Getting at Underlying Mechanisms of Far Transfer - the Mediating Role of Near Transfer

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Abstract

The extent that working memory training improves performance on untrained tasks is highly controversial. Here we address this controversy by testing the hypothesis that far transfer may depend upon near transfer using mediation models in three separate randomized controlled trials (RCTs). In all three RCTs, totaling 460 individuals, performance on untrained N-back tasks (near transfer) mediated transfer to Matrix Reasoning (a measure of fluid intelligence, representing far transfer). Untrained N-back performance also mediated transfer to a working memory composite (RCT 3). These findings support a model of N-back training in which transfer to untrained n-back tasks gates further transfer, at least in the case of working memory at the construct level, and matrix reasoning. This model can help adjudicate between the many studies and meta-analyses of working memory training that have provided mixed results but have not examined the relationship between near and far transfer on an individual differences level.

Key words: working memory; training; far transfer; matrix reasoning; mediation

Introduction

The potential that working memory training can transfer to untrained tasks that differ substantially from the training task (so-called ‘far transfer’) has generated substantial excitement in regard to better understanding the causal relationship between working memory and related cognitive processes¹⁻⁶, as well as to applied domains where such training can provide benefits to health and wellbeing⁷⁻¹⁰. In particular, the effectiveness of working memory (WM) training to improve fluid intelligence has been a controversial and highly debated topic, with some meta-analyses showing a small, but significant positive effect on fluid intelligence¹¹⁻¹⁵, while others argue that there is no evidence of generalization to fluid intelligence after training^{16,17}. A difficulty in reconciling across different studies is that individual differences in performance and learning are ubiquitous in this literature, which impact average benefits¹⁸. Furthermore, training procedures and outcome measures differ greatly across studies, making meaningful comparisons challenging¹⁹.

One of the most common tasks used in these WM training studies is the N-back, an updating task that correlates significantly with measures of higher-level cognition, such as matrix reasoning²⁰⁻²⁴. While there is little doubt that N-back training leads to improved performance on untrained N-back tasks^{13,25-27}, the extent to which this reflects generation of performance strategies rather than improvement in monitoring and updating of WM content, or improved inhibition of items that are no longer relevant, remains unknown²⁵. If we assume the former, we have little reason to expect post-test improvement on tasks that are not of the same structure as the N-back, such as matrix reasoning. On the other hand, if N-back training leads to enhanced efficiency of updating and/or inhibitory control processes, such far transfer effects would be plausible. From a theoretical perspective, ‘near’ transfer is thought to occur when the training task and outcome measure share many overlapping features and presumably recruit similar processes, whereas ‘far’ transfer refers

to improved performance on outcome measures that share fewer features with the training task. While the boundaries between near and far transfer are not clear and likely fall on a continuum²⁸, several meta-analyses of working memory training studies have demonstrated that near transfer effects are both more readily observable and show larger effect sizes than far transfer effects^{13,14}. Likewise, neuroimaging research suggests that the frontostriatal system mediates near transfer effects whereas the dorso- and ventrolateral prefrontal cortices appear to employ domain-general networks that facilitate learning more widely⁵.

Here we go beyond merely examining the effects of N-back training on matrix reasoning to attempt to understand *how* these effects occur in the first place²⁹. Specifically, we first present the results of a retrospective study in which mediation models were used to evaluate whether the effects of N-back training on matrix reasoning are transmitted via changes in an untrained variant of N-back. In addition, we used an inhibitory control task as a control measure for our analyses. Even though improvement in the training task itself may also serve as a useful mediator³⁰, this information is not available for control groups, nor is it necessarily indicative of near transfer. We hypothesized that N-back training groups would improve on matrix reasoning (far transfer) compared to no-contact control groups, and furthermore, that this effect would be mediated by post-test performance on an untrained N-back task (near transfer). This model enabled us to account for individual differences in responsiveness to WM training and subsequent transfer to untrained tasks, and to demonstrate that transfer to matrix reasoning tasks is completely mediated by near transfer in two independent datasets collected over two academic years (RCTs 1 and 2). Since demand characteristics during training and potential placebo effects were not controlled for in the retrospective study, we further report the results of a double-blind, pre-registered replication study with an active control group in which we replicate the finding that performance on untrained N-

back tasks mediates transfer to matrix reasoning and extend the discussion to other tasks and domains.

Results

Retrospective Study

Conventional general linear model analyses test for differences in means of different groups on one independent variable and therefore cannot be used to test our theoretical model in which *a given training intervention leads to far transfer completely or partially through near transfer gains*. Instead, we use mediation models with the following hypothesized sequence of events: random group assignment (N-back training/Control group) affects untrained N-back performance, which subsequently affects Matrix Reasoning performance. As a control analysis, performance on the Countermanding task, which also showed some training-related benefits, is entered as a parallel mediator to pit competing mechanisms against each other. We first evaluate the retrospective study as a whole sample and then apply parallel two-mediator models separately for each RCT.

Whole Sample. Linear regression results shown in Table 1 indicate that training group was a significant predictor of post-test performance on Matrix Reasoning, even after controlling for pre-test performance on Matrix Reasoning, N-back, and Countermanding. All variables except Training group (0 = No-contact Control, 1 = N-back Training) were z-transformed to account for study-specific unit of measurement differences.

Table 1: Linear model of predictors of post-test performance on Matrix Reasoning in the retrospective study

	<i>B</i>	<i>SE B</i>	<i>β</i>	<i>P</i>
Constant	0.12 (-0.04 – 0.28)	0.08		<i>p</i> = 0.140
Pre-test Matrix Reasoning	0.66 (0.56 – 0.76)	0.05	.60	<i>p</i> < 0.001
Pre-test N-back	0.09 (-0.02 – 0.19)	0.05	.08	<i>p</i> = 0.108

Pre-test Countermanding	-0.17 (-0.27 – -0.06)	0.05	-.15	$p = 0.002$
Training group	0.23 (0.03 – 0.43)	0.10	.10	$p = 0.022$

Note. 95% bias corrected and accelerated confidence intervals reported in parentheses. Confidence intervals and standard errors based on 1000 bootstrap samples. $R^2 = .51$

After adding post-test N-back and Countermanding as parallel mediators (cf. Figure 1A), the total effect (i.e. the sum of indirect and direct effects) of training group on post-test performance on Matrix Reasoning remained significant ($B = .23$, $p = 0.022$, $R^2 = .50$). Training group predicted performance on post-test N-back ($B = 1.05$, $p < .001$), which in turn predicted performance on post-test Matrix Reasoning ($B = 0.18$, $p < .001$). A bootstrap confidence interval for the indirect effect (IE) based on 5,000 bootstrap samples did not include zero (IE = 0.19, SE = 0.05, 95% CI = 0.09–0.31), providing evidence for significant mediation via post-test N-back. While training group predicted post-test reaction time performance on the Countermanding task ($B = -.25$, $p = .159$), this variable did not predict post-test Matrix Reasoning ($B = .07$, $p = .214$), indicating that this type of far transfer was not mediated by training-related improvement in inhibitory control (IE = -0.02, SE = 0.02, 95% CI = -0.06–0.01). Moreover, the two indirect effects differed significantly from each other (IE = 0.21, SE = 0.06, 95% CI = 0.09–0.34). These results suggest that the causal effect of training group (No-contact control/N-back training) on matrix reasoning is mediated by the extent to which participants improve on near transfer. To determine the reproducibility of these results, the same analyses were conducted on the two independent RCTs.

RCT 1. Linear regression results revealed that training group predicted post-test Matrix Reasoning ($B = .40$, $p = .048$, $R^2 = .50$) after controlling for pre-test Matrix Reasoning, N-back, and Countermanding. In the mediation analysis (cf. Figure 1B), the total effect of training group on matrix reasoning was also significant ($B = .40$, $p = .048$, $R^2 = .50$). Training group predicted performance on post-test N-back ($B = 1.07$, $p < .001$), which in turn predicted performance on

post-test Matrix Reasoning ($B = 0.17$, $p = .023$). A bootstrap confidence interval for the specific indirect effect did not include zero (IE = 0.19, SE = 0.09, 95% CI = 0.03–0.40), providing evidence for significant mediation.

In contrast, performance on the Countermanding task did not mediate the relationship between training group and matrix reasoning (IE = -0.02, SE = 0.04, 95% CI = -0.11–0.54). The two indirect effects differed significantly from each other (IE = 0.20, SE = 0.11, 95% CI = 0.02–0.45).

RCT 2. Linear regression results suggested that training group did not predict post-test Matrix Reasoning ($B = .17$, $p = .15$, $R^2 = .51$) after controlling for pre-test Matrix Reasoning, N-back and Countermanding.

Likewise, in the mediation analysis (cf. Figure 1C), the total effect of training group on matrix reasoning was not significant ($p = 0.15$, $R^2 = .51$). Nevertheless, training group predicted performance on post-test N-back ($B = 1.06$, $p < .001$), which in turn predicted performance on post-test Matrix Reasoning ($B = 0.20$, $p = .002$) after controlling for baseline performance on each test. At post-test, all three outcome measures correlated significantly with each other (Supplementary Table 2), yet only the indirect effect through the N-back task was significant (IE

Figure 1: Parallel two-mediator models for the Whole Sample (A; $N = 271$), RCT 1 (B; $N = 94$), and RCT 2 (C; $N = 177$). Path coefficients are standardized regression coefficients. Covariates (not displayed): Pre-test N-back, Pre-test Countermanding and Pre-test Matrix Reasoning. * $p < .05$, ** $p < .01$.

= 0.21, SE = 0.07, 95% CI = 0.07–0.36), whereas the indirect effect through the Countermanding task was not (IE = -0.02, SE = 0.03, 95% CI = -0.76–0.45). The two indirect effects differed significantly from each other (IE = 0.23, SE = 0.09, 95% CI = 0.06–0.40).

Consider two participants from this RCT who were assigned to the same training condition and who showed similar training gain of about two N-levels ($S102_{\text{gain}} = 2.25$; $S105_{\text{gain}} = 2.17$) yet showed very different transfer to Matrix Reasoning: S105 showed no change at post-test relative to pre-test in terms of accuracy, whereas subject S102 showed improved accuracy at post-test. Examining untrained n-back results reveals that S105 did not show evidence of near transfer, which may explain the lack of transfer to matrix reasoning, whereas S102 showed near transfer. In this case, training gain has little predictive validity towards matrix reasoning outcomes. It remains to be determined why these participants showed such different patterns of results - it is possible that individual differences in strategy sophistication³¹ and/or motivation³² affected training outcomes.

Alternative mediation models. To test the hypothesis that N-back gains also mediate other aspects of transfer, we tested whether post-test N-back mediated the relationship between training group and post-test Countermanding performance (Supplementary Figure 4). This was found in the whole sample (IE = -0.23, SE = 0.09, 95% CI = -0.42 to -0.08) and in RCT 2 (IE = -0.28, SE = .12, 95% CI = -0.55 to -0.08), but not in RCT 1 (IE = -0.19, SE = 0.12, 95% CI = -0.46 to 0.01).

Specific Training Effects and Near Transfer – N-back

Substantial individual differences in N-back performance were observed both as a function of training progression and at pre/post-test. For the N-back training groups, mean N-level on the first day of training ranged from 2.00 to 6.44 in RCT 1 and from 1.12 to 4.84 in RCT 2. While these results suggest large individual differences in performance of all groups, training gain showed

even greater variability: on the last day of training, mean N-level ranged from 1.76 to 11.37 in RCT 1 and from 2.00 to 11.00 in RCT 2, with increasing variability as a function of training time (cf. Figure 5).

No baseline differences between N-back training and control groups were observed for the untrained N-back task (average accuracy across 2-back and 3-back levels; called Near Transfer hereafter) within each RCT (Supplementary Table 4). In RCT 1, pre-test accuracy on the Near Transfer task ranged from .42 to .93 in the no-contact control group and from .18 to 1.0 in the N-back training group. In RCT 2, pretest accuracy on the Near Transfer task ranged from .22 to .82 for no-contact control and from .27 to .85 for the N-back training group. When examining pre-post effect sizes (ES) across RCTs 1 and 2, no-contact control groups showed little or no improvement at post-test relative to pre-test on near transfer, whereas N-back training groups showed a substantial increase in accuracy on this task ($ES = 0.80 - 0.92$; cf. Table 2).

Far Transfer Effects

No baseline differences between N-back training and control groups were observed for Matrix Reasoning or Countermanding (Supplementary Table 4). The two N-back training groups showed small performance benefits on Matrix Reasoning ($ES = 0.43-0.49$), whereas the control groups showed negligible change in performance ($ES < 0.20$). Further, N-back training groups, but not Control groups, showed a decrease in average RT on incongruent trials of the Countermanding task, an index of inhibitory control, particularly in RCT 2 ($ES = 0.44$; cf. Table 2).

Study	Pre-test			Post-test			Paired comparisons (pre vs. post)		
	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>r</i>	<i>d</i>	<i>BF</i> ₁₀
RETROSPECTIVE STUDY									
RCT 1									
<i>Near transfer</i>									
N-back training	72	.61	.16	72	.80	.20	.15	.80	> 100*
No-contact control	22	.61	.15	22	.62	.22	.52*	.06	.23
<i>Matrix reasoning</i>									
N-back training	72	.72	.13	72	.76	.14	.73*	.49	> 100*
No-contact control	22	.71	.11	22	.71	.16	.51*	-.02	.22
<i>Countermanding</i>									
N-back training	72	832.25	122.81	72	803.22	102.78	.48*	.25	1.05*
No-contact control	22	842.87	112.43	22	827.22	136.90	.58*	.14	.27
RCT 2									
<i>Near transfer</i>									
N-back training	109	.59	.15	109	.78	.18	.31*	.96	> 100*
No-contact control	68	.59	.15	68	.61	.14	.38*	.14	.24
<i>Matrix reasoning</i>									
N-back training	109	.58	.18	109	.63	.20	.76*	.43	> 100*
No-contact control	68	.56	.16	68	.59	.17	.52*	.19	.44
<i>Countermanding</i>									
N-back training	109	745.42	120.43	109	710.46	109.01	.77*	.44	> 100*
No-contact Control	68	756.61	129.13	68	757.37	179.04	.68*	-.01	.13
REPLICATION									
RCT 3									
<i>Near transfer</i>									
N-back training	128	.59	.14	128	.85	.16	.36*	1.52	> 100*
Active control	61	.60	.18	61	.66	.17	.63*	.35	4.18*
<i>Matrix reasoning</i>									
N-back training	128	.56	.18	128	.62	.20	.75*	.46	> 100*
Active control	61	.57	.21	61	.61	.21	.79*	.36	5.06*
<i>Countermanding</i>									
N-back training	128	784.49	126.81	128	750.19	113.70	.74*	.39	> 100*
Active control	61	775.01	15.09	61	782.83	18.20	.53*	.06	0.16
<i>Cancellation</i>									
N-back training	115	141.50	19.28	115	163.77	22.90	.80*	1.61	> 100*
Active control	55	139.24	18.43	55	157.11	23.03	.66*	1.02	> 100*

<i>Running Span</i>									
N-back training	115	23.38	9.33	115	26.62	10.72	.09	0.24	2.23*
Active control	55	24.18	10.25	55	26.36	11.09	.35*	0.18	0.34
<i>Sequencing</i>									
N-back training	115	8.58	3.28	115	9.44	3.74	.53*	0.25	2.94*
Active control	55	8.62	3.02	55	8.47	2.72	.69*	0.06	0.16
<i>Simple Span</i>									
N-back training	115	52.89	15.08	115	54.89	15.28	.49*	0.13	0.27
Active control	55	57.51	13.03	55	56.11	12.89	.20	0.09	0.18
<i>Complex Span</i>									
N-back training	115	45.30	15.94	115	48.15	15.20	.57*	0.20	0.87
Active control	55	45.96	13.26	55	45.96	15.19	.45*	0.00	0.15
<i>ETS Surface Development</i>									
N-back training	115	0.47	0.23	115	0.59	0.24	.69*	0.68	> 100*
Active control	55	0.48	0.27	55	0.62	0.24	.69*	0.72	> 100*
<i>ETS Space Relations</i>									
N-back training	115	0.66	0.20	115	0.71	0.19	.57*	0.24	2.30*
Active control	55	0.61	0.18	55	0.71	0.17	.44*	0.52	85.08*
<i>DAT Form Board</i>									
N-back training	115	50.04	15.78	115	57.70	15.34	.57*	0.53	> 100*
Active control	55	53.20	15.87	55	59.31	16.90	.75*	0.53	95.36*

* = $p < 0.05$ or $BF_{10} > 1$

Table 2: Descriptive statistics and within-group Pearson's r , Cohen's $d^{(a)}$ and Bayes Factor^(b) for proportion correct performance on pre-test and post-test on Near transfer (untrained N-back), Matrix reasoning, Countermanding task (in ms), as well as other outcome measures separated by RCT. Extreme evidence in favor of the alternative hypothesis based on BF_{10} is marked bold.

^(a) Accounts for the correlation between pre- and post-test measures: $(Mean_{Post} - Mean_{Pre}) / \sqrt{(SD_{Pre}^2 + SD_{Post}^2 - 2r_{PrePost} * SD_{Pre} * SD_{Post})}$

^(b) BF_{10} grades the intensity of the evidence that the data provide for H_1 versus H_0 . BF_{10} between 1 and 3 is considered to be only anecdotal evidence for H_1 ; 3–10: moderate evidence; 10–30: strong evidence; 30–100: very strong evidence; >100 extreme evidence^{33,34}.

Given that near and far transfer effects were measured with single tasks, we recognize that the results might still reflect task-specific learning to some extent, and as such, we make no claims to the mental constructs of WM, response inhibition, and fluid intelligence. Furthermore, due to the use of no-contact controls, it is possible that some of the performance advantage of N-back training groups stems from non-specific characteristics of the training protocol such as participant and/or experimenter expectancies and experimenter contact³⁵. Even though a recent meta-analysis found no meaningful performance difference between no-contact and active controls³⁶, we decided to conduct a pre-registered, double-blind replication study using an active control group to control for these effects. Further, we expanded the test battery to extend the analyses to other outcome measures and to be able to generate composite scores for each domain.

Pre-registered Replication Study

In RCT3, the analytical sample consisted of 189 participants: 128 participants completed 20 sessions of N-back training whereas 61 participants completed 20 sessions of general knowledge training (active control). The N-back training group showed similar gains on Near Transfer (ES = 1.52), Matrix Reasoning (ES = 0.46), and Countermanding (ES = 0.39) as the training groups in the retrospective study. Importantly, the basic assessment battery was expanded to include four additional WM tasks (Running Span, Sequencing, Simple Span, and Complex Span), one additional measure of executive function (Cancellation), and three additional spatial reasoning measures (ETS Surface Development, ETS Space Relations, DAT Form Board) to be able to construct composite scores in the three domains of interest. First, we present a replication of the 2-mediator parallel model, followed by models in which composite scores are entered as mediators, and finally, models in which a composite score represents the outcome variable.

Linear regression results shown in Table 3 indicate that training group was not a significant predictor of post-test performance on Matrix Reasoning after controlling for pre-test performance on Matrix Reasoning, N-back, and Countermanding. Note that a simple association between independent and dependent variables is not necessary for mediation analysis³⁷.

Table 3: Linear model of predictors of post-test performance on Matrix Reasoning in RCT3

	<i>B</i>	<i>SE B</i>	<i>β</i>	<i>P</i>
Constant	0.25 (0.08 – 0.41)	0.09		$p = 0.01$
Pre-test Matrix Reasoning	0.76 (0.65 – 0.88)	0.06	.71	$p < 0.001$
Pre-test N-back	0.10 (0.002 – 0.19)	0.05	.09	$p = 0.07$
Pre-test Countermanding	-0.15 (-0.32 – 0.01)	0.09	-.11	$p = 0.07$
Training group	0.07 (-0.12 – 0.29)	0.10	.03	$p = 0.50$
<i>Note. 95% bias corrected and accelerated confidence intervals reported in parentheses. Confidence intervals and standard errors based on 1000 bootstrap samples. $R^2 = .60$</i>				

205 Likewise, in the mediation analysis (cf. Figure 2A), the total effect of training group on matrix
 206 reasoning was not significant ($p = 0.07$, $R^2 = .60$). Importantly though, the parallel mediation model
 207 replicates the findings from Study 1: training group predicted performance on post-test N-back (B
 208 $= 1.34$, $p < .001$), which in turn predicted performance on post-test Matrix Reasoning ($B = 0.20$, p
 209 $< .001$) after controlling for baseline
 210 performance on each test. A bootstrap
 211 confidence interval for the specific indirect
 212 effect through post-test N-back did not
 213 include zero (IE = 0.26, SE = 0.08, 95% CI =
 214 0.10–0.43), showing evidence for
 215 significant mediation. Performance on the
 216 Countermanding task did not mediate the
 217 relationship between training group and
 218 Matrix Reasoning (IE = 0.04, SE = 0.03,
 219 95% CI = -0.003–0.11), which is in line with
 220 the results obtained in the retrospective
 221 study. These results provide further
 222 evidence that transfer to untrained N-back
 223 tasks is a vital mediator through which the
 224 N-back training intervention affects
 225 improved performance on Matrix
 226 Reasoning. Moreover, post-test
 227 performance on untrained N-back preceded

Figure 2: Parallel two-mediator models for RCT3. In all models, pre-test variables are added as covariates. Path coefficients are standardized regression coefficients. $N = 170$. * $p < .05$, ** $p < .01$ **A:** Replication of Study 1 ($N = 189$). **B:** WM Composite 1 consists of N-back, Sequencing and Span tasks. IC Composite consists of Countermanding and Cancellation tasks ($N = 170$). **C:** WM Composite 2 consists of Sequencing and Span tasks only ($N = 170$).

performance on Matrix Reasoning by one day, hence satisfying the recommendation that the mediator must intervene between the predictor and the outcome³⁸. The same pattern of results was obtained when the two mediators were replaced with composite scores (cf. Figure 2B). Note that the sample size for this and subsequent analyses is smaller ($N = 170$) due to outliers removed on WM and inhibitory control (IC) tasks. Post-test working memory Composite 1, which includes the N-back task, mediated transfer to Matrix Reasoning ($IE = 0.11$, $SE = 0.05$, $95\% CI = 0.02-0.22$), whereas the IC Composite did not ($IE = 0.05$, $SE = 0.04$, $95\% CI = -0.003-0.14$) thus replicating and extending the basic parallel model.

A question that arises is whether Matrix Reasoning is mediated solely by N-back or whether other WM measures contribute to the mediation as well. A multiple parallel

mediation model (cf. Figure 3A) showed that post-test N-back was the only significant mediator of Matrix Reasoning performance ($IE = 0.22$, $SE = 0.09$, $95\% CI = 0.07-0.41$). The indirect effect via post-test N-back was significantly different from all other indirect effects (N-back – Running Span: $IE = 0.22$, $SE = 0.09$, $95\% CI = 0.06-0.41$; N-back – Sequencing: $IE = 0.22$, $SE = 0.09$, 95%

Figure 3: Alternative mediation models of transfer to Matrix Reasoning. In all models, pre-test variables are added as covariates. Path coefficients are standardized regression coefficients. $N = 170$. * $p < .05$, ** $p < .01$. **A:** Parallel multiple-mediator model. **B-C:** Serial mediator models.

CI = 0.06–0.41; N-back – Simple Span: IE = 0.22, SE = 0.09, 95% CI = 0.06–0.41; N-back – Complex Span: IE = 0.21, SE = 0.09, 95% CI = 0.04–0.40). Given these results, it is not surprising that Working Composite 2, which does not include N-back or Running Span, did not mediate the relationship between training group and transfer to Matrix Reasoning performance (IE = 0.006, SE = 0.004, 95% CI = -0.012–0.015), nor did IC (IE = 0.011, SE = 0.007, 95% CI = -0.001–0.027) (cf. Figure 2C).

In the literature, untrained N-back is often seen as very near transfer, while structurally different WM tasks are classified as near transfer and non-WM tasks as far transfer¹³, implying a serial relationship among these task domains. While unlikely given the results above, a serial mediation model^c, in which the first mediator was post-test N-back and the second mediator was post-test Working Memory Composite 2, was ran to test this hypothesis (cf. Figure 3B). As expected, the indirect specific effect via untrained N-back was significant (Condition → N-back → Matrix Reasoning: IE = 0.20, SE = 0.09, 95% CI = 0.04–0.39) whereas the two indirect effects that included the working memory composite were not (Condition → WM Composite 2 → Matrix Reasoning: IE = 0.01, SE = 0.02, 95% CI = -0.03–0.05; Condition → N-back → WM Composite 2 → Matrix Reasoning: IE = 0.02, SE = 0.02, 95% CI = -0.01–0.06).

Since overriding dominant or prepotent responses is also required during N-back training (e.g., when switching N-levels, the player must inhibit responses related to the previous level), and this may play a role in solving matrix reasoning tasks, we replaced the second mediator (WM Composite 2) with the IC composite (cf. Figure 3C). Results showed that only the path via N-back mediated transfer to Matrix Reasoning (Condition → N-back → Matrix Reasoning: IE = 0.21, SE

^c Serial mediation models were not pre-registered and were added post-hoc.

272 = 0.09, 95% CI = 0.05–0.38), whereas the two indirect effects that included the IC composite were
 273 not significant (Condition → IC Composite
 274 → Matrix Reasoning: IE = 0.04, SE = 0.03,
 275 95% CI = -0.01–0.12; Condition → N-back
 276 → IC Composite → Matrix Reasoning: IE =
 277 0.02, SE = 0.02, 95% CI = -0.01–0.05).
 278 Overall, single mediator models explained
 279 the data better than serial models.
 280 There is no evidence that N-back training led
 281 to improved performance on other measures
 282 of visuospatial reasoning (ETS and DAT
 283 tests) relative to the active control group (cf.
 284 Table 1). Nevertheless, as planned during
 285 preregistration, we ran a mediation model in
 286 which post-test N-back and Countermanding
 287 were entered as mediators and a Gf composite
 288 involving Matrix Reasoning, ETS and DAT
 289 tests was entered as the outcome variable.

Figure 4: Alternative parallel two-mediator models for
 RCT3 wherein the dependent variables are post-test Gf
 (A), Working Memory (B), and Inhibitory Control (C)
 composite scores. In all mediation models, pre-test
 variables are added as covariates. Path coefficients are
 standardized regression coefficients. N = 170. *p < .05,
 **p < .01.

290 While training group (N-back/active control) predicted performance on post-test N-back ($B = 1.32$,
 291 $p < .001$) and on post-test Countermanding ($B = -0.24$, $p < .001$), neither N-back (IE = 0.06, SE =
 292 0.05, 95% CI = -0.03–0.16) nor Countermanding (IE = 0.02, SE = 0.02, 95% CI = -0.004–0.07)
 293 predicted performance on the Gf composite after controlling for baseline performance on these

tests. The same pattern of results was obtained when WM composite 1 and IC were entered as mediators (cf. Figure 4A).

Alternative mediation models

Taking a step back, we investigated whether N-back training-related changes are observed in WM tasks beyond untrained N-back and what the mechanisms might be that support this process. Specifically, we tested whether performance on untrained N-back mediates transfer to a WM composite consisting of sequencing and spatial span tasks (cf. Figure 4B) while entering post-test Countermanding as a control mediator. Results showed that performance on untrained N-back ($IE = 0.20$, $SE = 0.06$, 95% $CI = 0.07$ to 0.30), but not Countermanding ($IE = 0.01$, $SE = 0.02$, 95% $CI = -0.04$ to 0.05), mediated transfer to the WM composite. In addition, the total effect of training group on post-test WM composite performance was significant ($p = 0.03$, $R^2 = .65$). These results suggest that the effectiveness of the N-back training intervention to improve working memory ability depends on the extent to which an individual shows improvement on untrained N-back tasks. The same results were obtained when the Countermanding mediator was replaced with an IC composite consisting of Countermanding and Cancellation tasks (IE via $IC = 0.02$, $SE = 0.02$, 95% $CI = -0.01$ to 0.06).

We also ran a mediation model in which the IC composite was entered as the dependent variable. The indirect specific effects via untrained N-back ($IE = 0.05$, $SE = 0.05$, 95% $CI = -0.04$ to 0.15) and WM Composite 2 ($IE = 0.02$, $SE = 0.02$, 95% $CI = -0.01$ to 0.06) were not significant. However, the total effect of training group on IC was significant ($IE = 0.25$, $SE = 0.08$, 95% $CI = 0.09$ to 0.40), suggesting that N-back-training boosted IC performance relative to control training (cf. Figures 4C and 6), but that this process is independent of improvements in WM.

Specific Training Effects and Near Transfer

The N-back training group in RCT3 showed similar training performance as in the retrospective study, particularly with respect to RCT 2 (cf. Figure 5). Mean N-level on the first day of training ranged from 2.00 to 3.94 and on the last from 2.00 to 14.33. Likewise, individual differences were observed on the Near Transfer task with pre-test accuracy ranging from .22 to .95 in the active control group and from .23 to .95 in the N-back training group.

Figure 5: Average *n*-level achieved per day (40 minutes of training), for the N-back training groups, weighted by the number of trials. RCT differences may reflect the use of slightly different adaptive algorithms. Shaded areas represent standard error of the mean.

Far Transfer Effects

No baseline differences between N-back training and active control groups were observed for Matrix Reasoning or any of the other outcome measures (Supplementary Table 4). To confirm the results of mediation analyses, Bayesian repeated measures ANOVAs with within-subjects factor Time (Pre/Post) and between-subjects factor Group (Control, N-back Training) were conducted on composite scores (not preregistered). Inclusion Bayes Factor across matched models (BF_{incl}) were used to evaluate evidence of Time $\times$ Group interactions. Significant interactions in favor of the N-back training group (cf. Figure 6) were obtained for WM composite 1 ($BF_{incl} > 100$), WM composite 2 ($BF_{incl} = 2.46$), IC composite ($BF_{incl} = 9.59$), but not the Gf composite ($BF_{incl} = 0.22$), which is in line with the results reported above.

Figure 6: Pre- and post-test composite z-scores for N-back training (black circle) and Active Control (white circle) groups. WM 1: untrained N-back, Sequencing, Simple Span, and Complex Span; WM 2: Sequencing, Simple Span and Complex Span; IC composite: Countermanding and Cancellation; Gf Composite: UCMRT, ETS Surface Development, ETS Space Relations, and DAT Form Board.

Discussion

Previous studies have examined the relationship between training gain and far transfer, typically by comparing subgroups of participants who show low versus high training gain^{30,39,40}; however, this type of responder analysis can be problematic⁴¹. Here we demonstrate that there are alternative ways of analyzing transfer data that do not involve dichotomization and may reveal concealed associations and mechanisms to explain the effects of training. Three independent datasets from three separate RCTs involving a total of 460 participants showed that the mechanism that underlies transfer to matrix reasoning appears to be near transfer as measured by performance on untrained N-back tasks. This may explain some of the variability seen in the literature that reports only sporadic transfer to matrix reasoning. Importantly, transfer to untrained N-back tasks is often not reported, and thus, information is often missing about what participants learned, and thus, the extent of learning on measures of transfer remains unknown. For example, in a meta-analysis of WM training studies¹³, 35 experiments measured fluid intelligence, 28 experiments assessed WM, including tasks that correlate poorly with the N-back²⁴, but only 9 experiments also included untrained N-back tasks. In another meta-analysis of N-back training studies, only 37% of N-back training studies reported using N-back tasks as an outcome measure¹⁹, thus for the majority of studies, information is missing about what participants gained. If we do not know whether the minimal amount of near transfer occurred (e.g., to a different stimulus set), then how can we gauge improvements in WM and to far transfer measures beyond WM such as fluid intelligence tasks?

Our retrospective working memory training study using a no-contact control group showed that the mechanism that underlies transfer to matrix reasoning appears to be near transfer as measured by performance on untrained N-back tasks – at least in the two independent datasets collected in

our lab. An important outcome of these results is that N-back training does not seem to merely enhance task-specific strategies, but presumably leads to changes in underlying components of WM such as the capacity of the focus of attention⁴² or updating⁴³, which supports performance on matrix reasoning problems⁴⁴. Understanding how this occurs is a challenge, which is constrained by the lack of agreement about why WM and fluid intelligence correlate positively in the first place. One explanation suggests that WM is needed to maintain rules in mind to successfully solve matrix reasoning problems⁴⁵. This was not supported in a subsequent study, instead, the ability to manage proactive interference appeared to play a role in both constructs⁴⁶. Similarly, it has been shown that WM helps keep previously learned rule combinations from interfering when solving problems that require a new rule combination^{47,48}. However, since inhibitory control did not mediate transfer to matrix reasoning, the present results do not support interference-type accounts. Recent evidence also challenges these accounts, showing that the relationship between WM capacity and matrix reasoning can be explained by individuals' ability to maintain how they solved previous problems in memory⁴⁹. Our results are therefore in line with research showing that updating⁴³ and/or executive attention⁵², but not inhibition, show strong relations with fluid intelligence. Finally, it has been argued that WM and fluid intelligence are complementary processes that promote complex cognition, wherein the first reflects maintenance and the other disengagement, and both serve a single top-down executive attention⁵⁰. Extending this to the neural level, it is plausible that transfer occurs if the training and transfer tasks engage overlapping processes and neural circuits^{26,51}.

To verify this finding using a more rigorous design, we pre-registered a double-blind replication study and included an active control group, which was conducted online due to a ban on in-person

research amidst the COVID-19 pandemic. Further, we investigated whether the mediation model replicates using composite scores of WM, inhibitory control, and fluid intelligence as outcome measures. This study provided three important findings. First, we replicate the finding that transfer to Matrix Reasoning depends on the extent to which individuals show near transfer as measured by performance on untrained N-back, even after controlling for participant and/or experimenter expectancies with the use of an active control group and full blinding procedures. Overall, this key finding has now been observed in 3 independent RCTs that included a total of 460 individuals.

Second, no working memory measure other than the N-back task mediated transfer to Matrix Reasoning, even though post-test performance on all WM tasks except for Running Span correlated significantly with Matrix Reasoning performance (Supplementary Table 5). Span-based WM tasks might not share enough variance with Matrix Reasoning to explain individual differences in transfer, or the gain on these tasks might not be large enough to have an observable effect on transfer.

Third, it was shown that N-back-training led to small but significant improvements in a WM composite consisting of sequencing and span-based tasks and to enhanced IC performance relative to control training. Interestingly, untrained N-back performance only mediated transfer to the WM composite and not the IC composite. Transfer to sequencing and/or complex WM tasks has been reported by some^{53–59}, but not other N-back training studies^{54,60–66}. Likewise, there is no consensus regarding transfer to inhibitory control measures, with some WM training studies reporting training-related benefits^{55,56,67,68}, yet others failing to find evidence of transfer^{51,69}. Note that previous research often included Stroop tasks as an IC measure, whereas here we used a composite score based on speed of inhibitory control and a timed test of selective attention. Along with using a consistent set of measures across studies¹⁹, another solution that could bring some clarity is

examining individual differences in training and transfer with mediation and moderation analyses. For example, we used serial mediation models to confirm that viewing untrained N-back as very near transfer, which in turn affects transfer to other WM tasks, or to an inhibitory control composite, and finally to Matrix Reasoning, does not explain the results. Instead, training-related improvement in inhibitory control could be seen as a separate form of (far) transfer, and the processes that underly this change seem to be somewhat independent. There was no systematic change in *Gf* tasks as a function of WM training, and N-back did not mediate transfer to this composite. The matrix reasoning task used here (called UCMRT) has been shown to correlate highly with performance on Raven's Advanced Progressive Matrices⁷⁰; however, the correlations between UCMRT and spatial visualization measures used here were much lower, especially for Surface Relations and Form Board (cf. Table 4), suggesting that the tasks share few communalities. While UCMRT requires some spatial visualization, it is thought to tap mainly into abstract reasoning and logical problem solving. Thus, it is possible that UCMRT captures variance that's shared with N-back but is different from the spatial visualization tasks used here.

Overall, our findings challenge the notion that WM training only leads to performance gains in tasks that are closely related to the training⁷¹ and indicate that untrained N-back tasks provide important information regarding the effectiveness of an N-back intervention and should therefore be included as an outcome measure in future work. It remains to be seen whether a similar association between untrained tasks and transfer applies to other types of cognitive training paradigms or other types of transfer measures, including those capturing real-world performance. x Moreover, these results can inform studies examining neuroplastic changes associated with WM interventions, predicting weaker far transfer effects in individuals who show little to no near

transfer, both in terms of behavior and related plastic neural changes. From a practical perspective, a near transfer test administered half-way or early in the WM training intervention could indicate the likelihood of far transfer. If participants struggle in near transfer tasks at this point, and as such, far transfer appears unlikely, pivoting to a different type of intervention or providing additional support in terms of effective strategy use⁷² could be beneficial to study outcomes (but see⁷³). This simple yet presently untested step could help maximize the effectiveness of WM training interventions.

In sum, it is not surprising that inter-individual differences in responsiveness to WM training interventions exist^{74,75} - in non-invasive brain stimulation studies^{76,77} or other intervention studies, such as those focusing on physical exercise or nutrition⁷⁸⁻⁸¹, ‘non-responders’ are routinely excluded from data analyses or treated differently. To fully understand the underlying mechanisms of WM training, future research should depart from the traditional approach that attempts to determine whether an effect is present or not, and instead focus on how, for whom and why these effects occur^{30,82}. With the rise of precision medicine⁸³, investigating the efficacy of personalized cognitive training interventions^{84,85} will become increasingly important and ultimately, maximize intervention outcomes.

Methods

Retrospective study

Participants

Our sample consisted of 283 participants from the Universities of California, Riverside and Irvine, collected over two academic years: Winter - Spring 2017 ($N_{RCT1} = 102$) and Fall 2017 - Spring 2018 ($N_{RCT2} = 181$). Participants were randomly assigned either to N-back training ($N = 191$) or to no-contact control ($N = 92$)^(d) and completed all sessions in laboratories at the respective universities. They were included if they completed all pre- and post-assessments as well as at least 8 out of 10 training days (N-back training group). Participants provided informed consent and received monetary compensation for participation. The sample was relatively diverse, with 31-40% of participants identifying as Hispanic or Latinx and 42-44% identifying as Asian (Supplementary Table 6). All procedures were approved by the UCR and UCI Institutional Review Boards.

Procedure

Training and testing were administered on tablet computers via software developed in-house (“Recollect the Study”⁸⁶)^e, in combination with Qualtrics Software used to administer surveys and certain assessments (Qualtrics, Provo, UT). Participants completed pre- and post-test with a 10-day gap (excluding weekends), and in addition, the N-back training groups completed up to 10 working days of training. Across both RCTs, a variety of assessment tasks were used, including measures of WM, selective attention, mathematical problem solving, decision making, and convergent thinking, however, in order to maximize power, here, we only focus on the results of

^(d) Unequal sample size reflects randomization to multiple training conditions and one no-contact condition.

^e The same software for testing and training was used in both experiments.

the 3 tasks that were used by both RCTs and which did not undergo major changes from one year to the next^(f). Moreover, our goal was to test the specific hypothesis that a simple mediation model focusing on N-back and Matrix Reasoning can explain a substantial amount of variance in the data.

Training tasks

N-back training. Participants trained on an N-back task (“Recollect the Study”⁸⁶) for 10 working days, each day consisting of two 20-minute training sessions separated by a 10–20 minute break. Training parameters were varied in that they differed in terms of N-level progression, gamification, and reinforcement, but since these are not relevant to the present hypothesis, the data were collapsed across N-back training conditions. To provide context, in gamified N-back training, participants played a platform game called “Recollect the Study” (video can be found here: <https://www.youtube.com/watch?v=zhgL8Oe42Yk>) in which they were tasked with collecting stimuli that match those presented N items earlier. Stimuli consisted of simple colored objects and were paired with unique sounds to support multisensory processing of said objects⁵⁹. In nongamified N-back training (“Tapback”: <https://www.youtube.com/watch?v=GMGiDnJ53RU>), a series of colored circles was presented on a plain background and the participant tapped on the circles that were the same color as those presented N items earlier. In all training paradigms, stimuli were presented for 2500 ms (ISI = 500 ms), of which 30% were targets and another 30% lures (e.g. items that occur N-1 or N+1 of the target position)⁸⁶. The session was broken into short ~2 minute training blocks with typically 7-10 blocks per training session. Auditory and visual feedback was presented on every trial indicating correct or incorrect responses. Task difficulty was adaptively adjusted based on performance either

^(f) Many of the measures not included here were being continuously developed for the use of tablets and were included in the studies for validation purposes.

within or between blocks depending upon the training condition. The outcome measure used here was average N-level per day (weighted across the number of trials within each block).

Near transfer N-back. We used an untrained N-back task with two versions, featuring pictures of animals or vehicles. The versions were counterbalanced across individuals and sessions, with the exception of 40% of participants in RCT 1, who completed the same version twice due to a technical error⁽⁹⁾. All participants completed 1-back, followed by 2- and 3-back tasks. Before each level started, there were 10 trials of practice during which performance feedback was provided. In RCT 1, the test phase for each N-level consisted of 20 + N trials with 6 targets, whereas in RCT 2, each N-level consisted of 30 + N trials with 9 targets (30% target and 30% lure rates in both RCTs). Progression to 4-back (and beyond) was allowed if the participant made no more than 2 errors on the previous level, otherwise, the task stopped at 3-back. Accuracy was calculated for each N-level as hits/(hits + misses + false alarms), allowing for comparison across RCTs. 1-back accuracy was very high (RCT 1: Mean_{pre} = .88, SD_{pre} = .18, Mean_{post} = .94, SD_{post} = .14; RCT 2: Mean_{pre} = .90, SD_{pre} = .16, Mean_{post} = .95, SD_{post} = .11;) and only 7.4% and 4.8% of participants reached N-levels higher than 3 at pre-test respectively, thus, we used average accuracy across 2-back and 3-back levels as the dependent variable (at least 40 + N trials per participant).

Matrix Reasoning. Matrix reasoning problems were used to assess nonverbal problem solving ability⁸⁷. Different versions of the test were used at pre-test and post-test, counterbalanced across participants. While the number of problems and certain design features differed in the two RCTs, the basic structure of the task remained the same. Namely, each problem consisted of a 3 x 3 matrix with the lower right entry missing, and the participants were asked to select 1 out of 8 answer

⁽⁹⁾ Mann-Whitney tests indicated that there were no significant performance differences at post-test as a function of test version (different versus the same) in the no-contact ($U = 40$, $z = -.54$, $p = .88$) and N-back training ($U = 624$, $z = -1.01$, $p = .27$) groups.

options that best completes the matrix. Prior to the test phase, participants were presented with example problems and the opportunity to practice the task, during which feedback was provided. In RCT 1, participants were required to solve 42 problems with a time limit of 20 minutes⁸⁷, whereas in RCT 2, participants solved 23 problems with a time limit of 10 minutes (UCMRT)⁷⁰. The main outcome measure in both RCTs was the proportion of correctly solved problems; for RCT 1 there was a larger number of easy problems (i.e. one- and two-relation problems) than used in RCT 2, hence, accuracy was higher for RCT 1 (cf. Table 1).

Countermanding task. A modified countermanding task was used to assess inhibitory control^{88,89}. A series of pictures appeared either on the left or the right of the screen and participants were instructed to quickly and accurately tap one of 2 buttons presented below. The task involved pressing the button on the same side of the screen in response to pictures of a dog (congruent trials) and the button on the opposite side in response to pictures of a monkey (incongruent trials). There were 3 blocks of trials, each preceded by a practice session: block of 12 congruent trials, block of 12 incongruent trials, and a mixed block of 48 trials where congruent and incongruent trials were randomly intermixed. The main dependent measure was reaction time (RT) for correct responses on incongruent trials of the mixed block^(h) (index of inhibitory control).

Outliers and Exclusions

Six outliers were removed from the sample based on performance on near transfer and matrix reasoning ($|Z_{\text{accuracy}}| > 3$ at pre- or post-test separately for each RCT). In the N-back training group, 6 additional participants were removed due to a software error in the training program. The final

^(h) All RCTs showed high accuracy in the mixed block: 97% on average or higher at pre-test and post-test.

analytical sample consisted of 271 participants, 181 in the N-back training group and 90 in the no-contact control group (cf. Table 4).

Table 4: Demographics of the two studies.

	RETROSPECTIVE STUDY				REPLICATION STUDY	
	RCT 1		RCT 2		RCT 3	
	N-back training	No-contact control	N-back training	No-contact control	N-back training	Active control
Age	19.96 (1.75)	20.56 (1.72)	20.01 (2.90)	20.26 (2.35)	20.70 (4.07)	20.50 (1.82)
Female	55.56	36.36	61.47	73.53	76.56	81.97
Male	41.67	45.45	37.61	22.06	21.10	18.03
Gender Unknown	2.78	18.18	0.92	4.41	2.34	0
N	72	22	109	68	128	61

Note. Mean age in years with standard deviation in brackets, gender (%) and sample size (N). Ethnicity/race is reported in Supplementary Table 6.

Data analysis

Bayesian Paired Samples T-Tests with default priors were used to estimate changes in performance as a function of time separately for each condition and RCT (cf. Table 1) in JASP⁹⁰. All variables were z-transformed (based on pre-test scores, separately for each RCT) prior to regression-based analyses to control for RCT effects. Linear regression was used to test the relative contributions of training group (N-back training, Control), pre-test Matrix Reasoning scores, pre-test N-back, and pre-test Countermanding on post-test performance on Matrix Reasoning. We checked for multicollinearity, heteroscedasticity, and independent errors using a Durbin-Watson test⁹¹, and found these to be in appropriate ranges.

To determine whether the relationship between training group and matrix reasoning (far transfer) was mediated by near transfer, we conducted mediation analyses using ordinary least squares

regression via the PROCESS macro in SPSS³⁷. Performance on the Countermanding task was entered as a parallel mediator. In the next step, each RCT was evaluated separately using the same parallel two-mediator models. The independent variable was training group (N-back training, Control), the mediators were average post-test performance on untrained N-back tasks and average RT on incongruent trials of the Countermanding task, and the dependent variable was post-test performance on Matrix Reasoning. Note that no mediator was modelled as influencing another mediator in the model. To control for pre-existing individual differences in cognitive ability, we entered performance for the three aforementioned tasks as covariates. Since the antecedent variable is an experimental variable in a randomized study, its causal relation to the mediator and the outcome variable can be interpreted unambiguously^{92,93}. Since the post-test data was collected within the same session, causality between the mediator and the outcome variable cannot be established unequivocally; that said, we defend this causal claim on theoretical grounds, which should be sufficient to allow for interpretation of the model³⁷. However, to address this limitation, in the replication study, near transfer performance preceded post-test performance on Matrix Reasoning and other Gf tasks by 1 day, hence it represents a plausible causal agent for these outcome measures (see below).

Pre-registered replication study

Participants

A second experiment was conducted at the same universities in Summer and Fall of 2020 to investigate whether the mediation model replicates in a double-blind RCT with two N-back training groups and an active control group (cf. Table 2). The experiment was preregistered on AsPredicted (#40240) and was conducted online due to the COVID-19 pandemic. Participants

were randomly assigned to one of three groups: Gamified N-back training, Non-gamified N-back training, and General knowledge training (control group), with a target sample size of 64 participants per condition as determined by a power analysis for two-mediator models using Monte Carlo simulations in MPLUS. We recruited 258 participants, 201 of which completed all training and assessment sessions ($N_{\text{Gamified N-back}} = 70$, $N_{\text{Nongamified N-back}} = 67$, $N_{\text{control}} = 64$). Participants provided informed consent and received monetary compensation for participation; all procedures were approved by UCR and UCI Institutional Review Boards. As can be seen in Table 4 and Supplementary Table 6, sample demographics resemble those reported for the retrospective study. Unless stated otherwise, procedures, tasks, and training details match those described in the retrospective study.

Procedure

Since additional tasks were added to be able to examine latent constructs, the experiment consisted of 3 pre-test and 3 post-test sessions, with 3-4 tasks per session to prevent fatigue associated with prolonged testing. Supervision was provided via Zoom for all pre- and post-test sessions, as well as the first training session, and any additional sessions as needed, along with technical support via e-mail and phone. Different experimenters supervised pre/post-test sessions versus training sessions to ensure experimenter blinding; likewise, participants were not aware that there were multiple training conditions and which one they had been assigned to.

Training tasks

N-back training. The same training task was used as in the retrospective study and participants were encouraged to follow the same training protocol, i.e. to complete two 20-minute sessions per day over the course of two weeks. The program was set up to prevent access to more than two sessions in 24 hours. Participants were assigned to gamified or non-gamified N-back training as described in the retrospective study. Half of the participants in each N-back training group trained on a slightly different adaptive algorithm: miniblock-reset (each session starts at 2-back, level up: <3 errors in 40-trial block, level down: >6 errors in 40-trial block) and online weighted accuracy (level up: accuracy > 70%, level down: accuracy < 50%), which were collapsed for the purposes of the current analysis.

General knowledge training. Participants in the active control group trained on a task that consists of general knowledge, vocabulary, social science, and trivia multiple-choice questions as used previously^{75,94}. They were encouraged to follow the same schedule as the N-back training group (two 20-minute sessions per day). This task was selected for the control intervention because it taps into crystallized intelligence and should not engage fluid intelligence or WM. Previous research has shown that participants find this task engaging and enjoyable^{30,75}.

Transfer measures

The first and the last assessment sessions, which consisted of surveys and ETS and DAT tests, were administered via Qualtrics (Qualtrics, Provo, UT), whereas the rest were implemented within “Recollect the Study”. All assessment sessions were supervised via video conferencing by a researcher who was blind to the training condition the participant had been assigned to. Alternate versions⁵¹ of ETS Surface Development Test, ETS Form Board Test, and DAT Space Relations

were grouped (As and Bs together) for administration at pre- and post-test, the order of which was counterbalanced across participants. Alternate versions of Near transfer N-back, Running Span and Matrix reasoning were administered at pre- and post-test in an counterbalanced order (A-B, B-A).

Near transfer N-back. The same task was used as in the retrospective study, except that the vehicle stimulus set was replaced with pictures of fruit. The main dependent variable, average accuracy across 2-back and 3-back levels at pre-test, was comparable across experiments for the two stimulus sets (Retrospective study - vehicles: $\text{Mean}_{\text{pre}} = 0.57$, $\text{SD}_{\text{pre}} = 0.16$; Replication study: – fruit: $\text{Mean}_{\text{pre}} = 0.60$, $\text{SD}_{\text{pre}} = 0.14$).

Running Span. An updating WM task in which participants saw an unpredictable number of stimuli and were asked to report the last N items. The same stimuli were used as in Near transfer N-back (animals and fruit), but with different stimulus sets presented at pre- and post-test across the two tasks. Stimuli were presented for 500 ms with an ISI of 1500 ms. Before each trial, the participants were told how many items they will need to report. The response screen featured a “keyboard” of pictures of 8 stimuli (always shown at the same locations) and the participants were asked to select the last N pictures in order of appearance. The task started with 2 practice trials (set sizes 2 and 3) and if at least one trial was incorrect, practice was repeated. Feedback was provided during practice but not during the assessment. The assessment consisted of set sizes 2-4 (in that order) with 3 trials per set size. Progression to set size 5 (and beyond) was contingent upon having at least 2 out of 3 trials correct on the previous set size. The main dependent measure was the sum of all correctly recalled items (partial score), whereby each item correctly chosen in the correct serial position was assigned one point⁹⁵.

640 *Sequencing.* Participants were presented with a mixed sequence of letters and numbers that
641 appeared one by one, and were asked to enter the numbers in numerical order followed by letters
642 in alphabetical order⁵⁹. The main dependent variable was the sum of all correctly recalled trials
643 (score).

644 *Simple and Complex Spatial Span.* Simple Span was used to assess spatial WM storage while
645 Complex Span was used to measure WM storage-and-processing⁹⁶. In Simple Span, a sequence of
646 gophers appeared in 12 possible locations and the participants were tasked with reproducing the
647 sequence by tapping on the locations. In Complex Span, the same procedure was adopted, except
648 that in between each appearance of a gopher the participant completed a secondary sorting task
649 (dragging an item to the left or right). This secondary task presents interleaved processing demands
650 that are thought to limit the use of mnemonic strategies, such as chunking. In both tasks, set size
651 (i.e. the number of gopher locations in the sequence) ranged from 2 to 10; the test started with the
652 lowest set size and then increased (or decreased) using an adaptive algorithm. The main dependent
653 measure for each task was the sum of all correctly recalled items (partial-credit scoring⁹⁷).

654 *Countermanding.* The same task was used as in the retrospective study.

655 *Cancellation.* A timed test of selective attention and inhibitory control that has been validated
656 against the D2 Test of Attention (Brickenkamp & Zillmer, 1998)ⁱ. Participants were presented with
657 a series of rows featuring pictures of dogs or monkeys, some of which had inverted colors and
658 were reflected over the vertical axis or presented upside down. There were two types of targets: an
659 upright dog and an upside-down monkey and there were 3-5 of these targets per row. The goal was
660 to select all targets from left to right within a 6-second time limit. Each target type was practiced

ⁱ Manuscript under review in Behavior Research Methods

separately in 2 single blocks prior to proceeding to a mixed block. If a participant cleared a row before the 6-second time limit, they could press a button to continue to the next row, thus, participants completed bonus rows if a global time limit of 3 minutes and 10 seconds was not exceeded. The main dependent measure was Concentration Performance ($\sum \text{Hits} - \sum \text{False alarms}$) in the mixed block.

Matrix reasoning. The same matrix reasoning task, UCMRT, was used as in RCT 2⁷⁰.

ETS Surface Development Test^{75,98,99}. Surface Development involves visualizing how a piece of paper could be folded to form an object. Two images were presented on a computer screen: an unfolded piece of paper and an object and participants were asked to mark which edges go together. One practice problem was followed by 6 test problems, with a time limit of 6 minutes. The dependent variable was the proportion of correct responses within the time limit.

ETS Form Board Test^{75,99,100}. A given trial consisted of a set of five two-dimensional shapes that can be combined into a two-dimensional geometrical shape presented above the set. The goal was to indicate which of the pieces can be combined to match the geometrical shape given at the top of the page. Participants were given two practice problems and then 8 minutes to solve 24 problems. The dependent variable was the proportion of correctly solved items in the given time limit.

DAT Space Relations^{75,99,101} Participants were presented with a target pattern and four possible objects and were asked to select the appropriate object into which the pattern can be folded. Two practice problems preceded 17 test items, with a 5-minute time limit to complete the test. The dependent variable was the number of correctly solved items in the given time limit.

Outliers

Out of 201 participants who completed the study, 6 participants were removed due to administration error on ETS and DAT tests. Outliers were removed if a given data point was 3 or more standard deviations from the mean at pre- or post-test. No outliers were removed for Near Transfer or Matrix Reasoning; 6 outliers were removed based on Countermanding speed, hence the resulting sample size was 189 (128 N-back training, 61 Active control; cf. Table 2). This dataset was subject to initial replication mediation analyses. In the next step, additional outliers were removed for Running Span (N=8) as well as 11 participants who showed non-compliance on Sequencing and Spatial Span tasks. This second analytical dataset, which consisted of 170 participants (115 N-back training, 55 Active control) was used for the additional mediation analyses that included additional assessments /composite scores.

Composite variables

Pre-test correlations of performance on the test battery revealed significant correlations among all measures (cf. Table 5) except for Running Span, which correlated only with Sequencing, moreover, it showed the lowest test-retest reliability among measures as indicated by the pre-post correlation observed in the active control group ($r = .35$), hence it was excluded from subsequent analyses. Principal component analysis (PCA) with oblimin rotation was used to identify composite scores. The sample size for PCA was adequate ($KMO = .79$), Bartlett's test of sphericity was significant ($\chi^2(45) = 387.55, p < .001$), the diagonals of the antiimage correlation matrix were all over .7, and the communalities were all above .3, thereby confirming that each measure shared some common variance with other measures. A three-factor solution was obtained, which explained 58.5% of the variance (cf. Supplementary Table 7). The following factors were

identified: inhibitory control (Countermanding, Cancellation), reasoning ability (UCMRT, ETS Surface Development Test, ETS Form Board Test, DAT Space Relations), and working memory (Near transfer N-back, Sequencing, Simple Span, and Complex Span), which is in line with the theoretical structure proposed during preregistration. Composite variables were created by taking the mean of z-transformed dependent variables which had their primary loadings on each factor. Note that for models in which Near Transfer was used as a separate mediator, the WM composite consisted only of Sequencing and Simple and Complex spatial span tasks. For IC, the values on Countermanding were reversed so higher value indicates better performance.

Table 5: Pre-test correlations in the Replication Study. Shaded areas represent working memory (WM), inhibitory control (IC) and reasoning (Gf) composites.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Near Transfer	1.00										
2. Sequencing	.30**	1.00									
3. Simple Span	.24**	.24**	1.00								
4. Complex Span	.25**	.28**	.48**	1.00							
5. Running Span	.12	.27**	.05	.13	1.00						
6. Cancellation	.29**	.14	.26**	.38**	.04	1.00					
7. Countermanding	-.27**	-.11	-.26**	-.29**	-.11	-.57**	1.00				
8. UCMRT	.27**	.22**	.27**	.34**	.07	.28**	-.27**	1.00			
9. ETS SD	.29**	.19*	.13	.39**	.12	.25**	-.14	.47**	1.00		
10. ETS SR	.13	.09	.11	.17*	.15	.02	-.01	.22**	.48**	1.00	
11. DAT FB	.31**	.22**	.19*	.43**	.17*	.27**	-.14	.37**	.64**	.44**	1.00

Note. $N = 170$; * = $p < 0.05$, ** = $p < 0.01$. UCMRT = Matrix reasoning task, ETS SD = Surface Development, ETS SR = Space Relations, DAT FB = Form Board.

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726 **Data Availability:** The data that support the findings of this study are available from the
727 corresponding author upon reasonable request.

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