Psychonomic Bulletin & Review
2010, 17 (5), 673-679
doi:10.3758/17.5.673

Quantity, not quality: The relationship between fluid intelligence and working memory capacity

Keisuke Fukuda, Edward Vogel, Ulrich Mayr, and Edward Awh
University of Oregon, Eugene, Oregon

A key motivation for understanding capacity in working memory (WM) is its relationship with fluid intelligence. Recent evidence has suggested a two-factor model that distinguishes between the number of representations that can be maintained in WM and the resolution of those representations. To determine how these factors relate to fluid intelligence, we conducted an exploratory factor analysis on multiple number-limited and resolution-limited measures of WM ability. The results strongly supported the two-factor model, with fully orthogonal factors accounting for performance in the number-limited and resolution-limited conditions. Furthermore, the reliable relationship between WM capacity and fluid intelligence was exclusively supported by the number factor ($r = .66$), whereas the resolution factor made no reliable contribution ($r = -.05$). Thus, the relationship between WM capacity and standard measures of fluid intelligence is mediated by the number of representations that can be simultaneously maintained in WM, rather than by the precision of those representations.

Working memory (WM) enables the active maintenance of information in a readily accessible state. In addition to its core role in most large-scale models of cognition (e.g., ACT–R: Anderson, 1993; EPIC: Kieras & Meyer, 1997), a central motivation for research on WM is that it exhibits robust correlations with broader measures of intellectual ability, such as scholastic aptitude and fluid intelligence (Cowan et al., 2005; Cowan, Fristoe, Elliott, Brunner, & Saults, 2006; Engle, 2002; Engle, Tuholski, Laughlin, & Conway, 1999). The link between WM capacity and fluid intelligence has been observed across a broad range of experimental paradigms. One prominent approach has demonstrated correlations between fluid intelligence and WM capacity estimated using complex span measures (e.g., Daneman & Carpenter, 1980; Turner & Engle, 1989) that were designed to tap into both storage capacity and processing aspects of WM ability (e.g., Daneman & Carpenter, 1980; Engle et al., 1999; Kyllonen & Christal, 1990; Turner & Engle, 1989). Moreover, although several studies have emphasized the importance of the processing component in complex span tasks for the link with fluid intelligence, subsequent research has shown that even tasks that measure pure storage—in the absence of secondary processing loads—exhibit clear correlations with fluid intelligence (Colom, Flores-Mendoza, Quiroga, & Privado, 2005; Cowan et al., 2005). Specifically, such correlations are revealed when the task design prevents rehearsal and grouping processes that may skew a pure measure of storage capacity (e.g., Cowan, 2001; Cowan, Chen, & Rouder, 2004; Unsworth & Engle, 2007b).[1] For example, Cowan et al. (2005) examined the relationship between fluid intelligence and WM capacity measured in a simple change detection task introduced by Luck and Vogel (1997). In that experiment, observers saw an array of multiple colored squares and then, after a brief delay, indicated whether any of the items in a subsequent test array had changed. Although this task did not impose any other attention-demanding tasks or interfering stimuli, the resulting estimates of WM capacity were reliably correlated with fluid intelligence. Therefore, pure storage capacity alone is linked with the broader construct of fluid intelligence.

Evidence for a link between storage capacity in WM and fluid intelligence is an important step in our understanding of the basic determinants of intelligence. In particular, such simple tasks allow for relatively straightforward conclusions regarding the core cognitive operations that play a role in fluid intelligence, thereby complementing the data from complex span procedures that tap into a broader range of cognitive abilities, including dual task coordination, resistance to interference, access to secondary memory, and so on (e.g., Mogle, Lovett, Stawski, & Sliwinski, 2008; Unsworth & Engle, 2007a). Nevertheless, recent research has suggested that storage capacity in WM may not be a unitary construct. We refer here to a distinction between the number of items that can be held in WM and the resolution or precision of those representations. Xu and Chun (2006) provided neural evidence for such a dissociation with an imaging study that revealed distinct neural regions whose activity tracked the number of items that could be stored in

E. Awh, awh@uoregon.edu

WM, on one hand, and the complexity of the stored items, on the other hand. Given that more precise representations are required to support performance in memory tasks with complex stimuli, the results of Xu and Chun suggested that dissociable neural processes mediate number and resolution in visual WM. In line with this hypothesis, Awh, Barton, and Vogel (2007) examined individual differences in the number and resolution of representations in WM and found no correlation between these measures (despite having established the internal reliability of each measure). That is, the subjects who could maintain the largest number of items in WM were not necessarily the subjects who had the clearest memories. These data suggest a two-factor model in which number and resolution represent distinct facets of WM ability.

The two-factor hypothesis raises a fundamental question about the relationship between WM storage capacity and fluid intelligence. If number and resolution are distinct aspects of memory ability, which of these factors mediates the link with fluid intelligence? At first glance, it is reasonable to expect both factors to predict performance in standard measures of fluid intelligence. Consider two nonverbal measures of fluid intelligence that are prevalent in the literature, Raven's Advanced Progressive Matrices (RAPM) and Culture Fair Test (CFT). In each case, subjects are required to identify a missing item that completes a larger pattern defined across multiple complex objects.

To illustrate, Figure 1 depicts a problem styled in this fashion. The goal of the task is to identify the patterns presented across the eight figures and to indicate which item below (A, B, or C) completes the pattern. In this example, the correct answer is C, consistent with a pattern in which one additional vertical line appears for each rightward shift in the matrix. Here, a compelling intuition is that patterns of this kind will be more efficiently apprehended when more items can be simultaneously kept active in WM. At

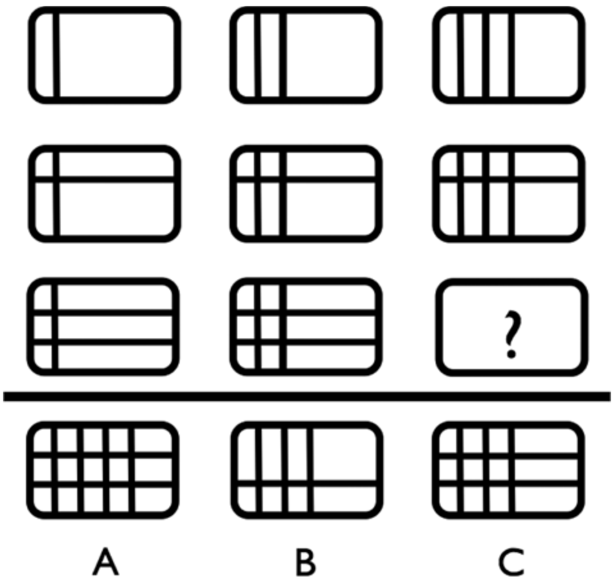

Figure 1. A typical example of a fluid intelligence task. The correct answer is C.

the same time, determining the nature of the pattern also requires a sufficiently detailed representation of these complex objects to capture variations in the critical feature.

Our central goal in the present work, therefore, was to provide a rigorous test of which components of storage capacity in WM mediate the relationship with fluid intelligence. The procedures that we used to measure number and resolution in WM were motivated by recent evidence that the primary limiting factors in change detection depend critically on the similarity between the sample items that are encoded into memory and the test items that are used to assess those memories (Awh et al., 2007; Barton, Ester, & Awh, 2009; Jiang, Shim, & Makovski, 2008; Scolari, Vogel, & Awh, 2008). When sample–test similarity is low, such that changes are relatively large, accurate change detection depends primarily on whether the critical item was represented in WM. This is a core assumption of the analytic procedure for estimating capacity developed by Pashler (1988) and refined by Cowan (2001). Thus, the probability of detecting such large changes provides an estimate of how many items were encoded from the sample array. Importantly, this interpretation of change detection performance has received strong converging support from studies of neural activity during the delay period of this task. Both electrophysiological (McCollough, Machizawa, & Vogel, 2007; Vogel & Machizawa, 2004; Vogel, McCollough, & Machizawa, 2005) and functional magnetic resonance imaging studies (Todd & Marois, 2004, 2005; Xu & Chun, 2006) have demonstrated that activity in the parietal cortex rises in a monotonic fashion as the number of items stored in WM increases. Critically, individual differences in neural responses during this task show that parietal activity reaches a plateau at the same set size at which the observer's capacity has been exhausted (McCollough et al., 2007; Todd & Marois, 2005; Vogel & Machizawa, 2004). This strong link between behavioral measures of (large) change detection and delay-specific neural activity bolsters the apparent validity of each method for estimating the number of items stored in WM. At the same time, behavioral performance (Awh et al., 2007) and neural activity (Xu & Chun, 2006) are qualitatively different when observers are asked to detect small changes between sample and test stimuli. Given that the same number of items is stored in these small-change tasks (Awh et al., 2007; Xu & Chun, 2006), we argue that errors in detecting these small changes may depend on whether the representations in WM have sufficient resolution for discriminating between psychologically similar sample and test items. Therefore, the present work employs a small-change detection task to operationalize resolution in visual WM.

We collected multiple measures of number and resolution in visual WM, enabling a latent variable analysis that attempted to identify the underlying pure constructs that determine memory performance. This allowed a rigorous evaluation of whether these two aspects of performance do indeed reflect distinct aspects of memory ability, as is proposed by the two-factor model. In addition, this approach provided a clear test of how these two aspects of WM capacity relate to fluid intelligence.

METHOD

Subjects

Seventy-nine undergraduate students from the University of Oregon participated for monetary compensation ($8/h). Each subject performed the two intelligence tests (CFT and RAPM) first and then performed the WM task.

Fluid Intelligence Measures

RAPM and the Cattell CFT were used to estimate individuals' fluid intelligence. The CFT consists of four subsets of tasks, each of which takes about 2.5–4 min. The score on each subtest was summed to create a single metric for the CFT score. We also administered RAPM, using Set I as practice and Set II for measurement. First, the subjects completed four questions from Set I for instruction. Then, from Set II, subjects completed as many questions as they could answer in 30 min. The RAPM score was calculated as the number of correct answers in Set II.

Obtaining Separate Measures of Number and Resolution in Visual WM

To assess number and resolution in visual WM, we adapted the change detection procedure employed by Awh et al. (2007). The possible stimuli consisted of four geometric shapes that were modeled after the line drawings used in the two nonverbal measures that we used to assess fluid intelligence, RAPM and CFT. The four shapes included two ovals and two rectangles. Thus, as Figure 2 illustrates, changes between the possible shapes varied systematically between large changes (i.e., when an oval shape changed to a rectangular shape, or vice versa) and small changes (i.e., changes from one oval to another or from one rectangle to the other). As the data will show, our assumptions regarding which types of changes were large or small were confirmed by large and reliable differences in change detection performance; accuracy in the large-change condition was more than twice as high as in the small-change condition. Next, we outline why performance in the large- and small-change conditions may be determined, respectively, by the number and the resolution of the representations stored in WM.

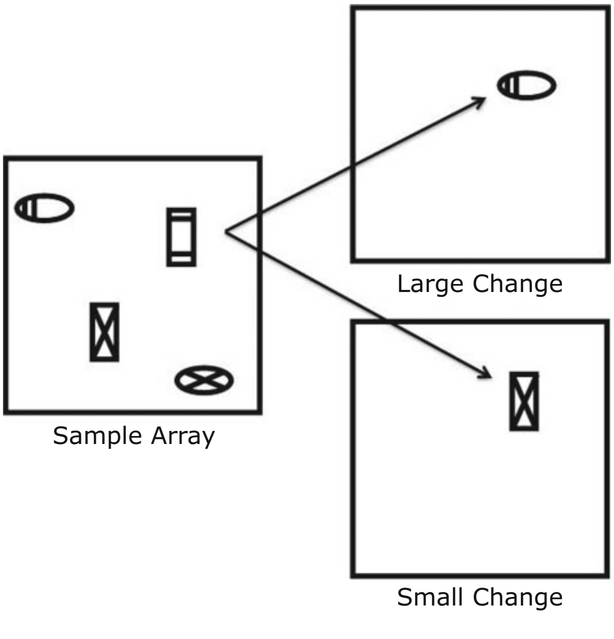

Figure 2. Illustration of a sample display (set size varied between 4 and 8) and the single-item probe display that appeared after a 1-sec retention period.

The rationale was that the detection of large changes would be limited primarily by whether the critical item was stored in WM, because the changes were large enough to minimize errors in the process of comparing an item in memory with the corresponding test item. By contrast, during small-change trials, we reasoned that even when the critical item was stored, the subjects' ability to detect the changes would be primarily determined by whether the critical item was stored with sufficient resolution to discriminate the difference between the sample and test items (see Awh et al., 2007, for further discussion).[2] Finally, we also included change detection trials with highly discriminable colored squares so that performance in this well-characterized variant of the change detection procedure could be compared with performance with the geometric shapes.

Stimuli

The stimuli in the change detection procedure were displayed on a centrally positioned light gray region (19.5º × 19.5º) that appeared over a dark gray background. Sample arrays contained either four or eight items, evenly divided between the four quadrants of the screen, with a minimum center-to-center distance of 4º between the items. Colored squares (1.5º on each side) were used to generate sample displays during color trials. The possible colors were red, blue, green, yellow, black, and white; these colors were randomly selected with the constraint that no color appeared more than twice in a single sample array. During the shape trials, sample arrays were created by randomly selecting from the four possible shapes (1.3º on the short side and 2.5º on the long side) with the constraint that at least one rectangle and one oval were included in each array.

Procedure

A sample array of either four or eight objects was presented for 500 msec, 1,092 msec after the onset of a central fixation point. A 1-sec retention interval started at the offset of the sample array, followed by the presentation of a single test item that remained visible until a response key was pressed. The subjects reported whether the object was the same object as the one presented at the same location in the memory array. The change detection procedure included nine blocks of 48 trials each. Within each block, 16 trials included color stimuli (8 *same* and 8 *change* trials, divided equally over set sizes 4 and 8). The set size 4 trials were included for two reasons. First, there has been some indication in the literature that performance with smaller set sizes may have a weaker link with fluid intelligence, perhaps because subjects differ in their ability to handle supraspan displays (Cusack, Lehmann, Veldsman, & Mitchell, 2009); thus, including both set sizes allowed us to replicate previous findings that set size may mediate the strength of the relationship with fluid intelligence. Second, set size 8 trials were very difficult (given that they contain approximately twice the number of items that an average subject can store), and set size 4 trials may help to keep subjects from deciding that the task is intractable. The remaining 32 trials included the geometric shapes (16 *same* and 16 *change* trials, divided equally over set sizes 4 and 8). Shape memory arrays were created by randomly selecting from the four possible shapes. When one of the shapes changed (which had a probability of .5), it was replaced by a shape randomly selected from the remaining three shapes, such that approximately two thirds of the change trials involved big changes (i.e., from oval to rectangle or rectangle to oval), and the remaining one third of the change trials were small changes (i.e., from oval to oval or rectangle to rectangle). To derive capacity estimates (k), we used the formula first invented by Pashler (1988) and refined by Cowan (2001): k = set size $*$ (hit rate $-$ false alarm rate), where k represents the number of objects stored, set size is the number of items in the sample array, hit rate is the proportion of *change* trials correctly detected, and false alarm rate is the proportion of *same* trials that elicited a *change* response. The k formula is a standard metric in the visual WM literature, because it corrects for response bias and enables a common metric of performance across different set sizes.[3] In the primary *SEM* analysis, we used the average k from the set size 4 and 8 trials. When the raw correlations between WM capacity and intelligence were examined separately for each set size, a qualitatively similar pattern of correlations was observed (see note 5).

RESULTS

First, we employed an exploratory factor analysis to test the hypothesis that two separate factors account for the number and the resolution of the representations that could be maintained in visual WM (see Tables 1A and 1B for descriptive statistics and a full correlation matrix).

This analysis included five separate measures of change detection performance defined by the type of item probed and the size of the change between the sample and test stimulus: (1) color *k* (color changes were always big); (2) big oval *k* (changes from ovals to rectangles); (3) small oval *k* (changes from one oval to another); (4) big rect *k* (changes from rectangles to ovals); and (5) small rect *k* (changes from one rectangle to the other). The two-factor hypothesis predicted that capacity estimates from the three large-change conditions (i.e., color *k*, big oval *k*, and big rect *k*) should load on a single factor related to the number of items that could be held in WM, whereas the two small-change conditions (small oval *k* and small rect *k*) should load on a distinct factor related to the resolution or precision of the representations stored in WM. The exploratory factor analysis confirmed that performance in the large- and small-change trials was best accounted for by a two-factor model. The three large-change conditions (color *k*, .84; big oval *k*, .88; big rect *k*, .90) all loaded strongly on a single factor, hereafter referred to as *the number factor*. By contrast, the small-change conditions (small oval *k*, $M = .87$; small rect *k*, $M = .88$) loaded on an orthogonal factor, hereafter referred to as *the resolution factor* (see Table 2).

There were no significant cross loadings ($p = .15$). These data therefore conform precisely to the predictions of the two-factor model, suggesting that number and resolution are distinct aspects of WM ability.

Having found strong support for a two-factor model of storage capacity, we examined which of these two aspects of storage capacity mediated the relationship with fluid intelligence. We carried out a confirmatory factor analysis of a model that included two independent factors for number and resolution and a third factor for fluid intelligence. The two measures of fluid intelligence loaded strongly on a common factor for fluid intelligence, or *g* (RAPM, $M = .83$; CFT, $M = .70$). The fit between the overall model and the observed data was excellent [$\chi^2(13,79) = 10.845$, $p = .6238$, RMSEA $= .00$, CFI $= 1.0$] (see Figure 3).

Moreover, the analysis demonstrated that the number and resolution factors had very different relationships with fluid intelligence. The number factor showed a strong positive correlation with fluid intelligence ($r = .66$, $SE = .1$), but the resolution factor showed no evidence of a reliable link with fluid intelligence ($r = -.05$, $SE = .13$). Moreover, constraining the path from mnemonic res-

Table 1A
Descriptive Statistics for Working Memory Tasks and Intelligence Tasks

	M	*SD*	Range	Skewness	Kurtosis
RAPM	22.00	4.61	11.00 to 32.00	−.27	−0.20
CFT	26.19	4.53	37.00 to 14.00	−.52	0.46
Color *k*	3.36	0.92	5.38 to 1.06	−.06	0.18
Small oval *k*	1.40	1.13	5.50 to −0.49	.83	1.13
Small rect *k*	1.16	1.05	4.66 to −1.17	.57	0.80
Big oval *k*	3.36	1.17	5.85 to 1.11	−.03	−0.72
Big rect *k*	3.52	1.13	5.77 to 0.81	.00	−0.42

Note—RAPM, Raven's Advanced Progressive Matrices; CFT, Cattel Culture Fair Test; Color *k*, *k* estimate from color conditions; Small oval *k*, *k* estimate from within-category oval conditions; Small rect *k*, *k* estimate from within-category rectangle conditions; Big oval *k*, *k* estimate from cross-category oval conditions; Big rect *k*, *k* estimate from cross-category rectangle conditions.

Table 1B
Correlations for Intelligence and Working Memory Capacity Measures

	RAPM	CFT	Color *k*	Small Oval *k*	Small Rect *k*	Big Oval *k*	Big Rect *k*
RAPM	–						
CFT	.58***	–					
Color *k*	.46***	.41***	–				
Small oval *k*	.06	.00	.22	–			
Small rect *k*	.04	.00	.13	.55***	–		
Big oval *k*	.44***	.34**	.63***	.22	.13	–	
Big rect *k*	.42***	.36**	.62***	.06	−.01	.70***	–

Note—RAPM, Raven's Advanced Progressive Matrices; CFT, Cattel Culture Fair Test; Color *k*, *k* estimate from color conditions; Small oval *k*, *k* estimate from within-category oval conditions; Small rect *k*, *k* estimate from within-category rectangle conditions; Big oval *k*, *k* estimate from cross-category oval conditions; Big rect *k*, *k* estimate from cross-category rectangle conditions. $^{**}p < .01$. $^{***}p < .001$.

Table 2
Factor Loadings of Working Memory Capacity Measures

	Number	Resolution
Color *k*	.841	
Big oval *k*	.877	
Big rect *k*	.897	
Small oval *k*		.869
Small rect *k*		.883

Note—Color *k*, *k* estimate from color conditions; Small oval *k*, *k* estimate from within-category oval conditions; Small rect *k*, *k* estimate from within-category rectangle conditions; Big oval *k*, *k* estimate from cross-category oval conditions; Big rect *k*, *k* estimate from cross-category rectangle conditions. Loadings for the missing cells were all less than .15.

olution to fluid intelligence to be 0 did not change the fit of the model [$\chi^2_{\text{difference}}(1,79) = 0.286, p = .59$] (Table 3), strengthening the conclusion that mnemonic resolution was unrelated to fluid intelligence.

These results suggest that the relationship between WM capacity and fluid intelligence is driven solely by the ability to hold multiple discrete representations in WM and not by the clarity of those representations.[4] Finally, although 79 participants is lower than the number employed in many analyses of this kind, we note that the standard errors around the correlations between fluid intelligence and slots (.1) and resolution (.13) are small. Thus, given the very strong contrast between the links observed between fluid intelligence and the two aspects of capacity (i.e., number and resolution), even a relatively large increase in the number of observations would be unlikely to change the core conclusions of this study.

CONCLUSIONS

The present work provides a new insight into the relationship between WM capacity and fluid intelligence. Using a simple change detection procedure, we obtained strong support for a two-factor model of WM capacity, in which the number and resolution of the representations in WM are determined by distinct aspects of memory ability. This two-factor model enabled a straightforward test of which aspects of WM capacity mediate its link with fluid intelligence. The data were very clear. The number of representations that could be held in WM showed a robust correlation with fluid intelligence ($r = .66$), whereas mnemonic resolution showed no trace of a reliable link with fluid intelligence ($r = -.05$). Thus, the relationship between storage capacity in WM and fluid intelligence appears to be mediated solely by the maximum number of items that can be simultaneously stored in WM, rather than by the resolution or precision of those representations.

One important consequence of these results is that in designing and selecting WM tasks, researchers need to be mindful of the aspects that they want to have reflected

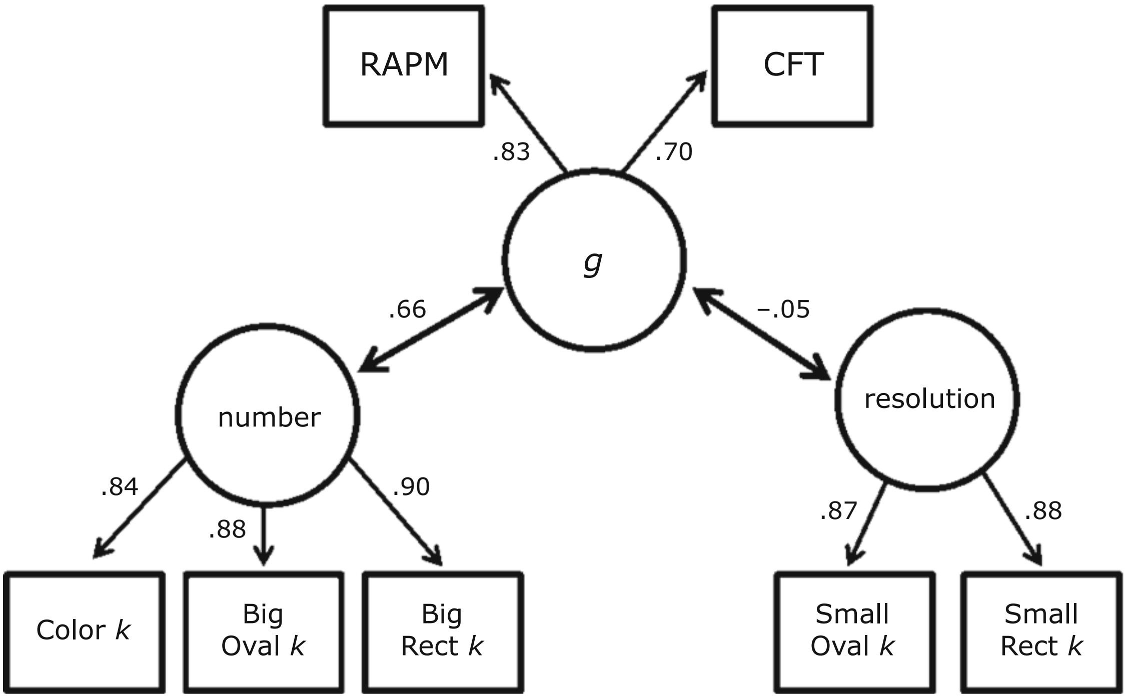

Figure 3. Results of the factor analysis. On the basis of the initial exploratory factor analysis, we generated three latent factors for *g*, working memory slots, and working memory resolution. The *g* factor was estimated from RAPM and CFT measures. The slots factor was generated from Color *k*, Big Oval *k*, and Big Rect *k*. Finally, the resolution factor was generated from Small Oval *k* and Small Rect *k*. The resulting model above was simultaneously tested. RAPM, Raven's Advanced Progressive Matrices; CFT, Cattel Culture Fair Test; Color *k*, *k* estimate from color conditions; Small Oval *k*, *k* estimate from within-category oval conditions; Small Rect *k*, *k* estimate from within-category rectangle conditions; Big Oval *k*, *k* estimate from cross-category oval conditions; Big Rect *k*, *k* estimate from cross-category rectangle conditions.

Table 3
Statistics for CFA Analysis

Model	df_M	χ^2	p	$\chi^2_{difference}$ With Model 1	p	RMSEA	90% CI	CFI
Model 1	13	10.845	.6238	–	.00	.00	.00, .09	1.0
Model 2	14	11.131	.6757	0.286	.5928	.00	.00, .09	1.0

Note—Model 1 is depicted in Figure 3. χ^2 values not significant at the .05 level indicate good fits to the data. Nonsignificant $\chi^2_{difference}$ values indicate that the model has an equivalent fit with the data. Lower values of root mean square error of approximation (RMSEA) indicate a better fit. An RMSEA value lower than .1 indicates a good fit to the data. Values above .95 for Bentler's comparative fit index (CFI) indicate excellent fit.

in the performance scores. Only tasks that assess sensitivity to large visual changes seem to relate to complex reasoning abilities as assessed in fluid intelligence tasks. Although the resolution aspect can be assessed reliably, future research is required to assess its external validity and its generality. One interesting possibility goes back to Spearman's distinction between general ability (*g*) and specific abilities (*s*): Possibly, *g* is reflected in the number of slots, whereas the resolution aspect reflects domain-specific and possibly experience-dependent characteristics of mnemonic processing.

Our findings fall in line with a recent observation that similar chunk limits have been observed in studies of capacity limits during abstract reasoning tasks and storage in WM (Halford, Cowan, & Andrews, 2007). Halford et al. suggested that a common attentional resource might be recruited to maintain individuated items in WM on one hand and to apprehend the interrelationships between relevant elements during reasoning on the other hand. In each case, average capacity estimates hover in the range of three to four items or interrelationships. The present data corroborate this finding by demonstrating that the abilities tracked by these memory and intelligence tasks strongly covary across individuals. Thus, the number of items that can be held in this online memory system may be a key limiting factor in our ability to apprehend abstract relationships between novel items.

Number of Slots or Control Over Slots?

The present data reveal a sharp contrast in how fluid intelligence relates to number and resolution in visual WM; whereas a robust correlation was found between the number and *g* constructs, no similar link was observed between resolution and *g*. Nevertheless, important questions remain regarding the core sources of variability in the number construct. One intuitive account of this measure is that it reflects variability across individuals in how many slots are available; from this perspective, low-capacity individuals are those that have less space in WM. An alternative view, however, is that apparent variations in the number of items stored may instead reflect individual differences in filtering efficiency, such that individuals with low capacity have difficulty excluding irrelevant information from reaching WM (McNab & Klingberg, 2008; Vogel et al., 2005). In this case, even if the number of slots available was relatively constant across observers, large variations in WM performance could emerge because of individual differences in filtering efficiency. Both the space and filtering accounts can account for individual differences in the number of relevant items represented in WM, but they posit distinct reasons for these differences.

In favor of the filtering account, a broad range of work has revealed strong correlations between WM capacity and filtering efficiency (Engle, 2002; Fukuda & Vogel, 2009; McNab & Klingberg, 2008; Vogel et al., 2005). Indeed, a recent study (Cusack et al., 2009) suggested that the link between visual WM and intelligence may be best explained by selection efficacy during these memory tasks, rather than by the total amount of space in WM.[5] At the same time, other studies have highlighted cases in which group differences in memory performance seem better accounted for by variations in space than by filtering (e.g., Cowan, Morey, AuBuchon, Zwilling, & Gilchrist, 2010; Gold et al., 2006); these results suggest that it may be useful to maintain a distinction between space and filtering effects on WM capacity. So far, it is not clear whether only one of these accounts can explain all of the variation across individuals in the storage of relevant items or whether these abilities are separate but strongly covarying aspects of memory function. Thus, an important goal for future work will be to determine whether space and filtering abilities account for unique variance in broad measures of intellectual function.

AUTHOR NOTE

Portions of this work were supported by Grant NIH-R01MH087214-01 to E.A. and E.V. We thank Nash Unsworth for valuable discussion of these findings. Correspondence concerning this article should be addressed to E. Awh, Department of Psychology, University of Oregon, 1227 University of Oregon, Eugene, OR 97405 (e-mail: awh@uoregon.edu).

REFERENCES

ANDERSON, J. R. (1993). *Rules of the mind*. Hillsdale, NJ: Erlbaum.

AWH, E., BARTON, B., & VOGEL, E. K. (2007). Visual working memory represents a fixed number of items, regardless of complexity. *Psychological Science*, **18**, 622-628.

BARTON, B., ESTER, E. F., & AWH, E. (2009). Discrete resource allocation in visual working memory. *Journal of Experimental Psychology: Human Perception & Performance*, **35**, 1359-1367.

COLOM, R., FLORES-MENDOZA, C., QUIROGA, M. Á., & PRIVADO, J. (2005). Working memory and general intelligence: The role of short-term storage. *Personality & Individual Differences*, **39**, 1005-1014.

COWAN, N. (2001). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *Behavioral & Brain Sciences*, **24**, 87-114.

COWAN, N., CHEN, Z., & ROUDER, J. N. (2004). Constant capacity in an immediate serial-recall task: A logical sequel to Miller (1956). *Psychological Science*, **15**, 634-640.

COWAN, N., ELLIOTT, E. M., SAULTS, J. S., MOREY, C. C., MATTOX, S. M., HISMJATULLINA, A., & CONWAY, A. R. A. (2005). On the capacity of attention: Its estimation and its role in working memory and cognitive aptitudes. *Cognitive Psychology*, **51**, 42-100.

COWAN, N., FRISTOE, N. M., ELLIOTT, E. M., BRUNNER, R. P., & SAULTS, J. S. (2006). Scope of attention, control of attention, and intelligence in children and adults. *Memory & Cognition*, **34**, 1754-1768.

COWAN, N., MOREY, C. C., AUBUCHON, A. M., ZWILLING, C. E., & GILCHRIST, A. L. (2010). Seven-year-olds allocate attention like adults unless working memory is overloaded. *Developmental Science*, **13**, 120-133.

CUSACK, R., LEHMANN, M., VELDSMAN, M., & MITCHELL, D. J. (2009). Encoding strategy and not visual working memory capacity correlates with intelligence. *Psychonomic Bulletin & Review*, **16**, 641-647.

DANEMAN, M., & CARPENTER, P. A. (1980). Individual differences in working memory and reading. *Journal of Verbal Learning & Verbal Behavior*, **19**, 450-466.

ENGLE, R. W. (2002). Working memory capacity as executive attention. *Current Directions in Psychological Science*, **11**, 19-23.

ENGLE, R. W., TUHOLSKI, S. W., LAUGHLIN, J., & CONWAY, A. R. A. (1999). Working memory, short-term memory and general fluid intelligence: A latent variable model approach. *Journal of Experimental Psychology: General*, **128**, 309-331.

FUKUDA, K., & VOGEL, E. K. (2009). Human variation in overriding attentional capture. *Journal of Neuroscience*, **29**, 8726-8733.

GOLD, J. M., FULLER, R. L., ROBINSON, B. M., MCMAHON, R. P., BRAUN, E. L., & LUCK, S. J. (2006). Intact attentional control of working memory encoding in schizophrenia. *Journal of Abnormal Psychology*, **115**, 658-673.

HALFORD, G. S., COWAN, N., & ANDREWS, G. (2007). Separating cognitive capacity from knowledge: A new hypothesis. *Trends in Cognitive Sciences*, **11**, 236-242.

JIANG, Y. V., SHIM, W. M., & MAKOVSKI, T. (2008). Visual working memory for line orientations and face identities. *Perception & Psychophysics*, **70**, 1581-1591.

KIERAS, D. E., & MEYER, D. E. (1997). An overview of the EPIC architecture for cognition and performance with application to human–computer interaction. *Human–Computer Interaction*, **12**, 391-438.

KYLLONEN, P. C., & CHRISTAL, R. E. (1990). Reasoning ability is (little more than) working-memory capacity?! *Intelligence*, **14**, 389-433.

LUCK, S. J., & VOGEL, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature*, **390**, 279-281.

MCCOLLOUGH, A. W., MACHIZAWA, M. G., & VOGEL, E. K. (2007). Electrophysiological measures of maintaining representations in visual working memory. *Cortex*, **43**, 77-94.

MCNAB, F., & KLINGBERG, T. (2008). Prefrontal cortex and basal ganglia control access to working memory. *Nature Neuroscience*, **11**, 103-107.

MOGLE, J. A., LOVETT, B. J., STAWSKI, R. S., & SLIWINSKI, M. J. (2008). What's so special about working memory? An examination of the relationships among working memory, secondary memory, and fluid intelligence. *Psychological Science*, **19**, 1071-1077.

PASHLER, H. (1988). Familiarity and visual change detection. *Perception & Psychophysics*, **44**, 369-378.

SCOLARI, M., VOGEL, E. K., & AWH, E. (2008). Perceptual expertise enhances the resolution but not the number of representations in working memory. *Psychonomic Bulletin & Review*, **15**, 215-222.

TODD, J. J., & MAROIS, R. (2004). Capacity limit of visual short-term memory in human posterior parietal cortex. *Nature*, **428**, 751-754.

TODD, J. J., & MAROIS, R. (2005). Posterior parietal cortex activity predicts individual differences in visual short-term memory capacity. *Cognitive, Affective, & Behavioral Neuroscience*, **5**, 144-155.

TURNER, M. L., & ENGLE, R. W. (1989). Is working memory capacity task dependent? *Journal of Memory & Language*, **28**, 127-154.

UNSWORTH, N., & ENGLE, R. W. (2007a). The nature of individual differences in working memory capacity: Active maintenance in primary memory and controlled search from secondary memory. *Psychological Review*, **114**, 104-132.

UNSWORTH N., & ENGLE, R. W. (2007b). On the division of short-term and working memory: An examination of simple and complex spans and their relation to higher order abilities. *Psychological Bulletin*, **133**, 1038-1066.

VOGEL, E. K., & MACHIZAWA, M. G. (2004). Neural activity predicts individual differences in visual working memory capacity. *Nature*, **428**, 748-751.

VOGEL, E. K., MCCOLLOUGH, A. W., & MACHIZAWA, M. G. (2005). Neural measures reveal individual differences in controlling access to working memory. *Nature*, **438**, 500-503.

XU, Y., & CHUN, M. M. (2006). Dissociable neural mechanisms supporting visual short-term memory for objects. *Nature*, **440**, 91-95.

NOTES

1. The core argument is that some types of grouping or rehearsal strategies (e.g., subvocal rehearsal or the elaboration of memoranda into meaningful chunks) may artificially inflate capacity estimates. Because these strategies are more effective for some subjects than for others, allowing such strategies to determine variance in the capacity measure may obscure real relationships between storage capacity and other measures.

2. Of course, even in small-change trials, the number of items stored determines the upper bound for performance. The experimental rationale, therefore, rests on the assumption that when the changes are small, the primary source of behavioral variance shifts from how many items are stored in memory to whether the stored representations are clear enough to enable the detection of a relatively subtle change.

3. Also, note that a shared pool of *same* trials contributed to k estimates in the large- and small-change conditions. Here again, the motivation was to provide a common metric for these two types of trials while correcting for the influence of response bias.

4. One alternative explanation of the correlation between large-change performance and fluid intelligence deserves comment. Given that large-change trials were twice as frequent as small-change trials, it is possible that the correlation between large-change performance and intelligence was because intelligent subjects are more likely to detect this contingency. However, the strength of the correlations between fluid intelligence and number were very similar across the color and shape change detection trials, even though all changes in the color condition were large (thereby obviating the need to notice this contingency). Moreover, even if large-change performance was affected by whether the subjects noticed the greater frequency of those trials, this would not explain why there was no apparent link between mnemonic resolution and fluid intelligence (despite high internal loadings that demonstrate the reliability of the resolution measure). Thus, the core conclusion that number and resolution in working memory have different relationships with fluid intelligence may hold even if sensitivity to trial proportions had an influence on large-change performance.

5. This argument was based on the observation that correlations between WM capacity and IQ were observed only for arrays larger than four items. This motivated the hypothesis that those correlations were driven more by the nature of the response to supraspan arrays than by capacity per se. In the present data set, the raw correlations with fluid intelligence were similar (and statistically reliable) between set size 4 (mean $r = .34$) and set size 8 (mean $r = .38$).

(Manuscript received December 14, 2009;
revision accepted for publication March 31, 2010.)