Subjective estimates of job performance after job preview: Determinants of anticipated learning curves

Phillip L. Ackerman a,⁎, Stacey Shapiro a, Margaret E. Beier b

a Georgia Institute of Technology, USA
b Rice University, USA

Abstract

When people choose a particular occupation, they presumably make an implicit judgment that they will perform well on a job at some point in the future, typically after extensive education and/or on-the-job experience. Research on learning and skill acquisition has pointed to a power law of practice, where large gains in performance come early in practice, with diminishing returns with greater experience. However, it is not clear whether young adults understand the nature of job learning and performance over time. In the current study, 153 university students were provided with job descriptions and video clips for 20 different jobs. They were asked to estimate the shape of their learning curves for each job, and to provide judgments of their performance levels from the first day on the job to a point after six months of job experience. We investigated the patterns of expected learning/performance curves, and explored the role of personality, interests, self-concept, self-estimates of abilities, entity/incremental theories of intelligence, and gender in prediction of the patterns of expected curves. Participants generally expected a power function or a linear function of improvement across the jobs, with notable differences in anticipated performance depending on job characteristics of gender dominance, ability demands, and interest themes. Traits and job engagement variables provided significant predictive power for accounting for individual differences in expected job performance over time. Implications for implicit theories of intelligence and occupational choice are discussed.

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Introduction

Several decades of vocational research and theory developments have converged to support the proposition that individual differences in the patterns of abilities, personality traits, and interests themes are major correlates of occupational choice (for reviews, see Brown & Lent, 2005). Demographic variables also play a role in occupational choice, including most notably for the current investigation, gender. Theories of occupational choice (e.g., Lent, Brown, & Hackett, 1994) posit that traits direct people to experiences that, in turn, contribute to the development of self-efficacy (a person's judgment about his/her ability to organize and execute the actions necessary to perform a specific task, Bandura, 1991). Self-efficacy is thought to be central to the development of occupational choice because it leads to the development of occupational interests, and because individual differences are thought to influence occupational choice through self-efficacy (Lent et al., 1994).

Even with consideration of the four categories of traits mentioned previously (abilities, personality traits, interests, and demographic factors), there is much unexplained variance in the prediction of occupational choice. Various efforts have been made to address this challenge by focusing on other factors such as self-estimates of abilities and interests (e.g., Beier, 2004; Lent et al., 1994).

Changes in abilities and interests are thought to be major contributors to changes in performance (e.g., Lent et al., 1994). However, it is not clear whether these changes are due to actual changes in abilities and interests, or to changes in self-estimates of abilities and interests. Indeed, a recent study by Beier (2004) found that self-estimates of abilities and interests were more strongly correlated with performance than actual changes in abilities and interests.

These findings suggest that self-estimates of abilities and interests may be more important than actual changes in abilities and interests for predicting changes in performance. This is consistent with the idea that self-efficacy is a key mediator of the relationship between abilities and interests and performance.

In the current study, we sought to investigate the role of self-estimates of abilities and interests in the prediction of changes in performance. We also sought to investigate the role of demographic variables, such as age and gender, in the prediction of changes in performance. Finally, we sought to investigate the role of personality traits, such as openness and conscientiousness, in the prediction of changes in performance.
devoted to expanding the range of constructs for understanding occupational choice over the past few decades, including self-efficacy (Lent et al., 1994), self-concept (Super, 1990), and more recently, stereotypes and implicit theories of intelligence (e.g., Dweck & Leggett, 1988). The latter two constructs also have been suggested to be integral contributors to the explanation of gender differences in occupational choice, even when trait measures are otherwise equivalent between men and women.

One limitation of many traditional approaches to understanding the occupational choice process, however, is that when individuals are asked to estimate their capability for performing well in a specific job or occupation (e.g., a judgment of self-efficacy, see Stajkovic & Luthans, 1998), the job/occupations are usually presented as if they are static or unchanging, when in fact, there are both substantial interindividual differences and intraindividual changes in interindividual differences in job performance over the course of training, practice, and job experience (e.g., see Ackerman & Humphreys, 1991; Wechsler, 1952). For example, it is well established that the abilities that predict performance when the individual first performs a task/job are usually not the same as the abilities that are associated with performance after substantial skill development has taken place (e.g., see Ackerman, 1987; Fleishman, 1972). A person making an occupational choice might base his/her self-efficacy expectations on the basis of expected performance on the first day of work, expected performance after a long period of time, or something in between. It is entirely unclear, however, whether people have any degree of understanding about the nature of job learning and skill acquisition for different types of jobs, and the dynamics of ability and personality influences on job performance (e.g., Helmreich, Sawin, & Carsrud, 1986). Inadequate understanding of these issues might distort self-efficacy judgments that in turn, may lead the individual to fall-back on well-known stereotypes to make occupational choices. In addition, given the suggested gender differences in implicit theories of intelligence, where women are posited to have a greater tendency to believe that their abilities are fixed and men are posited to have a greater tendency to believe that their abilities are malleable (e.g., see Dweck & Leggett, 1988), one might expect gender differences in implicit learning curves for a variety of jobs (e.g., more shallow or flat for women than for men).

Explicit and implicit learning theories

The study of curves of learning and skill acquisition is an area of extensive empirical research and theory over the course of modern psychology, starting with the seminal work on the acquisition of telegraphy skills by Bryan and Harter (1899). Although several qualitative theories of skill acquisition have been introduced, such as the three-stage framework involving cognitive, associative, and autonomous phases by Fitts and Posner (1967), and quantitative modeling approaches, such as the ACT-R framework proposed by Anderson (1993), there is a consensus that for production jobs where the time to complete a task is the criterion variable (e.g., assembly of a product), skill acquisition follows a “power law of practice” (Newell & Rosenbloom, 1981). That is, when the time to complete an item is plotted against the raw number of trials, the curve of practice shows large initial gains, and a negatively accelerating function of improvement. Or, when the time to complete an item is plotted against the log of the number of trials, the resulting curve of practice is linear. For jobs and tasks that are not characterized by production criteria, the development of expert performance levels is also non-linear, and follows at least a negatively accelerating function, if not perfectly described by a power function, when considered over long periods of time, such as 10 years in a profession (e.g., Ericsson, Krampe, & Tesch-Römer, 1993; Simonton, 1988).

In contrast to the extensive research on actual, or explicit, learning curves, there is little research that addresses the form of adults’ expected learning/skill acquisition functions. The vast majority of studies that assess self-expectations of performance either make no distinction about the amount of training or on-the-job experience the individual will have prior to the estimation of expected performance, or they only ask for short-term, self-efficacy expectations (e.g., ‘I have high confidence in obtaining a ___ level of performance in the next opportunity’—see Heggestad & Kanfer, 2005). Although many of these studies reveal individual and gender differences (for a review, see Judge et al., 2007), such results may not capture the expected dynamic nature of expected learning/skill acquisition. Given that the ability demands of jobs change over time, and that people make judgments about job performance based on their abilities, it is important to know if they change their expectations about job performance based on different time-course projections. If people make occupational choices on the basis of limited time-course projections, they may have distorted expectations of their ultimate job performance after even a few months of on-the-job experience.

Various explanations have been offered for gender differences in occupational choice (see the extensive review by Ceci, Williams, & Barnett, 2009). Dweck and her colleagues (e.g., Dweck, 2006; Dweck & Leggett, 1988) have proposed that one contributing factor to gender differences in occupational choice may be an individual’s implicit theory of intelligence (or “mindset”). Presumably, whether someone has an “entity” (fixed) or “incremental” (growth) implicit theory of intelligence, guides that person in approach or avoidance behaviors when faced with learning and performance opportunities. By definition, people with incremental implicit theories believe that the investment of cognitive effort will result in higher levels of ability and performance mastery. People with entity implicit theories believe that abilities are fixed, and that there is little to be gained by investing effort toward learning and mastery.

There is some lack of clarity about whether Dweck has suggested that individuals with an entity theory of intelligence expect shallow or flat learning curves in contrast to individuals with an incremental “theory of intelligence,” who would be expected to predict steep learning curves (e.g., similar to the explicit findings of the power law of practice). Nevertheless, the implication of Dweck’s theory (Dweck, 2006; Dweck & Leggett, 1988) is that individual differences in expected learning curves may indeed be related to differences in implicit theories of intelligence. The lack of clarity stems at least partly from the difficulty in distinguishing whether the entity theory (“fixed mindset”) pertains mainly to the immutability of intelligence or other abilities or to the
individual's skills. For example, Dweck noted that individuals with a fixed mindset have the belief that “If at first you don’t succeed, you probably don’t have the ability.” (pp. 9–10, Dweck, 2006). However, she also noted that endorsement of the statement “You can learn new things, but you really can’t change how intelligent you are” (p. 12, Dweck, 2006) is an indicator of the fixed mindset, even though this statement implies learning with investment of cognitive effort.

Aside from the general issues associated with individual and gender differences in implicit theories of intelligence, it seems that to be directly relevant to occupational choice, individual differences in these variables should be related to expected patterns of learning and skill acquisition on the job. That is, one might expect that individuals who have a fixed mindset are more likely to believe that their performance after a period of training or on-the-job experience would not improve from their initial performance on the job.

Expected patterns of job performance over time

The theoretical literature on self-concept is extensive, with early discussions of the topic by William James (1890/1950). The key notion of self-concept is that it represents “a person’s perception of himself/herself” (p. 411, Shavelson, Hubner, & Stanton, 1976). According to Shavelson et al. (1976), “Self-concept may be described as: organized, multifaceted, hierarchical, stable, developmental, evaluative, and differentiable.” (p. 411). Within Shavelson’s framework, there are four broad domains of self-concept that have been investigated, namely: academic, social, emotional, and physical (e.g. see Marsh, 1990). To date, self-concept for young adults has been considered as a relatively stable attribute. Even though there are clear developmental patterns of growth during childhood and adolescence, self-concept is traditionally measured as a reflection of current standing (e.g., “I am good at math”) or the individual’s prior experiences (e.g., “I have done very well in math classes”).

Although much is known about self-concept constructs, the extant research does not describe the pattern of self-concept for performance on tasks projected over a period of learning or on-the-job experience, or whether there are salient differences in expected learning curves across individuals or across job types. There are, however, several conjectures that can be made about the nature of expected performance over time. First, most people have a keen understanding that, although most novel tasks are effortful and error-prone, with practice, their performance typically improves. The reasoning behind this conjecture is that if it were not true, few individuals would persist in a task after initial failure or difficulties, whether the task to be learned is a video game or a new job. Second, although many people have an inadequate basis for predicting their final asymptotic performance on a task (much as psychometricians have difficulty in predicting the same criteria), they can fall back on prior experiences with similar tasks, whether the task be predominantly cognitive, physical, psychomotor, or social, and they can make predictions on the basis of these experiences. Individuals who have, for example, succeeded on math tasks in school, might expect that they will similarly acquire high levels of skills at jobs that have dominant math skill requirements. Conversely, those individuals who have struggled with math tasks might expect to only attain modest or mediocre levels of skills at the same jobs. One corollary of this conjecture is that the degree of coherence in expected learning curves for particular jobs will be critically dependent on the adequacy of descriptive information about the jobs and the skills required to perform well on the jobs.

Predictors of expected patterns of job performance over time

When people are asked to predict their job performance over time, we expect that the major trait ingredients for occupational choice are the key predictors of estimated performance, in addition to individual differences in implicit theories of intelligence. That is, individual differences in abilities, personality, and interests should be major predictors of expected job performance, with one qualification. Because people make predictions of performance (e.g., self-efficacy judgments) based on judgments of their own abilities, one might expect that self-concept and self-estimates of abilities are perhaps more central to individual expectations of performance over time than objective test scores. In support of this idea, a path analysis conducted by Kanfer, Ackerman, and Heggestad (1996) showed that academic self-concept measures were more directly related to self-efficacy judgments of performance on a complex task than were objective assessments of the abilities related to task performance (objective abilities were only indirectly related to self-efficacy through self-concept).

Self-concept and self-estimates of abilities

Because the main theme of self-concept is how the individual perceives his/her knowledge, skills, and abilities, it seems axiomatic that traditional measures of self-concept should be associated with self-estimates of performance over a period of learning and job experience. These measures are typically aimed at retrospective reports (e.g., “I have always done well in math classes”), which may not be optimal for understanding how an individual makes future-oriented judgments of performance. Measures of self-estimates of abilities are more abstract than self-concept measures, because they focus on the ability traits themselves, which are in turn, expected to be related to objective task performance. For example, if verbal abilities are expected to be associated with job performance after substantial time on the job, then one might expect that self-estimates of verbal abilities will also be associated with expected job performance, if the self-estimates of verbal abilities are accurate, and if the individual perceives that job performance is dependent on these abilities.

Self-estimates of abilities and job performance have been investigated in terms of their validity relative to objective measures of ability and job performance (Mabe & West, 1982). Research finds that the correlations between self-estimates and actual abilities range widely from small to substantial in magnitude (Ackerman & Wolman, 2007; Mabe & West, 1982). Accordingly, researchers range from pessimistic about people’s capacity to assess their own skills and abilities (DeNisi & Shaw, 1977; Paulhus,
Lysy, & Yik, 1998), to optimistic (Ackerman, Beier, & Bowen, 2002; Ackerman & Wolman, 2007; Levine, Flory, & Ash, 1977). In support of the value of self-estimates, a meta-analysis of the relation between self-estimates and actual performance identified various measurements problems with studies finding little correspondence between self-estimates and actual ability (Mabe & West, 1982). When only studies without measurement issues were included in the Mabe and West meta-analysis, the relationship between self-estimates and actual abilities was medium to large in magnitude (average $r = .63$). One measurement issue identified by Mabe and West (1982), that is especially relevant to the current study, is the specificity of the information provided to the person making the assessment (Ackerman et al., 2002; Ackerman & Wolman, 2007). That is, self-estimates and actual ability and performance will be more highly related when specific information about the domain in question is provided, or when the question is asked in a specific way. For example, people will tend to be more accurate when estimating whether they can dead-lift 50 lb or run 5 miles in under 40 min than they will be when estimating their “general physical condition.”

Although research shows that people can be accurate in self-estimates of ability, important questions remain about self-estimates of job performance. One question is, do people give different anticipated performance ratings for different types of jobs? Presumably, many people exploring careers may have little to no prior experience, which may affect their ability to differentially rate their anticipated job performance. A related question is whether or not people are able to anticipate learning in a job. That is, will self-estimates of performance vary when people are asked to provide them relative to the amount of experience they will have on the job (e.g., how will they perform on day one versus after 6 months)? Also, will these self-estimates of learning be different for different job types? Moreover, what are the determinants of self-estimates of job performance and self-estimates of job performance over time?

### Personality/motivational trait complexes

Although the five-factor model of personality typically provides a sufficient description of normal personality (McCrae & Costa, 2003), it is somewhat insular, in light of the commonality among personality and motivational traits that are relevant to vocational concerns (e.g., see Ackerman, 1997). For the current investigation, we expand the treatment of personality to take account of the common variance among both broad personality factors and occupationally-relevant motivational factors (e.g., see Kanfer & Heggestad, 1997). In this fashion, we can focus on a small set of broad trait measures that incorporate factors of achievement orientation, extroversion, neuroticism, and competitiveness, rather than examining regressions of a large number of related variables that might result in opportunistic correlations.

One framework that brings together personality, interest, and motivational trait variables is the “trait complex” approach proposed by Ackerman and Heggestad (1997), and subsequently validated by others (e.g., Staggs, Larson, & Borgen, 2007; Sullivan & Hansen, 2004) and extended by Ackerman and colleagues (e.g., Ackerman, Bowen, Beier, & Kanfer, 2001; Ackerman & Wolman, 2007). The trait complex approach draws on the fact that there are salient communalities among affective and conative trait variables. These communalities indicate that rather than examining a large number of variables for prediction of criteria of interest, which would be both impractical and not scientifically parsimonious, one can reduce the predictor space without great loss of predictive power by creating composites of trait measures that share substantial common variance. The trait complexes found through meta-analysis (Ackerman & Heggestad, 1997) and expanded through follow-up studies, also have been shown to be consistent with a theory of adult intellectual development (Ackerman, 1996). For instance, the PPIK (intelligence-as-process, personality, interests, and intelligence-as-knowledge) theory proposes that individuals high on some trait complexes (e.g., intellectual-cultural and science/math trait complexes) tend to orient toward the development of knowledge and skills in academic domains, while individuals who are high on other trait complexes (e.g., neuroticism/anxiety and social trait complexes) tend to orient away from acquisition of knowledge and skills in academic domains.

Although they have not been examined relative to self-estimates of job performance, trait complexes have been examined relative to self-estimates of abilities with college students. This research finds that trait complexes are generally related to self-estimates of general ability, although these relationships differ based on the ability and trait complexes (e.g., trait complexes related to neuroticism/anxiety were negatively related to abilities; a math–science trait complex was positively related to math and spatial abilities, Ackerman & Wolman, 2007). Notably, these correlations tend to be higher than the correlations between personality traits and measures of objective abilities (Ackerman & Wolman, 2007; Furnham, 2005; Furnham, Moutafi, & Chamorro-Premuzic, 2005). Very little is known, however, about the predictors of self-estimates of job performance over time.

### The current investigation

The aim of the current investigation is to examine the nature of expected learning curves for a variety of different occupations, with a sample of university students, and to examine the trait and gender determinants of these self-estimates. Rather than just provide a brief job title, we provided detailed information about each of 20 jobs to the participants before they estimated their job performance. Participants were given detailed information about each job including job descriptions compiled from the Occupational Information Network (O’Net; Peterson, Mumford, Borman, Jeanneret, & Fleishman, 1999) and a narrated video clip of an incumbent performing the job. The jobs were selected to represent a cross-section of different occupations. We asked participants to estimate their performance for each job on the first day-of-work, and at several times up to six months of on-the-job experience. We asked participants not only to estimate performance in raw criterion variables (e.g., sales in dollars, time to complete a report, etc.), but also to estimate performance in terms of normative criteria (in terms of percentile rank, compared to other workers), and in terms of the shape of the anticipated learning curves for each occupation. Prior to the ratings task, each
participant completed a battery of questionnaires that assessed personality traits, interest themes, self-concept, and implicit theories of intelligence (entity and incremental). Subsequent to the provision of job description information and the ratings task, participants were also asked to rate their “engagement” (i.e., whether they would be “willing to perform” the job) for each of the different occupations.

There is a substantial body of research examining the changes in ability requirements over time (Ackerman, 1987, 1988), and to a lesser extent, research indicating changes in personality correlates with job performance over time (see Helmreich et al., 1986). There are, however, no existing data on self-concept for projected job performance over time. Thus, the first major goal of the current investigation is to provide descriptive data on the nature of expected performance over a substantial period of time on the job for a variety of different occupations. In addition, given that there have been speculations on gender differences in entity and incremental theories, we will also examine whether there are salient gender differences in the patterns of expected learning curves for the various occupations. In this context, we also evaluate the commonality of anticipated learning curves across several different occupations.

The second major goal of this investigation is to determine the independent and combined contributions of individual differences in personality/motivation traits, interest themes, self-concept, job engagement, and gender to the prediction of individual differences in expected occupational learning curves. This study expands the literature on self-concept and self-estimates of abilities in that it includes assessment of self-estimates of job performance rather than broad abilities (Ackerman & Wolman, 2007; Furnham, 2005; Furnham et al., 2005). It is also unique in that this study examines self-estimates of performance and learning over time. Identifying the determinants of self-estimates of performance may inform how people identify and pursue jobs and other career opportunities (e.g., training, job promotions).

Hypotheses and study questions

The current study combines a set of hypotheses that are based on extant theoretical frameworks and prior empirical research with a set of exploratory research questions that reflect a lack of prior theory and research on the topic.

**Hypothesis 1.** Based on the self-concept and self-estimates of abilities literature, which indicates that once task information is provided to participants self-estimates of performance have moderate levels of validity, we expected that participants would predict that their job performance would show substantial improvement from the first day on the job to performance after six months of job experience. (Whether the general tendencies for predications would reflect a linear pattern of improvement or a power-law pattern of improvement is an open question for which we did not make a prediction.)

**Study Question 1.** We expected commonality among estimates of job performance across the cross-section of jobs selected for performance judgments. However, we did not make a specific prediction as to whether the most salient determinants of the communalities would be ability or personality requirements of the jobs, common interest themes, gender-stereotype or some other variables. Thus, the answer to this study question is inductive, that is, data-driven.

**Hypothesis 2.** Some research on gender differences in self-estimates of abilities (e.g., see Furnham, Hosoe, & Tang, 2002; von Stumm, Chamorro-Premuzic, & Furnham, 2009), indicates that men tend to rate their abilities higher overall than do women. If that is the case for job-performance predictions, then one would predict higher overall performance estimates from men across the jobs. However, the cross-section of jobs we selected for this study include some that are more traditionally held mostly by women, and others that are more typically identified as held mostly by men. In contrast to the overall gender differences identified in the self-estimates of abilities, we hypothesized that jobs that are more frequently held by women would have higher predicted performance levels by women, and those that are more frequently held by men would have higher predicted performance levels by men.

**Hypothesis 3.** If individuals who have an entity implicit theory of intelligence (i.e., a fixed mindset) believe that poor performance on a task is the result of low abilities, then they should also believe that additional practice or experience would have little positive impact on performance. Such individuals should show an increased tendency to endorse flat or shallow learning curves for job performance over time. Conversely, if individuals have an incremental implicit theory of intelligence (growth mindset) and believe that effort and practice will lead to improved task performance and improvement in abilities, then they should be more likely to endorse steeper learning curves. However, if implicit theories of intelligence scores are reflective only of an individual’s view of broad intellectual abilities, which are only indirectly associated (and indeed may only be weakly associated) with speed and level of learning, one would expect little or no association between implicit theories of intelligence scores and expected patterns of learning/skill acquisition. This hypothesis states that there will be an association between theory of intelligence scores and patterns of expected job performance over time.

**Hypothesis 4.** The major predictors of occupational choice (i.e., personality/motivational traits, vocational interest themes, job-specific interests/engagement, and self-concept/self-estimates of abilities) will together account for significant amounts of variance in estimated job performance levels. Which of these predictors will have the greatest contributions for which jobs will be dependent on which jobs are clustered together in terms of patterns of expected performance (e.g., by dominant interest themes, by ability demands, etc.).
Method

Participants

A total of 153 undergraduate students (73 men and 80 women) from the Georgia Institute of Technology participated in this study. The participants were recruited from the Psychology subject pool and received research credit for their participation.

Materials

Personality and motivational traits

The trait complexes assessed in this study include those identified in previous studies as being predictive of self-efficacy and performance (e.g., Ackerman & Wolman, 2007), namely: (1) Need for Achievement/Openness, (2) Extraversion, (3) Neuroticism/Anxiety, and (4) Competitiveness. In the following we describe the scales that formed the basis for the assessment of these trait complexes.

A 50-item measure of the Five-Factor section model of personality traits (10 items per scale for extraversion, neuroticism, openness, conscientiousness, and agreeableness) was selected from the International Personality Item Pool (IPIP; Goldberg, 2008; Goldberg et al., 1999). Responses were made on 6-point scales ranging from 1 = Strongly Disagree to 6 = Strongly Agree. Internal consistency reliabilities for these scales in the current study ranged from $\alpha = .78$ to .88.

Motivation was assessed using the short version of the Motivational Trait Questionnaire (MTQ; Kanfer & Ackerman, 2000; see also Heggestad & Kanfer, 2000; Kanfer & Heggestad, 1997). This 48-item measure contains six scales that serve as robust markers for three underlying motivational trait factors: (a) approach oriented motivation (desire to learn and personal mastery), (b) competitive excellence (other-referenced goals and competitiveness), and (c) avoidance-related motivational traits (worry and emotionality). Responses were made on a 6-point scale ranging from 1 = Very Untrue of Me to 6 = Very True of Me. Internal consistency reliabilities for these scales ranged from $\alpha = .76$ to .86.

The 82-item Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1993) contains 15 scales: extrinsic goal orientation, intrinsic goal orientation, self-efficacy for learning and performance, effort management, critical thinking, control beliefs about learning, management of time and study environment, peer learning, organization, rehearsal, elaboration, help seeking, metacognition, test anxiety, and task value. Responses were made on a 6-point scale ranging from 1 = Very Untrue of Me to 6 = Very True of Me. Internal consistency reliabilities for these scales ranged from $\alpha = .66$ to .89 in the current study.

Implicit theories of intelligence

A 13-item measure based on Dweck’s implicit theories of intelligence was administered (e.g., Hong, Chiu, Dweck, Lin, & Wan, 1999). The measure contained two scales: entity and incremental. Responses were made on a 6-point scale ranging from 1 = Strongly Disagree to 6 = Strongly Agree. Internal consistency reliabilities were $\alpha = .84$ for the Entity scale and $\alpha = .67$ for the Incremental scale.

Interests

The Unisex Edition of the American College Testing Interest Inventory (UNIACT; Lamb & Prediger, 1981) was used to provide information about the six interest types identified by Holland (1973): realistic, investigative, artistic, social, enterprising, and conventional. This 90-item measure (15 items per scale) assesses an individual’s preference for specific job-related tasks. Internal consistency reliabilities ranged from $\alpha = .86$ to .93.

Self-concept and self-estimates of ability

Composite measures of self-concept and self-estimates of abilities were created using two scales. Self-concept for competencies and aptitudes was assessed using a 44-item measure (adapted from Ackerman et al., 2001; Ackerman, Kanfer, & Goff, 1995; Ackerman & Rollhus, 1999). Participants were instructed to consider whether they had the skill or ability, while keeping in mind that people vary in the kinds of skills and abilities that they have. Self-concepts for verbal, math, spatial, science, psychomotor, perceptual speed, and interpersonal skills were obtained. Internal consistency reliabilities ranged from $\alpha = .59$ to .90.

Self-estimates of ability for verbal, math, spatial, science, psychomotor, perceptual speed, and interpersonal domains were obtained using a 23-item measure. Responses were made on a percentile scale ranging from 1 (Extremely Low) to 99 (Extremely High). Internal consistency reliabilities ranged from $\alpha = .55$ to .87 in the current study.

Job descriptions and video vignettes

Job descriptions and twenty narrated video clips depicting job incumbents performing a job were created. The video vignettes were intended to be “real world” previews of each job. For example, the video of a Dental Hygienist shows the job incumbent greeting a client, flossing/brushing their teeth, taking/showing the patient X-rays, and demonstrating proper oral hygiene. The Speech Pathologist video shows the job incumbent working with a young child on language development (i.e., playing word games, learning phonics, etc.). The Interior Designer video shows the job incumbent meeting with a client, going to a design showroom, and experimenting with fabrics, colors, and furniture in order to design a room. Each clip was approximately 1 min in duration. Video clips were obtained using a Sony HDR-SR8 Video Camera and were edited using Pinnacle Studio Ultimate Version 11. The High Definition video clips were viewed by participants on a large Plasma-screen television.

The 20 jobs included in this study were chosen to be generally representative of the dominant Holland interest themes (i.e., realistic, investigative, artistic, social, enterprising, and conventional) and major ability classes (i.e., verbal, math/spatial, and
psychomotor/perceptual speed). In addition, two were selected that represented jobs with primarily interpersonal ability/skill requirements. Six jobs were selected for the verbal, math/spatial, and psychomotor/perceptual speed ability domains (i.e., one for each interest area within each ability domain). Two jobs were selected for the interpersonal ability domain (see Table 1). Job descriptions (see Wolman, 2008) were written based on information found on O*Net (Peterson et al., 1999).

**Job questionnaires**

The job questionnaires contained three measures to assess anticipated job performance throughout the first six months on each of the 20 jobs: a learning curve shape choice, a normative rating of performance (percentiles), and an absolute performance score rating of performance. The absolute measure differed by job (e.g., number of reports completed/day, sales in dollars, etc.) and because the ratings were incommensurable across jobs we do not include them in the analysis below (see Wolman, 2008, for more information). The job questionnaire also included measures to assess task interest and attitudes that are not reported here.

**Self-estimated learning curves**

Participants were presented with the 6 learning curves shown in Fig. 1 and an option that indicated performance on the job could not be improved with time (i.e., “I don’t think I could improve my performance even with 6 months of on-the-job experience”), and were asked to select the option for each job that best represented their expected pattern of job performance and learning over time (i.e., from the first day on the job to a point after 6 months on the job [1000 h]).

**Normative assessment**

For each item, participants were instructed to enter a number between 1 and 99 that indicated their anticipated job performance (in percentile rank units) “relative to other people with similar levels of practice.” There were six items included for each job representing different amounts of time on the job: 1 = with no training or practice, 2 = with 1 full day on the job (10 h of practice), 3 = with 1 week on the job (40 h of practice), 4 = with 2.5 weeks on the job (100 h of practice), 5 = with 3 months on the job (500 h of practice), and 6 = with 6 months on the job (1000 h of practice).

**Task engagement**

A Task Engagement measure was created for this study. Items asked participants to indicate the degree to which they would be willing to perform each of the 20 jobs in the study. For each job, six items were adapted from Blau’s (1989) measure of career commitment to reflect the individual’s willingness to engage in the job. Responses were made on a 6-point scale ranging from 1 = Strongly Disagree to 6 = Strongly Agree.

**Procedure**

Prior to the laboratory session, participants picked up the at-home questionnaire containing the self-report measures (i.e., personality and motivational traits, interests, self-concept and self-estimates of ability) and were instructed to complete the questionnaire in a quiet, undisturbed environment and to bring it with them to the laboratory session. Laboratory sessions included assessments of up to 16 participants at a time. A sample job questionnaire was distributed that included learning curve assessments for each job and the job engagement measure. Participants were guided through the example. Following the example, a Blu-ray DVD containing the 20 video clips was played. After each video clip, participants were instructed to complete the corresponding job questionnaire, where they selected their expected learning curve and completed the individual job performance estimates. After all 20 job video clips had been reviewed, and the questionnaires completed, participants completed the measure of anticipated task engagement for the 20 jobs, and were debriefed.

**Results**

The results section is organized in four sections. First, we review the relative frequency of estimated learning curves. In the second section, we assess commonality among estimated learning curves, and we report a factor analysis that permitted a

<table>
<thead>
<tr>
<th>Interests</th>
<th>Abilities</th>
<th>Math/Spatial</th>
<th>Perceptual Speed/Psychomotor</th>
<th>Interpersonal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Realistic</td>
<td>Speech Language Pathologist</td>
<td>Seamstress</td>
<td>Locksmith</td>
<td></td>
</tr>
<tr>
<td>Investigative</td>
<td>School Psychologist</td>
<td>Applied Mathematician</td>
<td>Art restorer</td>
<td></td>
</tr>
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<td>Interior Designer</td>
<td>Floral Designer</td>
<td>Personal Trainer</td>
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<td>Motivational Speaker</td>
<td>Financial Advisor</td>
<td>Dental Hygienist</td>
<td>Real Estate Agent</td>
</tr>
<tr>
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<td>Commercial Leasing Agent</td>
<td>Hairstylist</td>
<td></td>
</tr>
<tr>
<td>Conventional</td>
<td>Court Reporter</td>
<td>Certified Public Accountant</td>
<td>Pharmacist</td>
<td></td>
</tr>
</tbody>
</table>

Table 1
Classification of jobs by interest and ability domains.
The first task for the participants after viewing each job description and video clip was to select the learning curve that represented expected job performance from the first day of the job to six months (Fig. 1). A graph of the relative frequencies of endorsing each learning curve by gender, across the 20 jobs, is shown in Fig. 2. Keeping in mind that each participant made 20 responses over the course of the study, and that the relative frequencies shown are dependent (endorsing one learning curve rules out endorsing others, so the frequencies sum to 100% for both men and women), the information shown in the graph provides some indication of how the participants viewed the learning/performance process. Notably, very few responses of “No learning” were made across the 20 jobs, and there were no appreciable differences in endorsing an inability to learn a particular job by gender; 2.3% of the responses for men and 1.8% for women indicated “No learning.” Gender differences across the other learning curves were quite modest in magnitude, though men showed a very slight tendency for selecting learning curves that put their six month-on-the-job performance at or above the 80th percentile (59.8% of the responses by men versus 58.3% responses by women).

Overall, 71.6% of the estimated learning curves responses had a power-law function (i.e., larger initial gains, followed by negatively accelerating, yet monotonically increasing performance over time), 26.3% of the estimated learning curves were linear functions (equal increases over each time period), and 2.1% of the responses indicated no learning over the six-month projected time period. We conclude that these results support Hypothesis 1, that is, participants had a general sense of performance
improvements with increasing time on the job, and that the dominant form of expected improvements was consistent with the power law of practice.

**Job classification**

Although primary examination of the data involved each of the 20 separate jobs (e.g., see Wolman, 2008), the scope of these individual analyses is far more extensive than would be feasible in this paper. The overarching goal of the remaining analyses is to provide a relatively parsimonious representation of the results by creating aggregations across job categories. The selection of jobs with a cross-section of interests and abilities allowed for a classification scheme with enough individual jobs in each category, either by aggregating across abilities or across interest themes. In addition, because we used individual jobs instead of job classifications, participants were free to make their judgments of expected learning curves and performance levels, independent of the cross-section of jobs selected in the study design.

To evaluate the commonality among estimated job performance judgments, we examined aggregations by ability demands and by dominant interest themes. We ultimately settled on a data-driven approach to examine similarities in judgments of expected performance on the first day on the job and after six months on the job. The most parsimonious representation of job classification was found with performance estimates at six months on the job. A representation of this classification can be found in Fig. 3, which

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**Fig. 2.** Frequency of endorsement for learning curves by Gender (see Fig. 1 for curves).

**Fig. 3.** KYST3 multidimensional scaling solution for correlation matrix of performance estimates after six months on-the job experience.
shows the results of a multidimensional scaling (MDS) of the intercorrelations of expected performance judgments. The scaling was accomplished with the KYST3 algorithm, following a procedure outlined by Marshalek, Lohman, and Snow (1983). Stress for the two-dimensional solution (Formula 1) was .164, which is consistent with similar analyses of correlation matrices (e.g., see Ackerman, 1988). The solution was rotated to a principal-components orientation, with Dimension 1 accounting for the greatest amount of variance. This solution clearly indicates that there are four major groupings of jobs, which we identified as “Female-Dominated,” “Mathematical,” “Realistic” theme and “Enterprising” theme. Even though ability demands (e.g., Mathematical) and dominant interest themes (Realistic and Enterprising) represent our a priori selection of the 20 original jobs, the Female-Dominated job classification was not anticipated from the interest/ability categorization of the jobs. To provide some validation for this particular categorization, we examined gender ratios for the 20 jobs in national U.S. databases (primarily from the Bureau of Labor Statistics [BLS], 2010; but also from professional organizations, when BLS statistics were not available). The average percentage of women in each of these job classifications was: 65.2% for Female-Dominated Jobs, 44.3% for Mathematical Jobs, 61.1% for Realistic Jobs, and 38.4% for Enterprising Jobs. The high average rate of women in the Realistic job group masks the heterogeneity of the individual jobs, which ranged from high-male percentage jobs (e.g., Locksmith) to high-female percentage jobs (e.g., Dental Hygienist). From this analysis, the answer to Study Question 1 appears to be that estimated job performance coalesced by dominant interest themes for two groups, ability domain for one group, and gender for the fourth group.

The classification of the 20 jobs into the four general job categories was also evaluated with a confirmatory factor analysis (CFA) using LISREL 8.72 (Jöreskog & Sörbom, 2001). We used performance estimates after 6 months for the 20 jobs as input to the factor analysis and factor loadings were determined using the MDS solution shown in Fig. 3 (e.g., locksmith loaded on Realistic Jobs; applied mathematician loaded on Mathematical Jobs). The fit of the model was good, $\chi^2 (164, N = 153) = 315.95, p < .05$; Comparative Fit Index (CFI) = .95 and Root Mean Square Error of Approximation (RMSEA) = .07. Based on the MDS and CFA solutions, we created unit-weighted $z$-score composites for each of the four job groups for each of the 6 options in our normative assessment of anticipated job performance (e.g., no training or practice through 6 months on the job). These composites are used in subsequent analyses.

**Expected relative performance levels over 6 months on the job**

The composites for each job group were subjected to a 2 (gender) by 6 (time) within-between repeated-measures ANOVA. The results of the ANOVAs are provided in Table 2 and the means by gender and job group are shown in Figs. 4a to d. There are several notable patterns in these data. First, the ANOVAs indicate that large effects of similar magnitude of time on the job (Partial eta-squared values ranged from .76 to .78 across the four job groups). As illustrated by the figure, the participants, on average, expected to perform worse than the 50th percentile on the first day of the job, but they also expected large increases in relative standing with each additional increment of time on the job, ending up with estimated performance well above average after 6 months on the job.

Significant main effects of gender were found for only two job categories: Female-Dominated Jobs and Mathematical Jobs. For the Female-Dominated Jobs, a difference of 6.9 percentile points favoring women was shown at the first day on the job, and persisted through the range of time on the job. The opposite pattern was found for the Mathematical Jobs, with men expecting higher average performance levels of 10.3 percentile points throughout. Gender differences in expected performance on the

<table>
<thead>
<tr>
<th>Table 2</th>
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<tbody>
<tr>
<td>ANOVA for estimated job performance (in percentile units) across four job categories.</td>
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</table>

<table>
<thead>
<tr>
<th>Group 1. Female-Dominated Jobs</th>
<th>Gender</th>
<th>Time (on the job)</th>
<th>Gender x Time</th>
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<tbody>
<tr>
<td>$F$</td>
<td>11.81 **</td>
<td>541.40 **</td>
<td>1.87</td>
</tr>
<tr>
<td>MS</td>
<td>14,808</td>
<td>23,305</td>
<td>80</td>
</tr>
<tr>
<td>Partial $\eta^2$</td>
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<td>.78</td>
<td>.01</td>
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</table>

<table>
<thead>
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<th>Group 2. Mathematical Jobs</th>
<th>Gender</th>
<th>Time (on the job)</th>
<th>Gender x Time</th>
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</thead>
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<td>$F$</td>
<td>12.87 **</td>
<td>466.81 **</td>
<td>.27</td>
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<tr>
<td>MS</td>
<td>22,652</td>
<td>22,254</td>
<td>13</td>
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<tr>
<td>Partial $\eta^2$</td>
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<td>.00</td>
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<table>
<thead>
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<th>Group 3. Realistic Jobs</th>
<th>Gender</th>
<th>Time (on the job)</th>
<th>Gender x Time</th>
</tr>
</thead>
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<tr>
<td>$F$</td>
<td>1.61</td>
<td>529.56 **</td>
<td>4.97 **</td>
</tr>
<tr>
<td>MS</td>
<td>1815</td>
<td>22,481</td>
<td>211</td>
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<tr>
<td>Partial $\eta^2$</td>
<td>.01</td>
<td>.78</td>
<td>.03</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Group 4. Enterprising Jobs</th>
<th>Gender</th>
<th>Time (on the job)</th>
<th>Gender x Time</th>
</tr>
</thead>
<tbody>
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<td>$F$</td>
<td>2.81</td>
<td>518.79 **</td>
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</tr>
<tr>
<td>MS</td>
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<tr>
<td>Partial $\eta^2$</td>
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<td>.77</td>
<td>.00</td>
</tr>
<tr>
<td>$df$</td>
<td>1,151</td>
<td>5755</td>
<td>5,755</td>
</tr>
</tbody>
</table>

Note. Partial $\eta^2$ for between, within, and between-within effects computed from G*Power 3.0. ** $p < .01$. 

Enterprising Jobs were small (.02) and did not reach a level of statistical significance. Finally, for the Realistic job category, there was no significant main effect of gender, but rather an interaction between gender and projected time on the job. Men started with higher estimated job performance, but the differences disappeared by projected three months on the job. From these data, Hypothesis 2, that gender differences in estimated performance would mirror the percentage of women in the respective jobs, was partially supported. Women had the highest percentages in the Female-Dominated Jobs and the Enterprising Jobs, but only had significantly higher expected performance in the Female-Dominated Jobs. Men had higher percentages in the Mathematical and Realistic Jobs, but only had significantly higher expected performance in the Mathematical Jobs. The discrepancy in the results for gender differences in the Realistic Jobs when compared to the other job categories may be partly attributable to the heterogeneity in the individual jobs in this group, with respect to gender percentages (e.g., Locksmith and Dental Hygienist had widely different gender profiles).

These results appear to support the notion that across the various types of jobs included in this study, participants expected to start off performing below the average employees, but with additional time on the job, they believed that they would perform much better than the average job incumbent with the same level of experience. Such results suggest that self-reports of competence that are based on static expectancies (which is typical of self-concept and self-estimates of abilities measures, see Ackerman & Wolman, 2007; Chamorro-Premuzic, Furnham, & Moutafi, 2004; Marsh et al., 2005) are perhaps too simplistic in assigning labels of over-confidence or under-confidence, especially in terms of gender differences. These participants clearly expected to improve markedly in their relative performance, yet the job demands and the likely gender stereotypes for the jobs affected the magnitude and extent of gender differences in self-estimates of performance over increasing time on the job.

**Implicit theories of intelligence**

Non-significant gender differences were found for mean scores for entity ($M_{men} = 20.63$, $M_{women} = 19.24$, $t (151) = 1.27$, ns, $d = .21$) and Incremental: $M_{men} = 24.08$, $M_{women} = 25.14$, $t (151) = 1.93$, ns, $d = -.31$) implicit theories of intelligence. Hypothesis 3 stated that entity theory scores would be positively associated with a greater frequency of “No learning” estimates or shallow learning curves, and negatively associated with a greater frequency of steep learning curves. Examination of the correlations between entity

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**Fig. 4.** a–d. Mean normative job performance estimates from Day 1 (0 h) on-the job (1000 h) by gender to the job group. Error bars presented 95% confidence intervals.
and incremental scores and frequency of endorsements with all of the different learning curves indicated that none of 12 correlations reached a level of statistical significance (the correlations did not exceed \( r = \pm .11 \)). Thus, Hypothesis 3 was not confirmed. That is, implicit theories of intelligence were essentially uncorrelated with expected learning curves across the 20 jobs. The statistical power to detect a "medium" sized effect (i.e., \( r = .3 \), see Cohen, 1988) was .97 (G*Power 3; Faul et al., 2007). With such a high power, a failure to reject the null statistical hypothesis indicates that we can conclude with reasonable confidence that there is no moderate or larger association between theory of intelligence scores and estimated learning curves.

**Personality/motivational trait complexes**

To derive the trait complexes, we first conducted an exploratory factor analysis of the 31 personality and motivational trait scales. This analysis yielded four factors identified as: Need for achievement/Openness (I), Extroversion (II), Neuroticism (III), and Competitiveness/Other-oriented goals (IV). Next, we created unit-weighted z-score composites of the scales that had primary loadings on the identified factors (see Cohen, 1990; Thorndike, 1986 for a discussion of this procedure). To provide an estimate of the breadth/heterogeneity of the resulting composites, the individual scales within each composite were also evaluated with measures of Cronbach’s alpha. The scales that compose each composite are provided in Table 3, along with Cronbach’s alpha statistics. Consistent with previous research (e.g., Ackerman & Wolman, 2007), these internal consistency indexes for the scales were high, especially given that the constituent scales were sampled across a wide range of personality and motivational traits.

**Self-concept/self-estimates of abilities**

Consistent with previous studies (e.g., see Ackerman & Wolman, 2007), the correlations of the respective self-concept and self-estimates of abilities measures were sufficiently high to merit combining them for the purposes of further analyses (i.e., the corresponding correlations were \( r’s = .69 \) for verbal, \( .76 \) for math, \( .73 \) for spatial, \( .75 \) for science, \( .54 \) for perceptual speed/psychomotor, and \( .70 \) for social, respectively). One notable result for the self-estimates is that the mean ratings for each ability were in a relatively narrow range (from 69th percentile to the 72nd percentile), indicating that the participants tended to rate themselves as above average on all of the ability domains. Also, large gender differences were found for self-estimates of math ability \( (M_{men} = 78.82, \ M_{women} = 71.06, \ t = 4.08, \ p < .01) \), spatial ability \( (M_{men} = 76.14, \ M_{women} = 66.06, \ t = 4.38, \ p < .01) \), and science \( (M_{men} = 75.99, \ M_{women} = 64.96, \ t = 4.07, \ p < .01) \), but no significant gender differences were found for the other self-estimates of abilities.

**Trait complexes, interests, self-concept, job engagement, and expected performance**

Table 4 shows the correlations among the various predictor measures, the composites for 6 month on the job expected performance measures, and gender. Examination of the table indicates patterns of convergent validity among many of the predictor measures (e.g., among the Holland interest themes, among the self-concept/self-estimate of ability composites, among job engagement measures, and among estimated performance measures). Notable among these correlations are the negligible correlations between Verbal Self-Concept/Self-Estimates (SC/SE) and Math SC/SE \( (r = -.10) \), consistent with extant research that shows people tend to polarize their estimates of verbal and math abilities. We found a similar pattern for both engagement and performance estimates across the Female-dominated job family and the Mathematical job family \( (r = -.12 \text{ and } .17, \text{ respectively}) \). This result supports the notion that these two job families may be viewed by the participants in a manner similar to the verbal/math self-concept perspective. The most substantial negative correlations with gender (coded as 1 = male, 2 = female) are found

---

**Table 3**

<table>
<thead>
<tr>
<th>Personality/motivational trait complexes and their intercorrelations.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Factor/Trait Complex</strong></td>
</tr>
<tr>
<td>I. Need for Achievement/Openness</td>
</tr>
<tr>
<td>Scales: Intrinsic Goals, Task Value, Desire to Learn, Metacognition, Elaboration, Self-Efficacy for Learning and Performance, Mastery, Critical Thinking, Openness, Need for Achievement, Control of Learning Beliefs, Conscientiousness</td>
</tr>
<tr>
<td>Number of scales = 12, ( \alpha = .85 )</td>
</tr>
<tr>
<td>II. Extroversion/Social</td>
</tr>
<tr>
<td>Scales: Social Closeness, Extroversion, Bem — Femininity, Rehearsal, Help Seeking, Peer Learning, Time and Study Environmental Management, Organization, Effort Regulation, Extrinsic Goals</td>
</tr>
<tr>
<td>Number of scales = 10, ( \alpha = .80 )</td>
</tr>
<tr>
<td>III. Neuroticism/Anxiety</td>
</tr>
<tr>
<td>Scales: Worry, Emotionality, Neuroticism, Test Anxiety</td>
</tr>
<tr>
<td>Number of scales = 4, ( \alpha = .80 )</td>
</tr>
<tr>
<td>IV. Competitiveness/Other-Oriented Goals</td>
</tr>
<tr>
<td>Scales: Bem — Masculinity, Competitiveness, Social Potency, Other-Oriented Goals, Agreeableness (reversed)</td>
</tr>
<tr>
<td>Number of scales = 5, ( \alpha = .68 )</td>
</tr>
</tbody>
</table>

Note. \( N = 153, \ df = 151 \).
for the Personality/Motivational trait complex of Competitiveness/Other-Oriented Goals ($r = -0.30$), for Spatial and Science SC/SE ($r = -0.33$ and $-0.31$, respectively). The most substantial positive correlations are for Engagement for Female-Dominated Jobs ($r = 0.57$) and expected performance on the job for the Female-Dominated Jobs ($r = 0.33$).

### Predicting self-estimated performance after 6 months on the job

#### Multiple regression approach

There are myriad ingredients that significantly contribute to an individual’s estimation of his/her performance on the job after a significant period of experience: personality and motivational traits, broad vocational interests, job-family interests/engagement, self concept and self-estimates of abilities, estimated performance on the job on Day 1, and in some cases, gender. Because of multicollinearity among these variables (e.g., see Table 4), it is useful to consider both their independent and incremental validity for predicting estimated job performance. Table 5 shows a series of multiple correlations that show both the independent and incremental contributions to prediction of 6-month on-the-job performance estimates. The multiple regression approach we adopted started with the most distal traits of personality and motivation in the first step, followed by broad vocational interests in

### Table 5

Summary of multiple correlations for predicting estimated performance at 6 months on-the-job.

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<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
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<th>20</th>
<th>21</th>
<th>22</th>
<th>23</th>
<th>24</th>
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</thead>
<tbody>
<tr>
<td>1 Female-Dominated Jobs</td>
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<td>$R^2$ in isolation</td>
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<td>Degrees of Freedom</td>
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Note: SC/SE (Self-concept; self-estimates of abilities); Est. = estimated; Abil = abilities; perf. = performance.
the second step, then narrow job-family interests/engagement in the third step. Once affective and conative traits accounted for individual differences in estimated 6-month job performance, we added cognitive traits of self-concept/self-estimates of ability in Step 4, followed by the participants’ estimates of performance at Day 1 on the job in Step 5. As a final step, we entered the participants’ gender, to evaluate whether gender accounted for any additional variance, after the affective, conative, and cognitive traits had been accounted for.

Trait measures of personality/motivation, vocational interests, job family engagement, and self-concept together accounted for 33.0% to 51.2% of the variance in predicted performance after six months on the job, supporting Hypothesis 4 (trait and engagement variables will account for significant amounts of variance in estimated job performance). Inclusion of estimated performance levels on the first day on the job increased the amount of variance accounted for from 45.2% to 61.6% for estimated performance at six months. However, it is important to note that the associations between estimated performance on the first day on the job, though significant, accounted for less than the variance in estimated performance after six months on the job. The range of common variances between these variables was from 21.3% (Realistic Jobs) to 40.2% (Mathematical Jobs). Interestingly, there was more common variance in predicted performance levels across job categories at Day 1 on the job ($r_{\text{mean}} = .68$) than there was at six months on the job ($r_{\text{mean}} = .50$), which were significantly different ($z = 2.30, p < .05$). Such a difference would also be expected for objective performance data, based on extant theories of individual differences in learning/skill acquisition (e.g., Ackerman, 1988, 1990; Fleishman, 1972). That is, given expected decreases in the influence of general and broad content abilities, and increases in the influence of task-specific or narrower ability factors (e.g., specific perceptual speed and psychomotor abilities, writing skills, etc.) in determining performance levels once skills are acquired.

**Structural equation modeling approach**

The multiple regression analysis provides information about the importance of each predictor for the four separate job groups independently. To permit an examination of the importance of each predictor for a specific job group while controlling for self-ratings of performance for other job types, we conducted a path analysis with latent dependent variables using structural equation modeling. We examined distal predictors (e.g., gender, vocational interests, and personality traits) and proximal predictors (e.g., job engagement for the particular job, self-estimates of ability and self concept) in two separate models to simplify the presentation. The dependent factors were based on job groupings that were derived from the performance estimates at 6 months (i.e., the MDS). We used the four-factor CFA solution described earlier as the basis for the models.

Both models were specified such that all predictors were allowed to load onto all factors. The model of distal predictors is shown in Fig. 5, with only significant paths shown. The fit of this model was adequate, $\chi^2 (340, N = 153) = 659.08, p < .05$, CFI = .92, RMSEA = .071. As can be seen in the figure, gender predicted performance for Female-dominated and Mathematical Jobs. With the exception of social interests, vocational interests were important predictors of performance estimates. Additionally, the relations between interests and performance estimates were aligned with job content: Realistic interests were related to

![Fig. 5. Structural equation model of distal predictors of estimated job performance.](image-url)
estimates of performance for Realistic Jobs, Investigative interests were related to Mathematical Jobs, and Enterprising interests were related to Enterprising Jobs (in addition to Female-Dominated Jobs). Some interests were more broadly related to predicted performance, but were not surprising given the types of jobs included in each group: Artistic interests were related to predicted performance in Female-dominated, Mathematical, and Enterprising job groups and Conventional interests were significantly related to Female-dominated, Mathematical, and Enterprising job groups.

Across all job types, only the Neuroticism/Anxiety and Extraversion personality trait complexes had significant relations with estimates of performance at six months. Surprisingly, Extraversion was related only to performance estimates for Realistic Jobs when all variables were estimated simultaneously, although zero-order correlations suggest that Extraversion is related to predicted performance for Female-dominated, Enterprising, and Realistic job groups. This is most likely a function of multicollinearity in the model: Enterprising interests and Extraversion are significantly correlated, and Enterprising interests are also correlated with predicted performance in these job groups.

The model with proximal predictors is shown in Fig. 6. Fit of this model was also adequate, \( \chi^2(324, N = 153) = 659.70, p < .05, CFI = .92, RMSEA = .076 \). As can be seen in this figure, engagement variables loaded exclusively on the job groups they were intended for, and these loadings were relatively large. Also, with the exception of the spatial domain, the SC/SE variables loaded on the factors that were most highly related in terms of content: Math SC/SE was related to predicted performance for Mathematical Jobs, Social SC/SE was related to Enterprising and Female-oriented jobs, Verbal SC/SE was related to Enterprising Jobs, and Perceptual Speed/Psychomotor SC/SE was related to Realistic Jobs. The one exception was for Science SC/SE, which we expected to be related to performance prediction for Mathematical Jobs. This finding is also likely related to the multicollinearity in the model: Science SC/SE is highly related to Math SC/SE, which is also related to performance prediction for Mathematical Jobs. Together, the two SEM analyses provide further support for Hypothesis 4, that trait and engagement variables will account for significant amounts of variance in estimated job performance.

Although we were more interested in examining determinants of judgments of job performance for different types of jobs, it is notable that there is substantial commonality among the job-family factors (shown in Figs. 5 and 6). Correlations among job families ranged from \( r = .39 \) for Female-Dominated Jobs and Mathematical Jobs to \( .55/.58 \) for Female-dominated and Realistic Jobs. The commonality among performance estimates across job types indicates that a higher-order factor could be extracted that reflects general confidence in estimated performance levels after six months of job experience.

**Discussion**

After receiving descriptive information for 20 different jobs and viewing short video clips that showed actual incumbents at their jobs, a sample of young adults estimated their expected performance on the jobs for six different periods, starting with the first day up to six months on the job. Although the jobs varied widely in terms of job demands and content, ranging from hairdressing to applied mathematics, only 2% of the responses indicated that the participants thought they could not improve in performance over the course of 6 months. Rather, the vast majority of the participants believed that their job performance would improve over time, either in a power function or linear function pattern. Expected patterns of performance improvement were
found to be statistically independent of the individual's scores on measures of entity or incremental theories of intelligence, suggesting that such constructs do not apply to how people view the process of acquiring job performance skills. In addition, no significant gender differences in the overall pattern of expected forms of learning curves were found.

Substantial commonality was found for expected job performance across the 20 jobs, which coalesced into four broad groups of jobs. Interestingly, the groupings appeared to be determined by whether the jobs were female-dominated, mathematical, realistic, and enterprising, even though jobs within each of the categories differed substantially in terms of educational credential and ability requirements (e.g., School Psychologist and Hairstylist in one category, Lawyer and Real Estate Agent in another category). As shown in both the regression and SEM analyses, women rated their expected performance higher than men on Female-Dominated Jobs, and men rated their expected performance higher than women on Mathematical Jobs, across the time periods (that is, there were no significant interactions between gender and time on-the-job factors). No significant main effect of gender was found for Realistic and Enterprising Jobs, but a significant interaction between gender and time on the job was found for Realistic Jobs, where the higher estimated performance for men at early time periods disappeared as estimated time on the job increased. The current data are insufficient to test specific hypotheses about why these different gender patterns occurred, however, they do raise the possibility that some portion of the gender differences in occupational choice may be influenced by the gender differences in expectations of job performance not just at job entry, but also after a substantial amount of job experience.

In addition to gender, we examined the affective and conative determinants of judgments of job performance. Our analyses show that trait complexes, which represent a person's overall developmental orientation, and vocational interests, are predictive of self-estimates of performance for most jobs. When estimated across job groups, our findings are concordant with previous research on objective abilities. That is, we found that vocational interests were aligned with the content of the job groups (e.g., Enterprising interests and Enterprising Jobs) and that trait complexes, for the most part, are related to judgments of job performance (e.g., a neurotic/anxious orientation negatively related to judgments of performance for Enterprising and Mathematical job groups). Our results for proximal determinants of judgments of job performance also show an alignment of self-concept, job engagement, and judgments of job performance based on job content (e.g., math self-concept related to the Mathematical job group). It is also noteworthy that both the proximal and distal predictors of judgments of job performance differed, based on job content, even though there was substantial commonality among the four job groups (as shown in the SEM analysis). These findings highlight the importance of measuring both broad and specific predictors in the context of vocational counseling.

Conclusion

Overall, the data from this study appear to indicate that young adults have a sophisticated understanding of the nature of learning and skill acquisition, when it comes to judgments of job performance up to six months on the job. Specifically, they believe that they will improve in performance over time on the job in either a power function or a linear function. This belief is consistent across a wide range of jobs. Notably, the incidence of participants who believed that they could not learn a particular job at all was extremely low (2% of all responses across 20 job judgments each for 153 participants). Such results suggest that even those participants who endorsed an entity theory of intelligence, did not view job performance as being something that was only driven by an immutable ability level.

For each job group, mean estimated performance levels were initially below average, but after six months of anticipated time on the job, mean ratings were well above average. These optimistic skilled performance ratings may have been partly due to the fact that the participants were students in a selective university setting, or they may be more general expectations associated with the better-than-average heuristic (Krueger & Mueller, 2002). We think it is especially interesting that self-estimates of abilities (which averaged at about the 70th percentile) were not well-aligned with Day 1 job performance estimates (which averaged at the 39th percentile across the four job groups), but were substantially aligned with the six-month job performance estimates (which averaged at the 71st percentile). Such an alignment appears to be so close across all abilities and jobs to be more than a coincidence, and may be quite illuminating about how individuals expect learning and on-the-job experience to lead to development to the individual's core capabilities. However, because there is no objective reason to expect that these participants would perform below average even on the first day of work, such results might also suggest that people tend to underestimate their performance when first attempting to do a novel task, at least from a normative perspective.

Ultimately, estimated performance was partly attributable to the type of job, but in all cases, it was also partly attributable to the individual's personality, interests, ability self-concepts, and estimated engagement for each type of job. When considered after trait, engagement, and estimates of initial job performance, the participant's gender was not a significant predictor of estimated job performance at six months on the job. The lack of gender differences that are not accounted for by differences in personality, interests, and so on, support propositions that gender differences in traits are fundamental properties that direct men and women toward or away from particular careers.

Estimates of job performance levels after six months on the job were only partly predictable from estimates of performance on the first day on the job. For occupational choice, it may be that greater clarity can be provided to the individual by not only providing job-specific previews, but also asking the individual to imagine himself/herself in the job after a substantial amount of on-the-job experience, and to explore the traits the individual views as most salient to the determination of his/her performance levels. Because performance judgments fundamentally influence occupational interests (Lent et al., 1994), providing enough information so people can make accurate judgments is essential. Such information, along with a check of the alignment of the individual's self-concept and objective ability scores, should serve to optimize occupational choice.
References


Cohen, J. (1990). Things I have learned (so far).


