to perform the same tasks to the same level of proficiency. Training consisted of approximately six hours of instruction per day for five days each week.

To successfully complete the foreign language requirement for their positions, trainees were required to demonstrate a pre-determined minimum level of proficiency on a standardized proficiency assessment at the conclusion of the course. This minimum standard was constant across all training languages. While meeting this minimum standard was required to remain in their position, trainees were given a monetary incentive to achieve proficiency above the minimum standard.

Measured Variables

Training outcomes were operationalized in two ways in this study, including early test performance and post-training skill demonstration.

Initial training performance. Tests of learner achievement were administered on five different occasions throughout training. All items on a given achievement assessment (or module skills test) covered only material taught in the previous training module. The content of the course curriculum and associated skills tests were professionally developed and standardized across training languages. That is, trainees in a given language learned and were tested on the same content in each training module as trainees in other languages.

Assessments were administered approximately three to five weeks apart during training, depending on the language being trained (i.e., more time elapsed between assessments for

languages with longer total training times). Prior to the first skills test, trainees took a practice quiz with the same test and item format as the skills tests.

Each skills test consisted of 50 multiple-choice items developed to assess trainees' ability to listen to and understand speech samples performed in the target language. For each test, trainees listened to spoken dialogue in the target language, and subsequently answered questions related to the speech sample. A sample item is presented in Appendix B. The final score on each test was calculated as the percentage of items answered correctly.

All skills test data were obtained from the training organization's official records. Because the purpose of this study is to examine who recovers from low levels of *early* training performance, only scores from the first skills test were analyzed. Specifically, initial training performance was operationalized as the score on the first skills test.

Post-training skill acquisition. Within one week after the conclusion of training, skill acquisition was assessed via performance on the listening proficiency portion of the Defense Language Proficiency Test (DLPT), a standardized language proficiency assessment developed by the Defense Language Institute. This assessment measured how effectively trainees could retain, perform, and generalize the language knowledge and listening skills developed during training. Importantly, as a broad proficiency assessment, the content of the DLPT was not tailored specifically to the content of the training course. Test items required trainees to demonstrate their language skills in performance contexts that were similar, but not identical, to those encountered during training.

The DLPT is a computer-based test consisting of approximately 60 multiple-choice items developed to measure ability at various levels of proficiency. For the listening exam,

test takers were exposed to spoken dialogue in the target language and subsequently answered questions related to the speech sample. Final raw proficiency scores were obtained prior to their conversion to the Interagency Language Roundtable (ILR) rating scale, which categorizes raw scores into 11 distinct levels from ‘no proficiency’ (lowest) to ‘functionally native proficiency’ (highest). Raw scores were used in place of the converted ILR rating to retain the full range of variability in test performance. Each trainee’s official raw score on the DLPT was obtained from the training organization for this study.

General cognitive ability. Trainees’ general cognitive ability was assessed using the Armed Forces Qualification Test (AFQT), which is a component of the Armed Services Vocation Aptitude Battery (ASVAB). All trainees took this assessment prior to enlisting in the military. The ASVAB can be completed either in paper-and-pencil form or as a computer-adaptive test. Extensive validation efforts have supported the ASVAB as a valid and reliable measure of general and specific cognitive abilities (Segall, 2004; Welsh, Kucinkas, & Curran, 1990).

Scores on the AFQT component used in this study are a composite of the word knowledge, paragraph comprehension, mathematics, and arithmetic reasoning subtests of the ASVAB. The AFQT has been used as a measure of general mental ability in prior research (e.g., Ree & Earles, 1991). Each trainee’s AFQT score was obtained from the training organization’s official testing records.

Pre-training motivation to learn. Like much organizational training, this training was required, not optional. Moreover, trainees did not choose which language they wished to learn; the target language was assigned. Accordingly, it was important to measure motivation

to train to differentiate trainees on their desire to learn the material. A five-item self-report measure of motivation to train was obtained prior to training. This measure was developed for the current study to assess trainees' motivation to learn the target language. Sample items from this scale are, "I would like to learn as many languages as possible" and "I am motivated to perform well in language training so that I will be able to perform my missions more effectively." All scale items are presented in Appendix C. Responses were provided on a 7-point Likert type scale, ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). The coefficient alpha for this scale was .67.

Control variable. The language to which trainees were assigned was used as a control variable in all analyses in this study for two reasons. First, approximately half of the languages required four months of training, while the other half required six months. Second, it is more difficult for native English speakers (i.e., the majority of the trainee population) to achieve higher training performance and proficiency in certain languages. Controlling for training language allows for the evaluation of the study hypotheses while adjusting for any effects attributable to length of training or language difficulty.

Procedure

Approximately two to three days prior to the beginning of training, trainees were asked to complete a questionnaire that included the motivation to train self-report measure, among other demographic items and psychological scales. This questionnaire was part of a larger ongoing foreign language training effectiveness study conducted with this specific military organization. Personal identifiers were collected on the pre-training questionnaire in

order to link official testing records to questionnaire responses. However, respondents were assured that their responses to the questionnaire would be kept confidential.

Trainees then began the foreign language training course. At pre-determined points in the curriculum, trainees completed skills tests covering the associated training module. The first test occurred three to five weeks after the beginning of the training course. Trainees received feedback on their test performance after each exam. At the conclusion of training, trainees took the standardized proficiency test (DLPT) assessing skill acquisition. All test results were obtained after trainees had completed the program.

Results

Skewness and kurtosis statistics were calculated for each univariate distribution to evaluate the assumption of normality of each study variable. See Table 1. Skewness and kurtosis values were within acceptable limits (i.e., less than .80 and 1.00, respectively) for all variables, with the exception of initial training performance. I determined there were no extreme observations that could unduly influence study findings.

Initial training performance scores were measured the percentage of correct test items. Proportions can be problematic if included in models that assume linear relationships among variables since proportions are bounded between zero and 1.00. These bounds lead to nonlinear relationships, particularly for smaller (e.g., $< .3$) and larger (e.g., $> .7$) proportions (Cohen, Cohen, West, & Aiken, 2003). Therefore, it is recommended to transform proportions to create more linear relationships between them and continuous variables (Cohen et al., 2003). Following Cohen et al.'s (2003) recommendation, I used the arcsine

transformation, which extends the lower and upper values to reduce floor and ceiling effects due to bounds. The arcsine transformation is obtained using Equation 1 (Zar, 1999).

$$A = \arcsine \sqrt{P} \quad (1)$$

Equation 1 can only produce A values for proportions *between* 0 and 1.00. Since proportions of 1.00 occurred in the raw data, all values were reduced by .001 prior to being transformed. The distributions of initial training performance before and after transformation are presented in Figure 2. Skewness and kurtosis values for the transformed distribution are reported in Table 1. Following the transformation, skewness and kurtosis for initial training performance were at acceptable levels.

Descriptive statistics and correlations for all study variables are presented in Table 2. The data showed small to moderate positive and significant correlations between study variables, with one exception. Pre-training motivation to learn was unrelated to cognitive ability.

Hierarchical linear modeling (HLM) was used to model the relationships between study predictors and outcomes. This method was used rather than ordinary least squares (OLS) regression to account for the interdependency among observations due to students (Level 1 units) nested within intact classes (Level 2 units). Whereas tests of statistical significance are biased in OLS regression when observations are not independent, these tests are unbiased under HLM (Raudenbush & Bryk, 2002). All continuous predictor variables were group-mean centered (or centered within cluster), while the outcome variable for each regression remained uncentered. Group-mean centering has been shown to provide both a meaningful zero point for predictors and unbiased estimates of Level 1 slopes (the focus of

this study), which is not always the case with grand-mean centering (Enders & Tofighi, 2007; Hofmann & Gavin, 1998; Raudenbush & Bryk, 2002).

Initial Training Performance

I conducted a series of two-level HLM models, with individual trainees at Level 1 and classes at Level 2, modeling initial training performance (after being transformed) as the outcome of interest. A total of 578 trainees in 87 classes were included in these models. Models were estimated using the MIXED procedure in SAS using restricted maximum likelihood (REML) estimation (see Singer, 1998). A null model (Model 0) was estimated first, in which no predictors were included (only the intercept) and variance components for Level 1 (between persons) and Level 2 (between classes) were estimated. These results are presented in Table 3. Results from Model 0 indicated that while there was substantial variability between classes [intraclass correlation (ICC) of .48], there was also significant between-person variability in initial training performance. Significant variability at Level 1 provided justification for subsequent models attempting to account for Level 1 variance.

Next, I added training language as a control (Model 1), followed by cognitive ability and motivation to learn (Model 2). Training language (dummy-coded) was uncentered, while cognitive ability and motivation to learn were group-mean centered. The addition of training language accounted for approximately 56% of the between-class variance in initial training performance scores. Results indicated a significant and positive relationship between cognitive ability and initial training performance, supporting Hypothesis 1a (see Table 3). Motivation to learn did not significantly predict initial training performance ($\beta = .005, p =$

.46). Thus, as stated in Table 4, Hypothesis 3a was not supported. The two predictors combined to account for approximately 8% of the between-person variance.

The previous models were reanalyzed using grand-mean centering (rather than group-mean centering) for the two continuous predictors to detect any differences in results due to the type of centering used. The results were consistent across the two types of centering. To ensure adequate power was achieved for detecting a moderate sized fixed effect, a post hoc power analysis was conducted. For this analysis, I calculated the observed power to detect an effect in which 10% of the between-person (i.e., within class) variance is accounted for by the target predictor. I followed steps recommended by Hox (2002) for computing post hoc power estimates for multilevel models. Results, presented in Table D1 in Appendix D, indicated there was sufficient power (i.e., $> .80$) to detect a moderate effect for each fixed effect of interest.

Post-training Skill Acquisition

Next, I conducted a series of two-level HLM models with post-training skill acquisition as the outcome of interest. Data from 511 trainees in 80 classes were included in these models. Results from the null model (Model 0) are presented in Table 5. Results from Model 0 indicated significant between-person variability in skill acquisition, as well as significant variability between classes ($ICC = .23$).

I then added training language as a control (Model 1), followed by cognitive ability and motivation to learn (Model 2). Training language was uncentered, while cognitive ability and motivation to learn were group-mean centered. Training language accounted for approximately 77% of the between-class variance in post-training skill acquisition scores.

Results indicated a significant and positive relationship between cognitive ability and skill acquisition, supporting Hypothesis 1b (see Table 5). Motivation to learn also significantly predicted skill acquisition, providing support for Hypothesis 3b. The two predictors combined to account for approximately 14% of the between-person variance, above and beyond training language. Next, initial training performance and its cross-products with cognitive ability and motivation to learn were added in Model 3. Results were nonsignificant for initial performance X cognitive ability ($\beta = .120, p = .24$) and initial performance X motivation to learn ($\beta = -2.524, p = .23$), thus failing to support Hypotheses 2 and 4. A summary of each hypothesis test's findings is presented in Table 4.

This study's research question was posed to examine the possibility of a more complex set of interactions than those posited by Hypotheses 2 and 4. A three-way interaction term among initial performance, cognitive ability, and motivation to learn was added (Model 4) to test this study's research question. The cross-product of cognitive ability and motivation to learn was also entered to aid interpretation of the three-way interaction term. Results indicated the three-way interaction was statistically significant ($p = .04$). Also, the addition of the three-way interaction term resulted in the main effect of motivation to learn (γ_{20}) on post-training skill acquisition no longer being significant. This indicates the effect of motivation to learn was fully qualified by the three-way interaction.

To determine the nature of the three-way interaction, model estimates resulting from Model 4 (see Table 5) were plotted. The two-way interaction between cognitive ability and motivation to learn is presented for both lower (i.e., -1 SD) and higher (i.e., +1 SD) initial training performance in Figure 3. The two plots clearly show a consistently positive effect for

cognitive ability, in that higher cognitive ability resulted in greater skill acquisition regardless of initial performance. However, the two plots show motivation to learn relates to acquisition differently depending on initial performance and cognitive ability. Given this study's focus on recovery from initial failure during training, the plot for lower initial training performance at the top of Figure 3 is of particular relevance. For those trainees with lower initial training performance, relatively high motivation (i.e., +1 SD) appeared, to some extent, to reduce the cognitive ability gap that is shown at lower levels of motivation (i.e., -1 SD). Said another way, motivation to learn appeared particularly important for the lower cognitive ability group (as evidenced by the steeper slope) in resulting skill acquisition levels. Though less relevant to this study's primary focus, the pattern of results for trainees with higher levels of early performance (Figure 3, bottom graph) also warrants consideration, as discussed below.

Results of a post hoc power analysis (presented in Table D2–Appendix D) indicated there was sufficient power (i.e., $> .80$) to detect a moderate effect for each fixed effect of interest. The model results were consistent whether the continuous predictors were group-mean centered or grand-mean centered, with the exception that the three-way interaction term was not statistically significant under grand-mean centering. This is not surprising or contradictory of the previous results because Level 1 slopes tend to be biased under grand-mean centering (e.g., Enders & Tofighi, 2007; Hofmann & Gavin, 1998; Raudenbush & Bryk, 2002), making interaction terms difficult to detect.

Discussion

The purpose of the present study was to investigate how individual differences interact with early training performance to influence learning and performance later in training. Specifically, I sought to identify conditions under which trainees could recover from poor initial performance. Several hypotheses and a research question were examined using a field sample of military personnel completing an intensive foreign language training program over a period of several months in preparation for the demands of their jobs.

Hypotheses 1a and 1b posited that general cognitive ability would positively predict both initial and end-of-training learning outcomes. The findings supported both hypotheses, replicating numerous previous studies linking cognitive ability to training outcomes (e.g., Colquitt et al., 2000; Hunter & Hunter, 1984). Hypothesis 2 posited that cognitive ability would moderate the relationship between initial and end-of-training outcomes. While support for this hypothesis was not obtained, other findings (discussed below) suggest the moderating relationship may be more complex than that which was hypothesized.

Hypotheses 3a and 3b stated pre-training motivation to learn would positively predict both initial training performance and end-of-training skill acquisition. The findings indicated motivation to learn was not related to the skills assessment administered early during training. Pre-training motivation to learn was, however, positively related to post-training skill-acquisition. This finding replicates those of previous studies linking trainee motivation to skill acquisition (e.g., Colquitt et al., 2000). The implication is that trainees who hold a stronger desire, at the onset of training, to develop the target skills go on to do so to a greater extent than less motivated trainees. Interestingly, this finding was obtained even though the

reliability of the motivation measure ($\alpha = .67$) was slightly below desirable levels, the sample as a whole was highly motivated to learn (i.e., mean level of 5.72 on a 7-point scale), and motivation was not found to uniquely relate to initial training performance.

An important implication of the finding that pre-training motivation was related to end-of-training skill acquisition but not to early training performance is that the beneficial effects of motivation on learning may take longer to emerge than do the effects of cognitive ability. This finding is consistent with Kanfer and Ackerman's (1989) assertion that, for cognitively demanding tasks, the positive influence of motivational processes (e.g., self-regulatory activities) on learning is expected to be greatest during the later stages of the skill acquisition process. That is, in the later stages of skill acquisition, the cognitive resource demands are reduced, freeing up attentional resources for motivational processes to have their greatest positive influence (Kanfer & Ackerman, 1989).

Hypothesis 4 posited pre-training motivation to learn would moderate the relationship between initial and end-of-training learning outcomes. The direct test of this hypothesis was not supported. Subsequent findings, however, provided insight into the lack of support for both Hypotheses 2 and 4. The research question explored in this study pointed to a three-way interaction between cognitive ability, pre-training motivation to learn, and initial training performance in predicting end-of-training skill acquisition. A thorough decomposition of this interaction revealed the complexity with which cognitive ability and motivation may jointly relate to skill acquisition. With respect to recovery from initially low performance, the findings suggested motivation to learn was particularly important for trainees with lower cognitive ability (see Figure 3, top graph). This finding is consistent with Kanfer and

Ackerman's (1989) resource allocation framework, in that motivation is theorized to drive the way in which learners allocate finite cognitive resources.

This study's purpose was to identify the characteristics that impact how likely people are to recover from initial deficiencies. Thus, I was especially interested in the top half of Figure 3, which focuses on trainees whose initial performance was low. Nevertheless, the bottom half of Figure 3 also provides noteworthy information. The negative effect of motivation on trainees with lower cognitive ability and higher initial performance was unexpected. The following represents speculation as to why this pattern of results emerged. Perhaps more highly motivated trainees with lower cognitive ability engage in strategies which help them up to a certain point (see Figure 3, top graph, where absolute levels of skill acquisition are lower) but become counterproductive at higher skill levels (see Figure 3, bottom graph, where absolute levels of skill acquisition are higher). Research supports the notion that learning strategies that are successful in early phases of skill acquisition are not necessarily successful in later phases (e.g., Ford & Schmidt, 2000). For example, rote memorization of statistical formulas may help achieve early success in a research methods course, but a fixation on memorizing formulas at more advanced stages of the course could tie up cognitive resources needed for alternative strategies necessary for further understanding and integration (i.e., high-level skills).

In effect, cognitive ability may help facilitate the development of high-level skills by helping trainees to effectively channel their motivation – that is, identify and execute effective learning strategies (Kanfer & Ackerman, 1989). If the once-effective learning strategies that resulted in initial success (e.g., rote memorization) become *counterproductive*

at the higher end of the learning continuum, then motivation could actually impede learning if new strategies are not employed. That is, motivation could encourage the effortful persistence of counterproductive strategies, which relatively unmotivated trainees are unlikely to vigorously pursue. Expanding on the example above, if rote memorization of formulas leads to early success in a research methods course, lower cognitive ability trainees who are also more highly motivated may be particularly likely to persist in using the same (or a similar) learning strategy for the duration of training to the detriment of end-of-course performance.

In the current foreign language training context, the aforementioned pattern may explain the declining slope for trainees with low cognitive ability and high initial performance presented in the bottom half of Figure 3. For instance, a learning strategy such as rote memorization of vocabulary lists may have resulted in initial higher performance. However, strict adherence to the rote memorization (or a similar) strategy for the duration of training could have limited one's resources to attain deeper understanding and integration of concepts, which are necessary components of high-level foreign language proficiency. Trainees who achieved early success using a learning strategy such as rote memorization, who were also more highly motivated to learn and had lower cognitive ability, may have failed to identify and employ new strategies (e.g., practicing in novel contexts) necessary for attaining high-level skills. In layperson's terms, perhaps "working harder" can compensate for low cognitive ability up to a point, but eventually "working smarter" becomes imperative.

Taken together, the results for lower and higher initial performers suggest that cognitive ability may matter most at the extremes. Trainees with "two strikes against them"

(i.e., lower initial training performance and lower motivation) especially need it to acquire skill (skill that might otherwise be achieved through motivation, for instance). If everything else is in the trainee's favor (i.e., higher initial training performance and higher motivation), then cognitive ability will set a trainee apart from less capable counterparts with equally high motivation and initial performance.

Implications for Practice and Theory

Understanding the role of motivation to learn may be especially important because of the emerging trends toward increased learner control of training processes (Beier & Kanfer, 2010; Ford & Kraiger, 1995) and its implications for effective training. That is, learners are increasingly becoming responsible for many tasks traditionally performed by instructors or trainers, resulting in learners more directly influencing training outcomes (Ford & Kraiger, 1995). Practically speaking, the current findings suggest there may be value in targeting interventions to learners who demonstrate lower cognitive ability or motivation *and* initial difficulty with training content. These interventions might provide additional encouragement or learning strategies for trainees to persist in their efforts through particularly challenging content. For example, interventions may seek to enhance motivation by vividly illustrating the value, or necessity, of trained skills to performing critical job tasks. The extent to which learners perceive training to be valuable and instrumental to job performance has been argued to affect learner motivation (e.g., Eccles, 2005).

Alternatively, there may be value in providing “facilitators,” or perhaps even substitutes, for certain cognitive processes which some trainees are less likely to engage in. For example, certain self-regulatory processes, such as self-monitoring, could be automated

to some extent in computer-based training environments. Self-monitoring (i.e., attending to one's behaviors and actions to ensure they correspond to valued learning goals; Kanfer, 1987), could be supplemented by software or hardware that closely monitors learner behaviors, such as content sequencing or pace, mouse movements, and eye tracking, and provides constructive feedback. Scholars (e.g., Cannon-Bowers & Bowers, 2010; Cannon-Bowers, Burns, Salas, & Pruitt, 1998) have called for research into incorporating such dynamic assessment, monitoring, and feedback into synthetic-learning environments used for workplace learning.

An important conclusion from this study is that cognitive ability and motivation to learn appeared to, in part, compensate for one another to allow initially unsuccessful trainees to attain greater levels of skill by the end of training. That is, while general cognitive ability was found to relate to skill acquisition, the extent of this relationship depended on trainee motivation and initial training success. Motivation to learn at the onset of training was also related to skill acquisition, but this relationship depended on both cognitive ability and initial training success. This finding suggests current models of training effectiveness do not capture the full complexity of the relationships between these key trainee characteristics and training outcomes. That is, the theory-driven predictors examined in this study clearly mattered to training success, but not always in the straightforward manner that was hypothesized. Given the practical value of better understanding how learners can cope with difficulty to achieve success during training, future research should further explore this issue and evidence-based solutions for training organizations.

Contributions

The present study contributes to prior research by (a) distinguishing between learning outcomes demonstrated early in training from those demonstrated later in training, (b) investigating how learner characteristics relate to both early and later training outcomes, and (c) examining how learner characteristics relate to the degree to which people recover from early failures during training. This study addresses calls for additional research into how context factors interact with individual differences to produce (or inhibit) learning outcomes (Alvarez et al., 2004; Gully & Chen, 2010; Herold et al., 2002).

One limitation of prior research into both training performance and skill acquisition involves the way in which these variables have been operationalized. Training performance and skill acquisition have typically been assessed using measures obtained at the conclusion of training or aggregates of assessments administered throughout training (e.g., Alliger, Tannenbaum, Bennett, & Traver, 1997; Kubeck, Delp, Haslett, & McDaniel, 1996). Aggregated and post-only measures of performance reflect the cumulative result or end-state of the training process. While not invalid approaches to the study of learning, such measures lack information on individual differences in the progression of learning (i.e., learning trends) during training (Herold et al., 2002). Thus, extending research to incorporate multiple measures of learning allows for a deeper understanding of learning dynamics.

Another notable limitation of prior research is the lack of field studies extending findings obtained in controlled laboratory settings to real-world instructional settings. As noted by prior authors (Aguinis & Kraiger, 2009; Chen & Mathieu, 2008), few prior empirical studies have provided evidence demonstrating how individual differences relate to skill acquisition during training when real-world benefits and consequences are at stake. The

current study addresses this deficiency by following a sample of trainees in a real-world training context with job implications contingent on training outcomes.

Prior research examining how individual differences relate to learning outcomes assessed throughout training has employed a narrow range of learning tasks. The majority of research has relied on computer-based simulations (e.g., air traffic control tasks, games, etc.). Researchers (e.g., Yeo & Neal, 2004) have called for more research employing novel learning tasks. In response to these calls, the current study extends prior research by focusing on a cognitively demanding training task seldom studied in industrial/organizational psychology and related disciplines.

Limitations and Future Research

One potential limitation of this study is the possible restricted range on the cognitive ability and motivation to learn variables. Members of the trainee population are selected into the organization based, in part, on their cognitive ability (i.e., AFQT) scores. This led to a direct restriction of range, such that trainees with higher than average cognitive ability were overrepresented in the study sample. However, trainee selection was not solely based on AFQT scores, providing sufficient variability in this measure.

In a similar vein, trainees self-select into this organization knowing that language training is required. This may have led to trainees lower in motivation being underrepresented in the study sample; trainees included may be more motivated to learn a foreign language than those found in other organizations. Within the sample population, there are individuals who consider the foreign language training to be an undesirable requirement (i.e., it is not central to what attracted them to the job). Nonetheless, future research should

seek to replicate these findings with training populations that are more diverse with respect to learning ability and training motivation.

Another potential limitation is the quasi-experimental nature of the current study design. With such a design, it is not possible to conclude with certainty that the predictor variables examined imposed a causal effect on any outcome variable. This study did employ strategies to reduce confounding influences on the observed relationships. For example, study variables were operationalized using both self-reports and objective performance measurements to reduce the likelihood of common method bias. All predictor variables also have temporal precedence with respect to the training outcome variables, in that measurement occurred over time and predictor measurement came before outcomes were assessed. Also, controlling for training language should help to reduce potential confounds due to situational factors unrelated to study hypotheses. While such steps have been taken to reduce threats to internal validity, it is important to acknowledge that the correlational design limits our ability to conclude causal relationships. Future research that replicates or extends the present findings in more controlled training environments would increase confidence that cognitive ability and learner motivation either directly or indirectly cause learning or skill acquisition.

There is also a need for future research on the role of performance feedback during training on the ability of trainees to recover from early difficulties. The current study did not investigate how specific characteristics of the performance feedback trainees receive may influence the relationships between cognitive ability, motivation, and subsequent performance. For instance, feedback designed to bolster trainees' internal locus of control

(Martocchio & Dulebohn, 1994) and to provide constructive encouragement (London, 1995) may result in relatively positive trainee reactions and learning outcomes. These and other features of performance feedback may change the nature of the relationships found in this study – an issue which warrants future research attention.

Summary and Conclusion

Training performs a vital function in organizations today. Organizations rely heavily on training to develop and sustain human capital, and the competitive advantage it creates (Salas & Kozlowski, 2010). However, the advantages of effective training are not without costs. The design, development, implementation, and evaluation of training are resource-intensive and time consuming processes. One goal of training research is to provide evidence that informs decision-making for each step in this process, enabling organizations to maximize the outcomes of training. There exist real-world complexities which may be difficult to detect in laboratory and cross-sectional studies. The current study identified several factors that may interactively influence learning outcomes in long-term training using trainees from a real-world organization training to meet the demands of their jobs. Among trainees with lower levels of initial performance, motivation to learn partially offset the detrimental effects of lower cognitive ability on skill acquisition. But motivation did not always benefit trainees. Among trainees who began with higher performance, motivation in the absence of sufficient cognitive resources appeared to impede skill acquisition.

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Table 1. *Skewness and Kurtosis of Study Variables*

Variable	Raw data		After transformation	
	Skewness	Kurtosis	Skewness	Kurtosis
Cognitive ability	-.45	-.26	-	-
Motivation to learn	-.66	.01	-	-
Post-training skill acquisition	.29	-.11	-	-
Initial training performance	-.97	1.52	0.17	0.21

Table 2. *Descriptive Statistics for Study Variables*

Variable	<i>n</i>	Mean	<i>SD</i>	Correlations			
				1	2	3	4
1. Cognitive ability	578	227.73	17.90	-			
2. Motivation to learn	578	5.72	0.85	.05	-		
3. Initial training performance ^a	578	86.20	3.31	.26**	.12**	-	
4. Post-training skill acquisition	511	35.23	5.55	.28**	.11*	.12**	-

^a Statistics were calculated after this variable was transformed. For descriptive purposes, mean and standard deviation were then reverse-transformed back into a percentage.

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

Table 3. *Unstandardized Coefficients of Multilevel Models of Initial Training Performance*

Fixed Effects	Model 0 (Null)	Model 1	Model 2
Intercept, γ_{00}	1.196***	1.163***	1.163***
Language—Arabic, γ_{01}	-	.114***	.115***
Language—French, γ_{02}	-	-.105**	-.104**
Language—German, γ_{03}	-	.126*	.127*
Language—Indonesian, γ_{04}	-	-.035	-.035
Language—Korean, γ_{05}	-	.211***	.211***
Language—Persian-Farsi, γ_{06}	-	-.022	-.023
Language—Russian, γ_{07}	-	.129*	.129*
Cognitive Ability _{cwc} , γ_{10}	-	-	.002***
Motivation to Learn _{cwc} , γ_{20}	-	-	.005
Random Effects			
Mean Initial Training Performance (τ_{00})	.016***	.007***	.007***
Within-class Variability (σ^2)	.018***	.018***	.016***

Note. $N(\text{students}) = 578$. $N(\text{classes}) = 87$. Spanish represented the reference language group.

CWC indicates variable was centered within cluster. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 4. *Summary of Study Findings*

Hypothesis/Research Question	Finding
1a. Cognitive ability will predict initial performance.	Supported
1b. Cognitive ability will predict end-of-training skill acquisition.	Supported
2. Cognitive ability and initial performance will interact to predict end-of-training skill acquisition.	Not Supported ^a
3a. Motivation to learn will predict initial performance.	Not Supported
3b. Motivation to learn will predict end-of-training skill acquisition.	Supported
4. Motivation to learn and initial performance will interact to predict end-of-training skill acquisition.	Not Supported ^a
RQ. Is there a three-way interaction between cognitive ability, motivation to learn, and initial performance?	Yes

^a Note that a three-way interaction including these variables was found when evaluating the Research Question.

Table 5. *Unstandardized Coefficients of Multilevel Models of Post-training Skill Acquisition*

Fixed Effects	Model 0 (Null)	Model 1	Model 2	Model 3	Model 4
Intercept, γ_{00}	35.205***	37.557***	37.551***	37.503***	37.436***
Language—Arabic, γ_{01}	-	-5.293***	-5.291***	-5.296***	-5.239***
Language—French, γ_{02}	-	-2.087*	-2.095**	-2.157**	-2.125**
Language—German, γ_{03}	-	-3.726**	-3.743**	-3.731**	-3.657**
Language—Indonesian, γ_{04}	-	2.095*	2.099*	2.183*	2.263*
Language—Korean, γ_{05}	-	-2.279*	-2.272*	-2.309*	-2.164
Language—Persian-Farsi, γ_{06}	-	-1.307	-1.301	-1.266	-1.732
Language—Russian, γ_{07}	-	-4.172**	-4.155*	-4.142**	-4.168**
Cognitive Ability _{cwc} , γ_{10}	-	-	0.100***	0.080***	0.081***
Motivation to Learn _{cwc} , γ_{20}	-	-	0.617*	0.544*	0.369
Init. Perf. _{cwc} , γ_{30}	-	-	-	10.380***	10.000***
Init. Perf. _{cwc} X Cognitive Ability _{cwc} , γ_{40}	-	-	-	0.120	0.105
Init. Perf. _{cwc} X Motivation to Learn _{cwc} , γ_{50}	-	-	-	-2.524	-2.842
Cognitive Ability _{cwc} X Motivation to Learn _{cwc} , γ_{60}	-	-	-	-	0.009
Init. Perf. _{cwc} X Cognitive Ability _{cwc} X Motivation _{cwc} , γ_{70}	-	-	-	-	0.246*
Random Effects					
Mean Post-training Skill Acquisition (τ_{00})	7.011***	1.593*	2.058*	2.269**	2.410**
Within-class Variability (σ^2)	23.818***	23.786***	20.534***	18.943***	18.767***

Note. $N(\text{students}) = 511$. $N(\text{classes}) = 80$. Spanish represented the reference language group. CWC indicates variable was centered

within cluster. * $p < .05$, ** $p < .01$, *** $p < .001$.

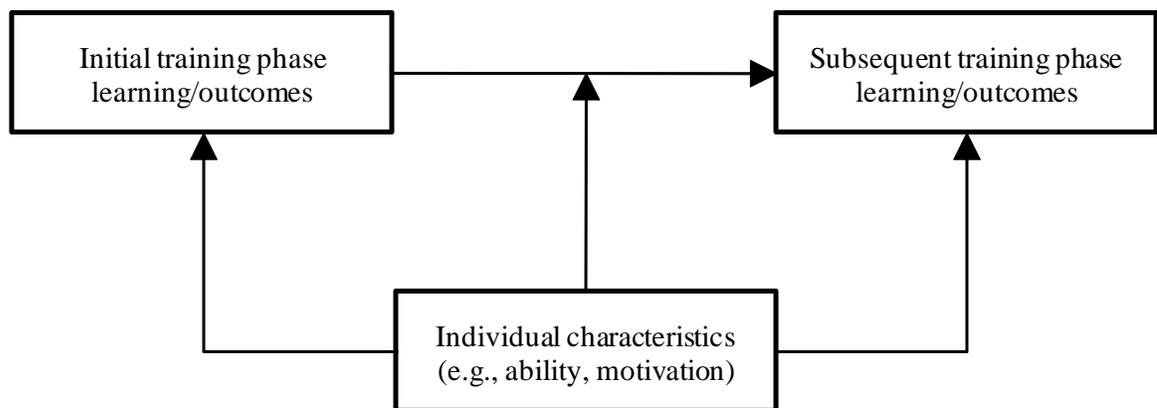


Figure 1. Conceptual Model of Individual Differences Relating to Early and Late Training Outcomes. Adapted from “Dispositional Influences on Transfer of Learning in Multistage Training Programs,” by D. Herold, W. Davis, D. Fedor, and C. Parsons, 2002. *Personnel Psychology*, 55, p. 853. Copyright 2002 by Wiley Periodicals, Inc.

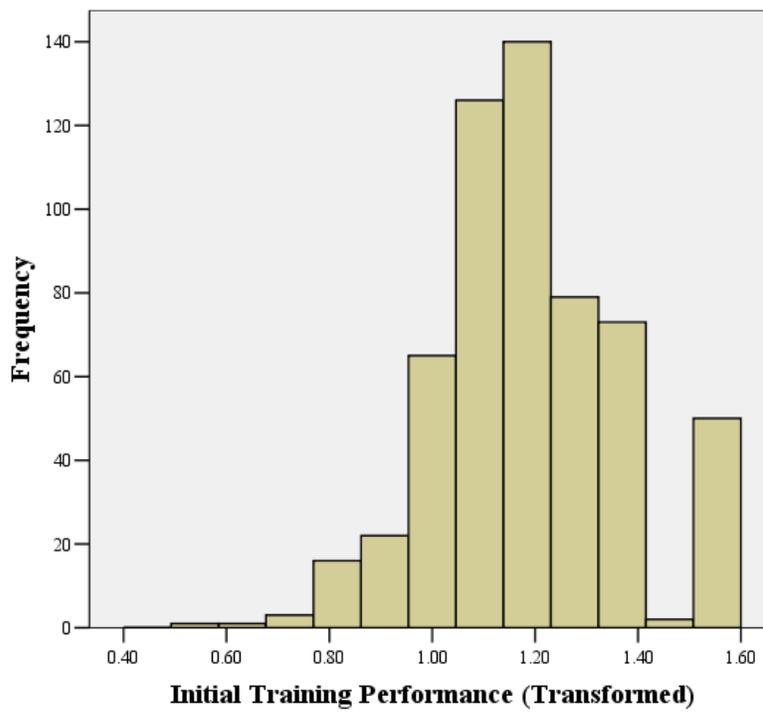
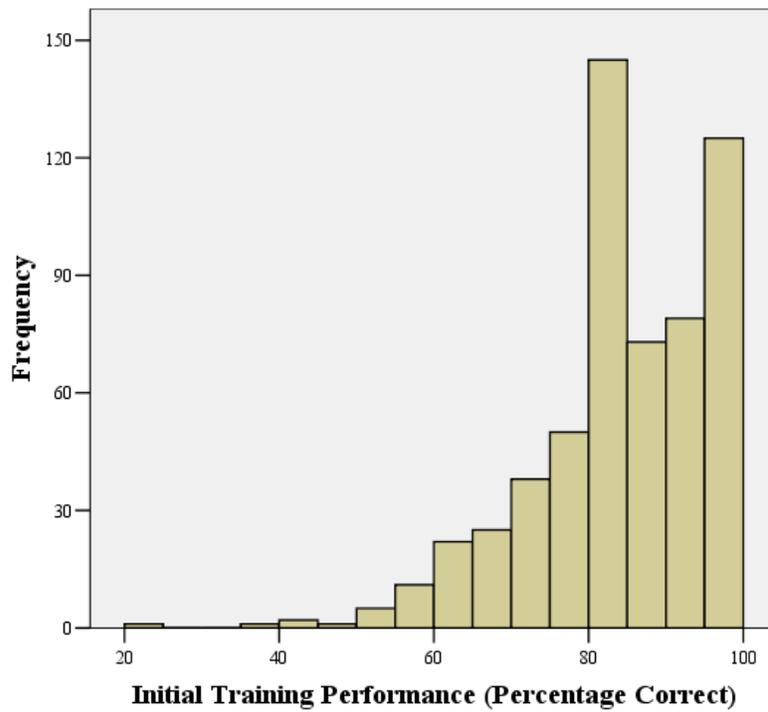


Figure 2. Original and Transformed Distributions of Initial Training Performance

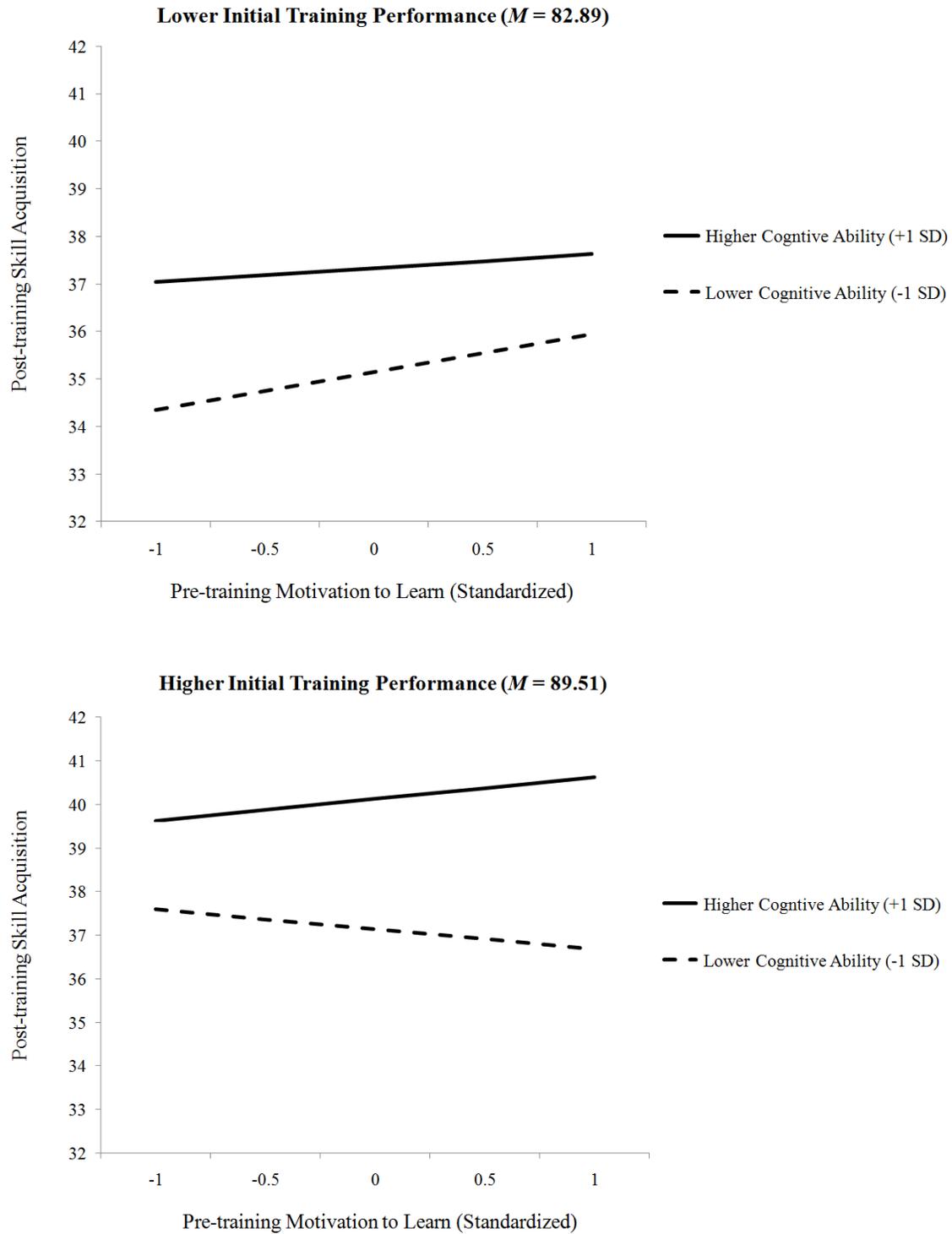


Figure 3. Three-way Interaction Plotted by Lower and Higher Initial Training Performance

Appendices

Appendix A

Dissertation Proposal

Cognitive and Motivational Influences on Performance Improvement during Training

By
Aaron Michael Watson

A proposal submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Psychology

Raleigh, North Carolina

2010

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Figure A3. Hypothesized Interaction between Motivation to Train and Initial Training Performance on End-of-Training Outcomes. 85

Employee training is both a vital and resource-intensive process in organizations. The changing nature of work, characterized by the increased necessity to adapt to changes both within and outside one's organization, has increased the need for ongoing training and personnel development in today's organizations. Training represents a necessary function for organizations to be successful in meeting the demands of a dynamic market environment (Goldstein & Ford, 2002), adapting to technological change, and accommodating the expansion of knowledge and human capital within organizations (Preskill, 1994). These conditions have increased the rate with which job roles change, requiring workers and their employers to continue to develop their knowledge, skills, and competencies (i.e., intellectual capital) (Mayo, 2000). In 2007, organizations in the United States spent approximately \$58.5 billion for training, which was an increase of 9.6% from the \$53.4 billion spent just five years earlier in 2002 (Training, 2007). With such high levels of investment in training and development, it is important for organizations to understand factors shaping the success of training on human capital and organizational capability.

Training effectiveness research has enhanced our understanding of the inputs, processes, results, and organizational impact of training initiatives (Salas & Cannon-Bowers, 2001). This line of research has identified a number of individual and situational characteristics that influence training outcomes (e.g., learning, transfer of training, etc.). While theory in this area continues to grow, there are certain areas in need of greater research to support, develop, and refine available theory. One such area pertains to the processes through which people learn and acquire new skills during training, particularly when faced

with challenges early in training. There remain unanswered questions regarding the trainee characteristics that impact how likely people are to recover from initial deficiencies during training. This area of research is particularly needed in long-term, cognitively demanding training contexts. Such training contexts are becoming increasingly prevalent in organizations, with corporate university courses providing an example of employee training which may take weeks or even months to complete (Prince & Stewart, 2002).

Practically speaking, it would be useful for organizations and learners to understand when and through which mechanisms people who struggle early in training subsequently recover and achieve acceptable results (Bandura, 1997; Schmidt & DeShon, 2009). There is limited empirical research addressing this issue, particularly in field settings. The purpose of the current study is to investigate how individual factors and early training performance interact to influence subsequent performance in long-term training. Specifically, this study sought to identify how motivation and cognitive ability relate to learners' ability to recover from early difficulties during training and achieve greater subsequent performance and skill acquisition at the conclusion of training.

Learners as Active Agents

The training effectiveness research field examines factors contributing to the success of training in organizational settings. This area of research seeks to better understand variables that impact "training outcomes at different stages (i.e., before, during, and after) of the training process" (Alvarez, Salas, & Garofano, 2004, p. 387). Several influential models of training effectiveness have emerged summarizing and integrating the state of knowledge in the field (e.g., Alvarez et al., 2004; Baldwin & Ford, 1988; Cannon-Bowers, Salas,

Tannenbaum, & Mathieu, 1995; Holton, 2005). For instance, Alvarez et al. (2004) reviewed 10 years of research in the training effectiveness and evaluation domain and, based on the consistency of available research findings, proposed an integrated model of training evaluation and effectiveness. This model posits how individual, training, and other characteristics impact changes in learners (i.e., learning) and organizational results.

In early training research, the predominant view of the learner was one of a “passive recipient, rather than an active participant, in training interventions” (Bell & Kozlowski, 2008, p. 296). That is, there was a strong emphasis placed on rigid structuring and sequencing of training content to produce a standardized experience with little or no learner control (Smith, Ford, & Kozlowski, 1997). Less emphasis was placed on understanding more learner-centered processes, such as self-regulation and information processing. This resulted in a notable gap in the literature.

More recent theory and research have emphasized the view of learners as active agents in the learning context (e.g., Beier & Kanfer, 2009; Bell & Kozlowski, 2008; Gully & Chen, 2009). Gully and Chen (2009) assert that learners “decide what to attend to, determine how much effort they will devote, and actively engage themselves, or disengage themselves” (p. 4-5). Increases in the availability and adoption of computer-based and other learner-driven training solutions have shifted much of the responsibility onto individual learners (as opposed to trainers or instructors) to engage and develop their skills (Beier & Kanfer, 2009). As learner control increases, individuals’ behavioral tendencies, cognitive capabilities, and attitudes are likely to exert more influence on the direction, intensity, and persistence of effort and, ultimately, training outcomes (Ford & Kraiger, 1995).

Examining Individual Differences in Performance Improvement

Although research evidence illuminating the mechanisms through which individual differences shape learning outcomes is limited, empirical research into active learning has enhanced our understanding of how distal and proximal learner characteristics impact learner choices and goals and, in turn, training outcomes (e.g., Bell & Kozlowski, 2008). There is virtual consensus that the success of training depends on both learner characteristics and contextual factors. However, a debate exists concerning the extent to which the contributions of each are additive or dependent on one another (e.g., Sackett, Gruys, & Ellingson, 1998). That is, training outcomes are thought to depend on the configuration of individual and contextual factors involved in the learning and organizational environment. The question is to what extent does the impact of specific individual differences vary as a function of contextual factors (and vice versa)? The possibility of such interactions renders broad claims of direct (i.e., main effect) relationships difficult to endorse without sufficient evidence ruling out more complex relationships (Alvarez et al., 2004). It is clear that additional research is needed to better understand potential complex interactive relationships to move the training effectiveness discipline forward (Aguinis & Kraiger, 2009; Alvarez et al., 2004).

One particular interaction which warrants investigation pertains to the manner in which individual differences interact with early training performance (and feedback) to predict subsequent performance and skill acquisition at the conclusion of training. Do early performance problems forecast later deficiencies for all trainees, or are certain types of trainees more likely than others to recover from difficulties encountered early in training? Past researchers have emphasized the benefits that may be gained from a clearer

understanding of how individuals cope with and respond to difficulties encountered in learning contexts. For instance, Bandura (1997) states that understanding how individuals cope with challenges in the learning process can advance theory, as well as lead to practical interventions enabling learners to more adaptively respond to such challenges.

To address this issue, empirical studies have investigated the mechanisms through which early training performance relates to later training performance (e.g., Herold, Davis, Fedor, & Parsons, 2002; Schmidt & DeShon, 2009). Some research (e.g., Chen & Mathieu, 2008; Herold et al., 2002) suggests dispositional characteristics may play a role in determining whether or not individuals can recover from poor performance early in training. In their study of a two-phase aviation training program, Herold et al. (2002) found that trainee personality characteristics interacted with training performance in the initial phase in the prediction of performance in the second stage. Specifically, these authors showed that highly conscientious learners were able to improve upon initially low training performance to a much greater extent than learners low in conscientiousness (Herold et al., 2002).

Schmidt and DeShon (2009) examined the interaction between goal-performance discrepancies and self-efficacy in the prediction of subsequent performance on a computer-based problem solving task. Results indicated that the nature of the relationship between self-efficacy and later task performance depended, in part, on initial task performance (Schmidt & DeShon, 2009). While Schmidt and DeShon's (2009) work substantially contributes to what is known about training dynamics, a key limitation to their study is the artificial nature of the training task, which was a computerized analytical game involving identifying visual patterns in a color-coded display.

The current study adds to the existing empirical evidence in this area by examining the roles of previously unstudied individual differences and doing so in a long-term, real-world training context. As discussed next, general cognitive ability and motivation to train are two individual differences which are likely to affect not only pre- and post-training outcomes, but also the degree to which trainees rebound after initial failures. We consider the direct effects of each individual difference variable on early and end-of-training performance and skill acquisition. In addition, we develop hypotheses addressing the manner in which cognitive ability and motivation to train should interact with early training performance to predict subsequent performance and skill acquisition.

General cognitive ability. General cognitive ability (hereafter referred to as cognitive ability) is defined as the knowledge and capacities needed to acquire, encode, retrieve, actively process, and use information and concepts in novel situations (Humphreys, 1979). Some have referred to cognitive ability simply as the ability to learn (e.g., Hunter, 1986). Cognitive ability has been linked to a variety of learning outcomes by many influential models of training effectiveness (e.g., Alvarez et al., 2004; Baldwin & Ford, 1988; Cannon-Bowers et al., 1995; Mathieu, Tannenbaum, & Salas, 1992).

Research has consistently demonstrated the positive influence of cognitive ability on task performance in simulated cognitively demanding learning contexts (e.g., Ackerman, 1986, 1990, 1992; Ackerman & Cianciolo, 2000; Kanfer & Ackerman, 1989). For instance, Kanfer and Ackerman (1989) examined the interaction between cognitive ability and goal-setting on learning performance on an air traffic control task. These authors found learners high in cognitive ability generally achieved higher task performance initially and sustained

high performance levels across multiple trials (Kanfer & Ackerman, 1989). Eyring, Johnson, and Francis (1993) tested the relationship between cognitive ability and performance on an air-traffic controller task in undergraduate students. These authors found high ability learners needed fewer practice trials to achieve the same level of performance as low ability learners (Eyring et al., 1993). In a field setting, Deadrick, Bennett, and Russell (1997) examined the production rate of sewing machine operators during their initial six months of employment. Workers higher in cognitive ability showed greater increases in production compared to those lower in ability (Deadrick et al., 1997). Thus, cognitive ability facilitates rapid skill acquisition and skills that are more robust to attrition.

Meta-analyses summarizing numerous primary studies have supported the linkage between cognitive ability, learning, and job performance (Colquitt, Lepine, & Noe, 2000; Hunter & Hunter, 1984). For instance, Hunter and Hunter (1984) found cognitive ability strongly predicted skills acquired in training (mean validity of approximately .55) across a variety of jobs. Research findings have generally supported theory in that cognitive ability has been found to be especially predictive of performance when training tasks are cognitively demanding (i.e., complex) (c.f. Kanfer & Ackerman, 1989). In the context of a cognitively complex training task, we therefore hypothesized the following.

H1: Trainees higher in cognitive ability will show greater (H1a) initial performance and (H1b) end-of-training learning outcomes compared to those who are lower in cognitive ability.

Cognitive ability may not only impact early and late learning outcomes, as suggested by Hypothesis 1. It should also influence the *relationship* between early and late outcomes.

That is, cognitive ability should help explain the degree to which people recover from early difficulties in training. Adapted from Herold et al. (2002), Figure A1 presents this conceptual relationship. As indicated in this conceptual model, early training outcomes (e.g., training performance, skills test scores) can serve as predictors of later training outcomes. That is, trainees' performance early on may be indicative of how they will perform during later phases of training. However, this may be truer for some trainees than others, which emphasizes the need for empirical work investigating who does and does not recover from early training performance problems.

While cognitive ability has been frequently studied in the training domain, relatively little is known about the way in which cognitive capabilities interact with early training performance to influence learning trends *during* long-term training. Scholars (e.g., Aguinis & Kraiger, 2009; Gully & Chen, 2009; Herold et al., 2002) have called for more research into the dynamics of the learning process during training as they relate to characteristics of the learner (e.g., cognitive ability). Aguinis and Kraiger (2009) specifically call for more research into how cognitive ability influences the “rate and depth of learning during training” (p. 467).

Past research suggests the complexity of the ability-acquisition relationship may be obscured with the cross-sectional designs so often employed in training research (Yeo & Neal, 2004). In a longitudinal field study, Yeo and Neal (2004) found evidence of a complex ability-acquisition relationship. These authors demonstrated that cognitive ability moderated the relationship between effort and performance improvement over time in undergraduate students learning an air-traffic control task (Yeo & Neal, 2004). Specifically, effort became

more strongly predictive of task performance over time for learners higher in cognitive ability compared to lower ability learners.

Previous theoretical development provides a solid foundation from which to hypothesize the role of cognitive ability in skill acquisition. Kanfer and Ackerman's (1989) resource allocation framework is an influential and well-supported model positing the roles of learner ability and motivation in the acquisition of new skills. This framework indicates that learner attention (or effort) is a limited resource, which can be directed toward on-task, off-task, or self-regulatory processes (Kanfer & Ackerman, 1989). Cognitive ability represents the amount of attentional resources available at any given time. When attentional demands are high (e.g., for challenging or novel tasks), trainees' cognitive ability will strongly relate to the acquisition of new skills (Kanfer & Ackerman, 1989). This relationship is expected to diminish in magnitude as resource demands of the training task decrease (Kanfer & Ackerman, 1989). That is, for cognitively demanding learning environments, people with greater cognitive resources (i.e., cognitive ability) should be more capable of acquiring and maintaining new knowledge and skills compared to those with fewer cognitive resources (e.g., Kanfer and Ackerman, 1989). Early training performance can serve as an indicator of the demands of training for individuals. That is, lower initial training performance is likely indicative of training that is more challenging to a given individual. Thus, under conditions in which the demands of training are high (as indicated, for example, by initial low training performance), people with greater cognitive ability will likely be able to subsequently outperform those with lower cognitive ability.

Said another way, cognitive ability is likely an important factor determining learners' ability to adapt to difficulties experienced in training. In their conceptual model of training effectiveness, Gully and Chen (2009) consider information processing capacity (i.e., cognitive ability), along with trainee motivation, metacognitive processing, and emotional regulation, to be an important intervening mechanism through which more distal individual differences and initial training performance may interact to influence later learning outcomes. Higher cognitive ability should allow for greater attentional resources to be dedicated to the on-task and self-regulatory processes (Kanfer & Ackerman, 1989) needed to “catch up” to those with higher initial performance.

Given the preceding rationale, it follows that the positive impact of cognitive ability on end-of-training performance outcomes should be more pronounced among learners whose initial level of training performance is low compared to those whose initial performance level is high, as high initial performers—even those who are relatively low in cognitive ability—are not taxed with the demands of “playing catch-up.” The following hypothesis (presented graphically in Figure A2) was evaluated in this study.

H2: Cognitive ability will moderate the relationship between initial training performance and end-of-training outcomes. Initial training performance will be more predictive for learners lower in cognitive ability than it is for learners higher in cognitive ability.

Pre-training motivation to learn. In addition to cognitive ability, pre-training motivation to learn is also considered a key antecedent of learning. Noe (1986) defines this as a trainee's specific desire to learn the content of a training program. In the learning context,

motivation has been characterized as governing one's choice of direction, level, and persistence of effort (Campbell, 1990; Kanfer & Ackerman, 1990). The critical mechanism linking learner motivation to training outcomes is the allocation of effort (Kanfer, 1990). That is, those motivated to learn the training task are expected to allocate greater cognitive and behavioral resources to relevant learning tasks compared to less motivated learners. Understanding the role of motivation to train may be especially important because of the aforementioned emerging trends toward increased learner control of training processes (Beier & Kanfer, 2009; Ford & Kraiger, 1995) and its implications for effective training. That is, learners are increasingly becoming responsible for many tasks traditionally performed by instructors or trainers, resulting in learners more directly influencing training outcomes (Ford & Kraiger, 1995).

As previously suggested, Gully and Chen (2009) consider trainees' motivation to learn to be an important mechanism through which distal individual differences and situational factors impact learning. Learner motivation is expected to influence the allocation of attentional resources, which are limited in capacity (Kanfer & Ackerman, 1989). At any given time, effort may be directed toward on-task, off-task, or self-regulatory processes (Kanfer & Ackerman, 1989). More highly motivated learners are expected to devote greater effort toward on-task and self-regulatory process (necessary for effective learning), rather than off-task processes and behaviors. This efficient allocation of learner resources should result in greater skill acquisition, particularly with difficult training tasks (Kanfer & Ackerman, 1989).

The relationships between learner motivation and training outcomes have been well-documented both theoretically (e.g., Beier & Kanfer, 2009) and empirically (e.g., Colquitt et al., 2000). In their meta-analysis, Colquitt et al. (2000) showed that motivation to learn predicts cognitive-based, skill-based, and affective-based learning outcomes. In addition, the impact of motivation on actual learning was independent of cognitive ability (Colquitt et al., 2000). Thus, given prior research, we hypothesized the following.

H3: Trainees higher in motivation to train will show greater (H3a) initial performance and (H3b) end-of-training learning outcomes compared to those who are lower in motivation to train.

Motivation to train may not only impact early and late learning outcomes, as suggested by Hypothesis 3. It is also expected to influence the relationship between early and late outcomes. As depicted in Figure A1, trainees' performance early in training is likely indicative of how they will perform during later phases of training—but more so for some trainees than others. As with cognitive ability, motivation to train should help account for the degree to which people recover from early training performance deficits. Although there is a great deal of evidence linking motivation to knowledge and skills attained at the conclusion of training, there is less empirical evidence documenting the influence of motivation on learning dynamics that take place during training.

Motivation upon entering training should play an especially important role in learning dynamics by influencing how trainees deal with early failures, thus affecting the likelihood that trainees will overcome challenges encountered early on. Goal setting theory speaks to this assertion. People who enter training with high levels of motivation are likely to set high

goals, which in turn foster subsequent motivation. Goal-setting is a specific self-regulatory process linked to increased learning over time (Locke & Latham, 2002). The learning goals one sets during training can be both an antecedent of learning, as well as an outcome of learning. For example, research suggests achievement during training is partially a function of learning goals (Locke & Latham, 2002). That is, trainees who set and strive for higher goals are expected to show greater achievement. Achievement, in turn, predicts future learning goals, which in turn predict future achievement (Locke & Latham, 2002).

Early training successes and failures represent important forms of feedback shaping learners' subsequent goals (e.g., Schmidt & DeShon, 2007). Feedback provides diagnostic information with which trainees can gauge progress towards their goals. When feedback indicates low performance, learners with high goals will experience greater goal-performance discrepancies than will their counterparts with more modest goals. In other words, when initial performance is low, trainees whose high levels of motivation have prompted them to set high goals will be especially prone to goal-performance discrepancies. Self-regulation theories suggest goal-performance discrepancies derived from performance feedback are particularly important in determining subsequent effort of trainees (e.g., Schmidt, Dolis, & Tolli, 2009).

Discrepancies between one's performance goals and actual performance result in either reallocating attentional resources or revising goals downward. Contextual pressures and individual differences may influence which of these strategies is chosen (DeShon & Gillespie, 2005). Many times, training goals equate to standards, which are imposed externally. Highly motivated trainees are unlikely to revise such goals downward. Instead,

motivated trainees with sub-standard performance are expected to reallocate attentional resources (e.g., increased effort level, decreased off-task time) due to the goal-performance discrepancy. In this manner, the degree to which initially low performing trainees remain “stuck” in a cycle of low performance should in part depend on motivation.

Motivation to learn could also impact how trainees respond to initial performance deficiencies by influencing the interpretation of feedback received early in training. High motivation to learn or master a trained skill may be considered analogous to the adoption of a mastery goal orientation, as described by Dweck and Leggett (1988). These authors state that trainees who are highly motivated interpret performance outcomes (e.g., training assessments) as feedback on their learning strategies and effort. These types of trainees tend to view critical feedback as a challenge to be overcome (DeShon & Gillespie, 2005). Negative feedback (e.g., poor task performance) thus results in shifts in learning strategies or increased effort for these trainees (Dweck & Leggett, 1988). Therefore, it is expected that trainees with high motivation to learn will respond more constructively to initial performance deficiencies compared to less motivated trainees.

Some researchers have examined how motivation to learn relates to outcomes across multiple training events. Sitzmann, Brown, Ely, Kraiger, and Wisher (2009) examined the longitudinal impact of motivation to train on learning over the course of several training programs (i.e., multi-phase training). Results were mixed and did not conclusively indicate higher motivation resulted in greater learning (Sitzmann et al., 2009). However, these authors did find that motivation positively related to reactions at the end of each training phase, which, in turn, led to higher motivation and expectations for subsequent phases (Sitzmann et

al., 2009). These findings support the notion that motivation to learn leads to a positive training experience and increased desire to participate and learn in subsequent training activities.

The role of motivation during training warrants further investigation. In accordance with training theory, the potential benefits of motivation (e.g., increased on-task effort, reduced off-task attention) are expected to be more fully realized in those who encounter initial difficulties in training (i.e., poor performance). Trainees who achieve high levels of performance early in training are not expected to show subsequent performance gains that are as strongly attributable to motivation compared to trainees with lower initial performance levels. The present study tested this hypothesis, which is presented graphically in Figure A3.

H4: Motivation to train will moderate the relationship between initial training performance and end-of-training outcomes. Initial training performance will be more predictive for learners lower in motivation than it is for learners higher in motivation.

Exploring a Higher-order Interaction between Ability, Motivation, and Initial Performance

The aforementioned hypotheses *independently* consider how cognitive ability and motivation to learn interact with early training performance in the prediction of subsequent training success. However, theory suggests both are necessary but not sufficient for maximizing skill acquisition. According to Kanfer and Ackerman's (1989) information processing framework, cognitive ability represents the upper limit of attentional resources available to dedicate to the on-task and self-regulatory processes necessary to acquire new skills. Motivation is expected to lead to the appropriate and efficient allocation of those

cognitive resources, which will result in maximal learning and performance for challenging tasks (Kanfer & Ackerman, 1989). For a demanding task, maximum performance requires both a high level and efficient allocation of available attentional resources. This is consistent with the notion learner *trainability* (Noe & Schmitt, 1986; Wexley & Latham, 1981), which varies as a function of both learner ability and motivation.

Thus, theory suggests the possibility of a higher-order interaction among the variables investigated in this study. As the research literature is arguably too young to support a specific prediction regarding the precise nature of the potential interaction, we examined this prospect in the form of a research question.

RQ: Will there be a three-way interaction among cognitive ability, motivation to learn, and initial training performance when predicting end-of-training learning outcomes?

Method

Sample

The sample consisted of (__) military personnel participating in foreign language training at a large military installation in the southeastern United States. Approximately (__%) of trainees were native English speakers. The highest level of education achieved by trainees was a high school diploma or GED (__), followed by (__) completing some college, (__) with a BA/BS, (__) with a Master's degree, and (__) with a Ph.D. While age was not measured in this study, the typical age range of this trainee population falls between 24 and 29 years-old.

Training Context

The training context was a foreign language training course participants were required to complete as a part of a broader job training and certification program. These trainees completed the course between July 2005 and July 2007. Training took place in a classroom setting, consisting of one instructor and between five and 12 trainees. The content of the training course consisted of a basic introduction to the language (e.g., sounds, alphabet, etc.) followed by training modules centered around job-related topic areas such as formal and informal greetings and social interactions, and conversing about personal backgrounds, regional and national geography, and job-specific (e.g., military-technical) tasks.

The total length of training was four to six months depending on the specific training language to which participants were assigned. Languages considered to be easier for native English speakers to learn (e.g., Spanish, French), as categorized by the Foreign Services Institute of the U.S. Department of State, received less training time compared to more difficult languages (e.g., Modern Standard Arabic, Korean). While total training time (i.e., in-class hours) varied across training languages, the training content was standardized across languages. That is, regardless of the language to which trainees were assigned, the program-of-instruction was designed to teach trainees to perform the same tasks to the same level of proficiency. Training consisted of approximately six hours of instruction per day for five days each week.

To successfully complete the foreign language requirement for their positions, trainees were required to demonstrate a pre-determined minimum level of proficiency on a standardized proficiency assessment at the conclusion of the training course. This minimum

standard was constant across all training languages. While meeting this minimum standard was required to remain in their position, trainees were given a monetary incentive to achieve proficiency above the minimum standard.

Measured Variables

Training outcomes were operationalized in three ways in this study, including early test performance, end-of-training test performance, and post-training skill demonstration.

Initial and end-of-training performance. Tests of learner achievement were administered on five different occasions throughout training. All items on a given achievement assessment (or module skills test) covered only material taught in the previous training module. The content of the course curriculum and associated skills tests were professionally developed and standardized across training languages. That is, trainees in a given language learned and were tested on the same content in each training module as trainees in other languages. Assessments were administered approximately three to five weeks apart during training, depending on the language being trained (i.e., more time elapsed between assessments for languages with longer total training times). Prior to the first skills test, trainees took a practice quiz with the same test and item format as the skills tests.

Each skills test consisted of 50 multiple-choice items developed to test trainees' ability to listen to and understand speech samples performed in the target language. For each test, trainees listened to spoken dialogue in the target language, and subsequently answered questions related to the speech sample. A sample item is presented in Appendix A-1. The final score on each test was calculated as the percentage of items answered correctly. *Initial* training performance was operationalized as the average score of the first and second skills

tests. *End-of-course* training performance was operationalized as the average of the final two skills tests. The decision to average scores from two skills tests was made to guard against chance fluctuations in performance on any given test that would give an overly positive or negative view of an individual's training performance. Averaging the first and last two tests provides a broader picture of early and later training performance than would be provided by considering only the first and last test. All skills test data were obtained from the training organization's official records.

Post-training skill acquisition. At the conclusion of training, skill acquisition was assessed via performance on the listening proficiency portion of the Defense Language Proficiency Test (DLPT), a standardized language proficiency assessment developed by the Defense Language Institute. This assessment measured how effectively trainees could retain, perform, and generalize the language knowledge and listening skills developed during training.

The DLPT is a computer-based test consisting of approximately 60 multiple-choice items developed to measure ability at various levels of proficiency. For the listening test, test takers were exposed to spoken dialogue in the target language and subsequently answered questions related to the speech sample. Final raw proficiency scores were obtained prior to their conversion to the Interagency Language Roundtable (ILR) rating scale, which categorizes raw scores into 11 distinct levels from 'no proficiency' (lowest) to 'functionally native proficiency' (highest). Raw scores were used in place of the converted ILR rating to retain the full range of variability in test performance. Each trainee's official raw score on the DLPT was obtained from the training organization for this study.

General cognitive ability. Trainees' general cognitive ability was assessed using the Armed Forces Qualification Test (AFQT), which is a component of the Armed Services Vocation Aptitude Battery (ASVAB). All trainees took this assessment prior to enlisting in the military. The ASVAB can be completed either in paper-and-paper form or as a computer-adaptive test. Extensive validation efforts (Segall, 2004; Welsh, Kucinkas, & Curran, 1990) have supported the ASVAB as a valid and reliable measure of general and specific cognitive abilities.

Scores on the AFQT component used in this study are a composite of the word knowledge, paragraph comprehension, mathematics, and arithmetic reasoning subtests of the ASVAB. The AFQT has been used as a measure of general mental ability in prior research (e.g., Ree & Earles, 1991). Each trainee's AFQT score was obtained from the training organization's official testing records.

Pre-training motivation to learn. Like much organizational training, this training was required, not optional. Moreover, trainees did not choose which language they wished to learn; the target language was assigned. Accordingly, it was important to measure motivation to train to differentiate trainees on their desire to learn the trained material. A five-item self-report measure of motivation to train was obtained prior to training. This measure was developed for the current study to assess trainees' motivation to learn the target language. Sample items from this scale are, "I would like to learn as many languages as possible" and "I am motivated to perform well in language training so that I will be able to perform my missions more effectively." All scale items are presented in Appendix A-2. Responses were

provided on a 7-point Likert type scale, ranging from 1(*strongly disagree*) to 7(*strongly agree*). The coefficient alpha for this scale was (___).

Control variable. The language to which trainees were assigned was used as a control variable in all analyses in this study for two reasons. First, approximately half of the languages required four months of training, while the other half required six months. Second, it is more difficult for native English speakers (i.e., the majority of the trainee population) to achieve higher training performance and proficiency in certain languages. Controlling for training language allows for the evaluation of the study hypotheses while adjusting for any effects attributable to length of training or specific language effects.

Procedure

Approximately two to three days prior to the beginning of training, trainees were asked to complete a pre-training questionnaire that included the motivation to train self-report measure, among other demographic items and psychological scales. This questionnaire was part of a larger ongoing foreign language training effectiveness study conducted with this specific military organization. Personal identifiers were collected on the pre-training questionnaire in order to link official testing records to questionnaire responses. However, respondents were assured that their responses to the questionnaire would be kept confidential.

Trainees then began the foreign language training course. At pre-determined points in the curriculum, trainees completed skills tests covering the associated training module. The first test occurred three to five weeks after the beginning of the training course. The last test occurred two to three weeks before the course's conclusion. Trainees received feedback on

their test performance after each exam. At the conclusion of training, trainees took the standardized proficiency test (DLPT) assessing skill acquisition. All test results were obtained after trainees had completed the training program.

Proposed Analyses

Prior to testing the study hypotheses, an analysis of the distribution of study variables was conducted to detect and assess potential outliers and to ensure assumptions of normality were not violated. Skewness and kurtosis statistics were calculated for each univariate distribution to evaluate the assumption of normality of each study variable.

Hierarchical multiple regression was used to evaluate the study hypotheses and research question. We followed recommendations by Cohen, Cohen, West, and Aiken (2003) for testing interactions between continuous variables and subsequent simple slopes analysis. For all models, training language was dummy coded prior to entry into the regression. All predictor variables were standardized, while the outcome variable for each regression remained unstandardized.

To test Hypotheses 1a and 3a, a model was run in which initial training performance was regressed onto training language in Step 1, followed by cognitive ability and motivation to train in Step 2. To test this study's remaining hypotheses and research question, end-of-training performance and skill acquisition were then modeled (separately) as outcome variables, while training language, initial training performance, cognitive ability, and motivation to train were entered as predictors. In Step 1, training language and initial training performance were entered as predictors of the outcome variable. In Step 2, cognitive ability and motivation to train were entered into the regression. Hypotheses 1b and 3b were

evaluated based on the statistical significance of parameter estimates following Step 2. In Step 3, cross-products between both cognitive ability and motivation to train and initial training performance were entered. A cross-product between cognitive ability and motivation to train was also entered at Step 3. Hypotheses 2 and 4 were evaluated based on the significance of the relevant parameter estimates following Step 3. To evaluate the research question, the cross-product of cognitive ability, motivation to train, and initial training performance was entered in Step 4.

Determining Minimum Sample Size

In order to determine the minimum number of study participants, we considered the sample size requirements for achieving acceptable power (.80) to detect both the main effects and interactions hypothesized. Aiken and West (1991) present a detailed analysis of sample size requirements to detect such parameters using common multiple regression techniques. These authors suggest a minimum sample size of 169-207 to detect a moderate interaction (with power of .80) with predictor variable reliabilities of .70. Since reliability of .70 is a reasonable assumption for the included predictor variables, we consider this recommended sample size to be the minimum necessary to detect a medium-sized effect. However, interactions in behavioral science research are often small in magnitude (Cohen et al., 2003), suggesting a larger sample will be necessary. Cohen et al. (2003) suggest sample sizes of 500 or more are needed to achieve adequate power to detect small interactions given predictor reliabilities common in the behavioral sciences. Therefore, we will include a sample size of at least 500 trainees to increase confidence that sufficient power was achieved.

Discussion

The present study contributes to prior research by (a) distinguishing between learning outcomes demonstrated early in training from those demonstrated later in training, (b) investigating how learner characteristics relate to both early and later training outcomes, and (c) examining how learner characteristics relate to the degree to which people recover from early failures during training. This study addresses calls for additional research into the factors contributing to the rate at which learning occurs (Aguinis & Kraiger, 2009) and how context factors interact with individual differences to produce (or inhibit) learning outcomes (Alvarez et al., 2004; Gully & Chen, 2009; Herold et al., 2002).

One limitation of prior research into both training performance and skill acquisition involves the way in which these variables have been operationalized. Training performance and skill acquisition have typically been assessed using measures obtained at the conclusion of training or aggregates of assessments made throughout training (e.g., Alliger, Tannenbaum, Bennett, & Traver, 1997; Kubeck, Delp, Haslett, & McDaniel, 1996). Aggregated and post-only measures of performance reflect the cumulative result or end-state of the training process. While not invalid approaches to the study of learning, such measures lack information on individual differences in the progression of learning (i.e., learning trends) during training (Herold et al., 2002). Thus, extending research to incorporate multiple measures of learning during training allows for a deeper understanding of learning dynamics.

Another notable limitation of prior research is the lack of field studies extending findings obtained in controlled laboratory settings to real-world instructional settings. With some exceptions (e.g., Deadrick et al., 1997), few prior empirical studies have provided

evidence demonstrating how individual differences relate to skill acquisition during training when real-world benefits and consequences are at stake (Aguinis & Kraiger, 2009; Chen & Mathieu, 2008). The current study addresses this deficiency by following a sample of trainees in a real-world training context with job implications contingent on training outcomes.

Lastly, prior research examining how individual differences relate to learning outcomes assessed throughout training has employed a narrow range of learning tasks. The majority of research has relied on computer-based simulations (e.g., air traffic control tasks, games, etc.). Researchers have called for more research employing novel learning tasks (e.g., Yeo and Neal, 2004). In response to these calls, the current study extends prior research by focusing on a cognitively demanding training task seldom studied in industrial/organizational psychology and related disciplines.

Limitations

One potential limitation of the proposed study is the possible restricted range on the cognitive ability and motivation to train variables. Members of the trainee population are selected into the organization based, in part, on their cognitive ability (i.e., AFQT) scores. This will likely lead to a direct restriction of range, such that trainees with higher than average cognitive ability will be overrepresented in the study sample. However, trainee selection was not solely based on AFQT scores, suggesting there will be variability in this measure.

In a similar vein, trainees self-select into this organization knowing that language training is required. Thus, trainees lower in motivation may be underrepresented in the study

sample and trainees included may be more motivated to learn a foreign language than those found in other organizations. However, there may also be individuals who consider the foreign language training to be an undesirable requirement (i.e., it is not central to what attracted them to the job).

Another potential concern is the decision to operationalize initial training performance as the average of the first two during-training skills tests and end-of-training performance as the average of the last two skills tests. As mentioned previously, this decision was made to reduce potential error variance in training performance scores. One problem with this approach is that trainees received performance feedback between the two tests being averaged, which may influence subsequent performance. Considering this study's focus on who recovers from early training deficiencies, an alternative would be to use the first and last test scores only. However, such a single-score approach would likely introduce increased error variance, which we consider to be a more substantial limitation than the one noted above.

A final potential limitation is the quasi-experimental nature of the proposed study design. With such a design, it is not possible to conclude with certainty that the predictor variables examined imposed a causal effect on any outcome variable. The proposed study does employ strategies to reduce confounding influences on the observed relationships. For example, study variables were operationalized using both self-reports and objective performance measurements to reduce the likelihood of common method bias. All predictor variables also have temporal precedence with respect to the training outcome variables, in that predictor measurement came before outcomes were assessed. Also, controlling for

training language should help to reduce potential confounds due to situational factors unrelated to study hypotheses. While such steps have been taken to reduce threats to internal validity, it is important to acknowledge that the proposed correlational design limits our ability to conclude causal relationships.

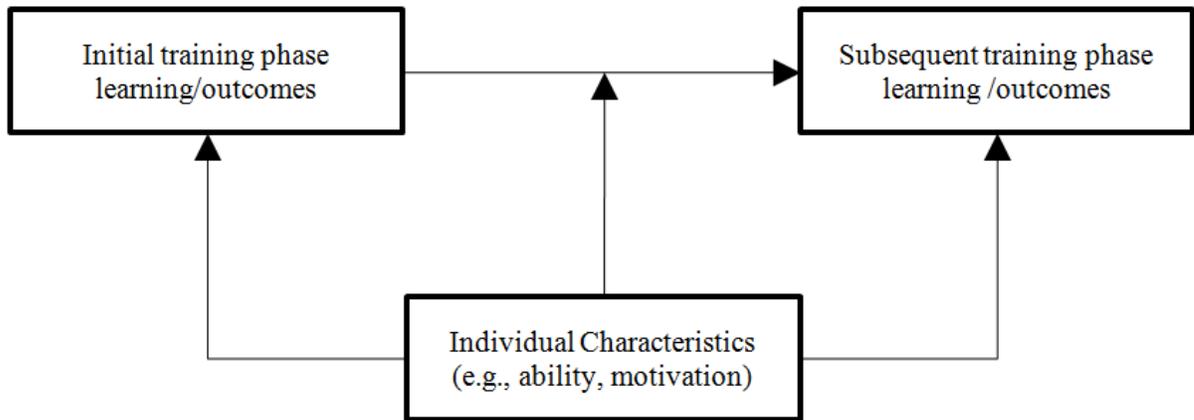


Figure A1. Conceptual Model of Individual Differences Relating to Early and Late Training Outcomes. Adapted from “Dispositional Influences on Transfer of Learning in Multistage Training Programs,” by D. Herold, W. Davis, D. Fedor, and C. Parsons, 2002. *Personnel Psychology*, 55, p. 853. Copyright 2002 by Personnel Psychology, Inc.

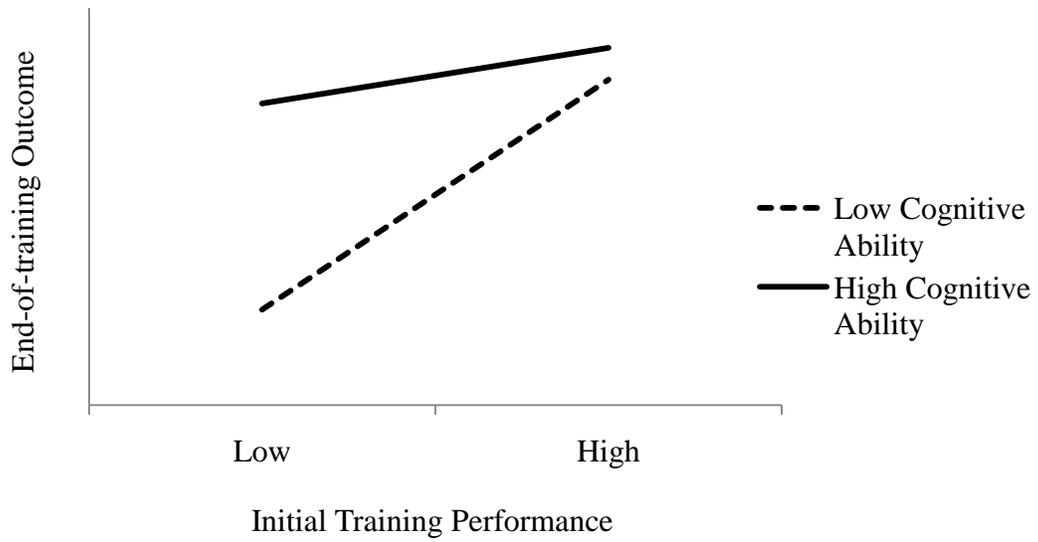


Figure A2. Hypothesized Interaction between General Cognitive Ability and Initial Training Performance on End-of-Training Outcomes.

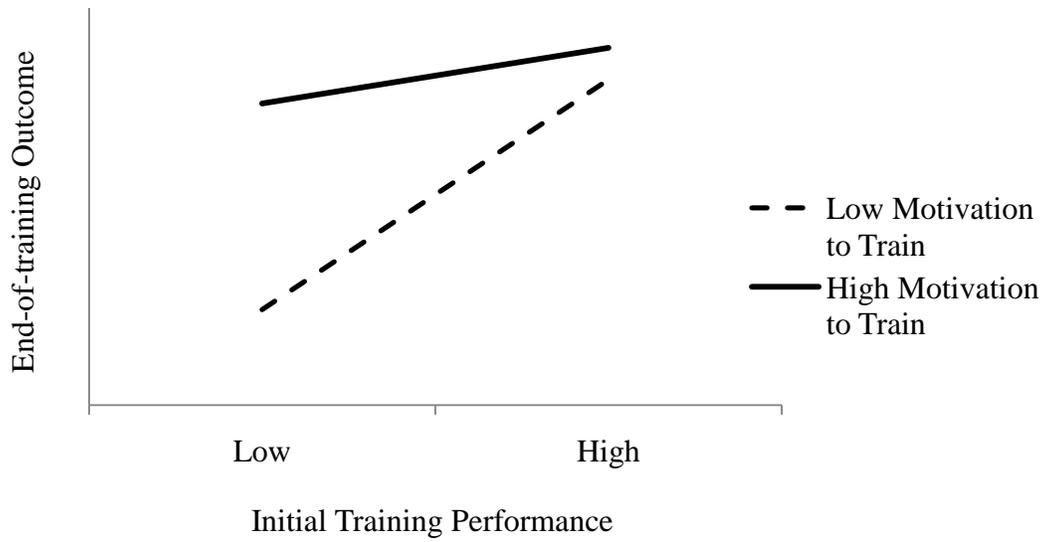


Figure A3. Hypothesized Interaction between Motivation to Train and Initial Training Performance on End-of-Training Outcomes.

Appendix A-1

Sample Item from a Training Skills Test from a Russian Language Course

Trainees hear the following radio report:

“Завтра день военно-воздушных сил. Следующие подразделения примут участие в Туровском параде: 11-е подразделение морской авиации, 2-я армейская бригада и 3-й батальон морской артиллерии.”

Which branch of the Armed Forces will NOT participate in the Turov parade?

- A. Army
- B. Air Force
- C. Marine Corps
- D. Navy

Answer: b

Appendix A-2

Pre-training Motivation to Learn Scale Items

1. I would like to learn as many languages as possible.
2. I don't particularly like the process of language learning and I do it only because I am required to participate in language training. (Reverse scored)
3. I would rather spend the time dedicated to language training on training other job skills. (Reverse scored)
4. I am motivated to perform well in language training so that I will be able to perform my missions more effectively.
5. If I learn to speak this language well, I will have many opportunities to use it.

Responses were made using a 7-point Likert scale, ranging from 1(*strongly disagree*) to 7(*strongly agree*).

Appendix B

Sample Item from a Training Skills Test from a Russian Language Course

Trainees hear the following radio report:

“Завтра день военно-воздушных сил. Следующие подразделения примут участие в Туровском параде: 11-е подразделение морской авиации, 2-я армейская бригада и 3-й батальон морской артиллерии.”

Which branch of the Armed Forces will NOT participate in the Turov parade?

- E. Army
- F. Air Force
- G. Marine Corps
- H. Navy

Answer: b

Appendix C

Pre-training Motivation to Learn Scale Items

1. I would like to learn as many languages as possible.
2. I don't particularly like the process of language learning and I do it only because I am required to participate in language training. (Reverse scored)
3. I would rather spend the time dedicated to language training on training other job skills. (Reverse scored)
4. I am motivated to perform well in language training so that I will be able to perform my missions more effectively.
5. If I learn to speak this language well, I will have many opportunities to use it.

Responses were made using a 7-point Likert scale, ranging from 1(*strongly disagree*) to 7(*strongly agree*).

Appendix D

Post Hoc Power Analysis for Multilevel Models

Table D1

Estimated Power to Detect a Moderate Fixed Effect for Initial Training Performance

	Variance	Model 1	Model 2		
Fixed Effects			Estimated SE	Target Effect (γ)	Power ^a
Cognitive Ability _{cwc} , γ_{20}	266.80	-	0.0003	0.0082	1.00
Motivation to Learn _{cwc} , γ_{30}	0.58	-	0.0070	0.1753	1.00
Random Effects					
Within-class Variability (σ^2)		0.0179	0.0164		

Note. SE represents the standard error of the regression coefficient from the estimated model. Target Effect refers to the regression coefficient associated with a moderate effect (or 10% of within-class variance accounted for).

^a Power was calculated for a two-tailed test.

Table D2

Estimated Power to Detect a Moderate Fixed Effect for Post-training Skill Acquisition

Fixed Effects	Variance	Model 1	Model 2		Power ^a
			Estimated SE	Target Effect (γ)	
Cognitive Ability _{cwc} , γ_{20}	257.58	-	0.0126	0.2843	1.00
Motivation to Train _{cwc} , γ_{30}	0.59	-	0.2508	5.9244	1.00
Initial Performance _{cwc} X Cognitive Ability _{cwc} , γ_{40}	3.98	-	-	-	-
Initial Performance _{cwc} X Motivation to Train _{cwc} , γ_{50}	0.01	-	-	-	-
Init. Perf. _{cwc} X Cognitive Ability _{cwc} X Motivation _{cwc} , γ_{70}	3.22	-	-	-	-
Random Effects					
Within-class Variability (σ^2)		20.8205	18.9583		

Note. SE represents the standard error of the regression coefficient from the estimated model. Target Effect refers to the regression coefficient associated with a moderate effect (or 10% of within-class variance accounted for).

^a Power was calculated for a two-tailed test.

Table D2 (continued)

Fixed Effects	Model 3			Model 4		
	Estimated SE	Target Effect (γ)	Power ^a	Estimated SE	Target Effect (γ)	Power ^a
Cognitive Ability _{cwc} , γ_{20}	0.0126	0.2823	1.00	0.0126	0.2715	1.00
Motivation to Train _{cwc} , γ_{30}	0.2512	5.8835	1.00	0.2634	5.6572	1.00
Initial Performance _{cwc} X Cognitive Ability _{cwc} , γ_{40}	0.1024	2.2721	1.00	0.1024	2.1847	1.00
Initial Performance _{cwc} X Motivation to Train _{cwc} , γ_{50}	2.0924	46.985	1.00	2.2291	45.1777	1.00
Init. Perf. _{cwc} X Cognitive Ability _{cwc} X Motivation _{cwc} , γ_{70}	-	-	-	0.1190	2.4267	1.00
Random Effects						
Within-class Variability (σ^2)	18.9430			18.7672		

Note. SE represents the standard error of the regression coefficient from the estimated model. Target Effect refers to the regression coefficient associated with a moderate effect (or 10% of within-class variance accounted for).

^a Power was calculated for a two-tailed test.