General Mental Ability and Two Types of Adaptation to Unforeseen Change

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1. Introduction

Adaptation originates from the Latin word “adaptare” which means “to make something fit” (Merriam-Webster, n.d.) and is a term which is frequently used in a variety of contexts in the psychological literature. Most notably, the term is used in psychological assessment, evolutionary psychology, biological psychology cognitive psychology, and industrial-organizational psychology to describe different phenomena.

In psychological assessment, adaptation refers to the rewriting of an assessment instrument into a new form to fulfill new or specific needs (e.g., Geisinger, 1994; Hambleton, 2001). Furthermore, psychological assessment scholars use the term “adaptive” or “adapting” in the context of a class of tests commonly labeled “adaptive tests” which surfaced in the late 1970s and are now common in large-scale assessment (Hornke, 1999; Wainer, 2000). In the context of this class of tests, adaptation refers to the way the test tailors the administration of test items to the ability of each examinee.

In evolutionary psychology, the term adaptation is frequently used in the context of a research strategy called adaptionism (see Andrews, Gangestad, & Matthews, 2002, for an overview). In this context, adaptations are adjustments of species or subpopulations of species to specific selective forces in past environments. The goal of adaptationism research is to understand the origin of these adaptations in order to derive a deeper understanding of psychological behavior dispositions (Andrews et al., 2002).

In biological psychology, adaptation refers to the decrease of an organism's responsiveness due to a sustained stimulus (Calin-Jageman & Fischer, 2007). The reduced responsiveness can be studied at either the neural or the behavioral level. Accordingly, it is labeled either sensory adaptation or behavioral adaptation. Sensory and behavioral adaptions reflect how organisms process information from the environment by adjusting their responsiveness to these information stimuli.

In cognitive as well as industrial-organizational psychology, adaptation is used to refer to two different classes of phenomena. The first class of phenomena refers to an individual's, team's or organization's ability to select more successful alternatives in decision-making tasks at a higher rate than less successful alternatives while the success rate of these alternatives remains constant. This adaptability has been labeled microlevel adaptability by Schunn and Reder (2001). In recent years, research building on this adaptability concept was conducted on the individual (Denrell, 2007; March, 1996; Schunn, Lovett, & Reder, 2001; Schunn & Reder, 2001) as well as on the organizational level of analysis (Denrell & March, 2001). The second class of phenomena deals with adaptation to change, which will be the focus of the present dissertation.

1.1. Adaptation to Change

> "I measure what's going on, and I adapt to it. I try to get my ego out of the way. The market is smarter than I am so I bend."—Martin E. Zweig, American stock investor, investment advisor and financial analyst (Domash, n.d., No second-guessing on sales, ¶ 2)

> "I just did a better job, I think, of adapting to the conditions this year... I've struggled [in the British Open]... Early in my career, I hit the ball very flat and low. I was known as a pretty good wind player. I adapted my game a little bit for the States to hit the ball higher to compete on some of the newer golf courses that we play, to hit the ball higher, to spin the ball more, to carry the ball farther. As I did that, I changed my equipment a little bit. I don't know if I changed my swing, but it adapted to hit the ball higher. And when I came over to play the Open I did a very poor job of adapting back. A good player should be able to do that, and I did a bad job of it."—Jim Furyk, American pro-golf player (Morfit, n.d.)

The two quotations above provide vivid accounts of the real-life occurrence of the second class of phenomena labeled adaptability in cognitive as well as industrial-organizational psychology. This class of adaptability phenomena becomes prevalent when changes in the environment in which a task is performed occur so that previously successful alternatives or strategies become unsuccessful while other alternatives or strategies become successful. Researchers have labeled this second class of phenomena global adaptability (Schunn & Reder, 2001), adaptation to change (LePine, 2005), adaptive flexibility (Bröder & Schiffer, 2006) or simply adaptability (e.g., Ployhart & Bliese, 2006). For brevity of presentation, I simply use the terms adaptability or adaptation to change to refer to this type of adaptability throughout the current dissertation.

In recent years, this type of adaptability has been extensively studied in applied as well as laboratory research and has been frequently discussed by practicioners. The peculiar interest in adaptation to change is fostered by what economic, management, and industrial-organizational psychology scholars have referred to as the changing nature of work (F. Ackerman, Goodwin, Dougherty, & Gallagher, 1998; Frese, 2000; Howard, 1995a; Ilgen & Pulakos, 1999; National Research Council, 1999; Ployhart & Bliese, 2006; S. E. Sullivan, 1999), or the new organizational reality (Gowing, Kraft, & Quick, 1998). The key aspect of the changing nature of work is that work is rapidly getting more dynamic and complex (Frese, 2000; Gowing et al., 1998; Howard, 1995b; Patterson, 2001; Ployhart & Bliese, 2006; Thayer, 1997; Waller & Roberts, 2003). This increasing complexity and dynamic is a result of the changing nature of markets and rapid changes in technological development.

With respect to markets, the most fundamental changes occurred and still occur at the product and financial markets (National Research Council, 1999). For product markets, globalization as well as increasing deregulation has led to an increased market competition. This increased competition confronts organizations with an increased downward pressure on prices and therefore on production and human resources costs as well as increased pressure to provide customers with innovative and customized products. In financial markets, mainly two trends have been identified which change the content of work. The first trend is an increased focus on shareholder interests, which requires companies to focus their resources on their "core competencies" and stopping service activities or product lines not considered compatible with the companies' main product line or service activity. The second trend is a considerable growth in the volume and volatility of global capital flows (Burtless, 1995). These increased global capital flows have led to an increased uncertainty for decision makers because decision makers in organizations can not easily predict which product lines will be competing in the near future and which international markets will enquire a specific product.

With respect to technology, the fact that technology changes is not noteworthy but the speed and the nature of these developments is what fundamentally changed and changes modern work environments. Work and technology have always been closely related as technology is needed for most types of work and is typically the mediator between resources and outputs (Applebaum, 1992; National Research Council, 1999). Technology typically changed the nature of work by eliminating occupations, creating new occupations and generally affecting the way in which work is conducted (National Research Council, 1999). What is new and fundamentally different to technological changes in earlier decades and centuries is the speed in which technological changes are now being introduced. In the new era of "digitalization" (National Research Council, 1999), nearly every work environment depends on computer technology as microelectronics, robotics and computer-integrated manufacturing or digital telecommunication technology (Ployhart & Bliese, 2006). While companies and researchers were very optimistic about the results of the changes in technology at the start of the digitalization era (Lovink, 2002), decision makers in organizations and research scholars in the past dotcom crash years (Investopedia, n.d.) are aware that rapid technological changes confront employees and organizations with considerable difficulties to overcome (Patterson, 2001; Ployhart & Bliese, 2006; Schmitt & Chan, 1998).

There is a consensus in the literature that for organizations, teams and individuals to remain competitive and to exhibit high performance in an environment of changing markets and changing technology, adaptability is a key factor (Patterson, 2001; Ployhart & Bliese, 2006; Schmitt & Chan, 1998). In recent years, the literature on adaptation to changes at the organizational, team and individual level has been growing. One stream of research has focused on properties of the environment (e.g., Bröder & Schiffer, 2006; Johnson et al., 2006; Marks, Zaccaro, & Mathieu, 2000) and interventions promoting or preventing adapting reactions to changes of individuals (e.g., Chan, 2000a; Smith, Ford, & Kozlowski, 1997; Salas, Priest, Wilson, & Burke, 2006), teams (e.g., Kozlowski, 1998; Marks et al., 2000; Salas et al., 2006), and organizations (e.g., Boeker & Goodstein, 1991; Greve, 1999; Short, Ketchen, Bennett, & du Toit, 2006). Predicting environmental conditions in which adaptation is particularly hard to achieve, and designing interventions working against these conditions would provide researchers and decision makers in organizations with the ability to limit the perils of maladjustment.

A second stream of research has focused on identifying individual differences predicting successful adaptation of individuals (e.g., Kozlowski et al., 2001; LePine, Colquitt, & Erez, 2000; Ployhart & Bliese, 2006; Thoresen, Bradley, Bliese, & Thoresen, 2004) or unit differences predicting successful adaptation of teams (e.g., LePine, 2003, 2005), and organizations (e.g., Boeker & Goodstein, 1991; Greve, 1999; Short et al., 2006). Identifying individual difference variables dependably predicting adaptive performance would provide organizations with the opportunity to (a) select individuals who are able to maintain their performance in frequently changing work environments, and (b) to tailor organizational work environments to these individuals in order to achieve maximal adaptive performance from them.

1.2. Aims of the Present Dissertation

Considering today's importance of adaptation in the occupational world, the aims of the present dissertation were twofold. First, I wanted to address conceptual and methodological problems in the definition and operationalization of adaptation to change. Conceptually, I propose that two different types of adaptation need to be separated from each other as well as both skill acquisition and basal task performance. Methodologically, I describe how these four processes can be separated using a discontinuous growth modeling approach (Singer & Willett, 2003).

Second, considering the stream of adaptability research regarding relevant individual differences, I wanted to demonstrate the fruitfulness of the proposed discontinuous growth modeling framework. To do so, I investigated the relationship between general mental ability (GMA) as a well-established individual difference variable (e.g., Lubinski, 2004; Schmidt & Hunter, 2004) and the two types of adaptation to complex and unforeseen environmental changes in an empirical study. The empirical study was conceptualized as a laboratory study using a complex decision-making scenario named TankSoar.

Following the two aims, the current dissertation is organized in three main sections. In correspondence with the two aims of the present work, the first two main sections each address one of the two aims. Finally, the third section integrates both parts by discussing the proposed definitions and methodological approaches and their potential implications for research as well as individuals, teams, and organizations. Furthermore, important avenues for future adaptability research are outlined and discussed.

2. Conceptual and Methodological Section: Defining and Operationalizing Adaptability to Change

2.1. Definitions of Adaptation to Change

There are two conceptualizations of adaptation to change that have received considerable attention in the literature. The first concept originates from a theoretical article by Chan (2000b). Chan proposed a general working definition for individual adaptation stating that "individual adaptation refers to the process by which an individual achieves some degree of fit between his or her behaviors and the new work demands created by the novel and often ill-defined problems resulting from changing and uncertain work situations" (Chan, 2000b, p. 4). Chan's working definition has recently been adopted by LePine (2005) to include the team and organizational level. This altered definition refers to adaptation in a more general way as "the manner or extent to which a theoretical unit (i.e., person, group, or organization) achieves correspondence between the unit's behavior and a set of novel demands faced by the unit" (LePine, 2005, p. 1154).

The second conceptualization has been proposed by Pulakos, Arad, Donovan, and Plamondon (2000, also see Pulakos et al., 2002; Pulakos, Dorsey, & White, 2006). Pulakos et al. pointed out that the concepts and operationalizations of adaptability in past research are too diverse to formulate a short definition adequately representing the different concepts of adaptability in the literature. Therefore, Pulakos et al. (2000) developed a taxonomy, by asking experienced industrial-organizational psychologists to scan 9,462 descriptions of critical incidents in 21 different jobs from 11 organizations. A total of 1,311 descriptions of adaptive behaviors were identified and classified into categories of adaptive behavior. The resulting taxonomy included eight different types of adaptability, covering a wide range of behaviors spanning from creative behavior to the handling of work stress. Table 2.1 provides the titles for each of the eight categories and the original definition of each category of adaptive behavior offered by Pulakos et al. (2000). Furthermore, Table 2.1 shows the results of a recent literature search conducted by Pulakos et al. (2006) aimed at identifying past research focusing on specific types of adaptability as defined by the taxonomy. Considering the previously discussed importance of speeding technological advances in the occupational world, especially the fourth and the fifth categories of “dealing with uncertain and unpredictable work situations” and “learning work tasks, technologies, and procedures” seem of major importance. Consequently, these two categories seem most similar to the type of adaptation required of individuals in the empirical study reported in the second main section of the present dissertation (pp. 35–82).

2.2. The Task-Change Paradigm

Despite some consensus among researchers that Chan's (2000a) working definition of adaptation and Pulakos et al.'s (2000) taxonomy include most types of adaptation to change described in the literature (Chan, 2000a, 2000b; LePine, 2005), these definitions do not provide clear hints to appropriate empirical operationalizations of adaptability to change. Therefore, past research on adaptation is marked by a variety and ambiguity towards the operationalization of the construct (Chan, 2000a; Pulakos et al., 2000).

This has particularly been the case in research using the most popular approach to study adaptation to change (e.g., Bröder & Schiffer, 2006; Chen, 2005; Chen, Thomas, & Wallace, 2005; Johnson et al., 2006; Kozlowski et al., 2001; LePine, 2003, 2005; LePine et al., 2000; Moon et al., 2004). I refer to this approach as the task-change paradigm. The basic task-change paradigm is an experimental or pseudo-experimental (in the context of research on individual differences) setup used in laboratory as well as field settings. In the task-change paradigm, individuals, teams or organizations are confronted with a novel and complex task until they achieve some mastery of the task. Then, suddenly, something unexpectedly changes in the task requiring adaptive behavior. In the majority of research on adaptation, changes in the environment happen while individuals, teams or organizations perform the task, and individuals are not aware that any type of change will occur (e.g., LePine, 2003, 2005; LePine et al., 2000). Alternatively, individuals are aware that a change will occur but are not informed about the nature of this change taking place (Chen, 2005; Kozlowski et al., 2001). Research studies on adaptation typically characterize

Table 2.1. Definitions and Sources for Pulakos et al.'s (2000) Eight Adaptive Performance Dimensions

Title	Definition	Sources
Handling emergencies or crisis situations	Reacting with appropriate and proper urgency in life threatening, dangerous, or emergency situations; quickly analyzing options for dealing with danger or crises and their implications; making split-second decisions based on clear and focused thinking; maintaining emotional control and objectivity while keeping focused on the situation at hand; stepping up to take action and handle danger or emergencies as necessary and appropriate.	Pulakos et al. (2000)
Handling work stress	Remaining composed and cool when faced with difficult circumstances or a highly demanding workload or schedule; not overreacting to unexpected news or situations; managing frustration well by directing effort to constructive solutions rather than blaming others; demonstrating resilience and the highest levels of professionalism in stressful circumstances; acting as a calming and settling influence to whom others look for guidance.	Pulakos et al. (2000)
Solving problems creatively	Employing unique types of analyses and generating new, innovative ideas in complex areas; turning problems upside-down and inside-out to find fresh, new approaches; integrating seemingly unrelated information and developing creative solutions; entertaining wide-ranging possibilities others may miss, thinking outside the given parameters to see if there is a more effective approach; developing innovative methods of obtaining or using resources when insufficient resources are available to do the job.	Hatano and Inagaki (1986); Holyoak (1991)
Dealing with uncertain and unpredictable work situations	Taking effective action when necessary without having to know the total picture or have all the facts at hand; readily and easily changing gears in response to unpredictable or unexpected events and circumstances; effectively adjusting plans, goals, actions, or priorities to deal with changing situations; imposing structure for self and others that provide as much focus as possible in dynamic situations; not needing things to be black and white; refusing to be paralyzed by uncertainty or ambiguity.	Asford (1986); Dix and Savickas (1995); Edwards and Morrison (1994); Goodman (1994); Hall and Mirvis (1995); Murphy (1989); Weiss (1984)

Learning work tasks, technologies, and procedures	Demonstrating enthusiasm for learning new approaches and technologies for conducting work; doing what is necessary to keep knowledge and skills current; quickly and proficiently learning new methods or how to perform previously unlearned tasks; adjusting to new work processes and procedures; anticipating changes in the work demands and searching for and participating in assignments or training that will prepare self for these changes; taking action to improve work performance deficiencies.	Hesketh and Neal (1999); Kinicki and Latack (1990); London and Mone (1999); Noe and Ford (1992); Patrickson (1987); Thach and Woodman (1994)
Demonstrating interpersonal adaptability	Being flexible and open-minded when dealing with others; listening to and considering others' viewpoints and opinions and altering own opinion when it is appropriate to do so; being open and accepting of negative or developmental feedback regarding work; working well and developing effective relationships with highly diverse personalities; demonstrating keen insight of others' behavior and tailoring own behavior to persuade, influence, or work more effectively with them.	Kozlowski, Gully, Salas, and Cannon-Bowers (1996); Paulhus and Martin (1988)
Demonstrating cultural adaptability	Taking action to learn about and understand the climate, orientation, needs, and values of other groups, organizations, or cultures; integrating well into and being comfortable with different values, customs, and cultures; willingly adjusting behavior or appearance as necessary to comply with or show respect for others' values and customs; understanding the implications of one's actions and adjusting approach to maintain positive relationships with other groups, organizations, or cultures.	Black (1990); Chao, O'Leary-Kelly, Wolf, Klein, and Gardner (1994); Ilgen and Pulakos (1999)
Demonstrating physically oriented adaptability	Adjusting to challenging environmental states such as extreme heat, humidity, cold, or dirtiness; frequently pushing self physically to complete strenuous or demanding tasks; adjusting weight and muscular strength or becoming proficient in performing physical tasks as necessary for the job.	Edwards and Morrison (1994); Fiedler and Fiedler (1975); Weinstein (1978)

Note. Titles and definitions: Copyright © 2000 by the American Psychological Association. Adapted with permission. The official citation that should be used in referencing this material is Pulakos, E. D., Arad, S., Donovan, M. A., & Plamondon, K. E. (2000). Adaptability in the work place: Development of a taxonomy of adaptive performance. *Journal of Applied Psychology, 85*, 612–624. The use of APA information does not imply endorsement by APA.

changes in the environment by an increase in complexity (e.g., Chen et al., 2005; Kozlowski et al., 2001; LePine, 2003, 2005; LePine et al., 2000; Marks et al., 2000), since complexity increases are generally considered to be the more frequent adaptive scenario in occupational settings and are also more difficult to master (LePine, 2005).

Although the task-change paradigm is frequently used in research on adaptation, there is no consensus on how to operationalize adaptation in this context. For example, as a measure of adaptation authors have used the overall level of performance after the change (Chen, 2005; Chen et al., 2005), the overall level of performance after the change controlling for performance before the change (Kozlowski et al., 2001), the overall level of performance relative to the level of performance before the change (Bröder & Schiffer, 2006; Johnson et al., 2006; LePine et al., 2000), the learning rate after the change (Chen, 2005), the level of performance after the change (Moon et al., 2004), indicators of specific adaptive behaviors surfacing after the change (Boeker & Goodstein, 1991; LePine, 2003, 2005; Schunn & Reder, 2001) or indicators of specific adaptive behaviors after the change relative to their occurrence before the change (Bröder & Schiffer, 2006).

Apart from the task-change paradigm, other methods have been used to study influences on adaptation to change. The most frequently used methods alongside the task-change paradigm are self-reports and situational judgment tests. Researchers using self-report methods assess adaptation using qualitative interviews on critical incidents (Pulakos et al., 2000), questionnaires (Fey & Denison, 2003; Ployhart & Bliese, 2006; Pulakos et al., 2000, 2002; Zedeck, Jackson, & Summers, 1983), biodata measures (Chan, 2000b) or structured interviews (Chan, 2000b), and ask individuals to report or rate their own ability to adapt or the adaptation process in their team and/or their organization. Situational judgment tests present descriptions of adaptive events to individuals and ask them for an adequate way to deal with these situations (Chan, 2000b). An example for a situational judgement item requiring adaptive competencies is provided below (Bruce & Learner, 1958, p. 208).

> If I made an error in assigning work to the group under my direction, I would:
>
> __ask for suggestions to correct the mistake.
>
> __explain the mistake so the employees would not lose respect for me.
>
> __correct the error as soon as it was detected.

In the current dissertation, I do not explicitly discuss the self-report or situational judgment methods to study influences on adaptation to change, but restrict illustrations of the arguments to the task-change paradigm. Both the self-report and situational judgment methods are conceptually similar to the task-change paradigm, as they primarily work with verbal descriptions of the processes measured in the task-change paradigm. Therefore, the conceptual aspects discussed in the present dissertation can easily be transferred to the self-report approaches to study adaptation to change.

2.3. Conceptual and Methodological Problems in Research on Adaptation to Change and Recent Methodological Approaches to Deal with Them

When studying adaptation to change in the task-change paradigm, researchers face two major issues, which are simultaneously conceptual and methodological in nature. First, researchers need to distinguish adaptive performance from other types of performance in the task-change paradigm. Second, researchers need to account for the process nature of adaptability. These issues are discussed in more detail below.

Both issues likely occur due to the fact that different performance components influence performance in the task-change paradigm. Common psychological data-analysis techniques like multiple regression, logistic regression, or repeated measurement ANOVA cannot adequately be used to separate the different performance processes from each other. Recently, researchers have made great strides towards addressing both issues by relying on modern data analysis techniques, which provide more flexible ways to analyze change over time than traditional methods (Ballinger, 2004; Bliese & Ployhart, 2002; Pinheiro & Bates, 2000).

2.3.1. Issue 1: Separating Adaptive and Non-Adaptive Performance

When planning a study on adaptive performance, researchers must begin by defining and operationalizing (a) the types of changes and performance that they consider to be indicative of adaptive behavior and (b) the types of changes and performance that they consider to be not unique to adaptive performance. Types of performance not unique to adaptive performance that are considered in the literature (e.g., Bliese & Ployhart, 2002) are basal task performance, which is—the general ability of individuals to perform the task,—and skill acquisition, which is—the individuals' ability to acquire the given task.

Theoretically and methodologically separating adaptive performance from other types of performance is crucially important for establishing the theoretical construct of adaptive performance in psychological research. Without a clear cut conceptual and operational distinction of adaptive task performance from other types of task performance, a strong counterargument against adaptability research using the task-change paradigm is that it cannot be shown that individual differences in adaptability actually exist. Instead, it could be argued that adaptive performance is basically identical to basal task performance or to skill acquisition. Therefore, the voluminous psychological literature on performance and skill acquisition in a great variety of different tasks and contexts may be applied to predict behavior in these situations, without requiring new research on adaptability.

Separating adaptive performance from non-adaptive types of performance is even an issue when researchers assess some specific adaptive behavior. As the specific adaptive behavior should be relevant to the respective task, it should be highly correlated with the post-change performance in the task. However, it is also very likely that the specific adaptive behavior is also correlated with the baseline of the pre-change behavior as well as skill acquisition in the task. As a result, the specific adaptive behavior is not only an indicator of the ability to adapt but also an indicator of the general ability of an individual to perform the respective task and skill acquisition in the task.

The only type of studies not affected by the issue of distinguishing adaptive performance from other types of performance are randomized studies using only experimental manipulations of the post-change task. These types of studies are not affected by these problems, since in experimental study designs, adaptation to change is not confounded with skill acquisition and basal task performance. As a result of the randomization and the identical pre-change task, basal task performance and skill acquisition are essentially fixed to zero due to missing differences between the groups when the change occurs. However, I was unable to find a study using this design in the literature, although there are experimental studies which may be reduced to this design by dropping experimental groups from the analyses (e.g., Bröder & Schiffer, 2006).[1]

In order to deal with the issues of separating adaptability from other types of performance, LePine et al. (2000) used generalized estimating equations (Ballinger, 2004) and operationalized adaptation as the interaction of individual difference variables and dummy variables contrasting pre-change and post-change performance (see also Bröder & Schiffer, 2006, for an experimental study using a similar approach). This approach provides a clear distinction between adaptation and other types of performance, which previous adaptability research lacked. Despite these crucial ad-

[1] It is important to note that the second issue of considering the temporal or process nature of adaptability discussed below still remains relevant within even the randomized studies, which refer to post-change tasks only. Thus the conceptual and methodological approach discussed in the present dissertation would nevertheless be fruitful to these (hypothetical) types of studies.

vantages, a limitation of this approach is that changes in performance over time in the pre-change, as well as the post-change period, are not considered.

2.3.2. Issue 2: Considering the Process Nature of Adaptive Performance

Considering that adaptability is conceptualized as a process of achieving correspondence in response to novel demands, adaptability should only exist for a limited amount of time implying change over time. In addressing this process nature of adaptability (Chan, 2000b), several researchers (Chen, 2005; LePine, 2005; Thoresen et al., 2004) recently applied multilevel mixed-effects models (Pinheiro & Bates, 2000) to study change in adaptation in the post-change period over time. This approach allowed LePine (2005) as well as Chen (2005) to separate performance slopes (change across the post-change period) from intercepts of performance (mean level of performance) in the post-change period, in order to derive a deeper understanding of the exact nature of the adaptation phenomenon. The main strength of this approach is researchers' ability to study adaptation as a change process by separating mean level of performance and change in the post-change period as two different components of adaptation. However, a limitation of this approach is that only post-change performance is measured without considering the pre-change level of performance, as well as change in the pre-change level of performance, and contrasting both to post-change performance and post-change performance change. This is the key rationale behind the application of discontinuous growth modeling techniques to adaptability research, targeted in the next section.

2.4. Multilevel Mixed-Effects Models

Multilevel mixed-effects models (Pinheiro & Bates, 2000) are also known as hierarchical linear models (Bryk & Raudenbush, 1987; Raudenbush, 2001; Raudenbush & Bryk, 2002), random coefficient models (Longford, 1993), or simply multilevel models (Goldstein, 1987, 1995) in the literature.[2] In psychological research, multilevel mixed-effects models have successfully been used to solve two data-analytic problems. The first problem arises when researchers want to study nested data as data from organizations, teams, families, or dyads. In this application, mixed-effects models have been used broadly in psychological research, since the late 1990s. The second problem arises in the study of change processes. Methodological problems in studying change have long plagued psychological research (Cronbach & Furby, 1970; Willett, 1997). In recent years, mixed-effects models and related advanced data-analytic techniques, such as generalized estimating equations (Ballinger, 2004) and latent curve analysis (Meredith & Tisak, 1990), have provided solutions to these problems in studying change (Willett, 1997).

A major advantage of mixed-effects models for the study of change processes in general is that these types of models are able to simultaneously estimate within-person (Level 1) and between-person (Level 2) effects (Raudenbush, 2001; Singer &

[2] Throughout this dissertation, I use the term mixed-effects models because this term is more frequently used in the recent literature than the term random coefficient models. The two other terms have major drawbacks. The term hierarchical linear models may occasionally be too narrow in the sense that mixed-effects models may be non-hierarchical (Rasbash & Browne, 2001) because modern mixed-effects models as implemented in statistical software like the lme4 package (Bates & Sarkar, 2007) can deal with cross-classified data structures attaching lower-order units to more than one higher-order unit. Despite mixed-effects models are prototypical multilevel models, the term multilevel models is broader than the term mixed-effects models as it also includes other techniques as general estimating equations (Ballinger, 2004) and multilevel structural equation models (Curran, 2003).

Willett, 2003). Within-person analyses models change across time by determining separate change model parameters for each person. Conceptually, these analyses are similar to calculating an ordinary least squares (OLS) regression analysis for each person using multiple measurement occasions as the dependent variable and one or more variables accounting for differences in time between the measurement occasions (Singer & Willett, 2003). Typically, one time variable is used and more complex change processes than simple linear change patterns are modeled using higher-order polynomials (e.g., quadratic, cubic and quartic). A notable difference between mixed-effects models and OLS regression calculations for each person is that the individual estimates in mixed-effects models also account for the regression estimates of the “average person” in order to increase the precision (reliability) of the change parameter estimates (Singer & Willett, 2003). The Level-1 model predicts the tth response from individual i using three types of parameters (notation adapted from Bryk & Raudenbush, 1992). First, the intercept π_{0i} indicates the level on the outcome measure with all change parameters being zero. Second, one or more change parameters π_{1i}, π_{2i}, π_{3i}, $\ldots$, π_{ni} indicate the way the outcome variable changes over time. Third, the random error e_{ti} accounts for unexplained measurement error on each measurement occasion.

$$Y_{ti} = \pi_{0i} + \pi_{1i}a_{1ti} + \pi_{2i}a_{2ti} + \pi_{3i}a_{3ti} + \ldots + \pi_{pi}a_{pti} + e_{ti}$$

Between-person analyses predict differences in the change parameters estimated for each person using individual difference variables (e.g., abilities or personality traits) or experimental variables (differences between experimental groups). Conceptually, this is similar to using an OLS regression to predict the individual b- or β- weights derived in individual OLS regressions for each person (Singer & Willett, 2003). Similar to the Level-1 model, the Level-2 model consists of three types of parameters. First, intercept parameters β_{00}, β_{10}, β_{20}, ..., β_{p0} indicate the value of the change parameter with all Level-2 predictors being zero. Second, one or more predictors β_{01}, β_{02}, β_{03}, ..., β_{pq} indicate differences in change among persons with high or low values on these predictors. Third, the level-2 residuals $r_{0i}, r_{1i}, r_{2i}, \ldots, r_{pi}$ represent the variance in the change parameters that are unexplained by the predictors of change. The level-2 residuals are also referred to as random effects in the context of multilevel mixed-effects models, whereas the level-1 and the level-2 predictors are typically labeled fixed effects.

$$
\begin{aligned}
\pi_{0i} &= \beta_{00} + \beta_{01}X_{1i} + \beta_{02}X_{2i} + \beta_{03}X_{3i} + \ldots + \beta_{0q}X_{qi} + r_{0i} \\
\pi_{1i} &= \beta_{10} + \beta_{11}X_{1i} + \beta_{12}X_{2i} + \beta_{13}X_{3i} + \ldots + \beta_{1q}X_{qi} + r_{1i} \\
\pi_{2i} &= \beta_{20} + \beta_{21}X_{1i} + \beta_{22}X_{2i} + \beta_{23}X_{3i} + \ldots + \beta_{2q}X_{qi} + r_{2i} \\
&\vdots \\
\pi_{pi} &= \beta_{p0} + \beta_{p1}X_{1i} + \beta_{p2}X_{2i} + \beta_{p3}X_{3i} + \ldots + \beta_{pq}X_{qi} + r_{pi}
\end{aligned}
$$

The methods to estimate multilevel mixed-effects models are diverse and continuously evolving (Singer & Willett, 2003). Readers with a statistical background may consult Pinheiro and Bates (2000) for a detailed account of the most frequently used restricted maximum likelihood and full maximum likelihood strategies, and to de Leeuw and Kreft (2001), Hox (2002), and Snijders and Bosker (1999) for more general overviews of the available estimation methods and software implementations of these methods.

2.5. Application of Discontinuous Growth Modeling Techniques to Adaptability Research

Discontinuous growth models are a specific group of multilevel mixed-effects models, which have gained increasing popularity in the literature and are now frequently used in a variety of contexts because of their unique ability to model transition processes (Bliese, Chan, & Ployhart, in press; Bliese, McGurk, Thomas, Balkin, & Wesensten, in press; Bliese, Wesensten, & Balkin, 2006; Lang & Kersting, 2007). Discontinuous growth models map complex change processes using multiple time variables. In the context of adaptability research, discontinuous growth models can be understood as an integration and extension of the two recently introduced methodological approaches. Similar to the second approach advanced by LePine et al. (2000), discontinuous growth modeling techniques allow one to account for pre-change performance, and thus allow a separation of adaptive performance from basal performance in the task. Similar to the approach of using multilevel mixed-effects models (Chen, 2005; LePine, 2005; Thoresen et al., 2004) to account for the temporal nature of adaptability, discontinuous growth modeling techniques allow one to separate two different types of adaptive performance from each other. However, these two different components of adaptability are not entirely conceptually identical to the two types of adaptation (change and mean level of performance) in the previous approach by LePine (2005) as well as Chen (2005). Nevertheless, they share some conceptual similarities. I refer to these two types of adaptation as transition adaptation and reacquisition adaptation throughout the present dissertation. An important extension beyond the two previously proposed approaches is that discontinuous growth modeling techniques allow researchers to simultaneously control for skill acquisition as well as basal task performance in both transition and reacquisition adaptation.

2.5.1. Basal Task Performance and Skill Acquisition

In describing the specifics of the discontinuous growth modeling framework, I first consider simple skill acquisition studies, in which basal task performance and skill acquisition in the task are the two performance components considered by researchers. In the context of the proposed discontinuous growth modeling framework, these two performance components are covariates, which need to be controlled for when measuring the two types of adaptation.

For instance, suppose a person performs a novel and complex task over a certain period of time. Typically, such a scenario is labeled a complex skill acquisition study (e.g., P. L. Ackerman, Kanfer, & Goff, 1995; Eyring, Johnson, & Francis, 1993; Yeo & Neal, 2004). In the context of a study on complex skill acquisition, individuals typically differ in two important aspects. First, individuals differ in their basal level of task performance. Second, individuals typically differ in how much they are able to improve their performance over time. The extent to which individuals are able to improve their performance is typically called the learning rate or the rate of skill acquisition. Often, the most simple and parsimonious model used to describe the two different aspects of performance over the skill acquisition period is a mixed-effects model with a linear change term (Bliese & Ployhart, 2002; Singer & Willett, 2003). In this model, the basal level of task performance is represented by the intercept and the skill acquisition rate is the slope of the linear parameter. Both the intercept, and the slope can be predicted in mixed-effects models by individual difference variables like GMA (e.g., Eyring et al., 1993; Yeo & Neal, 2004).

2.5.2. Transition Adaptation

Now suppose the skill acquisition scenario I described above is extended to the task-change paradigm. When changes in the task are unexpectedly introduced, the success rate of a variety of decisions might change so that behaviors which were successful before the change now fail, whereas other behaviors, which were not successful prior to the change, are now successful. As a result, the performance of all individuals will typically decrease because previously learned routines and procedures are now no longer helpful; however, their execution typically cannot be abandoned by the individual (e.g., Betsch, Brinkmann, Fiedler, & Breining, 1999; Bröder & Schiffer, 2006). To minimize performance decreases as much as possible, individuals need to possess what I call transition adaptation. The three defining aspects of transition adaptation are that (a) it occurs directly after a change in a task; (b) it is a flexible and immediate positive reaction to the new challenges that minimizes performance decrease; and (c) it is measured relative to the previous performance in the task. To model transition adaptation using a mixed-effects model, an additional change variable needs to be introduced in the mixed-effects model. The new variable indicates whether the scenario has changed or not (dummy-coded as 0 vs. 1). The inclusion of the dummy coded time variable allows for discontinuity in the change model (Singer & Willett, 2003). The change parameter, like other time parameters, can randomly or systematically vary across individuals (i.e., show inter-individual differences) and can be predicted by individual difference variables like GMA to explain inter-individual differences in transition adaptation.

2.5.3. Reacquisition Adaptation

Following the initial decrease in performance triggered by the changes in the task, individuals, teams or organizations typically are able to improve their performance as they continue to perform the changed task. Individuals, teams or organizations who are able to improve their level of performance in the task quickly possess what I call reacquisition adaptation. The three defining aspects of reacquisition adaptation are that (a) it refers to the process of recovery following the immediate performance loss after a change; (b) it is a systematic and analytical learning behavior which occurs in order to understand and learn the new challenges of the task; and (c) it is measured as the learning rate after the change in the task, controlling for the rate of skill acquisition prior to the change.

Reacquisition adaptation can be modeled in a discontinuous mixed-effects model by adding another variable to the skill acquisition model. This new variable captures deviations in the skill acquisition rate observed prior to the change. The main advantage of this type of coding is that it allows individuals to adapt to the post-change situation at a rate that differs from their initial acquisition rate on the new task (Singer & Willett, 2003). Similar to baseline performance, skill acquisition and transition adaptation, as well as interindividual differences on the ability of persons to reacquire the task can be modeled in the mixed-effects model using predictor variables like GMA.

2.5.4. Illustration and Summary

In sum, the full level-1 model of the proposed discontinuous mixed-effects model to study adaptability consists of time variables modeling skill acquisition (SA), transition adaptation (TA), and reacquisition adaptation (RA). The time variable modeling skill acquisition continuously rises across the full time window investigated using the model. The time variable modeling transition adaptation changes only at the transition point (typically coded 0 vs. 1). Finally, the time variable modeling reacquisition adaptation changes continuously in the period following the transition and does not change before the transition. In addition to these three time variables, another level-1 effect in the model is the intercept (π_{0i}) which indicates basal task performance. Thus, the full level-1 model may be written as follows.

$$Y_{ti} = \pi_{0i} + \pi_{1i} SA_{ti} + \pi_{2i} TA_{ti} + \pi_{3i} RA_{ti} + e_{ti}$$

At level-2, four different level-2 equations predict differences in the level-1 parameters between persons. These level-2 equations may include individual difference variables or experimental variables as level-2 predictors. In a general form, these four equations may be written as follows:

$$\begin{aligned}
\pi_{0i} &= \beta_{00} + \beta_{01}X_{1i} + \beta_{02}X_{2i} + \beta_{03}X_{3i} + \ldots + \beta_{0q}X_{qi} + r_{0i} \\
\pi_{1i} &= \beta_{10} + \beta_{11}X_{1i} + \beta_{12}X_{2i} + \beta_{13}X_{3i} + \ldots + \beta_{1q}X_{qi} + r_{1i} \\
\pi_{2i} &= \beta_{20} + \beta_{21}X_{1i} + \beta_{22}X_{2i} + \beta_{23}X_{3i} + \ldots + \beta_{2q}X_{qi} + r_{2i} \\
\pi_{3i} &= \beta_{30} + \beta_{31}X_{1i} + \beta_{32}X_{2i} + \beta_{33}X_{3i} + \ldots + \beta_{3q}X_{qi} + r_{3i}
\end{aligned}$$

The different types of change, which are modeled using the proposed discontinuous growth model are illustrated from Figure 2.1 to Figure 2.3. Figure 2.1 shows the expected hypothetical mean overall pattern of change predicted by a discontinuous growth model in a study using the task-change paradigm (e.g., Bröder & Schiffer, 2006). This model incorporates basal task performance, the rate of skill acquisition on the task, transition adaptation and reacquisition adaptation. Figure 2.2 demonstrates hypothetical change patterns for individuals who only differ in one of the four performance aspects—transition adaptation, reacquisition adaptation, skill acquisition, and basal task performance—discussed in this model to show how differences in each of the four components influence the overall pattern of change.

As shown in Figure 2.2A, an individual with a higher overall performance might be regarded as having a higher transition adaptation when the pre-change task performance is not considered. Figure 2.2B illustrates why not excluding skill acquisition may be problematic when the predictor variable under study is related to the learning rate. The individual with the higher level of skill acquisition may be regarded

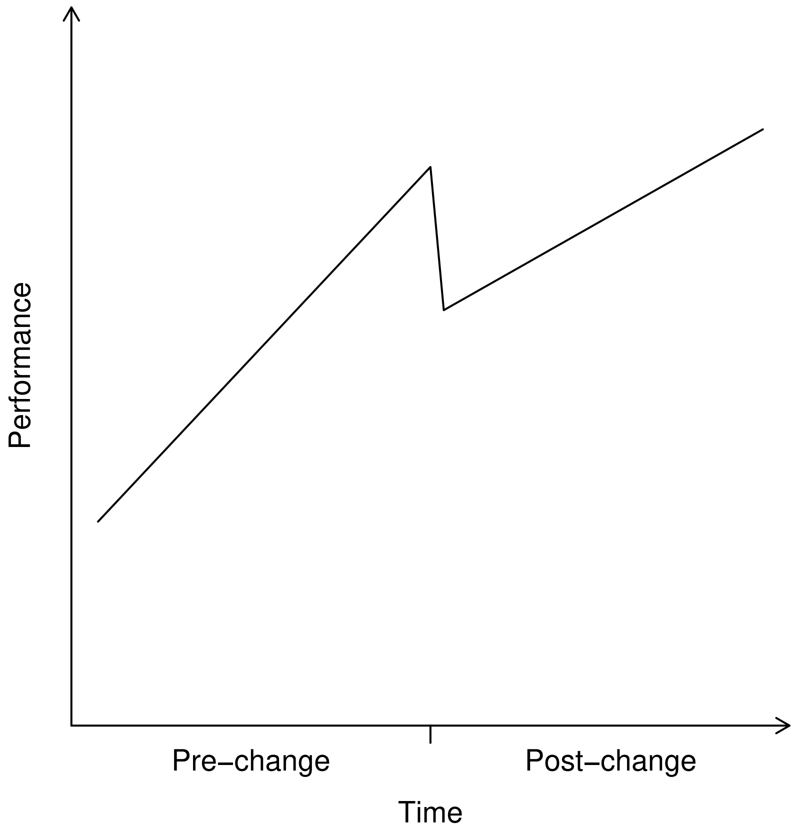

Figure 2.1. Typically expected mean pattern of change in a study using the task-change paradigm.

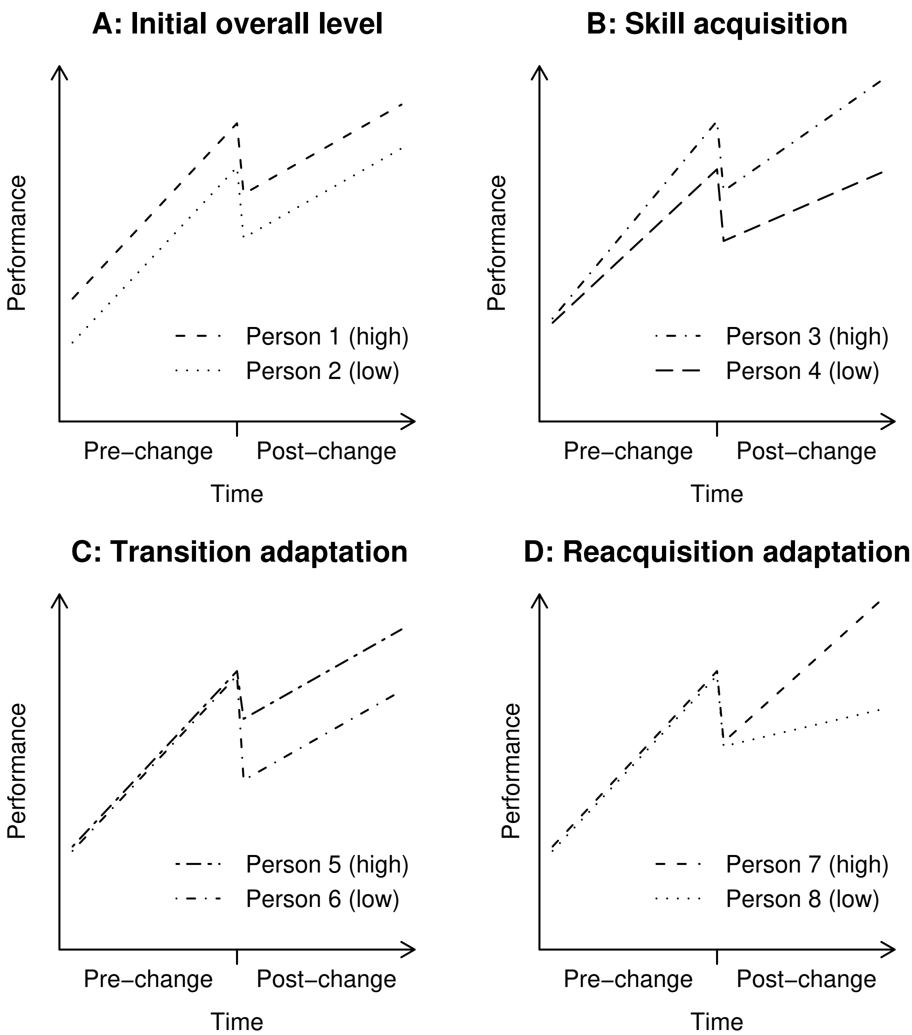

Figure 2.2. Hypothetical change patterns for individuals differing in (A) their initial overall level of performance, (B) their rate of skill acquisition, (D) transition adaptation and (D) reacquisition adaptation.

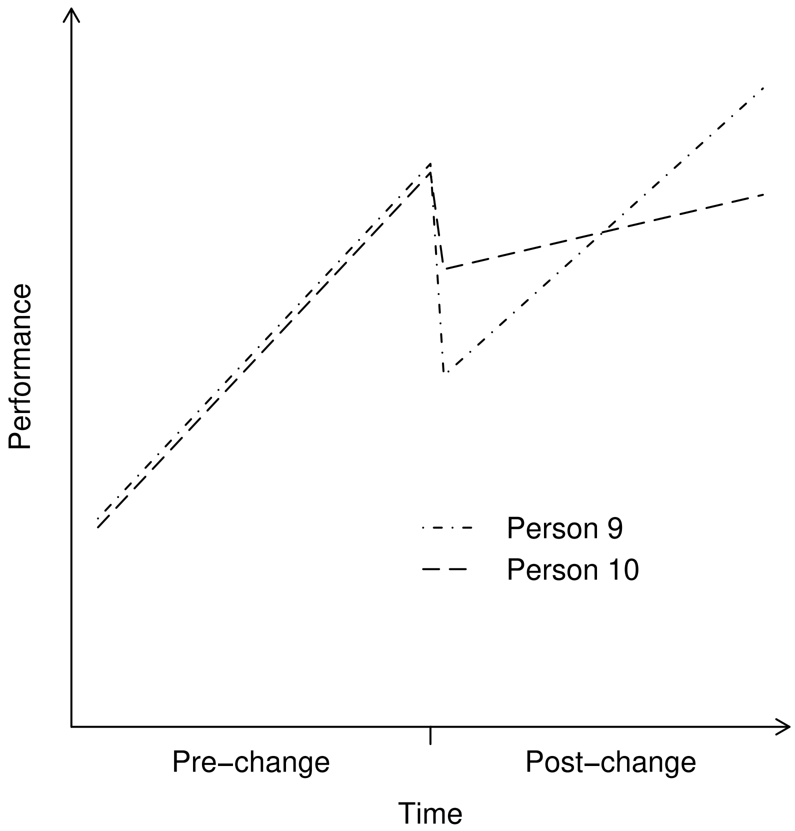

Figure 2.3. Hypothetical change pattern of a person with a high level of transition adaptation but a low level of reacquisition adaptation (Person 9) contrasted with the hypothetical change pattern of a person with a low level of transition adaptation but a high level of reacquisition adaptation (Person 10).

as having a higher level of both transition adaptation and reacquisition adaptation based only on differences in skill acquisition on the task. That is, the apparent differences in reacquisition adaptation may simply reflect differences in general skill acquisition, and therefore may not reflect anything unique about adaptation. Figure 2.2C and Figure 2.2D illustrate how differences in the two types of adaptation change the level of performance through the post-change period. Both types of adaptation lead to a higher overall level of performance during the post-change period. However, differentiating the two types of adaptation is important for deriving adequate predictions of behavior. Figure 2.3 illustrates this point. The figure shows the change patterns for two hypothetical individuals. Person 9 has high transition adaptation but is not high on reacquisition adaptation. In contrast, Person 10 has very low transition adaptation, but high reacquisition adaptation. In previous research, conclusions made regarding these two individuals would probably depend on the length of the post-change performance measurement period. Using a short post-change measurement period, Person 9 would likely be regarded as being more adaptive. Using a long post-change measurement period, Person 10 would likely be regarded as being more adaptive.

2.6. Brief Discussion

Figures 2.2 and 2.3 illustrate and summarize the advantages of utilizing discontinuous growth modeling, as well as the proposed two component conceptualization of adaptation for the study of individual differences in adaptation to change. Using this approach, both types of adaptation can be easily separated from each other.

Furthermore, adaptive processes can be studied while controlling for the effects of skill acquisition and the baseline level of performance in the respective task. Thus, the presented elaboration for studying adaptation to change within the task-change paradigm is a way to address the two major conceptual and methodological issues in adaptability research. First, the framework separates adaptation from other types of performance (i.e., basal task performance and skill acquisition). Second, it accounts for the process nature of adaptive performance.

An important question which remains is the usefulness of the proposed framework in research applications. Therefore, the following section reports a study contributing to one stream of adaptability research focusing on individual difference variables that allow successful prediction of adaptation to unforeseen changes.

3. Empirical Section: General Mental Ability and the Two Types of Adaptation

Regarding the second aim of the present dissertation, the following empirical section applies the discontinuous growth modeling framework, described in the conceptual and methodological section, into the context of an empirical study. This application is a starting point to potential future applications of the framework.

A key question in the adaptability literature is the relationship between adaptability and general mental ability (GMA) as an important individual difference variable (Lubinski, 2004; Schmidt & Hunter, 2004). This relationship has previously been investigated using the task-change paradigm (LePine, 2003, 2005; LePine et al., 2000). The focus of the present empirical study also explores this relationship. Interestingly, competing hypotheses either predicting a positive or a negative relationship between GMA and adaptability can be derived from the literature. In order to provide readers with an outline for the empirical section of the current dissertation, I briefly describe this theoretical and empirical evidence in the following paragraph. A more detailed and thorough review of this evidence will be provided later in the text (see pp. 39–44).

The flexibility hypothesis proposes that GMA provides individuals with more cognitive resources to process information and implement changes (LePine et al., 2000; Hunter & Schmidt, 1996). Thus, individuals with higher GMA should be proportionally better equipped to work on novel and complex tasks than on simple tasks. In an empirical investigation, LePine et al. (2000) found support for these predictions. In contrast to the flexibility hypothesis, motivational (Sternberg, 2004; Vancouver, Thompson, & Williams, 2001) and cognitive theories (e.g., Huguenard, Prietula, & Lerch, 1990) along with a considerable body of empirical research (e.g., Gobet & Waters, 2003; Huguenard et al., 1990; Rich, 1993) suggest that the performance of individuals performing a task at a high level decreases proportionally stronger when changes are introduced in a task. As GMA is typically related to almost all performance tasks (Jensen, 1998; Lubinski, 2004)—in particular work-related tasks (Schmidt & Hunter, 2004) and complex tasks (e.g., P. L. Ackerman et al., 1995; Gonzalez, Thomas, & Vanyukov, 2005)—a logical conclusion would be that high-ability individuals are less adaptable.

In the present study, I used an unforeseen task-change manipulation, which increased task complexity in the scenario environment. As mentioned in the introduction of the present dissertation, complexity increases are the most frequently used types of change manipulation in the task-change paradigm. The specific goals of this empirical study were twofold. First, I wanted to provide new insights on the question of whether people with high GMA are more adaptable than individuals with low GMA. Second, I wanted to study whether the two types of adaptation (transition adaptation and reacquisition adaptation) are differentially predicted by GMA. Differential prediction by GMA for the two types of adaptation would provide evidence that these two adaptational processes are not only conceptually distinct but also capture empirically distinct phenomena.

3.1. Theoretical Background: General Mental Ability

GMA, also called Spearman's g or general intelligence, is a construct which dates back to Charles Spearman's (1904) work more than 100 years ago. Spearman observed that nearly all cognitive tasks are correlated to some extent. Therefore, a general factor can be extracted from any larger set of diverse cognitive tasks (apart from more specific lower-order factors extracted from more homogeneous subsets). Verbal definitions of GMA are usually problematic because verbal definitions in general (Meehl, 1998, cited after Lubinski, 2004) and verbal definitions of GMA in particular (Lubinski, 2004) often lack consensus. Nevertheless, a group of 52 experts (including Meehl and Lubinski) developed a broad definition on the phenotypic essence of the GMA construct, which has been widely accepted in the literature. They defined GMA as follows:

> Intelligence is a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience. It is not merely book learning, a narrow academic skill, or test-taking smarts. Rather, it reflects a broader and deeper capability for comprehending our surroundings—"catching on," "making sense" of things, or "figuring out" what to do (Gottfredson, 1997a, p. 13).

Spearman's GMA concept has become and remains influential mainly for three reasons. First, factor-analytic studies normally show high intercorrelations among first-order factors. Thus, a hierarchical factor model with a higher-order GMA factor is describing the data more parsimoniously than a model with several intercorrelated single-factors.[3] Accordingly, the dominant intelligence models (Burt, 1940; Carroll, 1993; Gustafsson, 1994; Horn, 1994; Humphreys, 1962, 1979, 1985; Jäger, 1982; Snow, 1991, 1994, 1996; Snow & Lohman, 1989; Vernon, 1950) assume one general factor - GMA - to be superior to the specific subfactors (for counterexamples of multidimensional intelligence models without GMA see Guilford, 1956, 1967; Sternberg, 1985, 1999, 2003; Thurstone, 1938).

Second, GMA is a very stable trait (Deary, Whiteman, Starr, Whalley, & Fox, 2004). GMA changes only very slowly and in a systematic manner across the lifespan (McArdle, Ferrer-Caja, Hamagami, & Woodcock, 2002).

Third, GMA has proven to be a very successful and stable predictor of several criteria. Particularly, in the context of industrial-organizational psychology, GMA has been identified as the most important predictor of occupational performance through various meta-analyses and large-scale empirical studies (for an overview see Schmidt & Hunter, 2004). GMA is such a dominant predictor of job-related performance that the amount of incrementally explained variance of non-GMA procedures is usually quite small (Schmidt & Hunter, 1998). Normally, GMA explains about 30% of the performance variance in professionalized occupations. Besides job-related performance, GMA also predicts several common life events such as avoidance of

[3] In the context of confirmatory factor analyses, hierarchical models with second-order factors have less degrees of freedom than models with correlated first-order factors. Thus, these models are normally more parsimonious if there is a sufficient relationship among the factors.

risky health behavior, the ability to use public transportation systems or the avoidance of criminal behavior (Gottfredson, 1997b, 2004; Lubinski, 2004; Lubinski & Humphreys, 1997).

3.2. The Relationship Between General Mental Ability and Adaptation: Theoretical and Empirical Evidence

As mentioned above, there are arguments to either positively or negatively link GMA to adaptability in regard to changes in complex tasks. Predictions of a positive relationship between GMA and adaptational processes can be based on the flexibility hypothesis. The flexibility hypothesis (Hunter & Schmidt, 1996; LePine et al., 2000) which states that GMA provides individuals with additional cognitive resources to process information, and implement changes in adaptive situations has orginally been proposed by Hunter and Schmidt (1996). LePine et al. (2000) noted that the flexibility hypothesis is in line with meta-analytic research, and they provide evidence that GMA is an increasingly successful predictor of job performance in regard to increasing task complexity. Within the proposed discontinuous growth modeling framework, the flexibility hypothesis might be applied to both transition and reacquisition adaptation. The theoretical idea that individuals high in GMA could use more of their superior cognitive capacities in critical situations in order to implement changes is general in nature. Thus, the hypothesis can be applied to both an increased performance level—transition adaptation—as well as a superior ability to relearn the task—reacquisition adaptation (LePine, 2005).

In marked contrast to the predictions of the flexibility hypothesis, two arguments propose a negative relationship between GMA and adaptational processes. Both arguments may only be applied to transition adaptation and may not be linked to reacquistion adaptation.

The first argument originates from educational research on the relationship between abilities and transfer knowledge, as well as skills from a training context to a transfer task (Goska & Ackerman, 1996; Snow, 1992). Although most research on adaptation differs from most educational research on transfer, some general principles proposed in the educational transfer literature may be generalized to research on adaptation to changes. Particularly, transition adaptation can be seen as a construct which shares some important similarities with the phenomena studied in educational research on near transfer situations. Near transfer situations are situations with a high resemblance between training and transfer tasks and differ from far transfer tasks with a low resemblance between training and transfer tasks (Goska & Ackerman, 1996). A. M. Sullivan (1964, also see Goska & Ackerman, 1996) proposed that low-ability individuals show proportionally more transfer than high-ability individuals in near-transfer situations. A. M. Sullivan pointed out that low-ability individuals profit from pre-change performance proportionally more because pre-change performance allows these individuals to learn the concepts and routines of the task that they would not have learned without training. In contrast, high-ability persons benefit proportionally less from pre-change performance in near-transfer situations because they either already possess most of the concepts and routines, or they are quickly able to acquire them.

The second argument proposing a negative relationship between GMA and adaptation can be put forward based on research suggesting that people with higher GMA also have a higher basal task performance in complex tasks (P. L. Ackerman et al., 1995; Eyring et al., 1993; Gonzalez et al., 2005; Kanfer & Ackerman, 1989; Yeo & Neal, 2004). Theoretical arguments and empirical research suggest that the performance advantages of individuals with a high performance—who are likely to have a higher GMA—can diminish when changes are being introduced in a task (Gobet & Waters, 2003; Huguenard et al., 1990; Rich, 1993). This phenomenon can be explained both by motivational accounts as well as cognitive assumptions. Motivational accounts have proposed that higher performance leads to unrealistic optimism and expected self-efficacy due to earlier experiences of competence (Sternberg, 2004; Vancouver et al., 2001). These motivational attitudes are thought to diminish subsequent performance proportionally stronger for high-ability individuals than for low-ability individuals (for empirical investigations supporting this idea see Vancouver et al., 2001; Vancouver & Kendall, 2006; Vancouver, Thompson, Tischner, & Putka, 2002; Yeo & Neal, 2006; however, see Bandura & Locke, 2003 for a theoretical critique). Sternberg (2004) pointed out that unrealistically positive beliefs about oneself are particularly likely to result in performance losses when individuals are confronted with new environments requiring them to change and revise their approach to perform a given task. Cognitive theories share some similarity with the previously mentioned first argument from research on transfer and suggest that performance is becoming increasingly fragile as it becomes more skilled (Huguenard et al., 1990). Research on expertise has revealed that changes in tasks typically result in stronger performance degradations for experts than for novices in a wide variety of expertise behavior such as memory of chess positions (Gobet & Waters, 2003) or teaching (Rich, 1993). An explanation for this effect proposed in the literature is that the routines and knowledge of skilled individuals are more specialized and specific so that a proportionally greater amount of knowledge becomes obsolete after a change (Huguenard et al., 1990). As individuals with a higher GMA already perform the task at a higher level from the beginning of the pre-change period, their additional learning of the task through the pre-change period might be more fragile than the performance of individuals with a lower GMA.

Empirically, LePine et al. (2000) tested the relationship between GMA and adaptation to change when given complex tasks at the individual level of analysis in their aforementioned study, which used generalized estimating equations (Ballinger, 2004) and dummy variables to contrast post-change performance with pre-change performance. In this study, individuals made decisions on a series of 75 problems (unidentified aircrafts) from a naval command-and-control scenario (Hollenbeck et al., 1995). The task was to monitor the airspace surrounding an aircraft carrier. When an aircraft came into the airspace, individuals needed to gather information about nine particular attributes (cues) of the aircraft (like its speed, its type, and its direction) and then make a judgment on how to react to it. After each decision, participants received feedback reflecting the accuracy of each decision. After the 25th and 50th problem, the rules used in calculating decision accuracy (i.e., the weights that needed to be applied to the attributes in order to make a correct decision) were suddenly changed. Following the typical task-change paradigm, these changes were applied with no warning to participants. In line with the flexibility hypothesis, LePine et al. (2000) found a positive relationship between GMA and performance adaptability.[4] Although LePine et al.'s study adequately accounted for pre-change performance, a limitation considering the proposed discontinuous growth modeling framework is that their study did not control for pre-change skill acquisition differences between high and low-ability individuals. GMA has typically not only been linked to baseline performance in complex tasks as those used in research on adaptation (P. L. Ackerman et al., 1995; Eyring et al., 1993; Gonzalez et al., 2005; Kanfer & Ackerman, 1989; Yeo & Neal, 2004) but also to the rate of skill acquisition (Deadrick, Bennett, & Russell, 1997; Eyring et al., 1993; Kanfer & Ackerman, 1989; Yeo & Neal, 2004). While some studies found a positive relationship between GMA and skill acquisition (Deadrick et al., 1997; Eyring et al., 1993; Yeo & Neal, 2004), two studies found a negative relationship between GMA and the learning rate (Experiment 1 and Experiment 3 in Kanfer & Ackerman, 1989). Therefore, the existence and the direction of a potential bias due to not controlling for skill acquisition are unknown in the existing studies.[5] Considering the proposed discontinuous growth modeling framework, another limitation of LePine et al.'s study is that it did not specifically identify and test different types of adaptive performance in order to account for the process nature of adaptation to change.

Given the theoretically contradictory arguments in the literature either favoring

[4]For studies supporting the flexibility hypothesis at the team level see (LePine, 2003, 2005).

[5]In fact, a skill acquisition effect in LePine et al.'s (2000) study is the most plausible explanation for the strong and counterintuitive rise of mean performance from pre-change to post-change in their study. Without skill acquisition, a change in the task should lead to a decrease in performance when adaptability was needed. Yet, it is unknown whether skill acquisition was associated with GMA in their study.

a positive or a negative relationship between general mental ability and transition adaptation, I postulated a nondirectional hypothesis predicting a relationship between both constructs. Although the flexibility hypothesis may generally be applied to any type of increase in difficulty and complexity and therefore may also be applied to reacquisition adaptation, there is no theoretical research which generated concrete predictions on this type of adaptive performance. Due to this limited theoretical evidence regarding the process of reacquisition adaptation, I investigated the relationship between GMA and reacquisition adaptation as a research question in the present study.

> *Hypothesis.* There is a relationship between GMA and transition adaptation controlling for general skill acquisition, basal task performance, and reacquisition adaptation.

> *Research Question.* Does GMA predict reacquisition adaptation controlling for general skill acquisition, basal task performance, and transition adaptation?

3.3. Method

3.3.1. Participants

A total of 184 persons participated in the study; 91 were male and 93 were female. The average age of participants was 20.91 years (SD = 3.62, Range= $16 - 33$).

One hundred and four participants were recruited from the campus of a large university in Germany. These persons participated in the study at the local institute of psychology. Eighty participants were high school students from a high school (Gymnasium) in southern Germany and participated at their local high school. All participants provided informed consent and, if requested, received written feedback on their performance on the intelligence test used in the study. Furthermore, persons recruited from campus additionally received ten Euros for traveling to the institute of psychology, which was located outside the university's campus district.

3.3.2. Task

I chose a tank battle scenario as the complex task environment for the present study. Tank battle scenarios have been successfully applied in previous research on adaptability (Marks et al., 2000). The tank battle scenario used in the present study is named TankSoar and is included in the open source software Soar Suite 8.5.2 (Soar Group at the University of Michigan, 2004). Normally, the TankSoar Scenario is used in research and teaching with the Soar language—a general cognitive architecture employed in the field of artificial intelligence. The TankSoar Scenario was designed to have Soar programmed agents competing against one another within a simulated environment. In the present study, I used the TankSoar Scenario in a different way, which was similar to the use of artificial intelligence in strategic computer games. I used the scenario to let individuals compete against a Soar agent, or to have an individual and different Soar agents competing against one another. To accomplish this, I relied upon a specialized user interface for TankSoar, which has been developed for psychological research and allows participants to compete against soar agents while their activities are being logged (Köster, 2004). As TankSoar has not previously been used in psychological research, below I briefly describe its basic elements.

Overview

TankSoar simulates battles between tanks in a schematized environment. Participants control one tank while one or more tank(s) are controlled by a Soar agent. The scenario is comprised of separate rounds. Within each round participants have no restriction regarding the time they have available to plan their actions for the respective round. After having decided on which action to take, participants complete each round by confirming their decision. Based upon that decision, the program executes the participant's planned action. The computer-controlled adversarial tanks subsequently decide on their actions and execute them to complete the round.

Figure 3.1 shows the screen of the modified TankSoar Version, which was available for study participants. This screen provides the same information to "human" participants as to the computer-controlled soar agents. The window on the left side of the working screen represents the map of the scenario. All actions occur in this area. While participants are active in the scenario, they see only a partial view of their adjacent environment. The remaining part of the scenario is covered in black. However, to provide an overview of the two scenarios used in the present study Figure 3.2 and Figure 3.3 show both scenarios unrestricted (for a detailed explanation of the specific use for both scenarios see the procedure section). The window on the upper right side of the control screen (see Figure 3.1) provides additional information

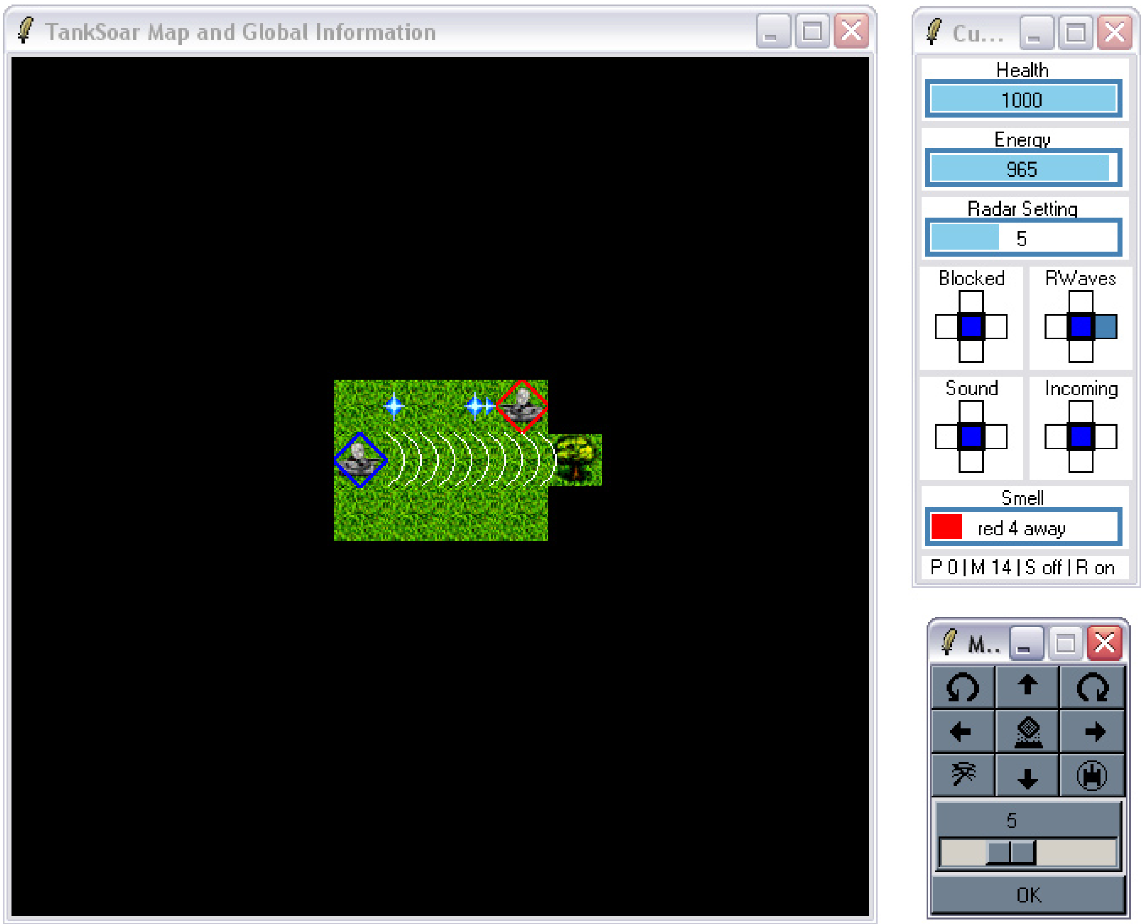

Figure 3.1. TankSoar working screen

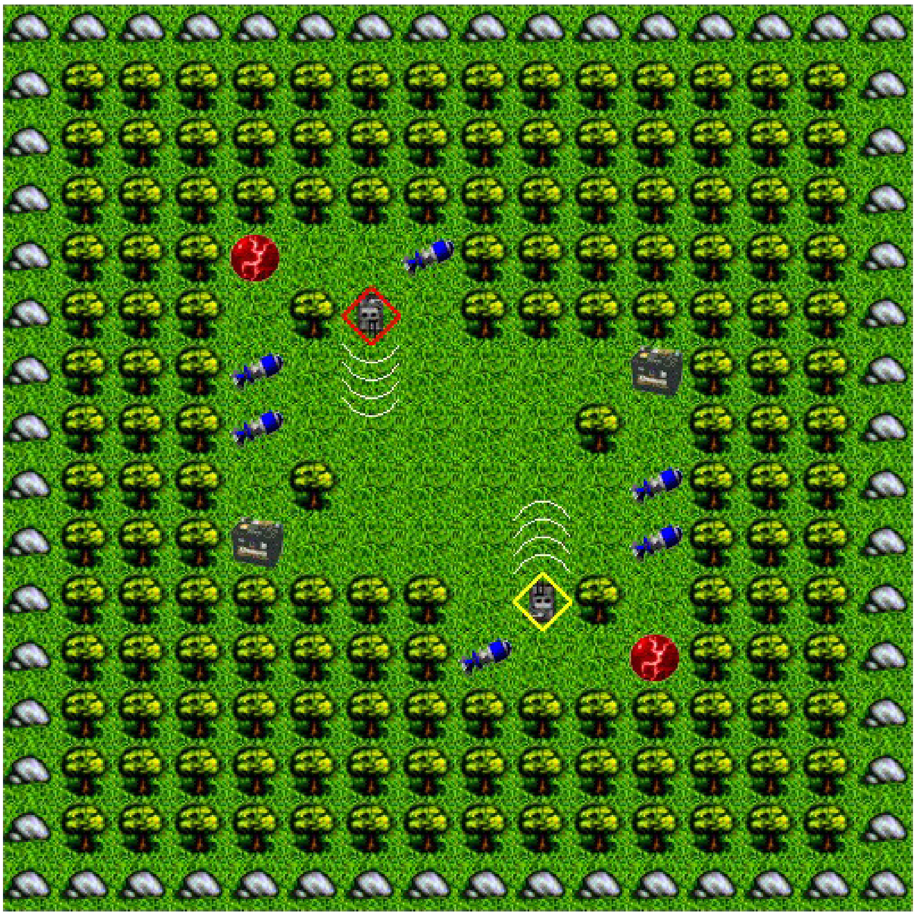

Figure 3.2. TankSoar scenario used in the pre-change period of the present study.

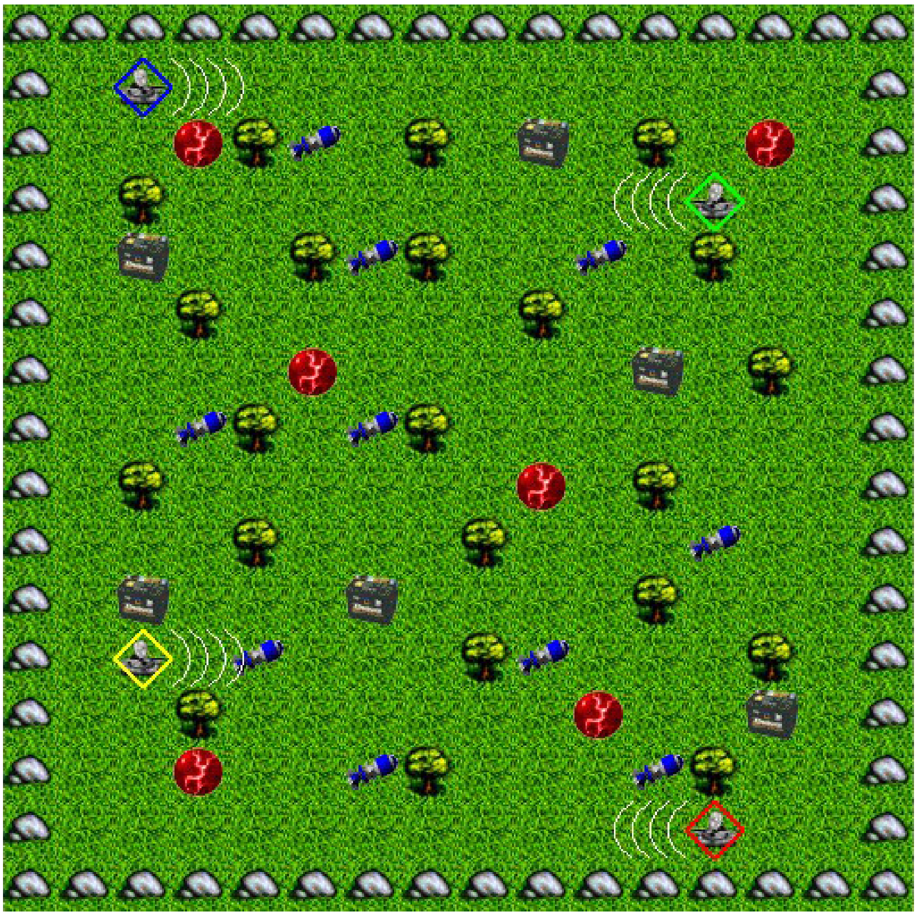

Figure 3.3. TankSoar scenario used in the post-change period of the present study.

for the scenario regarding the actual condition of one's tank and the environment around the tank. The window on the lower right side of the working screen contains the different control elements, which a participant uses to operate within the scenario. On the upper part of this window participants can select the respective actions and confirm them by clicking the OK button.

Health and health recharger

The upper right window of Figure 3.1 provides information on the tank's health. At the beginning of the scenario each tank has a health resource disposal of 1000 health points, which signifies the maximal possible health. During battle with other tanks, a tank loses health points when it is hit by missiles or it collides with obstacles (see below for details). To regain their health, tanks can be moved onto health recharger fields. On the scenario map, health rechargers are symbolized by a ball (see Figure 3.2 or Figure 3.3). For each round a tank spends on a health recharger it gains 150 health points. However, dwelling on a health recharger is dangerous because a missile hit on the health recharger leads to an immediate loss of all health resources and consequently to the tank's destruction, which deducts points.

Energy and energy recharger

The upper right window in Figure 3.1 provides information about energy resources (see Energy). At the beginning of the scenario each tank has an energy resource disposal of 1000 points, which signifies the maximal possible energy disposal. Energy is needed for various actions of the tank (see below), so this disposal is typically spent quickly. To regain energy, tanks can be moved onto energy recharger fields. On the scenario map, batteries symbolize energy rechargers (see Figure 3.2 or Figure 3.3). For each round a tank spends on an energy recharger it gains 200 energy points. As it is in the case with the health recharger field, a missile hit on an energy recharger field leads to an immediate loss of all health resources and consequently to the tank's destruction, which also deducts points.

Sensors

The TankSoar Scenario contains a total of six different sensors: the radar sensor, the blocked sensor, the r-waves sensor, the sound sensor, the incoming sensor, and the smell sensor.

The radar sensor allows the participant to see more on the scenario map than only the actual location of one's tank. The larger the radar range, the more spaces a player can see that lie directly in front of the tank. However, the radar is blocked by obstacles. Thus, the adjustment of a large radar range does not necessarily lead to an increased visibility range when there is a close obstacle. Radar range can be adjusted for the following round by moving the throttle in the control element window. The player also has the option to completely deactivate the radar sensor with the symbol located on the top left of the throttle. Activation or deactivation of the radar sensor and the selected radar range are displayed in the upper right window of the interface (see Figure 3.1, "R on"). In many gaming situations, when radar is not necessary, it is convenient to deactivate or down-regulate the sensor, as it consumes a lot of energy. The energy consumed per round is calculated from the radar range. For each space of radar range there is a loss of one energy point per round.

The blocked sensor detects obstacle blocks on adjacent squares of the tank (Sensor Blocked in Figure 3.1). The blocked sensor is specifically important to avoid collisions and prevent point losses when the tank moves backwards or without radar information.

The r-wave sensor detects whether the radar of another tank is detecting the tank as well as from which direction signals are coming (Sensor RWaves in Figure 3.1). The sound sensor detects movements of other tanks and also provides information of their direction (Sensor Sound in Figure 3.1). The incoming sensor detects whether other tanks shot missiles at one's own tank and from which direction these missiles are coming (Sensor Incoming in Figure 3.1). Finally, the smell sensor indicates how many fields on the map are between the tank and the next adversarial tank (Sensor Smell in Figure 3.1).

Missiles and shield

At the start of the scenario, each tank is armed with 15 missiles. Figure 3.1 shows the actual number of the missile resources on the upper right window under M (Missiles). Missiles can be fired with the control field, located between the arrow keys on the lower right window in Figure 3.1. Missile resources decrease with each missile shot. Tanks can recharge their missiles by moving onto the missile pick up packs. Pick up packs are symbolized by missiles on the map (see Figure 3.2 or Figure 3.3).

Each time a tank gets hit by a missile it loses one point, as well as 400 health points. The tank that shot the missile gains two points. After a missile hit, if a tank remains with no health resources, or is located on an energy or health recharger, it additionally loses two points (so that it loses a total of three points for the missile hit). Furthermore, the hit tank is moved to another field on the scenario and restarts with the initial resources. The tank that shot the missile gains three additional point (so that it gains a total of five points for the missile hit).

Tanks can protect themselves from missile hits by activating their shields. To activate a shield, one needs to press the control button located on the top right of the radar control on the lower right window of Figure 3.1 (The shield is deactivated in Figure 3.1 as indicated by the display “S off”). Missile hits with an activated shield lead to a loss of only 250 energy points but no loss of health points. Still, they lead to a general point deduction. Even though the shield protects against adversarial missile hits, an activated shield consumes 20 energy points per round.

Tank moves and obstacles

Participants control the moves of their tanks with the arrow keys located on the lower right window of the control screen (see Figure 3.1). The straight arrows pointing up, down, right, and left lead to a move of one space per round in the respective direction. The round arrows allow the tank to rotate 90° per round in the respective arrow direction. Each round only allows either a move of one space or one tank rotation on the same field.

As indicated by Figure 3.2 and Figure 3.3, the scenarios have two types of obstacles: Trees and stones. The stones form the outer border of the scenarios. Trees are distributed all around the scenario. Tanks cannot overcome these obstacles, which are immovable and undestroyable. A collision with an obstacle results in a deduction of 100 health points. Apart from obstacles, tanks can also collide with other tanks. This results in a deduction of 100 health points.

3.3.3. General Mental Ability Testing

Most researchers propose an inductive approach for assessing GMA (P. L. Ackerman, Beier, & Boyle, 2005; Jensen, 1998). From this point of view, GMA is a factor underlying the positive correlations among a variety of different cognitive ability tests. According to this inductive definition, it is not possible to directly assess general mental ability through a single homogeneous test. By using only one test, researchers would run the risk of contaminating GMA with test-specific variance (P. L. Ackerman et al., 2005). Instead, GMA has to be approximated by aggregating several g-saturated measures. In accordance with this procedure, the present study assessed participants' GMA with three typical ability tests differing in their content. The three tests stemmed from the revised Wilde Intelligence Test (WIT-2; Kersting, Althoff, & Jäger, in press) and from the abbreviated version of the WIT, recommended by the authors. The WIT is a battery of typical intelligence tests and is one of the most frequently used ability-test batteries in Germany.

The present study employed the folding boxes test (a spatial task), the completing number series test (a numerical task), and the verbal analogies test (a predominantly verbal task). All three tests are based on classic intelligence tasks. Specifically, the verbal analogies items resemble the items in the frequently used Miller-Analogy-Test (Miller, 1960). Early versions of the completing number series test and the folding boxes test have been used by Thurstone (1938). The folding boxes test is comprised of 20 figural patterns that, when mentally folded along the cut lines, result in three-dimensional objects (e.g., a cube or a pyramid). For each figural pattern, testees select among five alternatives the object that would result from folding the pattern.

Testees are given 9 minutes to work on all 20 figural patterns. The completing number series test comprises 20 incomplete number sequences (e.g., 7, 21, 18, 9, 27, 24, 12, ?), and testees are given 10 minutes to complete all sequences by writing down the next number in the logic of the sequence (here: 36). The verbal analogies test comprises 20 incomplete analogies (e.g., sheep : wool = bird : ?), and testees are given 4 minutes and 30 seconds to complete the analogies by choosing the correct word from five alternatives (here: feathers).

In order to test whether the three tests were valid indicators of a common intelligence factor, I conducted a confirmatory factor analysis (CFA). As one factor models with three manifest indicators do not possess enough degrees of freedom for a CFA, I built manifest variables from the even and uneven test items from each test and related them to a latent test-specific subfactor for each test. The resulting three test-specific subfactors were subsequently related to one global GMA-factor. Analyses were conducted using the sem package (Fox, 2004, 2006) included in the open source software R (R Development Core Team, 2004) and maximum likelihood estimation (ML). For model evaluation, I followed recommendations by Hu and Bentler (1998). They advised researchers to rely on a two-index approach. As a first index, researchers should use the standardized root-mean-square residual (SRMR) because SRMR is most sensitive to simple model misspecification. As the second index, Hu and Bentler (1998) recommended using an index that is sensible to complex model misspecification. They proposed using either the Tucker-Lewis index (TLI), the fit index by Bollen (BL89), the relative noncentrality index (RNI), the comparative fit index (CFI), the gamma hat, the McDonald's centrality index (Mc), or the root-mean-square error of approximation (RMSEA). All these indices are sensitive to complex model misspecification. I decided to use CFI as the second index and additionally report TLI and RMSEA because all three indices are very popular among researchers (Coovert & Craiger, 2000). Hu and Bentler (1998) suggested that cutoff values of SRMR$\leq .08$, RMSEA$\leq .06$, CFI$\geq .95$, and TLI$\geq .95$ are needed before one can conclude that there is a relatively good fit between the hypothesized model and the observed data. Based on these cutoff criteria, the hypothesized model (see Figure 3.4) provided a good fit to the data of the present study: $\chi^2(6, N = 184) = 9.20$, $p = .16$, SRMR$= .02$, CFI$= .99$, TLI$= .99$, RMSEA$= .05$. The standardized factor loadings of the three tests on the overall factor were .55 for the folding boxes test, .58 for the completing number series test, and .63 for the verbal analogies test.

For subsequent analyses, I built an indicator of GMA by assembling a composite total score based on equally weighted z-values of the three tests. This procedure is frequently employed by researchers (e.g., P. L. Ackerman & Beier, 2006) because it has the advantage of providing very robust values (Cohen, 1990; Thorndike, 1986), while at the same time avoiding the typical problems when using factor scores (i.e., inappropriate approximation of theoretic factor scores with methods to calculate factor scores for each individual, Tucker, 1971). In order to determine the internal consistency of this composite score, I calculated stratified Cronbach's α (Cronbach, Schoneman, & McKie, 1965). When test items are split into different content areas, stratified Cronbach's α represents a better predictor of the true reliability of a test than the regular Cronbach's α (Osburn, 2000). I found stratified Cronbach's $\alpha = .98$ indicating adequate reliability for the composite measure of GMA. The internal consistencies (Cronbach's α) for the three single tests were as follows: $\alpha = .85$ for folding boxes, $\alpha = .89$ for number series, and $\alpha = .77$ for verbal analogies.

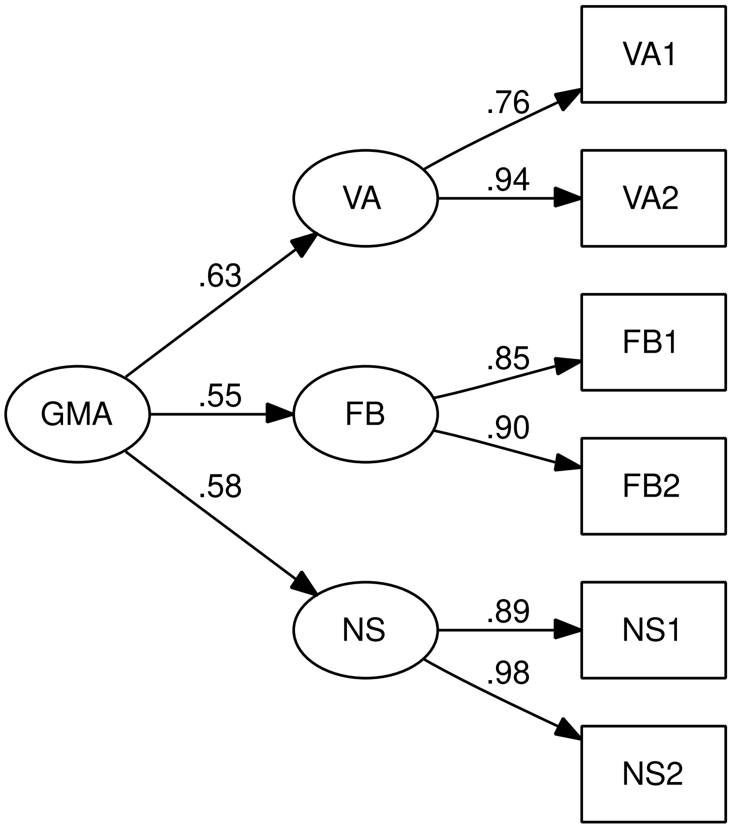

Figure 3.4. Confirmatory factor analysis of the ability measures used in the study. For clarity of presentation, uniquenesses and uniqueness covariances are not illustrated. VA = verbal analogies test; FB = folding boxes test; NS = completing number series test; GMA = general mental ability.

3.3.4. Procedure

The present study was held in two to three hour sessions. Sessions were conducted in groups of two to fifteen participants. Participants first completed the three GMA-tests, as well as a booklet of questionnaires. In a second step, participants received the instructions for working on the TankSoar Scenario. Instructions contained detailed explanations of the different elements of the TankSoar Scenario, which were also graphically illustrated. Participants received the instruction on paper. Additionally, the instructions were read out loud for the participants by the study's supervisor before starting the scenario.

In total, participants worked on 6 trials of the TankSoar Scenario each consisting of 100 rounds. In the first 3 trials, participants worked on the scenario presented in Figure 3.2. In the last 3 trials, participants worked on the scenario presented in Figure 3.3. There were no time constraints so that for each decision participants could take as much time as they liked. Mean time in minutes, standard deviation of time, and range of time are provided in Table 3.1.

Participants were not informed of the fact that the map switched after the third trial, and due to the limited view of the map (see Figure 3.1), changes were not immediately apparent. However, as can be seen in Figure 3.2 (see p. 48) and Figure 3.3 (see p. 49), there were some noticeable differences between the two scenarios.

The first scenario only has one adversarial tank. The health and energy recharger fields are relatively scarce and difficult to find. In contrast to the first scenario, in the second scenario, health and energy rechargers are more frequently available and much easier to detect. Furthermore, the map is much larger and there are three

Table 3.1. Completion Time (in Minutes): Mean, Standard Deviation, and Range for each Trial.

Variable	M	SD	Range
Trial 1	5.53	2.55	−0.85−21.44
Trial 2	5.04	2.05	−0.67−16.15
Trial 3	4.84	2.02	−0.64−12.53
Trial 4	4.54	1.73	−1.37−13.61
Trial 5	4.79	2.67	−0.87−23.95
Trial 6	4.48	1.68	−1.40−12.12

Note. $N = 184$.

opponents instead of only one adversarial tank in the scenario. Therefore, in contrast to the first map, multiple opponents often fire missiles simultaneously against the participant's tank, as well as against one another, and missiles fly over much longer distances. As the tank sensors only track the next tank and the nearest missile, sensor information frequently changes in this map.

3.3.5. Statistical Analyses

Discontinuous growth modeling analyses were conducted using the nlme package (Pinheiro & Bates, 2000; Pinheiro, Bates, DebRoy, & Sarkar, 2005) included in the open source software R (R Development Core Team, 2004) and restricted maximum likelihood estimation (REML). In the present investigation, all models were two-level multilevel models, with measurement occasions (3 pre-change measurement occasions and 3 post-change measurement occasions × 184 individuals = 1104) at level 1 nested within individuals at level 2.

In order to interpret results from mixed-effects models, it is crucial that the model is adequately specified (Bliese & Ployhart, 2002; Singer & Willett, 2003; Snijders & Bosker, 1999) and model assumptions are met. To make sure that this is the case, researchers typically run a series of routine procedures in order to adequately model random effects and error structures, and check the tenability of the model's assumptions before interpreting results from a multilevel model. These procedures are typically labeled model building procedures by mixed-effects modeling scholars.

In the current investigation, I relied on a seven-step model building procedure. This procedure was based on recommendations by Bliese and Ployhart (2002), Pinheiro and Bates (2000), and Singer and Willett (2003).

In line with recommendations by Bliese and Ployhart (2002), Step 1 included examining the intraclass correlation coefficient (ICC1) for the criterion measure prior to modeling change. The ICC1 is a measure of nonindependence in data due to hierarchical nesting of measurement occasions in persons. In the current study, the ICC1 indicates how much variability in decision-making performance is a result of between-person differences across the six measurement occasions. The ICC1 can be calculated by determining the amount of between person variance in the total variance in a mixed-effects model with no level-1 or level-2 variables.

Step 2 examined the level-1 change by adding level-1 change variables for skill acquisition (SA), transition adaptation (TA), and reacquisition adaptation (RA) to

Table 3.2. Coding of Change Variables in the Discontinuous Mixed-Effects Growth Model for the Study

	Trial					
Change variable	1	2	3	4	5	6
Skill acquisition	0	1	2	3	4	5
Transition adaptation	0	0	0	1	1	1
Reacquisition adaptation	0	0	0	0	1	2

the model to derive the aforementioned discontinuous level-1 change model proposed in the conceptual and methodological section of the current dissertation.

$$Y_{ti} = \pi_{0i} + \pi_{1i}SA_{ti} + \pi_{2i}TA_{ti} + \pi_{3i}RA_{ti} + e_{ti}$$

The origin of time for the level-1 change variables was placed at Trial 1 so that the intercept of the model reflected the initial level of basal performance at Trial 1. This coding scheme is recommended by most authors for level-1 analyses and as a starting point for level-2 analyses (e.g., Bliese & Ployhart, 2002). The coding of the change variables used to model skill acquisition, transition adaptation, and reacquisition adaptation is shown in Table 3.2.

Step 3 tested for variability in the fixed effects of the level-1 variables in order to fix the random effects to zero in the case of nonsignificant random variability. Fixing nonvarying random effects to zero has been recommended by several researchers (Bliese & Ployhart, 2002; Pinheiro & Bates, 2000; Snijders & Bosker, 1999), for it is crucial to avoid model overparameterization and to increase model parsimony. Tests for random effects were conducted by contrasting models with and without the respective random effects using a log-likelihood ratio test (see Pinheiro & Bates, 2000, for details) and starting with a model containing all random effects.

Step 4 tested for autocorrelation and heteroscedasticity in the error structure of the model. Testing for autocorrelation and heteroscedasticity has been recommended by Bliese and Ployhart (2002) and DeShon, Ployhart, and Sacco (1998) for all mixed-effects models with a logical ordering of the level-1 variables (all models modeling intraindividual change) in order to detect and control for both error structures when they are present in a model. Not controlling for autocorrelation and heteroscedasticity when these error structures are present in a model leads to inaccurate estimations of standard errors for the model parameters, and thus the power of the model can be seriously lowered (Bliese & Ployhart, 2002; DeShon et al., 1998; Singer & Willett, 2003). Tests for error structures were conducted by contrasting models with and without autocorrelation and heteroscedasticity, again, using the aformentioned log-likelihood ratio test (see Pinheiro & Bates, 2000, for details) and starting with a model containing no autocorrelation and heteroscedasticity.

In Step 5, GMA was added to the model as a level-2 predictor of the intercept (the basal task performance), the skill acquisition effect, the transition adaptation effect, and the reacquistion adaptation effect to derive the final model of the study. Note that GMA was added as a predictor not only of transition adaptation and reacquisition adaptation but also of skill acquisition and basal task performance. Including the basal task performance effect was mandatory as direct-effects need to be included when interactions involving the direct effect variables are being investigated (Cohen,

Cohen, West, & Aiken, 2003). But it was also desirable as a covariate since GMA is typically strongly correlated to complex task performance (P. L. Ackerman et al., 1995; Eyring et al., 1993; Gonzalez et al., 2005; Kanfer & Ackerman, 1989; Yeo & Neal, 2004). The skill acquisition effect was included as a potential covariate because relationships between GMA and skill acquisition have frequently been documented in the literature (Deadrick et al., 1997; Eyring et al., 1993; Kanfer & Ackerman, 1989; Yeo & Neal, 2004), and not considering this effect could potentially lead to an omitted variable problem (Judd & McClelland, 1989) in the analysis. Adding GMA as a level-2 predictor for all level-1 fixed effects resulted in the following model for level-2.

$$\begin{aligned}
\pi_{0i} &= \beta_{00} + \beta_{01} GMA_i + r_{0i} \\
\pi_{1i} &= \beta_{10} + \beta_{11} GMA_i + r_{1i} \\
\pi_{2i} &= \beta_{20} + \beta_{21} GMA_i + r_{2i} \\
\pi_{3i} &= \beta_{30} + \beta_{31} GMA_i + r_{3i}
\end{aligned}$$

In all level-2 analyses, GMA was centered at the sample mean so that the level-1 coefficients were not affected by the addition of the level-2 predictor and still reflected the average pattern of change for the sample.

Step 6 investigated the tenability of mixed-effects model assumptions for the final mixed-effects model. Evaluating model assumptions of mixed-effects models prior to drawing inferences from a model is an adequate way to make sure that findings are not strongly biased by violated model assumptions (Singer & Willett, 2003). However, since researchers lack information about the population from which a sample was drawn, they can never be completely certain about the tenability of assumptions (Pinheiro & Bates, 2000; Singer & Willett, 2003). Model assumptions need to be adequate for populational data and not for the data of a sample from the population. Nevertheless, the tenability of model assumptions from a sample provides some evidence on the tenability of the assumptions in the population of the sample. In the present study, evaluation of model assumptions were conducted following recommendations of Singer and Willett (2003). Singer and Willett (2003) propose to evaluate three aspects of mixed-effect models with respect to model assumptions using visual inspection of several graphs for each model assumption.[6]

First, researchers should check the functional form of the model on level 1 and level 2. On level 1, empirical change patterns should be compared to individual change trajectories that are estimated using an OLS and the proposed level-1 change model. Graphical inspection should confirm the suitability of the proposed level-1 change model. On level 2, Singer and Willett (2003) recommend to plot OLS-estimated growth parameters for each person against level-2 predictors (GMA in the current study). In multilevel mixed-effects models, the relationship between level-2 predictors and OLS-estimated growth parameters should be linear.

Second, researchers should examine the normality assumption, which states that level-1 residuals (within-group errors) and the level-2 residuals (random effects) in mixed-effects models should be normally distributed in the population. Singer and

[6]Some aspects of the model may also be evaluated using formal tests (e.g., Wilks-Shapiro and Kolmogorov-Smirnov statistics for normality). However, a major problem of formal tests is that they are typically too sensitive and reject plausible models because of marginal deviations from normality (Pinheiro & Bates, 2000). Therefore, most multilevel scholars do not recommend their use (e.g., Pinheiro & Bates, 2000; Singer & Willett, 2003; Snijders & Bosker, 1999).

Willett (2003) recommend using normal probability plots and plots of standardized residuals to examine normality. Normal probability plots display quantiles of the theoretical normal distribution against the sample distribution. Perfect normality is achieved when this relationship is a straight line. Plots of standardized residuals indicate normal distribution if 95% of the standardized residuals fall within ± 2 standard deviations of their center (i.e., about 5% will be greater than 2). In the current study, I additionally graphed histograms and calculated skewness and kurtosis statistics because psychologists are typically more accustomed to the use of histograms as well as skewness and kurtosis to evaluate normality. Histograms indicate normality if the distribution of densities is approximating a normal curve. A skewness of zero represents a perfect normal distribution. Nonzero skewness is indicative of a departure from symmetry. Negative skewness indicates a distribution with a left tail, whereas positive skewness indicates a distribution with a right tail (both relative to the symmetrical normal distribution). Kurtosis, which is particularly important for statistical inference, indicates the extent to which the height of the curve (probability density) differs from that of the normal curve. Normally, a kurtosis of 3 represents perfect normality. To simplify interpretation, many computer packages subtract 3 from the ordinary kurtosis measure (the standardized fourth-order moment; see West, Finch, & Curran, 1995, for details) so that kurtosis values are indicative of the excess kurtosis relative to the normal distribution. Thus, kurtosis will be 0 for a normal curve. I follow this convention in reporting values of kurtosis. In this nomenclature, positive kurtosis is associated with distributions with long, thin tails, whereas negative kurtosis is associated with shorter, flatter tails relative to the normal curve. As a general guideline to interpret skewness and kurtosis values when evaluating distributions, West et al. (1995) suggested that distributions with skewness> |2| and kurtosis> |7| substantially depart from normality.

Finally and third, Singer and Willett (2003) propose to evaluate the homoscedasticity assumption. On level 1, this can be done by plotting level-1 residuals (within-group errors) against time. If the level-1 residuals are homoscedastic, residual variability will be approximately equal at every measurement occasion. On level 2, the homoscedasticity assumption can be evaluated by plotting the relationship between level-1 residuals and the level-2 predictors (GMA in the current study). If the level-2 residuals are homoscedastic, residual variability will be approximately equal across the range of the level-2 predictors.

When all examinations of model assumptions support the notion that a model's assumptions are tenable, hypotheses and research questions can be evaluated. In the current investigation, this was done in a final Step 7.

For all mixed-effects analyses, I calculated and report both unstandardized and standardized coefficients for the fixed effects. Unstandardized coefficients provided valuable information on performance in the decision task (performance relative to the opponents' performance), whereas standardized coefficients provided effect size information. Standardized coefficients were derived by setting the standard deviation of all variables to 1 without altering the coding of the variables (change variables coded so that the intercept reflected performance at the origin of time and GMA centered at the sample mean).

Pseudo-R^2 statistics were not reported throughout all analyses because the interpretation of pseudo-R^2 in mixed-effects models is in general much less straightforward than the interpretation of R^2-statistics in OLS-regression. Consequently, most multilevel scholars advise researchers not to report pseudo-R^2 or to be cautious in interpreting these statistics (Hox, 2002; Singer & Willett, 2003; Snijders & Bosker, 1999). Specifically, a variety of different approaches to calculate pseudo-R^2 statistics in mixed-effects models exist (Bryk & Raudenbush, 1992; Gelman & Pardoe, 2006; Roberts & Monaco, 2006; Snijders & Bosker, 1994; Xu, 2003). Most approaches resemble selective aspects of R^2-statistics in OLS-regression but differ fundamentally in other aspects. Another problem is that the most popular approaches to calculate R^2-statistics in mixed-effects models proposed by Bryk and Raudenbush (1992) sometimes result in negative R^2 estimates even if a newly added predictor significantly improves the overall fit of the model (see Snijders & Bosker, 1994, for details).

3.4. Results

3.4.1. Descriptive Data

Before I conducted discontinuous growth modeling analyses, I examined the data descriptively. The main aim of the descriptive analyses were to compare previous research and general assumptions on research in the task-change paradigm.

The following analyses were conducted. First, I examined distributions of all study variables. Second, I compared means and standard deviations of the standardized ability measures in the study to the normative samples of the measures to provide information on the performance level of the sample compared with more representative samples. Third, I examined change in means as well as standard deviations of

TankSoar measurement occasions. Fourth, I investigated intercorrelations between measurement occasions to provide first evidence whether performance changed dynamically over time. Dynamic change over time or rank-order stability is generally considered to be strong evidence for the presence of individual differences variables. Finally, I investigated the intercorrelations between TankSoar performance and GMA to check whether GMA was actually related to performance in the task. A considerable correlation between GMA and TankSoar performance is needed in order to test the hypothesis and research question of the current study.

Variable Distributions

In general, discontinuous mixed-effects models do not require variables to be normally distributed. Instead, only the residuals in the population need to be normally distributed.[7] Nevertheless, normality in study variables is desirable for two reasons. First, normality may be interpreted as strong evidence for population normality, which in turn is an important assumption when comparing mean differences and intercorrelations. Second, normality is strong evidence that no irregularities, like ceiling effects, are present in the data. Ceiling effects typically occur when improvements on a given variable are impossible or disproportionately difficult beyond a certain level. They are likely to occur when a measurement instrument is not suited to measure a variable across the whole sample range.

To evaluate normality of study variables, I examined histograms, normal probability plots, as well as skewness and kurtosis statistics. Skewness and kurtosis for

[7] Some evidence on the appropriateness of this assumption can be obtained by examining the residuals of the fitted model—I return to this point later in this section when the discontinuous mixed-effects modeling analyses are conducted

all study variables are provided in Table 3.3. As indicated by Table 3.3, all variables had skewness$< |1|$ and kurtosis$< |1|$ and thus confirm the interpretation of the histograms and normal probability plots as providing no evidence for considerable deviations from normality.

For performance at each measurement occasion of the TankSoar task, histograms (see Appendix A.1), normal probability plots (see Appendix A.2), as well as skewness and kurtosis statistics (see Table 3.3) provided no evidence for strong ceiling effects or systematic and considerable non-normality. For the ability tests, histograms (see Appendix A.3), normal probability plots (see Appendix A.4), as well as skewness and kurtosis statistics (see Table 3.3), provided slight evidence of ceiling effects resulting from individuals who were able to solve all items on a given test. However, none of these deviations provided evidence for a serious deviation from normality. Furthermore, the composite scores derived from the three tests which were used as an indicator of GMA in the current research were almost perfectly normally distributed (see Figure A.5 and Figure A.6) indicating that the ceiling effects occurred only selectively on single subtests.

Overall, the histograms, normal probability plot, as well as skewness and kurtosis statistics provided no evidence that distributions of the study variables did considerably deviate from normality. Thus, empirical findings should not be influenced considerably by ceiling effects or extreme cases.

Means and Standard Deviations

Standard deviations and means of standardized ability measures in a sample can provide valuable information on the general characteristics of the sample compared

Table 3.3. Means, Standard Deviations, Range, Skewness, and Kurtosis of Study Variables

Variable	M	SD	Range	Skewness	Kurtosis
Trial 1	-5.29	15.36	−36−50	.79	.75
Trial 2	2.91	18.26	−31−63	.75	.42
Trial 3	7.47	21.90	−31−82	.77	.21
Trial 4	5.70	14.05	−29−55	.29	.32
Trial 5	7.05	15.39	−23−53	.58	.04
Trial 6	9.46	15.44	−31−52	.35	−.35
General mental ability	0.00	1.00	−2.51−2.38	.08	−.59
Verbal analogies	12.22	3.88	2−20	−.15	−.81
Folding boxes	13.02	4.31	3−19	−.34	−.64
Number series	10.96	4.79	0−20	−.07	−.52

Note. $N = 184$. Kurtosis = standardized fourth-order moment −3.

to the normative samples of the standardized measures. In the present sample, the means for the three ability tests (see Table 3.3) were higher than in the actual German normative sample for the three tests. However, the standard deviations were quite similar for all three tests so that no considerable range restriction existed in the data. For the verbal analogies test, the mean in the current study was $M = 12.21$ and the standard deviation was $SD = 3.89$. In contrast the normative data obtained by Kersting et al. (in press) had a considerable lower mean of $M = 7.88$ with the standard deviation being comparable at $SD = 3.98$. For the number series test, participants in the present study solved $M = 10.99$ items on average with a standard deviation of $SD = 4.77$. Kersting et al.'s sample solved only $M = 8.93$ items. Nevertheless, the standard deviation was slightly lower at $SD = 4.41$. Finally, for the folding boxes test, the mean in the current study was $M = 13.04$ with the standard deviation being $SD = 4.31$ compared to a mean of $M = 9.32$ and a standard deviation of $SD = 4.47$ in the normative sample of the test (Kersting et al., in press).

Means and standard deviations of the TankSoar measurement series are able to provide first evidence whether the general pattern of change is in line with results from previous task-change paradigm studies (e.g., Bröder & Schiffer, 2006) using multiple measurement occasions in the pre- and the post-change period. As indicated by Table 3.3, there was evidence of changes in performance across time, which is typically found in research on adaptation to change (e.g., Bröder & Schiffer, 2006), with pronounced increases in mean performance during the skill acquisition period between Trial 1 and Trial 3, a strong decrease in performance following the change from Trial 3 to Trial 4, and moderate increases during the reacquisition period from Trial 4 to Trial 6.

Intercorrelations

Correlations between study variables are provided in Table 3.4 (for scatterplots of each relationship see Appendix A, Figure A.7). As indicated by the correlations between the measurement occasions of the TankSoar task, rank-order performance appeared to be moderately instable across the three measurement occasions of skill acquisition and reacquisition adaptation. In both the skill acquisition period as well as the reacquisition adaptation period, there was some evidence of a simplex pattern (P. L. Ackerman, 1987; Ployhart & Hakel, 1998; Ployhart, Holtz, & Bliese, 2002) indicating dynamic change over time. As proposed by the idea of simplex patterns, proximate measurement occasions (for skill acquisition: Trial 1–Trial 2 and Trial 2–Trial 3; for reacquisition adaptation: Trial 4–Trial 5 and Trial 5–Trial 6) were more highly correlated than distant occasions in both periods (Trial 1–Trial 3 and Trial 4–Trial 6, respectively) indicating dynamic changes over time.

As mentioned, an important precondition to test the hypothesis and research question under study regarding change in the relationship between GMA and performance is that a considerable relationship between GMA and performance actually exists in the data. Table 3.4 shows that general mental ability was moderately correlated with performance at all six measurement occasions. Thus, this precondition was met justifying further analyses regarding GMA and adaptability.

Table 3.4. Intercorrelations of Study Variables

Variable	1	2	3	4	5	6	7	8	9
1. Trial 1	–								
2. Trial 2	.72	–							
3. Trial 3	.69	.79	–						
4. Trial 4	.59	.71	.69	–					
5. Trial 5	.58	.66	.75	.66	–				
6. Trial 6	.58	.61	.63	.63	.69	–			
7. General mental ability	.34	.39	.31	.26	.31	.27	–		
8. Verbal analogies	.17	.20	.14	.12	.19	.15	.74	–	
9. Folding boxes	.32	.38	.35	.32	.33	.30	.73	.29	–
10. Number series	.27	.27	.20	.14	.17	.15	.74	.32	.30

Note. $N = 184$. For two-sided tests, $p < .05$ at $|r| = .15$. For one-sided tests, $p < .05$ at $|r| = .13$.

3.4.2. Model Building and Model Evaluation

Analyses to determine the amount of nonindependence (Step 1) revealed an ICC1 = .59, indicating that individual properties explained 59% of the variance in performance across time. This value suggests a relatively high level of individual differences in change (Bliese, 2000) and confirms the previously offered interpretation of the data's correlation matrix as indicating dynamic changes in performance over time.

In the next step (Step 2), I added level-1 change variables to the model in order to examine the effects of level-1 change variables on performance. Analyses of these effects revealed that all level-1 change variables in the discontinuous mixed-effects model of the study significantly explained variability in the change pattern over time. Specifically, there was a significant amount of skill acquisition during the pre-change period, a significantly negative transition adaptation effect indicating that performance dropped from the pre-change to the post-change period, and a significantly flatter reacquisition adaptation slope during the post-change period relative to the skill acquisition slope during the pre-change period (see Table 3.5 for parameter estimates of the final model, which were similar to the parameter estimates of the starting model). Thus, this pattern of change was similar to the theoretical pattern found in previous task-change research (e.g., Bröder & Schiffer, 2006) and considered in the conceptual introduction of the discontinuous growth modeling framework.

Tests for random variation in the level-1 change variables between persons (Step 3) provided evidence for a significant amount of random variability in the skill acquisition effect ($\chi^2_{diff}[4] = 68.48$, $p < .001$), the transition adaptation effect ($\chi^2_{diff}[4] = 102.40$, $p < .001$), and the reacquisition adaptation effect ($\chi^2_{diff}[4] = 36.22$, $p < .001$). Thus, there was no evidence for a considerable amount of over-parameterization in the random effects of the model, and none of the three random effects of the level-1 change variables were fixed to zero (see Table 3.6 for parameter estimates for the final model, which were similar to the parameter estimates of the starting model).

Contrasting of models with and without autocorrelation and heteroscedasticity in the error structure in Step 4 revealed no evidence for a considerable amount of autocorrelation ($\chi^2_{diff}[1] = 0.55$, $p = .459$) and no evidence for heteroscedasticity ($\chi^2_{diff}[1] = 0.02$, $p = .875$). Consequently, the level-1 change model was not modified to account for autocorrelation and heteroscedasticity.

After determining the level-1 change model in Step 2 to Step 4, in Step 5, I added GMA as a level-2 predictor of the intercept (basal task performance), the skill acquisition effect, the transition adaptation effect and the reacquistion adaptation effect to the model. Before I interpreted the findings with respect to the hypothesis and research question of the present study, I examined the tenability of mixed-effects model assumptions for the final discontinuous mixed-effects model resulting from the model building procedures and including GMA as a level-2 predictor (Step 6).

Visual inspection of the shape assumption for the intraindividual change patterns (level 1) revealed that empirical change patterns showed only small deviations from the predicted change patterns (see Appendix B, Figure B.1). Thus, the discontinuous change model provided an adequate approximation of the empirical change patterns justifying the shape assumption for level 1. For level 2, the relationship between

Table 3.5. Fixed Effects for a Discontinuous Mixed-Effects Growth Model Predicting Change in Performance as a Function of General Mental Ability

	Standardized		Unstandardized				
Fixed Effects	Coef.	*SE*	Coef.	*SE*	*df*	*t* test	*p*
Final level 1 model (mean change pattern)							
(Intercept)			−4.68	1.03	914	−4.52	<.001
Skill acquisition (SA)	.63	.06	6.38	.58	914	10.95	<.001
Transition adaptation (TA)	−.25	.04	−8.93	1.48	914	−6.05	<.001
Reacquisition adaptation (RA)	−.20	.03	−4.49	.77	914	−5.83	<.001
Final level 2 model (individual differences in change)							
General mental ability (GMA)	.32	.06	5.61	1.04	182	5.41	<.001
SA × GMA	.08	.06	.80	.58	914	1.37	*ns*
TA × GMA	−.12	.04	−4.06	1.48	914	−2.74	.006
RA × GMA	−.02	.03	−.54	.77	914	−0.70	*ns*

Note. $N = 184$. $k = 1104$. Model deviance= 8507.37. The origin of time for the level-1 change variables was placed at Trial 1 so that the intercept reflects baseline performance at Trial 1. GMA was centered at the sample mean so that estimates for the change variables reflect the mean change pattern for the sample. Standardized coefficients were derived by setting the standard deviation of all variables to 1. Coef. = Coefficient.

Table 3.6. Random Effects for a Discontinuous Mixed-Effects Growth Model Predicting Change in Performance as a Function of General Mental Ability

		Standardized		Unstandardized		Correlations		
	Random Effects	Variance	*SD*	Variance	*SD*	1	2	3
1.	(Intercept)			137.13	11.71	–		
2.	Skill acquisition (SA)	.25	.50	26.49	5.15	.47	–	
3.	Transition adaptation (TA)	.14	.37	173.86	13.19	−.73	−.92	–
4.	Reacquisition adaptation (RA)	.07	.26	37.40	6.12	−.38	−.92	.89
	Residual	.23	.48	71.81	8.47			

Note. $N = 184$. $k = 1104$. Model deviance= 8507.37. Standardized coefficients were derived by setting the standard deviation of all variables to 1. Coef. = Coefficient.

OLS-estimated change parameters and GMA revealed no considerable deviations from bivariate linearity (see Appendix B, Figure B.2), also justifying the shape assumption for level 2.

Graphical examinations, as well as skewness and kurtosis statistics used to evaluate the normality assumption of the level-1 residuals (within-group errors) and the level-2 residuals (random effects), provided evidence that both level-1 and level-2 residuals were approximately normally distributed (see Appendix B, Figure C.2 to Figure C.7). Skewness and kurtosis statistics confirmed this evaluation with all statistics being considerably lower than the cutoff values of skewness$> |2|$ and kurtosis$> |7|$ proposed by West et al. (1995). Values of skewness were 0.20 for the within-group residuals, 0.84 for the intercept (basal task performance) random effects, -0.81 for the transition adaptation random effects, .71 for the skill acquisition random effects, and -0.80 for the reacquisition adaptation random effects. Kurtosis statistics yielded kurtosis values of .62 for the within-group errors, .63 for the intercept (basal task performance) random effects, .76 for transition adaptation random effects, .77 for the skill acquisition random effects, and 1.10 for the reacquisition random effects.

Evaluations of the homoscedasticity assumption also yielded no substantial evidence that the model was not adequate in terms of model assumptions. Variability of level-1 residuals was approximately equal across all measurement occasions (see Appendix B, Figure B.9) confirming the formal test of the model's error structure conducted in Step 4. Correspondingly, plots contrasting level-2 residuals with GMA scores also provided no evidence for systematic changes in variability (see Appendix B, Figure B.10).

In sum, checks of the model's assumptions provided no evidence that model assumptions were violated. The shape assumption, the normality assumption, and the homoscedasticity assumption for both the level-1 and the level-2 residuals were tenable.

3.4.3. Hypothesis and Research Question

Given that Step 6 revealed that the model's assumptions were tenable for the final mixed-effects model, the hypothesis and the research question of the current investigation could be evaluated using the final model (Step 7). Results for the final discontinuous mixed-effects model are presented in Table 3.5 and Table 3.6.

As indicated by Table 3.5, the study's hypothesis concerning the relationship between GMA and transition adaptation was confirmed by a significant negative relationship between GMA and transition adaptation indicating that individuals with a higher GMA were less adaptable in terms of transition adaptation. The model predicted that the performance of persons with a general mental ability of one standard deviation above the sample mean dropped by approximately two fifth of a standard deviation from the last pre-change measurement occasion to the first post-change measurement occasion ($-.39$ standard deviation units), whereas the performance of individuals with a GMA of one standard deviation below the sample mean dropped only by about one seventh of a standard deviation ($-.15$ standard deviations units).

Concerning the research question of the current investigation regarding reacquisition adaptability, results showed no evidence for a relationship between GMA and reacquisition adaptation indicating that persons with a high GMA were not faster in reacquiring mastery of the task following the initial drop in performance after the change in the present study (see Table 3.5). To make sure that the missing relationship between GMA and reacquisition adaptation was not attributable to low power (Cohen, 1992), I conducted a post-hoc power analysis using the procedures outlined by Hox (2002). Results revealed that the probability to detect a moderate effect of .30 with a two-sided test was 1.00, and the power to detect a small effect of .10 with a two-sided test was .84. Given that the probability to detect even a small effect exceeds the minimum power of .80, demanded in the literature (Cohen, 1992), indicates that the missing significant finding was not simply attributable to low power.

The study's findings with respect to adaptability are illustrated and summarized in Figure 3.5. Figure 3.5 graphs the effects of GMA on the overall change pattern of individuals by using the model parameters in Table 3.5 to estimate predicted performance at each measurement occasion for persons with a high (one standard deviation above the sample mean) and low (one standard deviation below the sample mean) GMA, contrasted with predicted performance for persons scoring at the sample mean of GMA. As indicated by Figure 3.5, individuals with a high GMA performed at a higher level across the whole time period captured by the study. Because individuals with high GMA had a lower level of transition adaptation ($-.39$ at one standard deviation above the sample mean of GMA, see above), their performance declined more strongly in the transition from Trial 3 to Trial 4 than for individuals with low GMA ($-.15$ at one standard deviation above the sample mean of GMA, see above). As individuals with a high GMA and a low GMA did not differ in their levels of reacquisition adaptation, high-GMA individuals were not able to make up for this performance decline in the post-change period from Trial 4 to Trial 6.

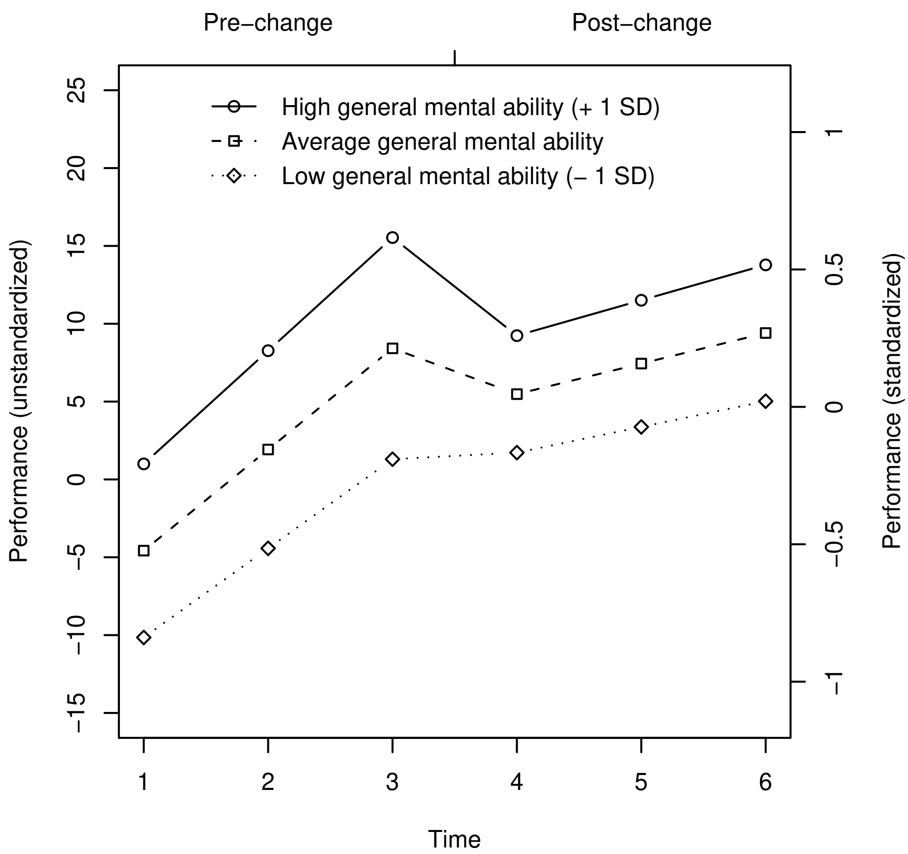

Figure 3.5. Predicted performance as a function of general mental ability.

In sum, the findings of the present study confirmed the undirected hypothesis that GMA is related to transition adaptation with a negative relationship between GMA and transition adaptation. With respect to the research question investigating a relationship between GMA and reacquisition adaptation, no evidence for a relationship between GMA and reacquisition adaptation was found even though the statistical power of the analysis would have been sufficient to detect even a small effect and relevant model assumptions were tenable.

4. Discussion

The present dissertation makes a number of conceptual, methodological, and empirical contributions to adaptability research. Conceptual contributions include an effort to address inconsistencies in the adaptability literature by proposing to differentiate two types of adaptation—namely transition adaptation and reacquisition adaptation—from each other as well as two neighboring components—skill acquisition and basal task performance. Methodological contributions focus on a discontinuous growth modeling approach allowing researchers to separate these frequently confounded constructs from each other. Finally, empirical contributions include a study on the relationship between GMA and the two types of adaptation drawing on the conceptual distinctions and the outlined methodological approach. In the following sections, I discuss these contributions in more detail with respect to theoretical and practical implications, limitations as well as avenues for future research.

4.1. Transition Adaptation, Reacquisition Adaptation, Skill Acquisition, and Basal Task Performance

4.1.1. Summary

Two major issues in research on adaptability are (a) to narrowly and precisely define and operationalize adaptive processes while (b) to clearly distinguish adaptation from other types of performance. In an effort to address these issues, I propose to differentiate two different types of adaptation from both skill acquisition and basal task performance. The first type of adaptation—transition adaptation—refers to an individual's ability to avoid immediate performance loss following environmental changes, whereas the second type of adaptation—reacquisition adaptation—denotes an individual's ability to recover from the initial performance loss by learning the changed task over time. Skill acquisition and basal task performance are processes occuring in any type of task performance and are also affecting performance in changing situations. I suggest that separating these four performance components is a fruitful way to overcome inconsistencies in the definition and operationalization of adaptation and to foster a deeper understanding of the adaptability process. Specifically, separating the two types of adaptation is crucial to derive adequate predictions of behavior. Not distinguishing adaptation from basal task performance and skill acquisition results in conceptual problems because researchers run the risk of interpreting ordinary types of task performance as indicating adaptability.

Separating the four proposed performance components from each other is a methodologically challenging enterprise, which cannot be accomplished using common data-analytic techniques. The present dissertation demonstrates how this goal can be accomplished by applying discontinuous growth modeling—a specific type of multilevel mixed-effects models, which makes use of multiple change variables. The proposed approach allows researchers to separate transition adaptation and reacquisition adaptation from each other while also accounting for skill acquisition and basal task performance. Furthermore, this approach allows researchers to test the influence of experimental and non-experimental predictors on the four different performance processes.

4.1.2. Implications

The conceptual distinction between transition adaptation, reacquisition adaptation, skill acquisition, and basal task performance has important theoretical and practical implications for researchers. From a theoretical perspective, the proposed definitions of transition adaptation and reacquisition adaptation are considerably narrower than previous definitions of adaptation. On the one hand, an adoption of these definitions in the literature might narrow the scope of adaptation research. On the other hand, the proposed conceptualizations allow researchers to communicate more precisely what type of process is exactly meant when they talk about adaptation. Thus, adaptation research might benefit from the adoption of the proposed definitions by fostering precision and subsequent falsifiability of theoretical hypotheses. From a practical perspective, a particularly important advantage of the proposed definitions is that they are closely linked to methodological operationalizations. Therefore, it might be easier for researchers to conduct studies on antecedents and environmental conditions influencing the individuals' ability to show particularly high or low levels of transition adaptation and reacquisition adaptation. These influence factors on the individuals' adaptability may then in turn be used for improving or restructuring workplace processes and procedures.

4.2. General Mental Ability and Adaptation

4.2.1. Summary

The reported empirical study on the relationship between GMA and adaptation draws on the proposed conceptual distinctions and used the methodological approach suggested here to study adaptation. Study goals were (a) to test contradictory arguments in the literature proposing either a positive or a negative association between concepts similar to what I refer to as transition adaptation and (b) to investigate the relationship between GMA and reacquisition adaptation as a research question. Results provide evidence for a negative relationship between GMA and transition adaptation indicating that individuals with a high general mental ability are less able to avoid performance loss following change than individuals with a low GMA. Furthermore, the study provides no evidence that reacquisition adaptation is predicted by GMA. Instead, individuals with a high GMA relearned the task at approximately the same rate as their ordinary skill acquisition rate in the initial task.

4.2.2. Current Findings and Previous Research

To the author's knowlegde the present study is the first to test the relationship between performance measures of adaptation while separating different types of adaptation based on conceptual aspects of the adaptation process and simultaneously accounting for skill acquisition and basal task performance. The finding of a negative relationship between GMA is in line with (a) theoretical ideas from research on transfer (Goska & Ackerman, 1996; A. M. Sullivan, 1964) when adaptation is considered a specific type of near transfer, (b) evidence from research on complex task performance suggesting that persons with a higher GMA tend to perform complex tasks at a higher level (e.g., Yeo & Neal, 2004), and (c) research on expert performance proposing that skilled performance is more fragile than performance at lower levels of skill (Huguenard et al., 1990). The finding contradicts previous theoretical propositions (Hunter & Schmidt, 1996; LePine et al., 2000) in that individuals with a higher GMA are more able to adapt to environmental changes. The present study suggests that this is not the case when both the basal task performance and skill acquisition of individuals are considered.

The negative relationship between GMA and transition adaptation might appear counterintuitive at first glance. However, it is important to note that I conceptualized transition adaptation relative to both skill acquisition and basal task performance. At any point during both the pre-change and the post-change period, the final discontinuous growth model of the study predicted a higher performance for individuals with a higher GMA. The negative transition adaptation effect for GMA refers only to individuals' relative change in performance across time. Thus, the finding does not contradict the general notion in the literature that high-GMA individuals are superior in dealing with nearly any type of life situation (Gottfredson, 1997b, 2004; Lubinski, 2004; Schmidt & Hunter, 2004). In general, I do not want to imply that high GMA is in any way detrimental. Rather, the current study primarily provides evidence that high performance—even when it is only slightly routinized through a limited amount of practice—can be fragile and will typically not be maintained when changes occur.

4.2.3. Proposed Framework and Current Findings

From a more general perspective, the study demonstrates that the conceptual distinctions and the proposed discontinuous growth modeling framework offer a promising new way to gain deeper insights into how individuals adapt to changes. The discontinuous growth modeling framework allowed me to exactly determine which performance components changed and which did not change. This would not have been possible with common data-analytic techniques. If I had adapted a common methodology (i.e., multiple regression) in studying change by using the mean performance in the complete post-change period and controlling for mean pre-change performance, conclusions would have been considerably different. A supplementary analysis revealed that such an methodological approach would have yielded no effect of GMA on post-change performance ($\beta = .01$, $p = .78$). Thus, if I had regarded post-change performance to be adaptive performance (controlling for mean pre-change performance), I would have concluded that GMA does not influence adaptive performance. In contrast, if I had used the post-change performance without controlling for pre-change performance, I would have concluded that there is a huge influence of GMA on adaptive performance ($\beta = .32$, $p < .01$). Finally, if I had used simple change scores, I would have found a small negative relationship between GMA and adaptive performance ($r = -.10$, $p < .10$). It might be quite obvious from these contradictory conclusions that none of these approaches is able to adequately describe and analyze the change pattern found in adaptability research and replicated in the present study, because none of these approaches is able to separate the four different components influencing performance in the task-change paradigm. As a result, concise conclusions regarding adaptive performance cannot be derived using these common data-analytic approaches.

4.2.4. Implications

The present finding of a negative relationship between GMA and transition adaptation might have important practical implications for the prediction of individual performance in a variety of settings of occupational and everyday life. Despite the effect size of the relationship between GMA and transition adaptation at .12 is only slightly stronger than what is considered a small effect (.10) in the nomenclatur proposed by Cohen (1992, see also Hox, 2002), this small effect is probably practically important. It is well documented in the literature that even small interaction effects between non-experimental continuous variables should be considered practically relevant as these types of interactions are typically difficult to detect. Small effect sizes are usually the result of a much stronger “true” interaction (Evans, 1985; McClelland & Judd, 1993). Even though mixed-effects models may slightly improve upon this problem (Davison, Kwak, Seo, & Choi, 2002), most sources of the problem result from data characteristics and thus cannot be solved using refined data-analytic methods. Thus, the interaction effect between GMA and reacquisition change should be considered practically relevant. Given that the effect is generalizable, it implies that, for example, in occupational decision-making settings, persons with a high GMA should show stronger performance losses when they are confronted with changes requiring tranisition adaptation. This might be the case when the nature of markets undergo a rapid transformation process, the attitudes of their customers shift or technological development leaps while they are performing their jobs.

This effect might span beyond the individual level to the prediction of performance at higher levels (i.e., team and organizational level). Even though lower-level constructs and processes do not necessarily generalize to aggregated constructs (Bliese, 2000), previous research on the influence of average GMA on the performance of higher-order units like teams (Edwards, Day, Arthur, & Bell, 2006; "Team Effectiveness: Beyond Skills and Cognitive Ability", 1999) or even nations (Templer & Arikawa, 2006) has typically found equal or even higher effect sizes. Thus, it seems likely that findings will generalize to the performance of higher-level units. Consequently, a company working with a smaller number of well-paid high-ability employees performing at high levels is likely to be more vulnerable to unforeseen environmental changes than a hypothetical company with equal organizational effectivity but working with a large number of employees performing at mediocre levels, given that the organizational effectiveness is not influenced by the size of a company or company size is controlled.

These implications are particularly interesting as there is a growing trend in organizations to occupy only high-skilled employees (Hunt & Madhyastha, 2006; "IQ Mismatch", 2007), which has started in the early 2000s (Greenspan, 2000; Marshall, 2000). This trend is triggered by the expansion of computer and information technology as a certain skill level is required to perform these kinds of jobs (Greenspan, 2000; Marshall, 2000). If the results of the current investigation are generalizable to the occupational world, this would mean that not only the frequency of adaptive situations will increase due to the increasing dynamical nature of modern work environments (Gowing et al., 1998; Howard, 1995b; Patterson, 2001) but also the amount of negative impact of changes on organizational performance will increase due to the the growing trend to occupy only high-skilled employees who are able to master the complexity of modern jobs (and as suggested by the current findings are less adaptable). As a result, given that these predictions hold, organizational problems regarding adaptation will potentially increase in the near future.

4.3. Limitations

The present dissertation has several limitations regarding the generalizability of the empirical findings and a limitation regarding the consideration of quadratic change in discontinuous mixed-effects models. In the following sections, I discuss each of these limitations in detail and offer additional analyses regarding quadratic change.

4.3.1. Generalizability

An important limitation of the present research is that the findings of the reported study may lack generalizability with respect to (a) the type of task, (b) the type of unforeseen change, and (c) sample characteristics.

With respect to the type of task under study, the current findings can only be reasonably expected to generalize to tasks with similar task characteristics—such as those that allow for changes in performance over time, that are complex, cognitively demanding and do not incorporate time pressure. Despite these task characteristics may be respresentative for work tasks consuming the majority of time in many jobs in the world of work, there are numerous tasks and jobs with fundamentally different characteristics.

Concerning the type of unforeseen change, the current findings are restricted to unforeseen changes with similar characteristics—such as those that incorporate an increase in task complexity stemming from a variety of unobvious changes in the task. Complexity increases are considered characteristic for adaptive situations in the majority of jobs in recent years (e.g., Chen et al., 2005; Kozlowski et al., 2001; LePine et al., 2000; LePine, 2003, 2005; Marks et al., 2000). However, even modern technological changes as inventions of computer technology may not always lead to complexity increases. Particularly in low-skilled and low-payed work, computer technology sometimes leads to a decrease in complexity. For example, Patrickson (1986) investigated the implementation of an electronic production process in newspaper production and found that two-thirds of tradesman felt that their jobs were deskilled and boring after the invention of the new technology. Naturally, it is not likely that the findings of the present research generalize to these types of jobs.

As a final generalizability issue, the current study employed a rather specific sample. Nevertheless, the sample was more diverse than the samples typically used in laboratory research. Participants were recruited from high-school classes and on the campus of a German university and not simply from psychology undergraduate classes as in most research. Yet, sample characteristics considerably differed from the general population. Particularly, the average GMA of the sample was considerably higher than the average GMA in the general population. However, adaptability issues may be more likely to occur in high-quality and high-skill work so that the sample may be quite representative for the population of employees facing adaptability demands.

4.3.2. Quadratic Change

Another limitation of the present research is that I restricted the descriptions of the discontinuous growth modeling approach and the empirical analyses to linear change models for the periods of skill acquisition and reacquisition adaptation. Thus, these models did not account for quadratic patterns of change in these periods. The reason for deciding to restrict conceptual and methodologial comments and empirical analyses to linear models was (a) to provide readers with a concise and easily comprehensible text, (b) to increase the interpretability of the findings, and (c) to increase model parsimony and robustness. In general, the proposed discontinuous growth modeling approach can be expanded to account for quadratic or even higher-order polynominal change in skill acquisition and reacquisition adaptation.

To do so, an additional quadratic variable would need to be added for skill acquisition, which changes only in the skill acquisition period and then remains constant and is used only for the quadratic term. The coding for this variable in the present study would be 0, 1, 2, 2, 2, and 2 for Trial 1 to Trial 6 (0, 1, 4, 4, 4, and 4 after quadratization). Note that simply adding quadratic change to the skill acquisition variable spanning across the pre-change and the post-change period is not feasible because accounting for quadratic deviation from the overall quadratic pattern of change in transition adaptation is not possible/reasonable as the transition period spans only across two time points (see Snijders & Bosker, 1999). For reacquisiton adaptation, quadratic change in the reacquisition-adaptation change variable can simply be accounted for by adding a quadratic term for this variable. An important disadvantage of this model is that the linear terms change as a function of the quadratic terms so that the linear terms in the model depend on the coding of the change variables. To derive linear terms which are comparable to the linear terms in the model without quadratic change, the change variables for skill acquisition and reacquisition adaptation need to be centered at the middle of the pre-change period and the post-change period, respectively (see Appendix C, Table C.1 for the the full coding scheme of the model).

The expanded model accounting for quadratic change can provide valuable additional information on the type of change in the skill acquisition and reacquisition period when this type of change is of special interest for the study but will typically not alter the basic conclusions with respect to transition and reacquisition adaptation. In fact, in the present study, this type of model yielded largely similar results as the more simple model accounting only for linear change.

Model building procedures for the model revealed that the quadratic skill acquisition change variables had no signficant random variability ($\chi^2_{diff}[4] = 7.40$, $p = .285$). Variability in the quadratic reacquisition adaptation change variable revealed a p-value slightly above the 5%-level ($\chi^2_{diff}[4] = 12.54$, $p = .051$). Because the χ^2-test used to compare the models tends to be slightly conservative (Pinheiro & Bates, 2000), researchers typically retain random variability on the 5%-border in comparable cases (e.g., Britt & Bliese, 2003). I followed this practice with the current model and included random variability for this change variable in the final model. Thus, only the the random effect for quadratic skill acquisition was fixed to zero, while all other random effects in the model were retained. Analyses of the error structure still revealed no heteroscedasticity ($\chi^2_{diff}[1] = 0.69$, $p = .407$) and no autocorrelation ($\chi^2_{diff}[1] = 0.20$, $p = .657$) after the addition of the quadratic level-1 change variables. Evaluation of the tenability of model assumption provided evidence that model assumption were still tenable for the expanded model (see Appendix C, for checks of model assumptions).

Examinations of the final model revealed significant negative quadratic change (unstandardized coefficient$= -1.82$, $p = .014$) in the skill acquisition period as typically found in skill acquisition research (Yeo & Neal, 2004, 2006) and no quadratic change in the reacquisiton period ($p = .289$). Both quadratic change terms were not associated with GMA ($p > .17$). The significance level of the relationship between GMA and transition adaptation (unstandardized coefficient$= -4.01$, $p = .011$) as well as GMA and linear reacquisiton adaptation (unstandardized coefficient= $-.54$, $p = .485$) were basically unaffected.

4.4. Conclusion

The newly introduced conceptual distinctions between transition adaptation, reacquisition adaptation, basal task performance, and skill acquisition and the outlined discontinuous growth modeling approach to operationalize these four processes offer a promising way to study adaptation. The present study on the relationship between GMA and adaptation provides first evidence that the conceptual distinctions and the discontinuous growth modeling approach offer valuable, new, and sharper insights into how individuals react to unforeseen changes.

Given the prominence of adaptability issues in applied settings, future research is needed and worthwhile to arrive at a deeper understanding of adaptability phenomena beyond GMA and the complex type of tasks employed in the current research. One important and easily accomplishable direction for future research is to reconsider and reanalyze previously gathered data also using the proposed discontinuous growth modeling approach.

A second important set of research questions for future studies is to investigate the role of other individual difference variables in transition and reacquisition adaptation when basal task performance and skill acquisition are controlled for. Additionally, these types of analyses should be expanded to field settings as well as to higher level units of analysis like the team and the organizational level.

Finally, a third interesting class of goals for future research is to use the proposed discontinuous growth modeling approach in research studies investigating the influence of environmental characteristic on adaptive performance of individuals, teams, and organizations.

5. Summary

In recent years, the globalization and the rapid emergence of new technologies have increased the complexity and dynamic of work life. Organizations, teams, and individuals face changes in the nature of their markets, as well as fundamental revolutions in technology, at a much higher rate than ever before. In the literature, there is a consensus that for individuals, teams, and organizations to exhibit high performance in this new work environment, the ability to adapt to unforeseen changes is a key factor.

Considering today's importance of adaptation in the occupational world, a growing stream of research has focused on identifying individual differences predicting successful adaptation. The majority of this research is based on the task-change paradigm. The task-change paradigm is an experimental or pseudo-experimental design, where individuals (or teams and organizations) are confronted with a novel and complex task until they achieve some mastery of the task. However, at some point during the skill acquisition process something changes, requiring adaptive behavior. Typically, this change happens unexpectedly for individuals (or teams and organizations). In order to investigate adaptability within the task-change paradigm, researchers are facing two major methodological and conceptual issues. The first issue is how to clearly differentiate adaptive performance from non-adaptive performance. The second issue is how to account for the temporal or process nature of adaptability. Recently, researchers made progress towards resolving each issue separately using modern methods to study change processes. Building on this previous research, the aims of the present dissertation were twofold.

The first aim of the dissertation was to propose a framework, which integrates and extends previous approaches to address these two issues in adaptability research. Methodologically, this framework is based on discontinuous mixed-effects growth modeling techniques. Conceptually, the framework distinguishes between two conceptual types of adaptation (i.e., transition adaptation and reacquisition adaptation), while at the same time controlling for other types of performance in the task not unique to adaptive situations (i.e., basal task performance and skill acquisition). Transition adaptation refers to an immediate loss of performance following a change, whereas reacquisition refers to the ability to relearn a changed task over time. Performance types not unique to adaptive situations include basal task performance—the general level of task performance not changing across time—and skill acquisition—an individual's capability to improve task performance across time.

The second aim of the dissertation was to apply the proposed framework to provide new insights on the relationship between general mental ability (GMA) and adaptive performance at the individual level of analysis. Importantly, competing hypotheses predicting either a positive or a negative relationship between GMA and adaptability can be derived from the literature. To test the competing theoretical ideas, an empirical study (N = 184) was conducted, which used a complex decision-making task. Adaptation was required because of an unforeseen task-change manipulation increasing task complexity following the task-change. Results revealed that GMA was negatively related to transition adaptation (standardized coefficient = .12, p = .006) but not related to reacquisition adaptation. The finding contradicts previously dominating theoretical ideas in adaptability research and has important implications. For example, in occupational decision-making settings, individuals with a high GMA should show stronger performance losses when markets undergo a rapid transformation process, the attitudes of customers shift or technological development leaps. From a more general perspective, the study demonstrates that the conceptual distinctions and the proposed discontinuous growth modeling framework offer a promising new way to gain deeper insights into how individuals adapt to changes.

Keywords: adaptability, general mental ability, intelligence, unforeseen change, discontinuous mixed-effect models

6. Zusammenfassung

Generelle mentale Fähigkeit und zwei Arten von Adaption an unvorhergesehene Veränderungen

In den letzten beiden Jahrzehnten hat sich durch die Globalisierung und den rasanten Vormarsch neuer Technologien die Komplexität und Dynamik des Arbeitslebens erhöht. Wie nie zuvor werden Organisationen, Arbeitsteams und der einzelne Mitarbeiter heutzutage mit immer schnelleren Veränderungen der Märkte sowie fundamentalen technischen Neuerungen konfrontiert. In der Literatur herrscht ein Konsens darüber, dass die Fähigkeit sich schnell an unvorhergesehen Veränderungen anzupassen für ein Schlüsselfaktor ist, damit Individuen, Arbeitsteams und Organisationen in dieser neuen Arbeitsumgebung hohe Arbeitsleistungen erbringen können.

Vor dem Hintergrund der zunehmenden Bedeutung von Adaptionsfähigkeit in der Arbeitswelt beschäftigt sich ein wachsendes Forschungsfeld mit der Identifizierung von individuellen Unterschieden, die erfolgreiche Adaption vorhersagen. Der Großteil dieser Forschung basiert dabei auf dem Aufgabenwechsel-Paradigma. Das Aufgabenwechsel-Paradigma ist ein experimentelles oder pseudo-experimentelles Design, in dem Individuen (oder Teams und Organisationen) mit einer neuen, komplexen Aufgabe konfrontiert werden, bis sie einen gewissen Kompetenzgrad zur Bewältigung der Aufgabe erlangt haben. Dann wird zu einem gewissen Zeitpunkt während der Fähigkeitsaneignungsphase etwas an der Aufgabe geändert, was adaptives Verhalten nötig macht. Typischerweise erfolgt diese Veränderung für die Individuen unerwartet (oder Teams und Organisationen). Bei der Untersuchung von Adaption innerhalb dieses Paradigmas sind Forscher in der Regel mit zwei zugleich konzeptionellen und methodischen Problemen konfrontiert. Das erste Problem ist, dass es notwendig ist adaptive Leistung klar von nicht-adaptiver Leistung abzugrenzen. Das zweite Problem ist in Forschungsdesigns zu berücksichtigen, dass Adaption ein dynamischer Prozess ist. Unlängst haben Forscher Fortschritte bei der Lösung beider Probleme gemacht, indem sie moderne Methoden zur Analyse von Veränderungsprozessen eingesetzt haben. Aufbauend auf dieser Forschung, verfolgte die vorliegende Dissertation zwei Ziele.

Das erste Ziel der Dissertation war es, einen konzeptionellen und methodischen Forschungsansatz vorzuschlagen, der die bisherigen Herangehensweisen an die beiden Hauptprobleme der Adaptionsforschung sowohl integriert als auch erweitert. Methodisch basiert dieser Forschungsansatz auf dem Einsatz von diskontinuierlichen Mischeffektmodellen. Konzeptionell unterscheidet er zwischen zwei unterschiedlichen Arten von Adaption (Übergangsadaption und Wiederaneignungsadaption). Gleichzeitig erlaubt dieser Forschungsansatz nicht-adaptive Leistungskomponenten zu kontrollieren. Die Übergangsadaption bezeichnet den sofortigen Leistungsabfall nach der Einführung der Veränderung, während die Wiederaneignungsadaption sich auf die Fähigkeit bezieht, über die Zeit die veränderte Aufgabe wieder zu erlernen. Leistungskomponenten, die sich nicht speziell auf die adaptive Situation beziehen, beinhalten zum Einen die basale Leistung in einer Aufgabe—das grundlegende Niveau der Leistungsfähigkeit, welches sich nicht über die Zeit verändert—und zum Anderen die Fertigkeitsaneignung—die Fähigkeit eines Individuums seine Leistungen in einer Aufgabe über die Zeit zu verbessern.

Das zweite Ziel der Dissertation war es, diesen neu entwickelten Forschungsansatz zur Anwendung zu bringen und dadurch neue Einblicke in den Zusammenhang zwischen der generellen mentalen Fähigkeit (GMF) und adaptiver Leistung auf der Individualebene zu erlangen. Diese Fragestellung ist bedeutsam, da sich in der Literatur gegensätzliche Hypothesen zu diesem Zusammenhang finden lassen, die entweder eine positive oder negative Beziehung zwischen der GMF und Adaption postulieren. Um diese gegenteiligen theoretischen Annahmen zu testen, wurde eine empirische Studie ($N = 184$) durchgeführt, die eine komplexe Entscheidungsaufgabe nutzte. Adaption wurde in der Studie durch eine unvorhergesehene Aufgabenwechsel-Manipulation notwendig, welche die Komplexität der Aufgabe erhöhte. Die Ergebnisse zeigten, dass die GMF negativ mit der Übergangsadaption zusammenhing (standardisierter Koeffizient = .12, p = .006) aber keinen Zusammenhang mit der Wiederaneignungsadaption in der Aufgabe aufwies. Diese Befunde widersprechen Ideen, die bisher die Adaptionsforschung dominieren, und haben bedeutende Implikationen. Demnach sollten z.B. in beruflichen Positionen, in denen Entscheidungen gefällt werden, Individuen mit hoher GMF einen stärkeren Leistungsabfall vorweisen, wenn etwa Märkte einen schnellen und unvorhergesehenen Transformationsprozess durchlaufen, Kundeneinstellungen umschwingen oder die technische Entwicklung einen Sprung macht. Aus einer generelleren Perspektive betrachtet, demonstriert die Studie, dass die konzeptionellen Unterscheidungen und der vorgeschlagene Forschungsansatz eine vielversprechende neue Möglichkeit darstellen, um zu einem tieferen Verständnis von Adaptionsprozessen zu gelangen.

Schlagwörter: Adaptionsfähigkeit, generelle mentale Fähigkeit, Intelligenz, unvorhergesehene Veränderungen, diskontinuierliche Mischeffektmodelle

References

Ackerman, F., Goodwin, N. R., Dougherty, L., & Gallagher, K. (Eds.). (1998). *The changing nature of work*. Washington, DC: Island Press.

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

Ackerman, P. L., & Beier, M. E. (2006). Determinants of domain knowledge and independent study learning in an adult sample. *Journal of Educational Psychology*, *98*, 366–381.

Ackerman, P. L., Beier, M. E., & Boyle, M. O. (2005). Working memory and intelligence: The same or different constructs? *Psychological Bulletin*, *131*, 30–60.

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

Andrews, P. W., Gangestad, S. W., & Matthews, D. (2002). Adaptationism - how to carry out an exaptationist program. *Behavioral and Brain Sciences*, *25*, 489–553.

Applebaum, H. (1992). *The concept of work: The ancient, medieval, and modern.* Albany, NY: State University of New York Press.

Ashford, S. J. (1986). Feedback-seeking in individual adaptation: A resource perspective. *Academy of Management Journal*, *29*, 465–487.

Ballinger, G. A. (2004). Using generalized estimating equations for longitudinal data analysis. *Organizational Research Methods*, *7*, 127–150.

Bandura, A., & Locke, E. A. (2003). Negative self-efficacy and goal effects revisited. *Journal of Applied Psychology*, *88*, 87–99.

Bates, D. M., & Sarkar, D. (2007). lme4: Linear mixed-effects models using s4 classes (Version 0.9975-13) [Computer software]. Vienna: R Foundation for Statistical Computing. Retrieved March 22, 2007, from `http://cran.r-project.org/`.

Betsch, T., Brinkmann, B. J., Fiedler, K., & Breining, K. (1999). When prior knowledge overrules new evidence: Adaptive use of decision strategies and the role of behavioral routines. *Swiss Journal of Psychology*, *58*, 151–160.

Black, J. S. (1990). Locus of control, social support, stress, and adjustment in international transfers. *Asia-Pacific Journal of Management*, *7*, 1–29.

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

Bliese, P. D., Chan, D., & Ployhart, R. (in press). Multilevel methods and statistics: Emerging issues and future directions. *Organizational Research Methods.*

Bliese, P. D., McGurk, D., Thomas, J. L., Balkin, T. J., & Wesensten, N. (in press). Modeling individual differences in sleep patterns and transitions using discontinuous growth models. *Aviation, Space and Enviromental Medicine.*

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

Bliese, P. D., Wesensten, N. J., & Balkin, T. J. (2006). Age and individual variability in performance during sleep restriction. *Journal of Sleep Research*, *15*, 376–385.

Boeker, W., & Goodstein, J. (1991). Organizational performance and adaptation: Effects of environment and performance on changes in board composition. *Academy of Management Journal*, *34*, 805–826.

Bröder, A., & Schiffer, S. (2006). Adaptive flexibility and maladaptive routines in selecting fast and frugal decision strategies. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *32*, 904–918.

Britt, T. W., & Bliese, P. D. (2003). Testing the stress-buffering effects of self engagement among soldiers on a military operation. *Journal of Personality*, *71*, 245–265.

Bruce, M. M., & Learner, D. B. (1958). A supervisory practices test. *Personnel Psychology*, *11*, 207–216.

Bryk, A. S., & Raudenbush, S. W. (1987). Applications of hierarchical linear models to assessing change. *Psychological Bulletin*, *101*, 147–158.

Bryk, A. S., & Raudenbush, S. W. (1992). *Hierarchical linear models: Applications and data analysis methods.* Newbury Park, CA: Sage.

Burt, C. (1940). *The factors of the mind.* London: University of London.

Burtless, G. (1995). International trade and the rise of earnings inequality. *Journal* *of Economic Literature*, *33*, 800–816.

Calin-Jageman, R. J., & Fischer, T. M. (2007). Behavioral adaptation of the aplysia siphon-withdrawal response is accompanied by sensory adaptation. *Behavioral Neuroscience*, *121*, 200–211.

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

Chan, D. (2000a). Conceptual and empirical gaps in research on individual adaptation at work. In C. L. Cooper & I. T. Robertson (Eds.), *International review of industrial and organizational psychology* (pp. 143–164). Hoboken, NJ: John Wiley & Sons.

Chan, D. (2000b). Understanding adaptation to changes in the work environment: Integrating individual difference and learning perspectives. In G. R. Ferris (Ed.), *Research in personnel and human resources management* (pp. 1–42). Oxford, UK: JAI Press/Elsevier.

Chao, G. T., O'Leary-Kelly, A. M., Wolf, S., Klein, H. J., & Gardener, P. D. (1994). Organizational socialisation: Its content and consequences. *Journal of Applied Psychology*, *79*, 730–743.

Chen, G. (2005). Newcomer adaptation in teams: Multilevel antecedents and outcomes. *Academy of Management Journal*, *48*, 101–116.

Chen, G., Thomas, B., & Wallace, J. C. (2005). A multilevel examination of the relationships among training outcomes, mediating regulatory processes, and adaptive performance. *Journal of Applied Psychology*, *90*, 827–841.

Cohen, J. (1990). Things I have learned (so far). *American Psychologist*, *45*, 1304–1312.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*, 155–159.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). Mahwah, NJ: Erlbaum.

Coovert, M., & Craiger, P. (2000). An expert system for integrating multiple fit indices for structural equation models. *New Review of Applied Expert Systems and Emerging Technologies*, *6*, 39-56.

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

Cronbach, L. J., Schoneman, P., & McKie, D. (1965). Alpha coefficient for stratified-parallel tests. *Educational and Psychological Measurement*, *25*, 291–312.

Curran, P. J. (2003). Have multilevel models been structural equation models all along? *Multivariate Behavioral Research*, *38*, 529–569.

Davison, M. L., Kwak, N., Seo, Y. S., & Choi, J. (2002). Using hierarchical linear models to examine moderator effects: Person-by-organization interactions. *Organizational Research Methods*, *5*, 231–254.

de Leeuw, J., & Kreft, I. G. (2001). Software for multilevel analysis. In A. H. Leyland & H. Goldstein (Eds.), *Multilevel modelling of health statistics* (pp. 187–204). Chichester, UK: John Wiley & Sons.

Deadrick, D. L., Bennett, N., & Russell, C. J. (1997). Using hierarchical linear modeling to examine dynamic performance criteria over time. *Journal of Management*, *23*, 745–757.

Deary, I. J., Whiteman, M. C., Starr, J. M., Whalley, L. J., & Fox, H. C. (2004). The impact of childhood intelligence on later life: Following up the scottish mental surveys of 1932 and 1947. *Journal of Personality and Social Psychology*, *86*, 130–147.

Denrell, J. (2007). Adaptive learning and risk taking. *Psychological Review*, *114*, 177–187.

Denrell, J., & March, J. G. (2001). Adaptation as information restriction: The hot stove effect. *Organization Science*, *12*, 523–538.

DeShon, R. P., Ployhart, R. E., & Sacco, J. M. (1998). The estimation of reliability in longitudinal models. *International Journal of Behavior and Development*, *22*, 493–515.

Dix, J. E., & Savickas, M. L. (1995). Establishing a career: Developmental tasks and coping responses. *Journal of Vocational Behavior*, *47*, 93–107.

Domash, H. (n.d.). *3 keys to by-the-numbers stock-picking.* Retrieved March 9, 2007, from `http://articles.moneycentral.msn.com/Investing/FindHotStocks/3keysToByTheNumbersStockPicking.aspx`.

Edwards, B. D., Day, E. A., Arthur, W., & Bell, S. T. (2006). Relationships among team ability composition, team mental models, and team performance. *Journal of Applied Psychology*, *91*, 727–736.

Evans, M. G. (1985). A monte carlo study of the effects of correlated method variance in moderated multiple regression analysis. *Organizational Behavior and Human Decision Processes*, *36*, 305–323.

Eyring, J. D., Johnson, D. S., & Francis, D. J. (1993). A cross-level units-of-analysis approach to individual differences in skill acquisition. *Journal of Applied Psychology*, *78*, 805–814.

Fey, C. F., & Denison, D. R. (2003). Organizational culture and effectiveness: Can

American theory be applied in Russia? *Organization Science*, *14*, 686–706.

Fiedler, F. E., & Fiedler, J. (1975). Port noise complaints: Verbal and behavioral reactions to airport related noise. *Journal of Applied Psychology*, *60*, 498–506.

Fox, J. (2004). sem: Structural equation models (Version 0.8-2) [Computer software]. Vienna: R Foundation for Statistical Computing. Retrieved March 21, 2005, from `http://cran.r-project.org/`.

Fox, J. (2006). Structural-equation modeling with the sem package in R. *Structural Equation Modeling*, *13*, 465–486.

Frese, M. (2000). The changing nature of work. In N. Chmiel (Ed.), *Introduction to work and organizational psychology: A European perspective* (pp. 425–439). Malden, MA: Blackwell.

Geisinger, K. F. (1994). Cross-cultural normative assessment: Translation and adaptation issues influencing the normative interpretation of assessment instruments. *Psychological Assessment*, *6*, 304–312.

Gelman, A., & Pardoe, I. (2006). Bayesian measures of explained variance and pooling in multilevel (hierarchical) models. *Technometrics*, *48*, 241–251.

Gobet, F., & Waters, A. J. (2003). The role of constraints in expert memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *29*, 1082–1094.

Goldstein, H. (1987). *Multilevel models in education and social research.* Oxford, UK: Oxford University Press.

Goldstein, H. (1995). *Multilevel statistical models.* New York: Halstead Press.

Gonzalez, C., Thomas, R. P., & Vanyukov, P. (2005). The relationships between cognitive ability and dynamic decision making. *Intelligence*, *33*, 169–186.

Goodman, J. (1994). Career adaptability in adults: A construct whose time has come. *The Career Development Quarterly*, *43*, 74–84.

Goska, R. E., & Ackerman, P. L. (1996). An aptitude-treatment interaction approach to transfer within training. *Journal of Educational Psychology*, *88*, 249–259.

Gottfredson, L. S. (1997a). Mainstream science on intelligence: An editorial with 52 signatories, history, and bibliography. *Intelligence*, *24*, 13–23.

Gottfredson, L. S. (1997b). Why *g* matters: The complexity of everyday life. *Intelligence*, *24*, 79–132.

Gottfredson, L. S. (2004). Intelligence: Is it the epidemiologists' elusive "fundamental cause" of social class inequalities in health? *Journal of Personality and Social Psychology*, *86*, 174–199.

Gowing, M. K., Kraft, J. D., & Quick, J. C. (1998). *The new organizational reality: Downsizing, restructuring and revitalization.* Washington, DC: American Psychological Association.

Greenspan, A. (2000, April 11). *The evolving demand for skill.* Speech given at the Department of Labor National Skills Summit, Washington, DC. Retrieved January 25, 2007 from `http://www.dol.gov/_sec/skills_summit/p1s3.htm`.

Greve, H. R. (1999). The effect of core change on performance: Inertia and regression toward the mean. *Administrative Science Quarterly*, *44*, 590–614.

Guilford, J. P. (1956). The structure of intellect. *Psychological Bulletin*, *53*, 267–293.

Guilford, J. P. (1967). *The nature of human intelligence.* New York: McGraw-Hill.

Gustafsson, J. E. (1994). Hierarchical models of intelligence and educational achievement. In A. Demetriou & A. Efklides (Eds.), *Intelligence, mind, and reasoning: Structure and development.* (pp. 45–73). Amsterdam: Elsevier.

Hall, D. T., & Mirvis, P. H. (1995). The new career contract: Developing the whole person at mid-life and beyond. *Journal of Vocational Behavior*, *47*, 269–289.

Hambleton, R. K. (2001). The next generation of the itc test translation and adaptation guidelines. *European Journal ofPsychological Assessment*, *17*, 164–172.

Hesketh, B., & Neal, A. (1999). The changing nature of performance: Implications for staffing, motivation, and development. In D. R. Ilgen & E. D. Pulakos (Eds.), *Technology and performance* (pp. 21–55). San Francisco: Jossey-Bass.

Hollenbeck, J. R., Ilgen, D. R., Sego, D., Hedlund, J., Major, D. A., & Phillips, J. (1995). The multilevel theory of team decision-making: Decision performance in teams incorporating distributed expertise. *Journal of Applied Psychology*, *80*, 292–316.

Holyoak, K. J. (1991). Symbolic connectionsim: Toward third-generation theories of expertise. In K. A. Ericsson & J. Smith (Eds.), *Toward a general theory of expertise* (pp. 301–336). Cambridge, UK: Cambridge University Press.

Horn, J. L. (1994). Theory of fluid and crystalized intelligence. In R. J. Sternberg (Ed.), *The encyclopedia of human intelligence* (Vol. 1, pp. 443–451). New York: Macmillan.

Hornke, L. F. (1999). Benefits from computerized adaptive testing as seen in simulation studies. *European Journal of Psychological Assessment*, *15*, 91–98.

Howard, A. (Ed.). (1995a). *The changing nature of work*. San Francisco: Jossey-Bass.

Howard, A. (1995b). A framework for work change. In A. Howard (Ed.), *The changing nature of work* (pp. 3–44). San Francisco: Jossey-Bass.

Hox, J. (2002). *Multilevel analysis: Techniques and applications.* Mahwah, NJ: Erlbaum.

Hu, L.-t., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods*, *3*, 424–453.

Huguenard, B. R., Prietula, M. J., & Lerch, F. J. (1990). Fragility in expertise: A study in reactive scheduling. *ACM SIGCHI Bulletin*, *21*, 36–40.

Humphreys, L. G. (1962). The organization of human abilities. *American Psychologist*, *17*, 105–120.

Humphreys, L. G. (1979). The construct of general intelligence. *Intelligence*, *3*, 105–120.

Humphreys, L. G. (1985). General intelligence: An integration of factor test, and simplex theory. In B. B. Wolman (Ed.), *Handbook of intelligence* (pp. 201–224). New York: John Wiley & Sons.

Hunt, E., & Madhyastha, T. (2006, December). *The market place for intelligence.* Paper presented at the meeting of the International Society for Intelligence Research, San Francisco, CA.

Hunter, J. E., & Schmidt, F. L. (1996). Intelligence and job performance: Economic and social implications. *Psychology, Public Policy, and Law*, *2*, 447–472.

Ilgen, D. R., & Pulakos, E. D. (1999). *The changing nature of performance: Implications for staffing, motivation, and development.* San Francisco: Jossey-Bass.

Investopedia. (n.d.). *Crashes: The dotcom crash.* Retrieved March 8, 2007, from `http://www.investopedia.com/features/crashes/crashes8.asp`.

IQ mismatch. (2007, January). *Science*, *315*, 21a.

Jensen, A. R. (1998). *The g factor: The science of mental ability.* Westport, CT: Praeger.

Jäger, A. O. (1982). Mehrmodale Klassifikation von Intelligenzleistungen: Experimentell kontrollierte Weiterentwicklung eines deskriptiven Intelligenzstrukturmodells. *Diagnostica*, *28*, 195–225.

Johnson, M. D., Hollenbeck, J. R., Humphrey, S. E., Ilgen, D. R., Jundt, D., & Meyer, C. J. (2006). Cutthroat cooperation: Asymmetrical adaptation to changes in team reward structures. *Academy of Management Journal*, *49*, 103–119.

Judd, C. M., & McClelland, G. H. (1989). *Data analysis: A model-comparison approach.* Orlando, FL: Harcourt Brace Jovanovich.

Kanfer, R., & Ackerman, P. L. (1989). Motivation and cognitive abilities: An integrative/aptitude-treatment interaction approach to skill acquisition. *Journal of Applied Psychology*, *74*, 657–690.

Kersting, M., Althoff, K., & Jäger, A. O. (in press). *Wilde-Intelligenz-Test 2 (WIT-2)* [Wilde-Intelligence-Test 2 (WIT-2)]. Göttingen, Germany: Hogrefe.

Kinicki, A. J., & Latack, J. C. (1990). Explication of the construct of coping with involuntary job loss. *Journal of Vocational Behavior*, *36*, 339–360.

Kozlowski, S. W. J. (1998). Training and developing adaptive teams: Theory, principles, and research. In J. A. Cannon-Bowers & E. Salas (Eds.), *Making decisions under stress: Implications for individual and team training* (pp. 115–153). Washington, DC: American Psychological Association.

Kozlowski, S. W. J., Gully, S. M., Brown, K. G., Salas, E., Smith, E. M., & Nason, E. R. (2001). Effects of training goals and goal orientation traits on multidimensional training outcomes and performance adaptability. *Organizational Behavior and Human Decision Processes*, *85*, 1–31.

Kozlowski, S. W. J., Gully, S. M., Salas, E., & Cannon-Bowers, J. A. (1996). Team leadership and development: Theory, principles, and guidelines for training leaders and teams. In M. Beyerlein, S. Beyerlein, & D. Johnsons (Eds.), *Advances in interdisciplinary studies of work teams: Team leadership* (pp. 253–291). Greenwich, CT: JAI Press.

Köster, I. (2004). *Diagnostik mit Hilfe von TankSoar Szenarien* [Psychological assessment using TankSoar scenarios] (Tech. Rep.). Aachen, Germany: Institute of Psychology, RWTH Aachen University.

Lang, J. W. B., & Kersting, M. (2007). Regular feedback from student ratings of instruction: Do college teachers improve their ratings in the long run? *Instructional Science*, *35*, 187–205.

LePine, J. A. (2003). Team adaptation and postchange performance: Effects of team composition in terms of members' cognitive ability and personality. *Journal of Applied Psychology*, *88*, 27–39.

LePine, J. A. (2005). Adaptation of teams in response to unforeseen change: Effects of goal difficulty and team composition in terms of cognitive ability and goal orientation. *Journal of Applied Psychology*, *90*, 1153–1167.

LePine, J. A., Colquitt, J. A., & Erez, A. (2000). Adaptability of changing task contexts: Effects of general cognitive ability, conscientiousness, and openness to experience. *Personnel Psychology*, *53*, 563–593.

London, M., & Mone, E. M. (1999). Continous learning. In D. R. Ilgen & E. D. Pulakos (Eds.), *The changing nature of performance: Implications for staffing,* *motivation, and development* (pp. 119–153). San Francisco: Jossey-Bass.

Longford, N. (1993). *Random coefficient models.* Oxford, UK: Oxford University Press.

Lovink, G. (2002). After the dotcom crash: Recent literature on internet, business and society. *Cultural Studies Review*, *8*, 130–153. Excerpt retrieved March 8, 2007, from http://www.lib.latrobe.edu.au/AHR/archive/Issue-September-2002/lovink.html.

Lubinski, D. (2004). Introduction to the special section on cognitive abilities: 100 years after Spearman's (1904) "'General intelligence,' objectively determined and measured". *Journal of Personality and Social Psychology*, *86*, 96–111.

Lubinski, D., & Humphreys, L. G. (1997). Incorporating general intelligence into epidemiology and the social sciences. *Intelligence*, *24*, 159–201.

March, J. G. (1996). Learning to be risk averse. *Psychological Review*, *103*, 309–319.

Marks, M. A., Zaccaro, S. J., & Mathieu, J. E. (2000). Performance implications of leader briefings and team-interaction training for team adaptation to novel environments. *Journal of Applied Psychology*, *85*, 971–986.

Marshall, R. (2000, April 11). *Statement from Ray Marshall.* Speech given at the Department of Labor National Skills Summit, Washington, DC. Retrieved January 25, 2007 from http://www.dol.gov/_sec/skills_summit/p1s4.htm.

McArdle, J. J., Ferrer-Caja, E., Hamagami, F., & Woodcock, R. W. (2002). Comparative longitudinal structural analyses of the growth and decline of multiple intellectual abilities over the life span. *Developmental Psychology*, *1*, 115–142.

McClelland, G. H., & Judd, C. M. (1993). Statistical difficulties of detecting interactions and moderator effects. *Psychological Bulletin*, *114*, 376–390.

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

Merriam-Webster. (n.d.). *adapt.* Retrieved February 24, 2007, from `http://www.m-w.com/dictionary/adapt`.

Miller, W. S. (1960). *Technical manual for the Miller Analogies Test.* New York: The Psychological Corporation.

Moon, H., Hollenbeck, J. R., Humphrey, S. E., Ilgen, D. R., West, B., Ellis, A. P., et al. (2004). Asymmetric adaptability: Dynamic team structures as one-way streets. *Academy of Management Journal*, *47*, 681–695.

Morfit, C. (n.d.). *To win, you must adapt.* Retrieved March 9, 2007, from `http://www.golfonline.com/golfonline/tours/britishopen/article/0,17742,1217988,00.html`.

Murphy, K. (1989). Dimensions of job performance. In R. Dillon & J. Pelligrino (Eds.), *Testing: Applied and theoretical perspectives* (pp. 218–247). New York: Praeger.

National Research Council (Ed.). (1999). *The changing nature of work: Implications for occupational analysis.* Washington, DC: National Academies Press.

Noe, R., & Ford, K. J. (1992). Emerging issues and new directions for training research. *Research in Personnel and Human Resource Management*, *10*, 345–384.

Osburn, H. G. (2000). Coefficient alpha and related internal consistency reliability coefficients. *Psychological Methods*, *5*, 343–335.

Patrickson, M. (1986). Adaptation by employees to new technology. *Journal of Occupational Psychology*, *59*, 1–11.

Patterson, F. (2001). Developments in work psychology: Emerging issues and future trends. *Journal of Occupational and Organizational Psychology*, *74*, 381–390.

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

Pinheiro, J. C., Bates, D. M., DebRoy, S., & Sarkar, D. (2005). nlme: Linear and nonlinear mixed effects models (Version 3.1-56) [Computer software]. Vienna: R Foundation for Statistical Computing. Retrieved March 21, 2005, from `http://cran.r-project.org/`.

Ployhart, R. E., & Bliese, P. D. (2006). Individual ADAPTability (I-ADAPT) theory: Conceptualizing the antecedents, consequences, and measurement of individual differences in adaptability. In S. Burke, L. Pierce, & E. Salas (Eds.), *Understanding adaptability: A prerequisite for effective performance within complex environments* (pp. 3–39). Oxford, UK: Elsevier.

Ployhart, R. E., & Hakel, M. D. (1998). The substantive nature of performance variability: Predicting interindividual differences in intraindividual performance. *Personnel Psychology*, *51*, 859–901.

Ployhart, R. E., Holtz, B. C., & Bliese, P. D. (2002). Longitudinal data analysis applications of random coefficient modeling to leadership research. *Leadership Quarterly*, *13*, 455–486.

Pulakos, E. D., Arad, S., Donovan, M. A., & Plamondon, K. E. (2000). Adaptability in the work place: Development of a taxonomy of adaptive performance. *Journal of Applied Psychology*, *85*, 612–624.

Pulakos, E. D., Dorsey, D. W., & White, S. S. (2006). Adaptability in the workplace: Selecting an adaptive workforce. In C. S. Burke, L. G. Pierce, & E. Salas

(Eds.), *Understanding adaptability: A prerequisite for effective performance within complex environments* (pp. 41–71). Oxford, UK: Elsevier.

Pulakos, E. D., Schmitt, N., Dorsey, D. W., Arad, S., Hedge, J. W., & Borman, W. C. (2002). Predicting adaptive performance: Further tests of a model of adaptability. *Human Performance*, *15*, 299–323.

R Development Core Team. (2004). R: A language and environment for statistical computing (Version 2.0.1) [Computer software]. Vienna: R Foundation for Statistical Computing. Retrieved March 21, 2005, from `http://cran.r-project.org/`.

Rasbash, J., & Browne, W. J. (2001). Modelling non-hierarchical structures. In A. H. Leyland & H. Goldstein (Eds.), *Multilevel modelling of health statistics* (pp. 93–105). Chichester, UK: John Wiley & Sons.

Raudenbush, S. W. (2001). Comparing personal trajectories and drawing causal inferences from longitudinal data. *Annual Review of Psychology*, *52*, 501–525.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Thousand Oaks, CA: Sage.

Rich, Y. (1993). Stability and change in teacher expertise. *Teacher and Teacher Education*, *9*, 137–146.

Roberts, J. K., & Monaco, J. P. (2006, April). *Effect size measures for the two-level linear multilevel model.* Paper presented at the annual meeting of the American Educational Research Association, San Francisco, CA. Retrieved September 25, 2006, from `http://www.hlm-online.com/papers/`.

Salas, E., Priest, H. A., Wilson, K. A., & Burke, S. C. (2006). Scenario-based training: Improving military mission performance and adaptability. In A. B.

Adler, C. A. Castro, & T. W. Britt (Eds.), *Military life: The psychology of serving in peace and combat: Vol. 2. operational stress* (pp. 32–53). Westport, CT: Praeger.

Schmidt, F. L., & Hunter, J. E. (1998). The validity and utility of selection methods in personnel psychology: Practical and theoretical implications of 85 years of research findings. *Psychological Bulletin*, *124*, 262–274.

Schmidt, F. L., & Hunter, J. E. (2004). General mental ability in the world of work: Occupational attainement and job performance. *Journal of Personality and Social Psychology*, *86*, 162–173.

Schmitt, N., & Chan, D. (1998). *Personnel selection: A theoretical approach.* Thousand Oaks, CA: Sage.

Schunn, C. D., Lovett, M. C., & Reder, L. M. (2001). Awareness and working memory in strategy adaptivity. *Memory & Cognition*, *29*, 254-266.

Schunn, C. D., & Reder, L. M. (2001). Another source of individual differences: Strategy adaptivity to changing rates of success. *Journal of Experimental Psychology: General*, *130*, 59–76.

Short, J. C., Ketchen, D. J., Bennett, N., & du Toit, M. (2006). An examination of firm, industry, and time effects on performance using random coefficients modeling. *Organizational Research Methods*, *9*, 259–284.

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

Smith, E. M., Ford, J. K., & Kozlowski, S. W. J. (1997). Building adaptive expertise: Implications for training design. In M. A. Quinones & A. Dudda (Eds.), *Training for 21st century technology: Applications of psychological research* (pp. 87–118). Washington, DC: American Psychological Association.

Snijders, T. A. B., & Bosker, R. J. (1994). Modeled variance in two-level models. *Sociological Methods and Research*, *22*, 342–363.

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

Snow, R. E. (1991). The concept of aptitude. In R. E. Snow & D. E. Wiley (Eds.), *Improving inquiry in the social sciences* (pp. 249–284). Amsterdam: Elsevier.

Snow, R. E. (1992). Aptitude theory: Yesterday, today, and tomorrow. *Educational Psychologist*, *27*, 5–32.

Snow, R. E. (1994). A person-situation interaction theory of intelligence in outline. In A. Demetriou & A. Efklides (Eds.), *Intelligence, mind, and reasoning: Structure and developmend* (pp. 11–28). Amsterdam: Elsevier.

Snow, R. E. (1996). Aptitude development and education. *Psychology, Public Policy, and Law*, *3/4*, 536–560.

Snow, R. E., & Lohman, D. F. (1989). Implications of cognitive psychology for educational measurement. In R. L. Linn (Ed.), *Educational measurement* (3rd ed., pp. 263–331). New York: Collier.

Soar Group at the University of Michigan. (2004). *Soar suite 8.5.2* [Computer software]. Retrieved October 10, 2004, from `http://sitemaker.umich.edu/soar/`.

Spearman, C. (1904). "General intelligence", objectively determined and measured. *American Journal of Psychology*, *15*, 201–292.

Sternberg, R. J. (1985). *Beyond IQ: A triarchic theory of human intelligence.* New York: Cambridge University Press.

Sternberg, R. J. (1999). The theory of successful intelligence. *Review of General Psychology*, *3*, 292–316.

Sternberg, R. J. (2003). A broad view of intelligence: The theory of successful intelligence. *Consulting Psychology Journal: Practice and Research*, *55*, 139–154.

Sternberg, R. J. (2004). Why smart people can be so foolish. *European Psychologist*, *9*, 145–150.

Sullivan, A. M. (1964). *The relation between intelligence and transfer*. Unpublished doctoral dissertation, McGill University, Montreal, Canada.

Sullivan, S. E. (1999). The changing nature of careers: A review and research agenda. *Journal of Management*, *25*, 457–484.

Team effectiveness: Beyond skills and cognitive ability. (1999). *Journal of Applied Psychology*, *3*, 376–389.

Templer, D. I., & Arikawa, H. (2006). Temperature, skin color, per capita income, and IQ: An international perspective. *Intelligence*, *34*, 121–139.

Thach, L., & Woodman, R. W. (1994). Organizational change and information technology. managing on the edge of cyberspace. *Organizational Dynamics*, *23*, 30–46.

Thayer, P. W. (1997). A rapidly changing world: Some implications for training systems in the year 2001 and beyond. In M. A. Quinones & A. Dudda (Eds.), *Training for 21st century technology: Applications of psychological research* (pp. 15–30). Washington, DC: American Psychological Association.

Thoresen, C. J., Bradley, J. C., Bliese, P. D., & Thoresen, J. D. (2004). The Big Five personality traits and individual job performance growth trajectories in maintenance and transitional job stages. *Journal of Applied Psychology*, *89*, 835–853.

Thorndike, R. L. (1986). The role of general ability in prediction. *Journal of Vocational Behavior*, *29*, 332–339.

Thurstone, L. L. (1938). *Primary mental abilities.* Chicago: Chicago University Press.

Tucker, L. R. (1971). Relations of factor score estimates to their use. *Psychometrika*, *36*, 427–436.

Vancouver, J. B., & Kendall, L. N. (2006). When self-efficacy negatively relates to motivation and performance in a learning context. *Journal of Applied Psychology*, *91*, 1146–1153.

Vancouver, J. B., Thompson, C. M., Tischner, E. C., & Putka, D. J. (2002). Two studies examining the negative effect of self-efficacy on performance. *Journal of Applied Psychology*, *87*, 506–516.

Vancouver, J. B., Thompson, C. M., & Williams, A. A. (2001). The changing signs in the relationships among self-efficacy, personal goals, and performance. *Journal of Applied Psychology*, *86*, 605–620.

Vernon, P. E. (1950). *The structure of human abilities.* New York: John Wiley & Sons.

Wainer, H. (Ed.). (2000). *Computerized adaptive testing: A primer* (2nd ed.). Mahwah, NJ: Lawrence Erlbaum.

Waller, M. J., & Roberts, K. H. (2003). High reliability and organizational behavior: Finally the twain must meet. *Journal of Organizational Behavior*, *24*, 813–814.

Weinstein, N. D. (1978). Individual differences in reactions to noise: A longitudinal study in a college dormitory. *Journal of Applied Psychology*, *63*, 458–466.

Weiss, S. J. (1984). The effects of transition modules on new graduate adaption. *Research in Nursing and Health*, *7*, 51–59.

West, S. G., Finch, J. F., & Curran, P. J. (1995). Structural equation models with nonnormal variables: Problems and remedies. In R. H. Hoyle (Ed.), *Structural equation modeling: Concepts, issues, and applications* (pp. 56–75). Thousand Oaks, CA: Sage.

Willett, J. B. (1997). Measuring change: What individual growth modeling buys you. In E. Amsel & K. A. Renninger (Eds.), *Change and development: Issues of theory, method, and application* (pp. 213–243). Mahwah, NJ: Erlbaum.

Xu, R. (2003). Measuring explained variation in linear mixed-effects models. *Statistics in Medicine*, *22*, 3527–3541.

Yeo, G. B., & Neal, A. (2004). A multilevel analysis of effort, practice, and performance: Effects of ability, conscientiousness, and goal orientation. *Journal of Applied Psychology*, *89*, 231–247.

Yeo, G. B., & Neal, A. (2006). An examination of the dynamic relationship between self-efficacy and performance across levels of analysis and levels of specificity. *Journal of Applied Psychology*, *91*, 1088–1101.

Zedeck, S., Jackson, S. E., & Summers, E. (1983). Shift work schedules and their relationship to health, adaptation, satisfaction, and turnover intention. *Academy of Management Journal*, *26*, 297–310.

Appendix A. Study Variables: Histograms, Normal Probability Plots, and Scatterplot Matrix

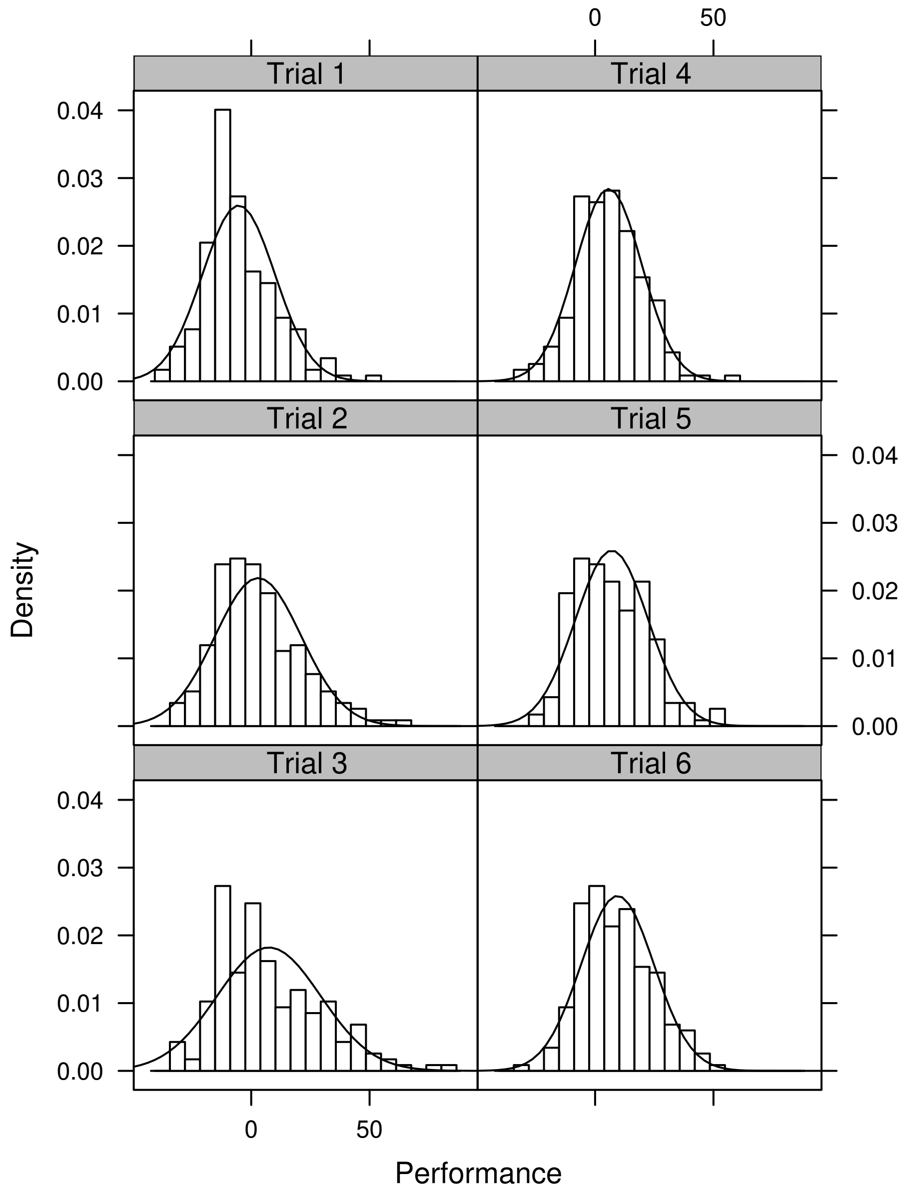

Figure A.1. Histograms for performance at each measurement occasion of the Tank-Soar task.

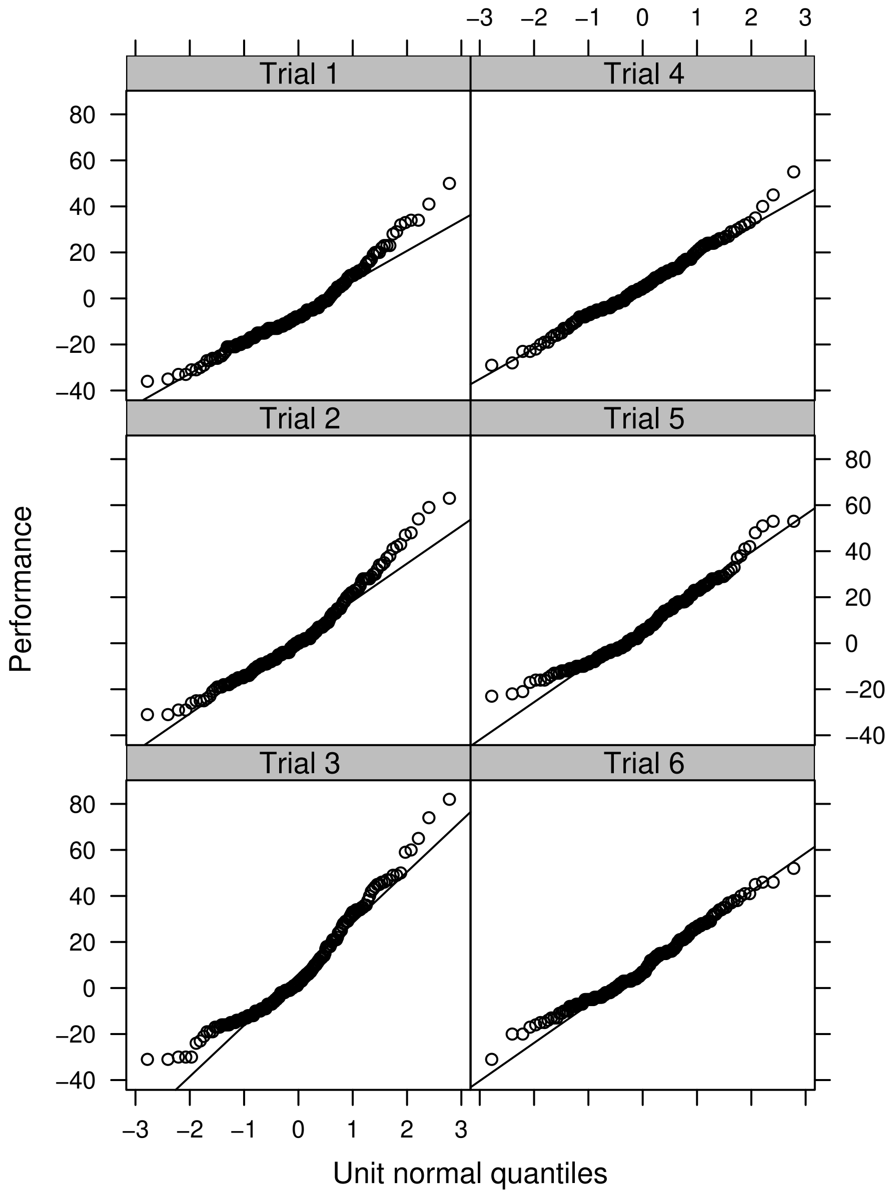

Figure A.2. Normal probability plots for performance at each measurement occasion of the TankSoar task.

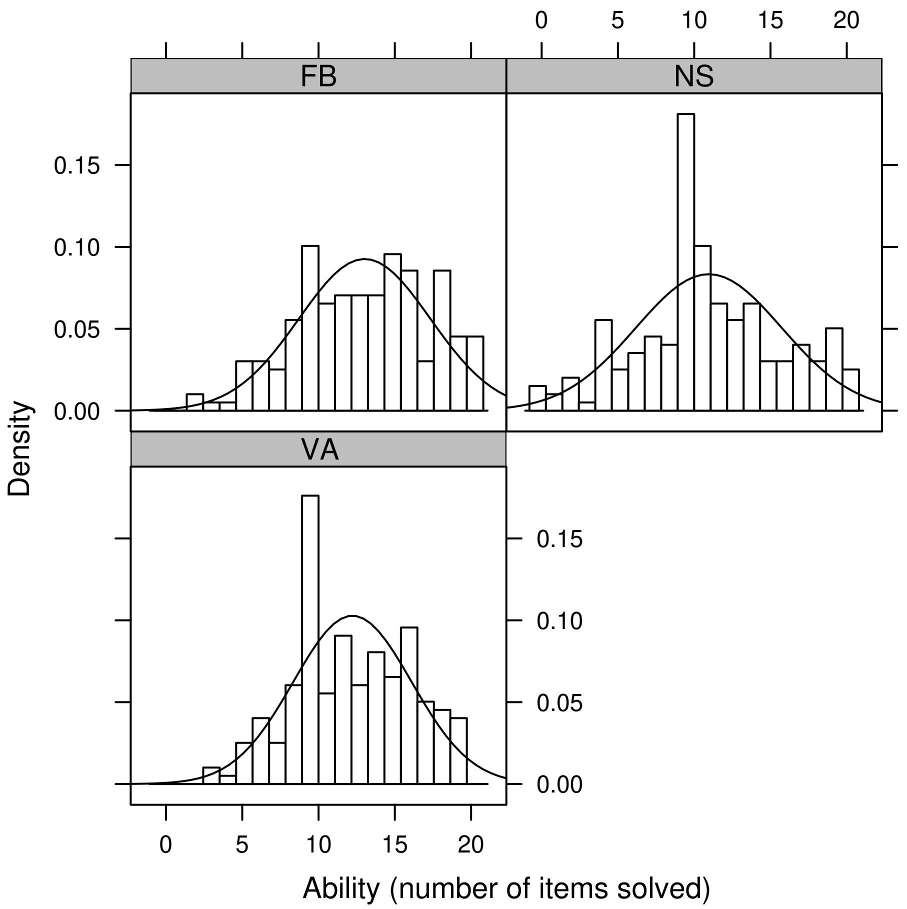

Figure A.3. Histograms of performance distributions for the folding boxes test (FA), the number series test (NS), and the verbal analogies test (VA).

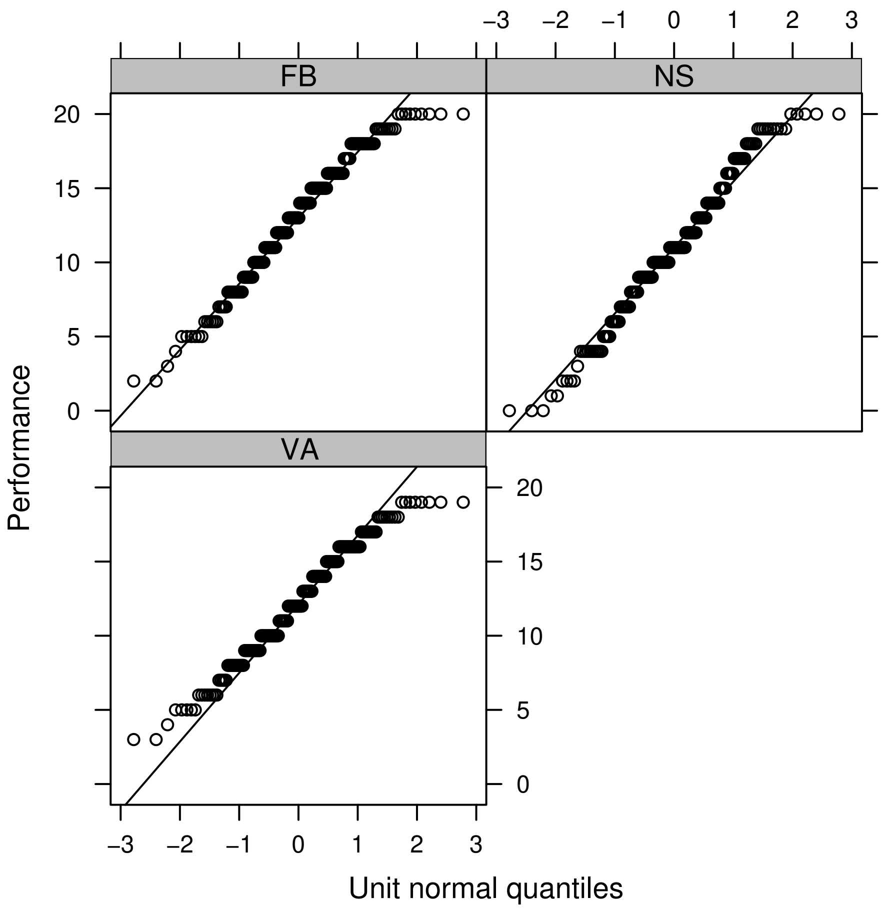

Figure A.4. Normal probability plots of performance distributions for the folding boxes test (FA), the number series test (NS), and the verbal analogies test (VA).

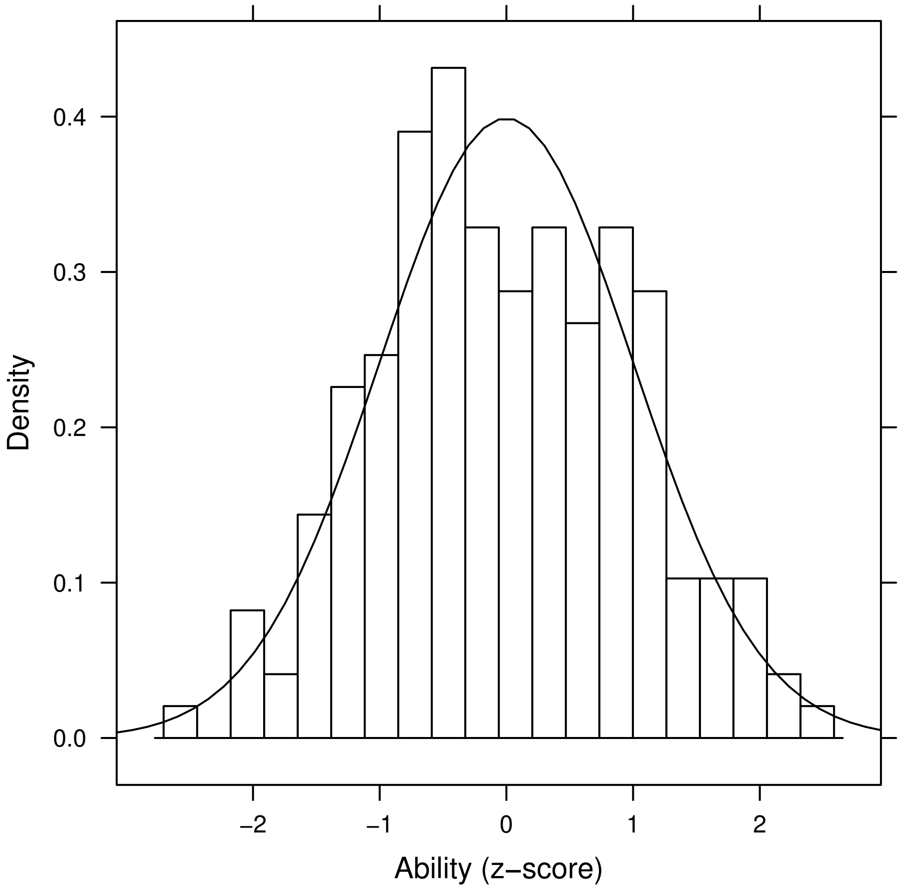

Figure A.5. Histogram graphing the distribution of performance on the composite measure derived from scores on three ability tests and used as an indicator of general mental ability in the study.

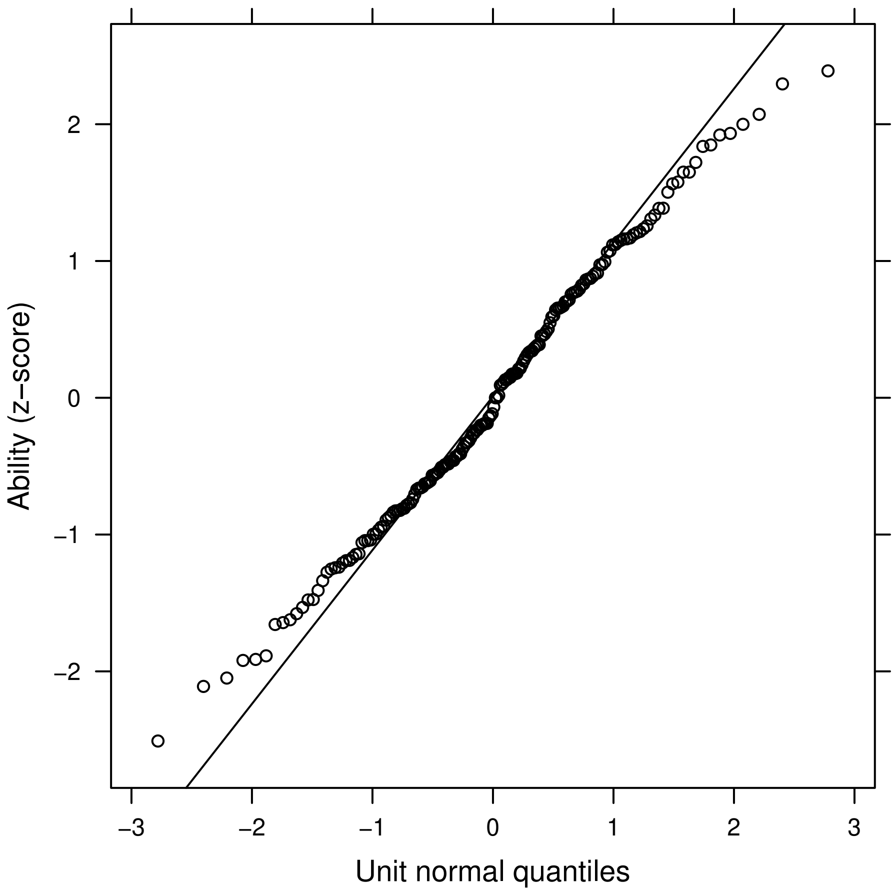

Figure A.6. Normal probability plot graphing the distribution of performance on the composite measure derived from scores on three ability tests and used as an indicator of general mental ability in the study.

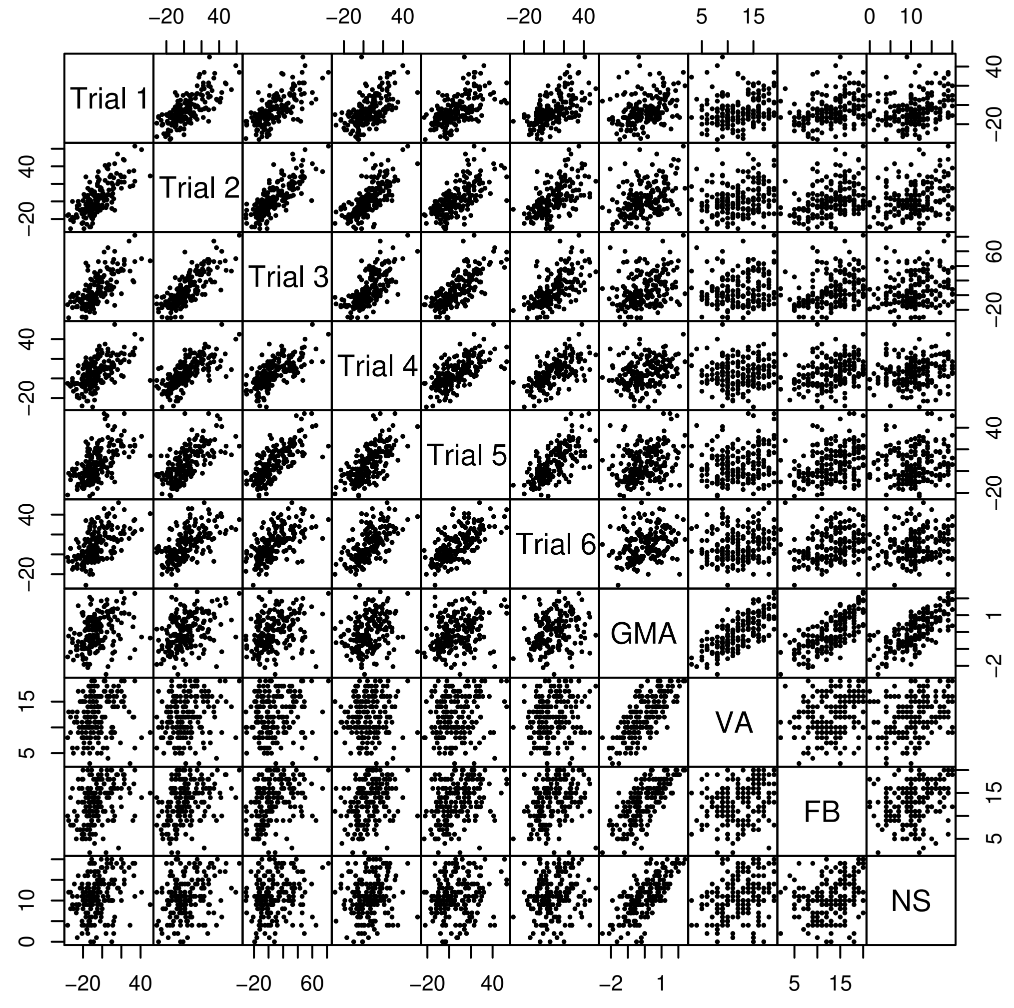

Figure A.7. Scatterplot matrix of study variables.

Appendix B. Discontinuous Mixed-Effects Model: Checks of Model Assumptions

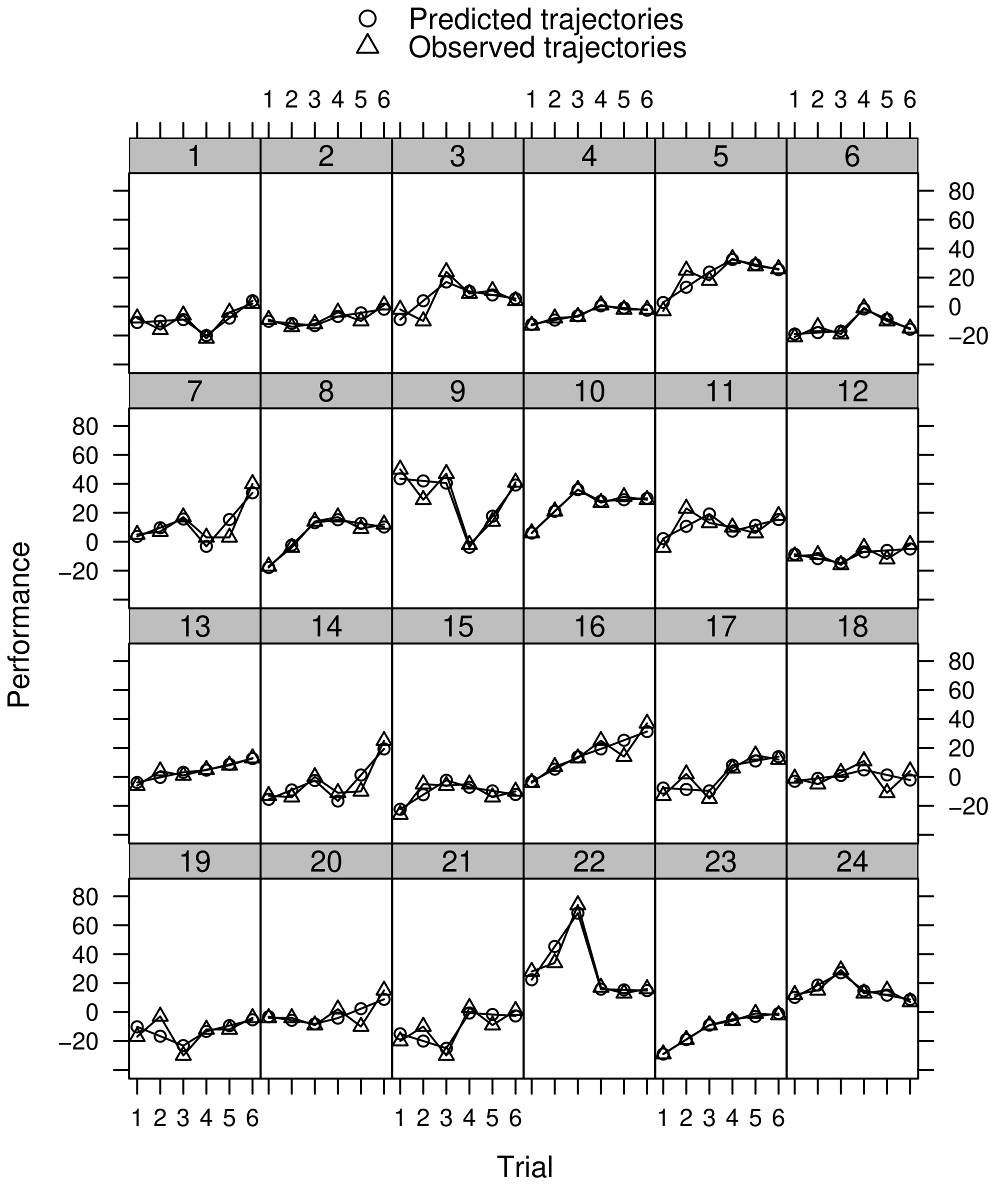

Figure B.1. Evaluation of the shape assumption at Level 1: Empirical change pattern vs. ordinary-least squares regression analysis for each individual.

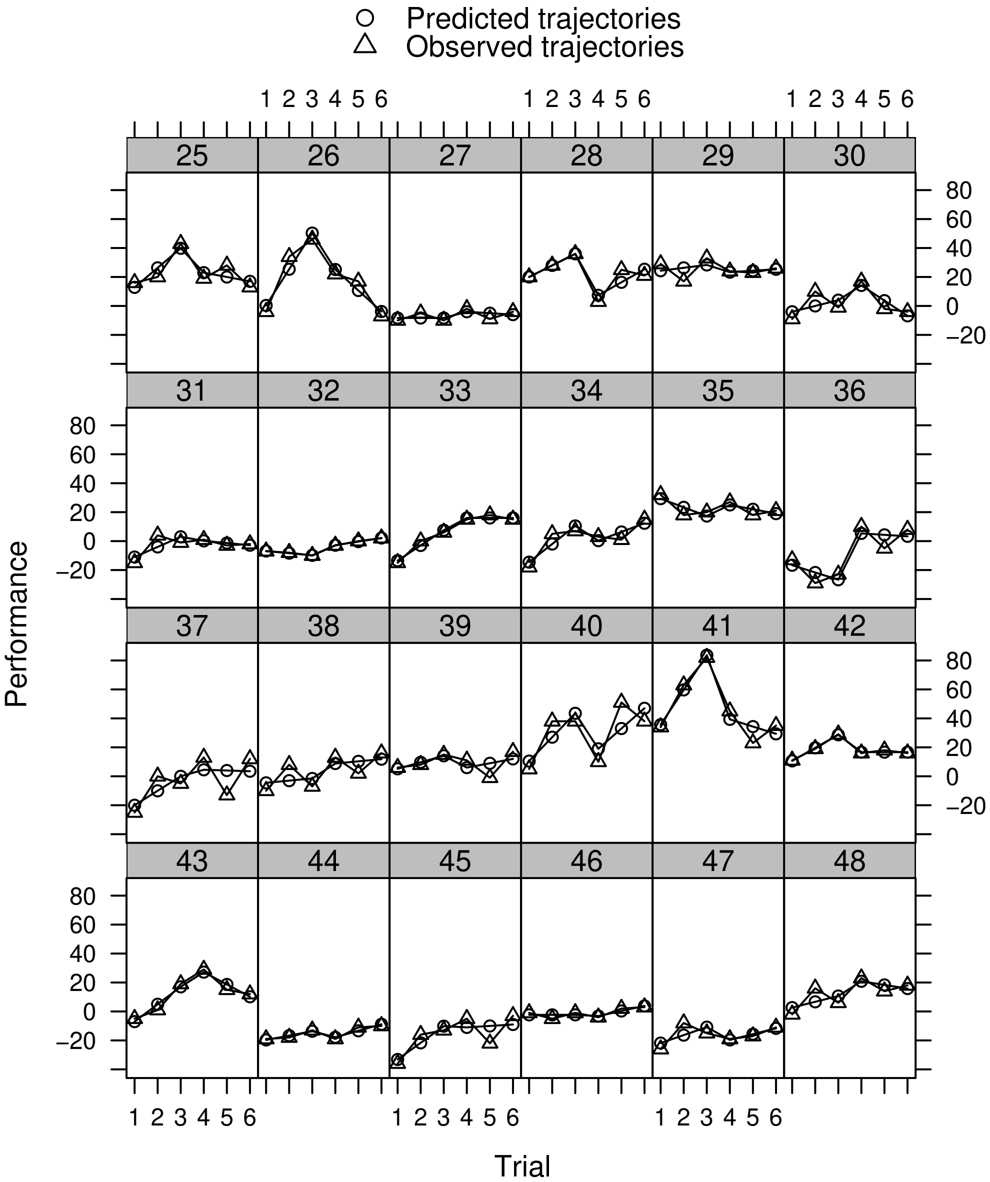

Figure B.1. (continued)

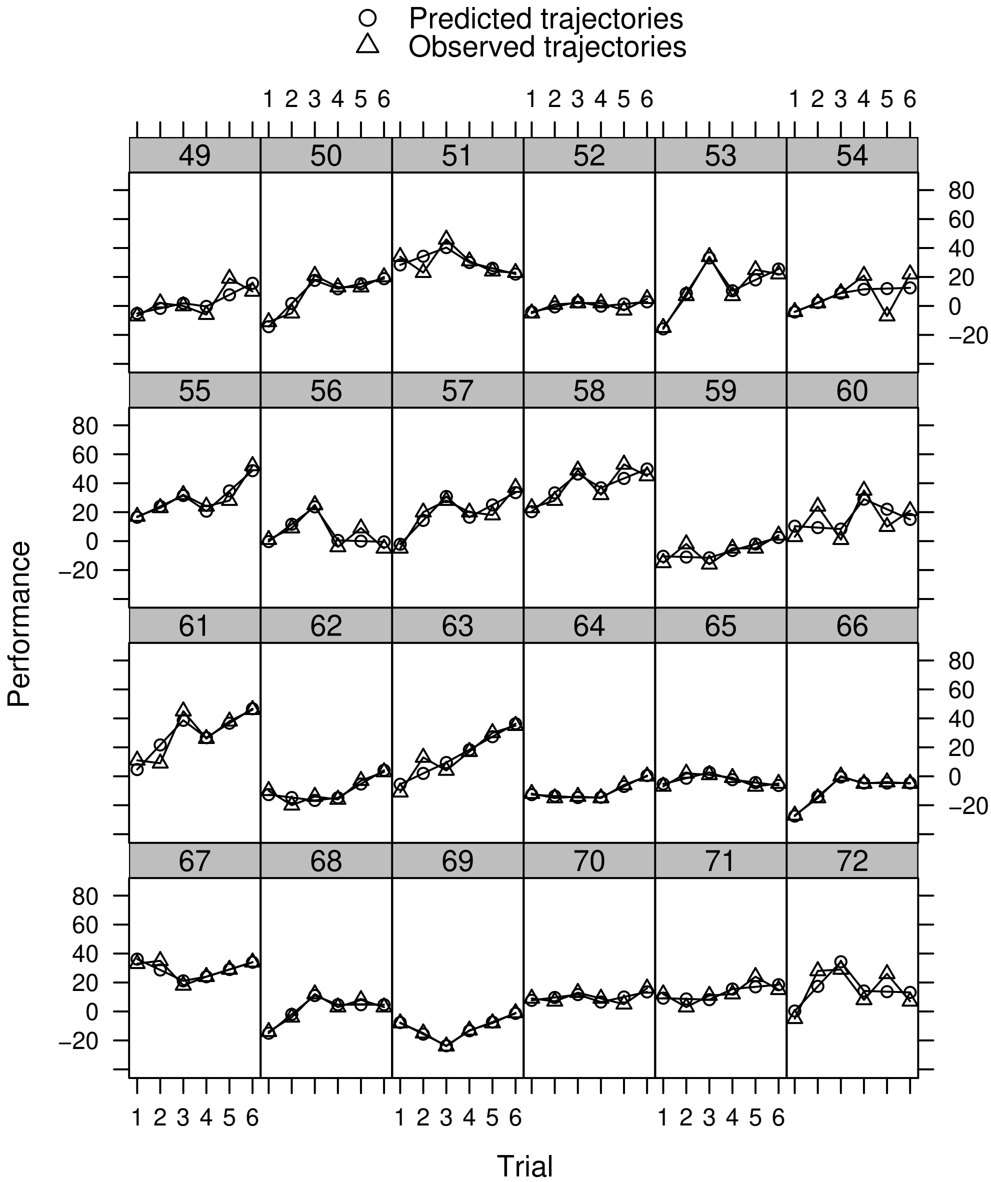

Figure B.1. (continued)

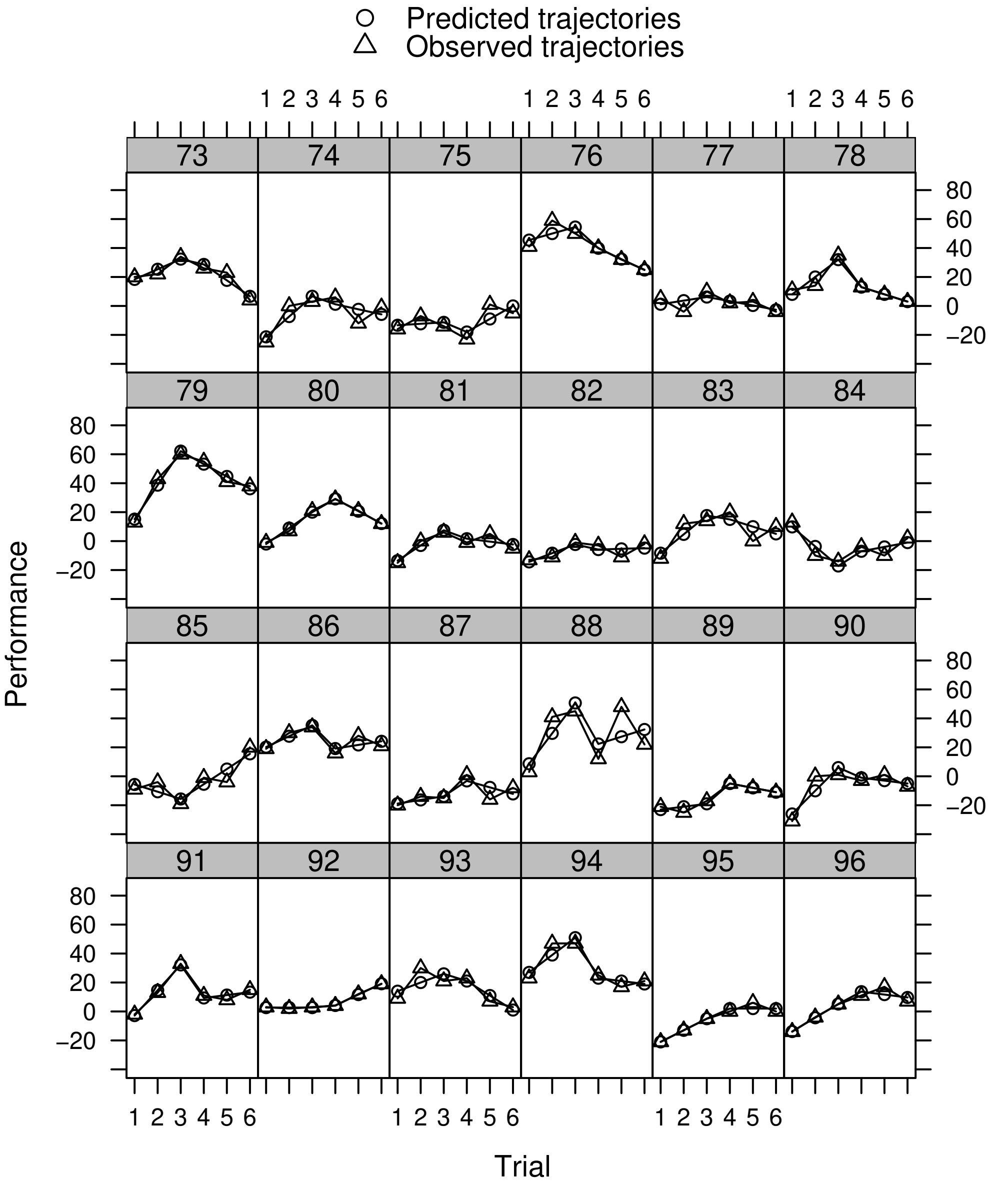

Figure B.1. (continued)

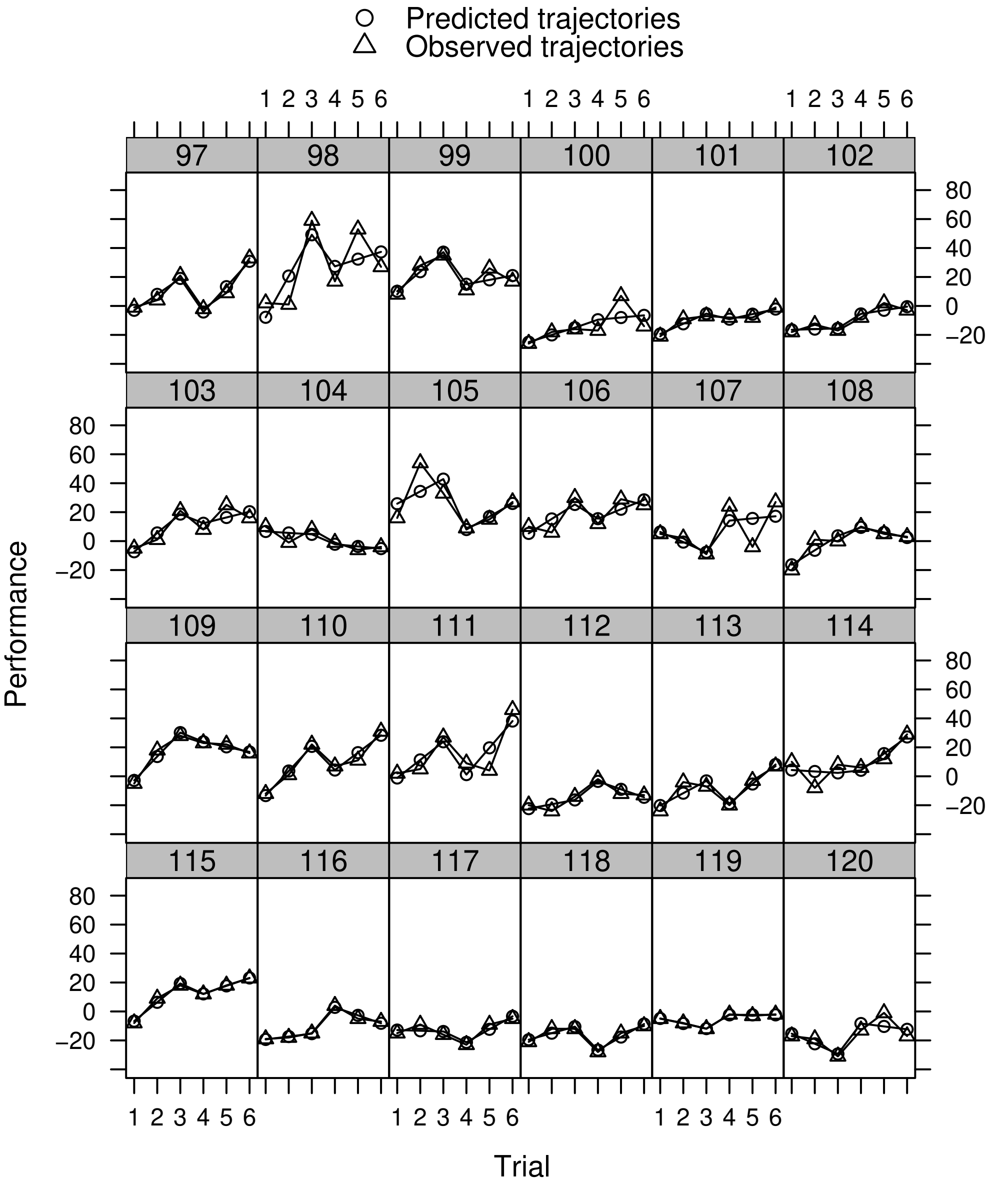

Figure B.1. (continued)

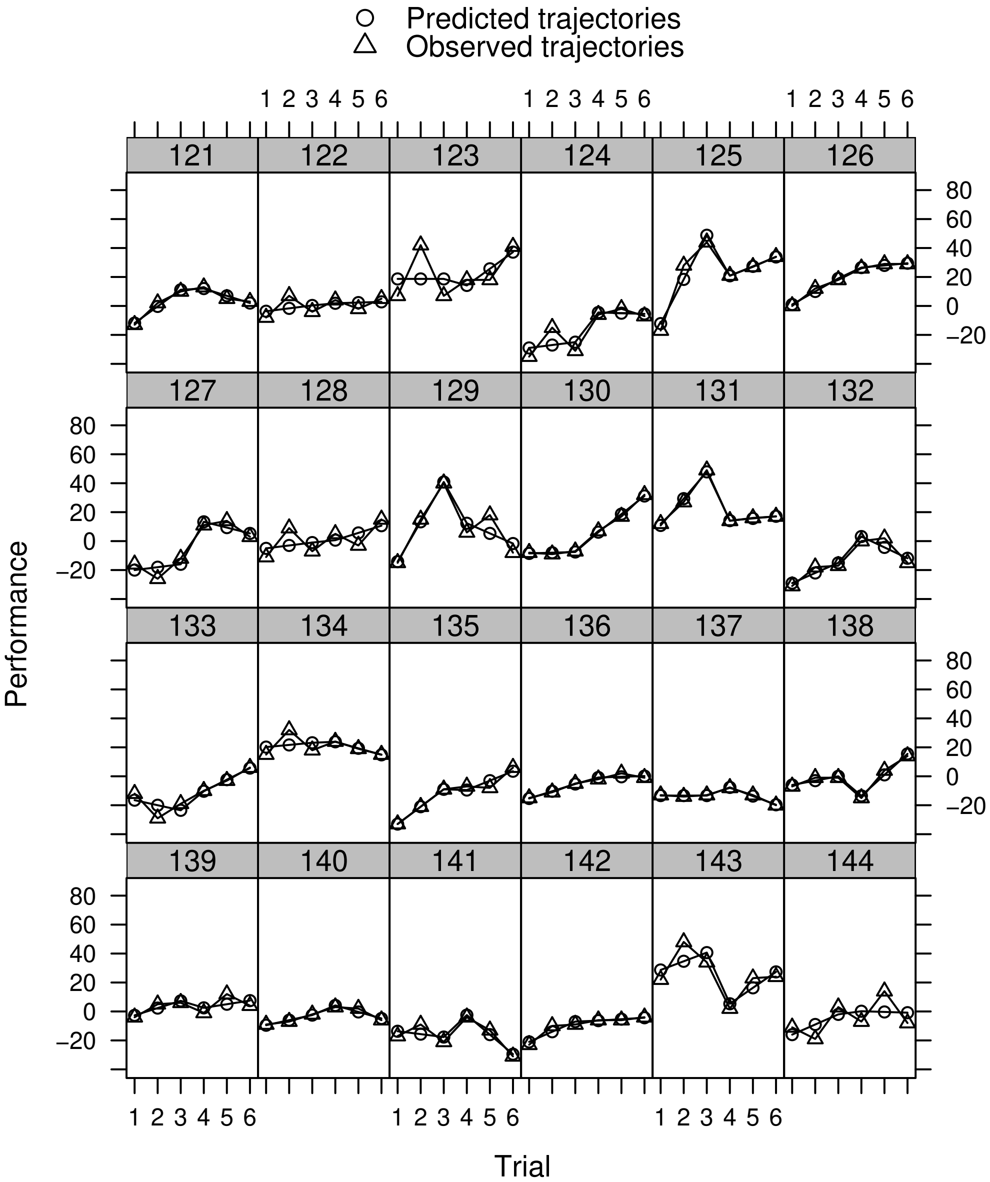

Figure B.1. (continued)

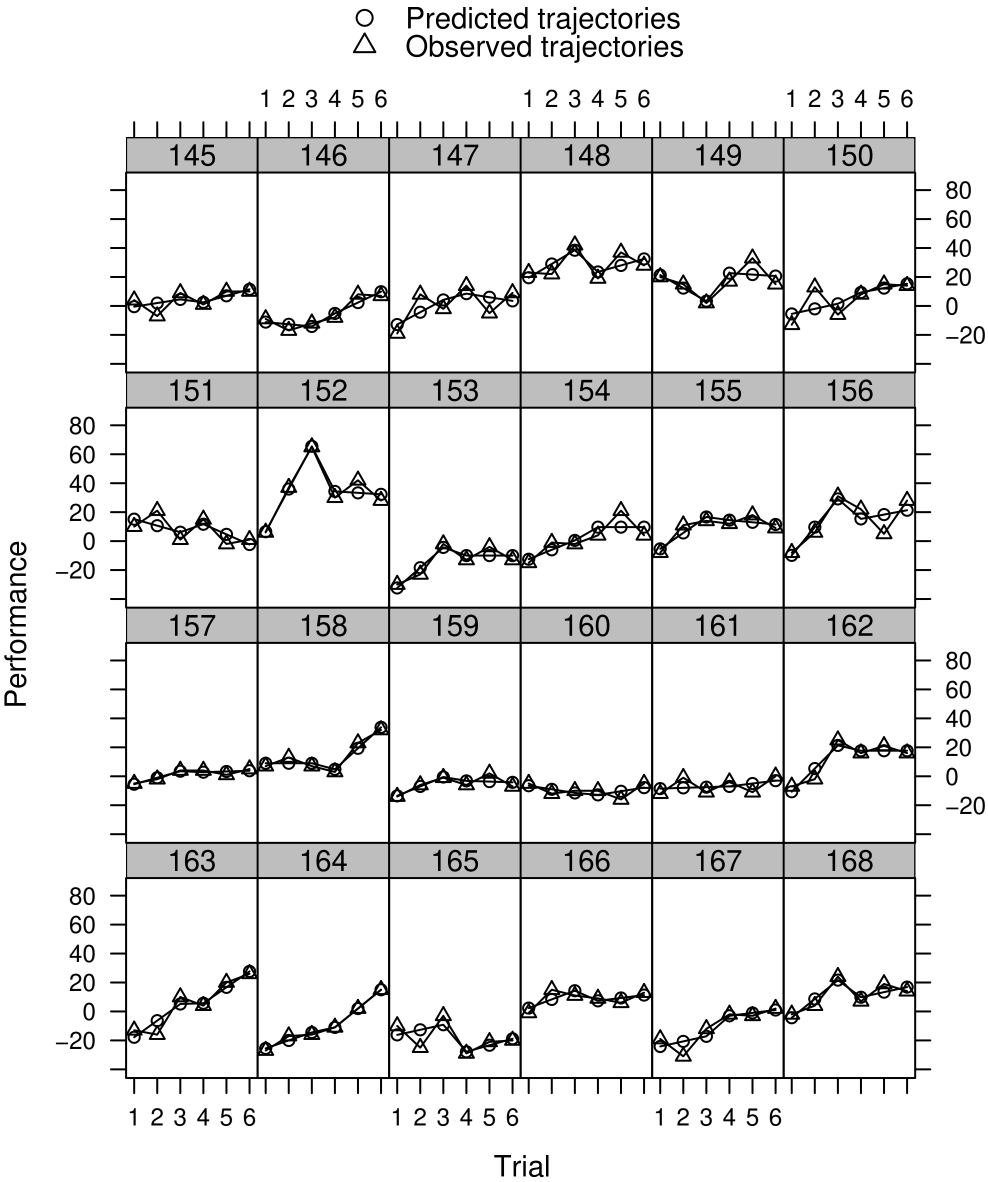

Figure B.1. (continued)

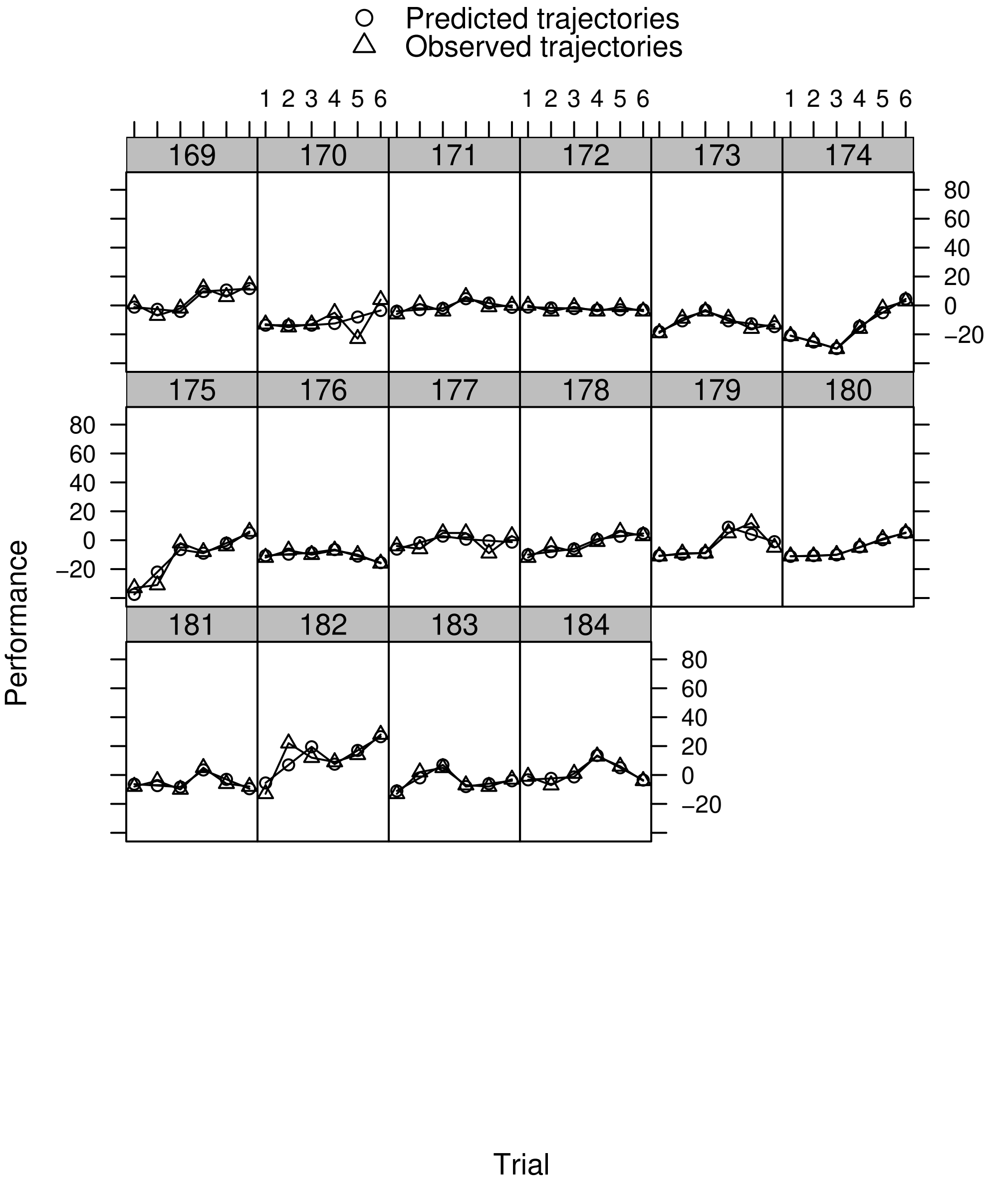

Figure B.1. (continued)

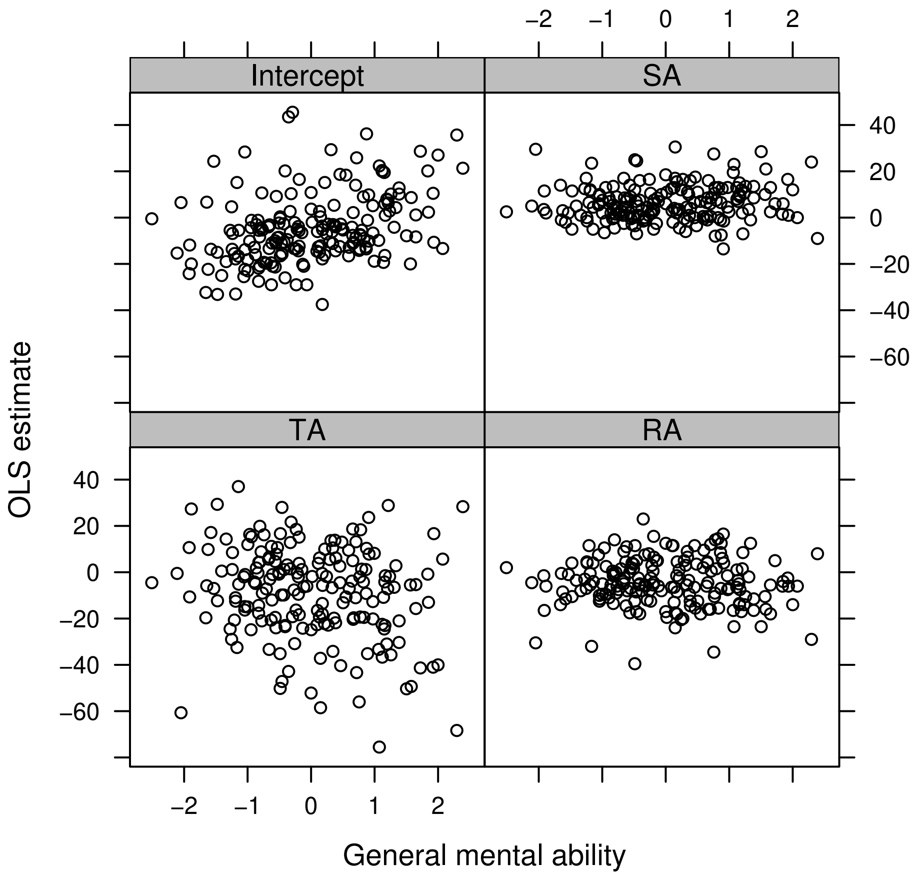

Figure B.2. Evaluation of the shape assumption at level 2: Ordinary-least square estimated growth parameters for each individual vs. general mental ability scores. SA = skill acquisition; TA = transition adaptation; RA = reacquisition adaptation.

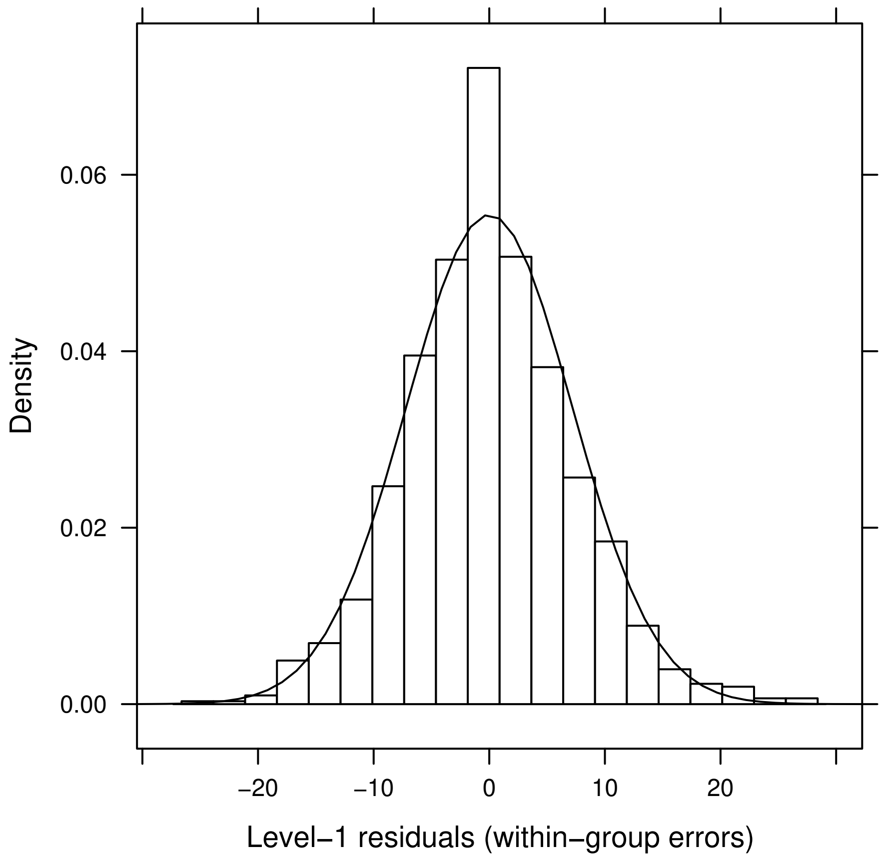

Figure B.3. Evaluation of the normality assumption at level 1: Histogram graphing the distribution of the level-1 residuals (within-group errors).

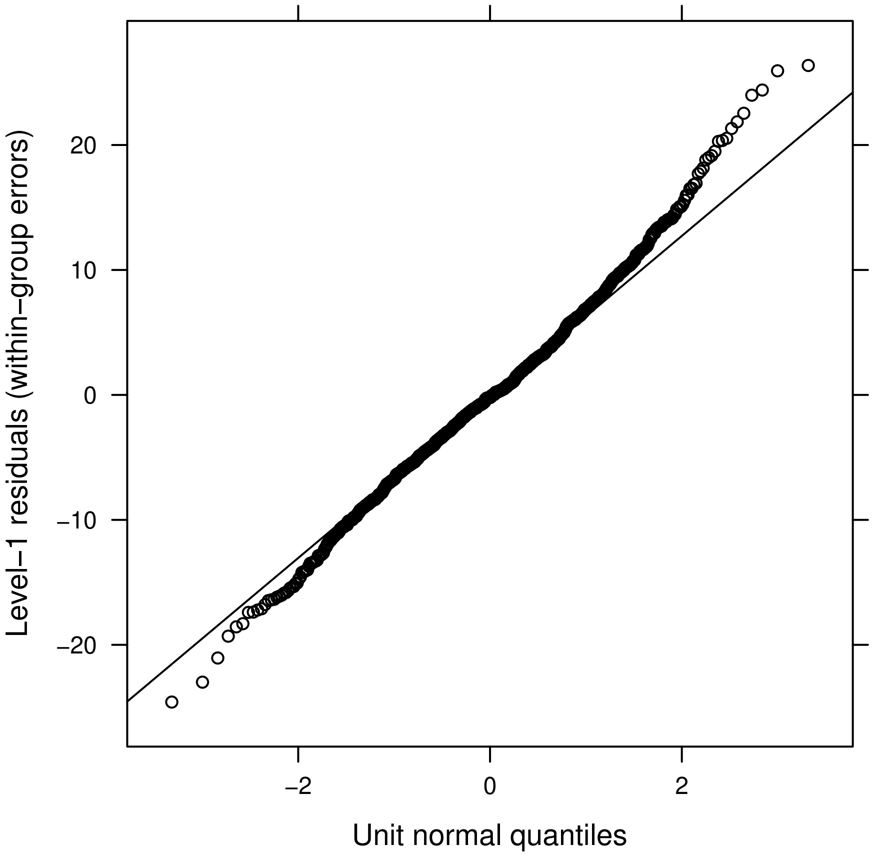

Figure B.4. Evaluation of the normality assumption at level 1: Normal probability plot for the distribution of the level-1 residuals (within-group errors).

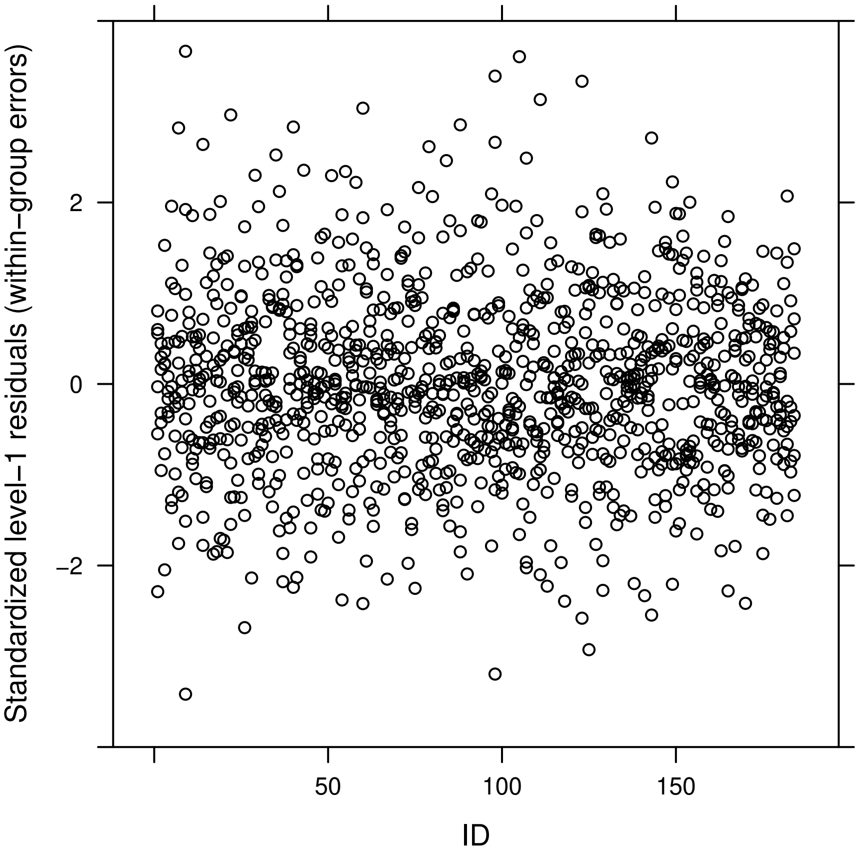

Figure B.5. Evaluation of the normality assumption at level 1: Plot of standardized level-1 residuals (within-group errors) against ID numbers.

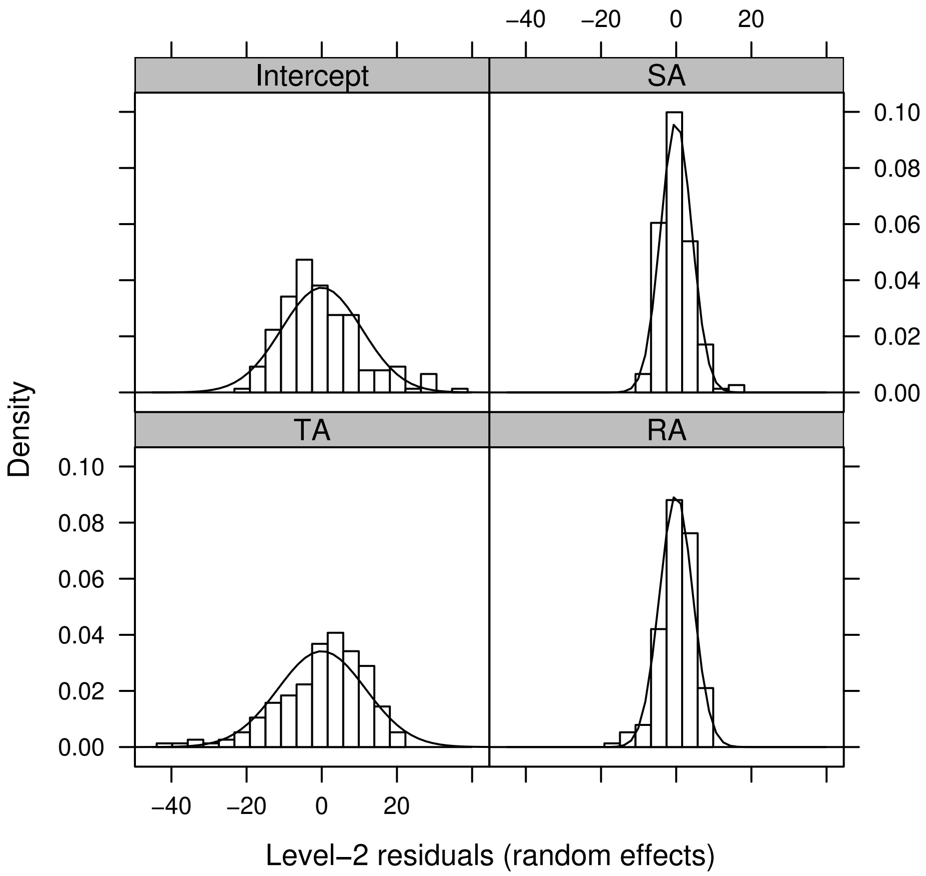

Figure B.6. Evaluation of the normality assumption at level 2: Histograms graphing the distributions of the level-2 residuals (random effects). SA = skill acquisition; TA = transition adaptation; RA = reacquisition adaptation.

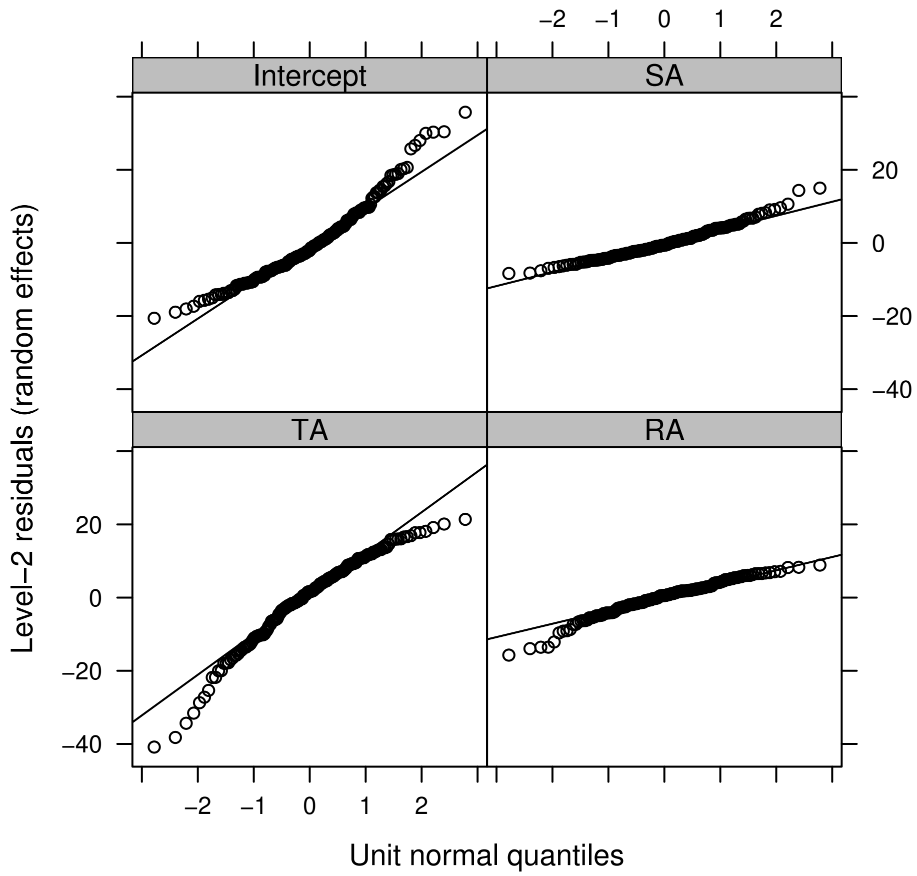

Figure B.7. Evaluation of the normality assumption at level 2: Normal probability plots for the distributions of the level-2 residuals (random effects). SA = skill acquisition; TA = transition adaptation; RA = reacquisition adaptation.

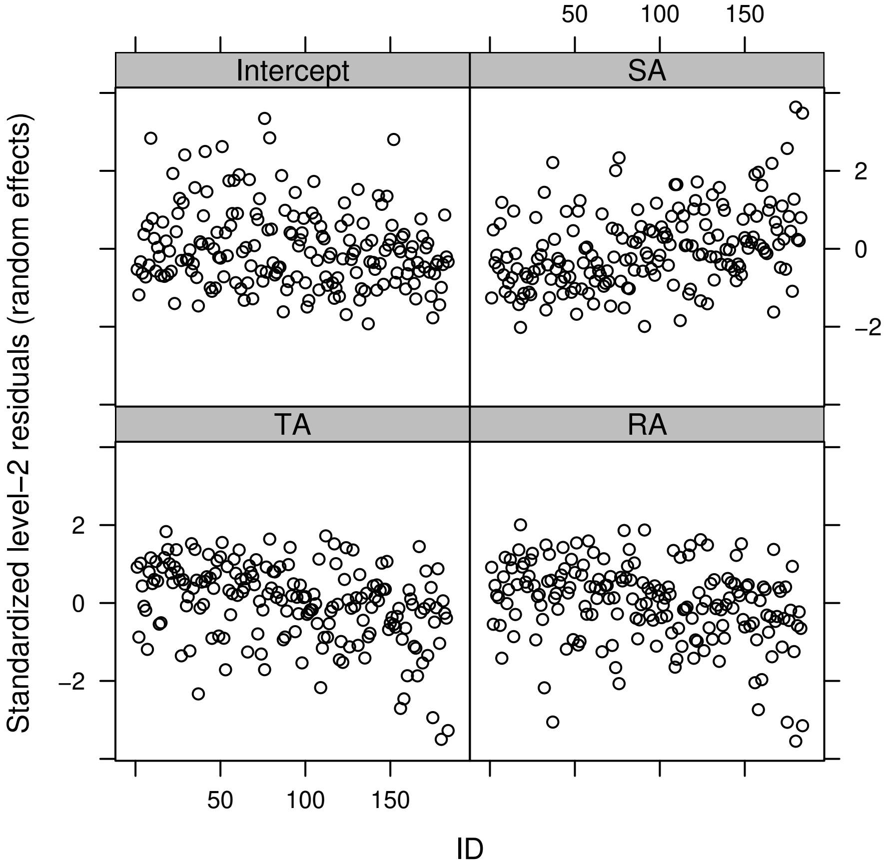

Figure B.8. Evaluation of the normality assumption at level 2: Plots of standardized level-2 residuals (random effects) against ID numbers. SA = skill acquisition; TA = transition adaptation; RA = reacquisition adaptation.

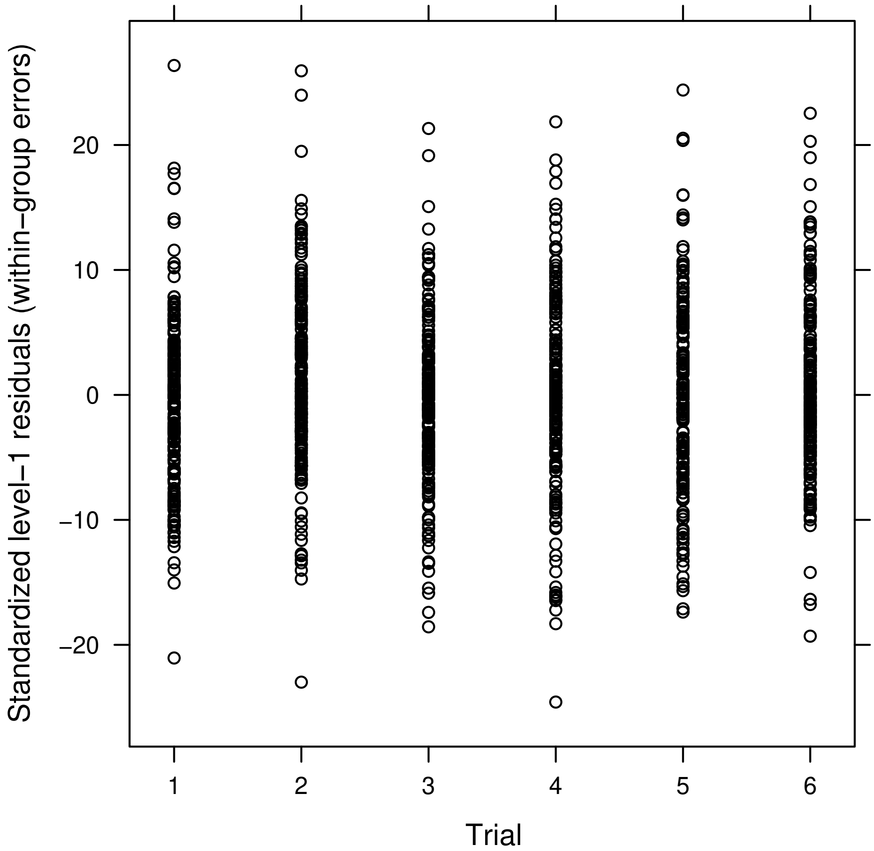

Figure B.9. Evaluation of the homoscedasticity assumption at level 1: Level-1 residuals (within-group errors) at each measurement occasion of the TankSoar task.

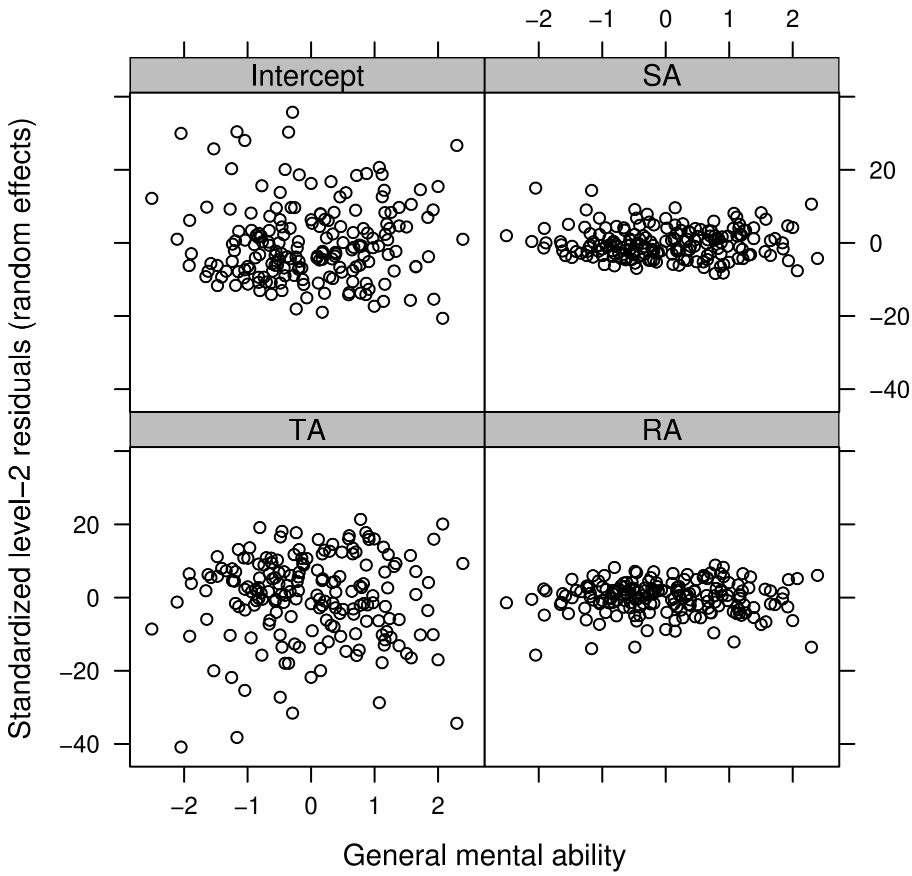

Figure B.10. Evaluation of the homoscedasticity assumption at level 2: Level-2 residuals (random effects) vs. general mental ability scores. SA = skill acquisition; TA = transition adaptation; RA = reacquisition adaptation.

Appendix C. Expanded Discontinuous Mixed-Effects Model Accounting for Quadratic Change: Coding of Change Variables, Checks of Model Assumptions, and Results

This Appendix provides additional information on the discontinuous mixed-effects model expanded to account for quadratic change in skill acquisition and reacquisition adaptation.

Graphs on the approximation of the empirical change pattern using OLS-estimated individual regressions for each individual are not provided as the OLS-version of the expanded model is able to perfectly approximate each empirical pattern. Therefore, these OLS-estimated patterns are identical to the empirical pattern graphed in Appendix B (see Figure B.1).

With respect to the interpretation of model parameters, note that skill acquistion was centered at Trial 2 so that the intercept effect reflects average performance across the pre-change period and the linear skill acquisition effect reflects average linear change across the pre-change period. Reacquisition adaptation was centered at Trial 5 so that the linear reacquisition effect approximately reflects average linear change across the post-change period. GMA was centered at the sample mean so that estimates for the change variables reflect the mean change pattern for the sample. Standardized coefficients in Table C.3 and Table C.4 were derived by setting the standard deviation of all variables to 1 without altering the centering of the variables.

Table C.1. Coding of Change Variables

	Trial					
Change variable	1	2	3	4	5	6
Linear Skill acquisition	-1	0	1	2	3	4
Quadratic Skill acquisition	1	0	1	1	1	1
Transition adaptation	0	0	0	1	1	1
Linear Reacquisition adaptation	-1	-1	-1	-1	0	1
Quadratic Reacquisition adaptation	1	1	1	1	0	1

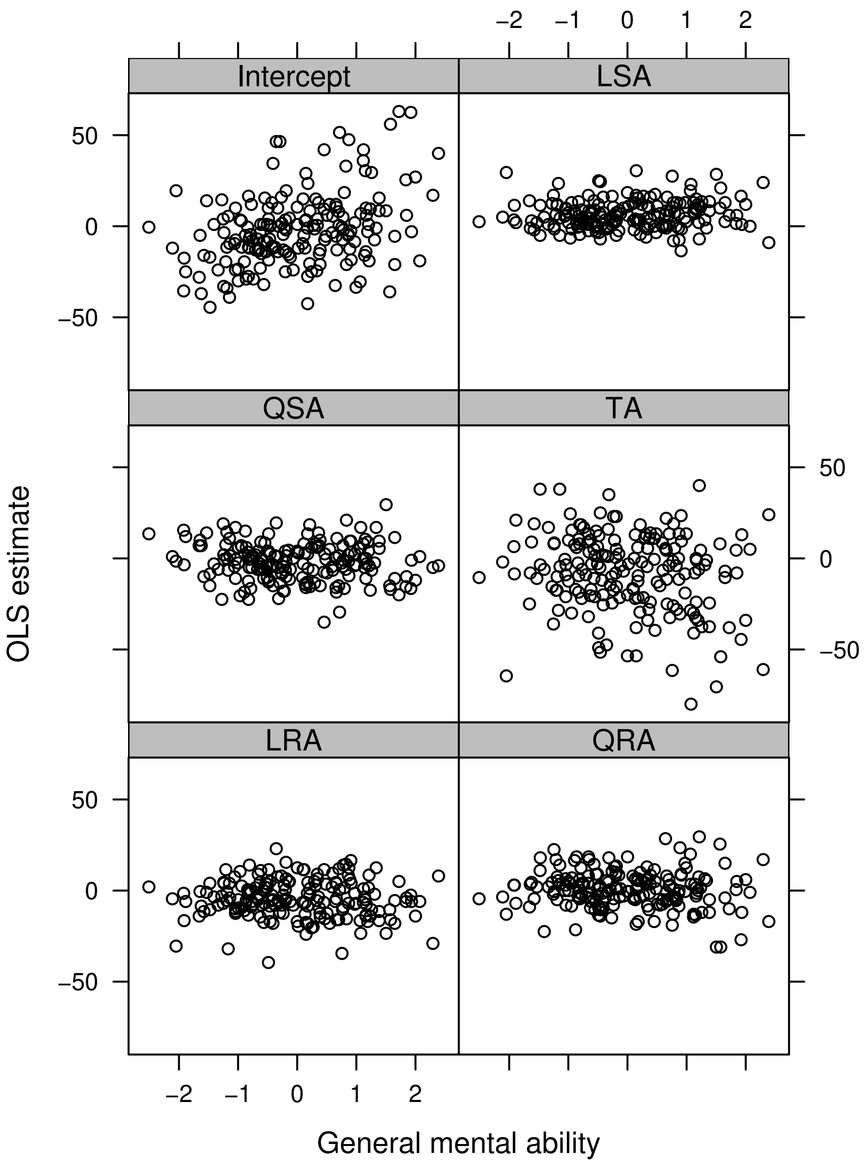

Figure C.1. Evaluation of the shape assumption at level 2: Ordinary-least square estimated growth parameters for each individual vs. general mental ability scores. LSA = linear skill acquisition; TA = transition adaptation; LRA = linear reacquisition adaptation; QRA = quadratic reacquisition adaptation.

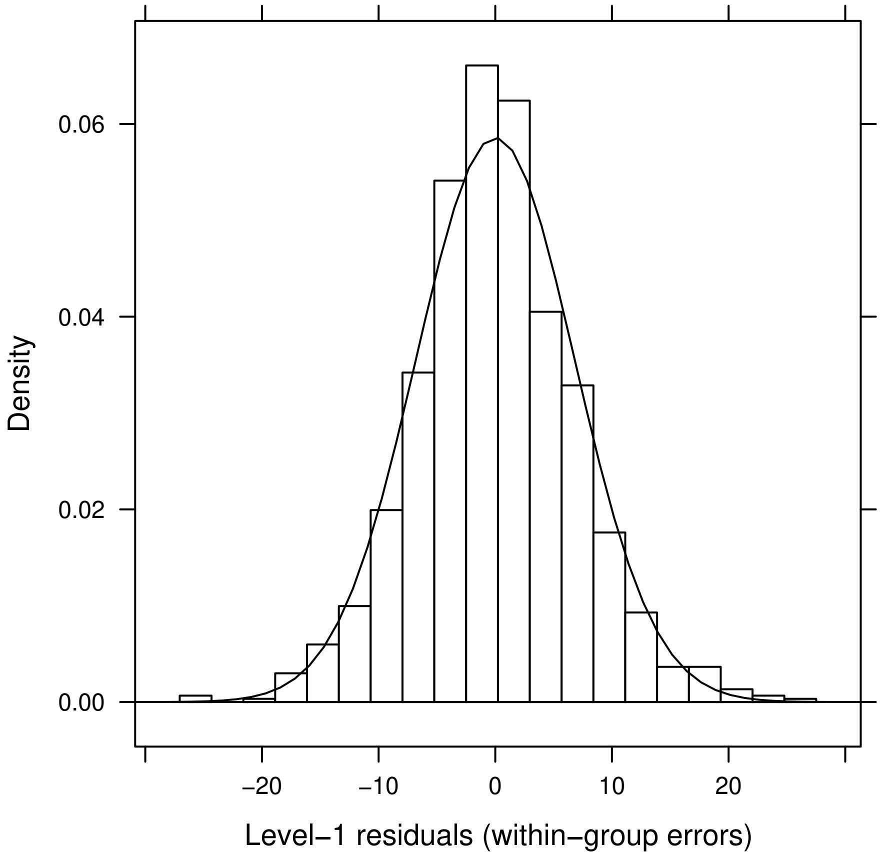

Figure C.2. Evaluation of the normality assumption at level 1: Histogram graphing the distribution of the level-1 residuals (within-group errors).

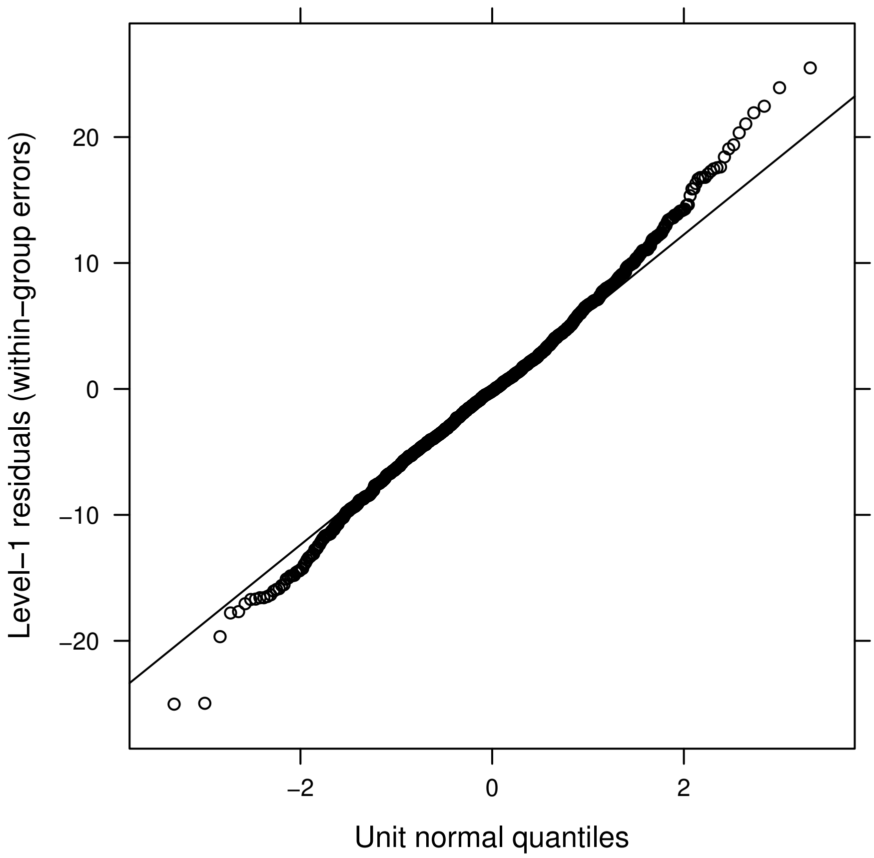

Figure C.3. Evaluation of the normality assumption at level 1: Normal probability plot for the distribution of the level-1 residuals (within-group errors).

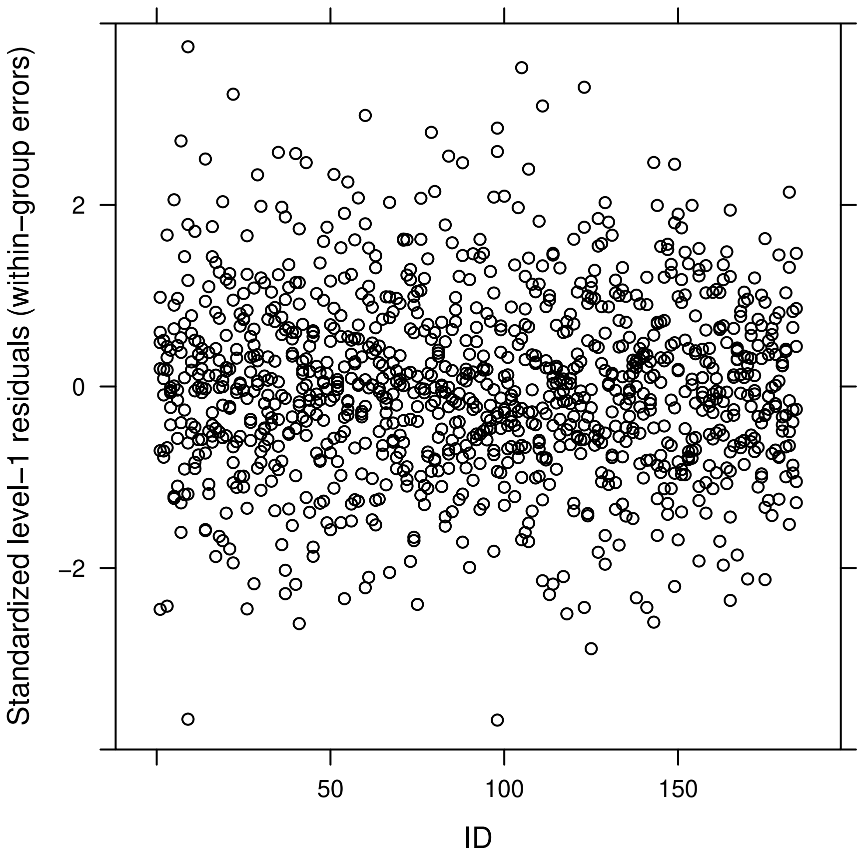

Figure C.4. Evaluation of the normality assumption at level 1: Plot of standardized level-1 residuals (within-group errors) against ID numbers.

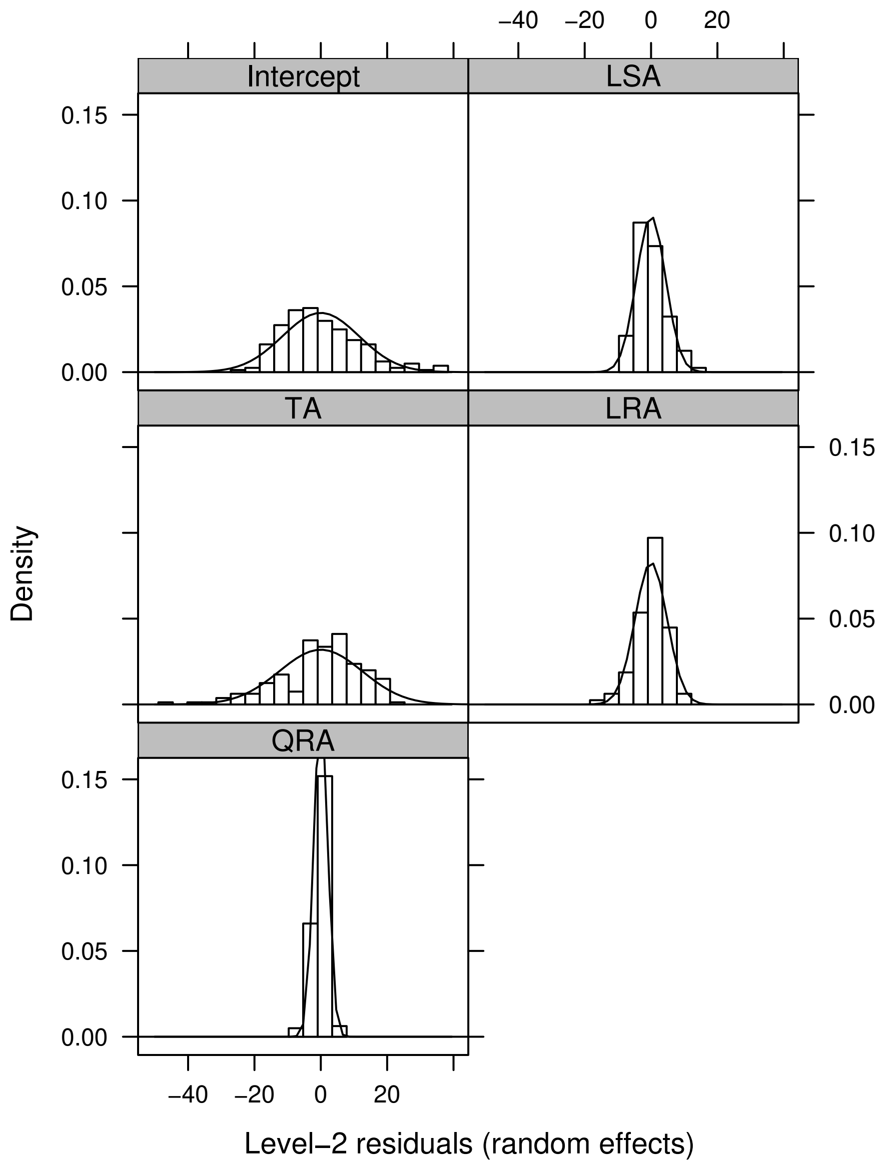

Figure C.5. Evaluation of the normality assumption at level 2: Histograms graphing the distributions of the level-2 residuals (random effects). LSA = linear skill acquisition; TA = transition adaptation; LRA = linear reacquisition adaptation; QRA = quadratic reacquisition adaptation.

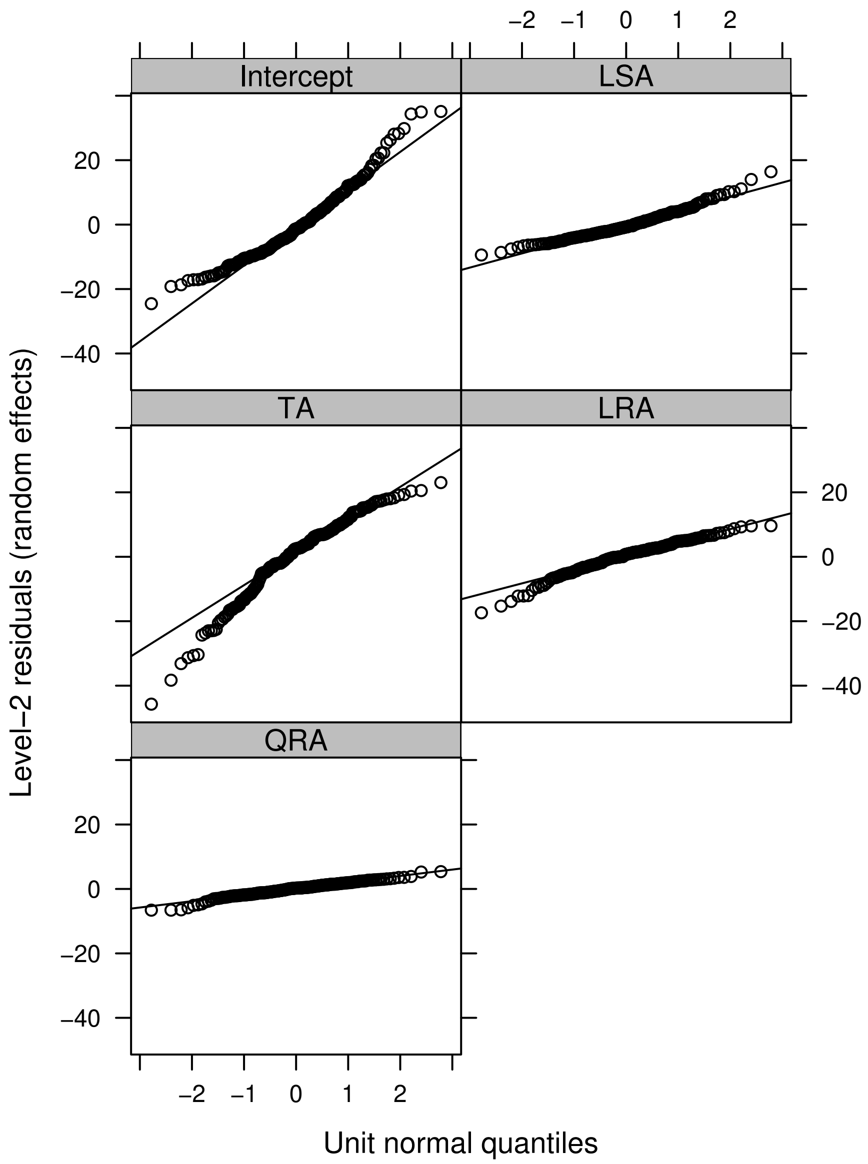

Figure C.6. Evaluation of the normality assumption at level 2: Normal probability plots for the distributions of the level-2 residuals (random effects). LSA = linear skill acquisition; TA = transition adaptation; LRA = linear reacquisition adaptation; QRA = quadratic reacquisition adaptation.

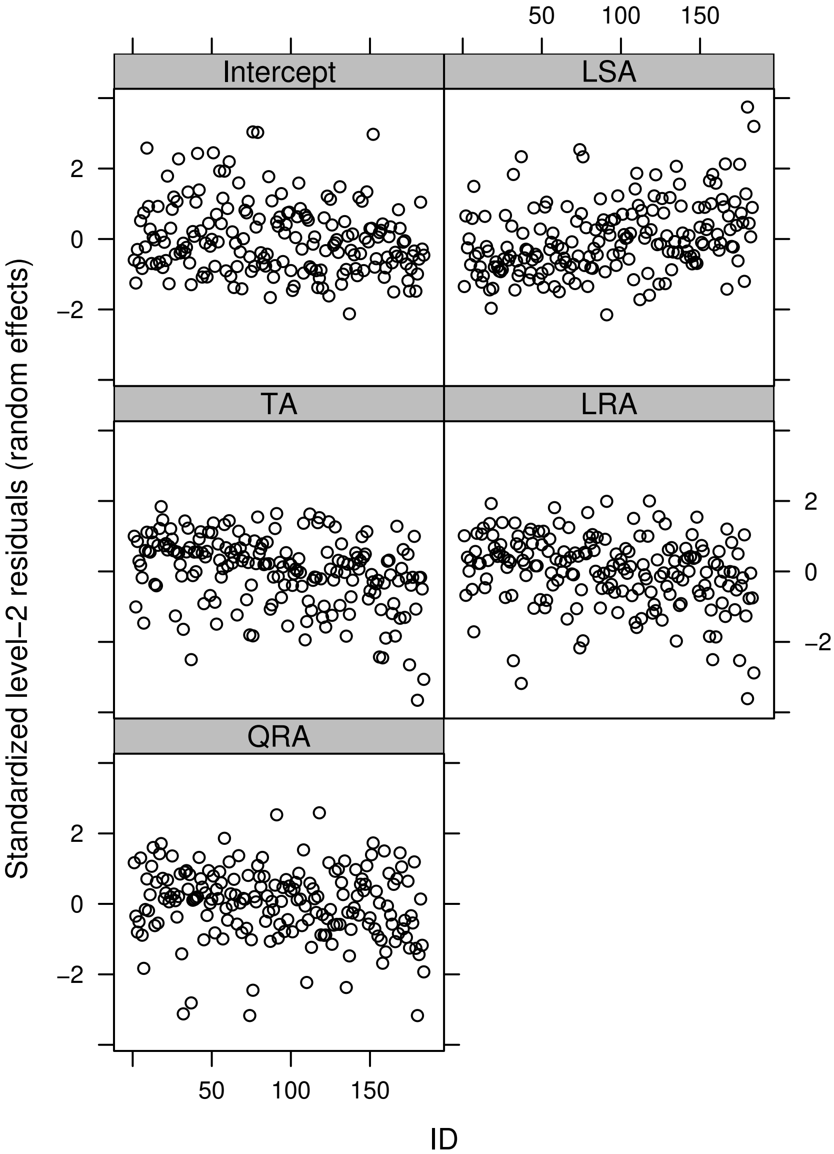

Figure C.7. Evaluation of the normality assumption at level 2: Plots of standardized level-2 residuals (random effects) against ID numbers. LSA = linear skill acquisition; TA = transition adaptation; LRA = linear reacquisition adaptation; QRA = quadratic reacquisition adaptation.

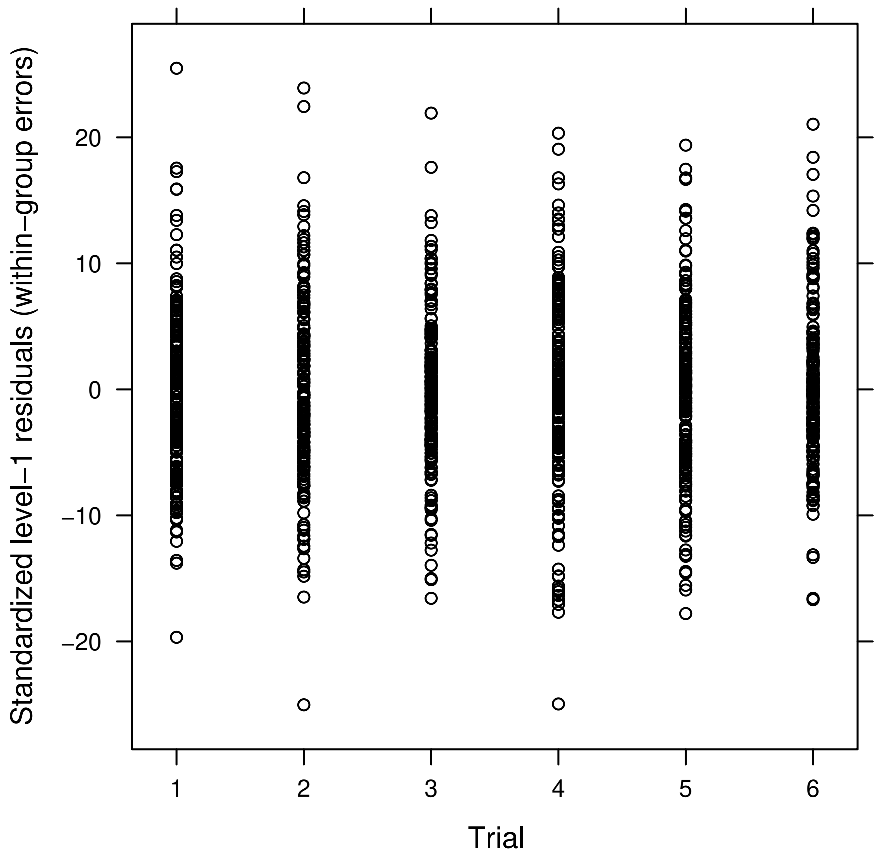

Figure C.8. Evaluation of the homoscedasticity assumption at level 1: Level-1 residuals (within-group errors) at each measurement occasion of the TankSoar task.

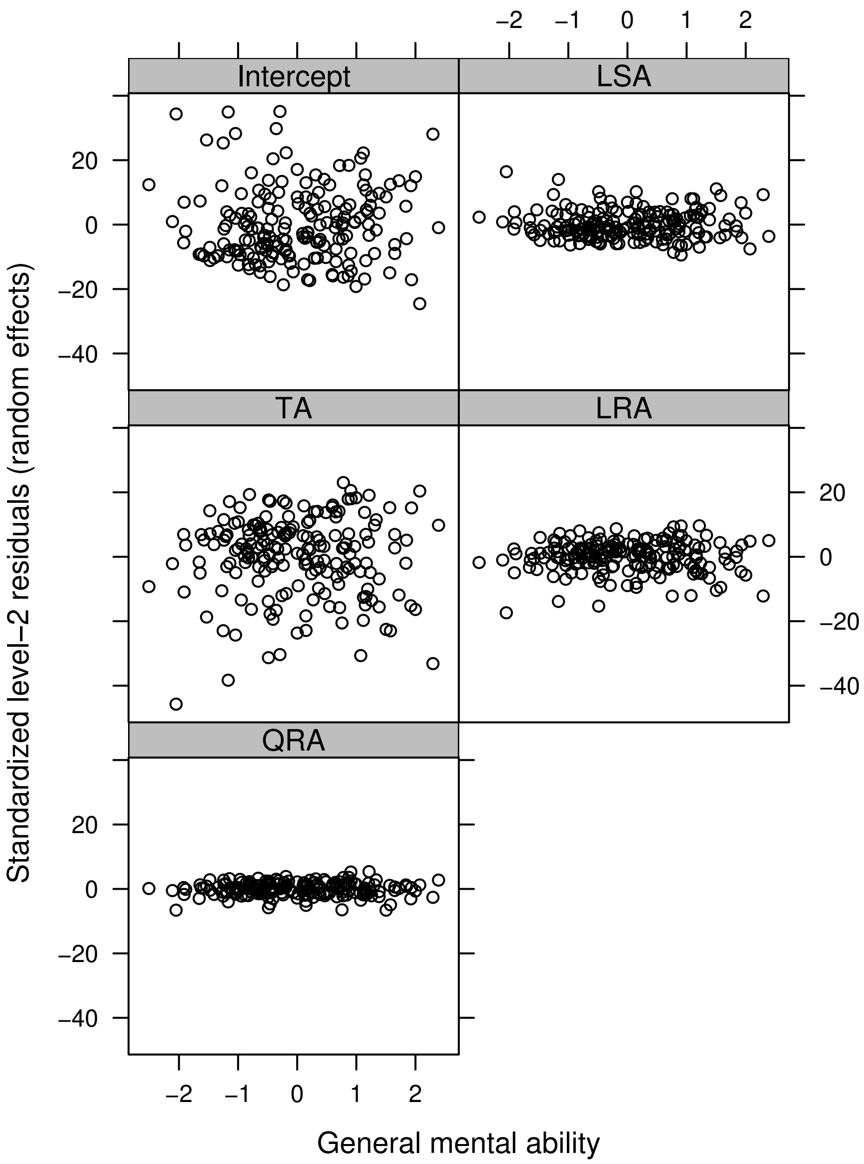

Figure C.9. Evaluation of the homoscedasticity assumption at level 2: Level-2 residuals (random effects) vs. general mental ability scores. LSA = linear skill acquisition; TA = transition adaptation; LRA = linear reacquisition adaptation; QRA = quadratic reacquisition adaptation.

Table C.2. Evaluation of Normality Assumptions: Skewness and Kurtosis for the Distributions of Level-1 and Level-2 Residuals

Residual distribution	Skewness	Kurtosis
Level-1 residuals (within-group errors)	.14	.66
Level-2 residuals (random effects)		
Intercept (Basal task performance)	.75	.40
Linear skill acquisition	.75	.73
Transition adaptation	−.81	.64
Linear reacquisition adaptation	−.77	.94
Quadratic reacquisition adaptation	−.56	.90

Note. Kurtosis = standardized fourth-order moment = −3.

Table C.3. Results: Fixed Effects

Fixed Effects	Standardized		Unstandardized				
	Coef.	*SE*	Coef.	*SE*	*df*	*t* test	*p*
Final level 1 model (mean change pattern)							
(Intercept)			−2.11	1.45	910	−1.46	*ns*
Linear skill acquisition (LSA)	.62	.06	6.38	.58	910	10.90	<.001
Quadratic skill acquisition (QSA)	−.04	.02	-1.82	.74	910	−2.46	.014
Transition adaptation (TA)	−.46	.09	−8.15	1.56	910	−5.24	<.001
Linear reacquisition adaptation (LRA)	−.20	.03	−4.49	.77	910	−5.83	<.001
Quadratic reacquisition adaptation (QRA)	−.01	.02	.53	.78	910	0.68	*ns*
Final level 2 model (individual differences in change)							
General mental ability (GMA)	.43	.09	7.38	1.45	182	5.08	<.001
LSA × GMA	.08	.06	.80	.59	910	1.36	*ns*
QSA × GMA	−.02	.02	-1.01	.74	910	−1.36	*ns*
TA × GMA	−.23	.09	−4.00	1.56	910	−2.56	.011
LRA × GMA	−.02	.03	−.54	.77	910	−0.70	*ns*
QRA × GMA	−.02	.02	−.83	.78	910	−1.06	*ns*

Note. $N = 184$. $k = 1104$. Model deviance= 8485.47. Coef. = Coefficient.

Table C.4. Results: Random Effects

	Random Effects	Standardized		Unstandardized		Correlations			
		Variance	*SD*	Variance	*SD*	1	2	3	4
1.	(Intercept)			150.04	12.25	–			
2.	Linear skill acquisition (SA)	.27	.52	29.23	5.41	.58	–		
3.	Transition adaptation (TA)	.67	.82	209.84	14.49	−.75	−.93	–	
4.	Linear reacquisition adaptation (RA)	.08	.28	41.75	6.46	−.42	−.91	.88	–
5.	Quadratic Reacquisition adaptation (RA)	.01	.07	11.37	3.37	−.14	−.84	.72	.83
	Residual	.22	.47	67.44	8.21				

Note. $N = 184$. $k = 1104$. Model deviance = 8485.47. Coef. = Coefficient.

Appendix D. Lebenslauf des Autors

geboren am 8.2.1980 in Aachen

Berufliche Erfahrung

04/04 –	Wissenschaftlicher Mitarbeiter am Lehrstuhl für Betriebs- und Organisationspsychologie (Prof. Dr. Lutz F. Hornke) der Rheinisch-Westfälischen Technischen Hochschule Aachen

Ausbildung

04/04 –	Promotionsstudium an der Philosophischen Fakultät der Rheinisch-Westfälischen Technischen Hochschule Aachen
10/98 – 03/04	Psychologiestudium an der Fakultät für Sozialwissenschaften der Universität Mannheim
08/86 – 06/98	Grundschule und Gymnasium in Aachen

Ehrenamtliche Tätigkeit (Freistellung vom Wehrdienst)

09/97 – 04/04	Bundesanstalt Technisches Hilfswerk

Zeitschriftenpublikationen

Lang, J. W. B. & Kersting, M. (2007). Regular feedback from student ratings of instruction: Do college teachers improve their ratings in the long run? *Instructional Science, 35*, 187–205.

Lang, J. W. B. & Fries, S. (2006). A revised 10-item version of the Achievement Motives Scale: Psychometric properties in German-speaking samples. *European Journal of Psychological Assessment, 22*, 216–224.

Buchbeiträge

Lang, J. W. B. & Kersting, M. (in Druck). Langfristige Effekte von regelmäßigem Feedback aus studentischen Lehrveranstaltungsevaluationen. In A. Kluge & K. Schüler (Hrsg.), *Qualitätssicherung und -entwicklung an Hochschulen: Methoden und Ergebnisse*. Lengerich: Pabst.

Lang, J. W. B. & Kersting, M. (in Druck). Statistische Modelle und Auswertungsverfahren. In H. Schuler & Kh. Sonntag (Hrsg.), *Handbuch der Arbeits- und Organisationspsychologie*. Göttingen: Hogrefe.