UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

ABILITY-GROWTH INTERACTIONS IN THE ACQUISITION OF A COMPLEX SKILL: A SPLINE-MODELING APPROACH

A DISSERTATION

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

DOCTOR OF PHILOSOPHY

By

MATTHEW J SCHUELKE
Norman, Oklahoma
2010

ABILITY-GROWTH INTERACTIONS IN THE ACQUISITION OF A COMPLEX SKILL: A SPLINE-MODELING APPROACH

A DISSERTATION APPROVED FOR THE DEPARTMENT OF PSYCHOLOGY

BY

____
Dr. Eric Day, Chair

____
Dr. Mark Bolino

____
Dr. Jorge Mendoza

____
Dr. Michael Mumford

____
Dr. Robert Terry

Acknowledgements

This is a great opportunity to express respect for my major professor, Dr. Eric Anthony Day, for his guidance during the completion of this project. I am also pleased to thank committee members, Drs. Mark Bolino, Jorge Mendoza, Michael Mumford, and Robert Terry, for their tremendous flexibility and valuable time.

I am pleased to thank a fellow student and dear friend Tom Zeni for his help in doing all the things I could not do while finishing this dissertation at a distance.

I would also like to thank my family and friends for their support. My graduate school experience taught me just how important they are. I would not be the person I am today without them.

Finally, I would especially like to thank my fiancée Alison Antes for putting up with my often neurotic and stressful behavior. She stood by me through the thick and thin. I would not have completed this dissertation without her.

Table of Contents

List of Tables

List of Figures

Abstract

While investigating how the relationship of abilities and skill acquisition changes over the course of training, researchers have unknowingly obscured the very relationship they sought to examine by relying on analyses that focused on attainment and did not model acquisition. Although more recent approaches have modeled acquisition independently of attainment (e.g., Voelkle, Wittmann, & Ackerman, 2006), these analyses have neglected to allow for changes in the overall acquisition rate, which would permit a determination of exactly when and how abilities contribute to acquisition in accordance with current learning-phase based theory (e.g., Ackerman, 1987, 1988; Fleishman, 1972). Using a sample of 131 young adult males and a complex computer-based criterion task, the present research investigated the contribution of three abilities: general mental ability (GMA), psychomotor ability (PM), and visual attention (VA), to acquisition in different phases of training. Collectively, the findings suggest abilities do contribute to attainment early in training as has traditionally been found, but affect little difference in changes to acquisition rates throughout training. Furthermore, the results support an initial restructuring of the combination of abilities that contribute to acquisition and a stable (e.g., Fleishman, 1972) but not dynamic (e.g., Ackerman, 1987, 1988) contribution thereafter (e.g., Keil & Cortina, 2001).

Ability-Growth Interactions in the Acquisition of a Complex Skill:

A Spline-Modeling Approach

The topic of human learning has been researched for over a century. Today, debate continues over newer or finer points of this research, but the overarching motivation for this pursuit has remained steadfast. A strong theoretical framework for the study of skill acquisition will guide future research and practical endeavors (Davids, Button, & Bennett, 2008).

Many important findings have developed from this fervor, and a few warrant increased attention in the current effort. One, skill acquisition progresses through stages (Fitts & Posner, 1967). Two, changes occur in the specific combinations of abilities contributing to performance across these stages (Fleishman, 1972), and three, theories have been developed that discuss the specific combinations of abilities contributing to performance during each stage (e.g., Ackerman, 1987, 1988; Fleishman, 1972). However, at least two weaknesses currently exist in the literature. First, researchers have done an inadequate job of identifying evidence for the relationship between ability and skill acquisition. They have either assumed patterns of correlations between ability and performance across time are evidence for a strong ability-acquisition relationship even though acquisition, that is growth, is not modeled (Woodrow, 1946), or, attempting to model acquisition with difference scores, they have failed to find consistent results (Voelkle et al., 2006). Second, although the role of ability in the early phases of skill acquisition is generally agreed upon, there is no consensus with respect to later stages (Ackerman, 2007).

Study Overview

The present research seeks to expand current knowledge regarding the contribution of abilities to skill acquisition. Unlike many previous studies, the present research employs a more sophisticated analytic approach that explicitly models skill acquisition as opposed to skill attainment (i.e., achievement) in an effort to provide a more accurate depiction of the relationship between abilities and complex skill acquisition. Specifically, the current research will investigate the contribution of three abilities to acquisition trajectories—general mental ability (GMA), psychomotor ability (PM), and visual attention (VA)—which will be modeled across different segments or stages of training. Based on a search of the empirical literature, this represents the first attempt at including the commonly accepted acquisition-stage concept in an analytic model. This approach will allow for the examination of changes in acquisition rates across time as well as changes in the composite of abilities contributing to that acquisition in each stage.

Definitions

Skill

Skill may be defined as the proficiency required for a certain level of task performance. It is the learned capacity of an individual to achieve desired outcomes often and at minimal outlay in terms of time and energy (Fleishman, 1972). Skills can typically be improved via practice.

Skills may differ in many ways, but one of the most useful psychological distinctions has been with the definition of complexity. Wood (1986) differentiated among three types of task complexity: component, coordinative, and dynamic. Component complexity describes the number of distinct acts, or task components, and amount of stimuli processing necessary in the production of a task product. Coordinative complexity describes the interrelation of different acts, stimuli processing, and task products. Dynamic complexity describes how coordinative complexity changes across time and can be thought of as the degree of inconsistency in information-processing demands. Accordingly, a complex skill is the proficiency required for task performance that contains some combination of strong component, coordinative, and dynamic complexity.

Acquisition

Acquisition is an internal process which produces a relatively permanent change in a learner's capabilities (Schmidt & Wrisberg, 2004). Skill attainment is distinct from skill acquisition because attainment describes performance at distinct time points (i.e., skill execution or attainment) whereas acquisition describes a gradual improvement in successive performances during practice and instruction or training. Skill acquisition requires a learner to detect and react to environmental stimuli in a correct and timely manner, and the result is a behavior less vulnerable to transitory factors such as emotion or fatigue (Davids et al., 2008). Skill attainment is often measured through the observation of performance at one point in time whereas skill acquisition can only be observed through such observations repeated across time.

Snoddy (1926) may have been the first to mathematically model skill acquisition with his power law of practice. His theory describes a linear relationship between the logarithmic functions of practice amount and performance and therefore predicts a quadratic or decelerating trend such that gains in performance slow over time (Davids et al., 2008). The performance of complex skills during practice typically improves according to this power law (Anderson, 2005).

Skill acquisition is typically described in three stages (Anderson, 1983; Fitts & Posner, 1967). In the first stage, termed the cognitive stage, learners memorize relevant facts and typically rehearse these facts during initial performance attempts. These performance attempts are often variable and error ridden. Two important things happen in the second or associative phase. One, errors in initial understanding are gradually detected and corrected, and two, associations facilitating successful performance are strengthened (Anderson, 2005). Therefore, performance attempts during this stage are more consistent and less error ridden. Both task complexity and learner abilities contribute to varying lengths of time across individuals in this stage. The third, autonomous stage requires extensive practice to achieve and is characterized by few errors and minimal mental effort (Davids et al., 2008). These stages can also be thought of in terms of novice, journeyman, and master stages of skill acquisition.

Ability

Ability reflects a general and relatively enduring capacity to learn tasks. Ability is typically considered stable, yet levels of ability may change over a lifetime. Such changes often occur during childhood and adolescence due to genetic and developmental factors (Bouchard, 2004; Fleishman & Mumford, 1989a; Plomin & Spinath, 2004). Because such factors are unique to each individual, rates and patterns of change, as well as actual levels of ability, differ across individuals. It is assumed that tasks differ in the extent to which they require different abilities, and tasks with similar ability requirements should have similar performance demands (Fleishman, 1972).

Although many taxonomies of human ability exist, two common ability specifications include GMA (also commonly referred to as general cognitive ability, general intelligence, or *g*: Hull 1928; Spearman, 1927) and broad-content abilities (Ackerman, 1988). GMA is defined as the factor common to tests of cognitive ability and is theorized to be the ability to efficiently acquire, process, and use information (also commonly referred to as fluid intelligence or simply Gf: Cattell, 1971). Broad-content abilities describe a class of abilities which pertain to the general content of a given task. For instance, a task primarily composed of oral or written components might require the broad-content ability termed verbal ability. Two other common abilities in skill acquisition research are perceptual-speed and PM (Ackerman, 1988). Perceptual-speed ability refers to speed of processing information. PM refers to the speed and accuracy of motor responding. Regardless of type or taxonomy, greater ability generally leads to faster acquisition of skill and higher levels of performance.

Fleishman's Work

Another important taxonomy central to the current discussion is Fleishman's ability requirements approach. Much of Fleishman's early work focused on the acquisition of skill in perceptual-motor tasks. This research ultimately led to a taxonomy that places 52 separate abilities into cognitive, physical, and perceptual-motor classes (Fleishman & Reilly, 1992). Although Fleishman's taxonomy represents the first useful organization of individual differences in performance and has contributed to research and applied activities in numerous ways, it is Fleishman's subsequent work utilizing his taxonomy that is more pertinent to the current discussion.

In general, this research showed that (a) changes occur in the specific combinations of abilities contributing to performance over the course of skill acquisition, (b) such changes are progressive and systematic and become stabilized, and (c) the importance of task-specific ability increases over the course of skill acquisition (Fleishman, 1972).

More specifically, Fleishman showed that the combinations of abilities contributing to individual differences early in training were often markedly different than the combinations of abilities contributing to individual differences later in training. Fleishman emphasized two points about this general pattern. One, the changes in ability combinations frequently occurred relatively early in training, and two, as soon as higher levels of skill were obtained, the changes in ability combinations seemed to stabilize (Fleishman & Mumford, 1989b). Furthermore, Fleishman and Mumford (1989a) suggested late-stage acquisition may be partly the result of abilities not already identified by prior study (e.g., Jones, Dunlap, & Bilodeau, 1984) and called on future research to investigate.

In a complex, perceptual-motor coordination task, Fleishman and Hempel (1954) found some abilities such as spatial orientation, visualization, and perceptual speed significantly contributed to performance early but declined in contribution to non-significant levels later in acquisition. On the other hand, PM either continually and significantly contributed or steadily increased in its contribution toward performance across acquisition. After the initial changes in the composition of abilities contributing to performance, the composition stabilized and PM became the primary contributor. Similar findings have been repeatedly found (e.g., Fleishman, 1960; Fleishman & Fruchter, 1960; Fleishman & Hempel, 1955; Fleishman & Mumford, 1989b; Fleishman & Rich, 1963). However, no abilities specifically related to late-stage performance were identified.

Ackerman's Work

Ackerman's dynamics of ability determinants of skill acquisition (1988, 1992) is a theory that attempts to address and explain the observation of dynamic criteria in complex skill acquisition. Borrowing from previous research (e.g., Anderson, 1982; Fitts & Posner, 1967; Fleishman & Hempel, 1954, 1955; Shiffrin & Schneider, 1977), Ackerman's model includes three stages of skill acquisition (i.e., cognitive, associative, and autonomous), but adds a component showing how different abilities contribute to each of the three stages. Various task-, person- and situation-related factors dictate the relative importance of various abilities during each time point during acquisition, but the factors of complexity and consistency are the most prominent. Complexity, particularly component and coordinative, primarily moderates the relationship between cognitive ability and performance, whereas consistency (i.e., dynamism) moderates learning-stage progression.

For complex yet consistent tasks, Ackerman suggests early skill acquisition will depend primarily on cognitive abilities—general and broad-content—because everything is new and learners must continually process new information. As the learner progresses to later stages of skill acquisition, cognitive ability will either remain or decrease in its contribution toward acquisition. For inconsistent tasks, cognitive ability should continue to contribute because performers must continually process inconsistencies. For consistent tasks, learners get better at processing the consistent information as acquisition progresses, and the contribution of cognitive ability thus declines. Perceptual-speed ability is particularly important during the middle of skill acquisition. As the production systems generated in the first cognitive phase are fine tuned in the second associative phase, perceptual-speed ability becomes important, but less so once the task becomes largely automated in the final autonomous phase. If a task is perceptual-motor in nature, PM should have a stronger role in the final stage of skill acquisition. Production systems are largely automated at this stage, and therefore, it is PM that determines further skill acquisition (Ackerman, 1988).

Complex tasks require the creation of more production systems which increase the contribution of cognitive ability toward skill acquisition but attenuate that of perceptual speed. This is because attention is utilized for increased system production while perceptual speed is not as effective across many uncompiled productions. Consistency moderates learning-stage progression because without some consistency learning is not possible. Therefore, inconsistency slows acquisition. For example, a learner may never progress beyond the first stage of learning in an extremely inconsistent task, suggesting that cognitive ability will strongly contribute to performance no matter the degree of practice (Ackerman, 1988).

Because skill acquisition differs depending on task complexity and consistency, high- and low-ability learners might converge in performance over the course of practice and instruction. The prediction of decreasing interindividual variance in performance (i.e., convergence) across time is consistent with the *lag hypothesis* (Singer & Willet, 2003) in that slower learners lag behind faster learners but may catch up given additional practice and instruction. That is, high-ability learners display stronger linear and quadratic relationships between practice and performance (i.e., reach asymptote more quickly) than their lower-ability counterparts. The opposite hypothesis involving divergence, termed the *deficit hypothesis* (Singer & Willett, 2003), *fan-spread effect*, or *Matthew effect*

(Merton, 1968; Stanovich, 1986), describes increasing interindividual variance. Less complex and more consistent tasks typically portray a lag pattern. More complex and inconsistent tasks require more cognitive resources, which may prevent some learners from ever progressing beyond earlier stages of acquisition. Divergence in performance is especially likely for tasks that are largely dependent on declarative knowledge yet do not involve a finite domain of knowledge than on tasks which primarily require speed and accuracy of motor responding (Ackerman, 2007).

Increasing Predictive Validity of GMA

Alternative Findings

Newer research suggests that the cognitive ability-performance relationship has been inadequately addressed because previous work does not predict a commonly observed general increase in the relationship between cognitive ability and performance (e.g., Arthur et al., 1995; Day, Arthur, & Shebilske, 1997; Deadrick, & Madigan, 1990; Rabbitt, Banerji, & Szymanski, 1989). Subjective reports collected at the end of the Day et al. (1997) study showed that the cognitive-ability and performance relationship increase occurred because executive attention control processes became increasingly important as strategies were discovered and utilized (Shebilske, Goettl, & Regian, 1999). This assertion extends the previously discussed research of Fleishman and Ackerman as well as other lines of research such as case-based and analogical reasoning, as well as, cognitive control theory.

Case-based and Analogical Reasoning

The structure of case-based knowledge is commonly thought to be like an indexed table of past experiences (Anderson, 1983; Gentner, 1983; Hammond, 1990; Kolodner, 1983; Schank, 1982). When any situation is encountered, a learner engages in a search of this table comparing case characteristics, such as information about causes, contingencies, and outcomes, from the current situation to past case attributes from the table (Hammond, 1990). The use of analogies, termed analogical reasoning, is necessary when no suitable past case can be identified (Mumford, Friedrich, Caughron, & Byrne, 2007). Under this paradigm, experts might require increased cognitive resources to wield their increased number of exemplar cases.

Executive System

The executive system is thought to be responsible for more complex cognitive activities not typically addressed with traditional skill acquisition theories such as planning, abstract thinking, initiation, inhibition, and selecting sensory information on which to focus (Stuss & Knight, 2002). Executive control is thought to be important throughout acquisition (Gopher, 1996; Norman & Shallice, 2000). For example, early stages of acquisition require decisions on which stimuli to focus and how information relates to other information while later stages require decisions regarding which compiled productions will be most effective or what changes may be necessary for a given production to be effective. As such, these models allow for a prediction of increased contributions of cognitive ability during skill acquisition as the number of productions increases.

Interactive Iterative Learning Phase Model

An interactive iterative learning phase model provides an explanation for the increasing predictive validities of GMA toward performance across skill acquisition. Such a model represents an extension as opposed to a contradiction of previous research by addressing complex tasks encompassing components of various complexities which can be both interdependent and hierarchically related. For example, Ackerman (1992) found increasing correlations between cognitive ability (i.e., reasoning and spatial) and performance over time but primarily discussed such findings in terms of support for the prediction that such correlations would be high and remain stable over time. However, it may be necessary to integrate component abilities later in skill acquisition (Fleishman, 1972), and cognitive ability might be used for this purpose. With an interactive iterative learning phase model, learners proceed through three phases of learning, but they do so in an interactive and iterative way such that the interplay of processes, ranging from totally controlled to completely automatic, is complex and present throughout skill development (Day et al., 1997). The complexities inherent to this system may grow during skill acquisition, and therefore, increased cognitive capacity may be necessary to deal with the growing dynamics.

Analytic Issues

Traditional Approaches

Traditional analytic approaches have relied on a "time-slice" approach where correlations between ability and performance or attainment are examined at discrete time points during practice and instruction or training. The traditional time-slice approach is appealing for a variety of reasons. For one, it is intuitive, meaning people generally accept the idea that changes in correlational patterns between abilities and attainment must be indicative of changes between ability and learning. Second, because no difference scores are computed, this method seems to avoid the issues associated with gain scores (e.g., Cronbach & Furby, 1970), and third, the method is easy to apply (Voelkle et al., 2006).

Unfortunately, the approach is also misleading for a variety of reasons. For one, the primary focus of the analysis is still on difference scores although these differences are among the correlations as opposed to raw scores, and this obscures the gain score issue. Second, skill acquisition is not modeled in these approaches, and therefore, contributions of ability toward that acquisition must be inferred from the disparate correlational observations (Preacher, Wichman, MacCallum, & Briggs, 2008). Third, the method is difficult to apply with more complex models (Voelkle et al., 2006). This third criticism is readily apparent when considering how necessary the control of indirect and mediated effects of past performance and ability is when assessing current ability-performance relationships. Traditional approaches have only modeled the "intra-slice" direct effects, thereby missing these crucial "inter-slice" indirect contributions, and this has resulted in the reporting of biased ability-performance relationship estimates in the literature (Fleishman & Mumford, 1989b). As an example, Ackerman's assertions have often been based on analytic models that did not correctly control for past performance and ability contributions to that past performance.

Growth Curve Models

Fortunately today, learning researchers have various techniques for analyzing growth (e.g., acquisition) by directly modeling it (Bollen & Curran, 2006; Duncan, Duncan, & Strycker, 2006; McArdle & Nesselroade, 2002; Muthèn; 2004; Singer & Willet, 2003). In this family of analyses, variance components are handled in such a manner as to put the focus of the analysis on the individual learning curve, like recommended by Rogosa

(1995), and not on gain scores, like Cronbach and Furby (1970) advised against. Using these techniques, skill acquisition can be easily modeled over time as a function of individual differences in any readily available hierarchical analysis software (e.g., SPSS Mixed, HLM 6, SAS Proc Mixed). Growth curve models allow for the separate modeling of performance or attainment as intercepts and growth or acquisition as slopes. In addition, more complex learning models can be fit (Meredith & Tisak, 1984, 1990). However, most recent studies utilizing these methods have modeled skill acquisition as a constant parameter (e.g., linear), or set of constant parameters (e.g., linear and quadratic), throughout practice and have neglected to model acquisition-stage information (Newell, Liu, & Mayer-Kress, 2001). Put another way, recent studies have not targeted growth in skill over specific performance intervals, periods of training, or stages of acquisition.

Spline Models

Splines may be defined as piecewise polynomials of degree n whose function values and first n-1 derivatives agree at all join points (i.e., knots: Smith, 1979). It is possible to fit any number of pieces provided there are enough observations (Suits, Mason, Chan, 1978). Spline models offer distinct advantages over ordinary polynomial regression. First, in low dimensions, polynomial regressions are not flexible enough to capture rapid slope change, especially at irregular intervals. In high dimensions, polynomial regressions fail due to Runge's phenomenon, an increased and often undesirable oscillation at the edges of an interval. In contrast, spline regressions offer more flexibility and control (Suits et al., 1978) and can be fit in any standard statistics package. If one seeks to find that the underlying mechanism contributing to observations is not of the same kind throughout the range of the independent variable, then splines may be used to model that assumption (Smith, 1979). That is, splines offer an opportunity to model skill acquisition in segments or phases, which extends recent studies (e.g., Voelkle et al., 2006) that did model acquisition but neglected to examine how acquisition changes at specific points during training.

Purpose of the Present Research

Together, spline and growth curve modeling will allow a more complete investigation into ability determinants of complex skill acquisition than has been attempted previously. The present research examines the contribution of GMA, PM, and VA to the acquisition of skill at performing the video game Space Fortress—a complex computer task that simulates the demands of a dynamic aviation environment (Mane & Donchin, 1989)—by fitting multiple, individual-focused spline segments throughout acquisition. This will allow a comparison of explicitly modeled contributions of ability to skill acquisition throughout training, and based on a search of the extant literature, no investigation like this has been attempted previously.

I focus on the three abilities of GMA, PM, and VA for a variety of reasons. The inclusion of GMA is consistent with previous ability-performance dynamics research (e.g., Ackerman, 1987, 1988; Fleishman, 1972), as well as interactive iterative learning phase models (e.g., Day et al., 1997), and has been shown to correlate with Space Fortress performance (Day, Arthur, & Gettman, 2001; Fein & Day, 2004). The inclusion of PM is similarly consistent with previous research (e.g., Ackerman, 1987, 1988; Ackerman & Cianciolo, 2000; Fleishman, 1960, 1972; Fleishman & Fruchter, 1960; Fleishman & Hempel, 1954, 1955; Fleishman & Mumford, 1989b; Fleishman & Rich, 1963) and has also been shown to be related to Space Fortress performance (Day et al., 1997; Gopher, Weil, & Siegel, 1989). Because VA has been shown to be related to Space Fortress performance and yield stronger relationships with Space Fortress performance compared to perceptual speed (Arthur, Bennett, Day, & McNelly, 2002) but is a relatively understudied ability, VA is an important ability variable to include. In particular, VA might be able to help better explain growth in late-stage skill acquisition, where researchers have historically had less success linking abilities to acquisition.

Voelkle et al. (2006) reanalyzed data from Ackerman, Kanfer, and Goff (1995) to investigate the relationship of two abilities (e.g., spatial-numerical and perceptual speed ability) assessed by two extensive test batteries (e.g., Aptitude Assessment Battery: Ackerman & Kanfer, 1993; and a new battery) on the air traffic controller task TRACON. Relying on latent growth curve analysis, they showed how both abilities significantly contributed to the latent intercept (i.e., attainment) and latent linear slope (i.e., acquisition). While spatial-numerical ability exhibited a larger relationship with the latent intercept term, the reverse was true with the latent linear term in that perceptual speed ability exhibited the larger relationship. Voelkle et al. (2006) interpreted this pattern as support for Ackerman's (1987, 1988) theory in that the broad-content ability (i.e., spatial-numerical) made a relatively larger contribution early (i.e., with the intercept modeled as initial status) and perceptual speed made a relatively larger contribution later (i.e., with the linear slope) in accordance with the theory. However, they did not model a relationship to the latent quadratic factor, and the analysis did not account for the interaction between the type of predictor and the phase of skill acquisition as originally posited by theory. This prevented them from examining how abilities could differentially contribute to acquisition and also help explain convergence or divergence in the performance trajectories across individuals throughout training.

The present research represents a logical extension of Voelkle et al. (2006) through the inclusion of acquisition-phase information directly in the analytic model. Doing so allows for a direct examination of when and how abilities contribute to skill acquisition as opposed to only being able to discuss ability contributions to static skill acquisition across training. Additionally, it was possible to better examine convergence and divergence of interindividual variance with the present approach.

Research Hypotheses and Questions

The fitting of power functions to performance data collected repeatedly across time has become a traditional approach in the understanding of learning (e.g., Lane, 1987; Mazur & Hastie, 1978; Snoddy, 1926). Newell and Rosenbloom (1981) saw fit to refer to these power functions as the "universal" law of learning (Gallistel, Fairhurst, & Balsam, 2004; Heathcote, Brown, & Mewhort, 2000; Newell et al., 2001). In this tradition, I tested the following hypothesis.

Hypothesis 1: The skill acquisition growth curve will follow the power law of practice such that gains in performance will slow over time.

Because researchers have long assumed a positive relationship between ability and skill acquisition, but have often failed to avoid a common confusion regarding correct variance decomposition when trying to produce evidence for that assumption (Voelkle et al., 2006), I tested the following hypothesis.

Hypothesis 2: Each ability—GMA, PM, and VA—will positively contribute to growth in skill.

Although theories have been forwarded regarding the dynamic contributions of ability toward skill performance (e.g., Ackerman, 1988; Fleishman, 1972), actual pattern prediction remains difficult in the later stages of skill acquisition (Ackerman, 2007; Fleishman, 1972), and this is especially true with new criterion tasks. Therefore, I explored the following set of research questions.

Research Question 1a: Will the contribution of GMA to growth in skill remain stable, increase, or decrease across early, middle, and later stages of skill acquisition (i.e., training sessions)?

Research Question 1b: Will the contribution of PM to growth in skill remain stable, increase, or decrease across early, middle, and later stages of skill acquisition (i.e., training sessions)?

Research Question 1c: Will the contribution of VA to growth in skill remain stable, increase, or decrease across early, middle, and later stages of skill acquisition (i.e., training sessions)?

Fleishman's research showed that changes occur in the specific combinations of abilities contributing to performance over the course of skill acquisition, that such changes are progressive and systematic and become stabilized, and that the importance of a task-specific factor increases over the course of skill acquisition (Fleishman, 1972). Therefore, I explored the following two research questions.

Research Question 2: What will the relative contributions to growth be among abilities at early, middle, and later stages of skill acquisition (i.e., training sessions)?

Research Question 3: Will the relative contributions to growth among abilities change or remain stable across early, middle, and later stages of skill acquisition (i.e., training sessions)?

Researchers have done an inadequate job of identifying evidence for the often accepted relationship between ability and skill acquisition. They have either relied on analyses that do not actually model acquisition or ones that produce inconsistent results (Voelkle et al., 2006). When research has modeled skill acquisition those models have neglected to account for phase information (e.g., Voelkle et al., 2006), and this precludes the examination of exactly when abilities interact with acquisition. The present analytic method does model acquisition in different segments or phases of training. If GMA is found to increase in its contribution toward skill acquisition, this might be viewed as evidence for cognitive restructuring or interactive iterative learning phase models as supported by case-based reasoning and cognitive control theory. If either PM or VA are found to increase in contribution toward late-stage skill acquisition, such findings might be viewed as evidence for how abilities contribute to the fine-tuning of skill later in acquisition. If none of the abilities investigated are shown to be related to late-stage acquisition, then task-specific ability and the building upon habits and skill developed in training could be interpreted as the primary determinant of late-stage skill acquisition. In any event, by applying a spline-modeling approach, the present research offers a unique investigation into the patterns of late-stage skill acquisition.

Method

Participants

Participants for this study initially included 170 males solicited through campus fliers posted around the University of Oklahoma. Participants were at least 18 years of age and were required to be right handed due to hardware constraints. Each was paid an hourly rate of $6 and had the opportunity to earn monetary bonuses of between $10 and $100 based on performance. As additional incentive, participants were also placed in a lottery for an extra $50 upon study completion. Twenty-nine participants did not complete the entire one-week training, and ten participants had missing data due to hardware failures. This resulted in a final sample size of 131. Attrition analysis using baseline performance indicated no significant difference between the complete (M = -1863.06, SD = 937.71) and incomplete (M = -2048.46, SD = 920.23) groups, $t'(63.36) = 1.10$, $p = 0.28$, $d = 0.17$.

Materials

Criterion Task. Space Fortress (Mane & Donchin, 1989), a game often used to study complex skill acquisition (Donchin, 1989; Gopher, Weil, & Bareket, 1994), was utilized as the performance task. Because the game was designed to simulate the information-processing and psychomotor demands of complex performance settings such as those found in dynamic aviation environments (Gopher, 1993), the game features short- and long-term memory loading, high workload, dynamic attention allocation, decision making, prioritization, resource management, discrete motor responses, and difficult manual controls (Day et al., 1997; Gopher et al., 1989), and therefore, exhibits positive transfer to actual flight in fighter jets (Gopher et al., 1994) and helicopters (Hart & Battiste, 1992). The game also measures quantifiable components that have been analyzed in terms of consistent and inconsistent processing as well as implicit-automatic and explicit-controlled processing (Corrington, 1996; Shebilske et al., 1999).

The primary objective of Space Fortress is to fly a ship in frictionless space while battling a stationary fortress located at the screen center. Battle is accomplished by firing missiles toward the fortress while evading ship damage or destruction from both fortress missiles or from pursuant mines, which periodically appear from random locations. Participants control ship path, speed, and rates of fire through joystick input. An information panel located at the bottom of the screen indicates fortress vulnerability which increases by one with each successful engagement from the ship. Once the vulnerability counter reaches ten or more, the fortress may be destroyed using a rapid double shot executed within a 250 millisecond interval.

In addition to controlling the joystick, participants also operate a three-button mouse. During battle with the fortress, participants are expected to monitor an area of the screen where symbols are presented in random succession. Once a bonus opportunity is indicated by two consecutive “$” symbols, participants can choose between a point or missile bonus by clicking a corresponding button on the mouse with their left hand. Foe mines may be destroyed by identifying a particular mine as foe through the instrument pane, double clicking the third mouse button within a 250 to 400 millisecond interval, and then striking the mine with a missile. Friend mines may be destroyed immediately without identification, and the destruction of any mine results in additional performance points.

The information panel also shows the number of remaining missiles, a total score, and component scores based on ship velocity, ship control, and the speed of dispatching mines. In addition to the feedback continuously presented in the bottom panel, detailed summary information is provided on a screen at the end of every game. This screen includes info such as counts of the number of times the participant's ship was damaged, destroyed, or wrapped around the screen. The final screen also displays the participant's component scores as well as the total score, which is a composite of the others. Scores on Space Fortress typically range from approximately -3000 to 6000 with maximum or asymptotic performance levels of approximately 7500. Interested readers are referred to Arthur et al. (1995) for a more comprehensive description.

GMA. GMA was assessed using Raven's Advanced Progressive Matrices (APM; Raven, Raven, & Court, 2004). The APM consists of pattern completion problems presented in an ascending order of difficulty. Previous research has demonstrated statistically significant correlations between APM scores and Space Fortress performance (e.g., Day et al., 2001; Fein & Day, 2004). The original 36-item form was used with an administration time of 40 min., and the test exhibited a Spearman-Brown odd-even split-half reliability of 0.88. Scores were converted to z-scores for ease of interpretation.

Psychomotor Ability. PM was assessed via the Space Fortress aiming task (Mane & Donchin, 1989). The task consists of three 3-min. trials, and the goal is to destroy as many mines as possible. Participants use a joystick to rotate a stationary ship and fire missiles. During each trial, stationary mines periodically appear in random locations, and participants attempt to quickly and accurately destroy the mines. The mines disappear after a few seconds or immediately if hit. Previous research has utilized this aiming task as a measure of PM and has demonstrated statistically significant correlations with Space Fortress performance (e.g., Day et al., 1997; Gopher et al., 1989). PM was operationally defined as the average total aiming score, a function of the number of mines destroyed and the speed with which they were destroyed, across the three trials and then converted to z-scores for ease of interpretation. A reliability analysis treating the separate games as test items produced a coefficient alpha of 0.85 in the present study.

Visual Attention. VA was assessed using the Computer-Administered Visual Attention Test (CA-VAT; Arthur, Strong, & Williamson, 1994; Arthur et al., 1995). The CA-VAT is a visual counterpart to the Auditory Selective Attention Test (ASAT; Gopher & Kahneman, 1971; Mihal & Barrett, 1976) and is based on protocol developed for the Visual Selective Attention Test (VSAT; Avolio, Alexander, Barrett, & Sterns, 1981). The short version of the CA-VAT was used in this study and consisted of 16 items, the first four of which were practice.

Items consisted of 19 sub-items with the first 16 of each item using one cue word and the last three using another cue word. Cue words dictate the set of response rules to follow when participants respond to pairs of symbols in each sub-item. If a participant fails to respond to a sub-item within two seconds, it is marked as incorrect, and the next sub-item is presented. The time between stimulus onset and response key press is recorded as the reaction time for each sub-item. Items were scored with the following formula.

$$\text{Item Score} = [\ 19 - E_i\ ] + [\ (\ 19 - E_i\ ) * (\ 1 / R_c\ )\ ] \text{ where} \tag{1}$$

E_i = number of errors, including incorrect answers and non-responses

R_c = reaction time for correct responses

Therefore, a participant's score is a function of both the number and reaction time of correct responses. The number of correct responses is multiplied by the inverse of the reaction time to reward speed and accuracy. VA was operationally defined as the average score on the 12 non-practice items and then converted to z-scores for ease of interpretation. A Spearman-Brown odd-even split-half reliability of 0.97 was obtained in the current sample. More detailed information regarding the test can be found in Arthur et al. (1994). It is important to note that within the Cattell-Horn-Carroll (CHC) theory framework of human abilities scores on the CA-VAT reflect reaction and decision speed more so than perceptual speed ability (Carroll, 1993; McGrew, 2009).

Procedures

The study protocol involved nine training sessions spread over the course of five consecutive days. On the first day (Monday), participants were informed that the purpose of the study was to examine how different people learn novel and complex tasks. Participants first performed the aiming task and then watched a 17-min. training video accompanied by a seven-page manual detailing instructions and strategies for performing Space Fortress. Afterward, participants performed four 3-min. warm-up games of Space Fortress and then watched a 5-min. review video. Participants were then given a two-page review of the instructions and strategies for reference throughout the remainder of their training. Participants then underwent a series of nine 10-game training sessions. Each session lasted approximately 30 mins.

The first training session took place following the review of Space Fortress instructions. The second and third training sessions took place on the second day of training (Tuesday), the fourth and fifth sessions took place on the third day (Wednesday), the sixth and seventh sessions took place on the fourth day (Thursday), and the eighth and ninth sessions took place on the fifth and final day of training (Friday).

The first eight games of every 10-game session were considered practice games. The last two games of every session were considered test games. Monetary bonuses were based solely on test game scores. All games lasted 3 mins. Skill acquisition was operationalized using the averages of each pair of test games from every session with the first two games from the four-game warm-up serving as baseline. The APM was administered on the third day of training in between the fourth and fifth training sessions, and the CA-VAT was administered on the last day of training in between the eighth and ninth sessions. Other measures not germane to the present investigation were administered in between training sessions on the second and fourth days of training.

Results

Table 1 presents descriptive statistics for all study variables. Important, underlying conditions for the present research are that the present abilities are indeed related to performance and that performance significantly improved across sessions. In Table 1 GMA showed an average zero-order correlation with performance across sessions of r = .41 (minimum = .34; maximum = .53) while PM demonstrated an average correlation of r = .48 (minimum = .34; maximum = .61), and VA showed an average of r = .53 (minimum .42; maximum .58). Therefore, the abilities are related to performance.

As apparent from the second and fourth columns (means and standard deviations) in Table 1, not only did the average performance seem to improve, but interindividual variance increased as well. In the last four sessions a leveling off of interindividual variation occurred, which is due to the beginning of asymptotic performance after a significant amount of task practice. Before conducting a repeated measures ANOVA to demonstrate performance improvement across sessions, a Mauchly’s test (Mauchly,

1940) indicated that the assumption of sphericity had been violated, $\chi^2(44, N = 131) = 454.40$, $p < .001$, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity, $\varepsilon = .48$ (Greenhouse & Geisser, 1959). The results show that mean performance improved significantly, $F(4.33, 563.36) = 663.89$, $MSE = 1{,}050{,}143.53$, $p < .001$, $\widehat{\omega}^2 = 0.83$. Planned t-tests indicated all pairwise differences were significant. Figure 1 shows the mean performance across the ten sessions and illustrates the intraindividual variation, as well as the interindividual differences in intraindividual change over time.

Before proceeding to test the hypotheses, I computed the intraclass correlation coefficient type 1 (ICC1; Bliese, 2000) for the criterion measure. In the current study, the ICC1 indicates how much of the variability in Space Fortress performance is a result of between-person differences across the ten measurement occasions. The ICC1 is calculated by determining the ratio of between-person variance to overall variance [between person variance / (between-person variance + residual within-person variance)] of an unconditional (random intercept) mixed-effects model (Bliese & Ployhart, 2002). Analyses revealed an ICC1 of .49, indicating that between-person variance explained 49% of the variance in performance. This value is consistent with other studies utilizing growth curve models (e.g., .44: Lang & Bliese, 2009), and suggests because considerable individual differences in performance exist across time, growth curve modeling is an appropriate analytic technique (Bliese, 2000).

Nature of the Growth Curve

Unconditional Quadratic Growth Model. Hypothesis 1, which predicted that the skill acquisition growth curve would follow the power law of practice, was best answered by an unconditional (no predictors) quadratic growth model because such a model offers the opportunity to examine both linear and quadratic trends without adding the complexity of Level 2 predictors. This model was as follows:

$$Y_{ij} = \pi_{0j} + \pi_{1j}(t)_{ij} + \pi_{2j}(t^2)_{ij} + r_{ij} \quad \text{where } r_{ij} \sim N(0, \sigma^2) \qquad (2)$$

and

$$\pi_{0j} = \beta_{00} + u_{0j}$$

$$\pi_{1j} = \beta_{10} + u_{1j}$$

$$\pi_{2j} = \beta_{20} + u_{2j}$$

where

$$\begin{pmatrix} u_{0j} \\ u_{1j} \\ u_{2j} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tau_{00} & \tau_{01} & \tau_{02} \\ \tau_{10} & \tau_{11} & \tau_{12} \\ \tau_{20} & \tau_{21} & \tau_{22} \end{pmatrix}\right]$$

In this model Y_{ij} is Space Fortress performance for a given individual at a given time. The intercept, π_{0j}, is coded to represent performance at baseline because t represents time from baseline. The parameters π_{1j} and π_{2j} are the linear and quadratic trends across time, respectively. All parameters were allowed to randomly vary across individuals as evident by the inclusion of random components in the Level 2 equations which include the beta coefficients.

This model was fit using maximum likelihood and converged in two iterations due to the balanced nature of the data (e.g., Singer & Willett, 2003). The model represents a significant improvement over the unconditional mixed-effects model used to compute the initial ICC1, $\chi^2(4, N = 131) = 2036.90$, $p < .001$. The model results are presented on the left side of Table 2. The intercept, $\beta_{00} = -1143.19$, $t(130) = -11.90$, $p < .001$, and linear slope, $\beta_{10} = 1174.15$, $t(1177) = 28.96$, $p < .001$, estimates suggest that on average individuals perform at -1143.19 points on Space Fortress during baseline and progress at a linear rate of 1174.15 additional points for each successive session played. More importantly, the quadratic estimate, β_{20} = -77.93, t(1177) = -19.88, p < .001, suggests that individual growth rates slow or decelerate across training sessions. Thus, these findings represent support for Hypothesis 1. Skill acquisition followed the power law of practice.

Furthermore, baseline performance also seems to be positively related to linear, r = .79, p < .001, and negatively related to quadratic rates of acquisition, r = -.80, p < .001. This suggests individuals with high baseline performance have stronger linear and quadratic rates of acquisition than their lower performing counter parts. The linear and quadratic growth rates were also related, r = -.97, p < .001. This suggests linear growth is strongly related to quadratic deceleration and therefore eventual asymptote. In other words, high ability trainees reach asymptote more quickly. These findings are consistent with the lag hypothesis (Singer & Willet, 2003).

Conditional Quadratic Growth Model. The unconditional quadratic growth model left a significant amount of unexplained variance in each of the random effects. Therefore, in accordance with Hypothesis 2, which predicted that each ability (e.g., GMA, PM, and VA) would positively contribute to growth in skill, a conditional quadratic growth model incorporating the abilities was fit to the data. This model replaced the Level 2 equations of the unconditional quadratic growth model with the following:

$$\pi_{0j} = \beta_{00} + \beta_{01}(z_{GMA}) + \beta_{02}(z_{PM}) + \beta_{03}(z_{VA}) + u_{0j} \quad (3)$$

$$\pi_{1j} = \beta_{10} + \beta_{11}(z_{GMA}) + \beta_{12}(z_{PM}) + \beta_{13}(z_{VA}) + u_{1j}$$

$$\pi_{2j} = \beta_{20} + \beta_{21}(z_{GMA}) + \beta_{22}(z_{PM}) + \beta_{23}(z_{VA}) + u_{2j}$$

In this model each of the parameters (intercept, linear, and quadratic) from the unconditional quadratic model are now predicted from the abilities (GMA, PM, and VA) of individuals yet still allowed to randomly vary. The abilities were grand mean centered and standardized for ease of interpretation and understanding.

This model was fit using maximum likelihood and converged in two iterations due to the balanced nature of the data (e.g., Singer & Willett, 2003). The model represented a significantly better fit to the data than the unconditional quadratic growth model, $\chi^2(9, N = 131) = 99.00$, $p < .001$, and the results can be found on the right side of Table 2. The performance of an average individual, represented by the Level 1 Model, as well as the growth parameter relationships, remained the same as in the unconditional quadratic growth model. Interestingly, although all abilities were related to intercepts (i.e., skill attainment), GMA: $\beta_{01} = 147.26$, $t(1177) = 1.68$, $p < .10$; PM: $\beta_{02} = 496.04$, $t(1177) = 79.28$, $p < .001$; VA: $\beta_{03} = 265.57$, $t(1177) = 3.03$, $p < .01$, only VA significantly contributed to the linear, $\beta_{13} = 172.28$, $t(1177) = 3.84$, $p < .001$, and quadratic, $\beta_{23} = -13.98$, $t(1177) = -3.12$, $p < .01$, growth rates. These results do not support Hypothesis 2 in that only VA, and not GMA nor PM, positively contributed to growth in skill.

Ability Contributions to Growth: Conditional Spline Growth Model

Collectively, the research questions address the contributions of ability to skill acquisition, and the current approach provides a more accurate depiction than past investigations which have examined the pattern of correlations between ability and performance, such as in the manner displayed in Figure 2. The pattern of correlations shown in Figure 2 suggest all the abilities contribute to skill acquisition throughout training, and as suggested by Fleishman (1972) this pattern stabilized after the early stages of training. All of the research questions were answered by fitting a conditional spline growth model to the data; the results of which can be found in Table 3.

Splines build off of each other in that to determine a model slope at a particular point in time, all previous spline coefficients must be added together. Figure 3 demonstrates this additive nature. Geometrically speaking, a slope can be represented as the angle between two vectors (Rodgers & Nicewander, 1988). Normally this angle is thought of as being in relation to the horizontal axis. However, while it is ultimately true that spline coefficients are in relation to the horizontal axis, it may be easier to think of the coefficients as being in relation to each other. The result is a model that can change slope as time progresses (e.g., the solid line in Figure 3). Table 4 specifies the cumulative and thereby instantaneous slopes of the Level 1 Model at the beginning of each spline from the conditional spline growth model. The pattern of decreasing but significant slopes indicates the average person continually improved at a decelerating rate throughout training.

Splines were fit to the data according to day of training to allow an examination of how acquisition and ability contributions to that acquisition changed day to day. Because performance was operationalized as the average performance of the two test games from every 10-game session, and only two 10-game sessions occurred per day, the maximum degree of each polynomial spline that could be fit was linear. Similar to the linear trend of both the unconditional and conditional spline models in Table 2, the first spline (Monday spline) represents the underlying linear trend occurring at the onset of acquisition. The next spline (Tuesday spline) represents the deviation from the linear trend in the first spline starting on Day 2 of acquisition. The third spline (Wednesday spline) represents the deviation from the deviation in the second (Tuesday) spline starting on Day 3 of acquisition. The fourth (Thursday spline) and fifth (Friday spline) splines followed this pattern of staggered summative deviation. As such the combination of linear splines is able to capture linear, quadratic, and potentially higher order polynomial trends over the course of training in a more precise and controlled manner than available with typical regression.

Because individual differences in change were of primary interest in the present research, I investigated not only differences in Level 1 change but also whether Level 1 change variables randomly varied across individuals. Following recommendations by several researchers (Bliese & Ployhart, 2002; Pinheiro & Bates, 2000; Snijders & Bosker, 1999), I restrained Level 1 parameters when I found no random variability. Following recommendations in the literature (Bliese & Ployhart, 2002; Pinheiro & Bates, 2000), I conducted tests for random variability by contrasting models with log-likelihood ratio tests. The results of these tests forced the last two spline segments to be modeled as fixed because individuals did not appear to differ much in changes to the set pattern of skill acquisition at that late stage of practice. This decision was also supported by the leveling off of interindividual variance in performance as discussed when reporting the descriptive statistics. The conditional spline growth model was as follows.

$$Y_{ij} = \pi_{0j} + \pi_{1j}(i) + \pi_{2j}D_{1i}(i - i_1) + \pi_{3j}D_{2i}(i - i_2) + \pi_{4j}D_{3i}(i - i_3) + \pi_{5j}D_{4i}(i - i_4) + r_{ij} \tag{4}$$

where $r_{ij} \sim N(0, \sigma^2)$

and

$$\pi_{0j} = \beta_{00} + \beta_{01}(z_{GMA}) + \beta_{02}(z_{PM}) + \beta_{03}(z_{VA}) + u_{0j}$$

$$\pi_{1j} = \beta_{10} + \beta_{11}(z_{GMA}) + \beta_{12}(z_{PM}) + \beta_{13}(z_{VA}) + u_{1j}$$

$$\pi_{2j} = \beta_{20} + \beta_{21}(z_{GMA}) + \beta_{22}(z_{PM}) + \beta_{23}(z_{VA}) + u_{2j}$$

$$\pi_{3j} = \beta_{30} + \beta_{31}(z_{GMA}) + \beta_{32}(z_{PM}) + \beta_{33}(z_{VA}) + u_{3j}$$

$$\pi_{4j} = \beta_{40} + \beta_{41}(z_{GMA}) + \beta_{42}(z_{PM}) + \beta_{43}(z_{VA})$$

$$\pi_{5j} = \beta_{50} + \beta_{51}(z_{GMA}) + \beta_{52}(z_{PM}) + \beta_{53}(z_{VA})$$

where

$$\begin{pmatrix} u_{0j} \\ u_{1j} \\ u_{2j} \\ u_{3j} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tau_{00} & \tau_{01} & \tau_{02} & \tau_{03} \\ \tau_{10} & \tau_{11} & \tau_{12} & \tau_{13} \\ \tau_{20} & \tau_{21} & \tau_{22} & \tau_{23} \\ \tau_{30} & \tau_{31} & \tau_{32} & \tau_{33} \end{pmatrix} \right]$$

In this model Y_{ij} is the performance of an individual at a given time point while π_{0j} is an intercept coded as performance at baseline. The parameter π_{1j} represents the initial spline and the underlying linear trend, conditional on the other splines, throughout training. The *i* variables (i_1, i_2, i_3, and i_4) are set number of observations (e.g., sessions) since the beginning of skill acquisition denoting spline starting points (e.g., knots). The *D* variables (D_{1i}, D_{2i}, D_{3i}, and D_{4i}) are all dummy variables equal to 0 when the number of observations since the beginning of skill acquisition *i*, is less than i_1, i_2, i_3, and i_4 respectively, and equal to 1 when i is greater than i_1, i_2, i_3, and i_4 respectively. The remaining parameters (π_{2j}, π_{3j}, π_{4j}, and π_{5j}) become summative decrements to the underlying trend when enough time passes according to the *D* dummy variables. Individually these splines represent acquisition in each phase, and collectively they can capture the negative deceleration of the learning curve. The abilities were again grand mean centered and standardized for ease of interpretation and understanding when predicting acquisition in each phase.

The conditional spline growth model was fit using maximum likelihood and converged in two iterations due to the balanced nature of the data (e.g., Singer & Willett, 2003). The results are presented in Table 3. This model represented a significant improvement in fit over the conditional quadratic growth model, $\chi^2(13, N = 131) = 415.60$, $p < .001$, and this model is closer to the actual average of performance at baseline than previous models, $\beta_{00} = -1601.01$, $t(127) = -24.74$, $p < .001$. The model suggests individuals start acquisition at a rapid rate, $\beta_{10} = 1612.89$, $t(127) = 29.30$, $p < .001$, and significantly slow in that rate on day two, $\beta_{20} = -1327.84$, $t(127) = -17.85$, $p < .001$. The average rates of acquisition change little past day two as signaled by the lack of any additionally significant spline coefficients. Although no significant changes to acquisition rates occurred after day two, it is important to note that acquisition rates were statistically significant across the remainder of training as shown in Table 4.

Interestingly, in this model GMA did not contribute to performance (i.e., attainment), $\beta_{01} = 124.90$, $t(778) = 1.60$, $p > .05$. However, similar to the conditional quadratic growth model, both PM, $\beta_{02} = 493.83$, $t(778) = 7.01$, $p < .001$, and VA, $\beta_{03} = 212.82$, $t(778) = 2.73$, $p < .01$, contributed to performance (i.e., attainment), and only VA significantly contributed to acquisition. However, in addition to the information provided by the conditional quadratic growth model, the spline model indicated the contribution of VA to acquisition only occurred early in training, $\beta_{13} = 209.59$, $t(778) = 3.16$, $p < .01$.

Ability Contributions to Growth: Stable or Dynamic?

The research questions all concern the ability-spline interactions from Table 3 because the interactions speak to how dynamic ability contributions influence growth curves. Research Question 1 addressed how the intra-ability contributions changed across skill acquisition. Research Question 2 addressed the relative contributions to growth among the abilities within each phase of skill acquisition. Research Question 3 addressed the relative contribution to growth among the abilities and whether or not the relationship among contributions changed over the course of skill acquisition.

As displayed in Figure 4, the results did not show a dynamic relationship between ability and skill acquisition. Specifically, GMA and PM made no significant contributions to skill acquisition at any point during training. On the other hand, VA made a significant early contribution, but successive contributions were not significant.

These patterns are displayed in a different way in Figure 5, which shows how each ability influences or does not influence both attainment (i.e., intercept) and acquisition (i.e., slope), while controlling for the other predictors. Specifically, all three plots show how abilities contribute to interindividual variance in attainment (i.e., intercept) when examining how far apart the high and low ability lines are within each plot. Additionally, in the VA plot, a pattern of increasing interindividual variance can be observed as training progresses whereas in the GMA and PM plots, interindividual variance remains constant. The pattern of VA contributing significantly to the initial, positive Monday spline and at the .10 level with the second, negative Tuesday spline could be construed as evidence of how VA contributes to an initial divergence, but later convergence, in performance between low and high ability individuals as consistent with the *lag hypothesis* (Singer & Willett, 2003).

Results without Visual Attention

Given that VA is not commonly investigated in ability-acquisition research, coupled with the fact that only VA was significantly related to skill acquisition in the primary results, ancillary analyses based on the analyses of Tables 2 and 3 but focusing on only GMA and PM were conducted and reported in Tables 5 and 6.

After removing VA, the results did not change with respect to PM, but the results did change with respect to GMA. In the conditional quadratic model the exclusion of VA resulted in the GMA intercept term becoming significant, Table 2: β_{01} = 147.26, $t(917)$ = 1.68, $p < .10$ vs. Table 5: β_{01} = 270.51, $t(917)$ = 3.37, $p < .001$, as well as the GMA interaction with the linear trend, Table 2: β_{11} = -0.20, $t(917)$ = 0.00, p = *ns* vs. Table 5: β_{11} = 79.75, $t(917)$ = 1.91, $p < .10$. Similarly, in the conditional spline growth model the exclusion of VA resulted in the GMA intercept term becoming significant, Table 3: β_{01} = 124.90, $t(778)$ = 1.60, p = *ns* vs. Table 6: β_{01} = 223.67, $t(778)$ = 3.15, $p < .01$, as well as the GMA interaction with the underlying linear trend (Monday spline), Table 3: β_{11} = 21.58, $t(778)$ = 0.33, p = *ns* vs. Table 6: β_{11} = 118.85, $t(778)$ = 1.95, $p < .10$.

These results highlight the stronger relationship of VA to GMA (r = .53) when compared to the relationship between VA and PM (r = .34) because much of the variance accounted for by the inclusion of VA was accounted for by GMA when VA was removed from the analyses. However, these results indicate that even in the absence of VA, both GMA and PM fail to contribute to acquisition beyond the first stage of practice.

Discussion

The present research offers a new perspective into the ongoing debate regarding the relationship between ability and skill acquisition. Through the combination of growth curve and spline modeling, I was able to model skill acquisition trends over different segments of training while properly controlling for the indirect and moderating effects of past performance and ability contributions to that performance (Fleishman & Mumford, 1989b). This is important because most early research failed to model skill acquisition and instead discussed correlations between abilities and performance as evidence of the ability-acquisition relationship (Voelkle et al., 2006). Although newer research is now modeling skill acquisition directly and independently of attainment, most studies still neglect to incorporate information about learning phases (e.g., Voelkle et al, 2006). The modeling of this phase information is imperative in any discussion about how abilities are related to skill acquisition because it allows for a more explicit examination of when and how abilities contribute to acquisition in accordance with the specification of current theory (e.g., Ackerman, 1988, 1989; Fleishman, 1972).

Furthermore, relatively little is known about contributions of ability to late stage performance (Ackerman, 2007; Fleishman & Mumford, 1989b). To this end, I incorporated VA into the present investigation as an understudied ability in this area, which might be one of many potential abilities that may contribute in the late stages of skill acquisition.

How the Choice of Analytic Approach Matters

Traditional. The type of analysis matters. Based on the traditional approach of interpreting patterns of correlations between ability and attainment as evidence for ability-acquisition relationships, one might conclude the pattern of results in Figure 2 shows all three abilities (GMA, PM, and VA) were moderate to strongly related to acquisition throughout training, which supports Ackerman's (1987, 1988) assertions regarding the contribution of abilities during skill acquisition for a complex and inconsistent task such as Space Fortress. Additionally, this observed pattern partially supports other lines of research such as case-based reasoning (Anderson, 1983; Gentner, 1983; Hammond, 1990; Kolodner, 1983; Schank, 1982), executive control (Norman & Shallice, 2000; Stuss & Knight, 2002), and interactive iterative learning phase models (Day et al., 1997) in that GMA modestly increased across training sessions. However, the traditional approach does not actually model skill acquisition, and therefore interpretations that discuss skill acquisition are suspect.

Growth. Models such as conditional growth models are an improvement over traditional analytic approaches because they directly model skill acquisition independently of attainment by distinguishing between ability contributions to growth slopes and intercepts. For instance, one might conclude based on the conditional quadratic model results presented in Table 2 that GMA, PM, and VA contributed to performance, but VA also influenced skill acquisition throughout training. However, these models have a limitation in that they do not address different segments or phases of acquisition as theory posits (e.g., Ackerman, 1988, 1989), and therefore, such models do not allow a critical examination of when and how abilities contribute to skill acquisition.

Splined Growth. Therefore, coupling growth curve approaches with spline modeling is an even more promising approach in that splines allow for the dissection of acquisition into segments or phases similar to that dictated by theory (e.g., Ackerman, 1988; 1989) and thereby allow for the direct examination of exactly when and how abilities contribute to acquisition. An interpretation of the conditional spline growth model results presented in Table 3 suggest similar findings as that of the conditional quadratic growth model findings of Table 2. However, the incorporation of splines into the conditional spline growth model allowed acquisition to be represented in segments, and therefore, the deterioration of the VA contribution to changes in acquisition was now observable after the second day of acquisition. This finding is consistent with Fleishman's (1972) assertion that the contribution of cognitive abilities will decline as acquisition progresses. As an added benefit, splines allowed for better control over the indirect and moderating effects of previous performance when examining the relationship of abilities to skill acquisition (Fleishman & Mumford, 1989b).

Implications

As a whole, the spline results offer mixed support for prior theory on the relationship between abilities and acquisition (e.g., Ackerman, 1987, 1988; Fleishman, 1972). For example, Ackerman's (1987, 1988) theory suggests that for complex yet inconsistent tasks, such as Space Fortress, early skill acquisition will depend primarily on cognitive abilities, such as GMA and possibly VA. His theory was supported in that VA significantly contributed to early attainment (i.e., intercept) as well as early acquisition (i.e., slope), and GMA offered similar support when VA was excluded from the model. Likewise, Fleishman (1972) predicted non-motor abilities such as VA and GMA would contribute to early acquisition in perceptual-motor tasks such as Space Fortress. His claims are also supported by the results of VA and to some extent GMA. On the other hand, both Ackerman and Fleishman were not supported in that the contribution of PM to growth did not increase later in training. In the present results PM made significant contributions early in training to attainment (i.e., intercept), but at no point, either in a model with or without VA, did PM contribute to later stages of skill acquisition.

Additionally, the spline results do not seem to support the implications of previously observed increasing predictive validities of GMA (e.g., Arthur et al., 1995; Day et al., 1997; Deadrick, & Madigan, 1990; Rabbitt et al., 1989) because GMA did not contribute to skill acquisition at any point during training. Accordingly, the spline results also do not support iterative learning-phase models because such models assume GMA contributions to acquisition increase during training (Day et al., 1997).

Furthermore, the results also support the idea that later growth is increasingly a function of habits and skills acquired in the task itself (Fleishman, 1972; Fleishman & Mumford, 1989b). Overall, ability does not seem to be as important of a determinant of growth as previous theory would suggest (e.g., Ackerman, 1987; 1988; Fleishman, 1972). However, it is important to note that ability is still important through its strong relationship to attainment.

These claims are bolstered when examining the results of other recent growth curve analyses such as that of Lang and Bliese (2009). In their study examining adaptation to task change, GMA was found to be significantly related to initial performance and performance after a change in the criterion task (i.e., transition adaptation) but unrelated to skill acquisition or acquisition after the task change (i.e., reacquisition adaptation).

Ability provides a strong edge for performance, but training and practice can compensate (Keil & Cortina, 2001). Because abilities seem to influence attainment but not acquisition (Lang & Bliese, 2009), and later performance may be a function of previous performance (Zyphur, Chaturvedi, & Arvey, 2008), training might be better tailored to knowledge and skills rather than abilities. Even though abilities are still important contributors to performance, a knowledge and skills approach to training needs assessment would prove useful when the costs of training are estimated and decisions regarding when to train or when to select individuals for a given job are made.

As a hypothetical example, consider how long it would take two individuals, one 2-standard deviations above and the other 2-standard deviations below average on VA, to reach an expertise level of performance on Space Fortress. Based on the spline model results, the high ability individual might attain that level of performance in 15 sessions or 7.5 hrs. whereas the low ability individual might require 45 sessions or 22.5 hrs. Therefore, the lower ability trainee would have to spend three times as long in training to reach the level of expert. If training is expensive, it may be more cost effective to simply select based on ability as opposed to training lower ability individuals.

Strengths

This study has a number of strengths that warrant note. In contrast to many previous analyses, skill acquisition was actually modeled, and random coefficients were used which allowed the analytic focus to remain on the individual as advised by Rogossa (1995). Spline modeling was incorporated which allowed for the inclusion of acquisition-phase information into the model and therefore the determination of exactly when and how abilities contributed to skill acquisition. Even in previous analyses that modeled acquisition (e.g., Voelkle et al., 2006), the failure to include phase information can lead to different conclusions as previously demonstrated. Splines allowed for better control over the indirect and moderating effects of previous performance when examining the relationship of abilities to skill acquisition (Fleishman & Mumford, 1989b). Additionally, VA represents an initial bridge between this type of research and a newer taxonomy of human ability (e.g., CHC Theory).

Limitations and Future Research

This study also has a number of limitations that should be mentioned. The sample size was moderate and not representative of the population at large. For instance, the over representation of undergraduates in the current sample led to some degree of range restriction on the measure of GMA. In addition, computer and game experience were both similarly restricted in range. It is possible these limitations may have combined to prevent any significant GMA-related findings. Future research should utilize larger, more representative samples to allow for improved generalizations.

The operational definitions of GMA and PM were limited. Instead of adhering to the psychometric definition of GMA as a factor common to tests of cognitive ability, I used a single measure (APM: Raven et al., 2004). For PM, I used a very specific operational definition unlike the broad definitions used in previous research (e.g., Ackerman, 1987, 1988). Future research could administer a number of test batteries and extract estimates that better fit the traditional operational definitions of the abilities under investigation. Moreover, this line of research should investigate additional abilities and might possibly continue to draw on the CHC framework.

Additionally, the present study utilized a relatively "closed" task as opposed to a more "open" task. Ackerman (2007) suggests the closed or open nature of a task appears to dictate whether individuals will converge or diverge in their performance levels throughout training. As compared to open tasks, closed tasks are those that draw on a well-defined and generally smaller amounts of requisite knowledge. Once the basics have been acquired, there is little more to learn that will markedly improve performance. Consequently, high-ability individuals exhibit task mastery relatively quickly. Lower-ability individuals might also achieve task mastery but after a longer period of time. Therefore, closed tasks typically exhibit the lag hypothesis (Singer & Willett, 2003).

Conversely, because open tasks are less specific and demarcated by the addition of novel components as soon as any one component is mastered, high performers of open tasks typically do not exhibit the same asymptotic performance as in closed tasks. As a whole, open-task knowledge demands are thought to be cumulative, and this suggests any given individual will eventually fail to master the increasing task complexities if the task is sufficiently “open” enough. As a result, a general decline in acquisition rate can be observed for all individuals. When this happens, the highest and lowest performing learners will separate in their performance across training. Therefore, open tasks generally portray the deficit hypothesis (Singer & Willett, 2003), fan-spread effect, or Matthew effect (Merton, 1968; Stanovich, 1986).

The findings from investigations using a relatively closed task, such as Space Fortress, may not generalize to other more open tasks. For instance, because open tasks are generally more knowledge based, PM ability may offer little to no contribution at any point during open task acquisition. As another, more general example, abilities in open tasks would not be expected to be related to subsequent splines after the initial spline because acquisition should portray increasing interindividual variation across time (deficit hypothesis, fan-spread effect, or Matthew effect: Merton, 1968; Singer & Willett, 2003; Stanovich, 1986).Therefore, future research should focus on cross-validation with other, more open tasks.

Because open tasks essentially change with the addition of new components whenever anyone prior component is mastered, different abilities may become more important at various points in acquisition (Ackerman, 1987, 1988). Because this type of task is continually reinvented, Fleishman and Mumford (1989b) suggest each change is a new task, and therefore, learners remain in early stages of skill acquisition where changes in the combination of abilities contributing to performance happen frequently. All of this points to the importance of matching specific abilities to specific components of the task at hand (Brunswik, 1956; Wittmann & Süß, 1999). In fact, the significant contributions of VA could be due to the nature of the Space Fortress task. The proper matching of abilities to task should be a primary endeavor of future studies as suggested by Voelkle et al. (2006).

The operational definition of time may have also been a limiting factor. Like other recent growth curve modeling research (e.g., Lang & Bliese, 2009; Voelkle et al., 2006), time was defined on an ordinal scale when fitting the present models. This definition may not adequately capture the differences in time among any three observations and may therefore affect model parameter estimates. In the present study, the time between baseline and the first session does not actually equal the time between the first and second sessions as the models applied might suggest. As Newell et al. (2009) advise, future research must be careful in the treatment of time.

Finally, the splines were fit to the data more as an artifact of methodological design than as determined by theoretical phase of skill acquisition. While this allowed for an examination of when and how abilities might contribute to acquisition at different time points during training and represents a closer approximation to existing theory, it is still not a direct mapping. The literature has often confused time vs. performance as the determinant of skill acquisition phase (Voelkle et al., 2006), and even the current spline approach does not address this. In future research it may be possible to allow the spline knot points to be estimated from the data and then to allow these knot points to vary across individuals. Such an analysis would represent the direct application of learning-phase theory to the examination of ability contributions to skill acquisition.

References

Ackerman, P. L. (1987). Individual differences in skill learning: An integration of psychometric and information processing perspectives. *Psychological Bulletin, 102(1)*, 3-27.

Ackerman, P. L. (1988). Determinants of individual differences during skill acquisition: Cognitive abilities and information processing. *Journal of Experimental Psychology: General, 117*(3), 288-318.

Ackerman, P. L. (1992). Predicting individual differences in complex skill acquisition: Dynamics of ability determinants. *Journal of Applied Psychology, 77*(5), 598-614.

Ackerman, P. L. (2007). New developments in understanding skilled performance. *Current Directions in Psychological Science, 16*(5), 235-239.

Ackerman, P. L., & Cianciolo, A. T. (2000). Cognitive, perceptual-speed, and psychomotor determinants of individual differences during skill acquisition. *Journal of Experimental Psychology Applied, 6*(4), 259-290.

Ackerman, P. L., & Kanfer, R. (1993). Integrating laboratory and field study for improving selection: Development of a battery for predicting air traffic controller success. *Journal of Applied Psychology, 78*(3), 413-432.

Ackerman, P. L., Kanfer, R., & Goff, M. (1995). Cognitive and noncognitive determinants and consequences of complex skill acquisition. *Journal of Experimental Psychology Applied, 1*(4), 270-304.

Anderson, J. R. (1982). Acquisition of cognitive skill. *Psychological Review, 89*(4), 369-406.

Anderson, J. R. (1983). *The architecture of cognition*. Cambridge, MA: Harvard University Press.

Anderson, J. R. (2005). *Cognitive psychology and its implications* (6th ed.). New York: Worth Publishers.

Arthur, W., Jr., Bennett, W., Jr., Day, E. A., & McNelly, T. L. (2002). Skill decay: A comparative assessment of training protocols and individual differences in the loss and reacquisition of complex skills [Final report] (AFRL-HE-AZ-TR-2002-0004). Mesa, AZ: Air Force Material Command, Air Force Research Laboratory Human Effectiveness Directorate, Warfighter Training Research Division.

Arthur, W., Jr., Strong, M. H., & Williamson, J. (1994). Validation of a visual attention test as a predictor of driving accident involvement. *Journal of Occupational and Organizational Psychology, 67*(2), 173-182.

Arthur, W., Jr., Strong, M. H., Jordan, J. A., Williamson, J. E., Shebilske, W. L., & Regian, W. (1995). Visual attention: Individual differences in training and predicting complex task performance. *Acta Psychologica, 88*(1), 3-23.

Avolio, B. J., Alexander, R. A., Barrett, G. V., & Sterns, H. L. (1981) Designing a measure of visual selective attention to assess individual differences in information processing. *Applied Psychological Measurement, 5*(1), 29-42.

Bliese, P. D. & Ployhart, R. E. (2002). Growth modeling using random coefficient models: Model building, testing, and illustrations. *Organizational Research Methods, 5*(4), 362-387.

Bliese, P. D. (2000). Within-group agreement, non-independence, and reliability: Implications for data aggregation and analysis. In K. J. Klein & S. W. Kozlowski (Eds.). *Multilevel theory, research, and methods in organizations: Foundations, extensions, and new directions* (pp. 349-381). San Francisco: Jossey-Bass.

Bollen, K. A., & Curran, P. J. (2006). *Latent curve models: A structural equation perspective*. Hoboken, NJ: Wiley-Interscience.

Bouchard, T. J., Jr. (2004). Genetic influences on human psychological traits. *Current Directions in Psychological Science, 13*(4), 148-151.

Brunswik, E. (1956). *Perception and the representative design of psychological experiments*. Berkeley, CA: University of California Press.

Carroll, J. B. (1993). *Human cognitive abilities: A survey of factor analytic studies*. New York: Cambridge University Press.

Cattell, R. B. (1971). *Abilities: Their structure, growth, and action*. Boston, MA: Houghton Mifflin.

Corrington, K. A. (1996). Implicit and explicit processes in complex skill acquisition. Unpublished doctoral dissertation, Texas A&M University, College Station, TX.

Cronbach, L. J., & Furby, L. (1970). How we should measure 'change': Or should we? *Psychological Bulletin, 74*(1), 68-80.

Davids, K., Button, C., & Bennett, S. (2008). *Dynamics of skill acquisition: A constraints led approach*. Champaign, IL: Human Kinetics.

Day, E. A., Arthur, W., Jr., & Shebilske, W. L. (1997). Ability determinants of complex skill acquisition: Effects of training protocol. *Acta Psychologica, 97*(2), 145-165.

Day, E. A., Arthur, W., Jr., Gettman, D. (2001). Knowledge structures and the acquisition of a complex skill. *Journal of Applied Psychology, 86*(5), 1022-1033.

Deadrick, D. L., & Madigan, R. M. (1990). Dynamic criteria revisited: A longitudinal study of performance stability and predictive validity. *Personnel Psychology, 43*(4), 717-744.

Donchin, E. (1989). The learning strategies project: Introductory remarks. *Acta Psychologica, 71*(1-3), 1-15.

Duncan, T. E., Duncan, S. C., & Strycker, L. A. (2006). *An introduction to latent variable growth curve modeling: Concepts, issues, and applications*. Mahwah, NJ: Lawrence Erlbaum Associates.

Fein, E. C. & Day, E. A. (2004). The PASS theory of intelligence and the acquisition of a complex skill: A criterion-related validation study of Cognitive Assessment System scores. *Personality and Individual Differences, 37*(6), 1123-1136.

Fitts, P., & Posner, M. I. (1967). *Human performance*. Belmont, CA: Brooks/Cole.

Fleishman, E. A. (1960). Abilities at different states of practice in rotary pursuit performance. *Journal of Experimental Psychology, 60*(3), 162-171.

Fleishman, E. A. (1972). On the relation between abilities, learning, and human performance. *American Psychologist, 27*(11), 1017-1032.

Fleishman, E. A., & Fruchter, B. (1960). Factor structure and predictability of successive stages of learning Morse Code. *Journal of Applied Psychology, 44*(2), 96-101.

Fleishman, E. A., & Hempel, W. E. (1954). Changes in factor structure of a complex psychomotor test as a function of practice. *Psychometrika, 19*(3), 239-252.

Fleishman, E. A., & Hempel, W. E. (1955). The relation between abilities and improvement with practice in a visual discrimination reaction task. *Journal of Experimental Psychology, 49*(5), 301-312.

Fleishman, E. A., & Mumford, M. D. (1989a). Abilities as causes of individual differences in skill acquisition. *Human Performance, 2*(3), 201-223.

Fleishman, E. A., & Mumford, M. D. (1989b). Individual attributes and training performance. In I. L. Goldstein (Ed.), *Training and development in organizations*. San Francisco, CA: Jossey-Bass.

Fleishman, E. A., & Reilly, M. E. (1992). *Handbook of human abilities: Definitions, measurements, and job task requirements*. Palo Alto, CA: Consulting Psychologists Press.

Fleishman, E. A., & Rich, S. (1963). Role of kinesthetic and spatial-visual abilities in perceptual-motor learning. *Journal of Experimental Psychology, 66*(1), 6-11.

Gallistel, C. R., Fairhurst, S., & Balsam, P. (2004). *The learning curve: implications of a quantitative analysis*. Proceedings of the National Academy of Science USA, 101, 13124-13131.

Gentner, D. R. (1983). The acquisition of typewriting skill. *Acta Psychologica, 54*(1-3), 233-248.

Gopher, D. & Kahneman, D. (1971). Individual differences in attention and the prediction of flight criteria. *Perceptual and Motor Skills, 33*(3), 1335-1342.

Gopher, D. (1993). The skill of attention control: Acquisition and execution of attention strategies. In: D. Meyer & S. Kornblum (Eds.). *Attention and Performance XIV: Synergies in experimental psychology, artificial intelligence and cognitive neuroscience* (pp. 299-322). MIT Press: Cambridge.

Gopher, D. (1996). Attention control: Explorations of the work of an executive controller. *Cognitive Brain Research, 5*(1-2), 23-38.

Gopher, D., Weil, M., & Bareket, T. (1994). The transfer of skill from a computer game trainer to actual flight. *Human Factors, 36*(3), 387-405.

Gopher, D., Weil, M., & Siegel, D. (1989). Practice under changing priorities: An approach to the training of complex skills. *Acta Psychologica, 71*(1-3), 147-177.

Greenhouse S. W. & Geisser S. (1959). On methods in the analysis of profile data. *Psychometrika, 24*, 95-112.

Hammond, K. J. (1990). Case-based planning: A framework for planning from experience. *Cognitive Science: A Multidisciplinary Journal, 14*(3), 385-443.

Hart, S. G., & Battiste, B. (1992). *Field test of a video game trainer*. Proceedings of the 36th Annual Meeting of the Human Factors Society, pp. 1291-1295.

Heathcote, A., Brown, S., & Mewhort, D. J. K. (2000). The power law repealed: The case for an exponential law of practice. *Psychonomic Bulletin & Review, 7*(2), 185-207.

Hull, C. L. (1928). *Aptitude testing*. Yonkers, NY: World Book Company.

Jones, M. C., Dunlap, W. P., & Bilodeau, I. (1984). Factors appearing late in practice. *Organizational Behavior and Human Performance, 33*(2), 153-173.

Keil, C. T., & Cortina, J. M. (2001). Degradation of validity over time: A test and extension of Ackerman's model. *Psychological Bulletin, 127(5)*, 673-697.

Kolodner, J. L. (1983). Reconstructive memory: A computer model. *Cognitive Science: A Multidisciplinary Journal, 7*(4), 281-328.

Lane, N. E. (1987). *Skill acquisition rates and patterns: Issues and training implications.* New York: Springer-Verlag.

Lang, J. W. B. & Bliese, P. D. (2009). General mental ability and two types of adaptation to unforeseen change: Applying discontinuous growth models to the task-change paradigm, *Journal of Applied Psychology, 94*(2), 411-428.

Mane, A. M., & Donchin, E. (1989). The space fortress game. *Acta Psychologica, 71*(1-3), 17-22.

Mauchly, J. W. (1940). Significance test for sphericity of a normal n-variate distribution. *The Annals of Mathematical Statistics, 11(2)*, 204-209.

Mazur, J. E. & Hastie, R. (1978). Learning as accumulations: A reexamination of the learning curve. *Psychological Bulletin, 85*(6), 1256-1274.

McArdle, J. J., & Nesselroade, J. R. (2002). Growth curve analysis in contemporary psychological research. In J. Schinka & W. Velicer (Eds.), *Comprehensive handbook of psychology. Volume two: Research methods in psychology* (pp. 447-480). New York: Wiley.

McGrew, K. S. (2009). CHC theory and the human cognitive abilities project: Standing on the shoulders of the giants of psychometric intelligence research. *Intelligence, 37*(1), 1-10.

Meredith, W., & Tisak, J. (1984, October). *"Tuckerizing" curves*. Paper presented at the annual meeting of the Psychometric Society, Santa Barbara, CA.

Meredith, W., & Tisak, J. (1990). Latent curve analysis. *Psychometrika, 55*(1), 107-122.

Merton, R. K. (1968). The matthew effect in science. *Science*, 159(3810), 56-63.

Mihal, W. & Barrett, G. V. (1976). Individual differences in perceptual information processing and their relation to automobile accident involvement. *Journal of Applied Psychology, 61*(2), 229-233.

Mumford, M. D., Friedrich, T. L., Caughron, J. J., & Byrne, C. L. (2007). Leader cognition in real-world settings: How do leaders think about crises? *The Leadership Quarterly, 18*(6), 515-543.

Muthèn, B. (2004). Latent variable analysis: Growth mixture modeling and related techniques for longitudinal data. In D. Kaplan (Ed.), *Handbook of quantitative methodology for the social sciences* (pp. 345-368). Newbury Park, CA: Sage Publications.

Newell, A., & Rosenbloom, P. S. (1981). Mechanisms of skill acquisition and the law of practice. In J. R. Anderson (Ed.), *Cognitive skills and their acquisition* (pp. 1-55). Hillsdale, NJ: Erlbaum.

Newell, K. M., Liu, Y-T., & Mayer-Kress, G. (2001). Time scales in motor learning and development. *Psychological Review, 108*(1), 57-82.

Newell, K. M., Liu, Y-T., & Mayer-Kress, G. (2009). Time scales, difficulty/skill duality and the dynamics of motor learning. In D. Sternad (Ed.), *Progress in motor control: A multidisciplinary perspective* (pp. 457-476). New York: Springer.

Norman, D. A., & Shallice, T. (2000). Attention to action: Willed and automatic control of behavior. In M. S. Gazzaniga (Ed.), *Cognitive neuroscience: A reader*, (pp. 376-390). Malden, MA: Blackwell.

Pinheiro, J. C. & Bates, D. M. (2000). *Mixed-effects models in S and S-PLUS*. New York: Springer.

Plomin, R., & Spinath, F. M. (2004). Intelligence: Genetics, genes, and genomics. *Journal of Personality and Social Psychology, 86*(1), 112-129.

Preacher, K. J., Wichman, A. L., MacCallum, R. C., & Briggs, N. E. (2008). *Latent growth curve modeling*. Sage University Paper series on Quantitative Applications in the Social Sciences, 07-157. Thousand Oaks, CA: Sage.

Rabbitt, P., Banerji, N., & Szymanski, A. (1989). Space Fortress as an IQ test? Predictions of learning and of practiced performance in a complex interactive video-game. *Acta Psychologica, 71*(1-3), 243-257.

Raven, J., Raven, J. C., & Court, J. H. (2004). *Manual for Raven's Progressive Matricies and Vocabulary Scales*. San Antonio, TX: Harcourt Assessment.

Rodgers, J. L. & Nicewander, A. (1988). Thirteen ways to look at the correlation coefficient. *The American Statistician, 42(1)*, 59-66.

Rogosa, D. R. (1995). Myths and methods: "Myths about longitudinal research" plus supplemental questions. In J. Gottman (Ed.), *The analysis of change* (pp. 3-66). Mahwah, NJ: Lawrence Erlbaum Associates.

Schank, R. (1982). *Dynamic memory: A theory of learning in computers and people*. New York: Cambridge University Press.

Schmidt, R. A., & Wrisberg, C. A. (2004). *Motor performance and learning*. Champaign, IL: Human Kinetics.

Shebilske, W. L., Goettl, B., & Regian, J. W. (1999). Executive control of automatic processes as complex skills develop in laboratory and applied settings. In D. Gopher & A. Koriat (Eds.), *Attention and Performance XVII: Cognitive regulation of performance: Interaction of theory and application* (pp. 401-432). Cambridge, MA: MIT Press.

Shiffrin, R. M., & Schneider, W. (1977). Controlled and automatic human information processing: II. Perceptual learning, automatic attending and a general theory. *Psychological Review, 84*(2), 127-190.

Singer, J. D., & Willett, J. B. (2003). *Applied longitudinal data analysis*. New York: Oxford University Press.

Smith, P. L. (1979). Splines as a useful and convenient statistical tool. *The American Statistician, 33*(2), 57-62.

Snijders, T. A., & Bosker, R. J. (1999). *Multilevel analysis: An introduction to basic and advanced multilevel modeling*. London: Sage.

Snoddy, G. S. (1926). Learning and stability. *Journal of Applied Psychology, 10*(1), 1-36.

Spearman, C. (1927). *The abilities of man; Their nature and measurement*. New York, NY: Macmillian Co.

Stanovich, K. E. (1986). Matthew effects in reading: Some consequences of individual differences in the acquisition of literacy. *Reading Research Quarterly, 21*(4), 360-406.

Stuss, D. T., & Knight, R. T. (2002). *Principles of frontal lobe function*. New York, NY: Oxford University Press.

Suits, D. B., Mason, A., & Chan, L. (1978). Spline functions fitted by standard regression methods. *Review of Economics and Statistics, 60*(1), 132-139.

Voelkle, M. C., Wittmann, W. W., & Ackerman, P. L. (2006). Abilities and skill acquisition: A latent growth curve approach. *Learning and Individual Differences, 16*(4), 303-319.

Wittmann, W. W., & Süß, H. -M. (1999). Investigating the paths between working memory, intelligence, knowledge, and complex problem-solving performances via Brunswik symmetry. In P. L. Ackerman, P. C. Kyllonen, & R. D. Roberts (Eds.), *Learning and individual differences* (pp. 77−108). Washington, DC: American Psychological Association.

Wood, R. E. (1986). Task complexity: Definition of the construct. *Organizational Behavior and Human Decision Processes, 37*(1), 60-82.

Woodrow, H. (1946). The ability to learn. *Psychological Review, 53*(3), 147-158.

Zyphur, M. J., Chaturvedi, S., & Arvey, R. D. (2008). Job performance over time is a function of latent trajectories and previous performance. *Journal of Applied Psychology, 93*(1), 217-224.

Table 1

Descriptive Statistics of All Study Variables

Variable	*M*	*SE*	*SD*	Skewness	Kurtosis	1	2	3	4	5	6	7	8	9	10	11	12
1. GMA	0.00	0.09	1.00	–0.58	0.63	—											
2. PM	0.00	0.09	1.00	0.41	–0.13	.34	—										
3. VA	0.00	0.09	1.00	–1.46	1.38	.53	.34	—									
4. Baseline	–1863.06	81.93	937.71	0.10	–0.21	.39	.61	.42	—								
5. Session 1	535.97	140.60	1609.24	–0.05	–0.40	.39	.49	.49	.69	—							
6. Session 2	1392.23	153.16	1752.97	–0.40	–0.41	.38	.47	.50	.66	.88	—						
7. Session 3	1850.77	160.47	1836.67	–0.53	–0.64	.39	.43	.51	.61	.85	.94	—					
8. Session 4	2213.51	166.13	1901.47	–0.41	–0.66	.41	.48	.56	.64	.85	.89	.93	—				
9. Session 5	2531.15	162.63	1861.42	–0.49	–0.64	.41	.48	.55	.63	.82	.90	.93	.94	—			
10. Session 6	2816.56	165.63	1895.74	–0.49	–0.58	.39	.50	.55	.64	.81	.88	.90	.91	.94	—		
11. Session 7	3042.15	161.67	1850.45	–0.65	–0.35	.41	.49	.57	.67	.82	.88	.90	.91	.93	.94	—	
12. Session 8	3277.38	159.75	1828.43	–0.63	–0.62	.44	.48	.56	.63	.74	.84	.86	.87	.90	.92	.94	—
13. Session 9	3398.96	163.81	1874.83	–0.73	–0.44	.45	.50	.58	.68	.78	.84	.86	.88	.90	.92	.95	.94

Note. $N = 131$. Abilities are grand mean centered and standardized. all $p < .001$.

Table 2

Unconditional and Conditional Quadratic Growth Models

		Unconditional Model				Conditional Model			
Fixed Effects	Sym.	Coef.	Coef. *SE*	*t*	Std. coef.	Coef.	Coef. *SE*	*t*	Std. coef.
Level 1 Model									
Intercept	β_{00}	–1143.19	96.05	-11.90^{a}***	0.04	–1143.19	72.80	-15.70^{c}***	–0.49
Linear	β_{10}	1174.15	40.54	28.96^{b}***	0.02	1174.15	37.21	31.55^{c}***	0.51
Quadratic	β_{20}	–77.93	3.92	-19.88^{b}***	0.00	–77.93	3.72	-20.98^{c}***	–0.03
Level 2 Model									
GMA	β_{01}					147.26	87.66	1.68^{d}†	0.06
PM	β_{02}					496.04	79.28	6.26^{d}***	0.21
VA	β_{03}					265.57	87.77	3.03^{d}**	0.11
Linear x GMA	β_{11}					–0.20	44.81	0.00^{d}	0.00
Linear x PM	β_{12}					30.33	40.53	0.75^{d}	0.01
Linear x VA	β_{13}					172.28	44.86	3.84^{d}***	0.07
Quadratic x GMA	β_{21}					1.03	4.47	0.23^{d}	0.00
Quadratic x PM	β_{22}					–2.30	4.05	-0.57^{d}	0.00
Quadratic x VA	β_{23}					–13.98	4.48	-3.12^{d}**	–0.01

				Correlations				Correlations	
Random Effects	Sym.	Variance	*SD*	1	2	Variance	*SD*	1	2
1. Intercept	τ_{00}	906953	952.34	—		392640	626.61	—	
2. Linear	τ_{11}	134506	366.75	.79***	—	100652	317.26	.85***	—
3. Quadratic	τ_{22}	1089	33.00	–.80***	–.97***	884	29.73	–.91***	–.96***
Residual	σ^2	487937	698.52			487937	698.52		

Note. $N = 131$. $k = 1310$. The intercept reflects baseline performance. Abilities are grand mean centered and standardized. Standardized coefficients were derived by setting the standard deviation of all variables to 1 without altering the centering of the variables. Coef. = coefficient. Std. coef. = standardized coefficient. Sym. = Symbol. ^{a} $df = 130$. ^{b} $df = 1177$. ^{c} $df = 127$. ^{d} $df = 917$. † $p < .10$. ** $p < .01$. *** $p < .001$.

Table 3

Conditional Spline Growth Model

Fixed Effects	Sym.	Coef.	Coef. *SE*	*t*	Std. coef.
Level 1 Model					
Intercept	β_{00}	–1601.01	64.71	–24.74[a]***	–1.69
Splines					
Monday	β_{10}	1612.89	55.05	29.30[a]***	0.70
Tuesday Deviation	β_{20}	–1327.84	74.40	–17.85[a]***	–0.57
Wednesday Deviation	β_{30}	29.53	58.34	0.51[a]	0.01
Thursday Deviation	β_{40}	–89.59	56.22	–1.59[b]	–0.04
Friday Deviation	β_{50}	–99.99	86.63	–1.15[b]	–0.04
Level 2 Model					
GMA	β_{01}	124.90	77.92	1.60[b]	0.05
PM	β_{02}	493.83	70.47	7.01[b]***	0.21
VA	β_{03}	212.82	78.02	2.73[b]**	0.09
Monday x GMA	β_{11}	21.58	66.28	0.33[b]	0.01
Monday x PM	β_{12}	32.61	59.94	0.54[b]	0.01
Monday x VA	β_{13}	209.59	66.36	3.16[b] **	0.09
Tuesday x GMA	β_{21}	–4.37	89.58	–0.05[b]	0.00
Tuesday x PM	β_{22}	–34.98	81.02	–0.43[b]	–0.02
Tuesday x VA	β_{23}	–153.92	89.69	–1.72[b]†	–0.07
Wednesday x GMA	β_{31}	–62.33	70.25	–0.89[b]	–0.03
Wednesday x PM	β_{32}	43.18	63.53	0.68[b]	0.02
Wednesday x VA	β_{33}	–42.69	70.34	–0.61[b]	–0.02
Thursday x GMA	β_{41}	110.19	67.69	1.63[b]	0.05
Thursday x PM	β_{42}	–79.65	61.22	–1.30[b]	–0.03
Thursday x VA	β_{43}	–45.53	67.78	–0.67[b]	–0.02
Friday x GMA	β_{51}	–66.43	104.31	–0.64[b]	–0.03
Friday x PM	β_{52}	74.81	94.34	0.79[b]	0.03
Friday x VA	β_{53}	86.23	104.44	0.83[b]	0.04

Random Effects	Sym.	Variance	*SD*	Correlations 1	2	3	4
1. Intercept	τ_{00}	298375	546.24	—			
2. Monday	τ_{11}	259252	509.17	.58***	—		
3. Tuesday Deviation	τ_{22}	311067	557.73	–.72***	–.92***	—	
4. Wednesday Deviation	τ_{33}	48086	219.29	.45†	–.29	–.05	—
Residual	σ^2	302038	549.58				

Note. N = 131. k = 1310. The intercept reflects baseline performance. Abilities are grand mean centered and standardized. Standardized coefficients were derived by setting the standard deviation of all variables to 1 without altering the centering of the variables. Coef. = coefficient. Std. coef. = standardized coefficient. Sym. = Symbol. [a] df = 127. [b] df = 778. † $p < .10$. ** $p < .01$. *** $p < .001$.

Table 4

Daily Acquisition Rates

Slope	Estimate	*SE*	*t*	Standardized Estimate
Monday	1612.89	55.05	29.30[a]***	0.70
Tuesday	285.05	36.16	7.88[a]***	0.12
Wednesday	314.57	32.99	9.54[a]***	0.14
Thursday	224.98	34.37	6.55[b]***	0.10
Friday	124.99	65.92	1.90[b]†	0.05

Note. N = 131. k = 1310. [a] df = 127. [b] df = 778. † p < .10. *** p < .001.

Table 5

Conditional Quadratic Growth Model without VA

		Conditional Model			
Fixed Effects	Sym.	Coef.	Coef. *SE*	*t*	Std. coef.
Level 1 Model					
Intercept	β_{00}	–1143.19	75.30	–15.18[a]***	–1.49
Linear	β_{10}	1174.15	39.25	29.91[a]***	0.51
Quadratic	β_{20}	–77.93	3.85	–20.24[a]***	–0.03
Level 2 Model					
GMA	β_{01}	270.51	80.28	3.37[b]***	0.12
PM	β_{02}	544.86	80.28	6.79[b]***	0.24
Linear x GMA	β_{11}	79.75	41.85	1.91[b]†	0.03
Linear x PM	β_{12}	62.00	41.85	1.48[b]	0.03
Quadratic x GMA	β_{21}	–5.46	4.11	–1.33[b]	0.00
Quadratic x PM	β_{22}	–4.87	4.11	–1.19[b]	0.00

				Correlations	
Random Effects	Sym.	Variance	*SD*	1	2
1. Intercept	τ_{00}	441165	626.61	—	
2. Linear	τ_{11}	121072	317.26	.87***	—
3. Quadratic	τ_{22}	1018	29.73	–.92***	–.97***
Residual	σ^2	487937	698.52		

Note. $N = 131$. $k = 1310$. The intercept reflects baseline performance. Abilities are grand mean centered and standardized. Standardized coefficients were derived by setting the standard deviation of all variables to 1 without altering the centering of the variables. Coef. = coefficient. Std. coef. = standardized coefficient. Sym. = Symbol. [a] $df = 127$. [b] $df = 917$. † $p < .10$. ** $p < .01$. *** $p < .001$.

Table 6

Conditional Spline Growth Model without VA

Fixed Effects	Sym.	Coef.	Coef. *SE*	*t*	Std. coef.
Level 1 Model					
Intercept	β_{00}	–1601.01	66.53	–24.06[a]***	–0.69
Splines					
Monday	β_{10}	1612.89	57.09	28.25[a]***	0.70
Tuesday Deviation	β_{20}	–1327.84	75.17	–17.66[a]***	–0.57
Wednesday Deviation	β_{30}	29.53	58.54	0.50[a]	0.01
Thursday Deviation	β_{40}	–89.59	56.25	–1.59[b]	–0.04
Friday Deviation	β_{50}	–99.99	86.67	–1.15[b]	–0.04
Level 2 Model					
GMA	β_{01}	223.67	70.93	3.15[b]**	0.10
PM	β_{02}	532.95	70.94	7.51[b]***	0.23
Monday x GMA	β_{11}	118.85	60.86	1.95[b]†	0.05
Monday x PM	β_{12}	71.14	60.86	1.17[b]	0.03
Tuesday x GMA	β_{21}	–75.80	80.14	–0.95[b]	–0.03
Tuesday x PM	β_{22}	–63.28	80.15	–0.79[b]	–0.03
Wednesday x GMA	β_{31}	–82.14	62.41	–1.32[b]	–0.04
Wednesday x PM	β_{32}	35.34	62.41	0.57[b]	0.02
Thursday x GMA	β_{41}	89.06	59.97	1.49[b]	0.04
Thursday x PM	β_{42}	–88.02	59.97	–1.49[b]	–0.04
Friday x GMA	β_{51}	–26.41	92.40	–0.29[b]	–0.01
Friday x PM	β_{52}	90.66	92.40	0.98[b]	0.04

				Correlations			
Random Effects	Sym.	Variance	*SD*	1	2	3	4
1. Intercept	τ_{00}	329394	573.93	—			
2. Monday	τ_{11}	289092	537.67	.62***	—		
3. Tuesday Deviation	τ_{22}	325774	570.77	–.73***	–.92***	—	
4. Wednesday Deviation	τ_{33}	50736	225.25	.35	–.35	–.01	—
Residual	σ^2	302319	549.84				

Note. N = 131. k = 1310. The intercept reflects baseline performance. Abilities are grand mean centered and standardized. Standardized coefficients were derived by setting the standard deviation of all variables to 1 without altering the centering of the variables. Coef. = coefficient. Std. coef. = standardized coefficient. Sym. = Symbol. [a] df = 127. [b] df = 778. † $p < .10$. ** $p < .01$. *** $p < .001$.

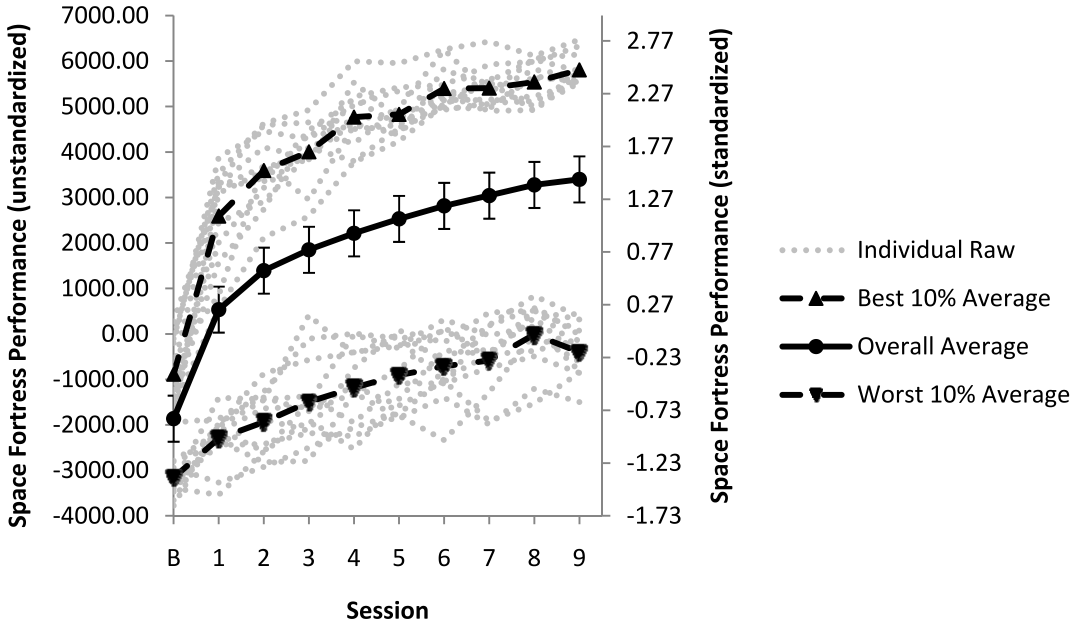

Figure 1. Space Fortress performance across all sessions. The points along the solid line indicate mean performance, as well as the corresponding standard errors, at each session. Dotted lines represent individual trajectories of the 10% best and 10% worst participants of the entire sample (at the ninth session). Dashed lines represent the average of the best and worst 10% groups.

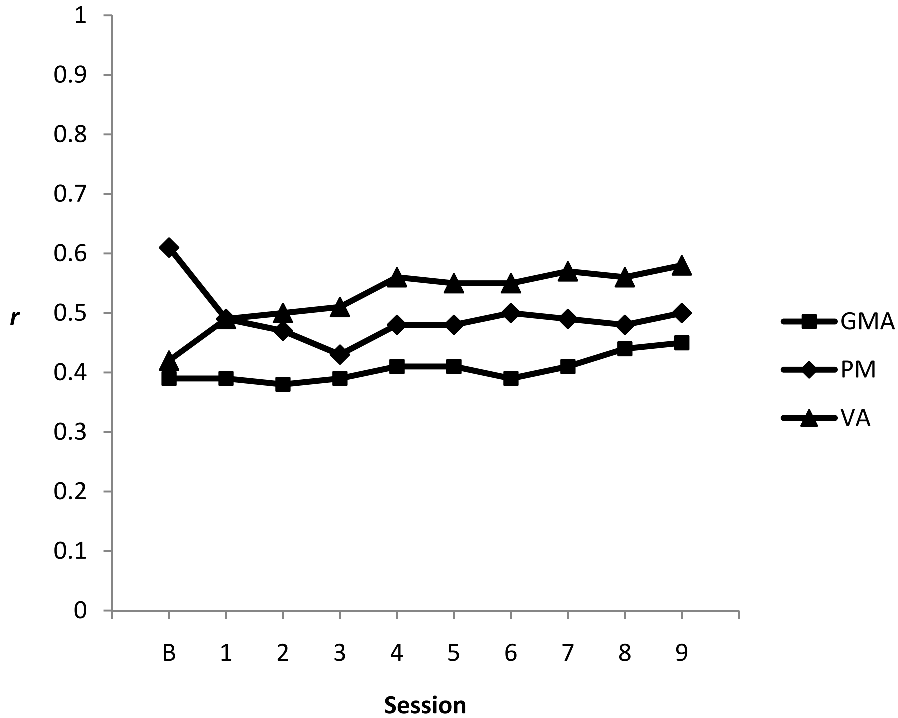

Figure 2. Ability-performance zero-order correlations across sessions.

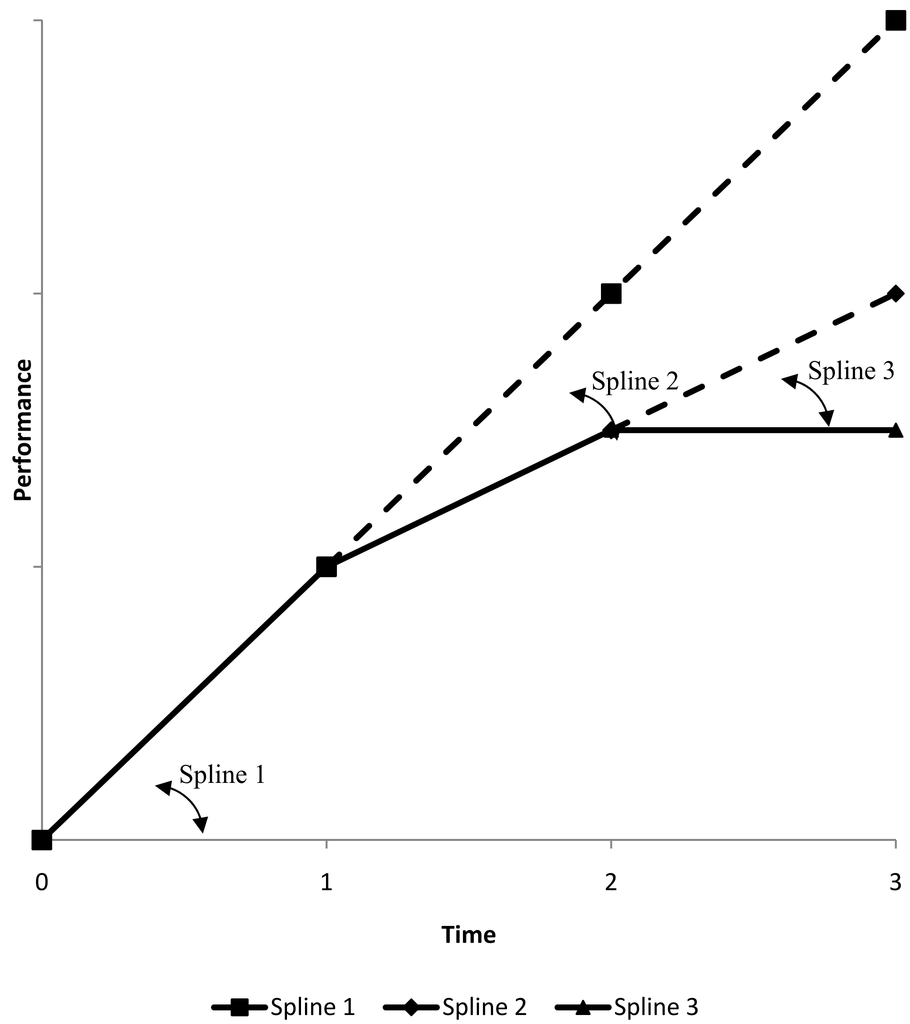

Figure 3. A hypothetical example of the additive nature of splines.

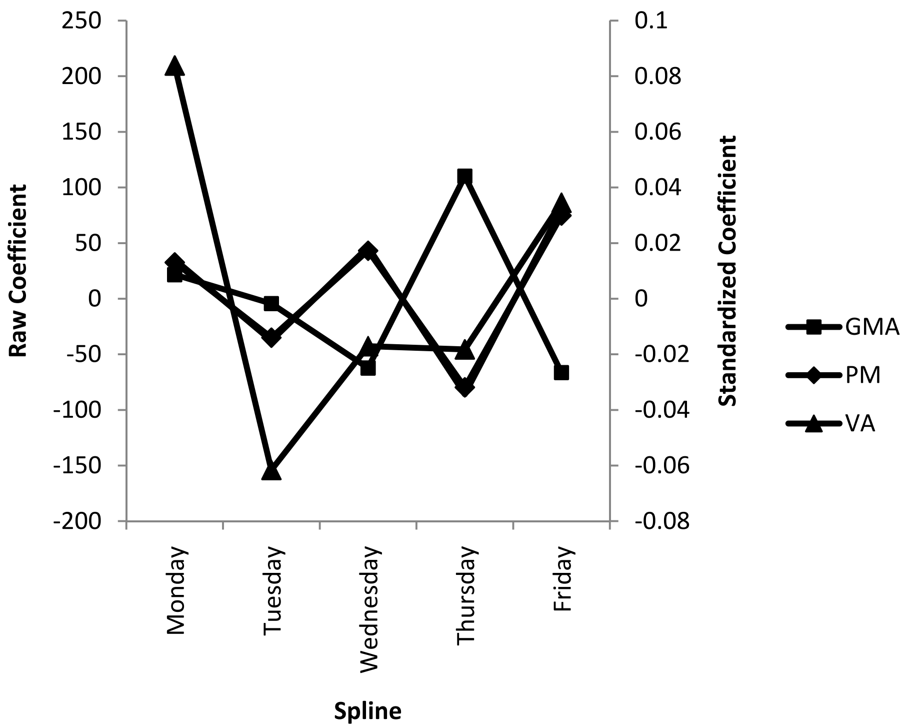

Figure 4. Conditional spline growth model ability-spline interactions.

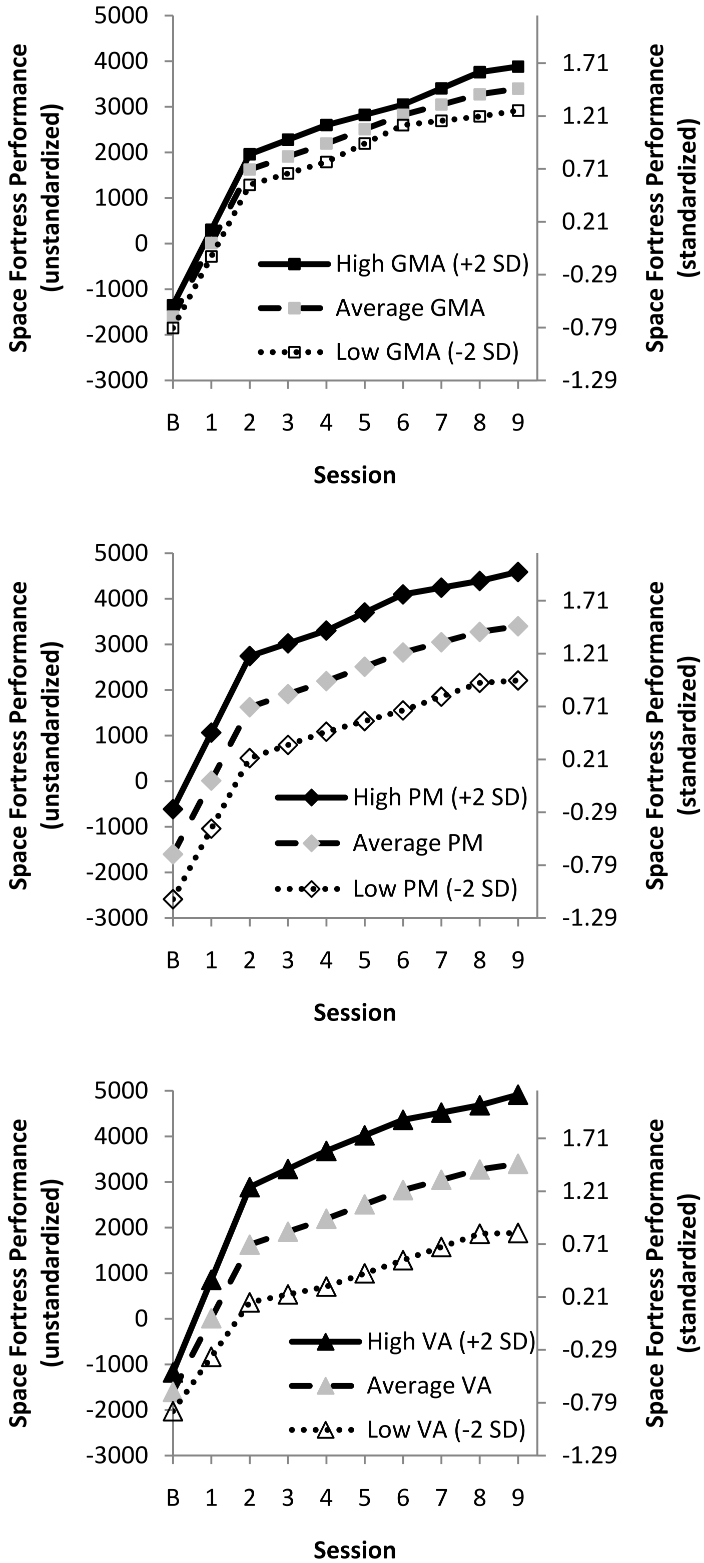

Figure 5. Predicted performance as a function of abilities.