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A Multilevel Analysis of Effort, Practice, and Performance: Effects of Ability, Conscientiousness, and Goal Orientation

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This article examines the relationship between motivation and performance during skill acquisition. The authors used multilevel analysis to investigate relationships at within- and between-person levels of analysis. Participants were given multiple trials of practice on an air traffic control task. Measures of effort intensity and performance were taken at repeated intervals. As expected, the relationship between effort and performance increased with practice. Furthermore, the rate at which this effect strengthened was faster for individuals with high-ability or low-performance orientation. There was also an interaction between learning and performance orientations that only emerged after practice. By the end of practice, the negative effects of performance orientation were stronger for individuals with high learning orientation. Results highlight the importance of adopting a multilevel framework to enhance understanding of the link between motivation and performance.

Job performance is commonly regarded as one of the most central constructs within the field of organizational behavior (Campbell, Gasser, & Oswald, 1996). A substantial body of research has attempted to identify the factors that are responsible for individual differences in job performance (Campbell et al., 1996). Factors that have been found to predict individual differences in job performance include cognitive ability (e.g., Hunter & Hunter, 1984), conscientiousness (e.g., Barrick & Mount, 1991), goal orientation (e.g., Button, Mathieu, & Zajac, 1996), and motivation (e.g., Ambrose & Kulik, 1999). Most studies in this field have taken measurements of performance at one point in time, despite a presumed interest in long-term as well as immediate performance. Recently, a number of researchers have started to investigate how performance changes over time (e.g., Deadrick, Bennett, & Russell, 1997; Hofmann, Jacobs, & Gerras, 1992; Ployhart & Hakel, 1998). These studies suggest that meaningful variation in performance exists at the within-person level as well as at the between-person level.

If performance is a construct that changes over time, then it is important to identify the variables that may explain these changes and the levels at which these variables exert their effects. The major construct that we focus on is motivation. Motivation is a construct that changes within individuals, over time, and across situations (e.g., Kanfer & Ackerman, 1989). In the current study, we examine the relationship between motivation and performance over time and the way in which individual-difference variables might moderate this relationship. We first review existing research regarding the relationship between motivation and performance and present a model of variables from two levels of analysis that might moderate this relationship. We then report the results from an empirical study designed to test components of this model.

Motivation and Effort

Motivation is assumed to affect performance by influencing the way that individuals allocate effort to tasks (Blau, 1993; Kanfer, 1990; Katzell & Thompson, 1990). The majority of motivation research has concentrated on assessing the predictive strength of motivational interventions, such as goal setting, or constructs, such as valence and self-efficacy, that are thought to influence the allocation of effort to tasks (Ambrose & Kulik, 1999; Kanfer, 1992). This research has demonstrated that these types of interventions and constructs influence task performance. However, there is a surprising lack of research that attempts to measure effort directly (Blau, 1993; Brown & Peterson, 1994). Thus, psychologists have empirical knowledge regarding how motivational concepts influence work behaviors, but there is comparatively little research on how effort directly relates to performance.

This situation is probably due to the difficulties associated with defining and measuring effort (Ambrose & Kulik, 1999; Kanfer, 1990). The reason effort is difficult to define and measure is that it is an invisible, internal, hypothetical construct that is not directly observable. Resource allocation theories have defined effort in terms of attention (Kanfer & Ackerman, 1989). Effort is assumed to be a limited-capacity resource that can be allocated to a range of different activities, including on-task, off-task, and self-regulation activities. These allocations can vary in terms of intensity and persistence. For the current study, we are interested in effort intensity, which refers to the amount of resources that are expended. In layperson terms, *effort intensity* refers to how hard a person tries to carry out a chosen behavior (Kanfer, 1990; Porter & Lawler, 1968; Vroom, 1964).

Some studies have measured effort intensity as time on task (e.g., Blau, 1993; Brown & Peterson, 1994; Fisher & Ford, 1998).

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However, this operational definition does not allow a direct measurement of how much effort was expended. Other studies have overcome this limitation by using self-report measures of intensity (e.g., Brown & Leigh, 1996; Rasch & Tosi, 1992; Terborg & Miller, 1978). These self-report measures typically ask how hard the person is trying. In combination, these studies have shown that self-reported effort and time on task are positively associated with task performance at a between-person level of analysis.

However, this research has not examined changes in effort allocations over time. Related studies have used within-person designs to examine the effect of choices between tasks on effort and have shown that individuals tend to allocate more effort to tasks that have higher valence or instrumentality (Van Eerde & Thierry, 1996). However, these studies have not directly investigated the relationship between effort and performance and have typically examined cross-sectional data rather than repeated measurements over time.

To our knowledge, there is only one study that has collected repeated measurements of effort and performance over time (Schmitz & Skinner, 1993). In that study, primary school children were asked to rate the amount of effort they had expended in performing each of (approximately) 20–25 assignments. These measurements were taken just after each assignment was completed. Contrary to expectations, the within-person relationship between effort and performance was not significant. However, individual time-series analyses showed that the relationship was significantly positive, or even negative, for some children. This finding suggests that some individual-difference variables might moderate the within-person relationship between effort and performance.

In the current study, we collected repeated measurements of effort intensity and investigated how changes in effort intensity relate to changes in performance during the early phases of skill acquisition. In the following sections, we consider the effects of effort intensity and task practice on performance at the within-person level of analysis and present a series of hypotheses regarding cross-level interactions with cognitive ability, conscientiousness, and goal orientation.

Antecedents of Performance at the Within-Person Level of Analysis

Effort Intensity and Task Practice

The resource allocation theory of motivation assumes that individuals regulate the amount of effort that they allocate to a task to maintain performance at a desired standard (Kanfer & Ackerman, 1989). The amount of effort that is required to maintain performance at a certain level is assumed to be dependent on task practice (Norman & Bobrow, 1975). The relationship between practice and performance is typically negatively accelerated (Newell & Rosenbloom, 1981). The rate of improvement in performance is fastest in the early stages of practice, and these gains typically diminish as performance approaches an asymptote. Kanfer and Ackerman (1989) have argued that during the early stage of practice, changes in effort should be positively associated with changes in task performance. During this stage of practice, individuals are thought to rely on analogical reasoning or declarative knowledge to perform the task (Anderson, 1983; Anderson & Fincham, 1994). The use of analogies and general principles is assumed to require cognitive effort (Neal, Hesketh, & Andrews, 1995).

If a task involves consistent information-processing demands, then continued practice eventually leads to automation (Shiffrin & Schneider, 1977). As an individual practices a task, she or he is assumed to pass through the compilation and procedural phases of skill acquisition. During these phases, individuals are assumed to compile their knowledge into more efficient chunks, termed *production rules* (Anderson & Fincham, 1994). As the process of compilation and proceduralization proceeds, individuals require less effort to reach their maximum level of performance. Greater experience, therefore, allows individuals to maintain higher levels of performance with less effort. As a result, the relationship between effort and performance is thought to become weaker with practice (Kanfer & Ackerman, 1989).

The prediction that the association between effort and performance should be positive at the start of practice depends on the assumption that individuals have sufficient knowledge and skill to perform the task when they first start. It is possible, however, that some tasks are sufficiently novel at the beginning of practice and that individuals have relatively little in the way of prior knowledge or examples they can draw on (Logan, 1988). Although research has shown that individuals often try to draw on prior experiences with other tasks, transfer between tasks is often poor (Gick & Holyoak, 1983). If performance on a task is at chance at the beginning of practice because the individual cannot successfully draw on prior knowledge or skill, then it is unlikely that effort will be associated with performance. In other words, trying hard will not help if the individual does not know how to perform the task (Vroom, 1964). In the current study, participants were asked to perform an air traffic control conflict-detection task. Results from previous studies using this task (Loft & Neal, 2002) demonstrate that individuals do perform at chance when they begin practice. For this reason, we expected that the relationship between effort and performance would increase throughout practice.

Furthermore, we expected that the relationship between effort and performance would remain positive during the course of the study. First, prior research suggests that air traffic control tasks are complex and involve elements of both consistent and inconsistent information processing (Ackerman, 1992). Kanfer and Ackerman (1989) pointed out that if the task involves inconsistent information-processing demands, then the relationship between effort and performance should remain positive over time. This is because people find it difficult to automate inconsistent information-processing tasks, and the attentional demands imposed by these tasks tend not to decline with practice (Fisk, Ackerman, & Schneider, 1987; Shiffrin & Schneider, 1977). Second, in the current study, we focused on the relationship between effort and performance during the first hour of practice. These arguments suggest that it is unlikely that participants in our study would automate the task during this period.

Our first set of hypotheses, therefore, is as follows:

> *Hypothesis 1a:* Practice will be positively associated with performance at the within-person level of analysis.

> *Hypothesis 1b:* The rate of improvement in performance will decline with practice.

Hypothesis 2: Effort will be positively associated with performance at the within-person level of analysis.

Hypothesis 3: There will be an interaction between effort and practice at the within-person level, such that the relationship between effort and performance will strengthen over time.

Perceived Difficulty

Perceived difficulty is included in the current model as a covariate of effort intensity. Theory and research suggest that difficulty and effort are related to each other. Resource allocation theory suggests that when a task is difficult, individuals are prompted to increase their allocation of effort toward on-task activities (Kanfer, 1990; Kanfer & Ackerman, 1989; Kanfer, Ackerman, & Heggestad, 1996). Some evidence to support this proposition is provided by Maynard and Hakel (1997), who demonstrated a positive association between subjective task complexity and task motivation at the between-person level. Research on goal setting also suggests that individuals with more difficult goals (objective or perceived) expend more effort than people with less difficult goals (Locke, 1997; Rasch & Tosi, 1992; Weingart, 1992).

It is also believed that perceived difficulty is related to performance in its own right. Difficult tasks require greater skill and effort (Hesketh & Neal, 1999). Resource allocation theory, therefore, suggests that performance should decline as task difficulty approaches and then exceeds an individual's available capacity. A number of between-person studies have shown that both objective (e.g., Steele-Johnson, Beauregard, Hoover, & Schmidt, 2000) and subjective (e.g., Mangos & Steele-Johnson, 2001; Maynard & Hakel, 1997) task difficulty are negatively associated with task performance.

Given that difficulty and effort are expected to have different relationships with performance yet be positively related to each other, it is important to account for the effects of perceived difficulty when investigating the effects of effort. In general, the link between effort and performance is expected to be positive; however, an increase in effort is also expected to occur when the task is difficult. Perceived difficulty, therefore, may confound the relationship between effort and performance.

Trait Variables as Moderators of Within-Person Relationships

In the current study, we were also interested in the way that stable individual-difference variables might moderate the within-person relationships among practice, effort, and performance. The individual-difference variables that we focused on were cognitive ability, conscientiousness, and goal orientation.

Cognitive Ability

The term *cognitive ability* refers to individual differences in the capacity to perform tasks that require the manipulation, retrieval, evaluation, or processing of information (Murphy & Davidshofer, 1998). There are a range of cognitive abilities, such as perceptual speed, psychomotor, general, and broad-content abilities. *General cognitive ability* refers to the source of variance that is common to most tests of cognitive ability. *Broad-content abilities* reflect the variance in performance that is attributable to the content of the items (e.g., verbal, numerical, or spatial). Ackerman (1992) argued that these two types of cognitive ability are important in the early phases of skill acquisition, when high levels of effort are required. This is because general cognitive ability and broad-content abilities are thought to underlie individual differences in attentional capacity (Kanfer & Ackerman, 1989).

Ackerman and colleague's (Ackerman, 1986, 1990, 1992; Ackerman & Cianciolo, 2000) theoretical and empirical work has shown that general cognitive ability and broad-content abilities are important predictors of performance during the early stages of practice for consistent information-processing tasks and remain important predictors of performance during all stages of practice for inconsistent information-processing tasks. More recently, some studies have demonstrated that general cognitive ability moderates the rate at which individuals acquire task skills after controlling for initial status (Deadrick et al., 1997; Eyring, Johnson, & Francis, 1993). As expected, high-ability individuals tend to learn faster than low-ability individuals.

It is widely believed that cognitive ability also interacts with motivation (e.g., Ambrose & Kulik, 1999; Maier, 1958; Pinder, 1998; Vroom, 1964). Vroom (1964) argued that when ability is low, increments in motivation result in smaller improvements in performance than when ability is high. This model predicts that the relationship between effort and performance should be stronger for individuals with high cognitive ability than for individuals with low cognitive ability.

Despite the intuitive appeal of models that propose a multiplicative relationship between cognitive ability and motivation, the existing body of empirical research has been unsupportive and mixed at best (e.g., Campbell & Pritchard, 1976; Kanfer & Ackerman, 1989; Pringle & DuBose, 1995). However, most studies that have tested ability–motivation interactions have conceptualized motivation as a stable trait that varies between people. It is possible, therefore, that the failure to find consistent evidence for ability–motivation interactions is due to a misspecification of levels.

The resource allocation model predicts that there should be a cross-level interaction between cognitive ability, effort, and practice. This model predicts that the rate at which the relationship between effort and performance changes over time should be moderated by general cognitive ability and relevant broad-content abilities. This is because individuals with high levels of these abilities should progress through the phases of skill acquisition more quickly than individuals with lower ability. These arguments suggest the following hypotheses:

Hypothesis 4a: Cognitive ability will moderate the relationship between practice and performance, such that individuals with higher cognitive ability will improve performance at a faster rate than their lower ability counterparts.

Hypothesis 4b: There will be a three-way interaction between cognitive ability, effort, and practice. The rate at which the relationship between effort and performance changes as a function of practice will be strongest for individuals with high cognitive ability.

Conscientiousness

Conscientiousness is a personality trait that reflects dependability through being careful, thorough, responsible, and organized (Barrick & Mount, 1991) while also incorporating volitional aspects, such as being hardworking, persevering, and achievement oriented (Digman, 1990). Results from meta-analyses indicate that conscientiousness is positively related to a variety of performance criteria across a variety of jobs (Barrick & Mount, 1991; Salgado, 1997; Tett, Jackson, & Rothstein, 1991). However, Tett, Jackson, Rothstein, and Reddon (1999) argued that it is unreasonable to believe that any personality trait is universally desirable. Indeed, their review of a number of meta-analyses (Barrick & Mount, 1991; Hough, 1992; Salgado, 1997) suggests that there is substantial variability in the average effect sizes that were reported, beyond that due to sampling error.

There are now a number of studies that have shown a negative relationship between conscientiousness and performance in certain types of situations (Bunce & West, 1995; Hogan, Hogan, & Murtha, 1992; LePine, Colquitt, & Erez, 2000; Martocchio & Judge, 1997; Robertson, Baron, Gibbons, MacIver, & Nyfield, 2000). These results suggest that being highly conscientious could be a disadvantage in jobs that require prompt completion of tasks, such as being a manager or a police officer (Tett, 1998; Tett et al., 1999). That is, the tendency for highly conscientious individuals to be careful and thorough can mean that they get fewer tasks done and/or take longer to complete a set of tasks (Deluga & Masson, 2000; LePine et al., 2000; Robertson et al., 2000). Therefore, although volitional traits might prompt highly conscientious people to try hard and persevere, the dependability component of conscientiousness may hinder overall performance in jobs that are characterized by time pressure.

Furthermore, there is also evidence to suggest that conscientiousness is negatively related to performance in learning contexts. Colquitt, LePine, and Noe's (2000) meta-analysis showed a negative relationship between conscientiousness and both skill acquisition and declarative knowledge (although, see Ackerman, Kanfer, & Goff, 1995, for a nonsignificant finding). It has been argued that highly conscientious individuals tend to be self-deceptive in learning situations (Martocchio, 1994) and may self-regulate excessively (Colquitt et al., 2000), which interferes with on-task learning (Kanfer & Ackerman, 1989). These studies have operationalized skill acquisition as overall performance or performance at the end of training. Our study extends this research by examining the rate of skill acquisition. Tett's theory (Tett, 1998; Tett et al., 1999) suggests that highly conscientious individuals might acquire task skills at a slower rate than their less conscientious counterparts because they tend to use cognitive strategies that are slow and deliberate, such as elaboration, repetition, and rehearsal.

In this study, we examined the rate of skill acquisition in a task that is characterized by time pressure. The two lines of research presented above suggest that individuals with low conscientiousness should improve their performance at a faster rate than individuals with high conscientiousness. If individuals with low levels of conscientiousness learn faster than individuals with high levels of conscientiousness, then the arguments made earlier with respect to cognitive ability suggest that the rate of change in the relationship between effort and performance should also be faster for these individuals. Our hypotheses with respect to conscientiousness, therefore, are as follows:

Hypothesis 5a: Conscientiousness will moderate the relationship between practice and performance, such that individuals with low levels of conscientiousness will improve their performance at a faster rate than their counterparts with higher levels of conscientiousness.

Hypothesis 5b: There will be a three-way interaction between conscientiousness, effort, and practice. The rate at which the relationship between effort and performance changes as a function of practice will be strongest for individuals with low levels of conscientiousness.

Goal Orientation

The term *goal orientation* refers to a mental framework for how individuals respond to and interpret achievement situations (Brett & Vandewalle, 1999). Two major goals that people pursue to varying degrees in achievement situations are learning and performance goals (Button et al., 1996; Sujan, Weitz, & Kumar, 1994). Individuals with a high learning orientation are more focused on improving their abilities and mastering the task than individuals with a low learning orientation. Individuals with a high performance orientation are more interested in achieving a positive, and avoiding a negative, evaluation of their abilities and performance standards than individuals with a low performance orientation. Recent empirical research provides strong evidence that these orientations are separate constructs (Button et al., 1996).

Individual differences in goal orientation have been proposed to influence the nature and quality of skill acquisition (Dweck, 1986). Fisher and Ford (1998) have suggested that this is because goal orientation influences the allocation and direction of effort within learning tasks. It has been argued that high learning-oriented people are more likely to seek challenging situations (Sujan et al., 1994), devote more effort to on-task activities (Fisher & Ford, 1998), focus their attention on the knowledge and skills needed for task proficiency (Kozlowski et al., 2001), and respond to feedback by maintaining the allocation of resources to the task itself (Vandewalle, Cron, & Slocum, 2001), compared with low learning-oriented individuals. Furthermore, high learning-oriented individuals, in comparison with low learning-oriented individuals, are expected to be more likely to interpret mistakes as feedback for developing strategies (Martocchio, 1994) and engage in deep processing (Colquitt & Simmering, 1998; Fisher & Ford, 1998; Mangos & Steele-Johnson, 2001; Steele-Johnson et al., 2000). Individuals with high performance orientation are expected to devote resources to ego management and focus their attention on performance indicators rather than on on-task activities (Brown, 2001; Fisher & Ford, 1998), view mistakes as evaluative threats (Martocchio, 1994), withdraw from the task in the face of obstacles (Button et al., 1996), respond to difficulty with a shift in focus to off-task thoughts (Colquitt & Simmering, 1998), and use strategies that minimize the amount of effort required (Fisher & Ford, 1998; Mangos & Steele-Johnson, 2001; Steele-Johnson et al., 2000), compared with individuals with low performance orientation.

Empirically, learning orientation has been shown to be positively associated with performance (Button et al., 1996; Sujan et al., 1994; Towler & Dipboye, 2001; although see Tenenbaum et al., 2001, for a negative finding) and with strategies that promote learning (Brett & Vandewalle, 1999; Fisher & Ford, 1998; Towler & Dipboye, 2001) at the between-person level. Results regarding performance orientation have been less consistent (Patrick, Ryan, & Pintrich, 1999; Vandewalle et al., 2001). Studies have shown negative (Ford, Smith, Weissbein, Gully, & Salas, 1998), positive (Hoover, Steele-Johnson, Beauregard, & Schmidt, 1999; Tenenbaum et al., 2001), and nonsignificant (Button et al., 1996; Kozlowski et al., 2001; Sujan et al., 1994) correlations between performance orientation and performance at the between-person level.

A number of authors have argued that the effects of learning and performance orientations emerge over time via reactions to task feedback (Dweck, 1986; Dweck & Leggett, 1988; Steele-Johnson et al., 2000; Tenenbaum et al., 2001). These arguments suggest that task practice should moderate the relationship between goal orientation and performance. Some studies have examined goal-orientation effects at two discrete time points. For example, Ford et al. (1998) showed that the effect of performance orientation was nonsignificant at the end of training but was negative for a transfer task, and Elliot and McGregor (1999) showed that the effect of learning orientation was nonsignificant for a midsemester exam but positive for an end-of-semester quiz. In the context of the current study, these results suggest that there should be a cross-level interaction between goal orientation and practice. Individuals with high learning orientation should learn faster than individuals with low learning orientation. Similarly, individuals with low performance orientation should learn faster than individuals with high performance orientation. These hypotheses have not been previously tested.

Resource allocation theory predicts that if goal orientation influences the rate of skill acquisition, then it should also influence the rate at which the relationship between effort and performance changes over time. Given that high learning- or low performance-oriented individuals are expected to learn at a faster rate, we expect the effect of effort to strengthen more quickly for these individuals.

A further issue that has emerged from the goal-orientation literature concerns the possibility that certain combinations of goal-orientation dimensions may be more or less beneficial for learning outcomes (Brett & Vandewalle, 1999; Elliot & McGregor, 1999). There is relatively little in the way of theory or data to inform the development of hypotheses in this regard. Some researchers have suggested that despite the maladaptive effects of a performance goal, this orientation should still be important for success and a balance of both orientations might be beneficial for work settings (Button et al., 1996; Elliot & McGregor, 1999; Farr, Hofmann, & Ringenbach, 1993; Hardy, 1997). This argument suggests that there should be a positive relationship between performance orientation and performance for those with high learning orientation but a negative relationship for those with low learning orientation.

However, we believe it is also possible that learning orientation may accentuate the negative effects of performance orientation. Resource allocation theory assumes that the allocation of resources toward on-task activities is a necessary condition for learning (Kanfer & Ackerman, 1989). As noted earlier, learning orientation is thought to influence the allocation of effort to on-task activities, whereas performance orientation is thought to influence the allocation of effort to ego management. Therefore, if an individual does not devote resources toward learning the actual task (low learning orientation), then the proportion of effort allocated toward ego management is unlikely to affect performance. For example, if an individual does not have any interest in learning a task, then she or he is unlikely to gain any benefits from being unconcerned with external evaluations. It is only when individuals are interested in learning the task that concern with external evaluation may have a detrimental effect. This argument suggests that there should be a negative effect of performance orientation for those with high learning orientation and a nonsignificant effect for those with low learning orientation.

To our knowledge, only two studies have tested for interactions between learning and performance orientation. Patrick et al. (1999) found no evidence of an interaction between learning and performance orientation at the between-person level. Duda, Sedlock, Noble, Cohen, and Chi (1990, as cited in Tenenbaum et al., 2001), in contrast, showed that a combination of high learning and low performance orientation led to lower perceptions of exertion and more positive affect associated with exercise than a combination of high performance and low learning orientations. These studies are limited by the fact that they only assessed performance at a single point in time, and the latter study did not assess performance. Given that previous research does not provide a sufficient basis for predicting the nature of any interaction between learning and performance orientation, we do not present a specific hypothesis in relation to this research question. However, given that the effects of goal orientation are only expected to surface after sufficient practice, it follows that any such interaction should strengthen over time. The hypotheses involving goal orientation are as follows:

> *Hypothesis 6a:* Learning orientation will moderate the relationship between practice and performance, such that individuals with high learning orientation will improve performance at a faster rate than individuals with low learning orientation.

> *Hypothesis 6b:* Performance orientation will moderate the relationship between practice and performance, such that individuals with low performance orientation will improve performance at a faster rate than individuals with high performance orientation.

> *Hypothesis 6c:* There will be a three-way interaction between goal orientation, effort, and practice. The rate at which the relationship between effort and performance changes as a function of practice will be strongest for individuals with high learning orientation or low performance orientation.

> *Hypothesis 6d:* The strength of the interaction between learning orientation and performance orientation will increase with practice.

Method

Experimental Task

The low fidelity conflict-recognition task from the ATC-lab suite (Loft, Hill, Neal, Humphreys, & Yeo, in press) was used in the current study. Air traffic control tasks are a common choice for studies of skill acquisition because they are cognitively complex and previous research suggests that there may be substantial variability in the allocation of effort between individuals and over time (Ackerman et al., 1995). Conflict detection is one of the major components of an air traffic controller's job (Griffin, Neal, & Neale, 2000). In this task, participants see pairs of aircraft converging on a common waypoint. The participants are informed that all aircraft are flying at the same altitude. Each aircraft has a data block attached to it, displaying a call sign and the speed. For each pair, participants are asked to decide whether the two aircraft will pass within 5 km of each other. If the participant believes that the aircraft will pass within 5 km of each other, then they are instructed to call it a conflict. If the participant believes that the aircraft will never pass within 5 km of each other, then they are instructed to call it a nonconflict. Participants are asked to respond as quickly and accurately as possible.

Four pairs of aircraft appear on the screen at the beginning of each trial. The pairs are situated in each of the four quadrants of the screen. Matching letters from A to D are used to designate aircraft pairs. A conflict-recognition box is used to register decisions and is displayed in the bottom right-hand corner. This box has a column for the aircraft pair labels, one for the decisions (with a check box for “conflict” and one for “nonconflict”), one for the actual outcomes, and one for the associated scores. When participants have made a decision, they click in either the “conflict” or “nonconflict” box associated with the relevant aircraft pair. The participants can then observe as the aircraft continue on their respective flight paths. If the distance between the aircraft reaches 5 km, the flight labels turn yellow. After a pair has either conflicted or passed safely, the word “correct” or “incorrect” appears in the appropriate row and the score for that decision is presented alongside it. When each of the four scores has been presented, the total score for that trial is shown in the point display box, which is situated in the top right-hand corner. The next trial is then presented in the same manner. The participants were presented with 58 conflicts and 58 nonconflicts over the course of the experiment.

The scores for correct decisions are based on the participant’s reaction time. The maximum number of points to gain for a correct decision is 40 points, which corresponds to a decision made in approximately the first quarter of the trial. Slower correct decisions receive 30, 20, and 10 points, respectively. For each incorrect decision or failure to make a decision, 25 points are deducted. The penalty of 25 points was chosen because it is the midpoint of the four possible scores for correct decisions. Therefore, the maximum possible score for one trial is 160 points and the lowest possible score is –100. The current trial number is shown above the point display box. There is a timer below the point display box, which shows how much time has passed in the current trial. Each trial lasted for 2 min.

Participants

One hundred one undergraduate psychology students participated in this study in return for course credit. Two data sets were incomplete because of software difficulties, so the final sample size was 99. There were 60 women, 38 men, and 1 participant who did not report his or her gender. The mean age was 19.56 years ($SD = 2.43$).

Measures

Effort, difficulty, and performance. To measure perceived difficulty and effort intensity, we froze the task twice during each 2-min trial (at 30 and 90 s) and asked participants to rate the following questions: “How difficult did you find the task just before the screen froze?” and “How hard were you trying just before the screen froze?” Participants responded on an 11-point scale[1] ranked from 0 (*not at all*) to 10 (*extremely difficult/extremely hard*). The questions within a trial were averaged to calculate a single score for effort and a single score for difficulty for each participant on each trial. The between-person reliability estimates for these variables were $\alpha = .98$ for both effort and difficulty. The within-person reliability estimates for effort ranged from $\alpha = .57$ (Trial 2) to $\alpha = .90$ (Trial 29; $M = .75$, $SD = .07$), and the reliability estimates for difficulty ranged from $\alpha = .74$ (Trial 12) to $\alpha = .94$ (Trial 29; $M = .83$, $SD = .05$). The total number of points accrued each trial were used as the performance scores.

Cognitive ability. In line with Ackerman’s (1986, 1990, 1992) research on the early phases of skill acquisition, we measured both general cognitive and broad-content abilities. In the current study, general cognitive ability was measured with Raven’s Advanced Progressive Matrices (Raven, 1990). The Advanced Progressive Matrices is one of the most popular measures of fluid intelligence (Bors & Stokes, 1998). A number of factor analyses have shown that the only variable that is reliably measured by this test is Spearman’s *g* (Winifred & Woehr, 1993). The Advanced Progressive Matrices also has minimal culture loading (Murphy & Davidshofer, 1998). This test is designed for the top 25% of the population and for this reason has been used widely for studies with undergraduate university students (Bors & Stokes, 1998). Reliabilities range from .70 to .90 (Murphy & Davidshofer, 1998).

To measure the appropriate content ability, we developed a test of dynamic spatial ability. These tests have been shown to be distinct from measures of static spatial ability (Hunt, Pellegrino, Frick, Farr, & Alderton, 1988; Peterson, 1987). Hunt et al. (1988) described the basic dynamic visual–spatial problem as predicting where a moving object is going and when it will arrive at its destination. Dynamic spatial ability is required for air traffic control because controllers are required to simultaneously assess and integrate information regarding the relative speeds and positions of moving objects (Law, Pellegrino, Mitchell, et al., 1993).

Relative arrival time and intercept-judgment tasks emerge as the clearest markers of dynamic spatial ability (Hunt et al., 1988) and have been used in a number of studies (Contreras, Colom, Shih, Alava, & Santacreu, 2001; Jackson, Vernon, & Jackson, 1993; Law, Pellegrino, & Hunt, 1993; Law, Pellegrino, Mitchell, et al., 1993). Dynamic spatial ability tests have also been used for selecting air traffic controllers (Broach & Manning, 1998; Peterson, 1987).

We modeled our test of dynamic spatial ability on the intercept-judgment task, which measures the ability to combine speed and path extrapolation. In line with this, we developed a task in which participants were required to shoot moving targets. An immobile “cannon” was placed on the “ground” in the bottom center of the screen, from which the shots were fired directly upward at the same speed every time. The targets were white squares that moved across the screen from left to right in a straight line parallel to the ground. The targets varied in altitude (high, medium, low) and speed (high, medium, low). The nine combinations of speed and altitude were ordered randomly within each trial. Participants completed seven trials, or 63 shots, which took approximately 10 min. Participants used the mouse to click on a “shoot” button, which was situated in the bottom right-hand corner. If the target was hit, it would turn into a red circle. Three information boxes were placed below the shoot button—one that shows the number of hits, one that shows the number of misses, and one that shows how many shots remain. We calculated the distance by which each target was missed. The average of these distances was used as the performance measure for this test, so high scores on the dynamic spatial ability test represent low ability. To provide a more stable measure of cognitive ability, we computed a composite ability measure using unit-weighted z scores (Ackerman & Cianciolo, 2000). The standardized dynamic spatial ability scores were recoded prior to computing the composite measure.

Conscientiousness. Conscientiousness was measured with the Revised NEO Personality Inventory (NEO-PIR), developed by Costa and McCrae (1992). This inventory is one of the most heavily used measures in the academic research area on personality (Furnham, 1996). One advantage is that it was specifically designed to measure the Big Five model of personality (Ferguson, Sanders, O’Hehir, & James, 2000). Internal consistency coefficients range from .76 to .86 (Leong & Dollinger, 1990). Research provides strong support for the construct validity of the Conscientiousness scale from the NEO-PIR (Costa, McCrae, & Dye, 1991; Piedmont & Weinstein, 1993). The reliability for the Conscientiousness measure in this study was $\alpha = .90$.

Goal orientation. Button et al.’s (1996) measure of goal orientation was used in this study; it consists of eight items each for learning and performance orientations. Button et al. demonstrated that a two-factor model provided a better fit of the data than a one-factor model in four

[1] An 11-point scale was used to be consistent with a self-efficacy scale that was included in the same experiment. The self-efficacy results are not reported in the current study.

samples and that the two dimensions were uncorrelated and related meaningfully to a range of variables. An example learning-orientation item is, “The opportunity to learn new things is important to me,” and an example performance-orientation item is, “The things I enjoy most are the things I do the best.” Participants responded on a 7-point scale ranked from 1 (*strongly disagree*) to 7 (*strongly agree*). The reliability coefficients for learning and performance orientation were $\alpha = .87$ and $\alpha = .80$, respectively.

Procedure

The experiment was conducted in sessions that lasted 3 hr, with a maximum of 6 participants in each session. The participants first completed the Advanced Progressive Matrices, NEO-PIR Conscientiousness scale, and goal-orientation measure in a classroom. The participants then moved to a computer laboratory and were seated in separate carols. The dynamic spatial ability test was then presented. Finally, we provided instructions for the conflict-recognition task. The instructions were read aloud from a script. Following task instructions, participants completed 30 2-min trials. The first one was treated as a practice trial and was excluded from the analyses. During each trial, the task froze twice and participants were asked to complete the self-report measures of effort intensity and perceived difficulty.

Analysis

The analyses of this study were conducted using hierarchical linear modeling (HLM; Bryk & Raudenbush, 1992), which allows the analysis of multiple levels simultaneously. That is, we could test for interactions between variables at different levels of analysis while accounting for their different sources of variance (Griffin, 2001; Hofmann, Griffin, & Gavin, 2000). The standard process for HLM is to run a series of models to test the hypotheses that relate to different levels of analysis. At the within-person level, or Level 1 analysis, a regression equation is calculated for each individual. The mean within-person effects from Level 1 are then used as dependent variables at the between-person level, or Level 2 analysis.

First, an empty model is run. This model examines the variance in performance scores before accounting for any predictor variables. This model is used to determine the intraclass correlation coefficient, which indicates how much of the total variance in performance scores varies between versus within individuals.

Second, an unconditional model is run. This model tests the within-person main effects. Fixed effect coefficients are used to test these relationships. Level 1 variables can be specified as random as well as fixed effects. The associated variance components are used to test whether the mean within-person effects vary significantly between individuals. Reliability estimates for the random effects represent the proportion of variance in that effect that is parameter rather than error variance. A random effect that has less than 5% parameter variance is considered unsatisfactory (Bryk & Raudenbush, 1992; Snijders & Bosker, 1999). If a random effect is significant and has satisfactory reliability, then it is appropriate to test whether the Level 2 variables can explain some of the variance in the associated Level 1 effect. If so, then the conditional model is run. This model introduces the between-person variables and tests the main effect relationships for these variables in addition to the cross-level interaction effects. Fixed effect coefficients are used to test these effects.

When one or more predictors are introduced into an HLM model, the reductions in magnitude of the various variance components are analogous to effect sizes (Zickar & Slaughter, 1999). This is similar to the use of R^2 in linear regression (Snijders & Bosker, 1999). The primary distinction between linear regression and HLM is that several R^2 values are relevant in HLM because there are several variance components (Snijders & Bosker, 1999). The intraclass correlation coefficient separates the total variability into within-person and between-person variance. The between-person variability is partitioned further and represented by the variance components of each random effect. This information can be used to determine how much of the variance within individuals and how much of the between-person variance around each parameter is accounted for by the Level 1 and Level 2 predictors.

As recommended by Aiken and West (1991), we mean centered the variables to aid in the interpretation of interaction effects. Therefore, the mean performance effects refer to the mean level of performance halfway through the training session. The quadratic practice variable was created by squaring the centered practice variable. Simple slope analyses were conducted by creating arbitrary variables that were one standard deviation above and below the mean (Aiken & West, 1991). All predictors were standardized prior to analyses so that the relative magnitude of effects could be compared.

Snijders and Bosker (1999) argued that the power to detect cross-level interactions in multilevel research is frequently low because of reductions in parameter reliability. For this reason, we set the criterion for cross-level interaction effects at the $p < .10$ level and other effects at $p < .05$.

Results

Tables 1 and 2 show the means and standard deviations of each variable as well as the intercorrelations between the variables at the between- and within-person levels, respectively. The mean for the Advanced Progressive Matrices in the current sample was higher and the standard deviation was lower than in other studies using similar populations (e.g., Bors & Stokes, 1998; Colom & Garcia-Lopez, 2002). The mean for Conscientiousness from our study appears to be higher than other research; however, the standard deviation is similar (e.g., Costa & McCrae, 1992; Ramanaiah, Sharpe, & Byravan, 1999). The means and standard

Table 1
Descriptive Statistics and Intercorrelations Among the Variables at the Between-Person Level (N = 99)

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9
1. Performance	54.22	50.01	—								
2. Effort	4.78	2.08	−.40***	—							
3. Perceived difficulty	4.93	2.11	−.41***	.89***	—						
4. Advanced Progressive Matrices	25.32	4.65	.30**	−.12	−.13	—					
5. Dynamic spatial ability[a]	61.08	14.79	−.42***	.12	.15	−.31**	—				
6. Composite ability[a]	0.00	0.81	.44***	−.15	−.18	.81***	−.81***	—			
7. Conscientiousness	159.78	18.79	−.09	.25*	.09	−.10	−.05	−.03	—		
8. Learning orientation	5.53	0.84	−.01	.18	.14	−.03	−.33***	.18	.47***	—	
9. Performance orientation	5.37	0.85	−.12	−.05	−.06	−.11	.02	−.08	.18	.16	—

[a] High scores on the dynamic spatial ability test reflect high ability; low scores on the composite ability measure reflect high ability.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 2
Descriptive Statistics and Intercorrelations Among the Variables at the Within-Person Level (N = 2,871)

Variable	M	SD	1	2	3	4
1. Performance	54.22	77.71	—			
2. Practice			.41***	—		
3. Effort	4.78	2.68	−.34***	−.27***	—	
4. Perceived difficulty	4.93	2.67	−.34***	−.26***	.85***	—

*** $p < .001$.

deviations for goal orientation from this study are comparable with other research (Chen, Gully, Whiteman, & Kilcullen, 2000; Phillips & Gully, 1997).

The intraclass correlation coefficient for performance scores was .43, which indicates that 43% of the variance in performance scores was at the between-person level whereas 57% of the variability was within individuals. Tables 3 and 4 show the results from the unconditional model for performance scores. In support of Hypotheses 1a and 1b, practice was a significant linear and quadratic predictor of performance scores, $t(98) = 13.80$, $p < .001$, and $t(2866) = –5.03$, $p < .001$, respectively, indicating that individuals improved their performance with practice and diminishing gains. A follow-up analysis revealed that at Trial 1, classification accuracy was not significantly different from chance, $t(98) = –1.16$, $p > .05$. Participants had to make classification decisions for four pairs of aircraft and yet the mean number of correct responses was only 1.87 ($SD = 1.13$). Contrary to Hypothesis 2, effort intensity was not a significant predictor of performance, $t(98) = 0.85$, $p > .05$. In combination, the Level 1 main effect variables accounted for 41.75% of the within-person variability in performance scores.

The interaction between task practice and effort was significant, $t(98) = 2.04$, $p < .05$, thus Hypothesis 3 was supported. This interaction effect reduced the Level 1 variance by a further 0.50%, which is only 0.26% of the within-person variability in performance scores. However, this interaction accounted for 12.89% and 32.44% of the variability around the practice and effort parameters, respectively. As expected, simple slope analyses indicated that the relationship between effort and performance was not significant at Trial 1 ($\beta = –3.14$), $t(98) = –0.76$, $p > .05$; however, there was a significant positive association at Trial 29 ($\beta = 8.52$), $t(98) = 2.11$, $p < .05$.

Tables 5 and 6 show the results from the conditional model for performance scores. Hypotheses 4a, 5a, 6a, and 6b predicted that cognitive ability, conscientiousness, and goal orientation would moderate the relationship between practice and task performance. Although it appeared that individuals scoring highly on the ability composite learned faster than individuals scoring poorly on this composite, this interaction did not reach significance, $t(93) = 1.44$, $p = .15$. Follow-up tests revealed that performance on the dynamic spatial ability test did moderate the relationship between practice and performance, $t(92) = –2.98$, $p < .01$, but performance on the Advanced Progressive Matrices did not, $t(92) = –1.23$, $p > .10$. Conscientiousness and performance orientation were also significant predictors, $t(93) = –1.96$, $p < .10$, and $t(93) = –2.04$, $p < .05$, respectively. Learning orientation did not moderate the relationship between practice and performance, $t(93) = 0.94$, $p > .10$. In combination, the four Level 2 variables presented in Table 5 explained 1.24% of the variability in the practice effect.

As expected, simple slope analyses for dynamic spatial ability indicated that individuals who performed well on this test improved their performance at a faster rate ($\beta = 38.93$), $t(92) = 14.04$, $p < .001$, than those with below average performance ($\beta = 25.74$), $t(92) = 7.65$, $p < .001$. Also as expected, individuals with below average Conscientiousness scores improved their performance at a faster rate ($\beta = 36.82$), $t(93) = 10.31$, $p < .001$, than their higher scoring Conscientiousness counterparts ($\beta = 27.82$), $t(93) = 10.11$, $p < .001$. In support of our prediction, individuals with low performance orientation learned at a faster rate ($\beta = 36.11$), $t(93) = 11.86$, $p < .001$, than those with high performance orientation ($\beta = 28.52$), $t(93) = 10.46$, $p < .001$. The practice–conscientiousness interaction is presented in Figure 1.

Hypotheses 4b, 5b, and 6c predicted that the rate at which the relationship between effort and performance changes over practice would be moderated by cognitive ability, conscientiousness, and goal orientation. The three-way interactions involving conscientiousness, $t(94) = –1.32$, $p > .10$, and learning orientation, $t(94) = 0.80$, $p > .10$, were nonsignificant. However, the effects of the composite ability measure, $t(94) = 2.40$, $p < .05$, and performance orientation, $t(94) = –2.54$, $p < .01$, did reach significance. In

Table 3
Unconditional Model—Fixed Effects

Fixed effects	Coefficient	SE
Midpractice intercept (π_{00})	64.03***	5.91
Practice (π_{10})	31.43***	2.28
Quadratic practice (π_{20})	−8.85***	1.76
Effort (π_{30})	2.51	2.94
Perceived difficulty (π_{40})	−8.34**	2.56
Practice × Effort (π_{50})	3.62*	1.77

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

Table 4
Unconditional Model—Random Effects

Random effects	Variance component	Reliability coefficient
Midpractice intercept (π_{00})	2,497.42***	.77
Practice (π_{10})	366.04***	.45
Effort (π_{30})	176.55***	.24
Practice × Effort (π_{50})	76.28***	.16
Level 1 error	1,992.11	

*** $p < .001$.

combination, these four Level 2 variables accounted for 25.35% of the variability around the practice–effort parameter.

As expected, the interaction between practice and effort was stronger for individuals who scored highly on the composite ability measure ($\beta = 6.55$), $t(94) = 2.79$, $p < .01$, than it was for those with lower scores ($\beta = 0.25$), $t(94) = 0.12$, $p > .05$. For low cognitive ability individuals, the effect of effort was nonsignificant at both Trial 1 ($\beta = 2.88$), $t(94) = 0.51$, $p > .05$, and Trial 29 ($\beta = 3.62$), $t(94) = 0.67$, $p > .05$. For individuals with high cognitive ability, the effect of effort strengthened from Trial 1 ($\beta = -9.18$), $t(94) = -1.80$, $p > .05$, to Trial 29 ($\beta = 11.94$), $t(94) = 2.34$, $p < .05$.

Also as expected, the practice–effort interaction was stronger for individuals with low performance orientation ($\beta = 8.22$), $t(94) = 3.01$, $p < .01$, than it was for those with high performance orientation ($\beta = -1.43$), $t(94) = -0.57$, $p > .05$. For high performance-oriented individuals, the effect of effort was nonsignificant at both Trial 1 ($\beta = 2.28$), $t(94) = 0.49$, $p > .05$, and Trial 29 ($\beta = -2.32$), $t(94) = -0.38$, $p > .05$. For individuals with low performance orientation, the effect of effort increased from Trial 1 ($\beta = -8.58$), $t(94) = -1.36$, $p > .05$, to Trial 29 ($\beta = 17.88$), $t(94) = 3.19$, $p < .01$. Both three-way interactions are depicted in Figures 2 and 3.[2]

Finally, Hypothesis 6d predicted that the strength of the interaction between learning orientation and performance orientation would increase with practice. As seen in Table 4, the two-way interaction between learning orientation and performance orientation was nonsignificant, $t(93) = -1.36$, $p > .10$. However, the three-way interaction term was significant, $t(93) = -2.68$, $p < .01$. This interaction explained a further 3.95% of the variance in the practice effect (beyond the 1.24% accounted for by the composite ability, Conscientiousness, and separate goal-orientation measures). As expected, the goal-orientation interaction strengthened from Trial 1 ($\beta = 2.28$), $t(93) = 0.69$, $p > .05$, to Trial 29 ($\beta = -14.65$), $t(93) = -2.06$, $p < .05$. At the beginning of practice, the relationship between performance orientation and performance was nonsignificant for both low ($\beta = -1.81$) and high ($\beta = 2.74$) learning-oriented individuals, $t(93) = -0.44$, $p > .05$, and $t(93) = 0.46$, $p > .05$, respectively. At the end of practice, the relationship between performance orientation and performance was nonsignificant for individuals with a low learning orientation ($\beta = 2.89$), $t(93) = 0.37$, $p > .05$, whereas it had a significant negative effect for individuals with a high learning orientation ($\beta = -26.40$), $t(93) = -2.38$, $p < .05$. This three-way interaction is depicted in Figure 4.

Table 5
Conditional Model—Fixed Effects

Fixed effect	Coefficient	*SE*
Midpractice intercept (π_{00})		
Intercept (λ_{00})	65.42***	5.46
Composite ability (λ_{01})	23.96***	4.16
Conscientiousness (λ_{02})	−3.68	5.43
Learning orientation (λ_{03})	−1.89	5.75
Performance orientation (λ_{04})	−5.44	4.30
Learning × Performance (λ_{05})	−5.89	4.48
Practice (π_{10})		
Intercept (λ_{10})	32.32***	2.21
Composite ability (λ_{11})	3.17	2.21
Conscientiousness (λ_{12})	−4.50†	2.30
Learning orientation (λ_{13})	2.45	2.62
Performance orientation (λ_{14})	−3.79*	1.86
Learning × Performance (λ_{15})	−5.24**	1.96
Quadratic practice (π_{20})		
Intercept (λ_{20})	−9.02***	1.77
Effort (π_{30})		
Intercept (λ_{30})	2.14	3.02
Composite ability (λ_{31})	−1.10	2.53
Conscientiousness (λ_{32})	−2.11	2.49
Learning orientation (λ_{33})	2.00	2.59
Performance orientation (λ_{34})	−2.09	2.36
Perceived difficulty (π_{40})		
Intercept (λ_{40})	−7.70**	2.52
Practice × Effort (π_{50})		
Intercept (λ_{50})	3.40†	1.79
Composite ability (λ_{51})	3.15*	1.31
Conscientiousness (λ_{52})	−2.77	2.10
Learning orientation (λ_{53})	1.53	1.91
Performance orientation (λ_{54})	−4.82**	1.90

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 6
Conditional Model—Random Effects

Random effect	Variance component	Reliability coefficient
Midpractice intercept (π_{00})	1,945.43***	.74
Practice (π_{10})	347.05***	.44
Effort (π_{30})	241.39***	.29
Practice × Effort (π_{50})	56.95***	.13
Level 1 error	1,982.01	

*** $p < .001$.

Discussion

The purpose of the current study was to investigate the antecedents of performance from two levels of analysis, with a particular emphasis on motivation as it varies within individuals. This study has shown that taking multiple measurements within individuals can identify how predictive relationships change over time and that variability in these within-person relationships can be explained by stable individual differences. In particular, we have demonstrated that the utility of effort can depend on the level of skill acquisition and on individual-difference variables that influence the rate of learning. In the following sections, we discuss the findings at the within- and between-person levels of analysis and consider the implications and limitations of the results in terms of the contribution that they make to the literature on motivation and performance.

[2] Given that effort and difficulty are highly correlated, we ran the analyses without difficulty for a comparison. The three-way interactions were still significant and in the same direction. However, the effect of effort for high-ability– and low-performance–oriented individuals was negative at the beginning of practice rather than nonsignificant. This finding supports our claim that difficulty might obscure the relationship between effort and performance if it is not controlled for. An individual is likely to expend a lot of effort when the task is difficult. Therefore, if difficulty is not controlled for, the relationship between effort and performance might appear negative.

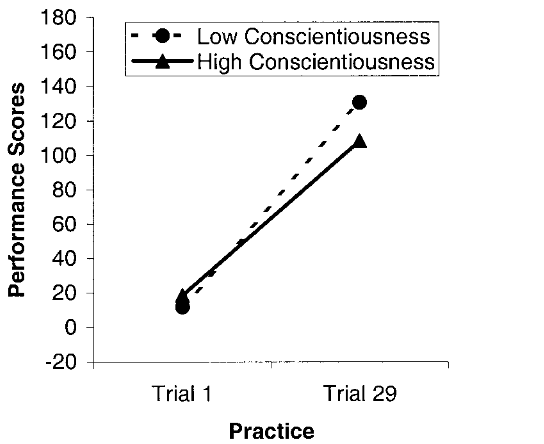

Figure 1. Cross-level interaction between conscientiousness and practice.

Within-Person Relationships

The results show that the relationship between effort and performance increased with practice. To our knowledge, this is the first study that has directly tested whether the relationship between effort and performance changes as a function of practice. Previously, it had been argued that the relationship between effort and performance should decrease with practice (Kanfer & Ackerman, 1989). We argued that the relationship between effort and performance should increase during the early stages of practice for novel tasks because increases in effort are unlikely to produce improvements in performance if the individual does not know how to perform the task. The current results support this prediction.

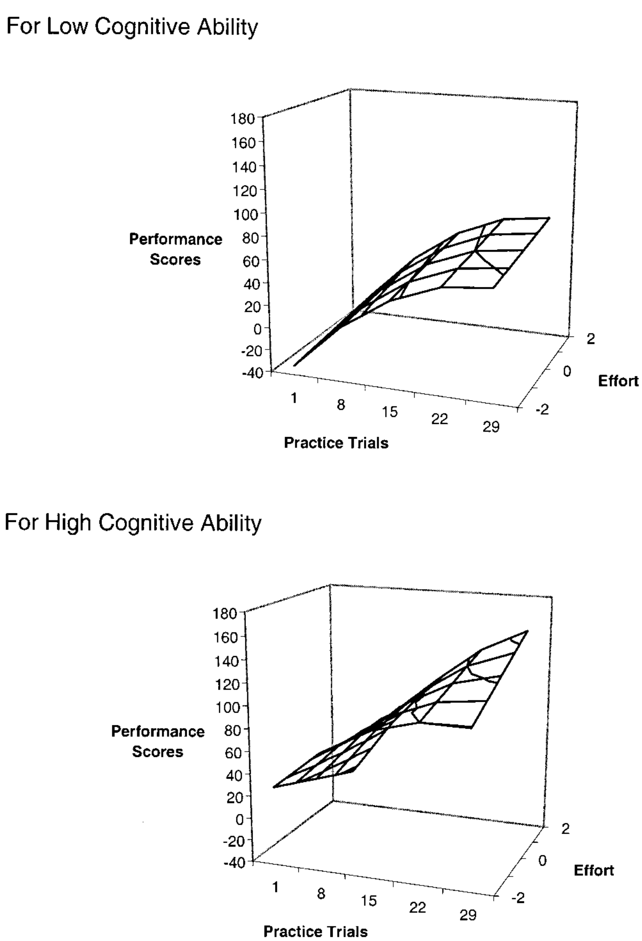

Figure 2. Three-way interaction between composite ability, practice, and effort.

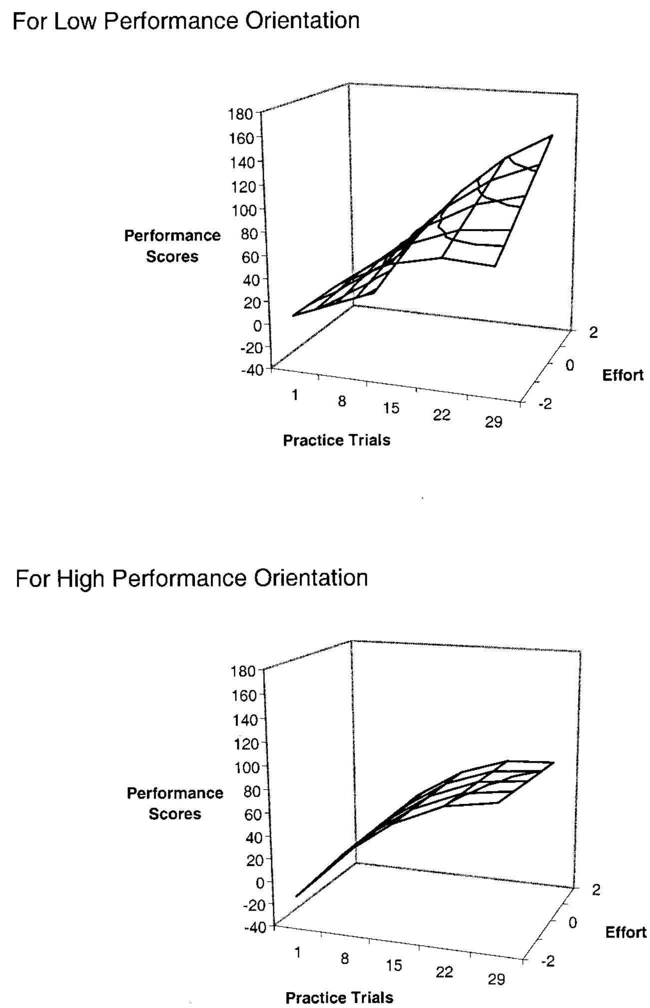

Figure 3. Three-way interaction between performance orientation, practice, and effort.

However, the current results do not answer the question of whether the relationship between effort and performance continues to strengthen or starts to weaken with further practice. The arguments that we advanced to support the prediction that the relationship between effort and performance should increase with practice only apply to the early phases of skill acquisition or to tasks that involve inconsistent information-processing demands. Resource allocation theory suggests that if the conflict-recognition task involves consistent information-processing demands, then the rate of increase in the relationship between effort and performance should slow down with further practice. The relationship between effort and performance should then start to decrease and ultimately become nonsignificant as individuals automate the task. The re-

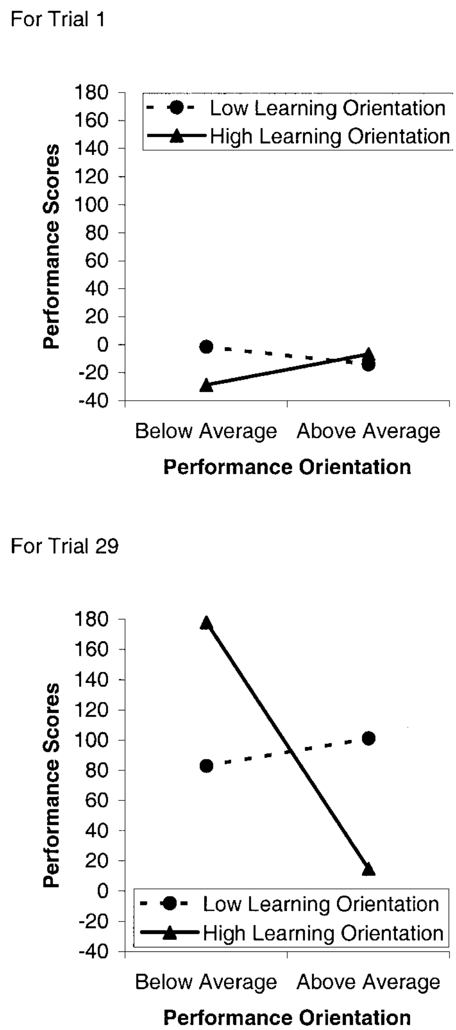

Figure 4. Three-way interaction between learning orientation, performance orientation, and practice.

sults do demonstrate that the rate of improvement in performance had started to slow down by the end of the experiment. Kraiger, Ford, and Salas (1993) have argued that these types of quadratic effects are indicative of a transition to the compilation phase of skill acquisition. However, in a series of exploratory analyses, we could find no evidence to suggest that the rate of change in the relationship between effort and performance was decreasing by the end of practice. One explanation for this finding may be that the parameter representing the interaction between the quadratic practice effect and the effort effect lacked sufficient reliability. Another possibility is that further practice is required before a decrease in the relationship between effort and performance can be observed.

One finding that needs to be noted is that effort and perceived difficulty were highly correlated ($r = .85$), suggesting that they are similar constructs.[3] Overall, the results were very similar when we ran the analysis without controlling for difficulty. However, there was one major difference: The relationship between effort and performance was negative at the beginning of practice if difficulty was not controlled for. This finding suggests that it is appropriate to control for difficulty when examining the effects of effort. The zero-order correlations also provide support for the construct validity of our effort and difficulty measures. Effort was positively correlated with conscientiousness ($r = .25$, $p < .05$), whereas difficulty was not ($r = .09$, $p < .05$). Furthermore, when the effects of difficulty were partialed out, the correlation between effort and conscientiousness strengthened ($r = .37$, $p < .001$). Theoretically, stable personality traits should be more strongly related to effort than to difficulty. Effort expenditure is under voluntary control (Freude & Ullsperger, 2000; Wickens, Gordon, & Liu, 1998). Perceptions of difficulty, in contrast, are more reliant on the situation because they are a function of the task and depend on other factors, such as ability.

Trait Variables

Cognitive ability. The finding that our composite measure of cognitive ability influenced the rate at which the relationship between effort and performance changed over time is novel. The resource allocation theory of motivation predicts that variables that influence the rate of skill acquisition should influence the rate at which the relationship between effort and performance changes over time. The current results support this prediction. The relationship between effort and performance changed faster for individuals who scored well on the composite ability measure. These results suggest that cognitive ability does interact with motivation, as predicted by early theorists (e.g., Vroom, 1964). By the end of practice, the relationship between effort and performance was stronger for individuals with high cognitive ability than for individuals with low cognitive ability. Furthermore, the current results provide some insight into why tests for ability–motivation interactions have produced inconsistent findings in the past. The current findings are consistent with the claim that ability–motivation interactions should be conceptualized as a cross-level effect rather than a between-person effect. The results demonstrate that the ability–motivation interaction is relatively complex, being contingent on another within-person variable, namely practice. It is, therefore, not surprising that cross-sectional studies conducted at the between-person level have not found consistent evidence for this interaction.

It was interesting that it was the test of dynamic spatial ability that moderated the effects of practice rather than the Advanced Progressive Matrices. This supports arguments in the personnel selection (Murphy, 1988) and ability measurement (Hunt et al., 1988) literatures that the ability type should be closely matched with the criteria. The dynamic spatial ability test was designed to closely simulate the skills that would be required for the air traffic conflict-recognition task. Specifically, it required individuals to estimate the time that it would take objects traveling at different speeds to reach the same position. This is very similar to the air traffic conflict-detection task. However, it is important to note that the dynamic spatial ability test and the conflict-detection task are not merely variants of the same task. The dynamic spatial ability test required individuals to judge the time at which they should fire a projectile, whereas the conflict-detection task required individuals to estimate whether the distance between the aircraft would ever be less than or equal to a specified distance. Although it should be the case that the same types of abilities are required for

[3] We thank an anonymous reviewer for making this observation.

both tasks, the tasks differ in the types of judgments that participants were required to make. Furthermore, the targets and the projectile in the dynamic spatial ability test traveled much faster than the aircraft in the conflict-detection test, making transfer between the tasks unlikely. Previous studies using the air traffic conflict task have demonstrated that even small changes in the speed of aircraft, the angle of convergence, or the position of the conflict severely disrupt transfer of training (Loft & Neal, 2002).

Other potential reasons for the apparent superiority of the dynamic spatial ability test could be that it had higher fidelity than the Advanced Progressive Matrices[4] or that the Advanced Progressive Matrices suffered from restriction of range. To test the former suggestion, researchers would need to systematically vary the fidelity of the different ability measures.

Conscientiousness. These results support recent findings that conscientiousness can have a negative effect on some performance outcomes in certain types of tasks (Colquitt et al., 2000; Feist, 1998; LePine et al., 2000; Martocchio & Judge, 1997; Tett, 1998; Tett et al., 1999). As expected, individuals with low conscientiousness improved their performance at a faster rate than those with high conscientiousness. There were two reasons for predicting this effect. First, the conflict-detection task was performed under time pressure. Tett et al. (1999) argued that the tendency of highly conscientious people to be thorough, careful, and meticulous interferes with performance for tasks that have to be performed under time pressure. Second, previous research has shown that conscientiousness is negatively related to performance in learning contexts (Colquitt et al., 2000).

The current findings extend those previously reported in the field by showing that conscientiousness influenced the rate of skill acquisition rather than overall performance. The main effect of conscientiousness in our study was nonsignificant, $t(93) = -0.68$, $p > .05$. This finding is consistent with that reported by Ackerman et al. (1995), who also used an air traffic control simulation. Our results suggest that the relationship between conscientiousness and overall performance may depend on the amount of practice that people are given on the task and the timing of performance measurement. For example, it is possible that with sufficient practice, highly conscientious individuals might “catch up” to their counterparts. With even more practice or transition to a transfer context, the highly conscientious individuals might surpass those with low conscientiousness. The latter point is supported by Colquitt et al.’s (2000) meta-analysis, which showed a strong positive relationship between conscientiousness and transfer ($\beta = 0.51$). Therefore, focusing on overall performance could mask the differences in rate of improvement. This suggests that, at least in some contexts, a multilevel approach is required for observing the complexity of relationships.

Although conscientiousness influenced the rate of skill acquisition, it did not moderate the rate at which the link between effort and performance changed. It is possible that the way in which higher versus lower conscientious individuals direct their effort confounds this relationship. The volitional traits of conscientiousness, such as being hard working, persevering, and achievement oriented, should influence both the direction and intensity of effort. Using Kanfer’s (1992) conceptualization of motivation, it follows that highly conscientious individuals, in comparison with their lower conscientious counterparts, are expected to direct more effort toward on-task activities and self-regulation and a lesser proportion toward off-task activities. The direction of effort toward self-regulation is likely to impair performance at the beginning of practice but should be beneficial at the end of practice (Kanfer & Ackerman, 1989). Thus, even though highly conscientious individuals were less skilled at the end of practice, they may have directed their effort toward more useful activities. This effective use of effort might cancel out the disadvantage of being less skilled.

Goal orientation. The results of the current study support the argument that performance orientation can have a negative effect on learning outcomes (Button et al., 1996; Dweck, 1986; Dweck & Leggett, 1988). Specifically, the current study shows that individuals with low performance orientation learn faster than individuals with high performance orientation. We expected this result because high performance-oriented individuals are more likely to avoid challenges, be focused on proving themselves to others, and withdraw from the task in the face of obstacles. These results support the claim that goal orientation does not affect performance until the orientation framework has been activated via learning events (Button et al., 1996; Dweck, 1986; Dweck & Leggett, 1988; Steele-Johnson et al., 2000; Tenenbaum et al., 2001). Most previous research has examined performance orientation at a single time point. The current findings suggest that the inconsistencies in the literature with respect to performance orientation may, at least in part, be attributable to the use of cross-sectional designs.

As expected, there was also a three-way interaction between performance orientation, practice, and effort. This is the first study to test for interactions between performance orientation and effort at the within-person level. The results showed that the rate of change in the relationship between effort and performance was strongest for individuals with low performance orientation. By the end of practice, the relationship between effort and performance was positive for low performance-oriented individuals but remained nonsignificant for individuals with high performance orientation. This finding supports theories of resource allocation and goal orientation for at least two reasons. First, this finding provides further support to the prediction that variables that influence the rate of skill acquisition also influence the rate of change in the relationship between effort and performance. Performance orientation moderated both effects. Furthermore, these theories predict that the relationship between effort and performance should be weaker for high performance-oriented individuals because they are less likely to direct their effort toward on-task activities than individuals with low performance orientation. That is, when highly performance-oriented individuals expend effort, it is likely to be directed toward ego management, and when faced with difficulty, they are likely to shift their focus toward off-task activities. Given that goal-orientation effects are argued to emerge over time in response to task feedback, it follows that the interaction between performance orientation and effort should become stronger as individuals practice the task. Demonstration of this interaction is useful because it places performance orientation in the nomological network of self-regulation, which aids understanding of why performance orientation has a negative influence on learning outcomes.

Finally, the current study also demonstrates that the negative effect of performance orientation at the end of practice only held for individuals with high learning orientation. Some researchers

[4] We thank an anonymous reviewer for making this observation.

have speculated that high performance orientation is necessary for successful performance (Button et al., 1996; Hardy, 1997). If so, then there should be a positive effect of performance orientation for individuals with high learning orientation and a negative relationship for those with low learning orientation. However, we argued that it is also possible that a low learning orientation might prevent the realization of the potential benefits of a low performance orientation. If this were the case, we would only expect to see the negative effects of performance orientation for individuals with a high learning orientation.

The current results support the second hypothesis. By the end of practice, there was a negative interaction between learning orientation and performance orientation. The benefits of having a low performance orientation only surfaced for individuals who had a high learning orientation. Presumably, there were no benefits to be gained from a low performance orientation if the individual had little concern for learning the task. This finding clearly contradicts the first hypothesis, which predicted a positive effect of performance orientation for individuals with a high learning orientation.

These findings with respect to goal orientation have important practical implications. A number of studies have shown that goal orientations can be effectively induced via situational characteristics, such as the experimenter's instructions (Mangos & Steele-Johnson, 2001; Martocchio, 1994; Steele-Johnson et al., 2000; Tabernero & Wood, 1999; Wood & Bandura, 1989). As with research on dispositional goal orientation, results regarding links with performance have been mixed. However, this research has not examined the effects of using instructions to create different combinations of learning and performance orientations. The current results suggest that the induction of a high performance orientation may have negative effects in a training context, particularly for individuals with a high learning orientation. Rather, it seems that it would be most beneficial to encourage individuals to adopt a high learning orientation in combination with a low performance orientation. Further research into the joint effects of learning and performance orientation is clearly needed using longitudinal designs.

The current results do not support the prediction that learning orientation would influence the rate of skill acquisition or the rate of change in the relationship between effort and performance. One explanation for this finding may be that the effects of learning orientation need a longer time span to evolve than do the effects of performance orientation, or at least for the current task. Similarly, it might only be in a transfer task that the benefits of a high learning orientation are truly realized. Kozlowski et al. (2001), for example, found that self-efficacy predicted performance on a transfer task but not on the training task in a decision-making simulation.

A further potential explanation relates to the importance of tailoring goal-orientation measures to the specific context (Vandewalle et al., 2001). That is, individuals can have different implicit theories of ability for different attributes, so they can display different goal orientations across situations (Tabernero & Wood, 1999). Vandewalle et al. (2001) noted that the Button et al. (1996) measure of goal orientation that was used in this study assesses the global level of learning and performance orientations, lacking any reference to specific contexts. It is possible that effects of learning orientation may have emerged if the measure had been contextualized. However, this does not explain why we were able to obtain an effect of performance orientation with a global measure, unless individuals' performance orientations are more stable across various skill acquisition contexts than their learning orientations are.

Measurement of Effort

As noted earlier, researchers have struggled with the measurement of effort for many years. In line with Brown and Leigh's (1996) experience, our review of the literature showed little agreement regarding the measurement of effort, even within the categories of time on task and self-report. Time-on-task and behavioral (e.g., task-relevant physical actions) measures (Blau, 1993; Brown & Peterson, 1994; Fisher & Ford, 1998; Terborg, 1977; Weingart, 1992) appear to have yielded slightly higher validity estimates than self-report measures (Bray & Whaley, 2001; Brown & Leigh, 1996; Terborg & Miller, 1978; Wolters, 2000; .30s rather than .20s). However, time on task is not a direct measure of effort, and it confounds intensity and persistence.

Our measure of effort intensity was based on a single item that assessed how hard participants were trying. The primary reason for using a single item was that we wanted to obtain two measures of effort intensity per trial for every trial. The use of multiple-item measures within this type of repeated measures design increases the risk that participants will experience fatigue and boredom. Furthermore, studies that have used multiple-item (Bray & Whaley, 2001; Brown & Leigh, 1996; Wolters, 2000) rather than single-item (Schmitz & Skinner, 1993; Terborg & Miller, 1978) measures of effort intensity do not seem to have yielded any systematic benefits for validity.

However, if researchers are using a relatively small number of repeated measurements, then there may be benefits in exploring the potential for additional items assessing effort intensity or for expanding the construct domain to incorporate other dimensions of effort, such as direction and persistence. There is some recent research that combines both of these options (Barrick, Stewart, & Piotrowski, 2002). Barrick et al. (2002) developed self-report items to assess three broad goals that are expected to influence behavior (communion striving, status striving, and accomplishment striving) and developed items to measure (a) attention and direction, (b) intensity and persistence, and (c) arousal in relation to those goals. For example, an intensity–persistence item associated with accomplishment striving is "I try hard to get things done in my job." The strength of this measure is that it comprehensively measures the construct space in the context of goal-directed behavior. However, this measure is not directly applicable for real-time repeated measurements because it is designed as a trait rather than a state measure and there are 11 items in the scale.

An area of research that might be useful for the measurement of effort is related to cognitive workload. *Cognitive workload* is generally defined as a multidimensional construct. One dimension refers to the effort exerted by an operator to accomplish task demands (Messick Huey & Wickens, 1993). Two widely used self-report measures of workload are the Subjective Workload Assessment Technique (Reid & Nygren, 1988) and the NASA Task Load Index (Hart & Staveland, 1988). The items that assess effort intensity in these measures and others are consistent with our operationalization of intensity as trying hard.

Perhaps the major contribution that research on cognitive workload can make to the measurement of effort relates to psychophysiology. Research suggests that changes in effort can be measured indirectly through changes in a number of physiological systems

(Meshkati, Hancock, Rahimi, & Suzanne, 1995). Measures that show some promise include heart rate variability, pupil diameter, blink rate, electroencephalograph recording (Tsang & Wilson, 1997; Wickens et al., 1998), autonomic space (Backs, 2001), and slow brain potentials (Freude & Ullsperger, 2000). Freude and Ullsperger (2000), for example, argued that slow brain potentials are a manifestation of voluntarily controlled effort, indicating the prepatory mobilization of resources and increased cortical activity under demanding conditions. Freude, Ullsperger, and Erdmann (1999) used a complex visual monitoring task and showed that slow brain potentials decreased over two practice blocks, suggesting a decrease in effort expenditure due to increased skill. Congruent with our findings, they also showed that a significant correlation between slow brain potentials and performance only emerged at the second block, after sufficient practice.

Limitations

There are a number of limitations that should be considered when interpreting the present results. First, it could be argued that the current sample lacked representativeness, given that the participants were undergraduate students, and that the results lack generalizability because we used a laboratory task. This is probably true to some extent, and more research (both experimental and field) is called for before we can know whether the current results generalize to other populations, tasks, and settings. As noted by Eyring et al. (1993), the findings obtained using laboratory-based air traffic simulations would only be expected to generalize to tasks with similar information-processing requirements. This would include tasks that are cognitively demanding, incorporate time pressure, and allow for changes in performance over time. However, as noted by Kanfer (1992), the use of more realistic and complex tasks in experimental settings is closing the gap between field and laboratory research. Indeed, a substantial body of previous research on skill acquisition has been carried out using similar tasks in laboratory settings with similar populations (Ackerman et al., 1995; Eyring et al., 1993; Kanfer & Ackerman, 1989; Mitchell, Hopper, Daniels, George-Falvy, & James, 1994). These studies have contributed substantially to psychologists' understanding of the effects of ability and motivation during skill acquisition.

A second potential limitation is related to the freezing function. That is, our measures of effort and difficulty involved freezing the task multiple times throughout each trial. It is possible that this interruption interfered with task performance. However, the strategy of freezing the task and asking participants a series of questions has been used in a number of contexts previously. Most relevant for current purposes is Endsley's (1995) Situation Awareness Global Assessment Technique (SAGAT). SAGAT is widely used for assessment purposes in dynamic tasks, such as air traffic control and flight training. This technique involves freezing the task and asking participants to answer a series of probe questions. Endsley conducted a series of validation studies using computerized air traffic control scenarios and concluded that the freeze and probe technique did not appear to be intrusive and did not disrupt participants' performance in the simulation.

We measured goal orientation using a two-factor measure. However, recent research suggests that goal orientation is a three-factor construct (Elliot & McGregor, 1999; Vandewalle, Brown, Cron, & Slocum, 1999; Vandewalle et al., 2001; Vandewalle, Ganesan, Challagalla, & Brown, 2000). In particular, the performance-orientation aspect appears to reflect two factors that capture the distinction between seeking positive (proving orientation) and avoiding negative (avoidance orientation) evaluations (Brett & Vandewalle, 1999). Vandewalle et al. (2001) found that the negative effects of performance orientation were associated with the avoidance rather than the proving orientation. Therefore, there may be some aspects of performance orientation that are beneficial, as some researchers have speculated. We encourage the specification of this three-factor model in future investigations of goal orientation.

Conclusion

This study has contributed to understanding of the way in which effort relates to performance during skill acquisition. We tested a number of previously untested theoretical propositions regarding the antecedents of performance in a dynamic context. We have shown that the relationship between effort and performance can change over the course of skill acquisition and depends on traits such as cognitive ability and goal orientation. The results of the current study suggest that cognitive ability does interact positively with motivation, as suggested by Vroom (1964), when motivation is assessed at the within-person level over time. Furthermore, we have demonstrated how two dimensions of goal orientation can interact and how their effects evolve over time. There is substantial scope for further research addressing the effects of other aspects of effort, such as direction and persistence, and additional predictors at the within- and between-person levels of analysis. This type of research has the potential to improve theoretical understanding of the motivational process and its link with performance.

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