Evidence for separate backward recall and n -back working memory factors:

A large-scale latent variable analysis

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ABSTRACT

There is growing interest in understanding what constrains transfer following working memory (WM) training with recent studies investigating what limits transfer within and across different WM paradigms. The primary aim of the current study was to conduct a large-scale latent variable analysis to identify distinct properties between WM tasks to provide further insight into task features that might constrain transfer following training. A secondary aim was to explore how the resulting WM factor(s) were linked to *Gf*. Participants ($N = 703$) completed multiple web-based versions of *n*-back and backward recall tasks and a test of non-verbal reasoning. The memory tasks contained different memoranda that varied across (spatial or verbal material) and within (verbal digits or letters) domain, allowing the variance specific to task content and paradigm to be assessed. The data were best-captured by two distinct but related backward recall and *n*-back constructs, each linked to a separate reasoning factor, in comparison to other plausible model constructions (including a single WM factor, two-factor domain, and three-factor materials model). This suggests these WM tasks measure distinct paradigm-specific processes, but share common variance with one another and with a reasoning task. The benefits of cognitive training targeting a single paradigm are therefore likely to be limited to the same paradigm. For broader transfer it will be necessary to target what is shared across paradigms.

KEYWORDS

Working memory, backward recall, *n*-back; fluid intelligence, latent variable analysis

INTRODUCTION

Working memory (WM) supports a wide range of complex behaviours, including reading comprehension, following instructions, and problem-solving (Feldman Barrett, Tugade, & Engle, 2004; Jaroslawska, Gathercole, & Holmes, 2018). WM tasks have been used increasingly over the past 15 years as training tools to improve cognitive function (see Simons et al., 2016 for a review). There is broad consensus that the benefits of practice on WM tasks are largely confined to trained tasks and untrained memory tests that are highly similar to the training activities (e.g. Blacker, Negoita, Ewen, & Courtney, 2017; Cortese et al., 2015; Melby-Lervåg & Hulme, 2013; Redick, Shipstead, Wiemers, Melby-lervåg, & Hulme, 2015; Schwaighofer, Fischer, & Bühner, 2015). This has sparked interest in understanding the task features that must overlap for transfer to occur (e.g. Byrne, Ewbank, Gathercole, & Holmes, 2019; Gathercole, Dunning, Holmes, & Norris, 2019; Holmes, Woolgar, Hampshire, & Gathercole, 2018; Minear et al., 2016; von Bastian, Langer, Jäncke, & Oberauer, 2013). The aim of this study is to conduct a large-scale latent variable analysis using variant forms of WM tasks to investigate their underlying factor structure. Identifying overlapping properties between tasks will provide further insight into task features that might constrain transfer following training.

The protocol for this study was preregistered with the Open Science Framework (<https://osf.io/h7yxm/register/565fb3678c5e4a66b5582f67>) and the data were collected online via Prolific Academic (www.prolific.ac; Palan & Schitter, 2018; Peer, Brandimarte, Samat, & Acquisti, 2017). This study is the first, to our knowledge, to both preregister a latent variable analysis of WM tasks and to test whether online data collection methods can be used to detect WM factors comparable to those identified by data collected in the lab. The

meta-scientific outcomes of the study using these methods have important implications for the broader scientific community.

WM paradigms combine the temporary storage of information with additional processing requirements such as reversing a sequence (backward recall), updating the contents of WM (*n*-back), or handling interpolated distractor tasks (complex span). There are verbal (digits, letters) and visuo-spatial (spatial locations) variants of each of these paradigms, and in the case of complex span tasks the distractor items can also vary by domain. Multiple latent variable analyses have examined the construct validity of WM tasks, and individual differences studies have explored how WM tasks predict other complex cognitive tasks such as fluid reasoning (Alloway, Gathercole, & Pickering, 2006; Chuderski, 2013; Engle, Tuholski, Laughlin, & Conway, 1999; Kane, Conway, Miura, & Colflesh, 2007; Oberauer, Süß, Schulze, Wilhelm, & Wittmann, 2000; Schmiedek, Hildebrandt, Lövdén, Lindenberger, & Wilhelm, 2009; Shamos et al., 2008).

Complex span tasks containing different memory items and distractor activities correlate extremely well with each other and with other measures of WM, including updating tasks such as *n*-back (e.g. Schmiedek, et al., 2009). They also predict performance on tests of language comprehension (Daneman & Carpenter, 1980; Kane et al., 2004), attentional control (Kane, Conway, Hambrick, & Engle, 2008), and general fluid reasoning (*Gf*; e.g. Schmiedek et al., 2009). Associations between different forms of *n*-back and other WM paradigms are weaker (Dobbs & Rule, 1989; Jaeggi, Buschkuhl, Perrig, & Meier, 2010; Jaeggi, Studer-Luethi, et al., 2010; Kane et al., 2007; McAuley & White, 2011; Miller, Price, Okun, Montijo, & Bowers, 2009; Redick & Lindsey, 2013; Roberts, 1998; Roberts & Gibson, 2002), and *n*-back has been used less often to predict other cognitive abilities (Kane et al., 2007).

Few studies have validated backward recall tasks against other tests of WM, and those that have done so typically focus on backward digit recall (BDR; e.g. Hilbert, Nakagawa, Puci, Zech, & Bühner, 2015). This task relies on short-term memory serial order mechanisms to maintain digit sequences. The additional requirement to recall items in reverse order imposes a substantial attentionally-demanding processing load similar to the executive loads of other WM tasks (Alloway et al., 2006; Bull et al., 2008). Evidence that backward span is more strongly related to *n*-back than to simple forward span tasks (Redick & Lindsey, 2013), and that it is associated with reasoning ability (e.g. Suß et al., 2002), supports the argument that backward recall has an executive component (although see Colom, Abad, Rebollo, & Shih, 2005; Engle, Laughlin, et al., 1999; St-Clair Thompson & Allen, 2013 for arguments that BDR is a short-term memory task). Indeed, Redick and Lindsey (2013) reported that the correlation between *n*-back and backward digit span ($r = .31$) was greater than the correlation between *n*-back and verbal complex span ($r = .18$), suggesting not only that it shares variance with other widely used WM tasks, but also that it may have more in common with some WM paradigms than others.

There are a number of methodological issues that limit the conclusions that can be drawn from the majority of previous studies exploring shared variance between WM tasks (Schmiedek et al., 2009; Schmiedek, Lovden & Lindenberger, 2014; Wilhelm, Hildebrandt, & Oberauer, 2013). First, task associations could be reduced due to a mismatch of content modality across paradigms (e.g. differences in the domain or category of the memory items). For example, weak correlations between *n*-back and complex span reported by Kane et al. (2007) could reflect differences in task stimuli (*n*-back contained letters, complex span combined word recall with numerical operations), rather than differences in paradigm.

Using a single indicator for each paradigm can also be problematic because variants of the same paradigm can provide different indices of an underlying factor. For example, Kane et al. (2004) reported that different complex span tasks (operation, reading, counting, navigation, rotation, or symmetry span) explained different amounts of variance in a single underlying WM construct. Using a single measure for any paradigm therefore introduces task-specific variance into latent models (Shipstead, Redick, & Engle, 2012). When performance is averaged across multiple versions of a WM task, stronger associations are found between constructs (Schmiedek, Lövdén, & Lindenberger, 2014). For example, Shamosh et al. (2008) reported a higher correlation between latent factors of two *n*-back tasks and four complex span tasks than Kane et al. (2007) who measured associated measures of performance on single *n*-back and complex span tasks.

In the present study we use a latent variable analysis to test whether backward recall and *n*-back measures of WM tap into the same underlying construct, or whether the tasks are distinguished by stimuli-, domain-, or paradigm-specific factors. The two paradigms have been reported to be weakly associated in previous studies (Dobbs & Rule, 1989; McAuley & White, 2011; Miller et al., 2009; Roberts, 1998; Roberts & Gibson, 2002; and for a meta-analysis, see Redick & Lindsey, 2013), but these studies have been limited by the shortcomings of using single task indicators and not controlling for the influence of domain- and task-specific variance. To address these issues, we included multiple indicators of WM that vary the overlap in task properties by WM paradigm (backward recall, *n*-back), stimulus domain (verbal, visuo-spatial), and stimulus material (digits, letters). Confirmatory factor analysis was used to test four competing models of the underlying structure of the tasks.

In the second stage we explore the association(s) between the WM factor(s) and fluid reasoning to test whether there is a single underlying general ability factor for all tasks (e.g. a

‘*g*’ factor; Duncan et al., 2000), or distinct but related constructs corresponding to WM and reasoning (e.g. Schmiedek et al., 2009, 2014). There is an ongoing debate about whether WM determines *Gf* by limiting mental information processing capacity (Ackerman, Beier, & Boyle, 2005; Chuderski, 2013; Fukuda, Vogel, Mayr, & Awh, 2010; Oberauer, Schulze, Wilhelm, & Süß, 2005), or whether high correlations between WM and *Gf* tests indicate that they are isomorphic constructs (Kyllonen & Christal, 1990). Recent work showing these correlations are only present under high time constraints for *Gf* tasks (Chuderski, 2013), suggests that *Gf* and WM are, in fact, separable constructs. The *Gf* task in the current study was timed, allowing us to test whether the tasks load on to a single underlying construct when a large sample is used.

Our first candidate model is a single-factor WM model where all backward recall and *n*-back tasks load on one factor (see Figure 1A). This is consistent with domain-general theories of WM proposing that performance on WM tasks is dependent on a domain-general central executive or attentional control system (Alloway et al., 2006; Baddeley, 1986; Engle & Kane, 2004; Engle, Kane, et al., 1999; Kane et al., 2004). In relation to training studies, improvements in one paradigm should generalise to other paradigms (e.g. Klingberg, 2010).

Our second candidate model is a two-factor, domain-specific model. Such models propose that separate pools of resources support the maintenance and processing of verbal and visuo-spatial information (Daneman & Tardif, 1987; Friedman & Miyake, 2000; Shah & Miyake, 1996). If this is the case, the benefits of training should be restricted to untrained tasks containing the same-domain materials (Minear et al., 2016). The two-factor model encompassed distinct but related verbal and visuo-spatial factors, and is shown in Figure 1B.

Our third candidate model tested was a two-factor paradigm model (e.g. Schmiedek et al., 2009). Both backward recall and *n*-back tasks require the temporary maintenance and

processing of information but differ in terms of processing demands (e.g. backward recall requires explicit serial recall, whereas an *n*-back task involves recognition-based responses; Oberauer, 2005). Patterns of transfer following WM training indicate that WM tasks might group based on paradigm-specific processes. WM paradigm is a boundary condition to transfer following training – transfer is rarely observed across paradigms (Byrne et al., 2019; Dunning & Holmes, 2014; Gathercole et al., 2019; Holmes et al., 2018; Li et al., 2008; Minear et al., 2016; Redick et al., 2013; Sprenger et al., 2013; Thompson et al., 2013). However, the stimulus domain of the memory items (i.e. verbal or visuo-spatial) and category of materials within paradigm (e.g. letters or digits) do appear to prevent transfer (Byrne et al., 2019; Holmes et al., 2018; Minear et al., 2016). The two-factor paradigm model assumes a correlation between two distinct backward recall and *n*-back latent constructs. This candidate model is shown in Figure 1C.

The final model tested was a three-factor ‘materials’ model that assumed performance across the tasks would be best captured by expertise related to the specific type of stimuli (e.g. basic skills or knowledge tied to digits, letters, or spatial materials). Within the training literature it has been suggested that transfer might be mediated by the acquisition of content-specific skills and knowledge (von Bastian & Oberauer, 2014). This three-factor model assumed separate constructs for each category of memory item as follows: (i) *n*-back with digits and backward recall with digits; (ii) *n*-back with letters and backward letter recall; and (iii) *n*-back with spatial locations and backward spatial recall. This model is shown in Figure 1D.

Figure 1. Candidate models for the primary analyses. Models A (single-factor working memory), B (two-factor domain), C (two-factor paradigm), and D (three-factor materials). Ovals represent latent factors and observed variables are shown in squares. BDR = backward digit recall, BLR = backward letter recall, BSR = backward spatial recall, NBD = n -back with digits, NBL = n -back with letters, NBS = n -back with spatial locations.

METHOD

Participants

Seven-hundred and seven native-English speaking participants aged 18-35 completed this study and were paid for participation. All had normal or corrected to normal vision, and no literacy difficulties. Data was excluded for four participants who did not follow the study instructions correctly. A total sample size of 703 participants (421 female) was used for the analyses. Participants were recruited through Prolific Academic (www.prolific.ac/; Palan & Schitter, 2018; Peer, Brandimarte, Samat, & Acquisti, 2017) and completed the tasks online. Informed consent was obtained online prior to testing. The study was approved by and

conducted in accordance with the guidelines of the University of Cambridge Psychology Research Ethics Committee (Reference: PRE.2017.001).

Procedure

Each participant completed six memory tasks and a fluid reasoning task in a single session according to one of 12 possible task orders. The backward recall tasks were grouped together (i.e. completed consecutively), and the n -back tasks were also grouped together. The task order within these two groups was counterbalanced (i.e. all possible permutations for the three tasks were used), yielding six orders for each of the two groups of tasks. The order of the two groups of backward recall and n -back tasks was then counterbalanced, resulting in six possible task orders in which the backward recall tasks were completed first, and six in which the n -back tasks were completed first. An additional reasoning task was completed in between the n -back and backward recall tasks in all conditions (i.e. it was always the fourth task completed). Participants completed practice trials before starting each task. Feedback for correct and incorrect responses was shown on screen for the practice trials, but was not provided during the proper tasks.

Materials

The tasks were created using the software program Gorilla (www.gorilla.sc; Anwyl-Irvine, Massonnié, Flitton, Kirkham, & Evershed, 2018). Participants completed the study on a laptop or desktop computer, and all responses were made using a mouse or keyboard.

Backward recall

Participants completed three backward recall tasks each containing different stimuli: (i) digits (1 to 9), (ii) letters (B H J L N Q R X Z), or (iii) spatial locations (nine random but fixed locations on the computer screen). Trials were presented in blocks, with each block

consisting of four trials. During each trial, items were presented visually one at a time (stimulus presentation = 750 ms, inter-stimulus interval = 250 ms). Participants were then prompted to recall the sequence in backward order via an onscreen keypad of digits, letters, or spatial locations. Participants began each task at a span of three items. Span length was increased by one item in each subsequent block if there were three or more correct responses out of the four trials at that length. The tasks were discontinued if two or more trials were incorrect within a block, or if the highest possible span level was reached (13 items). For each of the backward recall tasks, we scored participants according to their maximum span (i.e. the final span length in which the participant met the criterion of at least three out of four correct trials).

n-back

Participants completed three *n*-back tasks, each containing different stimuli: (i) digits (1 to 9), (ii) letters (B H J L N Q R X Z), or (iii) spatial locations. For each task, stimuli were presented one at a time on screen in a random order (stimulus presentation = 760 ms, inter-stimulus interval = 2000ms). Participants were required to indicate whether the current item on screen matched the one presented *n* items back in the sequence via a button press. In each block participants were presented with a continuous sequence of $20 + n$ items, during which there were a total of six possible targets (matches) and $14 + n$ non-targets. An error was scored if participants pressed the button for a non-target (false alarm), or if participants failed to press the button when a match was present (miss). Total errors were calculated as false alarms plus misses. The first block began at one-back and difficulty level was increased by one in each subsequent block if fewer than five errors were made (e.g. an increase from one-back to two-back). The task ended if five or more errors were made within a block, or if the highest possible level was reached (12-back). We scored each of the *n*-back tasks according

to the maximum *n*-level that the participant reached (i.e. the final level in which the participant met the criterion of less than five errors in a block).

Relational reasoning

Participants were presented with 80 puzzles one at a time (Knoll et al., 2016). The stimuli were developed from a set of materials that have recently been normed (Fuhrmann, Chierchia, Knoll, Sakhardande, & Blakemore, 2018). Although the stimuli used here are not identical to those normed by Fuhrmann et al. (2018), they were developed from the same source. Each puzzle consisted of a 3 x 3 matrix (nine spaces in total). Eight of the spaces contained shapes, and the bottom right space was always empty. Participants were also presented with four boxes at the bottom of the screen containing shapes, and were required to select the box with the correct answer – the box containing the piece that was missing from the empty space in the matrix. The shapes in the matrix varied by colour, size, shape, and position. Difficulty level also varied. Participants were given 30 s to complete each trial, and a prompt appeared on screen when only 5 s remained. Odd and even items were scored separately to generate two relational reasoning scores (so that a latent reasoning factor could be formed using the two measures for the secondary analyses). In each case the number of correct responses (out of 40) was used.

Analysis plan

To address the primary research question, we ran a series of confirmatory factor analyses to determine which of the four candidate models best explain the covariance structure among the six WM tasks. The following models were compared: (A) a single WM factor model, (B) a two-factor domain-specific verbal and visuo-spatial construct model, (C)

a two-factor backward recall and *n*-back paradigm model, and (D) a three-factor digit, letter, and spatial materials model.

After establishing the best-fitting WM model for the variables, a set of analyses were conducted to test how the two classes of WM measures were related to fluid reasoning. The parameters of the best-fitting WM model were fixed and a reasoning factor was added to explore whether the WM factor(s) and the reasoning tasks load on a single factor, or on distinct but related constructs. If a single-factor WM model was preferred, the plan was to examine whether the WM factor is very strongly or perfectly correlated with a fluid reasoning factor. Alternatively, if a multi-factor model was preferred, then the relationship between the WM factors and fluid reasoning would be examined to see whether the relationship was stronger for different WM sub-factors. The multi-factor models were compared to a single-factor general ability model including all WM and reasoning tasks.

Model fit and comparison

Models were estimated in the lavaan software package (Version 0.5-20; Rosseel, 2012) in R version 3.1.3 (R Core Team, 2015) using maximum likelihood estimation and robust standard errors, for which the Yuan-Bentler (YB) scaled test statistic is reported. Missing observations were dealt with using the full maximum likelihood (FIML) parameter estimation technique. The overall fit of each model was assessed using the χ^2 test, the comparative fit index (CFI; range: 0-1.0; acceptable fit: .95-.97, good fit: $\geq$.97; (Schermelleh-Engel, Moosbrugger, & Müller, 2003), and the root mean square error of approximation (RMSEA; range: 0-1.0; acceptable fit: $<$.08, good fit: $\leq$.05; Schermelleh-Engel et al., 2003) which is reported with 90% confidence intervals. The four models were also compared. When models were nested, they were compared via a likelihood ratio test (i.e.

the scaled χ^2 difference test); otherwise non-nested models were directly compared via the Akaike information criteria (AIC; Akaike, 1974).

RESULTS

The data and R analysis script of this study have been made openly available via the Open Science Framework online repository for this project, which can be accessed here: <https://osf.io/9qarp/>.

Preliminary analyses

The data were screened to identify outliers (i.e. scores deviating >3.5 SDs from the sample mean on each task). Twenty-nine observations were removed during data screening for outliers, and an additional 14 observations were missing due to technical problems during data collection (total missing observations = 37). Descriptive statistics are summarised in Table 1. Associations between tasks are displayed in Figure 2. All tasks were positively correlated (all $ps < .01$). The strongest patterns of association were observed between backward digit and backward letter recall ($r = .526$), and between the three n -back tasks (all $rs > .4$). The two relational reasoning scores were very highly correlated ($r = .91$), suggesting they are reliable indicators of the construct.

Table 1. Descriptive statistics for all variables

Variable	N	M	SD	$Skewness$	$Kurtosis$
Backward digit recall	698	5.307	1.695	0.479	-0.187
Backward letter recall	690	4.470	1.247	0.844	0.704
Backward spatial recall	702	5.068	1.214	-0.405	-0.734
n -back with digits	694	3.307	1.723	0.977	1.047
n -back with letters	698	3.032	1.658	0.757	0.380
n -back with spatial locations	699	2.774	1.511	0.984	0.591
Relational reasoning even	700	24.921	7.604	-0.096	-0.879
Relational reasoning odd	700	23.787	7.431	0.037	-0.683

Figure 2. Matrix of associations between pairs of tasks ($N = 703$). Simple correlation coefficients are displayed in the top segment (all significant at $p < .01$), density plots are shown along the diagonal, and scatter plots with trend lines are displayed in the lower section. BDR = backward digit recall, BLR = backward letter recall, BSR = backward spatial recall, NBD = *n*-back with digits, NBL = *n*-back with letters, NBS = *n*-back with spatial locations, RR_even = relational reasoning with even items, and RR_odd = relational reasoning with odd items.

Primary analyses

Confirmatory factor analysis was used to compare the preregistered measurement models of the six memory tasks. The models tested are displayed in Figure 1. Fit indices for each model are provided in Table 3. The fit statistics revealed that the single-factor model (Figure 1A), $\chi^2(9) = 195.825$, RMSEA = 0.172 (90% confidence interval [CI] = .151, .194), and CFI = .678, the two-factor domain model (Figure 1B), $\chi^2(8) = 204.926$, RMSEA = .187

(90% CI = .164, .211), and CFI = .660, and the three-factor materials model (Figure 1D), χ^2 (6) = 189.847, RMSEA = .209 (90% CI = .181, .237), and CFI = .683, were a poor fit to data. In contrast, the two-factor paradigm model (Figure 1C), χ^2 (8) = 29.108, RMSEA = .061 (90% CI = .038, .086), and CFI = .964, was an acceptable fit to the data.

The fit of the single-factor WM model (Figure 1A) was compared with each of the other models using the Yuan-Bentler χ^2 difference tests because it was nested within the other models. These analyses revealed that the fit of the single-factor model was not significantly different to the domain model (B), $\Delta \chi^2 = 0.150$, $\Delta df = 1$, $p = .700$, but it did provide a significantly better account of the data than the materials model (D), $\Delta \chi^2 = 22.367$, $\Delta df = 3$, $p < .001$. The two-factor paradigm model (C) outperformed the single-factor model (A), $\Delta \chi^2 = 272.820$, $\Delta df = 1$, $p < .001$. The AIC measurement was used to directly compare the other models to one another. The two-factor paradigm model (C) was the best fit with the lowest AIC value (see Table 3), suggesting that separate but related latent constructs corresponding to backward recall and *n*-back best capture the covariance across the tasks.

Table 3. Fit statistics for each model included in the primary confirmatory analysis

<i>Model</i>	χ^2	<i>df</i>	<i>YB</i>	<i>RMSEA</i>	<i>CFI</i>	<i>AIC</i>
(A) Single-factor WM	195.825	9	.932	.172 [.151, .194]	.678	14739
(B) Two-factor domain	204.926	8	.889	.187 [.164, .211]	.660	14741
(C) Two-factor paradigm	29.108	8	.977	.061 [.038, .086]	.964	14587
(D) Three-factor materials	189.847	6	.826	.209 [.181, .237]	.683	14720

Note. For root mean errors of approximation (RMSEAs), 90% confidence intervals are given. CFI = comparative fit index; AIC = Akaike information criterion. The χ^2 reported is the Yuan-Bentler scaled χ^2 , with the scaling factor reported as YB. WM = working memory.

Although the two-factor paradigm model fit best, the fit across the four models was generally quite poor. To better understand possible sources of poor fit of the multi-factor models, we inspected the modification indices (MI) and the standardised residual covariance (SRC) estimates. These converged on the same key path for the single-factor WM model (*MI*

= 17.976, *SRC* = 3.894) and two-factor domain model (*MI* = 149.144, *SRC* = 3.804), namely a strong residual correlation between the BDR and BLR tasks. On reflection, this residual correlation is to be expected due to both tasks depending on encoding and retrieval processes from verbal short-term memory (Norris, Hall, & Gathercole, 2019). As this system stores verbal material in phonological rather than semantic form (e.g., Salamé & Baddeley, 1982), the processes involved in encoding, maintaining, and retrieving representations from verbal short-term memory should be the same for letters as digits. For this reason, we allow this additional path for all models going forward, but report the fit for all models with and without this path. This additional parameter was not added to the three-factor materials model, as unlike the within-factor cross-loadings in the other models, the inclusion of a between-factor cross-loading would weaken the separation between the three individual factors which are central to demarcating this model as distinct from the others. As can be seen in Table 4 and the supplementary materials (Table 6), the addition of this path improved the fit of all models approximately equally, thus not substantively affecting the core goal of model comparison. The addition of this link to each model does not have any effect on the preregistered model comparisons.

Table 4. Fit statistics for each model included in the primary confirmatory analysis with a specific link between the two verbal backwards recall tasks allowing them to co-vary

<i>Model</i>	χ^2	<i>df</i>	<i>YB</i>	<i>RMSEA</i>	<i>CFI</i>	<i>AIC</i>
(E) Single-factor WM with BDR & BLR link	24.154	8	.996	.054 [.030, .079]	.972	14583
(F) Two-factor paradigm with BDR & BLR link	10.658	7	.970	.027 [.000, .059]	.994	14571
(G) Two-factor domain with BDR & BLR link	25.036	7	.953	.061 [.035, .088]	.969	14585

Note. **Bold** text denotes a non-significant χ^2 value. For root mean errors of approximation (RMSEAs), 90% confidence intervals are given. CFI = comparative fit index; AIC = Akaike information criterion. The χ^2 reported is the Yuan-Bentler scaled χ^2 , with the scaling factor reported as YB. WM = working memory, BDR = backward digit recall, BLR = backward letter recall.

The revised single-factor WM model (Model E) was a good fit to the data, $\chi^2(8) = 24.154$, RMSEA = .054 (90% CI = .030, .079), and CFI = .972. The revised domain model (Model G) also improved and was an acceptable fit to the data, $\chi^2(7) = 25.036$, RMSEA = .061 (90% CI = .035, .088), and CFI = .969. A χ^2 difference test revealed these two models were not significantly different to each other, $\Delta\chi^2 = 0.145$, $\Delta df = 1$, $p < .704$. The modified two-factor paradigm model (Model F) showed excellent fit to the data, $\chi^2(7) = 10.658$, RMSEA = .027 (90% CI = .000, .059), and CFI = .994. The χ^2 statistic for Model F was non-significant ($p = .145$), a further indication this model was a good fit. A χ^2 difference test demonstrated that the two-factor paradigm model with the link between BDR and BLR (Model F) outperformed the single-factor model with the same link between verbal backwards recall tasks (Model E), $\Delta\chi^2 = 11.668$, $\Delta df = 1$, $p < .001$. As they are not nested, a likelihood ratio test was not appropriate to compare the revised paradigm model (F) to the modified domain model (G), but the AIC values (see Table 3) suggested that model F fit was considerably better ($\Delta AIC=14$), suggesting that the best-fitting model of the WM tasks overall was the paradigm-based model with a specific link between the two verbal backward recall tasks (F). This model is displayed in Figure 3.

Figure 3. The best model from the primary analyses (Model G); a two-factor paradigm based model with a specific link between the two verbal backward recall tasks. Latent factors are shown in ovals and squares represent observed variables. BDR = backward digit recall, BLR = backward letter recall,

BSR = backward spatial recall, NBD = n -back with digits, NBL = n -back with letters, NBS = n -back with spatial locations. All parameter estimates shown are fully standardized.

Secondary analyses

A secondary aim of this study was to explore how the WM tasks are related to fluid reasoning to explore whether Gf and WM are, in fact, separable as recently proposed by Chuderski (2013). Specific aims were to test whether a model with all (WM and reasoning) tasks loading on a single factor provides a better account of the data than a model with a separate reasoning factor that is linked to the two paradigm factors defined by the best-fitting WM model. See Figure 4 for a schematic of these candidate models.

Figure 4. Candidate models for the secondary analyses. The top panel shows the three-factor paradigm and reasoning model (H), and the bottom panel displays the single-factor general ability model (I). Ovals represent latent factors and observed variables are shown in squares. BDR = backward digit recall, BLR = backward letter recall, BSR = backward spatial recall, NBD = n -back with digits, NBL = n -back with letters, NBS = n -back with spatial locations, RR_E = relational reasoning even items, RR_O = relational reasoning odd items.

For simplicity, we keep the proposed BDR/BLR link here for both candidate models as this link is theoretically defensible and benefits all models similarly, thus not affecting model comparisons (for a summary of the results and comparisons of models without additional links, see the supplementary materials). Table 5 provides a summary of the fit statistics of the two models. The first candidate model was comprised of three correlated latent variables – one for each set of backward recall, *n*-back, and reasoning tasks (model H; see Figure 4, top panel). The fit indices of this model excellent: $\chi^2(16) = 23.576$, $p = .099$, RMSEA = .026 (90% CI = .000, .047), and CFI = .996.

Table 5. Fit statistics for the model included in the secondary analyses

Model	χ^2	df	YB	RMSEA	CFI	AIC
(H) Three-factor paradigm & reasoning with BDR & BLR link	23.576	16	1.006	.026 [.000, .047]	.996	22752
(I) Single-factor general ability with BDR & BLR link, and RR_E & RR_O link	65.683	18	1.009	.061 [.046, .078]	.975	22791

Note. **Bold** text denotes a non-significant χ^2 value. For root mean errors of approximation (RMSEAs), 90% confidence intervals are given. CFI = comparative fit index; AIC = Akaike information criterion. The χ^2 reported is the Yuan-Bentler scaled χ^2 , with the scaling factor reported as YB. RR_E = relational reasoning even items, RR_O = relational reasoning odd items, BDR = backward digit recall, BLR = backward letter recall. The results of models without the links are summarized in the supplementary materials.

The second candidate model assumed a single latent construct for all measures (three backward recall, three *n*-back, and two reasoning tasks; model I, see Figure 4, bottom panel). As well as the BDR/BLR link, a link between the two reasoning tasks was added, as these are two halves of the same task. This model was an acceptable fit to the data, $\chi^2(18) = 65.683$, RMSEA = .061 (90% CI = .046, .078), and CFI = .975.

Figure 5. The winning model from the secondary analyses (Model H); a three-factor paradigm and reasoning model with a specific link between the two verbal backward recall tasks. Latent factors are shown in ovals and observed variables are represented by squares. BDR = backward digit recall, BLR = backward letter recall, BSR = backward spatial recall, NBD = *n*-back with digits, NBL = *n*-back with letters, NBS = *n*-back with spatial locations, RR_E = relational reasoning even items, RR_O = relational reasoning odd items. All parameter estimates shown are fully standardized.

Finally, a χ^2 difference test demonstrated that Model H outperformed Model I, $\Delta \chi^2 = 41.136$, $\Delta df = 2$, $p < .001$. This was confirmed by the AIC values (see Table 5), revealing that the best-fitting model of the WM and reasoning tasks was a three-factor model with latent constructs corresponding to backward recall, *n*-back, and fluid reasoning, that has a specific link between BDR and BLR. The winning model is displayed along with factor loadings in Figure 5. These distinct latent constructs were strongly related to each other, and the relationships between backward recall and reasoning, and between *n*-back and reasoning, were similar (.71 and .59, respectively), in line with previous findings suggesting *Gf* and WM are separable constructs unless time constraints are extreme (Chuderski, 2013). Individual task loadings on each paradigm factor were similar indicating no single task contributed substantially more variance than another.

DISCUSSION

This is the first large-scale online latent variable analysis testing the overlap in task features between backward recall and *n*-back tasks controlling for content- and material-specific variance. The data were best-captured by two distinct but related ($r = .66$) paradigm constructs for backward recall and *n*-back. This result is consistent with previous work reporting a paradigm-specific latent structure for complex span and updating tasks such as *n*-back (Schmiedek et al., 2014; Wilhelm et al., 2013). In these previous studies, high latent correlations were reported between paradigm factors represented by variant forms of each task. Together, these data help explain why transfer effects following training are constrained by paradigm (Byrne et al., 2019; Holmes et al., 2018; Li et al., 2008; Minear et al., 2016; Redick et al., 2013; Sprenger et al., 2013; Thompson et al., 2013): different WM tasks draw on different processes and routines (Gathercole et al., 2019).

The strength of the association between *n*-back and backward recall paradigms was higher here than in previous studies and meta-analyses (Dobbs & Rule, 1989; McAuley & White, 2011; Miller et al., 2009; Redick & Lindsey, 2013; Roberts, 1998; Roberts & Gibson, 2002). This difference is likely explained by task-specific variance in estimates of performance within paradigms, which lowered correlations in earlier studies (Kane et al., 2004; Schmiedek et al., 2014). A few studies included variant forms of *n*-back with different verbal and spatial materials (McAuley & White, 2011; Redick & Lindsey, 2013), but the majority used only a single indicator of *n*-back (Dobbs & Rule, 1989; Miller et al., 2009; Roberts, 1998; Roberts & Gibson, 2002), and all included only one backward recall task (BDR). Using a latent variable approach with multiple indicators of each paradigm, we have overcome the problem that correlations between single tasks are attenuated by paradigm-

specific and content-specific sources of individual variation and measurement error (Schmiedek et al., 2009, 2014).

Common sources of variance between the backward recall and n -back constructs could reflect commonalities across the tasks, for example in the mechanisms used for building, maintaining, and updating arbitrary bindings between memory items and their serial position (Chatham et al., 2011; Oberauer, Süß, Wilhelm, & Sander, 2007; Schmiedek et al., 2009). For backward recall, the relative serial positions of the memory items must be updated at the point of recall, and for n -back the serial position of items previously encoded must be updated as new items are continuously presented (Redick & Lindsey, 2013). The reordering processes and the role of (re)binding items to the appropriate temporal context may be similar across paradigms (Oberauer, 2005; Redick & Lindsey, 2013; Szmalec, Verbruggen, Vandierendonck, & Kemps, 2011). An alternative possibility is that individual differences in controlled attention (e.g. Engle, 2002) or executive control (e.g. Baddeley, 2000) contribute to performance on both n -back and backward recall tasks.

Despite some similarities, these tasks differ in important ways, and the importance of task-specific processes may explain why two separate paradigm-specific latent constructs best captured the data. That is, the paradigms may require different sequences of cognitive processes to be co-ordinated for task execution (e.g. Gathercole et al., 2019). The tasks can be distinguished in terms of retrieval demands: backward recall involves explicit serial recall and retrieval is guided by self-generated cues (Kane et al., 2007), whereas n -back requires recognition and can be completed using familiarity-based responding (Oberauer, 2005). The updating requirements also differ: for n -back, the full sequence must be refreshed as items are added and dropped; for backward recall the whole sequence must be maintained and transformed at the point of recall.

There was evidence for domain-specificity within the backward recall construct, but not in *n*-back. This indicates the mechanisms supporting *n*-back may be more domain-general and less dependent on stimulus material (Jaeggi, Buschkuhl, et al., 2010) and/or that subvocal rehearsal is a less optimal strategy for *n*-back than for backward recall. For backward recall, the two tasks using verbalisable materials, BLR and BDR, might be linked due to common maintenance processes. Both tasks may involve repeated cycles of forward verbal serial recall of diminishing lengths, peeling off the final item each time (Anders & Lillyquist, 1971; Gathercole et al., 2019; Thomas, Milner, & Hanerlandt, 2003). The encoding and retrieval processes required from verbal short-term memory for verbal serial recall are also the same for digits and letters (Norris, Hall, & Gathercole, 2019; Page & Norris, 1998): the system stores verbal material in phonological rather than semantic form (e.g. Salamé & Baddeley, 1982). In *n*-back there is less time for subvocal rehearsal as *n* increases, and the continuously-updating nature of the task might make rehearsal a sub-optimal strategy. This means that verbalising may be a less important maintenance strategy in *n*-back, making performance more similar across verbal and spatial domains.

Gathercole et al. (2019) have proposed that WM training leads to the development of skill-like cognitive routines for unfamiliar WM tasks. These routines specify that the processes required to accomplish particular WM tasks cannot be readily applied to other WM tasks with different structural properties. The current data fit this hypothesis, suggesting that variant forms of each WM paradigm share variance that is likely attributable to paradigm-specific features. Our data suggest training on a single WM paradigm should be constrained by paradigm, but not by material specificity within paradigm. This is consistent with reports of transfer across tasks with different materials within the same paradigm (Holmes et al., 2018; Küper & Karbach, 2016; Lilienthal, Tamez, Shelton, Myerson, & Hale, 2013). For

backward recall, our data suggest transfer should be greatest between verbal forms of the task, and reduced for backward tasks with visuospatial material. This is indeed the pattern of transfer reported in a recent training study demonstrating that transfer of BDR training to new stimuli was substantial for backward span for new verbal material (letters) and marginal for backward span for spatial locations, with no evidence of transfer to verbal *n*-back (Byrne et al., 2019). For *n*-back, transfer should occur across variant forms of *n*-back as they draw on common domain-general processes. Indeed, results of a recent meta-analysis show transfer to untrained *n*-back tasks following *n*-back training is common (e.g. Soveri, Antfolk, Karlsson, Salo, & Laine, 2017).

A model with separate WM and reasoning constructs was preferred to a single-factor model encompassing WM and reasoning. This supports the idea that WM and *Gf* are highly related but dissociable constructs (Kovacs & Conway, 2016), and is consistent with many previous individual differences studies showing strong associations between WM capacity and general fluid reasoning (Chuderski, 2013; Engle & Kane, 2004; Engle, Laughlin, et al., 1999; Kane et al., 2004; Kyllonen & Christal, 1990; Schmiedek et al., 2009, 2014). There is a debate concerning whether BDR is a measure of WM (Alloway et al., 2006) or a measure of short-term memory that draws on the strategic use of visual imagery (Rosen & Engle, 1997; St Clair-Thompson, 2010; St Clair-Thompson & Allen, 2013). The shared variance between the backward recall tasks and both the *n*-back and fluid reasoning constructs suggests backward recall shares common variance with other measures of higher-order complex cognition, indicating it may tap into more than just short-term memory.

An important and noteworthy feature of the current study is that it demonstrates the feasibility of online digital data collection methods for large scale cognitive individual differences studies. In a relatively short period of time, just 5.5 weeks, data was collected

from over 700 participants on 7 tasks lasting about 1.5 hours. The participant pool reached was far more diverse than that usually recruited for lab-based studies (i.e. less restricted to undergraduate students). Although many aspects of the testing environment are not under the experimenter's control with web-based data collection, only 29 out of over 5000 observations were identified as extreme outliers and there were only 14 cases of missing data due technical problems. The quality of the data enabled us to detect cognitive factor structure(s) underlying nuanced individual differences that are consistent with those reported in lab-based studies (e.g. Chuderski, 2013; Engle, Laughlin, et al., 1999; Schmiedek et al., 2009, 2014). Overall the data is in line with evidence showing that the quality of cognitive data collected via other web-browser platforms such as Amazon's Mechanical Turk is high and comparable to data collected in the lab (Crump, McDonnell, & Gureckis, 2013). This sets a precedent for future latent variable studies, exemplifying a way to increase statistical power in a time and cost efficient way that produces quality data.

A major strength of the current study is that the protocol and analysis plan were preregistered via the Open Science Framework online repository. Preregistering the models we planned to test has enabled us to be clear about what our data do and do not confirm, a central scientific principle of latent variable methods. Open science practices like these should be the norm for all confirmatory factor analytic studies - the burden will now fall on authors to argue why they have not preregistered. It is important to note that preregistration does not undervalue exploratory research, but instead encourages researchers to clearly distinguish between planned analyses that are confirmatory, and those that are exploratory as we have exemplified in this paper.

To conclude, backward recall and n -back tasks tap into distinct paradigm-specific processes, but share common variance with one another and with a reasoning task. These

commonalities may reflect shared attentional or executive control processes (Baddeley, 2000; Engle, 2002), or shared cognitive mechanisms between WM tasks and fluid reasoning (Oberauer et al., 2007). These data suggest that the benefits of cognitive training targeting a single paradigm will be limited to the same paradigm. For broader transfer it will be necessary to target what is shared across paradigms.

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SUPPLEMENTS

Primary analyses

Comparisons of original models versus the same models with the BDR and BLR link using the χ^2 difference test revealed that the revised single-factor WM model (Model E) was statistically superior to the single-factor model without the modification (Model A), $\Delta \chi^2 = 377.66$, $\Delta df = 1$, $p < .001$, the revised domain model (Model F) was significantly better than the original domain model (B), $\Delta \chi^2 = 357.63$, $\Delta df = 1$, $p < .001$, and that the the modified two-factor paradigm model was a statistically better fit than the same model without the additional link (Model B), $\Delta \chi^2 = 17.587$, $\Delta df = 1$, $p < .001$. The fit indices of these models are summarized in Tables 3 and 4 (main text), for the original and revised models, respectively.

Secondary analyses

A χ^2 difference test showed a superior fit for the paradigm/reasoning model with the BDR/BLR link (Model H) compared to the same model without the link (Model J), $\Delta \chi^2 = 67.627$, $\Delta df = 1$, $p < .001$, and for the single-factor general ability model (Model I) compared to the same single-factor model without the modifications (Model J), $\Delta \chi^2 = 196.310$, $\Delta df = 2$, $p < .001$. Fit indices of the models included in the secondary analyses with and without additional links are summarised in Tables 5 (main text) and 6 (supplement below), respectively.

Table 6. Fit statistics for each model included in the secondary analyses without additional links

<i>Model</i>	χ^2	<i>df</i>	<i>YB</i>	<i>RMSEA</i>	<i>CFI</i>	<i>AIC</i>
(J) Three-factor paradigm & reasoning	63.574	17	.980	.062 [.046, .079]	.976	22789
(K) Single-factor general ability	364.420	20	1.074	.157 [.143, .170]	.819	23112

Note. For root mean errors of approximation (RMSEAs), 90% confidence intervals are given. CFI = comparative fit index; AIC = Akaike information criterion. The χ^2 reported is the Yuan-Bentler scaled χ^2 , with the scaling factor reported as YB.