Short title: ACTIVE TRAINING, MOTIVATION, AND ABILITY

Active/exploratory training promotes transfer even in learners with low motivation and cognitive ability

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Active/exploratory training promotes transfer even in learners with low motivation and cognitive ability

Abstract

Active training approaches encourage self-directed exploration whereas guided training stresses direct instruction and external guidance during training. The present research investigated interactions of individual-difference variables—motivation and cognitive ability—and training approach on performance in tasks that are similar to training tasks (analogical transfer) and tasks that are novel and distinct from training tasks (adaptive transfer). In accordance with a resource allocation framework (Kanfer & Ackerman, 1989), we expected effects of individual differences on transfer performance to be reduced after active/exploratory training compared with guided training, because participants of exploratory training engage in the same kind of metacognitive processing during training and transfer. Consequently, attentional demands are reduced during transfer, whereas for participants of guided training the transfer situation imposes high attentional demands. Experiment 1 ($N = 37$) taught a word processing program and Experiment 2 ($N = 110$) taught a presentation program using either active/exploratory or guided training. Consistent with previous research, training methods were equally effective for analogical transfer but active/exploratory training led to better adaptive transfer. In addition, interaction hypotheses were supported. Contrary to common recommendations, results suggest that active/exploratory training is suitable for promoting transfer even in learners with relatively low motivation and ability.

Keywords: attentional resources, cognitive ability, motivation, self-regulation, active learning, aptitude-treatment interaction

Active/exploratory training promotes transfer even in learners with low motivation and cognitive ability

Identifying effective training methods for work-relevant skills is a major concern in training research (e.g., Wexley & Latham, 2002). Given the rapidly changing requirements of today's work, the development of skills which are easily transferred to the workplace and which help employees to cope with novel situations has become a central objective of every training approach (Hesketh, 1997). Since the rise of cognitive constructivism, many researchers regard active/exploratory training methods, which involve self-directed exploration and discovery learning, to be better for fostering adaptability and transfer than traditional guided training methods (Mayer, 2004). It may be argued, however, that a particular training method may not be equally effective for every training participant and that effectiveness of a particular training method depends on certain learner characteristics (Cronbach, 1957; Snow, 1986). For example, active/exploratory training may impose cognitive load on learners with relatively low cognitive ability and may therefore only be suitable for higher-ability participants; or lower-ability participants as well as participants with low training motivation may benefit more from the tighter structure and higher external control provided in guided training (e.g., Ivancic & Hesketh, 1995/1996; Kirschner, Sweller, & Clark, 2006).

In this paper, we will argue for a contrary proposition. We suggest that active/exploratory training can level out the negative impact of deficits in general cognitive ability and training motivation on transfer performance, whereas guided training is relatively inefficient in attenuating the effects of such deficits. We base this prediction on (1) a resource allocation perspective that views individual-difference variables (such as cognitive ability and motivation) as important resources during skill acquisition (Kanfer & Ackerman, 1989) and on (2) the finding that the effectiveness of active/exploratory training can be explained by self-regulatory skills which are practiced in active/exploratory training but not in traditional guided training (Keith & Frese, 2005). The following sections first describe principles of guided and active/exploratory training methods and then develop hypotheses concerning interactions of training methods with individual-difference variables such as motivation and cognitive ability.

Guided vs. Active/Exploratory Training: Two Approaches to Training

Training methods may generally be classified as belonging to one of two basic approaches: guided versus exploratory training (cf. Mayer, 2004). *Guided training* approaches conceptualize learners as rather passive recipients of instruction. Participants are provided with detailed instructions on how to solve particular training tasks. These instructions may be delivered orally, in writing, or by a model which carries out the steps necessary to accomplish the task. Participants are asked to practice these steps until they are able to carry them out on their own. When a complex skill is taught (e.g., a computer program), guided training typically starts with simple tasks (e.g., opening a file and using basic program functions) and gradually proceeds to more advanced tasks which build upon the content of the more basic lessons (e.g., using a sequence of program functions). An example for a guided training method is behavior modeling which is based on Bandura's (1986) social-cognitive theory. In behavior modeling, participants watch a model who demonstrates the steps that are necessary for task completion. Many conventional training programs use guided training in that they directly teach the necessary and correct steps for task solution. In these trainings, learning is mainly regulated externally, that is, by an external agent such as the trainer or instructor (cf. Bell & Kozlowski, 2008).

Active/exploratory training approaches view learners as active participants in the learning process (Bruner, 1966); learning is mainly regulated internally (i.e., by the learners themselves; cf. Bell & Kozlowski, 2008). In active/exploratory training, participants are given minimal information on how to solve a specific task and are otherwise encouraged to explore the task domain and to discover task solutions on their own. One example of an active/exploratory training approach is Carroll's (1990) minimal instruction framework which has been applied to the design of self-instruction materials for computer users (cf. the minimal manual, Carroll, Smith-Kerker, Ford, & Mazur-Rimetz, 1987-1988). Minimal instruction also incorporates the ideas that learners should be trained on meaningful, realistic, and self-contained tasks and that training should support error recognition and recovery from errors. The latter principle is central for another active/exploratory training method as well, which is called error management training (Frese et al., 1991). Error management training starts from the assumption that errors represent a valuable source of feedback and an opportunity for improving one's knowledge and skills (Ivancic & Hesketh, 1995/1996). Error management training combines minimal information on task solution and encouragement of exploration with assigning difficult tasks from early on—a procedure that inevitably causes participants to make errors. Error management training typically includes so-called error management instructions which prepare participants to expect errors and which inform them about the positive functions of errors (e.g., Dormann & Frese, 1994; Frese et al., 1991; Heimbeck, Frese, Sonnentag, & Keith, 2003; Wood, Kakebeeke, Debowski, & Frese, 2000). The main idea of these error management instructions are summarized and repeatedly presented throughout the training in brief statements such as "You have made an error? That's great, because now you can learn something new!"

Studies comparing the effectiveness of guided vs. active/exploratory training methods arrive at different conclusions. For example, studies in the tradition of cognitive load theory often compare active/exploratory training against a training method that provides worked out examples of a given problem. These studies typically find participants of the worked-example group to perform better on a transfer problem than participants of the exploratory training group (e.g., Tuovinen & Sweller, 1999). On the other hand, many studies that compared error management training with guided training found participants of error management training to outperform their counterparts of guided training on moderately to highly difficult transfer task (e.g., Chillarege, Nordstrom, & Williams, 2003; Dormann & Frese, 1994; Heimbeck et al., 2003; Nordstrom, Wendland, & Williams, 1998). A recent meta analysis on error management training (Keith & Frese, 2008) suggests that these seemingly contradictory results may be due to the type of transfer tasks that were used to evaluate training effectiveness. In this meta analysis, studies that used analogical transfer tasks (i.e., transfer tasks that were similar to those taught in training) yielded significantly smaller effect sizes than studies that used adaptive transfer tasks (i.e., transfer tasks that were structurally distinct from training tasks and that required that development of a novel problem solution; Ivancic & Hesketh, 2000). In other words, active/exploratory training methods seem to be most promising to boost performance on novel tasks that go beyond the contents covered during training. In contrast, guided training methods may be suited when a task needs to be performed exactly the way taught in training (cf. McDaniel & Schlager, 1990). In line with this reasoning, we expected the present studies to replicate effects of training method on analogical and adaptive transfer tasks found in previous research (Keith & Frese, 2008).

Hypothesis 1: Active/exploratory training leads to better performance than guided training on adaptive transfer tasks but not or to a lesser extent on analogical transfer tasks.

The performance advantage in favor of active/exploratory training may be explained by self-regulatory skills that are practiced during training. Participants in active/exploratory training, who do not receive much instruction but work independently on the training tasks, need to engage in metacognitive activities which involve planning, monitoring, and evaluation of one's progress toward the goal as well as revision of strategies where appropriate (Brown, Bransford, Ferrara, & Campione, 1983). Participants of guided training, in contrast, who receive detailed instructions during training which they merely need to follow to solve the tasks, do not need to engage in this type of mindful processing (Ivancic & Hesketh, 1995/1996). When confronted with novel and structurally distinct tasks (i.e., adaptive transfer tasks) participants of active/exploratory training can apply the metacognitive skills acquired during training to solve the new problems. Participants of guided training, however, have not learned the metacognitive skills which would be useful for dealing effectively with the transfer tasks. This proposition is in line with a study that found self-regulatory skills such as metacognitive activity to mediate training effectiveness of error management training (Keith & Frese, 2005; cf. Bell & Kozlowski, 2008).

Interactions of Active/Exploratory vs. Guided Training with Individual Differences in Motivation and Cognitive Ability

General cognitive ability positively predicts training success and job proficiency across a wide range of learning contexts and occupations (e.g., Salgado et al., 2003; Schmidt & Hunter, 1998). Consistent albeit somewhat lower correlations have been found between performance and motivational dispositions, self-efficacy expectations, as well as perceived utilities of outcomes (e.g. Colquitt, LePine, & Noe, 2000; Sadri & Robertson, 1993; Stajkovic & Luthans, 1998). The present paper suggests the training method to affect the relationships between cognitive ability and motivation on the one hand and training success on the other hand, that is, we predict interactions of training method and individual difference variables on training outcomes. This assumption is consistent with Kanfer and Ackerman's (1989) integrative theoretical framework which relates the effects of general cognitive ability, motivation, and skill acquisition to the concept of attentional resources. In the following sections, we sketch Kanfer and Ackerman’s theory and link its assumptions to the self-regulatory processes which are expected to underlie the effectiveness of active/exploratory training.

Cognitive Ability, Motivation, and Attentional Resources

Kanfer and Ackerman's (1989) theoretical framework is based on four general ideas from the information-processing approach in cognitive psychology. First, all kinds of activities rely on a limited pool of attentional resources (e.g., Kahneman, 1973; Knowles, 1963), second, some tasks are more resource-demanding than others (e.g., Navon & Gopher, 1979), third, people are able to regulate resource allocation by devoting more or less effort to a particular task or by dividing resources between concurrent tasks (e.g., Navon & Gopher, 1979; Watson & Klopton, 1969), and fourth, the amount of resources demanded by a particular task decreases with practice (e.g., Anderson, 1982; Schneider & Fisk, 1982). The *performance-resource function* postulated by Norman and Bobrow (1975) allows a systematic description of these relationships. Performance-resource functions model performance as a monotonically increasing function of the attentional resources mobilized for a particular task. Yet, the slope of the performance-resource function may vary between different segments of the performance-resource function and between different tasks. A steep slope indicates that changes in attentional effort are accompanied by large improvements in task performance. In this case, performance may be regarded as *resource-dependent*. A flat slope, in contrast, indicates that changes in attentional effort lead to only minimal improvements in task performance. In that case, performance is largely *resource-insensitive*. For example, very simple or extremely difficult tasks are largely resource-insensitive, because devoting additional effort leads to little improvement in task performance. New and challenging (but not too difficult) tasks, in contrast, are largely resource-dependent in that more effort usually means better performance. Skill acquisition through practice may be described as a change in the slope of the performance-resource function: Tasks that were initially resource-dependent become gradually more resource-insensitive as task-solving strategies get proceduralized and the necessity to rely on declarative knowledge representations declines (Anderson, 1982).

According to Kanfer and Ackerman (1989), attentional resources mediate the influence of individual differences in both motivation and cognitive ability on performance. *Motivation* is expected to regulate the attentional effort spent on a task via distal and proximal motivational processes. Distal motivational processes are judgments which underlie the decision to devote a certain amount of effort to the task. These judgments, first, affect the choice to engage in task-solving behavior and, second, set the initial level of resources which an individual is willing to allocate to the task. The *perceived performance utility* of a task is a central aspect of these judgments. For example, if an individual believes that mastering a computer program is useful for him or her (high perceived performance utility), he or she will try harder in a training of the computer program than an individual who perceives the utility of mastering the program to be low. For *cognitive ability*, Kanfer and Ackerman (1989) assume a direct correspondence with attentional resources: Individual differences in general intellectual ability reflect individual differences in the cognitive-attentional resource capacity available to an individual. As a result, from an individual difference perspective, resource-dependent tasks may be described as ability-dependent and resource-insensitive tasks can be described as ability-insensitive—turning the performance-resource function into a performance-ability function.

An important claim of Kanfer and Ackerman's (1989) theory is that the role of individual differences in both motivation and cognitive ability shifts in the course of skill acquisition and training. Distal motivational variables such as perceived performance utility and general cognitive ability are expected to influence performance in early phases of training when attentional demands are high (i.e., tasks are resource-dependent). These influences are expected to decline in later phases of training when attentional demands are reduced (i.e., tasks become resource-insensitive). This view is supported by a number of experiments which demonstrate a decline of cognitive ability-performance correlations with practice in consistent and moderately complex tasks (e.g., Ackerman, 1988).

Guided vs. Exploratory Training and Attentional Resources in Transfer Tasks

For performance on transfer tasks, the impact of distal motivational variables and cognitive ability may depend on the degree of overlap between the skills acquired during training and those necessary to accomplish the transfer tasks: The higher the degree of overlap, the lesser the attentional demands of the transfer task and, hence, the lesser the impact of distal motivational variables and cognitive ability. Providing partial support for this proposition, Goska and Ackerman (1996, Experiment 2) were able to demonstrate a positive relationship of cognitive ability and performance in an air-traffic control simulation only in a distant-transfer training condition (low similarity of training and transfer tasks), whereas there was no such relationship in a near-transfer training condition (high similarity of training and transfer tasks).

Integrating Kanfer and Ackerman's (1989) framework with the idea that self-regulatory processes (such as metacognition) underlie the effectiveness of active/exploratory training, we propose that the training method moderates the effects of distal motivational variables and of cognitive ability on transfer performance. In active/exploratory training, the same self-regulatory skills that are practiced during training are required in the transfer situation. Both during training and while working on transfer tasks, participants need to engage in metacognitive activities as they explore the task domain without external help. For this reason, there is a high degree of overlap between training and transfer tasks. The transfer tasks become more resource-insensitive—and thereby less motivation/ability dependent—for participants of active/exploratory training, and the relationship between distal motivational variables and cognitive ability on the one hand and transfer performance on the other hand will be reduced in these participants. In guided training, in contrast, the transfer situation imposes new and strong attentional demands as participants work independently and without the external help they received during training. For participants of guided training, therefore, the degree of overlap between training and transfer tasks is low. They are left on their own for the first time and may experience errors and setbacks—a situation they have been protected from during training. They now have to engage in self-regulatory activities such as metacognition which are largely resource-dependent because participants did not have the chance to practice these activities during training. Accordingly, a strong relationship of distal motivational variables and cognitive ability with transfer performance may be expected in participants who have received a guided training. In other words, a resource-allocation perspective on individual differences in motivation and cognitive ability in guided vs. active/exploratory training predicts the following interactional pattern between training method and individual-difference variables:

> *Hypothesis 2*: Training method (i.e., guided vs. active/exploratory training) interacts with individual differences in motivation and ability to affect transfer performance. (a) Motivation (i.e., perceived performance utility) has a positive effect on transfer performance in participants of guided training; in participants of active/exploratory training, the effect of motivation is reduced. (b) Similarly, cognitive ability has a positive effect on transfer performance in participants of guided training; in participants of active/exploratory training, the effect of cognitive ability is reduced.

Results of previous research are partially in line with this reasoning. Heimbeck et al. (2003) examined interactions of motivational goal orientations with guided vs. active/exploratory training conditions. They found goal orientations (prove goal orientation and avoidance goal orientation) to positively affect performance in guided training; in active/exploratory training, however, these person characteristics were unrelated to performance. A drawback to this study with regard to the present research question is that although goal orientations may enhance perceived performance utility, they are distal motivational variables which are highly general and which may be only indirectly relevant for resource mobilization on a particular task. Compared to the Heimbeck et al. study, the present experiments were designed to provide more direct tests of motivation/training method interactions. Also, one of the experiments included cognitive ability as another important individual difference variable.

Overview of the Present Experiments

To test our predictions, we conducted two experiments in which novice participants received either an active/exploratory or a guided training in common computer skills. Experiment 1 taught a text processing program and focused on individual differences in perceived performance utility which is an important distal motivational predictor of resource allocation. Experiment 2 taught a presentation program and focused on differential effects of general cognitive ability. It also aimed at replicating the effects of motivation in an independent sample and with a training content different from that of Experiment 1. Both experiments included separate measures of analogical and adaptive transfer as dependent variables.

Experiment 1

Method

Participants

Participants were 37 university students, majoring in psychology (90%) or education (10%). Their mean age was 28.4 years (SD = 7.7) and the majority of participants were female (92%). About two thirds of the participants (62%) had worked regularly before they started attending the university. All of the participants had experience with text processing programs but none of them was familiar with the specific type of tasks that were trained during the experiment.

Design and Procedure

Participants were trained in individual sessions to create and format tables with a common text processing program in one of two training conditions: guided training (n = 19) or exploratory training (n = 18). Each participant was randomly assigned to one of the two training conditions. Sessions lasted approximately 50 minutes. First, demographic data and perceived performance utility were assessed. Then, the actual experiment started with a training phase in which the experimental manipulation took place and a subsequent test phase (identical for all participants) in which transfer tasks were given to participants..

Training phase. In the training phase, participants worked on the task to reproduce a complex table (which was printed out on paper) as closely as possible, using the text processing program. The training task comprised several subtasks (e.g., creating a 5 x 5-table, inserting text and percent values, formatting the cell entries, assigning shadings to cells). Participants completed the training task in 1 of 2 training conditions: guided or active/exploratory training. In the *guided training* condition, participants received detailed written instructions explaining task solution in a step-by-step manner. They were told that these instructions would enable them to learn the most important program functions in the shortest time and that by following the instructions participants would become familiar with the program functions from the very beginning. In the *active/exploratory training* condition, participants were not provided with any additional information on task solution but were asked to solve the training tasks independently. They were told that working independently would help them to gain an in-depth insight of how the program operated and would help them to become familiar with it. Training time was held constant at 15 minutes for all participants. In case participants finished earlier with the task, the experimenter gave instructions in line with the experimental conditions to keep the duration of the training constant (cf. Heimbeck et al., 2003). In guided training, participants were told that practice makes perfect and they were asked to start over with the same table, again by following the written instructions. In exploratory training, participants were asked to use the remaining training time to freely explore and try out any functions they liked.

Test phase. Tasks and instructions in the test phase were identical for all participants. Participants were handed printed copies of two tables with the task to reproduce these tables as closely as possible. Reproduction of the first test table comprised subtasks similar but not identical to those encountered in training (*analogical transfer*). For example, participants were asked to format cell entries and to assign different shadings to the cells again, but letter fonts, letter sizes, and degrees of shadings differed from those which they had used in training. Reproduction of the second test table, in contrast, largely comprised subtasks which had not been required for creating the training table (*adaptive transfer*). The new subtasks included changing the alignment of text, separating cells, merging cells, changing the width of columns, and formatting cell borders. Participants were given 15 minutes to work on each of the test tables.

Measured Variables

Performance. Performance ratings for the transfer tasks were conducted on the basis of the tables that participants had created during the test phase. Each task was divided into clearly separable subtasks. These subtasks served as coding units and were rated on an 11-point scale ranging from 0 (not accomplished at all) to 10 (fully accomplished). One rater coded all tasks and a second rater coded blindly one third of all tables to determine inter-rater reliability (median ICC = .75). Measures for analogical transfer and adaptive transfer, respectively, were derived by computing the mean rating across all subtasks that were part of a transfer task.

Perceived performance utility. Perceived performance utility was measured by a subscale of the Questionnaire for the Content-Differentiated Assessment of Attitudes toward the Computer (Richter, Naumann & Groeben, 2000). The subscale captures the degree to which participants perceive the computer as a valuable tool in their everyday study and work activities. It comprises seven Likert-scaled items that specifically tap into the perceived usefulness of the computer as a tool for learning and working (e.g., *For a substantial part of my job or studies, the computer is a useful tool*). The scale has shown good internal consistencies (Cronbach’s α .85 or higher) and high discriminative and criterion validity in several independent samples (e.g., Richter et al., 2000; Richter, Naumann, & Groeben, 2001; Naumann, et al., 2001). In the present sample of participants, Cronbach's α was .75.

Time spent using the computer. In order to control for individual differences in the extent of actual computer use, we also asked participants to estimate how many hours per week they usually spend using the computer.

Statistical Analyses

We tested our hypotheses using ANCOVA with the two dependent variables (i.e., analogical and adaptive transfer) as within-subjects factor, with training condition (i.e., guided vs. active/exploratory training) as between-subjects factor, and with the individual difference variable (i.e., cognitive ability or perceived performance utility) as a continuous between-subjects covariate. This procedure is a simple generalization of ANOVA and (moderated) regression analysis that allows modeling within-subjects and between-subjects effects simultaneously (cf. J. Cohen, Cohen, West, & Aiken, 2003; Judd, Kenny, & McClelland, 2001). Hypothesis 1, which predicted the effect of training condition to be larger for adaptive than for analogical transfer, is represented by the interaction of the between-subjects factor and the within-subjects factor, because this interaction tests whether the effect of training condition (i.e., guided vs. active/exploratory training) is different between the layers of the within-subjects factor (i.e., analogical vs. adaptive transfer).

Hypothesis 2, which predicted the effect of the individual difference variable on transfer performance to be larger in guided than in active/exploratory training, is represented by the interaction of the between-subjects factor (i.e., training condition) and the between-subjects covariate (i.e., individual difference variable), because this interaction tests whether the effect of the covariate is different between the layers of the between-subjects factor (i.e., guided vs. active/exploratory training). As far as our hypotheses on the effects of perceived performance utility are concerned, one might argue that individual differences in this variable might be confounded with the time that learners use the computer in daily life. To weaken this potential alternative explanation, we also conducted control analyses based on a model that included the time participants spent each week using the computer and the two-way interactions of this variable with the experimental factors as additional predictors.

Results and Discussion

Descriptive statistics and intercorrelations of the variables included in Experiment 1 are displayed in Table 1. Unless indicated otherwise, type-I-error probability was set to .05 (two-tailed). Where applicable, we used one-tailed testing for directional hypotheses.

Effects of Active/Exploratory vs. Guided Training

The effects of guided vs. active/exploratory training on analogical and adaptive transfer (Hypothesis 1) were tested in an ANCOVA with training condition as between-subjects factor, perceived performance utility as covariate, and performance in analogical vs. adaptive transfer tasks as within-subjects factor. As expected, there was a significant interaction of training condition and analogical vs. adaptive transfer, $F\ (1,33) = 4.4$, $p < .05$, $\eta^2 = .12$. Analyses of simple main effects revealed that on analogical transfer tasks, there was no difference between training conditions, $t\ (35) = 0.9$, $p = .19$ (one-tailed), whereas on adaptive transfer tasks, participants of active/exploratory training outperformed participants of guided training, t (35) = 2.1, $p < .05$ (one-tailed), $d = 0.69$. Thus, Hypothesis 1, which predicted active/exploratory training to lead to better performance on adaptive transfer tasks but not on analogical transfer tasks, was supported.

Effects of Perceived Performance Utility

In addition, the ANCOVA revealed a main effect of perceived performance utility, F (1, 33) = 14.1, $p < .001$, $\eta^2 = .30$. As expected, however, this main effect was qualified by an interaction of training condition and perceived performance utility, F (1,33) = 4.6, $p < .05$, $\eta^2 = .12$. To examine the direction of the interaction, we calculated simple slopes for each training condition using the procedure outlined by Aiken and West (1991). Figure 1 provides scatterplots with simple regression lines for each group (we chose to present the scatterplots in addition to the regression lines, because the plots show that the interaction effect is not driven by outliers or extreme values). In both the analogical and the adaptive transfer task, there was a strong effect of perceived performance utility on performance in participants who had received guided training (for analogical transfer: $\beta = .81$, $p < .01$, one-tailed; for adaptive transfer: $\beta = .95$, $p < .01$, one-tailed). When participants had received active/exploratory training, in contrast, the relationship between perceived performance utility and performance was considerably lower for analogical transfer ($\beta = .33$, $p < .05$, one-tailed) and not significant for adaptive transfer ($\beta = .20$, $p = .13$, one-tailed). Thus, Hypothesis 2a, which expected perceived performance utility to predict transfer performance in participants of guided training more strongly than in participants of active/exploratory training, was supported.

Despite the fact that the effects of perceived performance utility are strong and in line with predictions, their interpretation remains somewhat ambiguous because it might be that perceived performance utility is confounded with the extent to which one uses the computer in everyday life. In order to counter this potential alternative explanation, we reran the analysis based on a model with the time that participants spent each week using the computer and the interactions of this variable with the experimental factors as control variables. In this analysis, the time that participants spent each week using the computer did not have any significant main or interaction effects on analogical or adaptive transfer performance (for all effects, $F < 1$). In contrast, the predicted interaction of training condition and perceived performance utility remained strong and marginally significant, $F(1,31) = 4.1$, $p = .05$, $\eta^2 = .11$. According to these results, the effects of perceived performance utility are in no way driven by the extent that participants use the computer in daily life.

In sum, the pattern of results corroborated the expectations concerning the effects of active/exploratory vs. guided training: Active/exploratory training was especially beneficial for adaptive transfer, while exploratory and guided training seem to be on par when learners were tested on analogical transfer tasks. Apparently, the skills acquired in active/exploratory training are more easily transferred to new tasks which differ from those encountered in training, compared with guided training. For new tasks that are similar to training tasks, both training methods seem to be equally effective. Moreover, the impact of perceived performance utility on both analogical and adaptive transfer performance was markedly lower for participants of active/exploratory training compared to participants of guided training. Interpreted against the background of the resource approach to motivation/aptitude-treatment interactions proposed by Kanfer and Ackerman (1989), these results suggest that in the active/exploratory training group, the overlap of skills learned in training and those necessary to accomplish the transfer tasks was larger than in the guided training group. As a result of active/exploratory training, distal motivational factors of resource mobilization influenced transfer performance to a lesser extent.

Experiment 2

Experiment 2 complemented the previous experiment by including a measure of general cognitive ability. In addition, we aimed to replicate the results for perceived performance utility using a different training content and an independent sample of participants. Again, participants received a short-term computer skills training (creating slides with a presentation program) either as a guided or as an active/exploratory training and analogical as well as adaptive transfer performance was assessed.

Method

Participants

Participants were 110 university students, most of them majoring in education (94%). Their mean age was 24.0 years (*SD* = 6.1) and the majority of participants were female (86%). Most participants reported having had work experience with 21% having worked regularly before they started attending the university, and 62% working on a regular basis while studying for an average of 8.6 hours per week (*SD* = 5.2). None of the participants had ever worked before with the specific software used in this study (this was a prerequisite for participation).

Design and Procedure

Participants were trained to create overhead slides with a common presentation program in one of two conditions: active/exploratory training (*n* = 54) or guided training (*n* = 56). Sessions were run in groups of 2 to 10 participants. Each group of participants was randomly assigned to one of the training conditions. Sessions lasted approximately three hours (including a 10-minute break). First, demographic data, perceived performance utility, and cognitive ability were assessed. Then, the training part of the session started, comprising three phases: (1) an introductory phase (identical for all participants), (2) the actual training phase in which the experimental manipulation took place, and (3) a test phase (identical for all participants) in which analogical and adaptive transfer were assessed.

Introductory phase. In the beginning, all participants received a 3-page manual containing general information about the program. The manual briefly explained the menu and toolbars, how specific functions can be activated to create objects (e.g., a rectangle), and how existing objects can be modified (e.g., moving a rectangle). Also, the manual informed about the *undo* function of the program and the *delete* key. To illustrate the position of the elements mentioned in the manual, the manual contained several figures (e.g., screenshots of the toolbars, picture of the delete key). All participants received the same manual so that task information was held constant across training conditions. It took participants approximately five minutes to read the manual. Participants were allowed to refer to their manuals during the entire training session (but not during the test phase). Before the actual training started, participants worked on a simple warm-up slide (the manual and the warm-up task were the same as in the study by Keith and Frese, 2005). This warm-up task included creating and modifying a circle, a rectangle, a text box, and an arrow while following written instructions. The experimenter demonstrated the first few steps by reading out the instructions and then carrying out the described actions. The picture on the experimenter's computer monitor was also projected on a screen, so that all participants were able to watch the experimenter's actions. Participants were asked to complete the introductory task by following the written instructions. No time limit was set for this introductory task.

Training phase. During the actual training phase, participants were given copies of two slides printed on paper. The task was to reproduce these slides as closely as possible. The first slide required creating, moving, and modifying (e.g., coloring) diverse objects such as rectangles, triangles, textboxes, and stars. The second slide involved creating and modifying a table by simple formatting such as coloring cells and centering cell entries. To complete each slide, participants were given 15 minutes, resulting in a training time of 30 minutes (the two slides and the training time were the same as in the study by Keith and Frese, 2005).

The experimental manipulation of training conditions was similar to the one given in Experiment 1. Again, participants received either a guided training with detailed written instructions that explained task solution in a step-by-step manner or an active/exploratory training in which they were encouraged to work on the tasks independently and to explore the program freely. (The original experimental design included a second experimental factor, namely, whether or not participants received error management instructions designed to convey a positive attitude toward errors during training. Because these error management instructions affected neither manipulation checks nor performance measures and because error management instructions are irrelevant for the present research question, we do not report on this second factor.)

As manipulation check for the guided training, participants were asked to tick off each step after finishing it. All but five participants followed this request, that is, the number of tick marks corresponded to the number of training tasks solved (to maintain statistical power, we kept these five cases in the analyses; the results were nearly identical when excluding the five cases). As in Experiment 1, training time was held constant for all participants by providing additional instructions in line with the experimental training conditions.

Test phase. Tasks and instructions in the test phase were identical for all participants. Participants were handed printed copies of four slides. As in the training phase, the task was to reproduce these slides as closely as possible. The first test slide comprised bullet points with test items and a figure consisting of several framed and colored text boxes and arrows. The main task of the second test slide was to produce and to format a table. For the third slide, a vertical bar chart had to be created and edited with the diagram function of the program. The fourth slide comprised animated objects. To demonstrate the sequence and type of animations that were to be programmed for the objects, this slide was continuously projected on a screen. Participants were given 10 minutes, respectively, to complete the first three slides and 15 minutes for the fourth slide. The first three slides were identical to those used by Keith and Frese (2005). The fourth slide was newly developed and added to the testing material to include an additional task that was difficult and dissimilar from the training tasks (see the next section).

Measured Variables

Performance. Performance ratings of transfer tasks were conducted on the basis of the slides that participants had created during the test phase. Each task was divided into meaningful subtasks which served as coding units and were rated as either correctly completed or not (dichotomous rating; cf. Heimbeck et al., 2003; Keith & Frese, 2005). One rater coded all test slides; a second rater coded a randomly chosen subset (approx. 30%). Both raters were blind to the experimental condition. Inter-rater agreement (based on the subset) was high (Cohen's kappa =.81). To arrive at a measure for *analogical transfer* performance, the number of completed subtasks in testing slides 1 and 2 was computed because these slides included tasks that were similar to training tasks. To arrive at a measure for *adaptive transfer* performance, the number of completed subtasks in testing slides 3 and 4 was computed because these slides included tasks that were distinct from training tasks.

Cognitive ability. Cognitive ability was assessed using the number combination test (Zahlen-Verbindungs-Test; Oswald & Roth, 1987). The number combination test is a German paper-and-pencil trail-making test. The task is to draw a continuous line to connect seemingly jumbled numbers (ranging from 1 to 90) in ascending order as quickly as possible. The number combination test is designed to be a measure of general cognitive ability (i.e., speed of information processing). It therefore corresponds to the concept of cognitive-attentional resource capacity in the model by Kanfer and Ackerman (1989). The test authors report a mean correlation of .50 (range .40-.83) with other intelligence measures (e.g., Standard Progressive Matrices and Wechsler Adult Intelligence Scale). Substantial correlations with other intelligence measures in English speaking samples have also been reported (Vernon, 1993; Vernon & Weese, 1993).

Perceived performance utility. For the measurement of perceived performance utility, we used the same scale as in Experiment 1 (Richter et al., 2000). In the present sample, the scale reached an internal consistency (Cronbach's α) of .85.

Time spent using the computer. As in Experiment 1, we asked participants to estimate how many hours per week they usually spend using the computer.

Results and Discussion

Descriptive statistics and intercorrelations of the variables included in Experiment 2 are displayed in Table 1.

Effects of Active/Exploratory vs. Guided Training and of Cognitive Ability

The effects of guided vs. active/exploratory training as well as cognitive ability on analogical and adaptive transfer were tested with an ANCOVA with training condition as between-subjects factor, cognitive ability as covariate, and performance in analogical vs. adaptive transfer tasks as within-subjects factor. As expected, there was a significant interaction of training condition and analogical vs. adaptive transfer, F (1,106) = 8.9, $p < .01$, $\eta^2 = .08$. Analyses of simple main effects revealed that on analogical transfer tasks, there was no difference between the training conditions, $t(108) = 0.9$, $p = .19$ (one-tailed), whereas on adaptive transfer tasks, participants of exploratory training outperformed participants of guided training, $t(108) = 1.8$, $p < .05$ (one-tailed), $d = 0.34$. Thus, in support of Hypothesis 1 and similarly to Experiment 1, active/exploratory training led to better performance on adaptive transfer tasks but not on analogical transfer tasks.

In addition, the ANCOVA revealed a main effect of cognitive ability, $F\,(1{,}106) = 22.5$, $p < .001$, $\eta^2 = .18$. As expected, however, this main effect was qualified by an interaction of training condition and cognitive ability, $F\,(1{,}106) = 5.4$, $p < .05$, $\eta^2 = .05$. To examine the pattern of this interaction, we calculated simple slopes for each training condition using the procedure outlined by Aiken and West (1991) for analogical and adaptive transfer tasks (Figure 2). In both the analogical and adaptive transfer task, there was a strong effect of cognitive ability on performance in participants who had received guided training (for analogical transfer: $\beta = .59$, $p < .001$, one-tailed; for adaptive transfer: $\beta = .52$, $p < .001$, one-tailed). When participants had received active/exploratory training, in contrast, the relationship between cognitive ability and performance was not significant for analogical transfer ($\beta = .12$, $p = .17$, one-tailed) and considerably lower for adaptive transfer ($\beta = .24$, $p < .05$, one-tailed). Thus, as predicted in Hypothesis 2b, cognitive ability had a strong positive effect on transfer performance only when participants had received guided training, but not when participants had received active/exploratory training. Again, interpreted against the background of the performance-resource approach by Kanfer and Ackerman (1989) these results suggest that in the active/exploratory training group, the overlap of skills learned in training and those necessary to accomplish the transfer tasks was larger than in the guided training group. As a result of active/exploratory training, attentional resources, as represented by individual differences in cognitive ability, influenced transfer performance to a lesser extent.

Effects of Perceived Performance Utility

We tested the interaction effect of active/exploratory vs. guided training and perceived performance utility (Hypothesis 2a) in an ANCOVA with training condition as between-subjects factor, analogical vs. adaptive transfer as within-subjects factor, and perceived performance utility as covariate. The expected interaction effect of training condition and perceived performance utility emerged, $F\,(1,106) = 3.9$, $p < .05$, $\eta^2 = .04$. Again, we conducted simple-slope analyses following Aiken and West (1991) to interpret this interaction effect. In both the analogical and the adaptive transfer task, there was an effect of perceived performance utility on performance in participants who had received guided training (for analogical transfer: $\beta = .56$, $p < .001$, one-tailed; for adaptive transfer: $\beta = .33$, $p < .05$, one-tailed). When participants had received active/exploratory training, in contrast, the relationship between perceived performance utility and performance was not significant (for analogical transfer: $\beta = .08$, $p = .24$, one-tailed; for adaptive transfer: $\beta = .11$, $p = .19$, one-tailed). In sum, the results obtained in Experiment 1 were replicated and Hypothesis 2a was supported: Consistent with a performance-resource interpretation, the influence of perceived performance utility on transfer performance was present after guided training but was substantially reduced after active/exploratory training.

Again, we estimated the parameters of an additional model that included the time that participants spent each week using the computer and the interactions of this variable with the experimental factors. As in Experiment 1, there were no significant main or interaction effects of the control variable (for all effects, $p > .10$). Importantly, despite the loss of power caused by the additional parameters in the model, the predicted interaction of training condition and perceived performance utility remained marginally significant, $F\,(1,104) = 3.4$, $p = .07$, $\eta^2 = .03$. Thus, the results indicate that the effects of perceived performance utility were not confounded with the extent to which participants use the computer in their daily lives.

General Discussion

Summary of Results and Implications for Theory and Practice

The present study contributes to training research in methodological, theoretical, and practical respects. Methodologically, our experiments underscore the importance of distinguishing different types of transfer tasks when evaluating training effectiveness (Ivancic & Hesketh, 2000). According to our results and in line with previous research (e.g., Keith & Frese, 2008), guided training may be on par with active/exploratory training for transfer tasks which are highly similar to training tasks (analogical transfer). For adaptive transfer, however, which requires the development of novel solutions, active/exploratory training leads to better performance. In training practice, either analogical or adaptive transfer may be legitimate training goals (Ivancic & Hesketh, 1995/1996). Yet, we propose that in many instances adaptive transfer performance is the more relevant type of transfer. In many organizational contexts, only a fraction of potential work-related problems and solutions can be taught within the allotted training time. Trainees, therefore, often need to adapt their acquired knowledge and skills when confronted with various work tasks (e.g, Hesketh, 1997; Smith, Ford, & Kozlowski, 1997). For this reason, training should convey skills which are widely applicable or may even help employees to master novel problems. Active/exploratory training seems to be better suited to serve this purpose than guided training, presumably because it promotes the development of metacognitive skills which prove useful for mastering novel problems (Bell & Kozlowski, 2008; Keith & Frese, 2005).

In line with a resource allocation approach to individual differences in skill acquisition, we were able to show that active/exploratory training reduces the effect of perceived performance utility and of general cognitive ability on transfer performance, both of them person characteristics which are central for resource allocation processes (Kanfer & Ackerman, 1989).

Theoretically, this reduction of the effects may be interpreted as indirect evidence for our assumption that performance in active/exploratory training and transfer tasks was indeed based on the same (meta-)cognitive processes—with the effect that transfer performance became less resource-dependent. Practically, these findings substantiate the utility of active/exploratory training as a method to convey skills which are readily transferable to novel tasks. Adaptive transfer performance of high-ability and of highly motivated participants was about the same for guided and active/exploratory training (cf. Figures 1b and 2b). Across a wide range of motivation and ability, however, active/exploratory training had a general advantage over guided training. In particular, active/exploratory training seems to compensate for negative effects of low motivation and low ability. The latter conclusion is particularly interesting because traditionally, guided training methods rather than active/exploratory approaches have been recommended for low ability learners (e.g., Ivancic & Hesketh, 1995/1996; Kirschner et al., 2006; Snow, 1986). Proponents of this view argue that low-ability learners lack the cognitive resources needed to cope with the high attentional demands of active/exploratory training and may be better off with a highly structured learning environment. Our findings show that the opposite applies: Providing low-ability learners with the opportunity to practice self-regulatory activities early on in training apparently lowers the attentional demands imposed by transfer tasks. Apart from that, active/exploratory training is also the better option for learners with average cognitive ability and motivation. Only for learners with above-average ability, both training methods appear to be equally effective. Stated in terms of the Kanfer-Ackerman theory, these learners can compensate for the relative ineffectiveness of the guided training because they are able and willing to spend more cognitive resources while working on the tasks.

Strengths, Limitations, and Directions for Future Research

Our experiments used the theory by Kanfer and Ackerman (1989) as a framework to investigate the moderating role of cognitive ability and perceived performance utility rather than testing the assumptions of this theory directly. One reason is that our predictions rely on the additional assumption that active/exploratory training is effective in part because it forces learners to apply and routinize general metacognitive skills. The fact that this additional assumption is backed up by previous research (Keith & Frese, 2005) notwithstanding, it would be desirable to include a measure of metacognitive skills in future experiments and test the mediated moderation hypothesis that these skills do in fact underlie the compensatory role of active/exploratory training (Muller, Judd, & Yzerbyt, 2005; for an example of applying such a model to training research, see Naumann, Richter, Christmann, & Groeben, 2008). Also, it would be informative to measure the amount of cognitive-attentional resources that learners actually spend while working on the analogical or adaptive transfer tasks, respectively. The dual-task paradigm that is frequently used in cognitive-psychological experiments on working memory and attention provides ways to measure cognitive-attentional resources concurrently, i.e. during task completion (for adaptations of this paradigm to computer-based learning, see Brünken, Plass, & Leutner, 2003). Finally, future research may counterbalance the order of presentation of transfer tasks (i.e., adaptive and analogical transfer) to control for the possibility that the particular task order affects the pattern of results.

The present research found compensatory effects of active/exploratory training in two independent participant samples and with different computer tasks. Future research may investigate whether our findings generalize to other types of skills (e.g, social skills). In addition, future research may specify the conditions which yield compensatory as opposed to overtaxing effects of active/exploratory training. Difficulty of the training task and the range of resource-relevant person characteristics that is considered in a given study may be crucial aspects in this respect. Task difficulty is important because it represents a direct antecedent of resource demands. If training tasks are too difficult, learners with low cognitive ability will not be able and learners with low motivation will be unwilling to mobilize the resources necessary for task completion (Kanfer & Ackerman, 1989). Also, in the samples of university students who participated in our experiments, cognitive ability and perceived performance utility of computer skills are probably at an overall higher level than in the general population. As for the main effects of cognitive ability and perceived performance utility as well as the effect of training condition on transfer performance, we are confident that these effects generalize to other populations (for similar results with other samples, cf. Chillarege et al., 2003; Frese et al., 1991). Yet, it is possible that the compensatory effect of active/exploratory training for deficits in cognitive ability and motivation operate only if these variables and, consequently, the attentional resources available during training exceed a certain threshold—which was presumably the case in our samples of university students.

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Table 1

Means, Standard Deviations, and Intercorrelations of Variables in Experiments 1 and 2

		Training conditions			Intercorrelations				
			Active/		1	2	3	4	5
	Total	Guided	Exploratory						
	M (SD)	*M (SD)*	*M (SD)*						
Experiment 1[a]									
1 Training condition[b]	-0.03 (1.01)	-1.00 (.00)	1.00 (.00)		--				
2 Performance utility	3.35 (0.53)	3.46 (0.40)	3.24 (0.64)		-.21	--			
3 Computer use	11.58 (14.22)	11.76 (12.36)	11.39 (16.32)		-.01	.41*	--		
4 Analogical transfer	7.23 (1.84)	7.19 (1.85)	7.28 (1.89)		.23	.44**	.14	--	
5 Adaptive transfer	5.32 (2.99)	4.75 (3.32)	5.91 (2.55)		.20	.36*	.21	.75**	--
Experiment 2[c]									
1 Training condition[b]	-0.02 (1.00)	-1.00 (.00)	1.00 (.00)		--				
2 Cognitive ability	47.90 (6.31)	47.85 (6.48)	47.96 (6.18)		.01	--			
3 Performance utility	3.10 (0.71)	3.08 (0.65)	3.12 (0.77)		.03	-.01	--		
4 Computer use	6.40 (6.66)	5.86 (6.83)	6.99 (6.49)		.09	.00	.18	--	
5 Analogical transfer	8.50 (4.28)	8.80 (4.53)	8.10 (4.02)		-.07	.37**	.29**	.10	--
6 Adaptive transfer	11.55 (5.30)	10.71 (5.38)	12.41 (5.13)		.16	.39**	.21*	.01	.64**

Note. Performance utility = perceived performance utility. Computer use = hours spent each week using the computer.

[a] $N = 37$ (guided training: $n = 19$, active/exploratory training: $n = 18$).

[b] Contrast-coded: guided training = -1, active/exploratory training = 1.

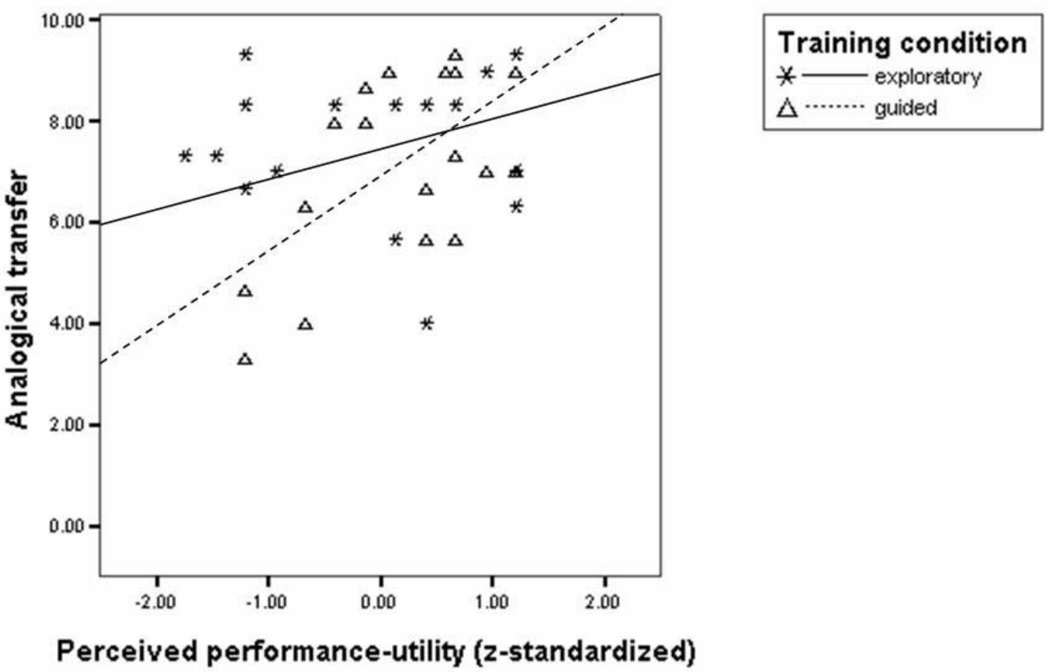
[c] $N = 110$ (guided training: $n = 56$, active/exploratory training: $n = 54$).

* $p < .05$, ** $p < .01$, two-tailed.

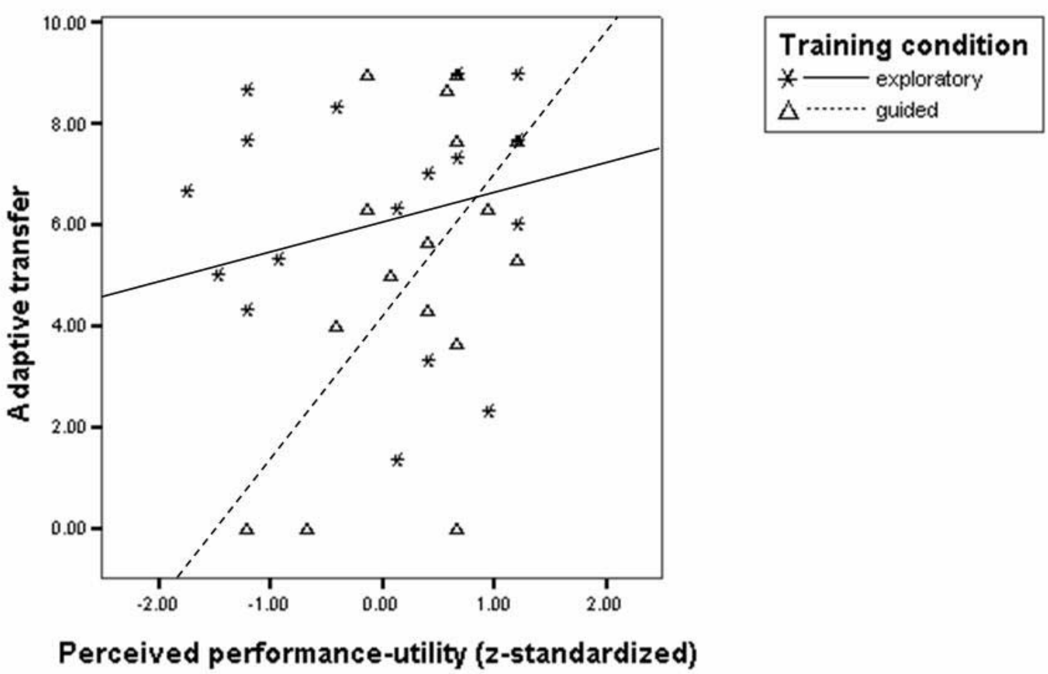
Figure Captions

Figure 1. Interaction effects of training condition and perceived performance utility on performance in analogical transfer tasks (a) and adaptive transfer tasks (b) in Experiment 1.

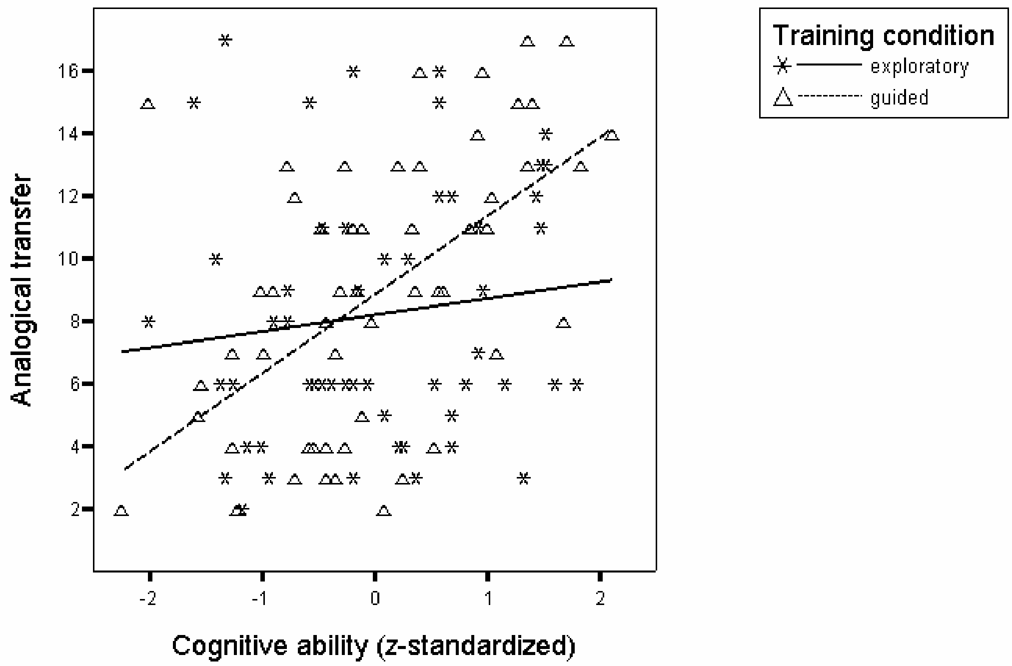
Figure 2. Interaction effects of training condition and cognitive ability on performance in analogical transfer tasks (a) and adaptive transfer tasks (b) in Experiment 2.


Training condition
exploratory
guided
Analogical transfer
Perceived performance-utility (z-standardized)

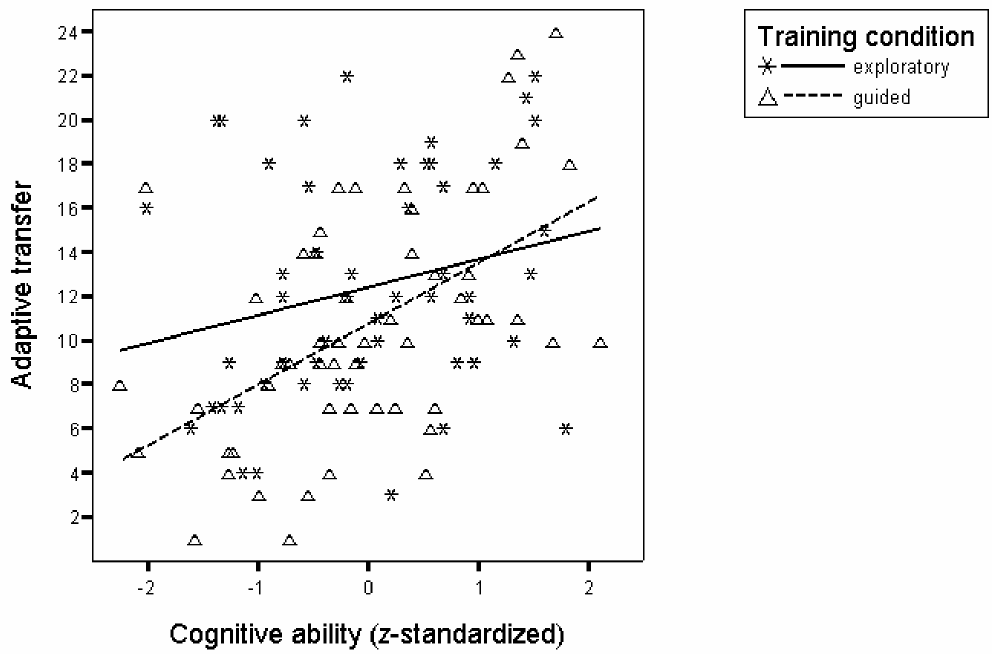
a)


Training condition
exploratory
guided
Adaptive transfer
Perceived performance-utility (z-standardized)

b)


Training condition
exploratory
guided
Analogical transfer
Cognitive ability (z-standardized)

a)


Training condition
exploratory
guided
Adaptive transfer
Cognitive ability (z-standardized)

b)