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Mechanisms Underlying Training-Induced Cognitive Change

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Abstract

The prospect of enhancing cognition through behavioural training interventions, for example, the repetitive practice of cognitive tasks or metacognitive strategy instruction, has seen a surge in popularity over the past 20 years. Although overwhelming evidence demonstrates that such training interventions increase performance in the trained tasks, controversy remains over whether these benefits transfer to other tasks and abilities beyond the trained context. In this Review, we provide an overview of the state of the evidence for the effectiveness of cognitive training in inducing transfer, with a particular focus on the theoretical mechanisms that have been proposed to potentially underlie training and transfer effects. We highlight that there is relatively little evidence that training enhances cognitive capacity, that is, the overall cognitive resource available to an individual. In contrast, substantial evidence supports training-induced improvements in cognitive efficiency, that is, optimised performance within the existing capacity limits. We conclude that shifting research focus towards identifying the cognitive mechanisms underlying gains in cognitive efficiency offers a fruitful avenue for developing effective cognitive training interventions. Critically, however, to truly advance our understanding of human cognition and cognitive plasticity, we must strive for developing and refining theories that allow for deriving falsifiable, testable hypotheses.

Mechanisms Underlying Training-Induced Cognitive Change

A multitude of mental processes is necessary for successfully managing even the most mundane situations. For example, when shopping in a supermarket, the item you wish to purchase first needs to be retrieved from your memory. Next, to identify the item, you need to perceptually process the visual information. Sometimes, when you cannot locate the desired item on the shelf right away, you will need to compare the appearance of the items on the shelf to the representations of the item you are looking for in your memory. Often, it can help to remember the last time you purchased the item in this store: Instead of a time-consuming visual search, you can simply focus your attention on the most likely location of the item. Finally, once you have located the item and put it into your shopping cart, you need to maintain and update your memory of other items you still want to buy.

To perform efficiently in such a mundane situation, people need to flexibly adapt to the demands of changing contexts and dynamic environments. If these demands exceed an individual's range of functional flexibility over a prolonged period of time, cognitive plasticity can be triggered[1]. Plasticity is the brain's capacity to implement lasting changes that alter its functional and behavioural repertoire[2,3]. One way to advance our understanding of plasticity is to study cognitive training **[G]** and measure its effects on cognitive performance in both the laboratory and everyday life.

Cognitive training interventions typically target fluid cognitive abilities central to human learning, problem solving, and innovation throughout the lifespan, including the basic abilities required in the situation described above. Fluid cognitive abilities first develop rapidly until young adulthood, and then begin to decline with progressing age[4]. Moreover, they are often affected by developmental neurocognitive disorders such as ADHD[5] or autism spectrum disorder[6], age-related disorders such as dementia[7], and impairments after acquired brain injury such as ischemic stroke[8]. Therefore, affordable, easy-to-administer interventions that may improve these cognitive abilities are highly desirable.

Due to the flexibility and upscaling potential of cognitive training, research exploring its effectiveness **[G]** has seen a surge in popularity over the past 20 years. Past studies have consistently demonstrated training effects **[G]**. However, the ultimate goal of cognitive training is to establish transfer **[G]** of training to contexts beyond the trained tasks. Inconsistent evidence for such transfer effects, pervasive methodological concerns, and an only relatively recent shift towards developing more refined theoretical accounts of the mechanisms **[G]** [9] underpinning training-induced cognitive change have led to heated debates in this field.

In this Review, a key emphasis will be on theories of training and transfer and the current state of evidence of the malleability of the most frequently targeted fluid cognitive abilities: perception **[G]** and attentional control **[G]** , working memory **[G]** , episodic memory **[G]** , and multitasking **[G]** . In contrast to previous reviews of the cognitive training literature[10-12],this comprehensive Review will highlight the importance of identifying the mechanisms that underlie training-induced cognitive performance improvements, and how a more in-depth theoretical understanding about these mechanisms can be harnessed to develop more robust, reliable, and powerful cognitive training interventions.

Designs of Cognitive Training Studies

The gold-standard for testing whether training generates transfer is to use a pretest-posttest study design (Figure 1). Training-induced improvements are measured by assessing cognitive performance and other outcomes of interest before and after cognitive training, with some studies additionally including a follow-up assessment **[G]** to evaluate the durability of effects. Training interventions vary regarding their content; some involve the repetitive practice of cognitive laboratory tasks, whereas others focus on metacognitive instructions, for example by teaching strategies. Many training interventions comprise 10 to 20 sessions, each taking between 20 and 60 minutes long; however, some past interventions consisted of just a few sessions[13] or hundreds of sessions[14].

The measures assessing training-induced improvements vary in the degree to which the processes they measure overlap with the processes targeted by the training tasks. Gains in tasks assessing the trained processes with a different stimulus materials and/or task structure are considered *near* transfer effects, whereas improvements in measures thought to rely on the trained processes to a lesser degree (for example, gains in related but different cognitive constructs or in everyday life functioning) are interpreted as *far* transfer effects[15,16].

To distinguish training-induced effects from simply repeatedly completing the same set of measures (“test-retest effects”), a group of participants undergoing the training intervention - the training group - is compared to passive control groups **[G]** or active control groups **[G]**. Active control groups have the advantage over passive control groups that they additionally control for placebo and expectancy effects[17,18] as well as other non-specific changes that occur due to taking part in an intervention in general, for example, benefitting from sticking to a regular training schedule[19]. Moreover, elaborated control group activities allow for pinpointing the specific mechanisms underlying and explaining training effects[20]. The design of these alternative activities is one of the biggest challenges in this field. The activities must be as plausible and believable as the training group’s activities to elicit similar expectations regarding training success. Importantly, though, the alternative activities must not demand the same cognitive processes as the training activities; otherwise, no conclusions can be inferred about the effects of training. What constitutes an ideal control group is still heatedly debated and varies between training approaches for different processes[19-21]. Regardless of the type of control group, it is critical to demonstrate that all included groups perform similarly in the transfer tasks pre-training to avoid confounding pre-training differences and regression-to-the-mean with post-training between-groups differences.

Other methodological considerations when designing a cognitive training study include the validity and statistical power of transfer assessment. In the past, the validity of transfer assessment has been questioned because cognitive abilities and other outcomes are often assessed by only a single measure[22,23] and, hence, do not account for the task impurity problem[24]. Specifically, single measures are not process-pure because they generate task-specific variance in addition to individual differences in the outcome of interest. For example, when measuring the ability to update contents in working memory only with a letter keep-track task, it is possible that any gains detected in this task mostly reflect better performance with the particular stimuli (letters) or the specific paradigm (keep-track). To adequately address the task impurity problem and to assess changes in cognitive abilities unconfounded with task-specific gains, performance needs to be assessed across multiple measures.

The statistical power of transfer assessment has been criticized because many training studies include only relatively small sample sizes although any potential transfer effects can be expected to be of a small or medium size at best[25]. Low statistical power is problematic because it can lead to false-negative results **[G]** [26]. For example, in the training literature, groups comprise typically no more than 30 participants[27,28]. For a medium effect size (Cohen's $d = 0.50$), this translates into a theoretical statistical power of 48%. Thus, even if we were to expect such sizable transfer effects, we would be able to detect them only in about every second study. Ironically, low statistical power also increases the likelihood of false-positive results **[G]** [29]. Finally, low statistical power can also lead to substantially inflated effect sizes[30]. For example, a simulation study demonstrated that, for a true medium effect that is tested with 30 participants per group, about 98% of effect sizes are inflated[31]. One way to address these problems is to more adequately power cognitive training studies and to evaluate the strength of evidence with Bayesian inference[25] (Box 1). Importantly, these methodological concerns should not translate into generally dismissing any evidence from past studies that did not include active control groups, broad assessment of transfer, and adequate sample sizes. However, the strengths and weaknesses of the methodologies used must be taken into account when evaluating the overall evidence for the effectiveness of cognitive training, in particular when interpreting findings of meta-analyses. Because meta-analyses average across effect-size estimates reported in the primary literature, they directly rely on the methodological quality of the empirical studies in the field they are summarising. For example, when averaging across overestimated effect sizes from studies with small sample sizes, the overall effect size estimate will be equally inflated; similarly, if meta-analyses do not distinguish between actively and passively controlled studies, non-specific training effects may contribute to the average effect size estimates.

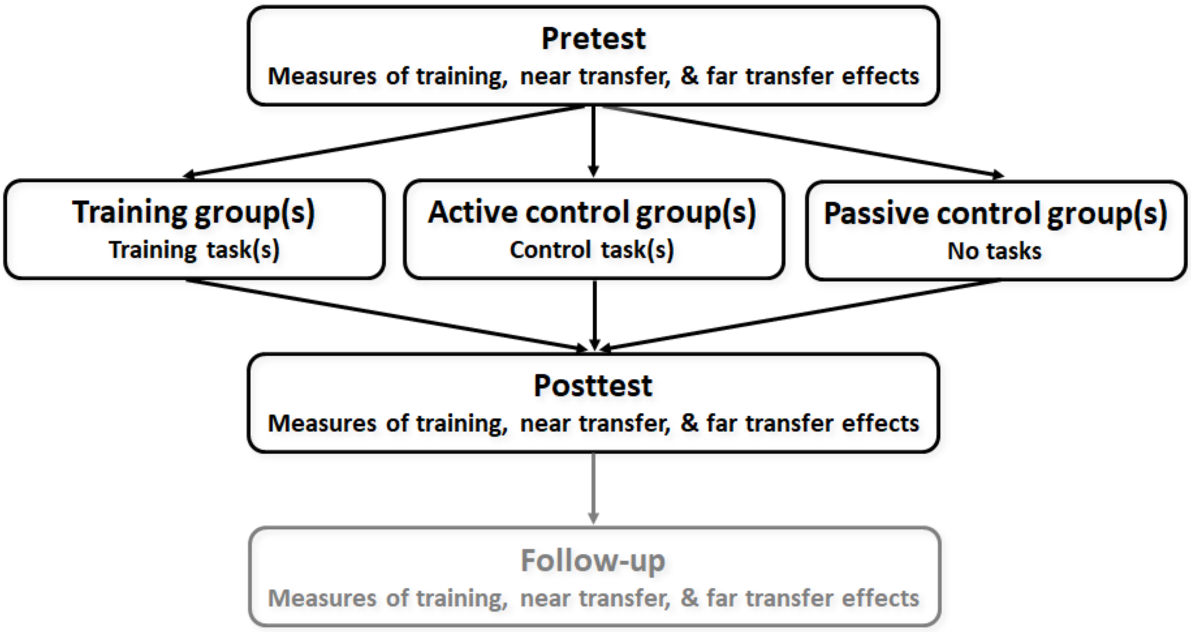

Figure 1. **A typical cognitive training study design.** Benefits of training are evaluated by comparing changes in measures of interest (training, near transfer, and far transfer effects) from pretest (before training) to posttest and follow-up (after the end of training) assessments between training group(s) undergoing cognitive training to control group(s) that complete alternative interventions (active control groups) and/or no intervention (passive control groups). Note that not all training studies conduct a follow-up.

Theories of Training and Transfer

The theoretical questions that propel cognitive training research are (1) when does training generalize, and (2) what cognitive processes change during training. These two questions represent two different, but partially overlapping, perspectives on training: To develop maximally effective interventions, we need to know not only when transfer occurs, but also which cognitive processes are prone to change so training interventions can target them more directly. The reverse is equally true: If we can predict how cognitive performance changes during training but lack any theoretical idea of how this change may transfer to other contexts, we cannot develop training interventions that are indeed effective in improving human cognition. Theoretical accounts and frameworks that speak towards both questions can help guide cognitive training research.

One such framework is the capacity-efficiency model of cognitive training and transfer[19] that proposes training can induce transfer through two pathways (Figure 2): (1) expanding the cognitive capacity **[G]**, or (2) increasing the efficiency **[G]** in how the existing capacity is used. Cognitive training has often been compared to physical training and, despite its limitations, this analogy can be helpful to better understand the distinction between training-induced enhancements in capacity and efficiency. For example, when training weightlifting with the goal to lift heavy objects, trainees who enhanced their *capacity* would have increased their actual muscle mass. In contrast, trainees for whom training improved *efficiency* could have figured out how to use leverage to lift heavy objects without increasing their actual muscle mass. Neurobiologically, an increase in capacity following cognitive training would be reflected in an increase in grey matter; enhanced efficiency would be reflected in changes in functional brain connectivity and/or a reduction in overall energy required to complete the tasks at hand. These two mechanisms are not necessarily mutually exclusive; for example, training may yield broad benefits through enhanced efficiency as well as capacity. Critically, different from other theoretical accounts[1,32], enhancing cognitive efficiency is not limited to the acquisition of strategies or general task knowledge. Other possible mechanisms that may underlie training-induced enhancements of efficiency include an increased level of automatization or speed of information processing that frees up cognitive resources for other concurrent tasks.

Generally, enhanced capacity can be expected to lead to broad transfer to any other task or activity that draws on the expanded capacity limit. Conversely, efficiency gains due to the acquisition of strategies or task-relevant knowledge tend to be task- or material-specific and, therefore, are often reflected by only narrow transfer effects. However, depending on their sources, gains in cognitive efficiency can also lead to relatively broad transfer effects. For example, a higher level of automatization of a core cognitive process can improve performance in a wide range of task contexts. Moreover, gains in capacity and efficiency are not necessarily mutually exclusive; training may yield broad benefits through enhanced efficiency as well as capacity. Consequently, gains in capacity and efficiency do not simply map on single indicators of behavioural near and far transfer effects, and a change in any particular neurobiological metric is not conclusively indicative of either enhanced capacity or efficiency[33]. For example, training-induced change in grey matter volume, structural integrity, or functional brain connectivity can be correlated with both gains in capacity and efficiency; similarly, gains can be accompanied by both a reduction in overall energy required to complete the task at hand[34], or even an increase in functional activity[16]. Therefore, relying on single behavioural tasks and neurobiological markers is too simplistic; instead, to conclusively distinguish between training-induced improvements in capacity and efficiency, it is necessary to theoretically identify the potential mechanisms of cognitive efficiency and select transfer outcomes that allow for systematically pitting them against changes in capacity, and to interpret the overall pattern of outcomes.

Transfer effects can manifest in behavioural, neural, and biopsychosocial outcomes. Past studies primarily assessed behavioural outcomes using laboratory tasks, with some also considering their neural correlates using techniques such as neuroimaging[35] (Box 2) and EEG[36]. Only few studies have also evaluated gains in everyday cognition outside of the laboratory[37] or biopsychosocial benefits such as increased quality of life, wellbeing, and physical and mental health[38]. Moderators at the level of training[39-41] or transfer[42,43] include factors related to the intervention (for example, training tasks[44] or conditions[45]), between-person differences (for example, age, initial cognitive ability, biological and neural predispositions, or personality), within-person fluctuations (for example, affect, motivation, wellbeing, physical and mental health, or everyday leisure activities), or the environment (for example, external events, environment of the intervention).

Most past cognitive training studies aimed at enhancing capacity based on the idea that it will maximally generalise to untrained outcomes. This basic rationale loosely builds on the common-elements theory[46], which hypothesizes that transfer occurs if knowledge components are identical across tasks. In later variations and extensions of this theory, identical knowledge has been replaced by process[47] or functional overlap[35]. Specifically, if two tasks overlap in the cognitive processes they demand, any gains in these underlying processes should transfer from training one task to performing the other task. However, this basic rationale of functional overlap comes with two challenges. First, training will involve more than just practising what is considered the underlying process. Second, tasks may appear to be similar because of similar surface structures or because they correlate well, but our understanding of the granularity of underlying processes might be wrong. Detailed task analyses and formalised models of cognition[48] (Box 3) are necessary to enable making testable predictions when transfer can be expected, but these models are rare.

One approach for deriving testable predictions of transfer effects is to consider the structure of individual differences in cognitive abilities[49]. Put simply, if individual differences in two cognitive abilities are more strongly correlated, it is assumed that they have more processes in common and, thus, transfer should be more likely. For example, one suggestion[16] is to define transfer distance based on the three-stratum model[49], which differentiates between 69 narrow abilities that are grouped into eight broader abilities, with general intelligence on top of the hierarchy. Transfer from one task to another within the same narrow ability would constitute nearest transfer, whereas transfer within one broad ability would be intermediate transfer, and transfer to a different broad ability would reflect far transfer through the change in general intelligence. One criticism towards this conceptualization is that it implies that correlation reflects causation, as changes in one ability are assumed to causally lead to changes in a correlated ability. However, it is possible that correlations between abilities do not reflect common processes but a common biological basis that contributed to their development[50]. Indeed, evidence from recent working memory training studies has shown that transfer may be absent even between strongly correlated tasks[51], with findings from statistical modelling speaking against the notion of correlations reflecting common cognitive processes[52]. Independent of how transfer abilities are determined though, enhanced capacity is assumed to manifest in transfer to a wide range of cognitive tasks.

Similar to changes in capacity, *enhanced efficiency* of overlapping processes or acquisition of strategies or routines that are useful across different contexts could translate into patterns of relatively broad transfer effects[19]. The triarchic theory of learning[53] proposes that, initially, novice learners of a new cognitive task will rely mainly on their metacognitive system to generate and establish new behavioural routines. These routines may also involve strategies such as grouping of information or mental imagery. Once these routines are formed, the metacognitive system's role will diminish, and learners will engage mostly their cognitive control network to execute these new routines. Finally, and with sufficient practice, learners will move from controlled towards automatic task execution. For example, students of arithmetic might first rely on explicit multiplication but, later, can automatically retrieve the previously stored answer (for example, when answering "what is two plus two?"). Using the acquired cognitive routines flexibly in different contexts with reduced involvement of the cognitive control network may establish transfer without necessarily increasing the capacity of the cognitive system.

In a similar vein, the cognitive routine framework[32] suggests that training a task involves learning a new skill by developing new cognitive routines. In the beginning of training, when the training task is still novel and unfamiliar, general cognitive resources are needed to identify and execute the routine, which later becomes automated by the end of the training regime. Transfer will be observed if that newly acquired cognitive routine can be applied also in the transfer measure.

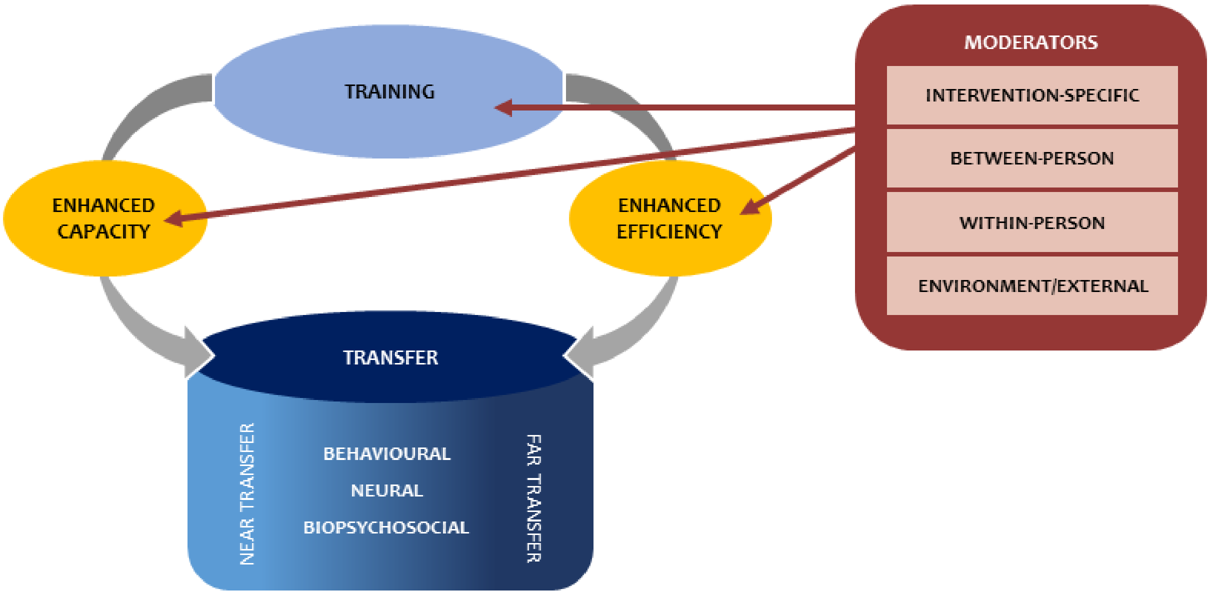

Figure 2. **The capacity-efficiency model of cognitive training and transfer**. Cognitive training can lead to transfer through enhancing capacity or enhancing efficiency. For example, increasing the amount of information that can be held accessible at one time would be an increase in capacity, whereas using a strategy allowing for remembering more items more easily stepwould reflect improved efficiency. Transfer can manifest in behavioural, neural, and/or biopsychosocial outcomes that overlap with the trained processes to a varying degree. Moderating variables can modulate performance gains during training but also the extent of transfer by affecting either or both mechanism(s) of transfer.

Training Effects and Mechanisms

The fluid cognitive abilities most commonly targeted by cognitive training include perception and attentional control, working memory, episodic memory, and multitasking. Below, we will discuss the empirical evidence for near and far transfer effects and the mechanisms assumed to underpin training and transfer effects for each of these target abilities.

Perception and Attentional Control

Perception and attentional control are critical for understanding the environment and executing goal-directed behaviours, for example when visually scanning the products in a supermarket aisle. Training interventions targeting early basic perceptual and attentional control range from using laboratory tasks such as in speed-of-processing training[54] to interventions building more directly on real-life activities such as mindfulness meditation[55,56] and action video gaming[57,58].

Speed-of-processing training is a process-based training **[G]** approach in which participants train variations of the useful field of view test **[G]** [59,60] to improve their visual search and divided attention abilities. Often, to keep the task challenging over the course of training, task difficulty is adaptively **[G]** adjusted to individual performance by displaying the stimuli for a shorter time or further apart from each other, or by increasing the amount of visual or auditory distraction, or the number of concurrent tasks. A recent meta-analysis[54] reported, on average, small training-induced improvements in measures assessing speed of processing (d = 0.22), in which participants have to identify, locate, and/or compare stimuli (for example letters, pictures, or digits) as quickly and as accurately as possible, and in measures of spatial and sustained attention. Thus, speed-of-processing training transfers to other laboratory tasks that measure the same cognitive constructs. Moreover, the same meta-analysis found evidence for small far transfer effects to real-word and biopsychosocial outcomes such as instrumental activities of daily living (d = 0.27), well-being (d = 0.21), and driving (d = 0.36).

Another family of cognitive training interventions involves training tasks that require top-down attention **[G]** , for example the go/no-go task[61-63] or stop-signal task[64,65]. In these types of tasks, participants have to respond to certain stimuli and inhibit their impulsive response to others. Although inhibitory control training rarely transfers to other laboratory tasks[66], a recent meta-analysis[67] across 19 studies revealed a small to medium overall benefit (d = 0.38)of this type of training intervention on health behaviours such as reducing the consumption of alcohol[68] or high-calorie food[69]. The meta-analytic effect was stronger for interventions using stimuli specific to the health-behaviour of interest such as food stimuli for interventions aiming at reducing high-calorie food intake.

Different from typical laboratory cognitive tasks, visual environments in action video games **[G]** are more complex and dynamic. The fast-paced and constantly changing task conditions of such games require players to perform multiple tasks simultaneously and to continuously update and adapt their task goals and actions. Moreover, action video games are typically also highly engaging and immersive. Therefore, a growing body of research has explored their potential as interventions for enhancing these abilities. However, evidence for the effectiveness of action video game training is mixed, with meta-analyses reporting non-significant (g = -0.12 to g = 0.10[70]) or small effects (g = 0.34[58]) on cognitive performance across domains. Estimates vary for more specific domains but, overall, suggest only small benefits if any. For example, there is some evidence for small effects on top-down attention (g = 0.31[58]), mixed evidence for improvements in spatial cognition (ranging from g = -0.04[70] to g = 0.45[58]), and no evidence for effects on perception (g = 0.26[58]), and visual attention and processing (g = -0.01 to g = 0.22[70]). In contrast to training, habitually playing action video games was consistently significantly associated with better cognitive performance across domains (g = 0.40[70] to g = 0.55[58]) and on measures of perception (g = 0.79[58]), visual attention and processing (g = 0.45[70]), spatial ability (g = 0.47[70] to g = 0.75[58]), attentional control (g = 0.27[70] to g = 0.31[58]), multitasking (g = 0.55[58]), and verbal cognition (g = 0.33[58]). Cross-sectional studies investigating habitual players cannot rule out self-selection effects though; nonetheless, these findings might indicate that playing action video games for a longer time than the typical duration of training interventions (that is, around 10 to 50 hours) may still yield cognitive benefits. Differences in study inclusion criteria, meta-analytic methods, corrections for publication bias, and characteristics of study designs and participants (for example, distinction between different control groups, participant age) likely contribute to the variations in effect sizes, and the discussion continues on best practices in those meta-analyses as well as in primary research methods[20,71].

Transfer effects of training interventions targeting perception and attention have been attributed predominantly to enhanced efficiency, specifically the acquisition of knowledge and skills that, although not being directly applicable to new tasks, nonetheless allow new tasks to be learned more efficiently due to improved probabilistic inference **[G]** [72-74]. Specifically, the learning-to-learn account[72] suggests that, training increases the effectiveness in extracting and accumulating evidence from the task environment, thereby optimising decision-making and resource allocation. The learning of how to use the evidence from repeated presentations for performing better is thought to take place on a single more general level of improvement, which therefore can yield performance improvements in other tasks.

Working Memory

Working memory capacity is particularly strongly correlated with many other abilities, such as fluid intelligence[75]. The hypothesis[76] that increasing working memory capacity through training could lead to neuroplastic changes benefitting these other related cognitive abilities, resulted in working memory training to become one of the most extensively studied cognitive training approaches.

Initial excitement about the promise of working memory training arose after seminal studies found large improvements in working memory capacity as well as far transfer to fluid intelligence[77,78]. However, subsequent studies addressing methodological concerns such as the lack of active control groups failed to replicate most of these far transfer effects using either similar n-back tasks[79] or other working memory training tasks[51,80-82]. To date, findings remain inconsistent even at the meta-analytic level, with some meta-analyses finding evidence of small, yet significant far transfer effects (estimates ranging from g = 0.18 to g = 0.20)[83-86], while others do not (estimates ranging from g = 0.01 to g = 0.20)[28,87,88]. Furthermore, there is even inconsistent support for the presence of near transfer within working memory, as it has been observed for transfer tasks using the same stimuli or paradigm but not for dissimilar tasks[32,86].

Given the narrow effects of working memory training at the behavioural level, the claim that training increases capacity[76] is not well supported. However, neuroplastic changes have been observed, including greater interconnectivity[89], and improved white matter integrity[90] amongst networks known to support working memory. These findings raise the question of how these apparent neuroplastic changes can be accommodated with the lacking evidence for behavioural transfer. Likely, these neural changes reflect more efficient processing and connectivity between existing structures rather than an increase in neural capacity per se. Indeed, no training-induced changes were found for potential biomarkers of increased capacity, such as in grey matter volume[91].

How might these changes in efficiency be reflected at a cognitive level? Some evidence points towards the acquisition of strategies that are difficult to apply to new contexts[92]. The context-specificity of acquired strategies is well exemplified in the case study of participant S.F.[93], who trained in a digit span task for two years. S.F. was a runner and, thus, re-coded the digit sequences into familiar running times he remembered from his long-term memory. With this strategy, he was able to expand his digit span from 7 to 79 items. However, his memory span for letter sequences remained unchanged because his strategy of utilising running times was not applicable to letter stimuli. The strategy remediation hypothesis posits that such task-specific strategies are developed during training to compensate for the challenges imposed by the training task[94], and therefore will benefit performance in highly similar tasks only. For example, working memory training has been shown to increase the use of strategies such as grouping, visualisation, and forming semantic associations, but only little training-related gains were observed in untrained tasks [94]. However, strategy acquisition can yield benefits in untrained tasks if they afford these strategies, with studies suggesting that improvements in untrained working memory tasks are moderated by the degree to which participants utilised various encoding strategies on similar untrained tasks[95].

Few studies investigated other mechanisms possibly underpinning working memory training and transfer effects, including interference resolution [51,96], removal of no-longer relevant information[51], and switching attention between representations[51,97], or more global strategies such as relying more on familiarity-based processing than recollection. Finally, a further change in efficiency may result in improvements in probabilistic learning[72], allowing participants to better take advantage of task regularities. For example, over the course of completing just a single working memory task, performance increased as participants learned to take advantage of statistical regularities in the task, allowing them to compress the presented information, thereby using their available working memory capacity more efficiently[98]. These statistical regularities may not appear in dissimilar transfer tasks, thereby explaining why improvements become apparent only in similarly structured tasks.

Episodic Memory

Episodic memory gives individuals a sense of continuity and identity and, therefore, is critical to maintain independence across the lifespan. Episodic memory training is often strategy-based **[G]** and involves teaching of mnemonics **[G]** to support depth and specificity of encoding[92,99-102], based on mental imagery (for example, method of loci) or elaboration (for example, semantic associations). Mnemonics are powerful and studies typically observe near transfer effects[98-103]. However, a key aspect is that mnemonics must be used with material that lends itself to these strategies. Hence, far transfer is usually not assessed with entirely different material but with self-report measures of metacognition in which people indicate whether they use the mnemonics in everyday life and whether this alleviates difficulties in complex activities. Although these interventions seem to improve knowledge and use of mnemonics in everyday life, there is little evidence for benefits on complex daily activities[37,100,102-104]. Nonetheless, a meta-analysis of 30 studies showed that strategy training can, on average, induce small benefits on activities of daily living (d = 0.32) and mood (d = 0.16), and metacognition, including a stronger sense of self-efficacy **[G]** (d = 0.37)[104].

To facilitate transfer of training, some studies have combined strategy training with explicit metacognitive approaches. For example, the *Méthode d'Entraînement pour Mémoire Optimale* (MEMO) programme[101,102] teaches a range of mnemonics but also includes explicit instructions regarding when and for which type of material the mnemonics are appropriate to use. The programme also educates about age-related memory changes and how to improve metacognition and self-efficacy. Similarly, strategy-adaptation training, which encourages participants to test strategies in different contexts was found to yield transfer[105]. These findings show that it is critical to instruct trainees how to adapt trained strategies to meet the demands of unpractised tasks and contexts.

Process-based approaches to improving episodic memory include interventions manipulating memory load, retrieval intervals, or interference during retrieval. Studies targeting memory load administered episodic associative memory tasks in which participants have to remember an adaptively increasing number of associations, for example, objects and their locations. Findings of these studies are mixed. In an object-location memory training study, transfer to spatial episodic memory and reasoning was observed four months after training[106]. However, a study administering paired-associates training found no transfer effects to untrained tasks involving episodic associative memory or reasoning[107].

Studies that manipulate the spacing of repeated retrieval build on the robust finding that memory is better after spaced than massed learning[108]. One explanation for the benefits of spaced retrieval is that the intervals introduce variability at encoding, hence allowing a larger spectrum of retrieval cues resulting in better performance. Another possible explanation is that spaced retrieval ensures an optimal balance between retrieval effort and retrieval[109]. Generally, practising with equal intervals can be equally effective as practising with expanded schedules where the intervals between recalls gradually increase over the learning phase[110,111] . Yet, the more frequent positive feedback during the early learning phase with expanded schedules might increase interest in the training task and reduce frustration.

Another approach is to manipulate the level of interference at retrieval by interspersing recall with varying materials, referred to as repetition-lag training. The rationale of repetition-lag training is to increase reliance on consciously controlled, recollection-based memory processes over automatic, familiarity-based memory processes[112-115]. Participants first study lists of items and are then probed for study items in recognition trials that include a gradually increasing number of lures that are repeated at increasingly longer intervals. This procedure has been shown to benefit recollection in younger and older adults[112-118] and in people with dementia[115]. These positive effects were found to last over a three month delay period[114]. However, transfer of those gains to novel materials or tasks is weak[112-114,116,117].

Multitasking

Multitasking entails flexibly switching between tasks (task switching) or performing them concurrently (dual tasking)[119]. Task switching training studies have demonstrated substantial reductions in switch costs **[G]** in the trained tasks across the lifespan (for meta-analyses, see[84,120]), including in clinical groups such as children with ADHD[121]. Most studies also reported near transfer effects in untrained switching tasks[122], suggesting improvements in the ability to flexibly switch tasks on a trial-to trial basis in the context of interference from other active, competing task sets. However, the amount of near transfer varies - for example, it is much larger in healthy children and older adults than in younger adults[123]. Findings of far transfer following task switching training are inconsistent, with some studies reporting transfer to other executive functions and fluid intelligence[123,124], others observing no far transfer at all[125,126].

The Primitive Information Processing Elements (PRIMs; see also Box 3) model can explain the mechanisms underlying task switching training and predict transfer effects[47]. Specifically, broad transfer has been demonstrated in task switching training regimes that administered alternating-run task switching paradigms, in which participants have to monitor the task sequence to switch tasks at the appropriate time, but they also have the opportunity to prepare for upcoming task switches in advance. Thus, participants are forced to use a proactive cognitive control strategy[48,127]. The PRIMs model conceptualises this proactive strategy in task switching as two operations acting in concordance. Before the stimulus appears, the first operator initiates task preparation and, if necessary, adjusts the task goals. Once the stimulus has appeared, the second operator carries out the task goal. Transfer will be demonstrated in tasks that can reuse these proactive operators. For example, in a Stroop task that requires naming the ink colour of a stimulus while suppressing the predominant tendency to read the word (for example, "GREEN" printed in red ink), the second operator focuses attention on the relevant stimulus dimension (the ink colour), thereby overruling the default operator that would attend all attributes of the stimulus. Hence, training task switching is thought to be effective because the proactive operators are trained and, therefore, become more efficient to use.

Similar to task switching training, research on dual-task training has shown that dual-task costs **[G]** can be extremely reduced and, under some conditions, even eliminated[128,129]. Training studies aiming to reduce dual-task costs often compare fixed-priority to variable-priority conditions. Under fixed-priority conditions, participants are asked to emphasise both tasks equally throughout training. In contrast, in variable-priority conditions, participants are instructed to flexibly vary their task response priorities, thereby constantly varying how attentional resources are split between the two tasks. Findings from these studies suggest that, during dual-tasks trainees acquire skills that optimise allocation of limited attentional resources when processing multiple competing tasks[130-136]. Moreover, consistent with this proposition, larger training-related improvements have been observed under the variable-priority than in fixed-priority conditions also for untrained dual tasks. Alternatively, dual-task training could induce acquisition of skills for improving coordination of multiple tasks. To test this hypothesis, effects of fixed-priority dual-task training were compared to pure single-task training, in which participants exclusively trained two tasks separately[128,137]. Indeed, dual-task training led to larger improvements in dual-task performance than single-task training, both in trained and in untrained dual tasks[129,138,139], thus demonstrating the acquisition of transferable gains in task coordination skills. It is disputed, however, whether these skills are accessible in other task contexts, with some studies showing short-term far transfer effects (for example in measures of sustained attention and working memory[36,140]) whereas others do not[141,142].

Summary and Future Directions

Independent of the cognitive ability targeted and of the approach taken, people undergoing cognitive training interventions usually show large improvements within the trained context. However, broad transfer to cognitive, neural, or biopsychosocial measures different to the training tasks is much more elusive. In this Review, we argue that, to advance our understanding of how to develop cognitive training interventions that are successful in generating transfer, it is critical to identify the mechanisms underpinning training and transfer effects. Evidence from past research in the cognitive domains we reviewed highlights several candidate mechanisms (Table 1).

Returning to the capacity-efficiency model of cognitive training and transfer we introduced earlier (Figure 2), these findings suggests that transfer, if it occurs, is primarily driven by improvements in cognitive efficiency, with little convincing evidence for gains in overall cognitive capacity. Shifting research focus from attempting to increase cognitive capacity towards how to use cognitive training to enhance cognitive efficiency might indeed be a more fruitful avenue for future research. Notably, until relatively recently[143,144], assuming a fixed capacity was indeed the predominant view[145]. At first, the notion of a fixed capacity limit may seem contradictory to that of a plastic brain. Importantly, however, as highlighted by the empirical evidence we reviewed, a fixed *capacity* does by no means imply that cognitive *performance* is immutable. Instead, some of the processes that appear to be prone to training-induced enhancements of cognitive efficiency could be potentially useful in a wider range of contexts. To advance our understanding of cognitive plasticity, future research will need to investigate these mechanisms further and identify how they can be harnessed for developing interventions that are effective in inducing generalisable cognitive improvements. For example, explicit metacognitive instructions to support trainees in applying strategies across contexts[101,102,146] and adaptive process-based metacognitive training, in which participants practise to more accurately estimate their own performance[147], appear to be promising avenues for achieving broader transfer. Metacognitive instruction could also be a potential avenue for maximising transfer of efficiency gains in probabilistic inference and attention allocation.

Cognitive training can be a powerful experimental tool for researching individual differences in cognition. Patterns of transfer can yield insights of how cognitive abilities are related, including advancing our understanding of the causality underlying these relationships[52]. Moreover, identifying the mechanisms that are prone to change through cognitive training can offer insights about the nature of individual differences in cognition. Especially when combined with neuroimaging (Box 2) and computational modelling approaches (Box 3), cognitive training can help to delineate the relative contribution of individual differences in cognitive capacity and cognitive efficiency to overall cognitive performance, on both a conceptual and analytical level. Critically, to fully exploit cognitive training as an experimental tool to advance our understanding of human cognition and cognitive plasticity, we must move past vague theoretical notions of common elements and strive for developing theories that allow for deriving falsifiable, testable hypotheses.

Table 1. Pattens and mechanisms of transfer with empirical support.

Ability	**Observed patterns of transfer**	**Mechanisms of transfer with empirical support**
Perception and attentional control	Near transfer, some far transfer	Improvements in probabilistic inference
Working memory	Near transfer, disputed far transfer	Acquisition of strategies More efficient attention allocation Improvements in probabilistic inference
Episodic memory	Near transfer, some far transfer	Acquisition of strategies Improved metacognition
Multitasking	Near transfer, disputed far transfer	More efficient attention allocation More efficient task coordination Engagement of proactive control strategies

Box 1: Using Bayesian statistics for evaluating the evidence of cognitive training effectiveness

Low statistical power has plagued the cognitive training literature, with the average working memory intervention only capable of detecting 38% of true effects[25]. This is particularly problematic when using null-hypothesis significance testing (NHST) for analysis: non-significant p-values do not distinguish between the true lack of an effect or there being insufficient data to detect the effect. In addition, significant p-values do not provide any information about the likelihood of the alternative hypothesis[148]. Finally, p-values 'dance' around the significance threshold[149], and repeated sampling artificially increases false-positive results[29].

To address these issues of NHST, many have advocated for the use of Bayesian statistical analysis[148,150,151]. A Bayesian analysis quantifies one's beliefs about a model after observing some data, and these posterior beliefs about different models can be compared in the form of Bayes factors. Bayes factors are ratios (ranging from 0 to ∞) of the relative belief in one model (the numerator, for example the null hypothesis) over another (the denominator, for example the alternative hypothesis). The magnitude of the Bayes factor indicates the strength of evidence in the data, which allows one to identify whether there is sufficient evidence to distinguish one model over the other, or whether further testing is warranted; a possibility not supported by NHST[148]. Different to NHST, where repeatedly peeking at the data increases the likelihood of false-positive findings[151], Bayesian experimenters can collect data until the Bayes factor passes a pre-selected (ideally pre-registered) threshold in favour of either model. Although rules of thumb exist about what constitutes an appropriate threshold[152,153], we suggest authors select a value appropriate to the field and phenomenon being studied.

Straightforward, accessible implementations of many Bayesian tests are now readily available[154,155]. The few cognitive training studies that have analysed their data with Bayesian inference focused mainly on working memory training. For example, a Bayesian re-analysis[156] of one meta-analysis[83] found that studies using a passive-control group showed strong evidence of transfer to other abilities. However, studies with active-control groups showed modest evidence in support of the null. A similar re-analysis[25] of another meta-analysis[27] found that 68% of working memory training interventions did not produce sufficient evidence to disambiguate the two competing hypotheses regarding transfer. Of the 9 studies which found sufficient evidence either way (Bayes factors > 3), 6 showed stronger evidence in support of the null than the alternative. Similarly, within studies on executive functioning and reasoning training, 55% had insufficient data to disambiguate the competing hypotheses, 38% strongly supported the null and 7% strongly supported the alternative.

Box 2: Contribution of brain imaging to the field of cognitive training

Brain imaging refers to a range of investigative methods that aim to reflect the structure, function, pharmacology or metabolism of the brain. Most studies that have used brain imaging as part of cognitive training have relied on structural or functional brain imaging. Imaging-derived quantitative information about the structure of the brain includes whole-brain and regional grey matter volumes, cortical thickness, and white matter integrity and other microstructure. Functional brain imaging reveals patterns of brain activation when participants are at rest or when they perform cognitive tasks. Brain imaging can contribute in several ways to the field of cognitive training.

Theory Development

Brain imaging can provide unique information on the neural and cognitive mechanisms by which training exerts its effect. For instance, the INTERACTIVE model[157] proposes that training-related activation varies according to the characteristics of the intervention (for example, intervention dosage) and characteristics of the individual (for example, pre-training brain status). Brain imaging can also be used to assess transfer models. For instance, findings from brain imaging provided support to the hypothesis that transfer depends on the overlap between the brain regions associated with the training task and those associated with the transfer task[35].

Brain imaging can also be used to better understand brain plasticity in humans by revealing neural compensatory mechanisms associated with patterns of cognitive changes[1,158-160]. Furthermore, brain imaging can contribute to refining cognitive reserve models measuring whether training-induced brain changes correspond to those observed in individuals who have lived a cognitively stimulating life[161].

Translational Research and Clinical Application

Neurobiological models of training can aid clinicians in the informed selection of suitable training programmes. For example, when selecting the best programme for a particular population, clinicians may choose training approaches that restore damaged regions or for approaches that rely on intact regions[157,162]. Brain imaging indicators can also be used as surrogate markers of cognitive training effects[163], that is, clinically meaningful measures of therapeutic effects when optimal clinical outcomes are difficult to obtain. For example, hippocampal volume or metabolic changes might serve as a surrogate marker of cognitive training benefits on dementia progression[103].

Finally, brain imaging can reveal who benefits best from cognitive training: Studies have used brain imaging to identify responders based on their brain structure and/or function. For instance, performance gain in variable-priority training was predicted by pre-training volume of the dorsal striatum but not by pre-training volume of the hippocampus[164].

Still, neuroimaging has caveats that should be recognized. Neuroimaging methods with high spatial accuracy usually lack temporal accuracy and vice versa. Functional neuroimaging methods are only indirect measures of brain activity. More work is needed to determine the sensitivity to change and reliability over time of these different techniques. Finally, the biological relationship to disease of surrogate markers should be well understood and relevant to the clinical effect they are intended to reflect.

Box 3: Using computational modelling approaches to advance understanding of training and transfer

As cognitive training research is moving beyond the dichotomous question of *whether* training can improve performance towards *how* it can induce change, there is a growing need for more precise theories of training and transfer that enable formulating quantifiable and testable predictions. Formalised, computational explanatory and measurement models can serve this purpose[165].

Explanatory models seek to explain why behaviour differs across conditions. These models are particularly useful for creating a shared, precise understanding of theoretical assumptions and their consequences[165]. For example, a puzzling empirical finding of some working memory training studies is the observation of far transfer in combination with a lack of near transfer[77,124]. Relying on a verbal account of common-elements theory[46], one interpretation of these findings is that the working memory training and transfer tasks do not measure overlapping processes[166]. Thus, training may well increase capacity, but the near transfer task is an inadequate measure to capture that capacity. However, this explanation is ultimately non-falsifiable: whenever near transfer is observed, the tasks must share elements; otherwise, they are too different. Falsifiability can be preserved by implementing a formal model that quantifies when two tasks are considered to share sufficient elements for generating transfer. The Primitive Information Processing Elements (PRIMs) model[48], which builds on the Adaptive Control of Thought—Rational (ACT-R) cognitive architecture[167], is such a formalised implementation. According to the PRIMs model, training specific tasks will hone general skills that can be reused in transfer tasks that share the same pattern of how information is directed through the cognitive system – consequently, training and transfer tasks can look highly dissimilar. Using PRIMs to model the patterns of information routing for two or more tasks allows for making falsifiable predictions when to expect transfer effects.

Measurement models allow for estimating latent variables from empirical data based on formalised theoretical assumptions. These types of models are particularly useful to gauge what cognitive processes change during training. For example, one common finding in cognitive training studies that involve practice of speeded tasks is a reduction of overall reaction times[124,168]: with increasing practice, participants become faster in the training tasks. There are multiple reasons for this improvement in speed: over the course of training, trainees might prioritise responding quickly over responding accurately, speed up their motor response, or increase the rate in which they can extract information from the environment to guide their response. The diffusion model is a measurement model that allows for disentangling these psychological processes assumed to underlie behaviour in speeded cognitive tasks[169]. Research has shown that these processes relate differentially to other behaviours; specifically, only the rate of information extraction – the drift rate – predicts individual differences in fluid intelligence[170,171]. Therefore, it is plausible to hypothesise that only people improving in drift rate exhibit transfer effects to outcomes related to the drift rate, such as fluid intelligence. Our group is currently testing this hypothesis in ongoing work.

Glossary Terms

Perception: Organization, identification, and interpretation of sensory information to form mental representations.

Attentional control: Ability to regulate information processing during goal-directed behaviour.

Working memory: Ability to temporarily access mental representations needed for complex cognition in the present moment.

Episodic memory: Ability to encode and retrieve information with their appropriate context.

Multitasking: Ability to shift and divide attention between different tasks.

Cognitive training: Behavioural interventions designed to improve cognitive performance.

Effectiveness: Positive training effects in ecologically valid, real-world settings with only little experimental control and in non-homogeneous samples.

Training effect: Performance improvement in the training tasks (also: training gains) from the first training session to the last training session.

Transfer: Performance improvement in outcomes that differ from the training tasks.

Mechanism: A theoretical construct specifying the function and organisation of one or more processes and their interplay with other processes and/or biological substrates.

Follow-up assessment: An additional assessment of outcomes some time, often around 3 to 6 months, after the end of training.

Passive control group: Group of participants who do not perform any cognitive training but take part in the pre-test and post-test (and follow-up).

Active control group: Group of participants who complete an alternative intervention that does not rely or relies less on the cognitive ability targeted by the cognitive training intervention.

False-negative results: A statistical test result which wrongly indicates the lack of an effect.

False-positive results: A statistical test result which wrongly indicates the presence of an effect.

Enhanced capacity: Training-induced increase in the overall cognitive resource available to an individual.

Enhanced efficiency: Training-induced increase in flexibility to optimize performance within the existing capacity limits.

Process-based training: Repetitive practice of tasks that are assumed to measure basic cognitive processes.

Useful field of view test: (UFOV test). Computer-based measure of the spatial area and speed with which a person can discriminate stimuli presented in central vision with or without concurrent tasks and distractors in peripheral vision.

Adaptive training: Task difficulty is (often automatically) adjusted as a function of individual performance in the training task, so that the challenge of the training tasks matches how well the trainee performs them.

Top-down attention: Goal-oriented, voluntary allocation of attention to particular features, locations, or objects.

Action video games: Video games with a fast-paced, complex, and dynamic visual environment with a high degree of visual clutter and distraction, demanding focused and distributed attention.

Probabilistic inference: Computing the probability of one or more random variables using a specific value or set of values.

Strategy-based training: Instruction of mental processes or strategies that differ from those typically involved in the task.

Mnemonic: Strategy that helps to remember larger amounts of information.

Self-efficacy: A person's belief in their ability to manage and succeed in a particular situation.

Switch cost: Difference in performance (for example, response times) between stay trials, in which participants perform the same task as in the previous trial, and switch trials, in which participants perform a different task than in the previous trial.

Dual-task cost: Difference in performance (for example, response times) between dual-task trials, in which participants perform two tasks simultaneously, and single-task trials, in which participants complete the two tasks separately.

References

1 Lövdén, M., Bäckman, L., Lindenberger, U., Schaefer, S. & Schmiedek, F. A theoretical framework for the study of adult cognitive plasticity. *Psychol Bull* **136**, 659-676, doi:10.1037/a0020080 (2010).

2 Kühn, S. & Lindenberger, U. in *Handbook of the Psychology of Aging (Eighth Edition)* (eds K. Warner Schaie & Sherry L. Willis) 105-123 (Academic Press, 2016).

3 Lindenberger, U. & Lövdén, M. Brain plasticity in human lifespan development: the exploration–selection–refinement model. *Annual Review of Developmental Psychology* **1**, 197-222, doi:https://doi.org/10.1146/annurev-devpsych-121318-085229 (2019).

4 Baltes, P. B. & Baltes, M. M. in *Successful aging: Perspectives from the behavioral sciences.* 1-34 (Cambridge University Press, 1990).

5 Martinussen, R., Hayden, J., Hogg-Johnson, S. & Tannock, R. A meta-analysis of working memory impairments in children with attention-deficit/hyperactivity disorder. *Journal of the American Academy of Child & Adolescent Psychiatry* **44**, 377-384, doi:https://doi.org/10.1097/01.chi.0000153228.72591.73 (2005).

6 Demetriou, E. A. *et al.* Autism spectrum disorders: a meta-analysis of executive function. *Molecular Psychiatry* **23**, 1198-1204, doi:10.1038/mp.2017.75 (2018).

7 Arvanitakis, Z., Shah, R. C. & Bennett, D. A. Diagnosis and management of dementia: Review. *JAMA* **322**, 1589-1599, doi:10.1001/jama.2019.4782 (2019).

8 Lugtmeijer, S., Lammers, N. A., de Haan, E. H. F., de Leeuw, F.-E. & Kessels, R. P. C. Post-stroke working memory dysfunction: A meta-analysis and systematic review. *Neuropsychology Review* **31**, 202-219, doi:10.1007/s11065-020-09462-4 (2021).

9 Hommel, B. Pseudo-mechanistic explanations in Psychology and Cognitive Neuroscience. *Topics in Cognitive Science* **12**, 1294-1305, doi:10.1111/tops.12448 (2020).

10 Simons, D. J. *et al.* Do "brain-training" programs work? *Psychological Science in the Public Interest* **17**, 103-186, doi:10.1177/1529100616661983 (2016).

11 Sala, G. *et al.* Near and far transfer in cognitive training: A second-order meta-analysis. *Collabra: Psychology* **5**, 18, doi:10.1525/collabra.203 (2019).

12 Sala, G. & Gobet, F. Cognitive training does not enhance general cognition. *Trends in Cognitive Sciences* **23**, doi:10.1016/j.tics.2018.10.004 (2019).

13 Borella, E., Carretti, B., Riboldi, F. & De Beni, R. Working memory training in older adults: Evidence of transfer and maintenance effects. *Psychology and Aging* **25**, 767-778, doi:10.1037/a0020683 (2010).

14 Schmiedek, F., Lövdén, M. & Lindenberger, U. Hundred days of cognitive training enhance broad cognitive abilities in adulthood: Findings from the COGITO study. *Frontiers in Aging Neuroscience* **2**, doi:10.3389/fnagi.2010.00027 (2010).

15 Barnett, S. M. & Ceci, S. J. When and where do we apply what we learn? A taxonomy for far transfer. *Psychol Bull* **128**, 612-637, doi:10.1037/0033-2909.128.4.612 (2002).

16 Noack, H., Lövdén, M., Schmiedek, F. & Lindenberger, U. Cognitive plasticity in adulthood and old age: Gauging the generality of cognitive intervention effects. *Restorative Neurology and Neuroscience* **27**, 435-453, doi:10.3233/RNN-2009-0496 (2009).

17 Foroughi, C. K., Monfort, S. S., Paczynski, M., McKnight, P. E. & Greenwood, P. M. Placebo effects in cognitive training. *Proceedings of the National Academy of Sciences* **113**, 7470, doi:10.1073/pnas.1601243113 (2016).

18 Boot, W. R., Simons, D. J., Stothart, C. & Stutts, C. The pervasive problem with placebos in psychology: Why active control groups are not sufficient to rule out placebo effects. *Perspectives on Psychological Science* **8**, 445-454, doi:10.1177/1745691613491271 (2013).

19 von Bastian, C. C. & Oberauer, K. Effects and mechanisms of working memory training: A review. *Psychological Research* **78**, 803-820, doi:10.1007/s00426-013-0524-6 (2014).

20 Green, C. S. *et al.* Improving methodological standards in behavioral interventions for cognitive enhancement. *Journal of Cognitive Enhancement* **3**, 2-29, doi:10.1007/s41465-018-0115-y (2019).

21 Green, C. S., Strobach, T. & Schubert, T. On methodological standards in training and transfer experiments. *Psychological Research* **78**, 756-772, doi:10.1007/s00426-013-0535-3 (2014).

22 Shipstead, Z., Redick, T. S. & Engle, R. W. Is working memory training effective? *Psychol Bull* **138**, 628-654, doi:10.1037/a0027473 (2012).

23 Hicks, K. & Engle, R. W. in *Cognitive and Working Memory Training: Perspectives from Psychology, Neuroscience, and Human Development* (eds M. F. Bunting, J. M. Novick, M. R. Dougherty, & Randall W. Engle) 3-13 (Oxford University Press, 2019).

24 Miyake, A. *et al.* The unity and diversity of executive functions and their contributions to complex "frontal lobe" tasks: A latent variable analysis. *Cognitive Psychology* **41**, 49-100, doi:https://doi.org/10.1006/cogp.1999.0734 (2000).

25 von Bastian, C. C., Guye, S. & De Simoni, C. in *Cognitive and working memory training: Perspectives from psychology, neuroscience, and human development* (eds M. F. Bunting, J. M. Novick, M. R. Dougherty, & R. W. Engle) 58-78 (Oxford University Press, 2020).

26 Hartgerink, C. H. J., Wicherts, J. M. & van Assen, M. A. L. M. Too good to be false: Nonsignificant results revisited. *Collabra: Psychology* **3**, doi:10.1525/collabra.71 (2017).

27 Lampit, A., Hallock, H. & Valenzuela, M. Computerized cognitive training in cognitively healthy older adults: A systematic review and meta-analysis of effect modifiers. *PLOS Medicine* **11**, e1001756, doi:10.1371/journal.pmed.1001756 (2014).

28 Melby-Lervåg, M., Redick, T. S. & Hulme, C. Working memory training does not improve performance on measures of intelligence or other measures of "far transfer": Evidence from a meta-analytic review. *Perspectives on Psychological Science* **11**, 512-534, doi:10.1177/1745691616635612 (2016).

29 Button, K. S. *et al.* Power failure: why small sample size undermines the reliability of neuroscience. *Nature Reviews Neuroscience* **14**, 365-376, doi:10.1038/nrn3475 (2013).

30 Ioannidis, J. P. A. Why most published research findings are false. *PLOS Medicine* **2**, e124, doi:10.1371/journal.pmed.0020124 (2005).

31 Halsey, L. G., Curran-Everett, D., Vowler, S. L. & Drummond, G. B. The fickle P value generates irreproducible results. *Nature Methods* **12**, 179-185, doi:10.1038/nmeth.3288 (2015).

32 Gathercole, S. E., Dunning, D. L., Holmes, J. & Norris, D. Working memory training involves learning new skills. *Journal of Memory and Language* **105**, 19-42, doi:https://doi.org/10.1016/j.jml.2018.10.003 (2019).

33 Park, D. C. & Bischof, G. N. The aging mind: Neuroplasticity in response to cognitive training. *Dialogues in Clinical Neuroscience* **15**, 109-119, doi:10.31887/DCNS.2013.15.1/dpark (2013).

34 Brehmer, Y. *et al.* Neural correlates of training-related working-memory gains in old age. *NeuroImage* **58**, 1110-1120, doi:10.1016/j.neuroimage.2011.06.079 (2011).

35 Dahlin, E., Neely, A. S., Larsson, A., Bäckman, L. & Nyberg, L. Transfer of learning after updating training mediated by the striatum. *Science* **320**, 1510-1512, doi:10.1126/science.1155466 (2008).

36 Anguera, J. A. *et al.* Video game training enhances cognitive control in older adults. *Nature* **501**, 97-101, doi:10.1038/nature12486 (2013).

37 Rebok, G. W. *et al.* Ten-year effects of the Advanced Cognitive Training for Independent and Vital Elderly cognitive training trial on cognition and everyday functioning in older adults. *Journal of the American Geriatrics Society* **62**, 16-24, doi:https://doi.org/10.1111/jgs.12607 (2014).

38 Motter, J. N., Grinberg, A., Lieberman, D. H., Iqnaibi, W. B. & Sneed, J. R. Computerized cognitive training in young adults with depressive symptoms: Effects on mood, cognition, and everyday functioning. *Journal of Affective Disorders* **245**, 28-37, doi:https://doi.org/10.1016/j.jad.2018.10.109 (2019).

39 Guye, S., De Simoni, C. & von Bastian, C. C. Do individual differences predict change in cognitive training performance? A latent growth curve modeling approach. *Journal of Cognitive Enhancement* **1**, 374-393, doi:10.1007/s41465-017-0049-9 (2017).

40 Wiemers, E. A., Redick, T. S. & Morrison, A. B. The influence of individual differences in cognitive ability on working memory training gains. *Journal of Cognitive Enhancement* **3**, 174-185, doi:10.1007/s41465-018-0111-2 (2019).

41 Bürki, C. N., Ludwig, C., Chicherio, C. & de Ribaupierre, A. Individual differences in cognitive plasticity: An investigation of training curves in younger and older adults. *Psychological Research* **78**, 821-835, doi:10.1007/s00426-014-0559-3 (2014).

42 Karbach, J., Könen, T. & Spengler, M. Who benefits the most? Individual differences in the transfer of executive control training across the lifespan. *Journal of Cognitive Enhancement* **1**, 394-405, doi:10.1007/s41465-017-0054-z (2017).
43 Hering, A., Meuleman, B., Bürki, C., Borella, E. & Kliegel, M. Improving older adults' working memory: The influence of age and crystallized intelligence on training outcomes. *Journal of Cognitive Enhancement* **1**, 358-373, doi:10.1007/s41465-017-0041-4 (2017).
44 Blacker, K. J., Negoita, S., Ewen, J. B. & Courtney, S. M. N-back versus complex span working memory training. *Journal of Cognitive Enhancement* **1**, 434-454, doi:10.1007/s41465-017-0044-1 (2017).
45 von Bastian, C. C. & Eschen, A. Does working memory training have to be adaptive? *Psychological Research* **80**, 181-194, doi:10.1007/s00426-015-0655-z (2016).
46 Thorndike, E. L. & Woodworth, R. S. The influence of improvement in one mental function upon the efficiency of other functions. *Psychological Review* **8**, 247-261, doi:10.1037/h0074898 (1901).
47 Taatgen, N. A. The nature and transfer of cognitive skills. *Psychological Review* **120**, 439-471, doi:10.1037/a0033138 (2013).
48 Taatgen, N. A. in *Cognitive training: An overview of features and applications* (eds Tilo Strobach & Julia Karbach) 41-54 (Springer, 2021).
49 Carroll, J. B. *Human Cognitive Abilities: A Survey of Factor-Analytic Studies*. (Cambridge University Press, 1993).
50 Garlick, D. Understanding the nature of the general factor of intelligence: The role of individual differences in neural plasticity as an explanatory mechanism. *Psychological Review* **109**, 116-136, doi:10.1037/0033-295X.109.1.116 (2002).
51 De Simoni, C. & von Bastian, C. C. Working memory updating and binding training: Bayesian evidence supporting the absence of transfer. *Journal of Experimental Psychology: General* **147**, 829-858, doi:10.1037/xge0000453 (2018).
52 Meiran, N., Dreisbach, G. & von Bastian, C. C. Mechanisms of working memory training: Insights from individual differences. *Intelligence* **73**, 78-87, doi:https://doi.org/10.1016/j.intell.2019.01.010 (2019).
53 Chein, J. M. & Schneider, W. The Brain's Learning and Control Architecture. *Current Directions in Psychological Science* **21**, 78-84, doi:10.1177/0963721411434977 (2012).
54 Edwards, J. D., Fausto, B. A., Tetlow, A. M., Corona, R. T. & Valdés, E. G. Systematic review and meta-analyses of useful field of view cognitive training. *Neuroscience & Biobehavioral Reviews* **84**, 72-91, doi:https://doi.org/10.1016/j.neubiorev.2017.11.004 (2018).
55 Eberth, J. & Sedlmeier, P. The effects of mindfulness meditation: A meta-analysis. *Mindfulness* **3**, 174-189, doi:10.1007/s12671-012-0101-x (2012).
56 Tang, Y.-Y. *et al.* Short-term meditation training improves attention and self-regulation. *Proceedings of the National Academy of Sciences* **104**, 17152, doi:10.1073/pnas.0707678104 (2007).
57 Green, C. S. & Bavelier, D. Action video game training for cognitive enhancement. *Current Opinion in Behavioral Sciences* **4**, 103-108, doi:https://doi.org/10.1016/j.cobeha.2015.04.012 (2015).
58 Bediou, B. *et al.* Meta-analysis of action video game impact on perceptual, attentional, and cognitive skills. *Psychol Bull* **144**, 77-110, doi:10.1037/bul0000130 (2018).
59 Ball, K. & Owsley, C. The useful field of view test: a new technique for evaluating age-related declines in visual function. *J Am Optom Assoc* **64**, 71-79 (1993).
60 Wood, J. M. & Owsley, C. Useful Field of View Test. *Gerontology* **60**, 315-318, doi:10.1159/000356753 (2014).
61 Benikos, N., Johnstone, S. J. & Roodenrys, S. J. Short-term training in the go/nogo task: Behavioural and neural changes depend on task demands. *International Journal of Psychophysiology* **87**, 301-312, doi:https://doi.org/10.1016/j.ijpsycho.2012.12.001 (2013).

62 Zhao, X., Chen, L. & Maes, J. H. R. Training and transfer effects of response inhibition training in children and adults. *Developmental Science* **21**, e12511, doi:https://doi.org/10.1111/desc.12511 (2018).
63 Hartmann, L., Sallard, E. & Spierer, L. Enhancing frontal top-down inhibitory control with go/nogo training. *Brain Structure and Function* **221**, 3835-3842, doi:10.1007/s00429-015-1131-7 (2016).
64 Maraver, M. J., Bajo, M. T. & Gomez-Ariza, C. J. Training on working memory and inhibitory control in young adults. *Frontiers in Human Neuroscience* **10**, doi:10.3389/fnhum.2016.00588 (2016).
65 Berkman, E. T., Kahn, L. E. & Merchant, J. S. Training-Induced Changes in Inhibitory Control Network Activity. *The Journal of Neuroscience* **34**, 149, doi:10.1523/JNEUROSCI.3564-13.2014 (2014).
66 Strobach, T., Salminen, T., Karbach, J. & Schubert, T. Practice-related optimization and transfer of executive functions: A general review and a specific realization of their mechanisms in dual tasks. *Psychological Research* **78**, 836-851, doi:10.1007/s00426-014-0563-7 (2014).
67 Allom, V., Mullan, B. & Hagger, M. Does inhibitory control training improve health behaviour? A meta-analysis. *Health Psychology Review* **10**, 168-186, doi:10.1080/17437199.2015.1051078 (2016).
68 Jones, A., Tiplady, B., Houben, K., Nederkoorn, C. & Field, M. Do daily fluctuations in inhibitory control predict alcohol consumption? An ecological momentary assessment study. *Psychopharmacology* **235**, 1487-1496, doi:10.1007/s00213-018-4860-5 (2018).
69 Houben, K. & Jansen, A. Training inhibitory control. A recipe for resisting sweet temptations. *Appetite* **56**, 345-349, doi:https://doi.org/10.1016/j.appet.2010.12.017 (2011).
70 Sala, G., Tatlidil, K. S. & Gobet, F. Video game training does not enhance cognitive ability: A comprehensive meta-analytic investigation. *Psychol Bull* **144**, 111-139, doi:10.1037/bul0000139 (2018).
71 Hilgard, J., Sala, G., Boot, W. R. & Simons, D. J. Overestimation of action-game training effects: Publication bias and salami slicing. *Collabra: Psychology* **5**, 30, doi:10.1525/collabra.231 (2019).
72 Bavelier, D., Green, C. S., Pouget, A. & Schrater, P. Brain plasticity through the life span: Learning to learn and action video games. *Annual Review of Neuroscience* **35**, 391-416, doi:10.1146/annurev-neuro-060909-152832 (2012).
73 Kattner, F., Cochrane, A., Cox, C. R., Gorman, T. E. & Green, C. S. Perceptual learning generalization from sequential perceptual training as a change in learning rate. *Current Biology* **27**, 840-846, doi:https://doi.org/10.1016/j.cub.2017.01.046 (2017).
74 Kemp, C., Goodman, N. D. & Tenenbaum, J. B. Learning to learn causal models. *Cognitive Science* **34**, 1185-1243, doi:https://doi.org/10.1111/j.1551-6709.2010.01128.x (2010).
75 Barrett, L. F., Tugade, M. M. & Engle, R. W. Individual Differences in Working Memory Capacity and Dual-Process Theories of the Mind. *Psychol Bull* **130**, 553-573, doi:10.1037/0033-2909.130.4.553 (2004).
76 Klingberg, T. Training and plasticity of working memory. *Trends in Cognitive Sciences* **14**, 317-324, doi:https://doi.org/10.1016/j.tics.2010.05.002 (2010).
77 Jaeggi, S. M., Buschkuehl, M., Jonides, J. & Perrig, W. J. Improving fluid intelligence with training on working memory. *Proceedings of the National Academy of Sciences* **105**, 6829, doi:10.1073/pnas.0801268105 (2008).
78 Klingberg, T. *et al.* Computerized training of working memory in children with ADHD---A randomized, controlled trial. *Journal of the American Academy of Child & Adolescent Psychiatry* **44**, 177-186, doi:10.1097/00004583-200502000-00010 (2005).

79 Redick, T. S. *et al.* No evidence of intelligence improvement after working memory training: a randomized, placebo-controlled study. *Journal of Experimental Psychology: General* **142**, 359, doi:https://doi.org/10.1037/a0029082 (2013).
80 Chein, J. M. & Morrison, A. B. Expanding the mind's workspace: Training and transfer effects with a complex working memory span task. *Psychonomic Bulletin & Review* **17**, 193-199, doi:10.3758/PBR.17.2.193 (2010).
81 Guye, S. & von Bastian, C. C. Working memory training in older adults: Bayesian evidence supporting the absence of transfer. *Psychology and Aging* **32**, 732-746, doi:10.1037/pag0000206 (2017).
82 Sprenger, A. M. *et al.* Training working memory: Limits of transfer. *Intelligence* **41**, 638-663, doi:10.1016/j.intell.2013.07.013 (2013).
83 Au, J. *et al.* Improving fluid intelligence with training on working memory: a meta-analysis. *Psychonomic Bulletin & Review* **22**, 366-377, doi:10.3758/s13423-014-0699-x (2015).
84 Karbach, J. & Verhaeghen, P. Making Working Memory Work: A Meta-Analysis of Executive-Control and Working Memory Training in Older Adults. *Psychological Science* **25**, 2027-2037, doi:10.1177/0956797614548725 (2014).
85 Schwaighofer, M., Fischer, F. & Bühner, M. Does Working Memory Training Transfer? A Meta-Analysis Including Training Conditions as Moderators. *Educational Psychologist* **50**, 138-166, doi:10.1080/00461520.2015.1036274 (2015).
86 Soveri, A., Antfolk, J., Karlsson, L., Salo, B. & Laine, M. Working memory training revisited: A multi-level meta-analysis of n-back training studies. *Psychonomic Bulletin & Review* **24**, 1077-1096, doi:10.3758/s13423-016-1217-0 (2017).
87 Sala, G. & Gobet, F. Working memory training in typically developing children: A multilevel meta-analysis. *Psychonomic Bulletin & Review* **27**, 423-434, doi:10.3758/s13423-019-01681-y (2020).
88 Sala, G., Aksayli, N. D., Tatlidil, K. S., Gondo, Y. & Gobet, F. Working memory training does not enhance older adults' cognitive skills: A comprehensive meta-analysis. *Intelligence* **77**, 101386, doi:10.1016/j.intell.2019.101386 (2019).
89 Langer, N., von Bastian, C. C., Wirz, H., Oberauer, K. & Jäncke, L. The effects of working memory training on functional brain network efficiency. *Cortex* **49**, 2424-2438, doi:https://doi.org/10.1016/j.cortex.2013.01.008 (2013).
90 Dziemian, S., Appenzeller, S., von Bastian, C. C., Jäncke, L. & Langer, N. Working Memory Training Effects on White Matter Integrity in Young and Older Adults. *Frontiers in Human Neuroscience* **15**, doi:10.3389/fnhum.2021.605213 (2021).
91 Lawlor-Savage, L., Clark, C. M. & Goghari, V. M. No evidence that working memory training alters gray matter structure: A MRI surface -based analysis. *Behavioural Brain Research* **360**, 323-340, doi:https://doi.org/10.1016/j.bbr.2018.12.008 (2019).
92 Laine, M., Fellman, D., Waris, O. & Nyman, T. J. The early effects of external and internal strategies on working memory updating training. *Scientific Reports* **8**, 4045, doi:10.1038/s41598-018-22396-5 (2018).
93 Chase, W. G. & Ericsson, K. A. in *Cognitive skills and their acquisition* (ed John R. Anderson) 141-189 (Erlbaum, 1981).
94 Dunning, D. L. & Holmes, J. Does working memory training promote the use of strategies on untrained working memory tasks? *Memory & Cognition* **42**, 854-862, doi:10.3758/s13421-014-0410-5 (2014).
95 Laine, M., Fellman, D., Waris, O. & Nyman, T. J. The early effects of external and internal strategies on working memory updating training. *Sci Rep* **8**, 4045, doi:10.1038/s41598-018-22396-5 (2018).
96 Redick, T. S., Wiemers, E. A. & Engle, R. W. The role of proactive interference in working memory training and transfer. *Psychological Research* **84**, 1635-1654, doi:10.1007/s00426-019-01172-8 (2020).

97 Zerr, P. *et al.* The development of retro-cue benefits with extensive practice: Implications for capacity estimation and attentional states in visual working memory. *Memory & Cognition*, doi:10.3758/s13421-021-01138-5 (2021).
98 Brady, T. F., Konkle, T. & Alvarez, G. A. Compression in visual working memory: Using statistical regularities to form more efficient memory representations. *Journal of Experimental Psychology: General* **138**, 487-502, doi:10.1037/a0016797 (2009).
99 Verhaeghen, P., Marcoen, A. & Goossens, L. Improving memory performance in the aged through mnemonic training: A meta-analytic study. *Psychology and Aging* **7**, 242-251, doi:10.1037/0882-7974.7.2.242 (1992).
100 Ball, K. *et al.* Effects of Cognitive Training Interventions With Older Adults: A Randomized Controlled Trial. *JAMA* **288**, 2271-2281, doi:10.1001/jama.288.18.2271 (2002).
101 Belleville, S. *et al.* Improvement of Episodic Memory in Persons with Mild Cognitive Impairment and Healthy Older Adults: Evidence from a Cognitive Intervention Program. *Dementia and Geriatric Cognitive Disorders* **22**, 486-499, doi:10.1159/000096316 (2006).
102 Belleville, S. *et al.* MEMO+: Efficacy, Durability and Effect of Cognitive Training and Psychosocial Intervention in Individuals with Mild Cognitive Impairment. *Journal of the American Geriatrics Society* **66**, 655-663, doi:https://doi.org/10.1111/jgs.15192 (2018).
103 Hampstead, B. M., Stringer, A. Y., Stilla, R. F., Giddens, M. & Sathian, K. Mnemonic strategy training partially restores hippocampal activity in patients with mild cognitive impairment. *Hippocampus* **22**, 1652-1658, doi:https://doi.org/10.1002/hipo.22006 (2012).
104 Chandler, M. J., Parks, A. C., Marsiske, M., Rotblatt, L. J. & Smith, G. E. Everyday Impact of Cognitive Interventions in Mild Cognitive Impairment: a Systematic Review and Meta-Analysis. *Neuropsychology Review* **26**, 225-251, doi:10.1007/s11065-016-9330-4 (2016).
105 Bottiroli, S., Cavallini, E., Dunlosky, J., Vecchi, T. & Hertzog, C. The importance of training strategy adaptation: A learner-oriented approach for improving older adults' memory and transfer. *Journal of Experimental Psychology: Applied* **19**, 205-218, doi:10.1037/a0034078 (2013).
106 Zimmermann, K., von Bastian, C. C., Röcke, C., Martin, M. & Eschen, A. Transfer after process-based object-location memory training in healthy older adults. *Psychology and Aging* **31**, 798-814, doi:10.1037/pag0000123 (2016).
107 Bellander, M. *et al.* No Evidence for Improved Associative Memory Performance Following Process-Based Associative Memory Training in Older Adults. *Frontiers in Aging Neuroscience* **8**, doi:10.3389/fnagi.2016.00326 (2017).
108 Glenberg, A. M. & Lehmann, T. S. Spacing repetitions over 1 week. *Memory & Cognition* **8**, 528-538, doi:10.3758/BF03213772 (1980).
109 Bjork, R. A. in *Practical aspects of memory: Current research and issues, Vol. 1: Memory in everyday life.* 396-401 (John Wiley & Sons, 1988).
110 Logan, J. M. & Balota, D. A. Expanded vs. Equal Interval Spaced Retrieval Practice: Exploring Different Schedules of Spacing and Retention Interval in Younger and Older Adults. *Aging, Neuropsychology, and Cognition* **15**, 257-280, doi:10.1080/13825580701322171 (2008).
111 Karpicke, J. D. & Bauernschmidt, A. Spaced retrieval: Absolute spacing enhances learning regardless of relative spacing. *Journal of Experimental Psychology: Learning, Memory, and Cognition* **37**, 1250-1257, doi:10.1037/a0023436 (2011).
112 Jennings, J. M. & Jacoby, L. L. Improving memory in older adults: Training recollection. *Neuropsychological Rehabilitation* **13**, 417-440, doi:10.1080/09602010244000390 (2003).
113 Jennings, J. M., Webster, L. M., Kleykamp, B. A. & Dagenbach, D. Recollection training and transfer effects in older adults: Successful use of a repetition-lag procedure. *Aging, Neuropsychology, and Cognition* **12**, 278-298, doi:10.1080/138255890968312 (2005).
114 Anderson, N. D., Ebert, P. L., Grady, C. L. & Jennings, J. M. Repetition lag training eliminates age-related recollection deficits (and gains are maintained after three months) but does not

transfer: Implications for the fractionation of recollection. *Psychol Aging* **33**, 93-108, doi:10.1037/pag0000214 (2018).
115 Boller, B., Jennings, J. M., Dieudonné, B., Verny, M. & Ergis, A.-M. Recollection training and transfer effects in Alzheimer's disease: Effectiveness of the repetition-lag procedure. *Brain and Cognition* **78**, 169-177, doi:https://doi.org/10.1016/j.bandc.2011.10.011 (2012).
116 Jennings, J. M., Lopina, E. C. & Dagenbach, D. in *Remembering* 276-292 (Psychology Press, 2014).
117 Stamenova, V. *et al.* Training recollection in healthy older adults: clear improvements on the training task, but little evidence of transfer. *Frontiers in Human Neuroscience* **8**, doi:10.3389/fnhum.2014.00898 (2014).
118 Bailey, H., Dagenbach, D. & Jennings, J. M. The locus of the benefits of repetition-lag memory training. *Aging, Neuropsychology, and Cognition* **18**, 577-593, doi:10.1080/13825585.2011.591921 (2011).
119 Koch, I., Poljac, E., Müller, H. & Kiesel, A. Cognitive structure, flexibility, and plasticity in human multitasking—An integrative review of dual-task and task-switching research. *Psychol Bull* **144**, 557-583, doi:10.1037/bul0000144 (2018).
120 Nguyen, L., Murphy, K. & Andrews, G. Immediate and long-term efficacy of executive functions cognitive training in older adults: A systematic review and meta-analysis. *Psychol Bull* **145**, 698-733, doi:10.1037/bul0000196 (2019).
121 Dörrenbächer, S. & Kray, J. The Impact of Game-Based Task-Shifting Training on Motivation and Executive Control in Children with ADHD. *Journal of Cognitive Enhancement* **3**, 64-84, doi:10.1007/s41465-018-0083-2 (2019).
122 Minear, M. & Shah, P. Training and transfer effects in task switching. *Memory & Cognition* **36**, 1470-1483, doi:10.3758/MC.336.8.1470 (2008).
123 Karbach, J. & Kray, J. How useful is executive control training? Age differences in near and far transfer of task-switching training. *Developmental Science* **12**, 978-990, doi:https://doi.org/10.1111/j.1467-7687.2009.00846.x (2009).
124 von Bastian, C. C. & Oberauer, K. Distinct transfer effects of training different facets of working memory capacity. *Journal of Memory and Language* **69**, 36-58, doi:10.1016/j.jml.2013.02.002 (2013).
125 Pereg, M., Shahar, N. & Meiran, N. Task switching training effects are mediated by working-memory management. *Intelligence* **41**, 467-478, doi:10.1016/j.intell.2013.06.009 (2013).
126 Zinke, K., Zeintl, M., Eschen, A., Herzog, C. & Kliegel, M. Potentials and limits of plasticity induced by working memory training in old-old age. *Gerontology* **58**, 79-87, doi:10.1159/000324240 (2012).
127 Braver, T. S. The variable nature of cognitive control: a dual mechanisms framework. *Trends in Cognitive Sciences* **16**, 106-113, doi:10.1016/j.tics.2011.12.010 (2012).
128 Schumacher, E. H. *et al.* Virtually Perfect Time Sharing in Dual-Task Performance: Uncorking the Central Cognitive Bottleneck. *Psychological Science* **12**, 101-108, doi:10.1111/1467-9280.00318 (2001).
129 Schubert, T. & Strobach, T. Practice-related optimization of dual-task performance: Efficient task instantiation during overlapping task processing. *Journal of Experimental Psychology: Human Perception and Performance* **44**, 1884-1904, doi:10.1037/xhp0000576 (2018).
130 Bier, B., de Boysson, C. & Belleville, S. Identifying training modalities to improve multitasking in older adults. *AGE* **36**, 9688, doi:10.1007/s11357-014-9688-2 (2014).
131 Gagnon, L. G. & Belleville, S. Training of attentional control in mild cognitive impairment with executive deficits: Results from a double-blind randomised controlled study. *Neuropsychological Rehabilitation* **22**, 809-835, doi:10.1080/09602011.2012.691044 (2012).
132 Lee, H. *et al.* Performance gains from directed training do not transfer to untrained tasks. *Acta Psychologica* **139**, 146-158, doi:https://doi.org/10.1016/j.actpsy.2011.11.003 (2012).

133 Voss, M. W. *et al.* Effects of training strategies implemented in a complex videogame on functional connectivity of attentional networks. *NeuroImage* **59**, 138-148, doi:https://doi.org/10.1016/j.neuroimage.2011.03.052 (2012).
134 Bherer, L. *et al.* Testing the limits of cognitive plasticity in older adults: Application to attentional control. *Acta Psychologica* **123**, 261-278, doi:https://doi.org/10.1016/j.actpsy.2006.01.005 (2006).
135 Bherer, L. *et al.* Training effects on dual-task performance: Are there age-related differences in plasticity of attentional control? *Psychology and Aging* **20**, 695-709, doi:10.1037/0882-7974.20.4.695 (2005).
136 Kramer, A. F., Larish, J. F. & Strayer, D. L. Training for attentional control in dual task settings: a comparison of young and old adults. *Journal of experimental psychology: applied* **1**, 50-76, doi:10.1037/1076-898X.1.1.50 (1995).
137 Hazeltine, E., Teague, D. & Ivry, R. B. Simultaneous dual-task performance reveals parallel response selection after practice. *Journal of Experimental Psychology: Human Perception and Performance* **28**, 527-545, doi:10.1037/0096-1523.28.3.527 (2002).
138 Liepelt, R., Strobach, T., Frensch, P. & Schubert, T. Improved Intertask Coordination after Extensive Dual-Task Practice. *Quarterly Journal of Experimental Psychology* **64**, 1251-1272, doi:10.1080/17470218.2010.543284 (2011).
139 Strobach, T., Frensch, P., Müller, H. & Schubert, T. Evidence for the acquisition of dual-task coordination skills in older adults. *Acta Psychologica* **160**, 104-116, doi:https://doi.org/10.1016/j.actpsy.2015.07.006 (2015).
140 Strobach, T., Frensch, P. A. & Schubert, T. Video game practice optimizes executive control skills in dual-task and task switching situations. *Acta Psychologica* **140**, 13-24, doi:https://doi.org/10.1016/j.actpsy.2012.02.001 (2012).
141 Strobach, T., Frensch, P. A., Soutschek, A. & Schubert, T. Investigation on the improvement and transfer of dual-task coordination skills. *Psychological Research* **76**, 794-811, doi:10.1007/s00426-011-0381-0 (2012).
142 Bender, A. D., Filmer, H. L., Naughtin, C. K. & Dux, P. E. Dynamic, continuous multitasking training leads to task-specific improvements but does not transfer across action selection tasks. *npj Science of Learning* **2**, 14, doi:10.1038/s41539-017-0015-4 (2017).
143 Klingberg, T. Is working memory capacity fixed? *Journal of Applied Research in Memory and Cognition* **1**, 194-196, doi:10.1016/j.jarmac.2012.07.004 (2012).
144 Sternberg, R. J. Increasing fluid intelligence is possible after all. *Proceedings of the National Academy of Sciences* **105**, 6791-6792, doi:10.1073pnas.0803396105 (2008).
145 Jensen, A. How much can we boost IQ and scholastic achievement? *Harvard Educational Review* **39**, 1-123, doi:10.17763/haer.39.1.l3u15956627424k7 (1969).
146 Jones, J. S., Milton, F., Mostazir, M. & Adlam, A. R. The academic outcomes of working memory and metacognitive strategy training in children: A double-blind randomized controlled trial. *Developmental Science* **23**, e12870, doi:10.1111/desc.12870 (2018).
147 Carpenter, J. *et al.* Domain-general enhancements of metacognitive ability through adaptive training. *Journal of Experimental Psychology: General* **148**, 51-64, doi:10.1037/xge0000505 (2019).
148 Rouder, J. N., Morey, R. D., Verhagen, J., Province, J. M. & Wagenmakers, E.-J. Is There a Free Lunch in Inference? *Topics in Cognitive Science* **8**, 520-547, doi:https://doi.org/10.1111/tops.12214 (2016).
149 Cumming, G. *Understanding the new statistics: Effect sizes, confidence intervals, and meta-analysis*. (Routledge, 2011).
150 Dienes, Z. Bayesian Versus Orthodox Statistics: Which Side Are You On? *Perspectives on Psychological Science* **6**, 274-290, doi:10.1177/1745691611406920 (2011).

151 Simmons, J. P., Nelson, L. D. & Simonsohn, U. False-Positive Psychology: Undisclosed Flexibility in Data Collection and Analysis Allows Presenting Anything as Significant. *Psychological Science* **22**, 1359-1366, doi:10.1177/0956797611417632 (2011).
152 Jeffreys, H. *The theory of probability*. 3rd ed. edn, (OUP Oxford, 1998 [1961]).
153 Kass, R. E. & Raftery, A. E. Bayes Factors. *Journal of the American Statistical Association* **90**, 773-795, doi:10.1080/01621459.1995.10476572 (1995).
154 Kruschke, J. K. *Doing Bayesian data analysis: A tutorial with R and BUGS*. (Elsevier Academic Press, 2011).
155 JASP (Version 0.14.1) [Computer Software] v. Version 0.14.1 (2020).
156 Dougherty, M. R., Hamovitz, T. & Tidwell, J. W. Reevaluating the effectiveness of n-back training on transfer through the Bayesian lens: Support for the null. *Psychonomic Bulletin & Review* **23**, 306-316, doi:10.3758/s13423-015-0865-9 (2016).
157 Belleville, S., Mellah, S., de Boysson, C., Demonet, J.-F. & Bier, B. The Pattern and Loci of Training-Induced Brain Changes in Healthy Older Adults Are Predicted by the Nature of the Intervention. *PLOS ONE* **9**, e102710, doi:10.1371/journal.pone.0102710 (2014).
158 Boyke, J., Driemeyer, J., Gaser, C., Büchel, C. & May, A. Training-Induced Brain Structure Changes in the Elderly. *The Journal of Neuroscience* **28**, 7031, doi:10.1523/JNEUROSCI.0742-08.2008 (2008).
159 Engvig, A. *et al.* Memory training impacts short-term changes in aging white matter: A longitudinal diffusion tensor imaging study. *Human brain mapping* **33**, 2390-2406 (2012).
160 Cabeza, R. *et al.* Author Correction: Maintenance, reserve and compensation: the cognitive neuroscience of healthy ageing. *Nature Reviews Neuroscience* **19**, 772-772, doi:10.1038/s41583-018-0086-0 (2018).
161 Stern, Y. *et al.* Whitepaper: Defining and investigating cognitive reserve, brain reserve, and brain maintenance. *Alzheimer's & Dementia* **16**, 1305-1311, doi:https://doi.org/10.1016/j.jalz.2018.07.219 (2020).
162 Belleville, S. *et al.* Training-related brain plasticity in subjects at risk of developing Alzheimer's disease. *Brain* **134**, 1623-1634, doi:10.1093/brain/awr037 (2011).
163 Belleville, S. & Bherer, L. Biomarkers of Cognitive Training Effects in Aging. *Current Translational Geriatrics and Experimental Gerontology Reports* **1**, 104-110, doi:10.1007/s13670-012-0014-5 (2012).
164 Erickson, K. I. *et al.* Striatal Volume Predicts Level of Video Game Skill Acquisition. *Cerebral Cortex* **20**, 2522-2530, doi:10.1093/cercor/bhp293 (2010).
165 Farrell, S. & Lewandowsky, S. *Computational modeling of cognition and behavior*. (Cambridge University Press, 2018).
166 Redick, T. S. & Lindsey, D. R. B. Complex span and n-back measures of working memory: A meta-analysis. *Psychonomic Bulletin & Review* **20**, 1102-1113, doi:10.3758/s13423-013-0453-9 (2013).
167 Anderson, J. R. *How can the human mind occur in the physical universe?* , (Oxford University Press, 2009).
168 Takeuchi, H. & Kawashima, R. Effects of processing speed training on cognitive functions and neural systems. *Reviews in the Neurosciences* **23**, 289-301, doi:doi:10.1515/revneuro-2012-0035 (2012).
169 Ratcliff, R. A theory of memory retrieval. *Psychological Review* **85**, 59-108, doi:10.1037/0033-295X.85.2.59 (1978).
170 Schmiedek, F., Oberauer, K., Wilhelm, O., Süß, H.-M. & Wittmann, W. W. Individual differences in components of reaction time distributions and their relations to working memory and intelligence. *Journal of Experimental Psychology: General* **136**, 414-429, doi:10.1037/0096-3445.136.3.414 (2007).

171 van Ravenzwaaij, D., Brown, S. & Wagenmakers, E.-J. An integrated perspective on the relation between response speed and intelligence. *Cognition* **119**, 381-393, doi:https://doi.org/10.1016/j.cognition.2011.02.002 (2011).