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The scope and control of attention as separate aspects of working memory

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The present study examines two varieties of working memory (WM) capacity task: visual arrays (i.e., a measure of the amount of information that can be maintained in working memory) and complex span (i.e., a task that taps WM-related attentional control). Using previously collected data sets we employ confirmatory factor analysis to demonstrate that visual arrays and complex span tasks load on separate, but correlated, factors. A subsequent series of structural equation models and regression analyses demonstrate that these factors contribute both common and unique variance to the prediction of general fluid intelligence (Gf). However, while visual arrays does contribute uniquely to higher cognition, its overall correlation to Gf is largely mediated by variance associated with the complex span factor. Thus we argue that visual arrays performance is not strictly driven by a limited-capacity storage system (e.g., the focus of attention; Cowan, 2001), but may also rely on control processes such as selective attention and controlled memory search.

Keywords: Working memory; Attention; Visual arrays; Complex span; Working memory capacity.

Working memory (WM) refers to a cognitive system in which attention and memory interact to produce complex thought (Cowan, 1988; Engle & Kane, 2004). However, in order for this statement to be meaningful, a concrete understanding of working-memory-related ‘‘attention’’ (and its relationship to memory) must be established. Cowan et al. (2005) offered clarification by identifying two prominent ways in which researchers have attempted to link attention and WM. The first regards the ‘‘scope’’ of attention, or individual differences in the amount of information people can maintain in WM at any point in time (Cowan, 2001; Fukuda, Vogel, Mayr, & Awh, 2010; Vogel & Machizawa, 2004). The second regards the ‘‘control’’ of attention, or individual differences in the ability to actively direct attention to goal-relevant information, and away from goal-irrelevant information (Fukuda & Vogel, 2009; Healey & Miyake, 2009; Kane, Bleckley, Conway, & Engle 2001; Kane & Engle, 2003; Unsworth & Engle, 2007b; Vogel, McCollough, & Machizawa, 2005). We attempt to define and validate these two components, as well as to understand the relative roles of each in higher cognitive functioning.

INDIVIDUAL DIFFERENCES IN THE CAPACITY OF FOCAL ATTENTION

According to Cowan (1988, 1999, 2001), the defining property of focal attention is *stable maintenance* of information in an *interference-free*

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state. From this perspective, information that is the object of attention is not subject to retrieval-based interference or time-based decay. Thus, within Cowan's embedded process model of WM, focal attention eliminates the need for retrieval from secondary (i.e., long-term) memory by keeping units of information active over short periods of time.

Within this framework, individual differences in the amount of information that people can maintain in WM at any one time are referred to as the "scope" of focal attention. In keeping with much of the available literature (cf. Awh, Barton, & Vogel, 2007; Cowan et al., 2005; Fukuda et al., 2010; Luck & Vogel, 1997; Rouder, Morey, Moray, & Cowan, 2011) we operationalise the scope of attention (or more generally, storage in WM) via the visual arrays task (Luck & Vogel, 1997; Pashler, 1988), an example of which is provided in Figure 1. This change-detection task begins with the brief presentation of an array of simple objects (such as coloured squares). After a short delay (i.e., ISI on Figure 1), the array reappears with one item encircled. The test-taker simply indicates whether or not a specific aspect of the object has changed, relative to its initial presentation (e.g., has the box's colour changed?).

When displays contain more than four items most people begin to experience difficulty detecting changes (Luck & Vogel, 1997). These performance decrements are interpreted as evidence that the number of to-be-remembered items in a given display has exceeded a person's capacity for maintaining information within the focus of attention (cf. Cowan, 2001; Rouder et al., 2011). Several data transformations take into account an individual's tendency to guess (i.e., false alarm rate; see *Tasks*, below) and thus allow for an estimate of the number of items to which a person is accurately responding, regardless of the absolute number of items contained in the display (Cowan et al., 2005; Pashler, 1988; Rouder et al., 2011). Using these corrections, Cowan et al. (2005; in particular see their appendices) argue that, across different set sizes, a typical person accurately responds to between three and five objects (see also Cowan, 2001). These estimates are thus taken as evidence for a discrete "slots" model of WM capacity in which people differ in the number of distinct chunks of information that can be actively maintained at any one point in time (Awh et al., 2007; Rouder et al., 2011).

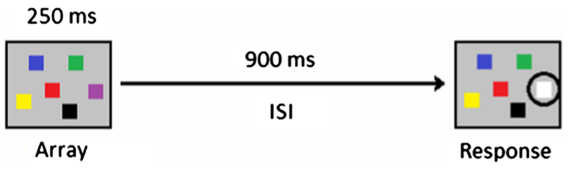

Figure 1. Illustration of the visual arrays task. An array of squares is presented for 250 ms. This is followed by a 900 ms interstimulus interval (ISI). Finally participants respond as to whether or not the encircled square has changed, relative to its initial presentation.

INDIVIDUAL DIFFERENCES CONTROLLING THE CONTENTS OF ATTENTION

Due to its abstract nature, attentional control is difficult to define. We broadly characterise it as processes that allow a person to *guide* focal attention to *goal-relevant* information. This ability, *as it relates to WM capacity*, will be operationalised via performance on complex span tasks (Daneman & Carpenter, 1980) such as the operation (Turner & Engle, 1989) and symmetry span (Kane et al., 2004). As depicted in Figure 2, complex span tasks combine memory and processing into one task. The memory component consists of the serial presentation of several items (e.g., letters, spatial locations). The processing component is an interpolated task that interrupts any attempt to rehearse these items. Intuition suggests that complex span tasks require mental processes that are distinct from those involved in a scope of attention task. Specifically, the interleaved processing component is attention demanding. Successfully remembering list items will therefore require test takers to either (1) maintain information in the face of intermittent distraction, or (2) return attention to critical information, following distraction. Thus, for present purposes, when we speak of "control of attention" (or more specifically, control of *the contents* of attention), we will actually refer to two separate processes: selective attention and controlled search of memory (cf. Unsworth & Spillers, 2010).

Evidence for the relationship between complex span and selective attention is ample. Performance on complex span tasks predicts performance on several measures of controlled attention, such as the anti-saccade (Hallett, 1979; Hutchison, 2007; Kane et al., 2001; Unsworth, Schrock, & Engle, 2004), Stroop (Hutchison, 2007;

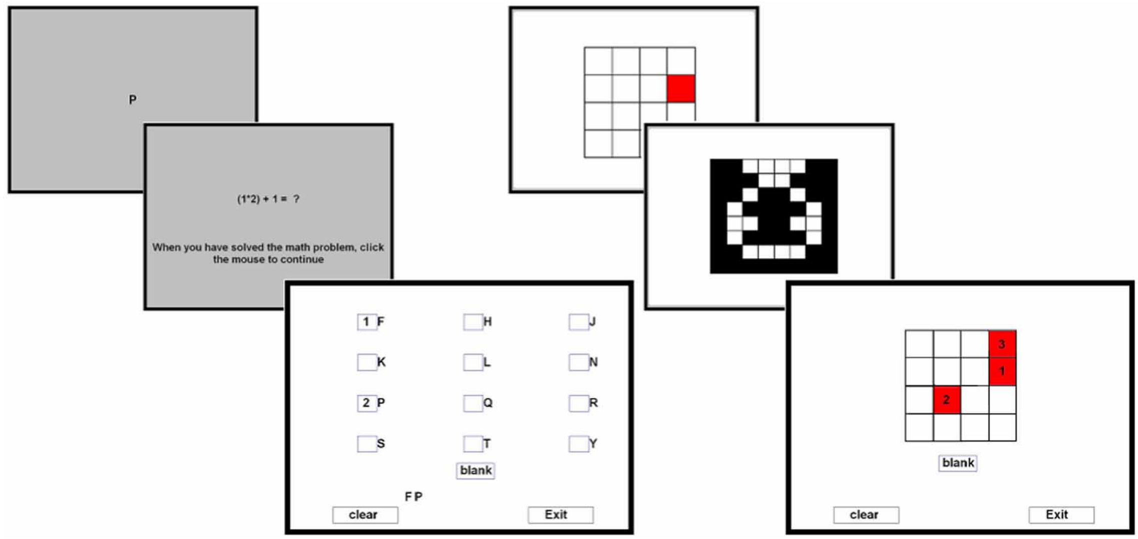

Figure 2. Operation span begins with presentation of a letter, which is followed by a simple mathematical operation that must be solved. Symmetry span begins with the presentation of a spatial location, followed by a grid-based picture the symmetry of which must be judged. After several item/problem pairs, the participant attempts to reconstruct the list via a response screen.

Kane & Engle, 2003; Miyake et al., 2000; Stroop, 1935), Eriksen flanker (Eriksen & Eriksen, 1974; Heitz & Engle, 2007; Redick & Engle, 2006; Shipstead, Harrison, & Engle, 2012), and the dichotic listening task (Colflesh & Conway, 2007; Conway, Cowan, & Bunting, 2001). Common to these tasks is a requirement that test-takers attend to goal-relevant information, despite strong environmental distraction. This has led to the hypothesis that complex span performance is largely driven by the ability to use attention to maintain access to critical information, particularly when interference or distraction is high (Engle & Kane, 2004; Kane, Conway, Hambrick, & Engle, 2007).

However, this perspective has limitations. In particular, given the assumption of a three- to five-item attentional capacity (Cowan, 2001), all people are apt to lose track of critical information at some point (Unsworth & Engle, 2007a). In these situations controlled searches of secondary memory allow for retrieval of displaced information (Unsworth & Engle, 2007a, 2007b, 2007c). The major hindrance to successful memory search is proactive interference, or competition between relevant and irrelevant information for retrieval into the focus of attention (cf. Davelaar, Goshen-Gottstein, Ashkenazi, Haarman, & Usher, 2005). One way to understand proactive interference is to assume that over the course of several trials the memory cues that are used to retrieve information (e.g., attempting to remember information from a specific time-frame; Baddeley, 1976; Watkins, 1979) become associated with several lists. Thus over these trials the cues become less specific, resulting in diminished efficacy (Watkins & Watkins, 1975; Wixted & Rohrer, 1994). The end result is an increase in the amount of irrelevant information that is cued, which in turn results in a decreased probability of specific information being retrieved. This phenomenon is evidenced by the well-documented tendency of test-takers to recall fewer and fewer items from subsequent lists in an experiment (Keppel & Underwood, 1962; Turvey, Brick, & Osborne, 1970; Wickens, Born, & Allen, 1963).

High performers on complex span tasks are less prone to these build-ups of proactive interference than are low performers (Bunting, 2006). That is, they experience less forgetting over the course of several trials (Friedman & Miyake, 2004; Kane & Engle, 2000; Unsworth, 2010). This resistance to proactive interference is hypothesised to reflect an ability to utilise relatively specific retrieval cues (i.e., trial-specific cues; Unsworth & Engle, 2007b), as well as an ability to use the products of a given retrieval attempt to refine memory searches (Spillers & Unsworth, 2011; see also Norman, 1968; Raaijmakers & Shiffrin, 1981).

We do not intend to argue that complex span performance is strictly driven by selective attention and controlled memory search. However, a recent study by Unsworth and Spillers (2010) found that complex span performance fully mediates the relationship between both of these processes and general fluid intelligence (Gf; novel reasoning ability). Conversely, selective attention and controlled retrieval accounted for 75% of the relationship between complex span performance and Gf. Thus, while complex span is not perfectly explained by these processes, we contend that the relationship is strong enough to warrant construal of complex span tasks as ''control of attention'' tasks (at least for present purposes).

THE DISTINCTION BETWEEN SCOPE AND CONTROL TASKS

Despite a clear conceptual distinction between the scope and control of attention, the role of these mechanisms in WM is unclear. For instance, Cowan et al. (2005) examined the relative contributions of each component to predicting general intelligence, ACT scores, and high school grades. In this study the scope of attention was defined via a variety of tasks (including visual arrays) while control of attention was represented via two complex span tasks. The scope and control tasks were entered into separate steps of a regression analysis, and it was determined that variance that was common to all tasks explained the largest portion of individual differences on the three criterion measures. The complex span tasks did predict variance above and beyond scope. However, contrary to the assumption that this added prediction represented control of attention, further analyses determined that it was task-specific. That is, either one or the other complex span task (but not both) added incremental prediction to the model.

Cowan et al. (2005) subsequently concluded that the explanatory powers of WM capacity tasks are primarily determined by the scope of attention. Specifically, it was argued that valid WM capacity tasks prevent strategic grouping of information and thus allow for an uncontaminated estimate of the number of items that may be attended at one time. For visual arrays tasks, chunking is presumably minimised by the use of stimuli that are not verbally rehearsable. For complex span tasks the inclusion of interpolated distraction ostensibly prevents strategic grouping.

However, the assumption that the scope of attention plays an important role in complex span performance leads to a specific prediction regarding the relationship between complex span tasks and higher-order cognition. Specifically, complex span performance should be least predictive of abilities such as Gf at list lengths of two, since this is an amount of information that most people can easily maintain within focal attention. On the other hand, list lengths of five items should be maximally predictive of Gf, since this is an amount of information that most people will struggle to maintain within focal attention.

Contrary to this prediction, several studies have since found that complex span performance predicts Gf with equal fidelity at all list lengths (Bailey, Dunlosky, & Kane, 2011; Salthouse & Pink, 2008; Unsworth & Engle, 2006; see also Unsworth & Engle, 2007b). This finding creates a philosophical problem for interpreting the relationship between visual arrays and complex span WM tasks as well as their ability to predict higher-order cognition. If these tasks are indeed driven by a single underlying factor (e.g., Cowan et al., 2005), then it is difficult to understand why the visual arrays task should be construed as a measure of storage capacity. On the other hand, if these tasks reflect distinct (but related) mechanisms of WM, how does one interpret common variation? This is an issue to which we will return, following the main analyses.

THE PRESENT STUDY

The present study extends the findings of Cowan et al. (2005); also Cowan, Fristoe, Elliott, Brunner, & Saults, 2006) by investigating the scope and control of WM-related attention at the latent level. Rather than examining the degree to which certain tasks predict cognitive ability, we are concerned with how variation that is *common* to certain *types* of task predicts cognitive ability.

We first explore whether visual arrays and complex span tasks reflect common or distinct aspects of WM. If these tasks respectively represent separable aspects of WM, then they should converge on separate factors. If, on the other hand, visual arrays and complex span are essentially driven by the same processes (as was argued by Cowan et al., 2005), a one-factor solution would obtain.

To preview our results, confirmatory factor analysis revealed that, while individual differences in visual arrays and complex span tasks are related at the latent level, they nonetheless represent separate aspects of WM. We thus examined the degree to which each of these components contributes to general cognitive function. A series of structural equation models and regression analyses was conducted in which Gf served as a criterion latent variable. These analyses revealed that each WM component made a contribution to the prediction of Gf above and beyond the other. However, they also revealed that a large portion of the relationship between visual arrays (i.e., the scope of attention) and Gf was best explained via processes that are more strongly associated with complex span tasks (i.e., the control of attention).

Data sets

Analyses were performed on two previously collected samples that were selected based on (1) inclusion of the visual arrays task, (2) multiple complex span tasks, and (3) several measures of Gf. Similar to a method reported by Kaufman, DeYoung, Gray, Brown, and Mackintosh (2009) and Kaufman et al. (2010), we separated the visual arrays task by set size, and thus treated it as three tasks.

The first sample (Data Set A) was collected at the Georgia Institute of Technology, University of Georgia, University of North Carolina-Greensboro, and Michigan State University. Both college students and community members were included. These data were collected in the autumn semester of 2009 as part of a larger study (Redick et al., 2011). All participants were between the ages of 18 and 30. The initial sample contained 534 participants. Due to missing data 29 participants were excluded, leaving a final sample of 505.

The second data set (Data Set B) was collected as part of a general screening procedure that was conducted in summer 2008. These data have not been previously reported in any complete form. A total of 170 people between the ages of 18 and 35 were tested. The sample included students from several regional colleges and universities (e.g., Georgia Tech, Georgia State University), as well as members of the Atlanta community.

Tasks

Working memory capacity tasks (Visual arrays)

Visual arrays (Data Sets A & B; Luck & Vogel, 1997; Morey & Cowan, 2004, 2005). The visual arrays task was similar to the no-load task reported in Morey and Cowan (2004, 2005). White, black, red, yellow, green, blue, or purple served as the potential square colours. Visual arrays sets were composed of four, six, or eight coloured blocks (see Figure 1) and presented against a grey/silver background within a $19.1^\circ \times 14.3^\circ$ display. Although squares were presented in random patterns, they were constrained such that they could not come within 2° of one another. Attentional capacity (k) was estimated at each set size using equation A.6 from Cowan et al. (2005; i.e., $k = \text{set size} * [\text{hits} + \text{correct rejections} - 1]$). On each trial the target array was presented for 250 ms. The inter-stimulus interval lasted for 900 ms. Participants performed 20 trials at each set size; 10 were no-change, 10 were change. Different set sizes were presented randomly. A person's mean k at each of the three set sizes served as separate dependent variables.

Working memory capacity tasks (Complex span)

All other WM tasks were automated complex span tasks (Unsworth, Heitz, Schrock, & Engle, 2005; Unsworth, Redick, Heitz, Broadway, & Engle, 2009) in which participants complete a processing task that is followed by a to-be-remembered item (see Figure 2). After several processing task/item pairs, participants attempt to reconstruct the list of to-be-remembered items, via mouse click. List length varied randomly. Task performance was quantified via the partial scoring method in which participants received one point for each item that was recalled in its correct position. These tasks are available for download at http://www.psychology.gatech.edu/renglelab/

Operation span task (Data Sets A&B; Turner & Engle, 1989; Unsworth et al., 2005). The processing task in the operation span is a simple mathematical equation. Letters serve as the to-be-remembered items. List lengths varied from three to seven items. Each list length appeared three times.

Reading span task (Data Set A; Daneman & Carpenter, 1980; Unsworth et al., 2009). The processing task in the reading span is a sentence that participants judge as making sense or nonsense. Letters serve as the to-be-remembered items. List lengths varied from three to seven items. Each list length appeared three times.

Symmetry span task (Data Sets A&B; Kane et al., 2004; Unsworth et al., 2009). The processing task in the symmetry span displayed a black and white figure on an 8×8 grid. Participants judged whether or not the figure was symmetrical. Spatial locations on a 4×4 grid served as the to-be-remembered items. List lengths varied from two to five items. Each list length appeared three times.

Rotation span task (Data Set A; Kane et al., 2004; Shah & Miyake, 1996). The processing task in the rotation span required participants to judge whether a rotated letter was normally oriented, or a mirror reflection. The orientation of a series of arrows served as the to-be-remembered items. List lengths varied from two to five items. Each list length appeared three times.

General fluid intelligence tasks

All fluid intelligence tasks were administered via computer. Participants provided answers via mouse click.

Raven's advanced progressive matrices (Data Sets A&B; Raven, 1990). Ravens presents eight shapes arranged in a 3×3 matrix. The final location is blank. Participants choose which of several options completes the series. Participants were allowed 10 minutes to complete the odd set (18 problems). Number of correct responses served as the dependent variable.

Paper folding (Data Set A; Ekstrom, French, Harman, & Dermen, 1976). Participants saw a diagram in which a sheet of paper is folded several times and then hole-punched. Participants are required to choose (from five options) how the sheet would look if it were unfolded. Participants were allowed 4 minutes to complete Set A (10 problems). The number of correct responses served as the dependent variable.

Letter sets (Data Sets A&B; Ekstrom et al., 1976). Participants were shown five sets of four letters. They were required to discover a rule that was common to four of the sets and indicate the set that violated that rule. Participants were allowed 5 minutes to complete 20 problems.

Number series (Data Sets A&B; Thurstone, 1938). Participants saw a series of numbers. They selected which of several options logically completed the series. Participants were allowed 4.5 minutes to complete 15 problems.

Other tasks

Running span (Data Set B; Pollack, Johnson, & Knaff, 1959). The running span is not part of our main analysis, but is included in a supplemental analysis. This task presented a series of five to nine letters and required participants to remember the last three to seven items. Participants were informed of how many items they would need to remember at the beginning of a block of three trials. There were a total of 15 trials. Items were presented for 300 ms followed by a 200 ms pause.

RESULTS AND DISCUSSION

Descriptive statistics

Table 1 provides descriptive statistics for the two data sets. In both sets the skew and kurtosis for visual arrays set size 4 are noticeably larger than other tasks. For present purposes these values are not problematic (extreme skew > 3; problematic kurtosis > 10; Kline, 1998). Correlations are provided in Table 2. All tasks were significantly correlated ($p < .01$). Further information regarding our treatment of different visual arrays set sizes as separate tasks, as well as the presence of negative k values, can be found in the Discussion section.

Reported fit statistics

Several fit statistics are reported for each model. Non-significant p-values are preferable, as they indicate that the reproduced covariance matrix does not differ from the observed matrix. With large samples (such as Data Set A), a significant difference may be unavoidable. Root mean square error of approximation (RMSEA) estimates the model fit to the population, while standardised root mean square residual (SRMR) reflects average deviation of reproduced covariance matrix from the observed. For these indices, a well-fitting model would have values below .05, while up to .08 is acceptable (Browne & Cudeck, 1993; Kline, 1998). Non-normed fit index (NNFI) and comparative fit index (CFI) test the model relative to a null model in which observed variables are assumed to be uncorrelated. A value of .95 or higher represents a good fit (Hu & Bentler, 1999). Finally, Akaike's (1987) information criterion (AIC) addresses overall model

TABLE 1
Descriptive statistics for Data Sets A and B

Task	*M*	*SD*	*Range*	*Skew*	*Kurtosis*
			DATA SET A		
VA-4	3.12	1.01	−2–4	−2.06	5.12
VA-6	3.49	1.67	−3–6	−0.91	0.77
VA-8	3.65	1.94	−3.2–8	−0.33	−0.09
OSpan	54.52	14.63	2–75	−1.00	0.67
ReSpan	52.12	14.27	0–75	−0.86	0.57
SymSpan	25.66	9.09	0–42	−0.54	−0.26
RotSpan	27.57	8.82	0–42	−0.82	0.40
RAPM	9.03	3.67	0–17	−0.32	−0.50
PapFold	5.90	2.68	0–10	−0.45	−0.63
LettSet	10.24	3.15	1–18	−0.01	−0.27
NumSeries	8.74	2.98	1–15	−0.20	−0.32
			DATA SET B		
VA-4	3.26	0.87	−1.2–4	−2.01	5.12
VA-6	3.80	1.60	−2.4–6	−1.22	2.00
VA-8	3.95	2.10	−2.4–8	−0.63	0.23
OSpan	57.06	14.28	12–75	−1.17	0.94
SymSpan	26.53	8.59	5–41	−0.44	−0.47
RAPM	8.82	3.60	1–17	−0.26	−0.60
LettSet	10.18	3.37	1–17	−0.18	−0.35
NumSeries	9.03	3.01	2–14	−0.46	−0.39
RunSpan	39.89	13.47	6–71	−0.15	−0.58

VA-4 = visual arrays, set size 4; VA-6 = visual arrays, set size 6; VA-8 = visual arrays, set size 8; OSpan = operation span; REspan = reading span; SymSpan = symmetry span; RotSpan = rotation span; RAPM = Raven's advanced progressive matrices; PapFold = paper folding task; LettSet = letter sets task; NumSeries = number series task; RunSpan = running memory span.

parsimony by taking into account both goodness-of-fit and number of to-be-estimated parameters. Lower values are preferred.

Confirmatory factor analysis: One or two WM factors?

We performed a confirmatory factor analysis in order to determine whether the visual arrays and complex span tasks are better represented via a one-factor (i.e., *1-Factor* in Table 3) or two-factor (i.e., *2-Factor* in Table 3) solution. In 1-Factor all complex span and visual arrays tasks loaded onto a common WM factor. In 2-Factor the complex span and visual arrays tasks loaded on separate factors. Correlated errors were allowed between the operation and reading span for all models involving Data Set A. This decision was based on prior analysis of the data set (Redick et al., 2011).[1]

[1] When correlated errors were not allowed, both models provided a poor fit to the data. This is likely due to an overall bias towards visuo-spatial tasks. Correlating the errors between operation and reading span essentially controlled this bias. The two-factor model provided a better fit, regardless of whether we included correlated errors.

The results of these analyses, which support the two-factor solution, are presented in Table 3. First, examining Data Set A (Table 3), the two-factor model provided a better fit to the observed data than did the one-factor model. Relative to 1-Factor, 2-Factor resulted in a significant χ^2 reduction ($\Delta\chi^2 = 238.91$; $p < .001$). Moreover, while 1-Factor provided a poor fit to the data, 2-Factor resulted in a good fit across all fit statistics.

Data Set B (Table 3) replicated these results. Once again the one-factor solution provided a poor fit to the data. The two-factor model, on the other hand improved χ^2 ($\Delta\chi^2 = 30.11$; $p < .001$), did not differ from the observed covariance matrix ($p = .26$) and had good fit statistics.

The resulting models are displayed in Figure 3. The latent factors that drive performance in the visual arrays and complex span tasks have been labelled VA and CS respectively. This convention will be maintained throughout our analyses. In keeping with previous discussion we will typically interpret VA as being akin to the focus of attention and CS as being an amalgam of control processes. However, while the two-factor solution clearly provided a better summary of the data, it should be noted that these factors are correlated. Thus, while it is suggested that visual

TABLE 2
Correlations among variables in Data Sets A and B

Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
					DATA SET A						
1. VA-4	–										
2. VA-6	.67	–									
3. VA-8	.49	.50	–								
4. OSpan	.19	.23	.18	–							
5. ReSpan	.25	.33	.20	.64	–						
6. SymSpan	.35	.41	.31	.39	.43	–					
7. RotSpan	.32	.45	.32	.40	.47	.60	–				
8. RAPM	.47	.43	.31	.29	.38	.46	.45	–			
9. PapFold	.24	.26	.19	.27	.33	.40	.35	.43	–		
10. LettSet	.25	.37	.23	.30	.36	.39	.39	.47	.38	–	
11. NumSeries	.35	.40	.26	.33	.35	.43	.46	.56	.41	.54–	–
					DATA SET B						
1. VA-4	–										
2. VA-6	.66	–									
3. VA-8	.50	.58	–								
4. OSpan	.29	.35	.39	–							
5. SymSpan	.45	.48	.48	.57	–						
6. RAPM	.48	.48	.38	.51	.52	–					
7. LettSet	.31	.36	.31	.45	.45	.51	–				
8. NumSeries	.45	.40	.36	.42	.44	.51	.54	–			
Other											
9. RunSpan	.42	.41	.34	.57	.46	.58	.56	.53	–		

VA-4 = visual arrays, set size 4; VA-6 = visual arrays, set size 6; VA-8 = visual arrays, set size 8; OSpan = operation span; REspan = reading span; SymSpan = symmetry span; RotSpan = rotation span; RAPM = Raven's advanced progressive matrices; PapFold = paper folding task; LettSet = letter sets task; NumSeries = number series task; RunSpan = running memory span. All tasks were significantly correlated, $p < .01$.

arrays and complex span tasks do indeed reflect separable components of WM, they tap many of the same cognitive processes.

Structural equation models: The relationship of VA and CS to Gf

Figure 4 displays three structural equation models (SEMs) that were conducted in order to validate the relationship between the separate WM factors and Gf. Based on the strength of correlation between VA and CS we allowed each factor to have an indirect effect on Gf. The double-headed arrows connecting VA and CS represent this assumption. SEM-VA assumes that the link between CS and Gf is mediated by processes that are strongly associated with the visual arrays task. SEM-CS assumes the opposite relationship, with CS exerting the only direct influence on Gf. This model represents the view in which the predictive power of visual arrays and complex

TABLE 3
Fit indices for confirmatory factor analyses

Model	χ^2	*df*	*p*	*RMSEA*	*SRMR*	*NNFI*	*CFI*	*AIC*
				DATA SET A				
1-Factor	256.70	13.00	0.00	0.19	0.09	0.82	0.89	286.70
2-Factor	17.79	12.00	0.12	0.03	0.02	0.99	1.00	49.79
				DATA SET B				
1-Factor	35.36	5.00	0.00	0.19	0.07	0.85	0.93	55.36
2-Factor	5.25	4.00	0.26	0.04	0.05	0.99	1.00	27.25

RMSEA = root mean square error of approximation; SRMR = standardised root mean square residual; NNFI = non-normed fit index; CFI = comparative fit index; AIC = Akaike's information criterion.

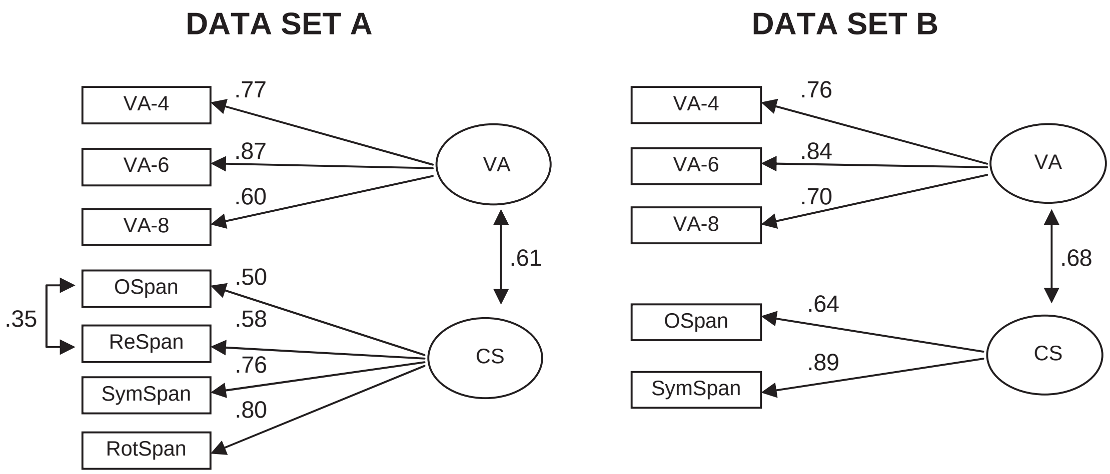

Figure 3. Two-factor solutions for Data Sets A and B. Note. VA-4 = visual arrays, set size 4; VA-6 = visual arrays, set size 6; VA-8 = visual arrays, set size 8; OSpan = operation span; REspan = reading span; SymSpan = symmetry span; RotSpan = rotation span; RAPM = Raven's advanced progressive matrices; PapFold = paper folding task; LettSet = letter sets task; NumSeries = number series task; RunSpan = running memory span; VA = visual arrays; CS = complex span.

span task is commonly determined by memory and control processes associated with complex span tasks. Finally, SEM-both assumes that the VA and CS make individual contributions to Gf (cf. Cowan et al., 2006; see also Unsworth & Spillers, 2010). As will be seen, this model provides the best explanation of the data.

Data Set A. Results of these SEMs are displayed in Table 4. Focusing on Data Set A, SEM-VA provides a reasonable representation of the data; however, by all indications, SEM-CS provides a better fit. Between the first two models, the data would be best represented with a path from CS to Gf.

However, fit statistics for SEM-both (Data Set A) indicate that a two-path solution is preferable. Relative to SEM-CS, the addition of a path from VA to Gf resulted in a significant reduction in χ^2 ($\Delta\chi^2 = 238.91$; $p < .001$) as well as a lower AIC (121.05 vs 131.69). Thus the two-path solution (Figure 5) is favoured over either one-path solution.

Data Set B. The same analyses were repeated on Data Set B (Table 4). As with the first set, SEM-VA provided an acceptable fit. However, the model fit improved when CS served as the mediating factor. Relative to SEM-VA, SEM-CS reduced χ^2 ($\Delta\chi^2 = 21.34$) and did not differ from the observed covariance structure ($p = .09$). Moreover, it produced better fit statistics and a lower AIC.

Contrary to Data Set A, model fit for Data Set B was not improved by including a path from both factors to Gf ($\Delta\chi^2 = 2.57$; $p < .10$). Strict concern for parsimony would thus favour the one-path model. However, SEM-both fits the data well (RMSEA = .05, SRMR = .04, NNFI = .98, CFI = .99) and the additional path did not inflate

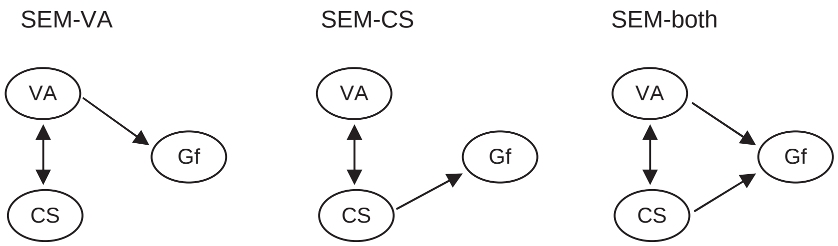

Figure 4. Hypothesised relationships between latent variables that drive visual arrays (VA), complex span (CS), and general fluid intelligence (Gf).

TABLE 4
Fit indices for structural equation models

Model	χ^2	*df*	*p*	*RMSEA*	*SRMR*	*NNFI*	*CFI*	*AIC*
				DATA SET A				
SEM-VA	172.76	41.00	0.00	0.08	0.08	0.96	0.97	222.76
SEM-CS	81.69	41.00	0.00	0.04	0.03	0.99	0.99	131.69
SEM-both	69.05	40.00	0.00	0.04	0.03	0.99	0.99	121.05
				DATA SET B				
SEM-VA	47.75	18.00	0.00	0.10	0.07	0.95	0.97	83.75
SEM-CS	26.41	18.00	0.09	0.05	0.04	0.98	0.99	62.41
SEM-both	23.84	17.00	0.12	0.05	0.04	0.98	0.99	61.84

RMSEA = root mean square error of approximation; SRMR = standardised root mean square residual; NNFI = non-normed fit index; CFI = comparative fit index; AIC = Akaike's information criterion.

AIC (i.e., our quantitative parsimony criterion). We therefore favour the two-path model, as it allows direct comparison of Data Sets A and B.

Despite the exclusion of several tasks, and an appreciably smaller sample, Data Set B essentially replicates Data Set A (Figure 5). In both cases it is clear that, while complex span and visual arrays tasks tap separate aspects of WM, they are highly related to one another. The obvious inconsistency between these models is the lack of a significant path between VA and Gf in Data Set B. However, the path coefficients are striking in their similarity.

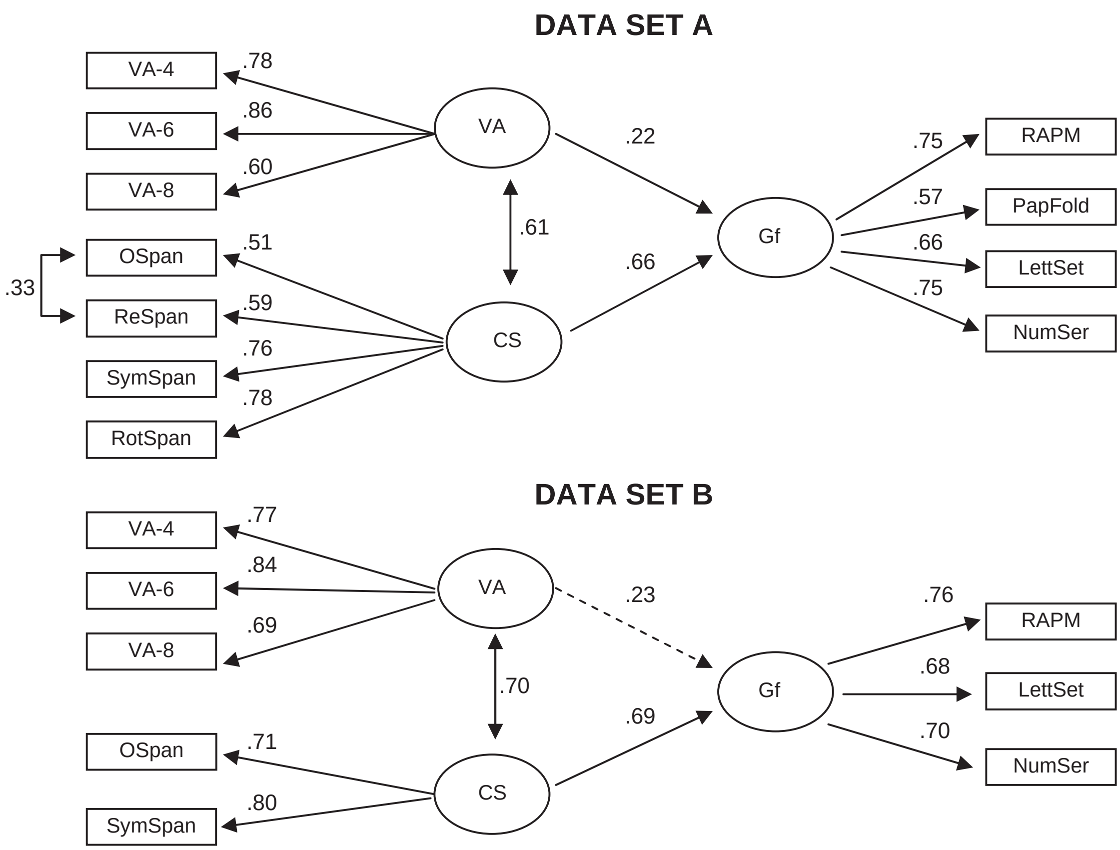

Figure 5. Two-path structural equation models for Data Sets A and B. Solid lines are significant at the .05 level; VA-4 = visual arrays, set size 4; VA-6 = visual arrays, set size 6; VA-8 = visual arrays, set size 8; OSpan = operation span; REspan = reading span; SymSpan = symmetry span; RotSpan = rotation span; RAPM = Raven's advanced progressive matrices; PapFold = paper folding task; LettSet = letter sets task; NumSeries = number series task; VA = visual arrays; CS = complex span; Gf = general fluid intelligence.

We thus attribute this non-significant path to a combination of a relatively small correlation and a relatively small sample (i.e., $n = 170$ in Data Set B, but $n = 505$ in Data Set A).

Regression analysis

In order to clarify the unique contributions that VA and CS make to predicting Gf we conducted a follow-up regression analysis. For both data sets, z-score composites of visual arrays (VAz) and complex span (CSz) were created. These measures were then separately entered into a stepwise regression as predictors of a z-score composite of all Gf tasks in a given data set.

The results of these analyses are outlined in Table 5. In the first step only one of the two predictors was entered. Thus R^2 in Step 1 provides the total variation in Gf that is accounted for by a given predictor. The other predictor was then added in the second step. Thus R^2 in Step 2 provides the total proportion of variance in Gf that is accounted for by both predictors. ΔR^2 therefore represents the amount of variation in Gf that is attributable to the second predictor above-and-beyond the first (i.e., unique prediction).

The results of both regression analyses indicate that, while VAz and CSz do share prediction of Gf, each also contributes unique prediction. In Data Set A, CSz uniquely accounted for 17% of variation in Gf, while VAz uniquely accounted for 7%. In Data Set B, CSz uniquely accounted for 16% of variation in Gf, while VAz uniquely accounted for 7%.

Thus the regression analyses confirm that visual arrays and complex span tasks tap dissociable (but related) constructs, each of which contributes unique variation to the prediction of Gf. Several observations are relevant. First, the proportion of unique variance accounted for by each predictor was consistent across data sets. Second, VAz and CSz also commonly predict variance in Gf (18% in Data Set A; 24% in Data Set B). Third, in both cases, CSz accounted for a larger proportion of unique variance in Gf than did VAz. This may be interpreted as an indication that CSz represents a wider variety of processes than VAz.

TABLE 5
Stepwise regression with scope and control of attention predicting Gf

		Data Set A		*Data Set B*	
Step	*Predictor*	*R2*	*ΔR2*	*R2*	*ΔR2*
1	VAz	.25	–	.31	–
2	CSz	.42	.17*	.47	.16*
1	CSz	.35	–	.40	–
2	VAz	.42	.07*	.47	.07*

VAz is a z-score composite of visual arrays sizes 4, 6, and 8. CSz is a z-score composite of all complex span tasks included in a given data set. $*p < .001$.

Reconciling with Cowan et al. (2005). The present analyses indicate that the visual arrays and complex span represent separable, but related, aspects of WM, each of which has distinct implications for the prediction of higher cognition. These results contrast with Cowan et al. (2005) who reported a nearly complete overlap in the predictive powers of complex span and scope of attention tasks. However, the discrepancy of these findings may be due to the manner in which Cowan et al. (2005) defined the scope of attention.

In an attempt to thoroughly measure of the scope of attention Cowan et al. (2005) defined this variable via several tasks (including visual arrays). Among the included measures was the running memory span (Pollack et al., 1959). This task presents test takers with a series of items, of which the last three to seven must be recalled. By the account of Bunting, Cowan and Saults (2006), participants passively attend to items during the initial presentation. When signalled for recall they then use attention to retrieve as many list items as possible from a decay-prone short term store (Cowan, 1999, 2001). A large scope of attention would thus allow for greater transfer of information.

Assuming the validity of this account, the running span and visual arrays can be justifiably grouped into the same category of measurement. However, Broadway and Engle (2010) argue that the running span is actually closely related to the complex span. In particular they found that the correlation between these tasks is strong and robust to changes in running span administration (e.g., speed of item presentation, pre- vs post-warning of how many items would need to be recalled). Moreover, complex and running span were shown to predict the same variation in Gf (Broadway, 2008). In light of the present argument that visual arrays and complex span tasks tap dissociable aspects of WM, one might argue that the overlap between scope and control tasks found by Cowan et al. (2005) is the result of a "control" task (i.e., running span) being entered into a stepwise regression analysis as a "scope" task.

The procedure from which Data Set B was collected included the running span task, and thus provided an opportunity to test whether this task related to CS (e.g., Broadway & Engle, 2010) or VA (e.g., Bunting et al., 2006; Cowan et al., 2005) factor. Running span was allowed to freely load on VA and CS from Figure 3. The first model (i.e., RunSpan-both; Table 6) included paths from running span to both factors. This provided an adequate fit to the data. However, while running span loaded on CS (factor loading = .63), it did not load on VA (factor loading = .08). We therefore conducted a second analysis in which running span loaded only on CS. As can be seen in Table 6 (RunSpan-CS), the overall fit did not improve, however, the extra degree of freedom did not inflate χ^2, and AIC decreased from 48.33 to 46.27. The resulting model, which indicates that running span directly taps the same cognitive processes as complex span tasks, is presented in Figure 6.

Despite the lack of a processing component, running memory span is strongly related to complex span tasks at the latent level. Its relationship to visual arrays (i.e., the focus of attention) is, on the other hand, indirect. We therefore reran our regression analysis (i.e., Table 5; Data Set B) with running span included as a separate step. It was predicted that running span would share more common prediction of Gf with the complex span composite than with the visual arrays composite.

The results of this analysis are displayed in Figure 7. The three predictors commonly account for 21% of the variation in Gf. Consistent with our hypothesis, the next largest source of prediction was the variation that was common to CSz and running span (11%). The variation common to running span and VAz was, on the other hand, the smallest source of Gf prediction (3%). This analysis thus provides a reasonable explanation for the disparity between the present conclusions and the near-perfect overlap between scope of attention and complex span tasks found in the regression analysis of Cowan et al. (2005). Running memory span (which Cowan et al. grouped with visual arrays) is more closely identified with complex span tasks than it is with visual arrays.

It should be noted that the running span used by Cowan et al. (2005) featured items presented at the rate of four per second, while the present running span presented items at the rate of two per second. It may be only at higher presentation rates—when rehearsal and chucking processes are interrupted—that the running span taps the focus of attention (Bunting et al., 2006). However we note that Broadway and Engle (2010) found that, although running span scores decreased as rate of presentation is increased (an indication that rehearsal/chunking was interrupted; Bunting et al., 2006), this did not change correlations between running span performance and complex span tasks or Gf. Thus, while the present analyses do not allow for an unqualified test of our assumptions, they nonetheless provide an informative step towards understanding the relationship between these various WM tasks.

DISCUSSION

The present results indicate that the *unique* contribution of visual arrays (our proxy for the scope of attention) to Gf is small. Returning to Figure 5, the regression path from VA to Gf implies that, other influences aside, VA accounts for approximately 5% of the variation in Gf. The subsequent regression analyses (Table 5) found a similar result. This should not be taken as an indication that visual arrays tasks provide a poor reflection of Gf. In fact the SEMs indicate that the total latent correlation between VA and Gf is in the range of .62 to .72. The critical point to be made is that the majority of this relationship is

TABLE 6
Fit indices for confirmatory factor analyses involving running memory span

Model	*χ2*	*df*	*p*	*RMSEA*	*SRMR*	*NNFI*	*CFI*	*AIC*
RunSpan-Both	20.33	7.00	0.00	0.11	0.05	0.95	0.97	48.33
RunSpan-CS	20.27	8.00	0.01	0.10	0.05	0.95	0.98	46.27

RMSEA = root mean square error of approximation; SRMR = standardised root mean square residual; NNFI = non-normed fit index; CFI = comparative fit index; AIC = Akaike's information criterion.

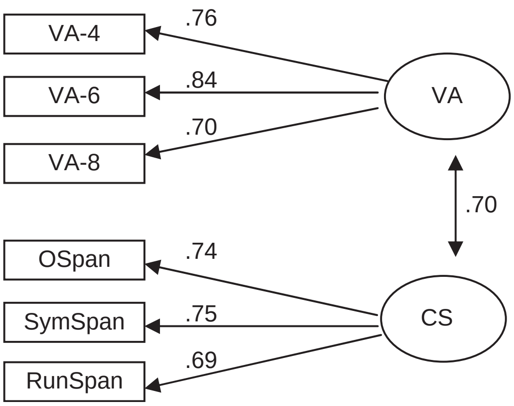

Figure 6. Two-factor solution with running memory span loading on CNTRL. VA-4 = visual arrays, set size 4; VA-6 = visual arrays, set size 6; VA-8 = visual arrays, set size 8; OSpan = operation span; SymSpan = symmetry span; RunSpan = running span; Scope = scope of attention; CNTRL = control of attention.

mediated by processes that are shared with CS. Thus, while we have interpreted VA and CS as different aspects of WM capacity, it may be their common mechanisms that ultimately define WM. So while we have generally interpreted these factors as the scope and control of WM-related attention, it is important to consider potential common mechanisms.

Focal attention as a common mechanism

The assumption that variance that is common to VA and CS represents the scope of a person's attention (e.g., Cowan et al., 2005) relies, in part, on the assumption that control processes that are present in complex span performance are absent from visual arrays. For instance, in a typical visual arrays display all information is goal-relevant (but see Vogel et al., 2005). Thus selective attention provides an unintuitive explanation of performance in this task. Perhaps more important, visual arrays are often assumed (at least implicitly) to provide a pure measure of storage in focal attention (Awh et al., 2007; Cowan, 2001; Cowan et al., 2005; Fukuda et al., 2010; Luck & Vogel, 1997). Given this assumption, controlled memory search would not be expected to be common to visual arrays and complex span tasks.

However, fixed capacity models of focal attention (e.g., Cowan, 2001) provide a problematic explanation of complex span performance. Specifically, the correlation between complex span and Gf is stable across list lengths (Bailey et al., 2011; Salthouse & Pink, 2008; Unsworth & Engle, 2006). This suggests that what complex span tasks index is an overall aptitude for retaining or retrieving critical information, rather than *how much* information a person can simultaneously maintain.

Oberauer's (2002); Oberauer, Süß, Wilhelm, & Sander, 2007) concentric model of WM can reconcile this concern. In this model focal attention is limited to one chunk of information. Temporary associations between this item and activated elements of long-term memory form a region of direct access. This region approximates

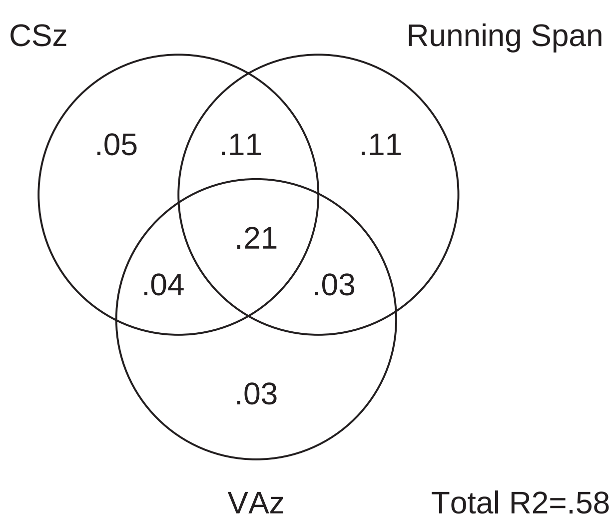

Figure 7. Venn diagram displaying unique and shared contributions of the scope of attention, control of attention, and running span to predicting Gf in Data Set B. VAz is a *z*-score composite of the three visual array set sizes. CSz a *z*-score composite of operation and symmetry span.

Cowan's (2001) focus of attention. WM capacity, however, is not simply the number of bindings that can be simultaneously maintained, but rather is driven by an individual's ability to both establish and break bindings. Complex span tasks may thus provide a measure of the efficacy with which this process is carried out, while visual arrays reflect some form of absolute capacity (e.g., number of bindings).

Selective attention as a common mechanism

The relationship between complex span performance and selective attention is well established (Kane et al., 2007). The presently employed visual arrays task, on the other hand, does not have an intuitively obvious component of controlled attention: This task does not require selection of specific information or suppression of prepotent responses. Rather, performance appears to reflect the amount of information a person can simultaneously maintain.

Fukuda and Vogel (2009, 2011), however, have demonstrated that individual differences in visual arrays predict individual differences in attention capture effects. Specifically, although WM capacity does not predict susceptibility to capture by response-compatible distraction, visual arrays performance does predict the rate at which a person disengages attention from distraction and reorients to critical information.

This finding comports with attention research conducted using the complex span task. For instance, Heitz and Engle (2007) attribute WM-related differences on flanker tasks (e.g., which way is the middle arrow pointing?: → → ← → →) to the rate at which attention is constrained to exclude distraction. Additionally, performance on the anti-saccade task, which requires test-takers to rapidly look away from a peripheral flash, is predicted by complex span performance (Kane et al., 2001; Unsworth et al., 2004). Interestingly, a person cannot perform this task without first noting the location of distracting information. Efficient performance thus requires a process of disengagement and reorientation, as described by Fukuda and Vogel (2009, 2011).

It might be reasonably argued that the relationship between visual arrays and controlled attention is mediated by a common relationship to WM as measured by complex span performance. The available literature cannot yet address this question. However, there are proposals that allow for a direct relationship between visual arrays and attention. Cusack, Lehman, Veldsman, and Mitchell (2009) hypothesise that visual arrays does not reflect temporary storage, per se, but storage that has been constrained by attention to allow for stable memory of a few items, rather than fragile memory for many items. Wheeler and Treisman (2002), on the other hand, propose that accurate memory in the visual arrays requires attention to bind features together (e.g., colour and location). In either case, memory limitations may be a product of attentional limitations.

Retrieval from secondary memory as a common mechanism

Although visual arrays performance is often interpreted as reflecting a person's capacity for multi-item storage (e.g., Cowan et al., 2005; Fukuda et al., 2010; Vogel & Machizawa, 2004), there are contradictory data. For instance, Makovski and Jiang (2008) demonstrated that participants experience difficulty detecting colour-changes when a visual arrays task is designed such that target objects occupy the same spatial location on multiple trials. In particular this occurs when an object on trial n changes to match the colour of the respective object from trial $n-1$. This implies the presence of proactive interference: Placing items in the same spatial location across trials apparently increases the difficulty involved in discriminating between critical information from the most recent trial and irrelevant information from older trials. This would be expected to arise during a search of secondary memory.

Furthermore, Shipstead and Engle (2012) have demonstrated that visual arrays performance is subject to manipulations of temporal discriminability (Baddeley, 1976; Glenberg & Swanson, 1986; Neath, 1998; Neill, Valdes, Terry, & Gorfein, 1992). That is, when two trials occur in rapid succession (relative to other trials), estimates of attentional capacity decrease. When two trials are separated in time (relative to other trials), estimates of focal attention increase. In other words the scope of a person's attention is subject to the difficulty involved in cuing a specific period of time. Temporally compressing two trials increases proactive interference and thus less information can be retrieved into focal attention. On the other hand, temporally separating two trials decreases proactive interference and more information can thus be retrieved into focal attention.

We thus assume that controlled retrieval into the focus of attention is among the processes that mediate the relationship between visual arrays and complex span. From the perspective of Oberauer's (2002; Oberauer et al., 2007) concentric model of WM capacity this interpretation simply requires an assumption that controlled retrieval is one of the mechanisms through which the region of direct access is maintained.

However, it can be argued that the manipulations of Makovski and Jiang (2008) and Shipstead and Engle (2012) do not act on secondary memory retrieval, but rather interfere with a person's ability to effectively maintain the region of direct access. Although this second interpretation is parsimonious, it is contradicted by a recent study (Lin & Luck, 2012) that concluded interference effects are not present in the visual arrays task when brief encoding and retention intervals are used. That is, interference was not present in a situation in which the updating of bindings would ostensibly be most difficult.

Lin and Luck (2012) propose that focal WM functions in at least two stages. The first is a stable memory representation similar to that proposed by Cowan (2001) and Luck and Vogel (1997). Given a long enough interval (unspecified, but greater than 1 second), secondary memory representations consolidate and begin to affect performance. However, regardless of explanation, it is clear that further research is needed in order to clarify the contribution that retrieval makes to visual arrays performance and, by extension, to the measurable capacity of focal attention.

Memory-related considerations

Although we have largely focused on the aspects of attention that are present in WM tasks, it is important to consider the differential demands that visual arrays and complex span make on memory. Visual arrays require a test-taker to process and retain information that is presented in parallel. As a consequence, information is ordered spatially, rather than temporally. Span tasks, on the other hand, present information sequentially. Accurate recall is not a simple matter of remembering which items were presented, but also recalling their relative position in time. Thus it is entirely possible that the difference between visual arrays and complex span tasks largely represents a difference of spatial/temporal organization (e.g., McElree & Dosher, 2001), while the common variance represents a WM system that is important to both types of memory demand.

Additionally, because the visual arrays task does not contain a processing component, one may argue that it is a measure of visuo-spatial short-term memory, rather than WM capacity. One method for exploring this question involves redefining Gf to be biased towards the visuo-spatial or verbal modalities and examining changes to the relationship between VA and Gf. By the logic of Kane et al. (2004) a visuo-spatial short-term memory task should be most strongly related to Gf when the Gf factor is composed of reasoning tasks that have strong visual components and most weakly related when Gf is composed of tasks with weak visual components. A modality-free WM component, on the other hand, would be unaffected by these changes.

Figure 5 provides relevant information. In Data Set A, Gf is defined by two tasks with strong visuo-spatial components (RAPM and PapFold) and two tasks with relatively weak visuo-spatial components (LettSet and NumSer). Data Set B, on the other hand does not include PapFold, and thus the Gf factor is likely biased towards the verbal/numerical dimension. Despite this change, the relationship of VA to Gf is numerically stable at .22 to .23.

Taking this logic one step further, we redefined Gf in Data Set A as RAPM and PapFold. Thus Gf now had a strong bias towards the visuo-spatial dimension. This resulted in a slight increase in the regression path between VA and Gf (.27) and a slight decrease in the regression path between CS and Gf (.63). Next we redefined Gf as LettSet and NumSer. Under these circumstances, the regression path between VA and Gf dropped slightly (.18) and the path between CS and Gf again showed a slight decline (.63).

These analyses suggest that VA is more sensitive to extreme changes in the modality of Gf tasks than is CS. This may be evidence of a visuo-spatial short term memory component in the visual arrays task. However, we also note that a similar analysis by Kane et al. (2004) resulted in a total path change of .25 between a factor composed of visuo-spatial simple span tasks (i.e., a more traditional measure of short-term memory) and Gf. In the present analysis the total change in the relationship between VA and Gf was a relatively small .09. Moreover, in all analyses the correlation between VA and CS remained stable at .61. Thus, regardless of how Gf was defined, VA's relationship to reasoning was largely expressed through the modality-free CS variable. While, we concede that VA may have a stronger short-term memory component than CS, this factor also reflects general WM capacity (e.g., Saults & Cowan, 2007).

Limitations and further directions

These analyses are only preliminary steps towards understanding the relationship between WM-related attentional maintenance and WM-related attentional control. As such, limitations are present and will need to be addressed by future research.

Critically, the two WM factors were created using one type of task each (i.e., visual arrays and complex span). The strength of this type of analysis is that it allows us to interpret the nature of the latent factors on the basis of previous research (Kane et al., 2004). The shortcoming of this approach is that aspects of the tasks that are not critical to WM are likely present, and thus generality of the factors is limited (Oberauer et al., 2007). For instance, complex span tasks require dual-task performance. However, the analyses using the running memory span (see also Broadway & Engle, 2010) indicate that dual-task performance is not a necessary component. Thus future research will need to (a) uncover a greater variety of tasks that converge on the scope and control of WM-related attention and (b) apply these tasks to latent-level analysis in order to improve the fidelity and generalisability of results.

Related to this concern, the CS factor was created using multiple types of complex span task, while only one type of visual arrays task was used to define VA. Thus this latter factor likely includes a relatively high proportion of task-specific variance (e.g., memoranda, type of change detection performed), which may reduce the generality of the path from VA to Gf in our SEMs. This is a serious concern and future studies will need to define VA via a broader range of change-detection tasks.

That said, several pieces of evidence justify our treatment of the different set sizes as separate tasks. First, while the matrices in Table 2 indicate that the visual arrays tasks had stronger inter-correlations than many of the complex span tasks, these correlations were far from unity. Although a given set size was a good predictor of the others, no two shared more than 45% of their variance (i.e., squared correlations).

Building off this point, examination of the factor loadings on Figures 3 and 5 reveals that VA was no more strongly related to each visual arrays set size than the CS was to each complex span task. This again suggests that, despite strong similarities between each set size, there were also substantial differences that were eliminated by the factor analysis.

Finally, we performed a series of simultaneous regression with each set size predicting z-score composites of the complex span and Gf tasks. As can be seen in the Appendix, each set typically predicted complex span and Gf above and beyond the other set sizes. In other words the separate set sizes have different implications for measurement of WM and Gf. Our factor and composite scores served to reduce these differences, thus allowing for a more pure measure.

Thus while our present measurement of the focus of attention is crude, it is obvious that the different array sizes contain both shared and unique variance. We postulate that the common variance represents the scope of attention. While further refinement may strengthen the regression path between VA and Gf (Figure 5), we assume that this factor is what drives the relationships between disparate visual-arrays-style change detection tasks.

Negative *K* values

Table 1 reveals that some participants had substantially negative scores on the visual arrays task. An obvious concern regards the possibility that these participants had misunderstood the directions and reversed the keys they were using to respond. We addressed this by examining negative scores at each set size for individual participants. Although a small number of participants had negative k values at one or two set sizes, no participant had negative values at all three. This reduces concern that they did not understand the response method.

Our own interpretation of this trend is that it is a by-product of participants who have a true k score at or near 0. These participants should be prone to guessing, leading to positive values at some set sizes and negative values at others (e.g., regression to the mean). Indeed, when we averaged *k* scores across set sizes, participants with negative values at one or more set sizes became much less extreme, ranging from -1.3 to $+1.3$.[2]

CONCLUDING REMARKS

The present investigation sought to address the individual roles of the scope of attention (as measured by the visual arrays task) and the control of attention (as measured by complex span task) in producing WM capacity. Further we explored the unique relationships of each to Gf. Two data sets confirmed that the visual arrays and complex span tasks are best explained by separate, but strongly correlated factors. Critically, each of these factors proved meaningful to the prediction of Gf.

Although we have argued that the scope of attention is, to a degree, reliant on control processes, we also note that it also uniquely contributes to prediction of Gf. Thus, regardless of whether focal attention is construed as stable maintenance (e.g., Cowan, 2001) or a process of continual retrieval (Jonides et al., 2008; McElree, 2006), the present data substantiate the view individual differences in the amount of information that people can ''hold'' in a readily accessible state are meaningful. WM capacity, however, should not be strictly conflated with these differences, or conceptualised as a capacity-bound storage system. The *processes* that allow appropriate information to enter the focus of attention clearly make the stronger contribution to higher-order cognition.

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[2] To further assuage concern that these values were affecting our outcomes, we reran the SEMs in Figure 5, first removing all participants who had more than two negative k values then removing all participants who had any k values that reached or exceeded –1. Neither analysis resulted in substantive changes.

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APPENDIX

Simultaneous regression of separate visual arrays set sizes on complex span and general fluid intelligence

Data Set A

	CSz			*Gfz*		
Array size	β	p	sr	β	p	sr
4	.05	.35	.04	.18	.001	.13
6	.36	<.001	.26	.30	<.001	.21
8	.12	.01	.10	.08	.07	.07

Data Set B

	CSz			Gfz		
Array size	β	p	sr	β	p	sr
4	.19	.03	.14	.27	.002	.20
6	.22	.02	.16	.23	.01	.16
8	.26	.002	.20	.15	.06	.12

CSz is a z-score composite of all complex span tasks used in a given data set. Gfz is a z-score composite of all general fluid intelligence tasks used in a given data set.