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ORIGINAL ARTICLE

Who Benefits the Most? Individual Differences in the Transfer of Executive Control Training Across the Lifespan

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Abstract Training studies have shown that cognitive plasticity, that is the potential modifiability of a person's cognitive abilities, is considerable across the lifespan and extends to very old age. Cognitive training can not only result in significant performance improvements on the trained tasks, but also benefit performance on new untrained tasks (transfer). However, even though interventions can be very successful at the group level, individual differences in training gains tend to be large. Why do some individuals benefit more than others? In the present study ($N = 168$), we investigated transfer of executive control training in children ($N = 56$, 8–10 years of age), younger adults ($N = 56$, 18–28 years of age), and older adults ($N = 56$, 62–77 years of age) in a pretest-training-posttest design. Results of latent change modeling showed a training-induced reduction of age differences and individual differences across training and transfer tasks in all age groups. Moreover, individuals with lower cognitive abilities at pretest showed larger training and transfer benefits after the training. This effect was significantly higher in the training group compared to an active control group, indicating that it was based on the executive control training and not on non-focal effects (e.g., regression to the mean). These findings reveal a pattern of compensation effects with the largest training-induced improvements in participants who needed them the most.

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Introduction

In everyday life, we frequently have to select one specific action out of many possible action alternatives and to flexibly adapt to continuous changes in our environment. In these situations, interference needs to be controlled and goal-directed actions have to be selected appropriately, maintained, and coordinated. The higher order cognitive processes responsible for controlling these actions are referred to as executive control functions (e.g., Miyake et al. 2000).

Recent evidence shows that executive control can be improved by training across a wide range of ages (for reviews, see Hertzog et al. 2008; Karbach and Kray 2016; Lustig et al. 2009; Noack et al. 2009; Strobach et al. 2014: Titz and Karbach 2014; von Bastian and Oberauer 2014). Importantly, these training-related benefits usually benefit performance on untrained similar tasks assessing the same ability as the training tasks (near transfer) and oftentimes also to performance on tasks measuring untrained related abilities (far transfer), even though these far transfer have not been reported consistently across the literature (for meta-analyses see Au et al. 2015; Karbach and Verhaeghen 2014; Schwaighofer et al. 2015). All in all, previous research shows that cognitive plasticity (i.e., the potential modifiability of a person's cognitive abilities) seems to be present across the lifespan, even up to very old age (Buschkuehl et al. 2008; Karbach et al. 2010; Li et al. 2008; Schmiedek et al. 2010; Zinke et al. 2012). Still, even though many training regimes have yielded significant improvements at the group level, we also know that individual differences in the degree of improvement are often relatively large (Jaeggi et al. 2014; Karbach et al. 2015; Kliegel and Bürki 2012; Zinke et al. 2014).

So why is it that some individuals benefit more than others? This question is closely related to the long-standing debate on aptitude by treatment interactions (ATI), i.e., the assumption that any intervention has to be closely tailored to the abilities of a learner in order to achieve the best training outcome (Cronbach 1957; Ferguson 1956). Specifically, ATI assumes that optimal learning results when the instructions and the task demands are exactly matched to the aptitudes of the learner (Snow 1989). As a consequence, learning outcomes can be predicted from combinations of aptitudes and treatments. However, Cronbach and Snow (1977) proposed that ATI combinations are complex and different ATI effects need to be sufficiently understood to be the basis for instructional practice and training. Thus, understanding why some individuals benefit more than others is of high relevance both for the understanding of the cognitive and neural underpinnings of cognitive plasticity and for the adaptation of training interventions to populations with specific needs, for instance, individuals in older age and in clinical or educational settings.

In the literature, two different accounts have been proposed to explain individual differences in cognitive plasticity (Lövdén et al. 2012): The first one has been referred to as the magnification account and assumes that individuals that already perform very well before the training would show larger training-induced benefits because they have more efficient cognitive resources to acquire and implement new strategies. Evidence for this view comes often—but not exclusively—from memory strategy training studies applying mnemonic techniques, such as the method of loci (e.g., Baltes and Kliegl 1992; Brehmer et al. 2007; Lindenberger et al. 1992; Verhaeghen and Marcoen 1996). The second and opposing account, referred to as the compensation account, assumes that high-performing individuals would show less benefit because they are already functioning at the optimal level and have less room for improvement. Evidence for this view comes from a number of training studies from the domain of executive control (e.g., Bherer et al. 2008; Cepeda et al. 2001; Karbach and Kray 2009; Kramer et al. 1995; Kray et al. 2008; Kray and Lindenberger 2000; Zinke et al. 2014; but see Brehmer et al. 2012). However, most of these findings are still based on comparisons at the group level, and a systematic analysis of individual differences in training-related performance gains is still scarce. This is particularly critical in childhood and in aging populations, because individuals in these groups are likely to differ more from each other than young adults and merely analyzing group means does little justice to individual strengths and weaknesses. Thus, instead of investigating whether a paradigm is either generally successful or unsuccessful, it also makes sense to test for whom the training actually works, preferably by assessing individual differences in training-induced changes on the level of latent factors instead of single manifest scores (Schmiedek et al. 2010). Understanding the nature and origin of individual differences in training-related gains is an important step towards the development of tailored adaptive interventions designed to meet the needs of specific individuals or aimed at improving specific cognitive processes.

So far, only very few studies have analyzed training-induced cognitive plasticity from an individual differences perspective. A study by Lövdén et al. (2012) examined individual differences in training gains after intensive episodic memory strategy training across the lifespan by means of structural equation modeling. Whereas initial mnemonic instructions reduced individual differences in memory performance, further strategy practice magnified individual differences. The authors suggested that strategy instruction may have compensated inefficient processing strategies in low-performing individuals while intensive training magnified individual differences by uncovering individual differences in memory plasticity.

When it comes to executive control training, Bürki et al. (2014) examined individual learning curves to test for intra-individual change in training as well as inter-individual differences in intra-individual change after 10 days of working memory training in younger and older adults. Latent growth curve modeling (LGCM) showed a magnification of age differences by the end of the training. Initial training performance and training improvement were mediated differently by age and by individual differences in cognitive performance. The authors concluded that "the individual analysis of plasticity should begin at the training performance, and not only focus on the difference in performance between pretest and posttest. With the sole analysis of pretest and posttest performances, important information is neglected" (Bürki et al. 2014, p. 832).

In two studies on working memory training in old and old-old adults, Zinke and colleagues found a negative correlation between training-related gains and participants' baseline working memory performances (i.e., individuals scoring lower on the baseline working memory test gained more on the trained tasks; compensation effect; Zinke et al. 2012; Zinke et al. 2014).

Finally, a recent study analyzed individual differences and the effects of working memory training in older adults (Borella et al. 2017). Using linear generalized mixed effects modeling, the authors tested age, formal education, general cognitive ability, and working memory baseline performance as predictors of the short- and long-term training and transfer effects. They found a differential pattern of results depending on the type of transfer tasks: Participants that were younger and scored higher on the crystallized intelligence measure benefitted more on some measures of working memory, inhibition, and reasoning (magnification effect). In contrast, participants who were older and scored lower on the crystallized intelligence or working memory measure benefitted more on short-term memory tasks and other working memory tasks (compensation effect). The authors concluded that compensation and magnification effects are not mutually exclusive and may both contribute to explain the effects of training.

Still, developmental studies on individual differences in training-related performance gains are lacking. Given that executive functions are not fully matured until late adolescence and subject to marked age-related decline in older individuals (for a review, see Wiebe and Karbach 2017), it is particularly important to be able to provide training interventions that are designed to compensate developmental and age-related deficits in executive control.

Therefore, the aim of the present study was to systematically test the magnification account against the compensation account after executive-control training in different age groups. We had children, younger adults, and older adults perform a task-switching training intervention. Adopting this lifespan approach allowed comparing young adults with fully developed executive control functions to groups with developing and declining control functions. We assessed individual differences in the performance on the switching task at the beginning and the end of training (training gain) as well as the switching task applied at pretest and posttest (transfer gain). In order to investigate the effects of baseline cognitive performance on training and transfer gains, we also analyzed the correlation between the performance on a cognitive test battery at pretest and these gains.

Based on previous evidence from task-switching and dual-task studies comparing performance at the group level (e.g., Bherer et al. 2008; Cepeda et al. 2001; Karbach and Kray 2009; Kramer et al. 1995; Kray et al. 2008; Kray and Lindenberger 2000), we expected to find a pattern of results more consistent with the compensation account than the magnification account, yielding a specific set of predictions: (1) Age differences as well as individual differences in task-switching abilities should be reduced after the training (because low-performing individuals benefit more that high performers), and (2) baseline cognitive ability (i.e., performance at pretest) should be correlated with training (i.e., low-performing individuals should show larger training-induced performance gains). In addition, we tested whether the pattern was comparable (3) across training and transfer tasks. In order to show that performance improvements from pretest to posttest were not the result of non-focal effects (such as regression to the mean or retest effects), we compared the performance of the training group to an active control condition.

In contrast to many previous studies, the present one did not assess effects of age and treatment at the group level but applied statistical techniques (structural equation modeling), allowing the assessment of individual differences on the latent level, including individual differences in performance changes and correlations between baseline cognitive ability and training and transfer benefits (cf. Lövdén et al. 2012; Schmiedek et al. 2010).

Method

Participants

We investigated a total of 168 participants. The training group included 126 individuals, 42 children (mean age = 9.2 years, SD = 0.6; age range 8–10; 45% female), 42 young adults (mean age = 22.0 years, SD = 2.3; age range 18–28; 45% female), and 42 older adults (mean age = 68.7, SD = 3.2; age range 62–77; 60% female). The active control group consisted of 42 participants, 14 children (mean age = 9.3 years, SD = 0.5; age range 8–10; 43% female), 14 young adults (mean age = 23.4 years, SD = 2.3; age range 19–26; 50% female), and 14 older adults (mean age = 69.7, SD = 2.5, age range 66–76; 43% female). They were recruited from the subject pool at Saarland University, tested individually, and paid 60 € for participating in the eight sessions of the study. Note that part of the sample was reanalyzed from a previous study (75% of the sample; corresponding to groups 1–3 from Karbach and Kray 2009). This previous publication, however, was restricted to the comparison of mean performances at the group level. It showed gains in the training task and transfer to an untrained switching task in all age groups (i.e., larger gains in the training group than in the control group).

Design and Procedure

We applied a pretest-training-posttest design to assess training and transfer gains. Transfer was defined as performance improvement at posttest relative to baseline performance at pretest (compared to an active control condition). The two pretest sessions included baseline measurements of task-switching and single-task performance (including tasks A and B described below) as well as a battery of cognitive tasks. In the training group, they were followed by four task-switching training sessions (including tasks C and D described below) and in the active control condition by four sessions including training on the single tasks C and D (see below). Finally, all participants performed two posttest sessions that were identical to the pretest sessions.

Pretest and Posttest Assessments

At pretest and posttest, we applied an untrained switching task (transfer task) as well as a battery of tasks assessing baseline cognitive ability at pretest (working memory, reasoning, perceptual speed, and semantic knowledge).

Task Switching We used a modified version of the task-switching paradigm including performance in single-task (task A or B only) and mixed-task blocks (switching between both tasks) (see Karbach and Kray 2009). In mixed-task blocks, subjects were instructed to switch tasks on every second trial. Task A required participants to decide whether a picture showed a fruit or a vegetable ("food" task) and task B whether a picture was small or large ("size" task). Participants completed 8 single-task and 12 mixed-task blocks (each one including 17 trials).

Cognitive Test Battery at Pretest To assess baseline cognitive performance at pretest, participants performed a test battery including measures for the following four abilities. For each one of the tasks, the test score referred to the mean number of correctly solved items across tasks.

Working Memory We applied the symmetry span task and the navigation span task adapted from Kane and colleagues (Kane et al. 2004). In the symmetry span task, participants recalled sequences of locations marked by red squares in a 4×4 matrix against a background symmetry-judgment task. In the navigation span task, participants recalled the paths of moving balls across the screen against a background task of counting the corners of polygons. The test score was the sum of correctly recalled items averaged across both tasks (inter-task correlation $r = .63$, $p < .01$).

Reasoning Figural reasoning and letter series served as measures for reasoning ability (Lindenberger et al. 1993). In the figural reasoning task, items followed the format, "A is to B as C is to ?." In the letter series task, subjects saw items consisting of five letters followed by a questions mark (e.g., a c e g i ?) and named the letter that would logically fill the position of the question mark. The test score was the sum of correctly solved items averaged across both tasks (inter-task correlation $r = .45$, $p < .01$).

Perceptual Speed Participants performed the digit-symbol and letter-symbol substitution test (Lindenberger et al. 1993; Wechsler 1982). The test sheet displayed nine digit/letter-symbol mappings. Below, 100 digits/letters without the corresponding symbols were displayed. Participants were instructed to fill in as many symbols as possible within 90 s. The test score was the sum of correctly solved items averaged across both tasks (inter-task correlation $r = .92$, $p < .01$).

Semantic Knowledge Participants performed the spot-a-word test (Lehrl 1977). They were successively presented items containing one word and four pronounceable pseudowords and instructed to identify the one word. The test score was the sum of correctly solved items. We used this as a proxy for semantic knowledge (as it reflects a single bit central part of the construct).

Task-Switching Training (Training Group)

Across the four training sessions, participants practiced a switching task that was structurally similar to the one at pretest and posttest. In task C, subjects had to decide whether a picture showed planes or cars and in task D whether one or two planes/cars were presented. In order to maximize demands on executive control, participants only performed mixed-task blocks during training (with a total of 1768 training trials).

Single-Task Training (Active Control Group)

Participants in the active control condition performed the same tasks C and D as the training group but only in single-task blocks. Thus, demands on executive control were minimized while the rest of the protocol was identical to the training condition.

Statistical Analyses

Dependent Variables For the switching tasks, we calculated two types of switch costs measuring two aspects of executive control: General switch costs were defined as the difference in mean performance between single-task and mixed-task blocks (i.e., measuring task-set selection and maintenance), and specific switch costs were defined as the difference between stay and switch trials within mixed-task blocks (i.e., measuring cognitive flexibility on trial-to-trial transitions).

Measurement Invariance Over Time All our models were estimated assuming scalar measurement invariance over time. Thus, the latent variables are constrained to have exactly the same unstandardized factor loadings and unstandardized intercepts across time. We tested this assumption by comparing different levels of invariance (configural, metric, scalar, and strict) with χ^2 difference tests (e.g., Cheung and Rensvold 2002). If scalar invariance constraints are satisfied, latent variable scores at each time of measurement are on the same metric and stronger conclusions are warranted (cf. Widaman et al. 2010).

Modeling Training and Transfer Gains Transfer effects to general switch costs in the training group can be compared with the active control group, because both groups completed the same tasks at pretest and posttest. However, training effects in specific switch costs in the training group cannot be compared with the active control group, because the active control group completed single tasks as control condition. Thus, analyses of training effects in specific switch costs were modeled as single-group models (the training group), whereas analyses of transfer effects to general switch costs were modeled as multi-group models (the training vs. active control group).

In order to test for training-induced changes in individual differences, we tested in latent state models whether the variance in specific switch costs decreased during training (i.e., from the first training session to the last training session; training gain) and whether the variance in general switch costs significantly decreased after training (i.e., from pretest to posttest; transfer gain). Therefore, we used χ^2 difference testing and compared a model with freely estimated variances to a nested model in which the variances at the two measurement occasions were constrained to be equal. The latent state model included two latent unobserved variables representing participants' performances on the switching task before and after training, respectively (see Fig. 1a). Importantly, this model allows estimating the means of pretraining and posttraining performance, individual differences in pretraining and posttraining performance, as well as the correlation between them. Pre- and posttraining were represented by a factor with odd and even numbered task blocks as indicators in the switching tasks. We fitted this model as single-group model to the training task data in the training group (with specific switch costs in the first and the last session as indicators for the pretraining and posttraining performances). For the transfer task, we fitted the model as multi-group model comparing the training and active control group (with general switch costs at pretest and posttest as indicators for the pretraining and posttraining performances). In addition, we included cognitive composites of working memory, reasoning, perceptual speed, and semantic knowledge as covariates (which were allowed to freely covary among themselves and with both pretraining and posttraining performance). Considering the large age range in our sample, we included age as linear and quadratic predictors in both models (see Fig. 1a, b) because there is ample evidence for both types of age effects on general and specific switch costs (e.g., Cepeda et al. 2001; Kray et al. 2008; Reimers and Maylor 2005; see Karbach and Unger 2014 and Verhaeghen and Cerella 2002, for a reviews). Thus, the correlations of the other variables (working memory, perceptual speed, reasoning, and semantic knowledge) with pretraining switch costs and gain are controlled for age.

Our main analyses were then based on latent change models representing the changes between either the first and last training session (specific switch costs) or baseline and posttest performance (general switch costs). Latent change models are just reparametrizations of the respective latent state models (Steyer et al. 1997), but they include the changes between two measurement occasions explicitly as variables. Latent change variables (e.g., Fig. 1b) include individual differences in these changes and are less affected by measurement error than manifest difference scores. We tested their correlations with relevant predictors to understand which individuals benefited the most during training. For the transfer task (general switch costs), we also tested whether these correlations were significantly higher in the training compared to the active control group. This would indicate that the effects were based on the training and not on non-focal effects (e.g., regression to the mean).

All models were calculated with Mplus 7.4, using full information maximum likelihood (FIML) estimations. Thus, all cases were included without loss of information. For model identification, the first factor loading of each latent variable was fixed to one. Model fit was evaluated with the χ^2 test, the Comparative Fit Index (CFI), the Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR) in reference to Beauducel and Wittmann (2005). We reported the RMSEA, but this index has to be interpreted with caution in our case as it is known to overreject properly specified models with small degrees of freedom (Kenny et al. 2015).

Results

Descriptive statistics can be found in Table 1. Means and standard deviations of pretest performance are reported for the three different age groups separately for the training and control group.

Between-Group Differences at Baseline

We tested for between-group differences (control, training) in baseline cognitive abilities (general and specific switch costs, working memory, perceptual speed, semantic knowledge, reasoning) by means of one-way analyses of variance (ANOVA) as a function of age. None of these comparisons was significant (all p values $> .17$; see Table 1), indicating that training and control groups were comparable at baseline in each of the age groups.

Measurement Invariance Over Time

We tested measurement invariance by comparing different levels of invariance (configural, metric, scalar, and strict, see for example Cheung and Rensvold 2002) with χ^2 difference tests. Table 2 includes the fit indices for all levels of invariance over time. Overall, all models fitted the data well (all χ^2 with ps $> .29$), with the exception of general switch costs with strict measurement invariance (χ^2 with $p < .01$). This was further the only case in which the χ^2 difference test was significant. Up to scalar measurement invariance, however, there were no significant drops in χ^2 or the descriptive fit indices (for both specific and general switch costs). Taken together, we estimated latent change models with scalar measurement invariance across time demonstrating perfect model fit (all χ^2 with ps $> .29$; Table 2). Scalar measurement invariance allows for the comparison of means across time (e.g., Steenkamp and Baumgartner 1998) and is thus essential in latent change modeling.

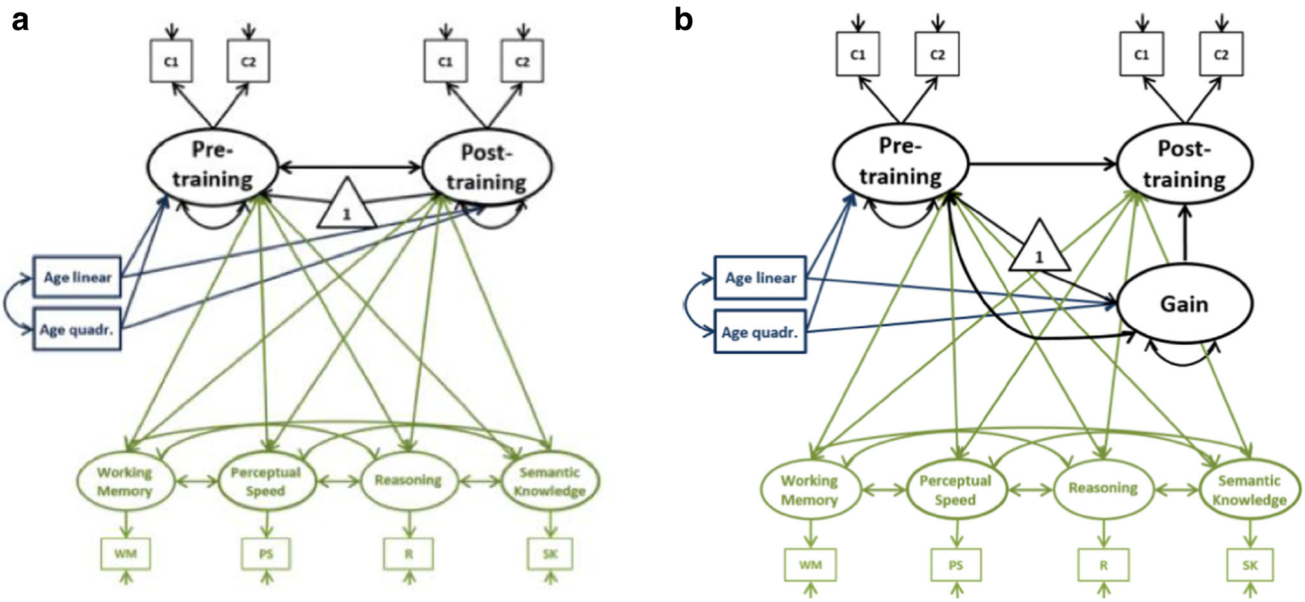

Fig. 1 Illustration of the models (**a** latent state; **b** latent change) to estimate correlations between baseline cognitive ability and training/transfer gains. The models were estimated with scalar measurement invariance over time. Observed variables are represented by squares, latent variables by circles, regression weights by one-headed arrows, and variances and correlations by two-headed arrows. The triangle indicates means. Please note that age linear and age quadratic are predictors, and thus, the correlations of working memory, perceptual speed, reasoning, and semantic knowledge with pretraining and gain are controlled for age. C1/C2 = switch costs in odd/even numbered blocks, pretraining = performance in the first training session/at pretest, posttraining = performance in the last raining session/at posttest, WM = working memory, PS = perceptual speed, R = reasoning, SK = semantic knowledge, Gain = training/transfer gain (i.e., performance improvements in the last training session/at posttest relative to the first training session/pretest). Parts of the figure are displayed in color in order to support the readability

Training-Related Reductions of Variance

At first we tested in a confirmatory factor model (latent state model) with two factors (first and last training session), two indicators each (switch costs in odd/even blocks), and scalar measurement invariance over time whether the variance in latent specific switch costs decreased over time in the training group. Therefore, we compared a model with freely estimated variances to a nested model in which the variances at two measurement occasions (i.e., first and last training session) were constrained to be equal. The model with freely estimated variances fitted the data well [χ^2 (df = 3) = 0.58, p = .90; CFI = 1.00; RMSEA = 0 (90% CI = 0.00–0.06); and SRMR = 0.01] but constraining the variances to be equal resulted in a significant drop of model fit [$\Delta\chi^2$ (df = 1) = 24.24; p < .01], indicating that the variance was significantly reduced from the first to the last session (variance first session = 8192.59, variance last session = 3453.00).

Then, we tested in another confirmatory multi-group factor model with two factors (pre- and posttest) per group (training and control), two indicators each (switch costs in odd/even blocks), and scalar measurement invariance over time whether the variance in latent general switch costs decreased over time in the training or active control group. Again, the model with freely estimated variances fitted the data well [χ^2 (df = 7) = 11.52, p = .12; CFI = 0.99; RMSEA = 0.09 (90% CI = 0.00–0.18); and SRMR = 0.06] but constraining the variances in the training group to be equal resulted in a significant drop of model fit [$\Delta\chi^2$ (df = 1) = 24.06; p < .01], indicating that the variance was significantly reduced from pre- to posttest (variance pretest = 28,503.73, variance posttest = 10,960.90). Constraining the variances in the control group to be equal, however, did not change the model fit [$\Delta\chi^2$ (df = 1) = 0.97; p = .33], indicating that the variance was comparable at pre- and posttest.

Latent Change Modeling

Via reparametrization (Steyer et al. 1997), we transferred the state models into latent change models. Latent state and change models are equivalent models with exactly the same model fit (see above for both models). Latent means of the state and change models indicated that both specific switch costs [M_{pre} = 126.12 (SE = 8.67), M_{post} = 54.94 (SE = 6.27), $M_{\text{Difference}}$ = − 71.18 (SE = 6.75), z = − 10.55, p < .01] as well as general switch costs [M_{pre} = 280.17 (SE = 17.63), M_{post} = 92.26 (SE = 12.65), $M_{\text{Difference}}$ = − 187.91 (SE = 13.33), z = − 14.10, p < .01] were on average reduced over time in the training group, indicating that the participants on average benefited from training. In the control group, general switch costs also decreased over time [M_{pre} = 311.16 (SE = 37.23), M_{post} = 258.52 (SE = 12.65), $M_{\text{Difference}}$ = − 52.65 (SE = 22.00), z = − 2.39, p = .02], but significantly less compared to the training group (cf. Karbach and Kray 2009).

Table 1 Descriptive statistics for cognitive baseline performance (pretest) as a function of age group (children, younger adults, older adults) and experimental group (training group, active control group); significance (*p* value) for tests of between-group differences (training, control)

		Training group ($N = 126$)		Active control group ($N = 42$)		Test for between-group differences
		M	SD	*M*	SD	*p*
Children	General switch costs	388.59	159.62	362.51	227.39	.64
	Specific switch costs	343.52	145.26	380.86	175.43	.43
	Working memory	1.26	0.87	1.50	0.89	.38
	Perceptual speed	34.59	7.87	35.86	8.57	.61
	Reasoning	15.06	2.16	15.19	2.77	.85
	Semantic knowledge	10.57	3.49	10.14	3.23	.69
Young adults	General switch costs	166.89	117.18	170.23	184.06	.94
	Specific switch costs	207.03	137.35	217.20	195.21	.83
	Working memory	3.57	1.58	3.54	1.12	.94
	Perceptual speed	68.19	10.29	69.07	8.81	.78
	Reasoning	18.52	1.29	18.90	1.45	.36
	Semantic knowledge	23.17	3.24	23.79	4.30	.57
Older adults	General switch costs	372.11	187.96	344.92	243.49	.67
	Specific switch costs	337.44	159.98	343.98	243.80	.91
	Working memory	1.62	1.33	1.89	1.39	.51
	Perceptual speed	52.65	10.73	52.29	12.27	.92
	Reasoning	15.23	2.43	16.24	2.11	.17
	Semantic knowledge	27.50	3.37	27.86	3.98	.74

$N_{\text{children}} = 56$; $N_{\text{Adults}} = 56$; $N_{\text{Old}} = 56$

M mean (number of correctly solved items/milliseconds), *SD* standard deviation

The Role of the Participants' Age and Baseline Performance

Further, we correlated the latent change variables of specific and general switch costs (one model each for specific and general switch costs) to baseline cognitive performance and age to understand which individuals benefited the most during training. Training effects in specific switch costs were analyzed in a single-group model (the training group), whereas transfer effects to general switch costs were analyzed in a multi-group model (the training vs. active control group). Both models are conceptually depicted in Fig. 1 and fitted the data well [specific switch costs: χ^2 (df = 15) = 15.82, $p = .39$; CFI = 1.00; RMSEA = .02 (90% CI = 0.00–0.08); and SRMR = 0.03] or acceptable [general switch costs: χ^2 (df = 31) = 54.08, $p < .01$; CFI = 0.98; RMSEA = 0.09 (90% CI = 0.05–0.14); and SRMR = 0.05].

Considering the large age range in our sample, we included age as linear and quadratic predictors in both models (see Fig. 1a, b). Thus, the correlations of the other variables (working memory, perceptual speed, reasoning, and semantic knowledge) with pretraining switch costs and gain are controlled for age. In the training group, age predicted both latent differences in specific switch costs ($b_{\text{linear}} = -9.54$; $z_{\text{linear}} = -2.74$, $p < .01$; $b_{\text{quadratic}} = 4.78$, $z_{\text{quadratic}} = 2.88$, $p < .01$; pseudo-$R^2 = 12\%$) and general switch costs ($b_{\text{linear}} = -26.74$; $z_{\text{linear}} = -4.09$, $p < .01$; $b_{\text{quadratic}} = 14.50$, $z_{\text{quadratic}} = 4.72$, $p < .01$; pseudo-$R^2 = 42\%$) in a way that children and older adults benefited more than young adults (see Fig. 2). Age further predicted baseline specific switch costs ($b_{\text{linear}} = 22.99$; $z_{\text{linear}} = 5.67$, $p < .01$; $b_{\text{quadratic}} = -12.24$, $z_{\text{quadratic}} = -6.27$, $p < .01$; pseudo-$R^2 = 29\%$) as well as baseline general switch costs ($b_{\text{linear}} = 29.11$; $z_{\text{linear}} = 3.62$, $p < .01$; $b_{\text{quadratic}} = -22.82$, $z_{\text{quadratic}} = -5.94$, $p < .01$; pseudo-$R^2 = 31\%$) in a way that children and older adults demonstrated lower baseline performance than young adults. In the control group, age was unrelated to the latent change in general switch costs (*p*s > .19) but the quadratic age-term was related to baseline general switch costs ($b_{\text{linear}} = 30.57$; $z_{\text{linear}} = 1.68$, $p = .09$; $b_{\text{quadratic}} = -20.17$, $z_{\text{quadratic}} = -2.46$, $p = .01$; pseudo-$R^2 = 16\%$) in a way that children and older adults demonstrated lower baseline performance than young adults.

Correlations Between Baseline Cognitive Ability and Training/Transfer Gains

We assessed the correlations among pretest performance, gain, and cognitive covariates (see Tables 3 and 4). Tables 3 and 4 include correlations of working memory, perceptual speed, reasoning, and semantic knowledge at

Table 2 Tests of measurement invariance over time for latent state and change models of specific and general switch costs

Measure	Invariance level	χ^2 (df)	CFI	RMSEA (90% CI)	SRMR	$\Delta\chi^2$ (df)	ΔCFI
Specific switch costs	1. Configural	0.05 (1), $p = .83$	1.00	0 (0–0.14)	0.002		
	2. Metric	0.35 (2), $p = .83$	1.00	0 (0–0.10)	0.012	0.31 (1), $p = .58^{1,2}$	0
	3. Scalar	0.58 (3), $p = .90$	1.00	0 (0–0.06)	0.013	0.23 (1), $p = .63^{2,3}$	0
	4. Strict	6.12 (5), $p = .29$	0.995	0.04 (0–0.14)	0.055	5.54 (2), $p = .06^{3,4}$	0.005
General switch costs	1. Configural	0.65 (1), $p = .42$	1.00	0 (0–0.19)	0.006		
	2. Metric	0.75 (2), $p = .69$	1.00	0 (0–0.11)	0.009	0.10 (1), $p = .75^{1,2}$	0
	3. Scalar	3.73 (3), $p = .29$	0.998	0.04 (0–0.14)	0.030	2.98 (1), $p = .08^{2,3}$	0.002
	4. Strict	18.76 (5), $p < .01$	0.953	0.13 (0.07–0.19)	0.060	15.06 (2), $p < .01^{3,4}$	0.045

Notes. There are no distinctions between latent change and state models in this table because latent change models are reparametrizations of latent state models and have therefore exactly the same model fit. Training effects in specific switch costs were analyzed in the training group only ($N = 126$) and the transfer effects to general switch costs were analyzed in both the training and active control group ($N = 168$, see the "Statistical Analyses" section for details)

CFI Comparative Fit Index, *RMSEA* Root Mean Square Error of Approximation, *CI* confidence interval, *SRMR* Standardized Root Mean Square Residual

baseline with latent pretraining performance and latent gain after controlling for a linear and quadratic age predictor (see Fig. 1).

In the training group, we found strong positive correlations between pretest performance and gain, indicating that participants with lower pretest performance gained more from the training than those with higher pretest performance. Out in other words, higher pretraining switch costs were related to higher training success (i.e., reduction in switch costs; $r = .75$ and .81). Moreover, lower baseline cognitive performances were related to higher training success (i.e., reduction in switch costs; $r = -.20$ to $-.29$). The transfer task (general switch costs) allowed for comparing the strength of these correlations in the training and active control group (Table 4, Notes) because both groups completed the same task. Therefore, we compared a model in which all correlations were freely estimated to a model in which one correlation was constrained to be equal in both groups, respectively. The correlation between baseline perceptual speed and training gain was not significantly different in the training and active control group (Table 4, Notes). However, baseline general switching costs and baseline working memory performance were significantly higher correlated with training gains in the training group than in the active control group (Table 4, Notes). This indicates that they were more likely based on the effects of executive control training than on non-focal effects (e.g., regression to the mean or retest effects).

Discussion

In the present study, we investigated the question why some individuals benefit more than others after executive-control training. Even though results regarding the transfer of cognitive training are heterogeneous across the literature, the vast majority training of training studies has shown that executive functions can be improved by training across a wide range of ages (for reviews, see Hertzog et al. 2008; Karbach and Kray 2016; Lustig et al. 2009; Noack et al. 2009; Strobach et al. 2014: Titz and Karbach 2014; von Bastian and Oberauer 2014). Recently, however, a lot of work has also shown that not every participant benefits to the same degree, that is, individual differences in training-induced gains are often significant (cp. Borella et al. 2017). While studies from the domain of strategy-based memory training mostly reported magnification effects (i.e., larger gains in high performing individuals), training of executive control has often resulted in compensation effects (i.e., larger gains in low-performing individuals), at least at the group level. In the present study, we systematically tested the magnification account against the compensation account by analyzing training-induced changes on the latent level. Children, younger adults, and older adults performed a task-switching training and we analyzed training gains (i.e., the reduction of specific switch costs from the first to the last training session) as well as transfer gains (i.e., the reduction of general switch costs from pretest to posttest) compared to an active control group performing single-task training.

The analyses yielded four important main findings: (1) Individual differences in performance were reduced after the training, (2) age differences in performance were reduced after the training (i.e., children and older adults benefitted more), (3) baseline cognitive abilities were significantly correlated with the training-induced gain (i.e., low-performing individuals benefitted more), and (4) these findings were consistent across training and transfer

Fig. 2 Training gains (**a**) and transfer gains (**b**) in the training group as a quadratic function of age. Please note that higher values indicate training and transfer success (costs are reduced). ms milliseconds

gains and significant compared to an active control group. Considering that training and transfer task were very similar (task-switching paradigms with a different set of tasks and stimuli), it is not surprising that the pattern of results was comparable across tasks but supports the robustness of the effects. All in all, this pattern of findings is exactly in line with the compensation account and strongly contradicts the magnification account.

Thus, our analysis is consistent with previous findings showing that executive control training resulted in a reduction of age differences in performance at the group level (e.g., Bherer et al. 2008; Cepeda et al. 2001; Karbach and Kray 2009; Kramer et al. 1995; Kray et al. 2008; Kray and Lindenberger 2000; but see Brehmer et al. 2012) and extends these findings by showing that they hold on the interindividual level and that they are significant for both training and transfer gain as well as in comparison to an active control condition.

The fact that we found compensation effects after the training of executive control is in stark contrast to evidence from strategy-based memory training, which often resulted in magnification effects (e.g., Baltes and Kliegl 1992; Brehmer et al. 2007; Lindenberger et al. 1992; Verhaeghen and Marcoen 1996). This pattern has been explained by younger adults having more cognitive resources to acquire and implement new strategies. However, the finding provides further evidence indicating that process-based and strategy-based trainings may tap very different cognitive processing capacities and therefore yield very different training outcomes. In contrast to strategy-based trainings, process-based trainings, like the one applied in the present study, target more general processing capacities, such as working memory or executive functions. And not only have these trainings been more beneficial for low-performing individuals, but they also tend to result in larger transfer effects of training (Karbach and Verhaeghen 2014; Rebok et al. 2007; Verhaeghen et al. 1992). Knowing about these differential outcomes of different types of cognitive training may help explaining inconsistent findings in the literature and—more importantly—may

Table 3 Correlations of latent training gains with pretraining switch costs and baseline cognitive performance after controlling for age (in the training group)

	1	2	3	4	5
1. Training gain specific switch costs	1				
2. Pretraining specific switch costs	0.75*	1			
3. Baseline working memory	− 0.20*	− 0.25*	1		
4. Baseline perceptual speed	− 0.06	− 0.16*	0.57*	1	
5. Baseline reasoning	− 0.18	− 0.25*	0.68*	0.48*	1
6. Baseline semantic knowledge	− 0.01	− 0.05	0.26*	0.60*	0.26*

Notes. The interpretation is in the direction that higher pretraining switch costs and lower baseline cognitive performance were related to higher training success (i.e., reduction in switch costs)

**p* < .05

Table 4 Correlations of latent transfer gains with latent pretraining switch costs and baseline cognitive performance after controlling for age (in the training group/active control group)

	1	2	3	4	5
1. Training gain general switch costs	1				
2. Pretraining general switch costs	0.81*/0.41[a]	1			
3. Baseline working memory	− 0.29*/0.07[b]	− 0.30*/− 0.27*	1		
4. Baseline perceptual speed	− 0.28*/− 0.10[c]	− 0.25*/− 0.17	0.57*/0.54*	1	
5. Baseline reasoning	− 0.19/0.14	− 0.18*/− 0.07	0.68*/0.75*	0.48*/0.56*	1
6. Baseline semantic knowledge	− 0.13/0.01	− 0.10*/− 0.03	0.26*/0.29*	0.60*/0.59*	0.26*/0.39*

Notes. The interpretation is in the direction that higher pretraining switch costs and lower baseline cognitive performance were related to higher training success (i.e., reduction in switch costs). All results are based on a model with metric invariance across groups to compare correlations between groups (Chen et al. 2005). Value before the slash = training group/value after the slash = active control group

*$p < .05$

[a] Correlations are significantly different [between the training and control group: $\Delta\chi^2$ (df = 1) = 15.40; $p < .01$]

[b] Correlations are significantly different [between the training and control group: $\Delta\chi^2$ (df = 1) = 4.26; $p = .04$]

[c] Correlations are not significantly different [between the training and control group: $\Delta\chi^2$ (df = 1) = 0.76; $p = .38$]

have significant implications for designing tailored trainings for individuals or populations with specific needs or deficits.

One benefit of this study certainly is the lifespan sample, providing the opportunity to examine the validity of the magnification and compensation accounts across a wide range of ages and across a training and a transfer task. Given that we also assessed baseline cognitive abilities in several domains (task switching, working memory, perceptual speed, fluid intelligence, and semantic knowledge), our data showed that the correlations between baseline ability and gains were not domain specific, even though they were most pronounced for working memory. Again, it should be noted that training and transfer task were very similar and performance on both tasks showed a similar pattern of correlations with baseline cognitive abilities. Considering that general and specific switch costs are also significantly correlated, it is not surprising that the correlations between baseline abilities and gains were comparable across tasks.

Moreover, the findings that (1) pretest-posttest performance improvements were larger in the training group than the control groups, (2) individual differences in performance decreased in the training group but not in the control group, and (3) baseline cognitive performance was significantly higher correlated with transfer gains in the training group than in the active control group indicate that the compensation effects found in the present study are indeed more likely to reflect the effects of executive-control training than non-focal effects (e.g., regression to the mean or retest effects).

Finally, our use of advanced statistical procedures for estimating latent change extends past research, circumvents some of the methodological problems discussed in the training literature (cf. Lövdén et al. 2012; Schmiedek et al. 2010), and allowed us to extend the analysis of training-induced gains from the group level to the level of individual differences.

However, the study also has a number of limitations. We realize that the sample size was relatively small for this type of latent change modeling. Even though our findings are very consistent across the different analyses we ran, we acknowledge that the statistical power for addressing our research questions is limited. In addition, we realize that instead of having two indicators from the same task (derived from an odd/even split) load on a latent factor, multiple independent measures would have been more ideal. Still, the advantages of analyzing the data by latent change modeling instead of just comparing manifest group means outweigh this disadvantage. Also, our design did not include a follow-up assessment and the longevity of the effects we report has to be tested in another study. Finally, the training task in the present study was not adaptive—a feature which seemed to be key to elicit reliable training and transfer effects (e.g., Holmes et al. 2009; Karbach et al. 2015). Yet, a recent study demonstrated that training at different levels of difficulty may just be sufficient, independent of whether that difficulty is adjusted to the participant's performance or randomly altered (von Bastian and Eschen 2016). Thus, given that task difficulty in our training kept constantly changing between switch and stay trials, changing task difficulty was constantly implemented in the training procedure.

Despite these limitations, the findings of the present study have brought us one step closer to understand aptitude-treatment interactions and, more specifically, individual differences in the outcome of executive-control training. Future studies need to examine whether results based on this specific type of process-based training (task switching) hold for other types of executive-control training and across wider range of transfer tasks. Importantly, process-based task-switching training clearly yields compensation effects across the lifespan. Considering, for instance, clinical or educational issues, it is very obvious that understanding the mechanisms mediating individual differences in the effectiveness of cognitive interventions may bear important practical and scientific implications. This knowledge may help design interventions for patients with specific cognitive impairments in clinical contexts or interventions for students with specific learning impairments in educational settings.

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