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Running Head: TWO TYPES OF ADAPTATION

General Mental Ability and Two Types of Adaptation to Unforeseen Change: Applying Discontinuous Growth Models to the Task-Change Paradigm

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Abstract

The present research provides new insights into the relationship between general mental ability (GMA) and adaptive performance by applying a discontinuous growth modeling framework to a study of unforeseen change on a complex decision-making task. The proposed framework provides a way to distinguish two types of adaptation (transition adaptation and reacquisition adaptation) from two common performance components—skill acquisition and basal task performance. Transition adaptation refers to an immediate loss of performance following a change, whereas reacquisition adaptation refers to the ability to relearn a changed task over time. Analyses revealed that GMA was negatively related to transition adaptation and found no evidence for a relationship between GMA and reacquisition adaptation. The results are integrated within the context of adaptability research, and implications of using the described discontinuous growth modeling framework to study adaptability are discussed.

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

General Mental Ability and Two Types of Adaptation to Unforeseen Change: Applying Discontinuous Growth Models to the Task-Change Paradigm

As a result of the globalization and rapid emergence of new technologies, the occupational world is becoming progressively more dynamic and complex (Burke, Pierce, & Salas, 2006; Pulakos, Arad, Donovan, & Plamondon, 2000). Consequently, employees increasingly face changes in the nature of their work environments and a need to keep pace with dynamic, global, and unpredictable markets. To address these developments, researchers have begun to examine how individuals respond to changes in complex environments. In this context, one important stream of research has focused on identifying individual differences which enhance persons' successful adaptation to changes in their work environments (e.g., Kozlowski et al., 2001; LePine, Colquitt, & Erez, 2000; Thoresen, Bradley, Bliese, & Thoresen, 2004).

Understanding the role of individual differences in adaptation has a number of practical implications. First, with respect to training, knowledge about individual differences has the potential to produce more effective training interventions (e.g., Burke et al., 2006; Ford & Kraiger, 1995; Smith, Ford, & Kozlowski, 1997). Specifically, organizations may determine adaptability-training needs and tailor training approaches to the specific individual characteristics of major groups of employees (e.g., sales personnel) or individual members of the organization. Second, research on the relationship between individual differences and adaptability has practical implications regarding selection, hiring, and salary decisions. Adaptability is increasingly considered to be a useful addition to contemporary multidimensional conceptualizations of the job performance domain (e.g., Pulakos et al., 2000).

The most frequently used approach to study adaptation to change is the task-change paradigm (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). 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 degree of mastery of the task. During the skill acquisition process, however, some aspect of the task unexpectedly changes requiring adaptive behavior. In the majority of research on adaptation, individuals are unaware that changes in the task environment will occur (e.g., LePine, 2003, 2005; LePine et al., 2000). Alternatively, individuals may be aware that a change will occur, but are not informed about the nature of the change (Chen, 2005; Kozlowski et al., 2001). Research studies on adaptation typically characterize 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, Zaccaro & Mathieu, 2000) because complexity increases are generally considered to be a frequent adaptation scenario in occupational settings and are also difficult to master (LePine, 2005).

Two important aspects of research using the task-change paradigm are that (a) complete task mastery is rarely (if ever) a prerequisite for introducing the unexpected change (Betsch, Haberstroh, Molter, & Glöckner, 2004), and (b) there is no clear consensus on how best to approach the analysis of data such that components of individual adaptability are uniquely identifiable relative to other attributes such as overall ability and differences in skill acquisition.

In the present research, we build off of previous research and propose a conceptual and methodological framework to identify two separate forms of adaptability in the task-change paradigm. These two different types of adaptability—transition adaptation and reacquisition adaptation—capture conceptually distinct forms of adaptability within the task-change paradigm. We detail the conceptual and methodological framework within the context of the relationship between adaptability and general mental ability (GMA; Lubinski, 2004; Schmidt & Hunter, 2004), and in so doing we also conduct a detailed examination of the role of GMA in adaptability research.

General Mental Ability and Adaptive Performance

The relationship between GMA and adaptability is complex. Indeed, competing hypotheses predicting either a positive or a negative relationship between GMA and adaptability can be derived from the literature. Some authors suggested that GMA provides individuals with more cognitive resources to monitor, react to changes and actively implement new routines while working on complex tasks (LePine et al., 2000; Hunter & Schmidt, 1996). Consequently, individuals with high GMA are presumably well-equipped to adapt to changes in complex tasks. In contrast, individuals low on GMA theoretically need the majority of their cognitive processing capacities to perform a given complex task. Therefore, they should have difficulties recognizing and responding to the changes.

LePine et al. (2000) noted that these ideas are in line with meta-analytic research suggesting that the relationship between GMA and performance is stronger for complex tasks than for simple tasks (Hunter & Hunter, 1984). LePine et al. also conducted an empirical study to directly investigate the relationship between GMA and performance in a complex task. In this study, individuals made decisions on a series of 75 problems (unidentified aircrafts) from a naval command-and-control scenario. 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 unexpectedly changed. To investigate the influence of the changes on performance, LePine et al. compared performance in the pre-change period with performance in both post-change periods. In line with LePine et al.'s expectations, the relationship between GMA and performance was stronger in both post-change periods than in the pre-change period.

In contrast to the theoretical idea that GMA enhances adaptability, a negative relationship between GMA and adaptation can be predicted based on three streams of cognitive research on individual differences in working memory ability—an ability closely related to GMA which has either been considered to be a subfacet of GMA (Ackerman, Beier, & Boyle, 2005) or an explanatory construct actually causing individual differences in GMA (Kane, Hambrick, & Conway, 2005; Oberauer, Schulze, Wilhelm, & Süß, 2005). All three streams of research have investigated how high- and low-ability persons react when additional task demands surface in a task.

The first stream of research suggesting a negative relation between GMA and adaptability has investigated how high- and low ability persons' performance in complex tasks is affected by pressure to perform (Beilock & DeCaro, 2007, see also Beilock & Carr, 2005; Gimmig, Huguet, Caverni, & Cury, 2006). According to research in this area, pressure alters the problem solving strategies used by high-ability persons. In non-pressure situations, high-ability persons use their superior cognitive processing capacities to execute more advanced and complex problem-solving strategies. When the task at hand is complex and well-suited for advanced and complex problem-solving strategies, this behavior leads to performance advantages. In contrast, when high-ability persons are put under pressure, attention and cognitive processing capacities are focused on the pressure invoking features of the task leading to an inability to execute complex problem-solving strategies. As a result, they need to opt for simpler and less advanced strategies and experience a loss in their performance advantages. Adaptive situations do not involve strong manipulations of pressure from outside the task (e.g., monetary or social pressure); nonetheless, repeated and unpredicted failures following unforeseen changes presumably put pressure on individuals to regain their previous level of performance. This pressure may differentially impact high and low GMA individuals such that high GMA individuals experience a particularly strong loss of performance.

Largely similar findings and predictions have emerged from an interrelated stream of research on dual-task performance (Kane & Engle, 2000, 2002; Rosen & Engle, 1997). Dual-task performance is relevant to adaptability research because the unforeseen increases in complexity commonly invoked in adaptability research using the task-change paradigm frequently require people to execute additional new and advanced routines interfering with an already complex task. The core research strategy of dual-task research is to compare the performance of high- and low-ability persons in different tasks executed under single- and dual-task demands. Findings suggest that the results depend on the nature of the task. In simple tasks, additional demands from a second task lead to performance improvements for high-ability persons. Researchers (Beilock & Carr, 2005; Kane & Engle, 2002) have interpreted these findings as evidence that high-ability persons can use their advanced processing capacities to their advantage in simple tasks (i.e. to execute the second task alongside the first task more efficiently). In contrast, in complex and demanding tasks similar to the tasks commonly considered in adaptability research, a similar pattern of findings like that observed in research on pressure emerges (Kane & Engle, 2000, 2002; Rosen & Engle, 1997). On a relative basis, high-ability persons are less able to react to the dual-task demands than low-ability persons. Analogous to the findings from research on pressure, scholars have suggested that the additional cognitive demands occupy high-ability persons' cognitive processing capacities and prevent them from using these capacities to their advantage.

Finally, a third and recently emerging stream of research suggesting a negative relation between GMA and adaptability has investigated the performance of high- and low-ability persons in detecting new problem solutions when they are faced with unexpected problems in familiar tasks (Ricks, Turley-Ames, & Wiley, 2007). This research may be particularly relevant to adaptability research because the detection of changes is basically a core feature of successful adaption to unforeseen changes. To provide evidence of the role of ability in detecting new problem solutions, Ricks et al. investigated problem solving in verbal tasks as a function of ability and domain-relevant knowledge. Individuals high in both ability and domain-relevant knowledge tended to stick to wrong problem solutions much more often than individuals who were high in domain-relevant knowledge but low in ability. Beilock and DeCaro (2007) have argued that Ricks et al.'s findings may be explained by high-ability persons' tendency to focus all attention on selected task properties and ignore non-needed components of a task. While these skills are certainly useful to execute a familiar task at a very high level, they have the potential to prevent persons from finding new problem solutions after unforeseen changes.

In sum, two divergent perspectives regarding the relation between GMA and adaptive performance exist as the vantage point for the present investigation. The first perspective is based on the assumption that high-ability persons have superior cognitive processing capacities allowing them to implement changes, and is supported by empirical studies such as LePine et al. (2000). This perspective proposes that GMA is positively related to adaptation to changes. Conversely, the second perspective proposes that GMA is negatively related to adaptive performance. This alternative perspective relies on theoretical arguments and evidence from three interrelated streams of working memory research and suggests that high-ability persons face several unique problems when they need to adapt to unforeseen changes. Specifically, the findings suggest that compared to low-ability individuals, those with high-ability (a) tend to switch to simpler problem-solving strategies, (b) devote proportionally less cognitive processing capacities to the execution of the task, and (c) have difficulties finding new solution strategies when they face task demands likely to occur in situations requiring adaptive performance because they focus their attention on core features of the task. Each of the two perspectives is supported by empirical evidence. However, the two perspectives have not been investigated in the context of the task-change paradigm in a manner that accounts for the fact that pre-change performance and skill acquisition significantly vary as a function of ability. As we detail, these differences provides both methodological and theoretical challenges in isolating adaptive performance from common task performance.

Conceptual and Methodological Issues in Adaptability Research

In order to test the competing predictions about GMA within the task-change paradigm, researchers face two major issues which are simultaneously conceptual and methodological in nature. The first issue is how to clearly distinguish adaptive performance from other types of performance. A second issue in the task-change paradigm is the need to account for the temporal or process nature of adaptability following the change (Chan, 2000).

Distinguishing Adaptive Performance from Other Types of Performance

Theoretically and methodologically separating adaptive performance from other types of performance is crucial for establishing the theoretical construct of adaptive performance in the task-change paradigm. The need to distinguish adaptive performance from other types of performance results from the fact that (a) high- and low-ability persons typically have different skill acquisition trajectories and (b) differ in their level of performance at the end of the skill acquisition prior to the change requiring adaptability. These differences, in turn, result from several characteristics of common task-change paradigm research.

One characteristic of task-change paradigm research causing ability-related variability is the fact that adaptatation research routinely uses complex and inconsistent tasks. Presumably, researchers use complex and inconsistent tasks to enhance the generalizability to the work context as the vast majority of real world jobs are considered to be complex and inconsistent (cf. Ackerman, 1988, 1992; Farrell & McDaniel, 2001). However, the use of complex and inconsistent tasks has important consequences for performance differences between high- and low-ability persons in general and in particular at the end of the skill acquisition period prior to the task-change.

Research and theoretical work (Ackerman, 1988, 1992; Anderson, 1982; Fitts & Posner, 1967; Kanfer & Ackerman, 1989; Schneider & Shiffrin, 1977) on skill acquisition has established some fundamental characteristics of skill acquisition processes. Specifically, researchers increasingly agree that skill acquisition processes can be segmented into three phases (Ackerman, 1988). The first phase commonly labeled the cognitive stage of skill acquisition includes the initial confrontation with a novel task. In this phase, people aim to understand the core features of the task and try to develop successful strategies. These activities require intensive information processing and lead to slow and erroneous performance. As people continue to perform a task, the first phase of skill acquisition begins to fade into the second phase of skill acquisition commonly labeled the associative phase (Ackerman, 1988; Fitts & Posner, 1967). This phase is characterized by increasing speed and accuracy in the execution of the task. During this second phase, the strategies needed to execute the task are formulated. As both the first and the second stage of skill acquisition require individuals to process information, persons with high GMA commonly have considerable advantages in skill acquisition (Ackerman, 1988, 1992, Völkle, Wittmann, & Ackerman, 2006).

Towards the end of the second phase, the skill acquisition process moves towards a third phase commonly referred to as the autonomous phase (Ackerman, 1988; Fitts & Posner, 1967). When this phase is fully reached, individuals are able to perform the task very fast and accurate and without even devoting attention to task execution. In practice, the third stage of skill acquisition can only fully be attained when a task has certain characteristics (Ackerman, 1988; Völkle et al., 2006). Most importantly, the task needs to be consistent in the sense that individuals repeatedly need to execute identical routines. When the task is partially inconsistent, like the majority of work tasks and the tasks used in adaptability research, the third phase is only attained to a limited degree. The level of task execution in these types of tasks is likely to remain primarily in the second phase even after a (theoretically) unlimited amount of practice. Furthermore, perfect routinization is unlikely to be reached even if certain elements can be automated and proceduralized by the learner. As a consequence, task execution will continue to require considerable information processing abilities and thus high-ability persons should continue to perform considerably better than low-ability persons in these types of tasks.

In contrast to task inconsistency, task complexity influences the skill acquisition process more broadly. Specifically, complexity increases the cognitive processing demands to perform a task successfully and thus will generally enhance the benefits of having high GMA (Ackerman, 1988; Völkle et al., 2006). Thus, both task complexity and task inconsistency contribute to strong performance variability at the end of the skill acquisition period prior to the task change.

Another factor contributing to ability-related performance differences at the end of the skill acquisition period prior to the task change is the fact that task-change paradigm research commonly asks people to acquire a task for a considerable but not extensive amount of time prior to the task-change (in laboratory research commonly a single experimental session, cf. Bröder & Schiffer, 2006; Chen, Thomas, & Wallace, 2005; Johnson et al., 2006; Kozlowski et al., 2001; LePine, 2003, 2005; LePine et al., 2000). The amount of practice is limited because (a) a modest level of practice has been found to be sufficient to detect adaptive performance (Betsch et al., 2004) and (b) high routinization is not considered a typical characteristic of work environments requiring high levels of adaptability. Rather, the jobs for which adaptability is considered to be particularly important are complex and dynamic jobs (Ployhart & Bliese, 2006; Pulakos, et al., 2000) where asymptotic levels of performance are unlikely to occur because of frequent changes in the environment.

The starting point for identifying adaptive performance in this context is to note that two types of performance are well established and clearly differentiated (e.g., Deadrick, Bennett, & Russell, 1997; Thoresen et al., 2004; Yeo & Neal, 2004). Basal task performance (or mean level performance) refers to mean differences in the overall level of performance across a specified period of time. Skill acquisition denotes the rate of change across the specified period. Thus, a clear conceptual and operational distinction between these two common types of performance and adaptive types of performance is needed to unequivocally model individual differences in adaptability.

The need to separate adaptability from basal task performance has been recognized by others. For instance, LePine et al. (2000) used generalized estimating equations (Ballinger, 2004) and operationalized adaptation as the interaction between 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 provided a clear distinction between adaptation and basal task performance, but may not go far enough in understanding relationships between adaptability and ability in the complex longitudinal designs engendered by the task-change paradigm.

Temporal Nature of Adaptability

Separating adaptive performance from basal task performance and skill acquisiton may not be sufficient to fully understand adaptability phenomena. Therefore, a second issue in the task-change paradigm is the need to account for the temporal or process nature of adaptability following the change (Chan, 2000). In addressing this issue, several researchers (Chen, 2005; LePine, 2005; Thoresen et al., 2004) have applied mixed-effects growth models (Pinheiro & Bates, 2000) to analyze post-change data. 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). The strength of this methodological approach lies in its ability to separate mean levels of performance from change in the post-change period as two different components of adaptation. The commonly used forms of the mixed-effects models, however, may not fully capture the temporal nature of the change process in the task-change paradigm.

Conceptual and Methodological Framework of the Present Study

In the present article, we examine the relationship between GMA and adaptability using a conceptual and methodological framework based on discontinuous mixed-effects growth modeling (Singer & Willett, 2003). Discontinuous growth models are a specific form of multilevel mixed-effects models which use multiple time variables to model transition processes over time and individual differences in transition processes. These advantages have led to recent interest in this approach in the several areas of research (Bliese, Chan, & Ployhart, 2007; Bliese, McGurk, Thomas, Balkin, & Wesensten, 2007; Bliese, Wesensten, & Balkin, 2006; Lang & Kersting, 2007).

The discontinuous growth modeling framework used in the current research provides a way to examine conceptual and methodological issues in adaptability research in two ways. First, the framework provides a way to account for the temporal or process nature of adaptability by identifying two specific forms of adaptive performance. These two forms are transition adaptation and reacquisition adaptation. Conceptually, these two components of adaptability are similar but not entirely identical to the two types of adaptation (change and mean level of performance) identified by LePine (2005) and Chen (2005). By defining the two conceptually distinct types of adaptation (transition and reacquisition), we are able to isolate the role of GMA in individual performance following unexpected change in the task-change paradigm.

Second, the proposed framework provides a way to clearly separate adaptive performance from basal task performance. This feature of our framework is similar to the methodological approach advanced by LePine et al. (2000). However, the proposed discontinuous growth modeling framework provides an important extension because it accounts not only for basal task performance but also for skill acquisition over time. Thus, both common types of performance can be controlled for when studying adaptive performance.

Basal Task Performance and Skill Acquisition

In describing the specific elements of the discontinuous growth modeling framework, we first consider simple skill acquisition studies where basal task performance and skill acquisition are the two performance components considered by researchers. We then argue that in the context of the proposed discontinuous growth modeling framework, these two performance components are covariates which need to be controlled when measuring transition adaptation and reacquisition adaptation.

Suppose a person performs a novel and complex task over a period of time. Typically, such a scenario is labeled a complex skill acquisition study (e.g., Ackerman et al., 1995; Eyring et al., 1993; Yeo & Neal, 2004). For example, in the context of a study on complex skill acquisition, individuals are likely to differ in two important ways. First, individuals differ in their basal or mean level of task performance. Second, individuals frequently differ in the rate at which they are able to improve their performance over time. The extent to which individuals are able to improve their performance is referred to as the learning rate or the rate of skill acquisition.

A simplified model 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; Chan, 2000; Singer & Willett, 2003). In a linear skill acquisition model, the basal level of task performance is represented by the intercept and the skill acquisition rate is the slope of the linear parameter. Individual differences in both the intercept and the slope can be predicted in mixed-effects models by individual attributes such as GMA (e.g., Eyring et al., 1993; Yeo & Neal, 2004; Völkle et al., 2006). Note that a linear-only change model is a simplified model because skill acquisition or learning processes are frequently non-linear. In describing the rationale of the proposed discontinuous mixed-effects modeling approach, however, we introduce the ideas using a simplified linear-only skill acquisition model. Based on this description, we then extend the model to account for curvilinear change.

Transition Adaptation

Now suppose the simple skill acquisition scenario we described 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 decrease because previously learned routines and procedures are now no longer helpful even if their execution cannot be abandoned by the individual (e.g., Betsch, Brinkmann, Fiedler, & Breining, 1999; Bröder & Schiffer, 2006). To minimize performance decreases, individuals need to possess what we 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 reaction that minimizes performance decrease, and (c) it is measured relative to the previous performance in the task and the learning rate in the pre-change period. One may also think of transition adaptation as a performance component which captures the degree to which routines and expertise from the pre-change period are immediately transferred to the changed 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 such as GMA to explain inter-individual differences in transition adaptation.

Reacquisition Adaptation

Following the initial decrease in performance triggered by the changes in the task, individuals presumably improve their performance as they continue to perform the changed task. Individuals who are able to quickly regain their performance levels possess what we call reacquisition adaptation. The three defining aspects of reacquisition adaptation are that (a) it refers to the process of recovering following the immediate performance loss after a change (b) it is a systematic and analytical learning behavior 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. In contrast to transition adaptation, reacquisition adaptation is a less temporally-defined performance component, because it depends on performance over the full post-change period rather than the temporally-defined period immediately at the change. Presumably, reacquisition is a performance component which depends less on the immediate application of routines and expertise acquired through the pre-change period. Rather, reacquisition adaptation is dependent on individuals' ability to fundamentally re-evaluate the applicability of already acquired expertise.

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 after the change from 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 in the new task (Singer & Willett, 2003). As with other change parameters, inter-individual differences in reacquisition can be modeled in the mixed-effects model using predictor variables like GMA.

Extensions to Account for Curvilinear Change

So far, our description of the discontinuous mixed-effects modeling approach has been discussed in the context of linear change in the pre-change and the post-change period. As noted, though, skill acquisition processes are typically non-linear such that performance accelerates quickly early in the process, but with practice the rate of change declines (a negative accelerating curve). Modeling curvilinear change in mixed-effects growth models (e.g., Snijders & Bosker, 1999) provides a way to reflect the non-linear nature of the change process and is detailed in the Methods and Results sections. Importantly, however, the theoretical distinctions between the two types of adaptability, skill acquisition, and basal performance apply equally well to models with curvilinear change.

Illustration

The different types of change modeled using the proposed discontinuous growth model are illustrated in Figure 1. Figure 1A contrasts the linear discontinuous growth model with the curvilinear model to illustrate how key parameters of the model apply to both the linear and curvilinear models. The curvilinear model is graphed under the assumption that skill acquisition follows a negative accelerating learning curve. Panels 1B to Figure 1F illustrate 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.

Figure 1B shows two individuals who differ only in terms of the intercept (mean difference). The figure illustrates how an individual with higher overall performance might be regarded as having a higher transition adaptation if pre-change task performance is not considered. Figure 1C illustrates a case where the acquisition rates vary for two individuals. Even though the two change patterns do not differ in their level of reacquisition adaptation after the change, the two individuals may be regarded as having different levels of reacquisition adaptation due to differences in skill acquisition. That is, the apparent differences in reacquisition adaptation may reflect differences in general skill acquisition and may therefore not reveal anything unique about adaptation.

Figure 1D and Figure 1E 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 accurately describing adaptive behavior. Figure 1F 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 the two individuals would have probably depended on the length of the post-change performance measurement period. Using a short post-change measurement period, Person 9 would have been regarded as more adaptive. Using a long post-change measurement period, Person 10 would have been regarded as more adaptive.

Figure 1B to Figure 1F illustrate and summarize the advantages of the proposed conceptual and methodological framework based on our two component conceptualization of adaptation and the proposed discontinuous growth modeling approach for the study of individual differences in adaptation. Both types of adaptation can be easily separated while controlling for the effects of skill acquisition and the baseline level of performance in the respective task.

Hypotheses

Building on the proposed discontinuous growth modeling framework and the opposing theoretical ideas linking GMA to adaptive performance, we generated two hypotheses. For transition adaptation, we postulated a non-directional hypothesis predicting a relationship between GMA and transition adaptation. The hypothesis is nondirectional because one can find arguments for a positive relationship (on the basis of the idea that GMA provides individuals with more cognitive resources to monitor, changes to react to, and new routines to actively implement) while one can also link GMA to performance declines following fundamental task changes (on the basis of the idea that high-ability persons are not able to use their superior cognitive capacities under pressure, cannot equally well execute additional routines alongside a task, and tend to focus their attention so successfully to task execution that they have difficulties to detect changes).Specifically, we hypothesized that:

Hypothesis 1: GMA is significantly related to transition adaptation controlling for basal task performance, skill acquisition, and reacquisition adaptation.

For reacquisition adaptation, we formulated a directional hypothesis predicting a positive relationship between GMA and reacquisition adaptation. This decision was made because the arguments for a positive relation between GMA and adaptability can readily be applied to reacquisition adaptation as the core idea behind these arguments is that GMA boosts individuals' ability to re-learn following changes. Specifically, we hypothesized that:

Hypothesis 2: GMA is positively related to reacquisition adaptation controlling for basal task performance, skill acquisition, and transition adaptation.

Method

Participants

A total of 184 persons participated in the study (91 males, and 93 females). The average age of participants was 20.91 years *(SD* = 3.62, Range= 16-33). One hundred-four participants were recruited from the campus of a large university in western Germany. These persons participated at the local institute of psychology. Eighty participants were 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 in the intelligence test used in the study. Furthermore, persons recruited from campus additionally received 10 Euros for traveling to the institute of psychology, which was located outside the university's campus district.

Task

We chose a tank battle scenario as the complex task environment. Tank battle scenarios have successfully been 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). The TankSoar Scenario was designed to have Soar programmed agents competing against each other within a simulated environment. In the present study, we used the TankSoar Scenario to let individuals compete against a Soar agent, or to have an individual and different Soar agents compete against each other. To do so, we 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).

TankSoar simulates battles between tanks in a schematized environment. Participants control one tank while one or more tanks are controlled by a Soar agent. The scenario is comprised of separate decision trials. Within each trial, participants have no restriction regarding the time they have available to plan their actions for the respective round. After deciding on which action to take, participants complete each trial. 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 trial.

Figure 2 shows the screen of the modified TankSoar Version used with 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 take place in this area. When participants are active in the scenario, they only see a restricted 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 3A and Figure 3B show both scenarios unrestricted. The following paragraphs offer a description of the generic task. More detailed descriptions of task and each of its elements are available from the program documentation as well as the Soar Tutorial (Soar Group at the University of Michigan, 2004).

Armed with missiles the aim of the scenario is to shoot adversarial tanks and avoid getting hit by the enemy. Missile resources decrease with each missile shot. Tanks can recharge their missiles by moving onto the missile pick up packs.

To help the tank navigate through the partly covered playing field, participants can rely on six different sensors shown in the upper right window of Figure 2. These sensors provide information about the area around the tank, obstacles such as trees and stones, the direction and position of adversarial tanks as well as on the direction of incoming missiles. For additional protection, the tank can activate a shield to prevent destruction by a missile.

A tank has a certain amount of energy, which is consumed by the shield and the radar sensor when active. Additionally, health points get lost when an enemy hits the tank or the tank collides with an obstacle (i.e., stones or trees). Both health and energy can be restored by moving the tank on the equivalent recharger fields.

Performance in TankSoar is measured by points. Each time a tank gets hit by a missile it loses one point. 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 points (so that it gains a total of five points for the missile hit). Tanks can protect themselves from missile hits by activating their shields.

General Mental Ability Testing

Most researchers strongly recommend using more than one GMA-saturated test to assess GMA in order to avoid potential contamination of GMA with test-specific variance (e.g., Ackerman, Beier, & Boyle, 2005). In accordance with this recommendation, the present study assessed participants' GMA with three typical ability tests that differed in their content. The three tests were taken from the revised Wilde Intelligence Test (WIT-2; Kersting, Althoff, & Jäger, 2008), which is a frequently used German ability-test battery. The present study employed the tests “folding boxes” (a spatial task), “completing number series” (a numerical task), and “verbal analogies” (a predominantly verbal task), which form the abbreviated version of the WIT recommended by the authors.

In order to test whether the three tests were valid indicators of a common GMA-factor, we conducted a confirmatory factor analysis (CFA) using the sem package (Fox, 2004, 2006) included in the open source software R (R Development Core Team, 2004) and maximum likelihood estimation (ML). As one-factor models with three manifest indicators do not possess enough degrees of freedom for a CFA, we built two 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. The hypothesized model 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, we 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., Ackerman & Beier, 2006) and 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 (Tucker, 1971). In order to determine the internal consistency of this composite score, we 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). We found stratified Cronbach’s $\alpha = .98$ indicating adequate reliability for the composite measure of GMA.

Procedure

The present study was held in 2 to 3 hour sessions. Sessions were conducted in groups of

2-15 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. In total, participants worked on 600 trials of the TankSoar Scenario. After 100, 200, 300, 400, and 500 decision trials, the scenario was restarted. This was done for two reasons. First, restarting the scenario provided low-scoring individuals with a new chance to master the task and thus avoided demotivation of these individuals, because of a low score. Second, regular restarts of the scenario accustomed participants to these restarts and consequently allowed us to introduce an unforeseen environmental change with the restart at trial 300. Specifically, the scenario environment switched from the scenario presented in Figure 3A to the scenario presented in Figure 3B after 300 trials. Due to the limited view of the map (see Figure 2) changes were not immediately apparent. Nonetheless, as can be seen in Figure 3A and Figure 3B, there were some important 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 larger and there are three opponents instead of only one. Therefore, in contrast to the first map, multiple opponents often fire missiles simultaneously against the participant's tank 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 the second scenario.

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 mixed-effects models, with measurement occasions at level 1 nested within individuals at level 2. For the purpose of data-analysis, we grouped the 600 decision trials into blocks of 50 trials. Consequently, there were six measurement occasions in the pre-change (skill acquisition) period and six measurement occasions in the post-change period.

Following recommendations by several researchers (Bliese & Ployhart, 2002; Pinheiro & Bates, 2000), we first examined level-1 change by calculating a sequence of models with level-1 predictors only. In the next step, we examined the level-2 model by adding GMA as a level-2 predictor to explain differences in level-1 change.

For all mixed-effects analyses, we calculated standardized coefficients for the fixed effects to provide relative effect size information. Standardized coefficients were derived by setting the standard deviation of all variables (including the time variables) to 1 without altering the centering of the variables (origin of time for the change variables as described below and the sample mean for GMA).

Results

Descriptive Data and Intercorrelations

Table 1 presents the means, standard deviations and intercorrelations for pre-change performance, post-change performance, and GMA. An important precondition for testing the hypotheses under study is that a considerable relationship between GMA and performance actually exists in the data. In line with this precondition, Table 1 shows that GMA was moderately correlated with performance in both the pre-change and the post-change period.

Amount of Individual Differences in Change

Before proceeding to test the hypotheses using the proposed discontinuous mixed-effects model, we examined the intraclass correlation coefficient (ICC1) for the criterion measure. In the current study, the ICC1 indicates how much of the variability in decision-making performance is a result of between-person differences across the twelve measurement occasions. The ICC1 is calculated by determining the proportion of between-person variance in the overall variance (between person variance/[between-person variance + residual within-person variance]) of an unconditional (random intercept) mixed-effects model (Bliese & Ployhart, 2002). Analyses revealed an ICC1 = .44, indicating that between-person variance explained 44% of the variance in performance across time. This value suggests that considerable individual differences in performance across time exist (Bliese, 2000).

Level-1 Analyses

We started discontinuous growth modeling analyses by examining the basic version of the proposed discontinuous level-1 model accounting only for linear change. To do so, we added level-1 change variables modeling skill acquisition (SA_{ti}), transition adaptation (TA_{ti}), and reacquisition adaptation (RA_{ti}) to the null model.

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

The coding of the change variables is shown in Table 2 and is adopted from Singer and Willett (2003). This coding provides coefficients for the amount of transition adaptation at the transition from the pre-change to the post-change period and operationalizes the coefficient for the post-change slope relative to the pre-change slope for skill acquisition.

Analyses revealed 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 (for details, see Table 3). Notice that this pattern of mean performance across time is similar to previously documented change patterns in research on adaptation to change (e.g., Bröder & Schiffer, 2006). That is, there were pronounced increases in mean performance in the skill acquisition period, a strong decrease in performance following the change and moderate increases during the reacquisition period.

In the next step, we extended the basic linear discontinuous mixed-effects model to account for quadratic change in the pre-change and post-change periods using polynominal coding adopted from Snijders and Bosker (1999). The exact coding is provided in the bottom portion of Table 2. Notice the model adds an additional time variable for quadratic skill acquisition ($SA2_{ti}^{2}$), which changes only in the skill acquisition period and then remains constant at 5^2 (25). Snijders and Bosker (1999) use a constant value of zero rather than 5^2 (page 189); however with the inclusion of a discontinuity parameter (TA) the value of 25 rather than zero helps provides an un-confounded estimate of TA. Specifically, this coding allows one to center both skill acquisition terms at the origin of time and then determine the discontinuity parameter (TA) relative to skill acquisition at the origin of time. Importantly, though, the use of either constant (zero or 25) leads to the same pattern of significance and produces identical predictive plots. For reacquisition adaptation, curvilinear change was modeled by adding the additional quadratic term for the reacquisition variable (RA_{ti}^{2}). The final level-1 model was:

$$Y_{ti} = \pi_{oi}+\pi_{1i}SA_{ti}+\pi_{2i}TA_{ti}+\pi_{3i}RA_{ti}+\pi_{4i}SA2_{ti}^{2}+\pi_{5i}RA_{ti}^{2}+e_{ti}$$

The results for the linear parameters in the extended discontinuous level-1 model were similar to those for the basic linear level-1 model (see Table 3). Additionally, we found evidence for significant quadratic change in the skill acquisition period. Specifically, the learning rate declined with increasing practice on the task indicating evidence of a learning curve. For the reacquisition period, we found no significant quadratic change.

Because individual differences in change were of primary interest in the present research, we investigated not only differences in level-1 change but also whether level-1 change variables randomly varied across individuals. Following recommendations by several researchers (Bliese & Ployhart, 2002; Pinheiro & Bates, 2000; Snijders & Bosker, 1999), we restrained level-1 parameters when we found no random variability. Following recommendations in the literature (Bliese & Ployhart, 2002; Pinheiro & Bates, 2000), tests for random variability were conducted by contrasting models using log-likelihood ratio tests.

Analyses provided evidence for a significant amount of random variability in (a) the skill acquisition effect, simple model: χ^2_{diff} (4) = 50.45, p < .001; quadratic model: χ^2_{diff} (4) = 51.82, p < .001); (b) the transition adaptation effect, simple model: χ^2_{diff} (4) = 76.69, p < .001; quadratic model: χ^2_{diff} (4) = 78.37, p < .001; and (c) the reacquisition adaptation effect, simple model: χ^2_{diff} (4) = 26.97, p < .001; quadratic model: χ^2_{diff} (4) = 28.06, p < .001, between persons. These tests indicate significant individual variability on initial skill acquisition, transition adaptation, and reacquisition adaptation.

For the discontinuous model accounting for quadratic change, we additionally tested for random variability in the quadratic change terms. We found no random variation in either the quadratic change term for the (pre-change) skill acquisition, χ^2_{diff} (5) = 6.71, p = .24, or the (post-change) reacquisition period χ^2_{diff} (5) = 4.07, p = .52. Thus, we included no model term accounting for random variability in these level-1 change parameters in the curvilinear level-1 change model.

In concluding level-1 analyses, we followed recommendations by DeShon, Ployhart, and Sacco (1998) and tested for autocorrelation and heteroscedasticity in model error structures. Both error structures should be controlled for when present in a model to derive accurate standard errors of model parameters (DeShon et al., 1998). Analyses revealed evidence of autocorrelation, simple model: φ =.12; χ^2_{diff} (1) = 14.01, p < .001; quadratic model: φ = .13; χ^2_{diff} (1) = 15.49, p < .001, and models accounting for heteroscedasticity ran into convergence problems. Consequently, the final level-1 change models accounted for autocorrelation in error structures.

Level-2 Analyses

To test for systematic differences in change between individuals resulting from different levels of GMA, GMA was added as a level-2 predictor for each of the level-1 components in the basic linear and the extended curvilinear discontinuous models. Consequently, the following level-2 equations for both the basic linear and the extended curvilinear discontinuous models emerged.

$$\pi_{0i} = \beta_{00}+\beta_{01}GMA_i+r_{0i}$$

$$\pi_{1i} = \beta_{10}+\beta_{11}GMA_i+r_{1i}$$

$$\pi_{2i} = \beta_{20}+\beta_{21}GMA_i+r_{2i}$$

$$\pi_{3i} = \beta_{30}+\beta_{31}GMA_i+r_{3i}$$

Additionally, for the curvilinear discontinuous model, the following two level-2 equations to investigate differences in quadratic change in skill acquisition and reacquisition adaptation were specified.

$$\pi_{4i} = \beta_{40}+\beta_{41}GMA_i$$

$$\pi_{5i} = \beta_{50}+\beta_{51}GMA_i$$

While the two quadratic change parameters did not significantly vary across individuals in the log-likelihood tests, there was a clear theoretical basis to examine the role of GMA on the quadratic terms. Furthermore, log-likelihood tests tend to be conservative (Snijders & Boskers, 1999). Therefore, Snijders and Boskers as well as others recommend testing cross-level effects in absence of significance, when there is a theoretically solid rationale to assume that a level-2 parameter (i.e., GMA) influences a level-1 parameter (i.e., quadratic change).

Results for the final discontinuous mixed-effects models are presented in Table 3. As indicated by Table 3, the first hypothesis concerning the relationship between GMA and transition adaptation was confirmed by a significant negative relationship between GMA and transition adaptation. This result indicates that individuals with a higher GMA had a more pronounced decline in performance after the unforeseen change.

With respect to the hypothesis concerning GMA and reacquisition adaptation, results showed no evidence for a relationship between GMA and the rate of reacquisition performance. This suggests persons with high GMA were not faster than those low in GMA in reacquiring mastery of the task following the initial drop in performance after the change (see Table 3).

The study's findings with respect to adaptability are illustrated and summarized in Figure 4.

Figure 4 graphs the effects of GMA on the overall change pattern of individuals by using the model parameters for the extended curvilinear discontinuous model in Table 3 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 4, individuals with a high GMA performed at a higher level across the whole time period captured by the study. However, due to the negative relationship between GMA and transition adaptation and the non-significant relationship between GMA and reacquisition adaptation these individuals performed relatively less well following the unforeseen change in the task.

Supplemental Analyses

To further examine the role of GMA with respect to the transition, we examined a subset of low-GMA individuals who were performing similarly to the high-GMA subjects prior to the change. If the results revealed a differential decline for high and low GMA individuals, it would provide additional evidence that the observed findings were due to GMA rather than some other facet of the task-change paradigm.[1]

To contrast the transition decline of high-performing individuals who varied in terms of GMA, we used the curvilinear mixed-effects model to generate empirical Bayes estimates of the transition (TA) parameter for each individual. Second, we took individuals who performed above the median (of all participants) in terms of the last pre-transition performance point and split them into groups of individuals with high (top 3rd), average (middle 3rd), and low (lower 3rd) levels of GMA. This left us with 20 low GMA individuals who performed above the median, 28 average GMA individuals who performed above the median, and 44 high GMA who performed above the median (a result that reflects the GMA main-effect).

When we contrasted the high GMA individuals with the low GMA persons, results indicated that the 44 high GMA persons declined 9.91 points while the 20 low GMA persons declined

7.65. A simple Kolmogorov-Smirnov (K-S) test indicated that this was significant (D = 0.45, p = .004). We used the K-S test because the splits can cause non-normal and unusual distributions and the K-S test is a non-parametric test able to deal with these circumstances (Wilcox, 1997). A one-sided t test was nevertheless also significant, $t(29.18) = -1.88$, $p = .035$.[2] When we contrasted the high GMA individuals with a combined group of average GMA and low GMA individuals, we got similar results. The high-performing combined group of 48 average and low GMA individuals dropped 8.19 points at the transition point. Both a K-S and a t-test indicated that this drop was significantly smaller than the average drop of the 44 high-performing and high GMA individuals (D = 0.31, p = .019), $t(89.57) = -2.11$, p = .037.

To make this test even more conservative we noted that while both groups were in the upper half of performance, the high GMA group had a mean score of 14.89 at the last pre-transition performance point while the low GMA group had a score of 13.05, and the combined group of average and low GMA persons had an average score of 13.21. Although the performance differences between the high GMA group and the two other groups were not significant (high vs. low: p = .44; high vs. average and low: p = .32), we wanted to ensure that the TA differences were not caused by the slightly different starting points. To rule out this possibility, we conducted an additional analysis in which we first created high (top 3rd) and low GMA (lower 3rd) groups. Second, we adjusted upper and lower performance cutoffs for both groups until we had two groups with almost perfectly equal levels of performance at the last pre-transition performance point (equal median and almost identical mean). We targeted a mean/median approximately similar to the level of performance predicted for high GMA individuals in the model (see Figure 4) and excluded performance higher than 12 points because the number of individuals at such high levels of performance was generally small (particularly for low GMA). The final two groups consisted of 19 high GMA individuals with a performance mean of 5.79 points and a performance median of 6 as well as 12 low GMA individuals with a performance mean of 6.50 points and (similar) performance median of 6. Results indicated that the high GMA individuals still had more of a transition decline (TA = -6.78 points) than the low GMA individuals (TA = -4.51 points). A K-S and *t* test revealed that the difference between the two groups was significant ($D = 0.57$, $p = .009$), $t(28.78) = -2.11$, $p = .035$. Note that this finding emerged although the high GMA individuals had equal (even slightly lower) performance at the end of the skill acquisition period.

Discussion

The present study contributes to the growing field of adaptability research by providing a theoretical and empirical framework for identifying adaptable performance in the context of the task-change paradigm—a research setting where individuals are routinely given a set number of performance trials upon which to develop task familiarity, but where asymptotic performance is rarely, if ever, universally achieved. The primary goal of this manuscript was to delineate the conceptual distinctions among transition adaptation, reacquisition adaptation, skill acquisition, and basal task performance and to illustrate how discontinuous mixed-effects growth models could be used to examine these four components. A secondary goal was to provide a detailed examination of the role of GMA in adaptability. We begin by summarizing and discussing the GMA findings.

General Mental Ability and Adaptability

By using the proposed framework, we identified that individuals higher in GMA had a significantly larger decline in performance than did individuals with low GMA when the nature of the task unexpectedly changed (negative relation between GMA and transition adaptation). The missing evidence for a relation between GMA and reacquisition adaptation implies that this is not a short-term phenomenon as people with high GMA do not quickly make up the relatively stronger losses in performance through a higher level of reacquisition adaptation.

The findings related to both transition adaptation and reacquisition adaptation appear to contradict the theoretical proposition (Hunter & Schmidt, 1996; LePine et al., 2000) that individuals with higher GMA are better able to adapt to fundamental environmental changes.

Indeed, based on the components of transition adaptation and reacquisition adaptation, one would conclude that high GMA provides no enhanced benefit in terms of adapting to unexpected change (we will address this issue in more detail in the next section).

Importantly, though, the negative relationship between GMA and transition adaptation does not contradict the general notion in the literature that high-GMA individuals generally have superior task performance (Gottfredson, 1997; Lubinski, 2004; Schmidt & Hunter, 2004). The proposed discontinuous growth modeling approach conceptualizes transition adaptation relative to both skill acquisition and basal task performance. Therefore, at any point during both the pre-change and the post-change period, the final discontinuous growth model of the study predicted higher performance for individuals with a higher GMA (recall the level-2 main effect for GMA). Thus, the negative transition adaptation effect for GMA refers only to individuals' relative change in performance across time. In general, the current study provides evidence that high performance may not be fully maintained when high GMA individuals are confronted with unforeseen changes. The study demonstrates that it is important to differentiate the overall role of GMA on performance (i.e., that it is positively related to performance) from the role of GMA on adaptability (i.e., does not necessarily infer relatively superior performance after changes).

Theoretical Explanations for the Negative Relation Between General Mental Ability and Transition Adaptation

Theoretically, the literature suggests that the negative relation between GMA and transition adaptation results from differences in the cognitive-attentional system between low- and high-GMA individuals. Nevertheless, a reviewer and the associate editor of this journal offered two plausible alternative explanations for our findings. Both explanations draw on the fact that even an equal amount of practice for all persons and our effort to control for the rate of skill acquisition using discontinuous mixed-effects models do not rule out that individuals at higher levels of skill react differently to practice on the task prior to the change.

The first alternative explanation is that high-GMA individuals simply learn more about the task during practice and thus have more to lose when the task changes. In fact, in research on implicit sequence learning, an indirect measure of learning is inferred using a paradigm similar to the task-change paradigm—specifically, the serial reaction time task (Koch, 2007; Wilkinson & Shanks, 2004). In the serial reaction time task, a fixed stimulus sequence is presented to individuals several times. Then, the stimulus sequence is replaced by a random sequence. The difference in response times between the stimulus sequence and the random sequence is considered to be indicative of the amount of learning. Arguably, the discontinuous mixed-effects modeling results related to GMA would be consistent with such an interpretation—higher GMA individuals had learned more about the task and therefore had more to lose in terms of task proficiency.

The second alternative explanation is somewhat related to the first one. This explanation is similar to the first explanation but replaces the notion that individuals may have learned more with the idea that they may have reached more automaticity with the task during skill acquisition. Automaticity may lead to less adaptability to changes because research contrasting experts (those with the highest possible degree of automated performance in a task) with briefly trained novices suggests that novices are relatively better able to adapt to unfamiliar changes in tasks than experts, when these changes fundamentally alter the nature of the task (Beilock & Carr, 2001, 2004). Beilock and Carr have proposed that these findings emerge because experts need to switch from a proceduralized form of task execution back to a step-by-step mode in order to modify and alter task execution, whereas novices already execute tasks in a step-by-step mode and thus can readily implement changes. Arguably, the discontinuous mixed-effects modeling results related to GMA would also be consistent with such an interpretation—because higher GMA individuals attained higher performance in the task prior to the change, they executed the task in a more proceduralized fashion and thus had difficulties to retain to a less proceduralized from of task execution in order to adapt.

While these are plausible explanations, the supplemental analyses suggest that these explanations cannot fully account for the findings from the discontinuous mixed-effects modeling analyses. Specifically, even when we examined individuals with equally high levels of pre-change performance in the supplemental analyses, those with high GMA still experienced larger performance declines. These findings are not fully congruent with the alternative learning and automaticity explanations.and suggest that the findings are due to some characteristics of high GMA individuals not specifically related to prior skill acquisition.

Study Limitations

In concluding our discussion of the results related to GMA we acknowledge that the findings may lack generalizability with respect to (a) the type of task, (b) the type of unforeseen change, and (c) sample characteristics. With respect to task type, we would expect the results to generally apply to complex tasks where individuals have not universally obtained asymptotic performance and where levels of GMA are related to the levels of performance. Concerning the type of unforeseen change, the current findings are likely to be primarily applicable to cases where there are fundamental unforeseen changes in the nature of the task. We would not necessarily expect the results to apply to situations where the change simply involved increasing work load. Finally, with respect to sample characteristics, we note that the current study employed a rather specific sample, which likely differed from the general population. Nevertheless, the sample was more diverse than the samples typically used in laboratory research. Participants were recruited from high-school classes and the campus of a German university and not simply from psychology undergraduate classes as in most research.

Methodological and Conceptual Implications for Adaptability Research

While the results related to GMA are important, our other goal was to build off previous work and provide a way to differentiate among transition adaptation, reacquisition adaptation, skill acquisition, and basal task performance in the task-change paradigm. Fundamentally, the use of discontinuous growth models within the task-change paradigm provides a way to mathematically mirror what is occurring in the experimental setting. That is, the analytic technique uniquely captures each distinct phase of the task-change paradigm and provides a way to model individual differences in each phase. Other analytic approaches may approximate the experimental design, but by failing to capture each component of the experimental design they run the risk of leading to interpretational ambiguity. We believe that our examination of GMA within this theoretical and methodological approach provides a precise summary of the role of GMA (see Figure 4). Our position is that other approaches would not be able to offer the same degree of interpretational clarity. This particularly applies to reacquisition adaptation. Our approach provides a clear, intuitive, and conceptually concise rationale for differentiating between reacquisition adaptation and skill acquisition. This is an important contribution because it provides a theoretical rationale for considering reacquisition adaptability separately from other types of performance and thus provides a conceptual basis upon which to build future adaptability research.

This is not to say that the proposed framework resolves all theoretical or interpretational ambiguity surrounding adaptability. This point is illustrated by the fact that the discontinuous mixed-effects modeling framework alone was not able to rule out different theoretical explanations for our findings regarding the relation between GMA and transition adaptation. Still, the use of the modeling framework in conjunction with the results based on the empirical Bayes' estimates produced a consistent and empirically coherent set of findings. The way the task-change paradigm is commonly used in adaptability research almost necessarily provokes a certain degree of theoretical ambiguity regarding the functional relation between different performance components as individuals differing in one performance components likely will also differ in another. This is a core problem of correlational research strategies in general which naturally generalizes to adaptability research. The approach we provide is an important step towards reducing interpretational ambiguity in adaptability research because it differentiates the necessary components. Building on the proposed approach, researchers might also explore several additional steps towards reducing ambiguity in future adaptability research.

Other ways to reduce ambiguity regarding the functional role of performance components such as transition adaptation may be to combine individual difference variables and the proposed discontinuous mixed-effects modeling approach with experimental task manipulations in order to systematically isolate the role of different performance components. Naturally, experimental manipulations cannot, per se, clear up all ambiguity in adaptability research because they will likely always alter several performance components simultaneously to a certain degree. Nevertheless, evidence on how the relation between individual difference variables and performance components is moderated by different situation contexts might provide important supplemental insights.

Another and perhaps complimentary way to work towards reducing theoretical ambiguity in task-change paradigm research may be to consider covariates more broadly. The way skill acquisition is controlled in the proposed discontinuous mixed-effects model is already illustrative of this point. In a similar vein, we note that researchers using the task-change paradigm may also need to use GMA as a covariate when the focus is on adaptability factors other than GMA. This may be particularly important if the tasks used in the task change paradigm (analogous to the vast majority of real world jobs cf. Ackerman, 1992; Farrell & McDaniel, 2001) are so complex and inconsistent that low GMA individuals may never asymptotically reach performance levels of high GMA individuals (Ackerman, 1988, 1992; Farrell & McDaniel, 2001; Keil & Cortina, 2001).

In the current data, the strategy of using GMA as a covariate appears promising. We base this observation on the fact that strong random effects were found for individual variability in transition adaptation—some individuals had large performance declines at the transition point and others did not. As noted, our results revealed that a significant part of the variance in performance change at the transition was related to GMA. In subsequent tests, however, we examined whether the inclusion of the interaction between GMA and the transition parameter in the final models (see Table 3) explained all the individual variance related to the transition.

These tests indicated that a considerable amount of variability in the transition parameter existed even after GMA had been included (simple model: χ^2_{diff} [4] = 67.75, $p < .001$; quadratic model: χ^2_{diff} [4] = 69.64, $p < .001$). This strongly suggests that there are other factors related to performance changes at the transition. Indeed, it is possible that transition adaptation is best operationalized as the residual change in performance once GMA effects are controlled in studies where the complexity of the task lead to differential pre-change performance in high and low GMA individuals. With this example, we are again emphasizing that the proposed theoretical and methodological framework leads to a series of empirically testable research hypotheses that have the potential to advance our knowledge of adaptability.

Practical Implications

The present empirical findings related to GMA may have important practical implications for individual performance in work settings, because many scholars agree that the frequency of situations requiring adaptability is consistently increasing due to the increasing dynamic nature of modern work environments (e.g., Burke et al., 2006). Our finding of a negative relationship between GMA and transition adaptation implies that in occupational decision-making settings, persons with a high GMA may show stronger performance losses when they face unforeseen changes requiring rapid responses like, for example, when markets undergo a rapid transformation process. The missing evidence for a relation between GMA and reacquisition adaptation implies that this is not a short-term phenomenon as people with high GMA do not make up the relatively stronger losses in performance through a higher level of reacquisition adaptation.

The findings suggest that there is a need for organizations to counter the relatively stronger performance losses of high-GMA people. This might be conducted by implementing training tailored for high-GMA people to increase competencies relevant to adaptive performance. In so doing, organizations can benefit from several recent research efforts which have suggested and studied ways to increase adaptive transfer by redesigning training interventions (e.g., Burke et al. 2006; Ford & Kraiger, 1995; Smith et al., 1997). Alternatively, organizations may develop strategies to applying specific training to high-GMA people directly in response to an unforeseen change. In terms of selection, the results indicate that organizations needing highly adaptable individuals should consider other selection criteria in addition to GMA when hiring individuals. As we previously demonstrated, there is considerable variability in both transition and reacquisition adaptation that was not explained by GMA. This implies that there may be other measurable selection criteria for identifying adaptable individuals.

Conclusion

We encourage researchers to conduct future studies on adaptability and individual differences (e.g., GMA, personality or motivational variables) using the proposed framework. In our opinion, the advantage of the framework over other approaches is that it mathematically mirrors what is occurring in the task-change design and provides precise estimates of each critical performance component. While the use of the framework does not definitively resolve all of the theoretical issues surrounding the research on adaptability, it clearly provides a foundation for advancing adaptability research.

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Footnotes

[1]We thank the associate editor for suggesting this type of analysis.

[2]A one-tailed test is justified at this point because of the previous discontinuous mixed-effects modeling results.

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Table 1.

Means, Standard Deviations, and Intercorrelations of Study Variables

Variable	*M*	*SD*	1	2	3
1. Pre-change performance (Trial 1-300)	5.09	50.54	–		
2. Post-change performance (Trial 301-600)	22.21	39.46	.81	–	
3. General mental ability	0.00	1.00	.38	.32	–

Note. $N = 184$. All intercorrelations are significant at $p < .001$.

Table 2

Coding and Interpretation of Change Variables in the Discontinuous Mixed-Effects Growth Models for the Study

	Measurement occasions												
Variable	1	2	3	4	5	6	7	8	9	10	11	12	Interpretation
Coding of change variables													
Skill acquisition (SA)	0	1	2	3	4	5	6	7	8	9	10	11	
Transition adaptation (TA)	0	0	0	0	0	0	1	1	1	1	1	1	
Reacquisition adaptation (RA)	0	0	0	0	0	0	0	1	2	3	4	5	
Skill acquisition 2 (SA2)	0	1	2	3	4	5	5	5	5	5	5	5	
Change terms entered into the linear model													
SA	0	1	2	3	4	5	6	7	8	9	10	11	linear change in the pre-change period
TA	0	0	0	0	0	0	1	1	1	1	1	1	performance drop as a result of the switch from the pre-change to the post-change period
RA	0	0	0	0	0	0	0	1	2	3	4	5	linear change in the post-change period relative to the linear change in the pre-change period
Change terms entered into the curvilinear model													
SA	0	1	2	3	4	5	6	7	8	9	10	11	linear change at the start of the pre-change period
TA	0	0	0	0	0	0	1	1	1	1	1	1	performance drop as a result of the switch from the pre-change to the post-change period
RA	0	0	0	0	0	0	0	1	2	3	4	5	linear change at the start of the post-change period relative to the linear change at the start of the pre-change period
$SA2^2$	0	1	4	9	16	25	25	25	25	25	25	25	quadratic change in the pre-change period
RA^2	0	0	0	0	0	0	0	1	4	9	16	25	quadratic change in the post-change period

Table 3

Discontinuous Mixed-Effects Growth Models Predicting Change in Performance as a Function of General Mental Ability

	Model 1 (simple linear model)				Model 2 (extended curvilinear model)			
Fixed effects	Coef.	Coef. *SE*	*t*	Std. coef	Coef.	Coef. *SE*	*t*	Std. coef
Final level 1 model								
(Intercept)	−3.53	.54	−6.54[a]**		−4.60	.60	−7.65[c]**	
Skill acquisition (SA)	1.76	.14	12.82[a]**	.60	3.32	.41	8.10[c]**	1.12
Transition adaptation (TA)	−4.79	.68	−7.06[a]**	-.23	−5.18	.74	−7.02[c]**	-.25
Reacquisition adaptation (RA)	−1.19	.18	−6.55[a]**	-.20	−2.80	.59	−4.79[c]**	-.48
Quadratic skill acquisition ($SA2^{2}$)					-.31	.08	-4.04[c]**	-.31
Quadratic reacquisition adaptation (RA^{2})					.01	.08	.09[c]	.01
Final level 2 model								
General mental ability (GMA)	2.91	.54	5.37[b]**	.28	2.47	.60	4.09[b]**	.24
SA × GMA	.12	.14	.89[a]	.04	.75	.41	1.83[c]†	.25
TA × GMA	−1.81	.68	−2.66[a]**	-.09	−2.41	.74	−3.26[c]**	-.12
RA × GMA	−.01	.18	−.07[a]	-.00	−.06	.59	-.10[c]	-.01
$SA2^{2}$ × GMA					-.12	.08	-1.61[c]	-.12
RA^{2} × GMA					-.12	.08	-1.52[c]	-.09

			Correlations					Correlations		
Random effects	Variance	*SD*	1	2	3	Variance	*SD*	1	2	3
1. (Intercept)	33.73	5.81	–			34.08	5.84	–		
2. Skill acquisition	1.28	1.13	.41	–		1.30	1.14	.40	–	
3. Transition adaptation	29.40	5.42	–.74	–.89	–	29.30	5.41	–.73	–.88	–
4. Reacquisition adaptation	1.81	1.35	–.36	–.91	.87	1.90	1.38	–.34	–.91	.86
Residual	44.01	6.63				43.48	6.59			

Note. N = 184. k = 2208. All change variables were centered at the origin of time so that the intercept reflects baseline performance at Trial 1. GMA was z-standardized and centered at the sample mean. Standardized coefficients were derived by setting the standard deviation of all variables to 1 without altering the centering of the variables. Coef. = Coefficient. Std. coef.=Standardized coefficient.

[a]*df*=2018 [b]*df*=182 [c]*df*=2014

† p <.05, one-sided ** p <.01, two-sided

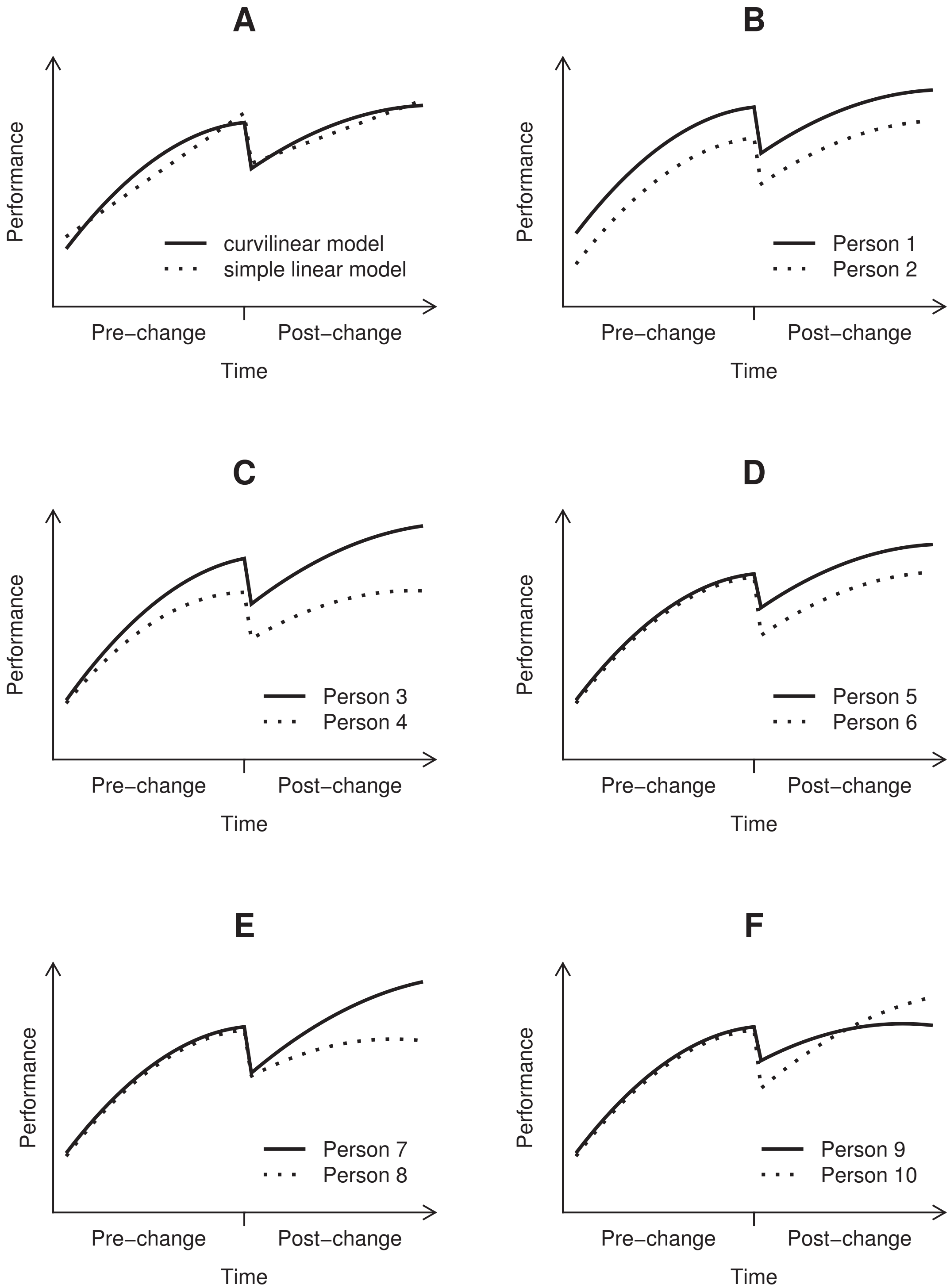
Figure Captions

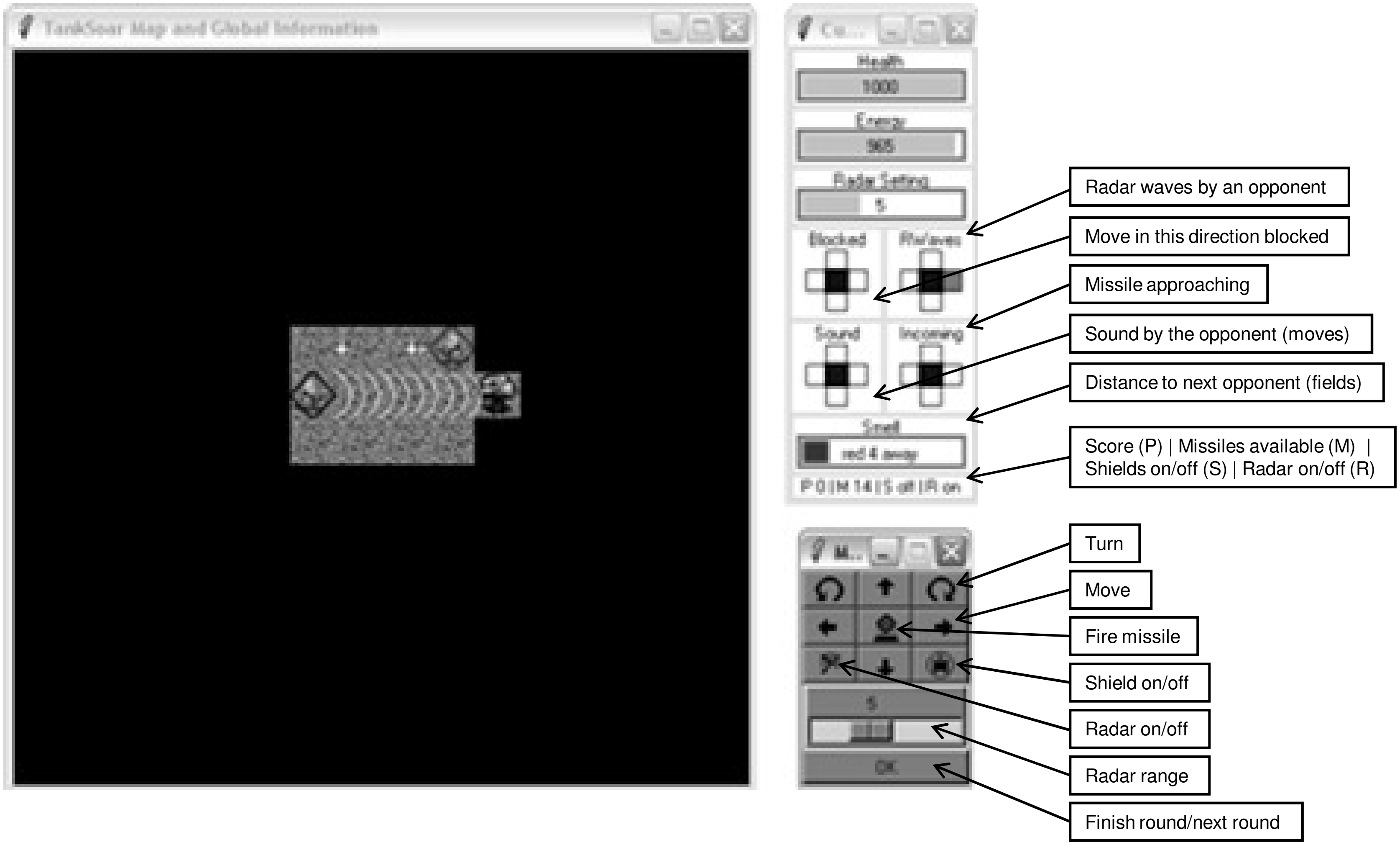
Figure 1. Hypothetical change patterns modeled using a discontinuous growth model: (A) Typically expected mean pattern of change in a study using the task-change paradigma, (B) change patterns of two individuals differing in their initial overall level of performance, (C) change patterns of two individuals differing in their rate of skill acquisition, (D) change patterns of two individuals differing in transition adaptation and (E) change patterns of two individuals with different levels of reacquisition adaptation, and (F) change pattern of a person with a high level of transition adaptation but a low level of reacquisition adaptation contrasted with the change pattern of a person with a low level of transition adaptation but a high level of reacquisition adaptation.

Figure 2. TankSoar working screen.

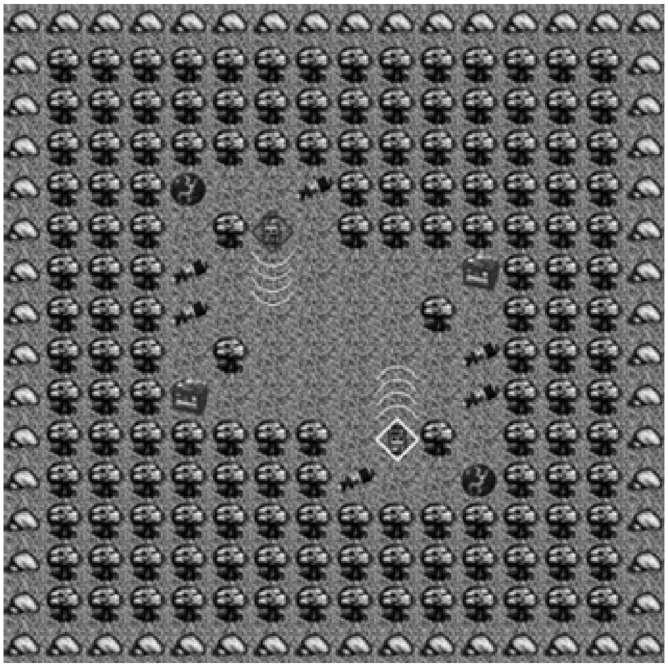
Figure 3. TankSoar-Scenarios used in the pre-change period (A) and post-change period (B) of the present study.

Figure 4. Predicted performance as a function of general mental ability.

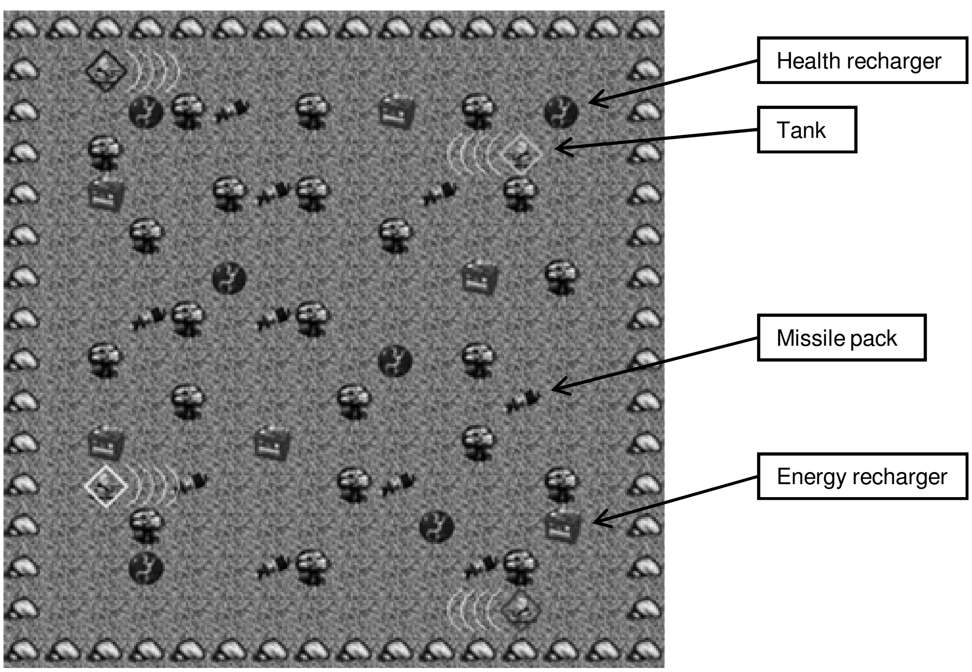

A
Performance
curvilinear model
simple linear model
Pre−change
Post−change
Time
B
Performance
Person 1
Person 2
Pre−change
Post−change
Time
C
Performance
Person 3
Person 4
Pre−change
Post−change
Time
D
Performance
Person 5
Person 6
Pre−change
Post−change
Time
E
Performance
Person 7
Person 8
Pre−change
Post−change
Time
F
Performance
Person 9
Person 10
Pre−change
Post−change
Time

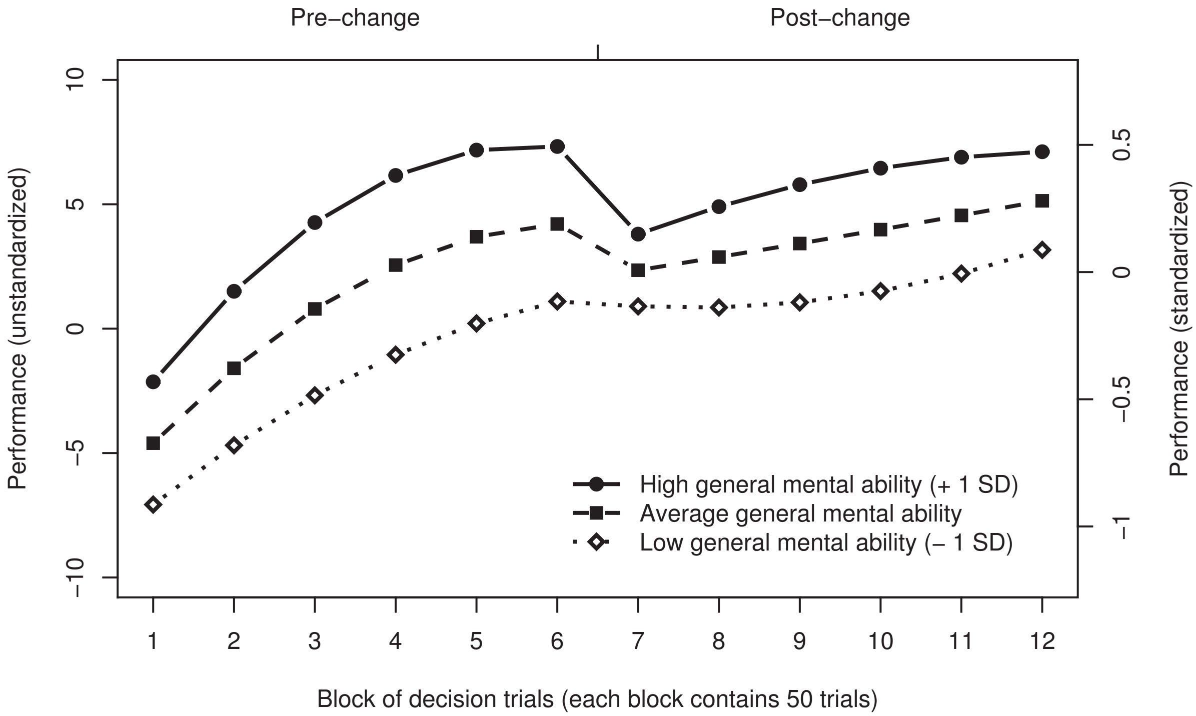

Radar waves by an opponent
Move in this direction blocked
Missile approaching
Sound by the opponent (moves)
Distance to next opponent (fields)
Score (P) | Missiles available (M) | Shields on/off (S) | Radar on/off (R)
Turn
Move
Fire missile
Shield on/off
Radar on/off
Radar range
Finish round/next round

A



B




Pre−change
Post−change
Performance (unstandardized)
Performance (standardized)
10
5
0
−5
−10
0.5
0
−0.5
−1
1
2
3
4
5
6
7
8
9
10
11
12
High general mental ability (+ 1 SD)
Average general mental ability
Low general mental ability (− 1 SD)
Block of decision trials (each block contains 50 trials)