Intelligence 52 (2015) 18–23

Contents lists available at ScienceDirect

Intelligence

There may be nothing special about the association between working memory capacity and fluid intelligence

Gilles E. Gignac [a,*], Marley W. Watkins [b]

[a] University of Western Australia, Australia
[b] Baylor University, United States

ARTICLE INFO

Article history:
Received 7 March 2015
Received in revised form 17 June 2015
Accepted 26 June 2015
Available online xxxx

Keywords:
Working memory capacity
Fluid intelligence
General intelligence

ABSTRACT

The association between working memory capacity (WMC) and fluid intelligence (g_f) has been described as substantial and important. In a recent investigation, Gignac (2014a) contended that WMC and g_f share closer to 60% of their variance, rather than the commonly cited 50%, based on an analysis of the Wechsler Adult Intelligence Scale—IV (Wechsler, 2008) normative sample ($N = 2200$). However, Gignac's (2014a) investigation was limited in that it included only completely homogeneous g_f (spatial) and WMC (verbal) subtests, as well as only adults in the sample. Consequently, the purpose of this investigation was to replicate and extend Gignac (2014a) by estimating the association between WMC and g_f, based on the Wechsler Intelligence Scale for Children—Fifth Edition (Wechsler, 2014) normative sample ($N = 2200$), which includes a mix of verbal and spatial WMC subtests. Based on a correlated two-factor model, the correlation between WMC and g_f was estimated at .77 ($r^2 = .59$) which is a perfect replication of Gignac (2014a). However, based on a higher-order model which included all 18 of the WISC-V's subtests, the association between WMC and g_f was found to be non-significant ($-.10$, $p = .152$) after controlling for the effects of general intelligence. Consequently, the commonly suggested notion that WMC and g_f share unique cognitive and or neural processes was not considered supported, based on the results of this investigation.

1. Introduction

The nature and magnitude of the association between working memory capacity (WMC) and fluid intelligence (g_f) has been the subject of a substantial amount of empirical and theoretical research (Conway & Kovacks, 2013). The nature of the association between WMC and g_f has been described as fundamental, as WMC is considered a rate limiting factor in the performance of g_f problems (Carpenter, Just, & Shell, 1990; Fry & Hale, 1996; Oberauer, Su, Wilhelm, & Sander, 2007). From an empirical perspective, it is commonly stated that approximately 50% of the true score variance between WMC and g_f is shared, as Kane, Hambrick, and Conway (2005) reported a meta-analytically derived latent variable correlation of .72 ($r^2 = .52$), based on 14 samples (total $N = 3168$).

In a recent investigation, Gignac (2014a) suggested that the commonly cited 50% shared variance reported by Kane et al. may be smaller than what would be expected at the adult population level, as the vast majority of the samples included in the Kane et al. meta-analysis were based on university students (i.e., range restricted samples). Consequently, Gignac (2014a) tested a correlated two-factor model based on the WAIS-IV (Wechsler, 2008) normative sample data ($N = 2200$) and obtained a correlation of .77 ($r^2 = .59$) between WMC (Digit Span Backward, Digit Span Sequencing, and Letter–Number Sequencing) and g_f (Matrix Reasoning, Figure Weights, and Block Design), which suggested that they share closer to 60% of their true score variance.

Although a correlation of .77 may be considered substantial, Gignac (2014a) hinted at the possibility that the association between WMC and g_f may not be particularly special, by pointing out that the latent variable association between WMC and crystallised intelligence (g_c) was also very large ($r = .66$). Arguably, a more rigorous method that could be used to evaluate the question of special or unique association between WMC and g_f would be to use a higher-order model. Specifically, one would expect to observe a correlation between the residuals associated with the WMC and g_f first-order factors within a comprehensive higher-order model of intelligence, if there were cognitive and/or neural processes unique to WMC and g_f that caused them to correlate with each other. By contrast, the absence of a correlated first-order factor residual between WMC and g_f within a well-fitting higher-order model would imply that the association between WMC and g_f is mediated completely by g (see Gignac, 2008, for a discussion on the higher-order model and mediation). In such a case, the association between WMC and g_f would not be considered special or unique.

* Corresponding author at: School of Psychology, University of Western Australia, 35 Stirling Highway, Crawley, Western Australia 6009, Australia.
E-mail address: gilles.gignac@uwa.edu.au (G.E. Gignac).

http://dx.doi.org/10.1016/j.intell.2015.06.006
0160-2896/

Instead, WMC and g_f would simply be considered two indicators of g, much like g_c and processing speed (g_s), only perhaps stronger.

Based on a higher-order model, Gignac (2014a) did in fact report that WMC (.84) and g_f (.94) were superior indicators of g in comparison to g_c and g_s. Furthermore, Gignac (2014a) found g_f to be superior to WMC as an indicator of g ($p < .001$). Although not discussed by Gignac (2014a), it is worth noting that the results associated with his well-fitting higher-order model of the WAIS-IV did not include a correlation term between the WMC and g_f first-order factor residuals, which suggests the absence of a special or unique association between these two constructs. Additionally, the product of the WMC and g_f second-order factor loadings ($.84 * .94 = .79$) corresponded nearly exactly to the WMC and g_f correlated two-factor model correlation ($r = .77$), which suggests that the WMC and g_f association was mediated completely by g.

A distinct limitation associated with the Gignac (2014a) investigation, however, was that all of the g_f subtests were spatial in nature, while all of the WMC subtests were verbal in nature. Such inter-construct subtest homogeneity may have, to some degree, caused the WMC and g_f inter-association to be smaller than it would otherwise be. Gignac (2014a) suggested that a more convincing approach to the estimation of the WMC and g_f association would be to include at least some mix of spatial and verbal subtests across the two constructs. Fortuitously, the recently released WISC-V (Wechsler, 2014a) includes a spatial working memory subtest, Picture Span. Consequently, the opportunity to model a WMC and g_f correlated two-factor model, as well as a comprehensive higher-order model with a somewhat content heterogeneous WMC latent variable is now possible with a large normative sample ($N = 2200$).

Gignac's (2014a) investigation was also limited in that the sample consisted solely of adult participants (ages: 16 to 90 years). Consequently, Gignac (2014a) could only assume that the WMC and g_f .77 correlation extended to children. Based on the differentiation and de-differentiation hypotheses (see Tucker-Drob, 2009, for example), it is possible that the association between WMC and g_f may decrease or increase in magnitude across human development. Alternatively, it is also possible that the approximate 60% shared variance between WMC and g_f remains relatively constant throughout life, from childhood to old age, consistent with the indifferentiation hypothesis (Juan-Espinoza, Cuevas, Escorial, & Garcia, 2006). Based on a large number of normative Wechsler battery samples (not including the WISC-V), Gignac (2014b) found that that the strength of the g factor remains relatively constant from ages 2.5 to 90 years. In light of the above, the attempt to replicate the results of Gignac (2014a) in a sample of children aged 6 to 16 years of age was considered useful.

In summary, the purpose of this brief investigation was to replicate the results of Gignac (2014a) with a cognitive ability test battery that included a mix of verbal and spatial working memory subtests, as well as a large normative sample of children. Additionally, it was considered beneficial to evaluate specifically the possibility that the WMC and g_f association may not be special or unique, as determined within a higher-order modeling framework.

2. Method

2.1. Sample

The analyses were performed upon the complete normative sample ($N = 2200$) inter-subtest correlation matrix associated with the WISC-V (Wechsler, 2014b). The WISC-V normative sample was obtained based on a stratified sampling strategy to reflect the US census results relevant to gender, age, race/ethnicity, education, and geographic location (Wechsler, 2014b). The WISC-V normative sample age range is 6 to 16 years. In addition to the total sample, the analyses were performed across the following age groups: 6–7 years ($N = 400$), 8 to 9 years ($N = 400$), 10 to 11 years ($N = 400$), 12 to 13 years ($N = 400$), and 14 to 16 years ($N = 600$).

2.2. Materials

The WISC-V consists of a total of 18 core and supplemental subtests (Wechsler, 2014a). Matrix Reasoning (MR) and Figure Weights (FW) may be considered excellent indicators of g_f, as they consist of novel problems that require the identification of patterns in stimuli to be solved (Wechsler, 2014a). In addition to MR and FW, the Block Design (BD) subtest is often considered an indicator of g_f (Goldstein, 2008), although perhaps not as pure a measure of g_f as MR and FW. The WISC-V (Wechsler, 2014b) technical manual specifies a Perceptual Reasoning first-order factor defined by MR, Picture Concepts (PC), FW, and AR. However, based on a bifactor model of the WISC-V normative sample, Canivez and Watkins (in press) found that PC had a very negligible loading (.06) on the nested Perceptual Reasoning latent variable. Therefore, PC was not considered a good indicator of g_f in this investigation. Visual Puzzles (VP) may be argued to be a good indicator of g_f, however, to-date, very little research has been conducted with the VP subtest within the Wechsler scales. Because Gignac (2014b) did not use VP as an indicator of g_f, we opted to use MR, FW, and BD as indicators of g_f for the purposes of consistency. However, for the purposes of robustness analyses, some re-testing was performed with VP as an indicator of g_f.

We did not consider Arithmetic a measure of g_f, as it requires the application of previously learned operations to solve the items successfully. Furthermore, based on a bifactor model of the WISC-V ($N = 2200$), we found that Arithmetic loaded negatively ($-.10$) onto a nested Perceptual Reasoning factor (full results available upon request). Canivez and Watkins (in press) found Arithmetic to be, at best, a very negligible loader (.13) onto a nested WM factor (see also Gignac & Watkins, 2013). Consequently, in light of the above, we considered Arithmetic to be only an indicator of g within the context of the WISC-V.

Digit Span Backwards (DSB), Digit Span Sequencing (DSS), and Letter–Number Sequencing (LN) may be considered very good to excellent measures of WMC (Sattler & Ryan, 2009). Finally, Picture Span (PS) is described by Wechsler (2014a) as a working memory subtest, as it requires the participant to identify on a response sheet the stimuli that were presented on a stimulus page in the order with which they were presented. Canivez and Watkins (in press) found PS to be an appreciable loader (.30) on a nested working memory factor, based on the WISC-V normative sample.

Verbal Comprehension subtests within the WISC-V include Vocabulary (VOC), Information (IN), Comprehension (CO) and Similarities (SI). In our view, Similarities contains too much abstraction skill to be considered a relatively pure measure of g_c, although it does appear to share a non-negligible amount of variance with a nested Verbal Comprehension factor (Canivez & Watkins, in press). All things considered, we regarded Similarities a good indicator of g within the context of the WISC-V, as per Gignac (2014a) in the context of the WAIS-IV. However, for the purposes of robustness analyses, some re-testing was performed with Similarities as an indicator of g_c.

Finally, Processing Speed is measured within the WISC-V with three subtests: Symbol Search (SS), Coding (CD), and Cancellation (CA). According to the bifactor model tested by Canivez and Watkins (in press), all three of these subtests are good indicators of Processing Speed, independently of the effects of g.

2.3. Data analysis

All analyses were conducted with Amos 21 (Arbuckle, 2012). As can be seen in Fig. 1, the association between g_f and WMC was estimated with a correlated two-factor model, first excluding the PS subtest (panel A), in order to replicate Gignac (2014a), then including PS as an indicator of WMC (panel B) to extend Gignac (2014a). Next, to

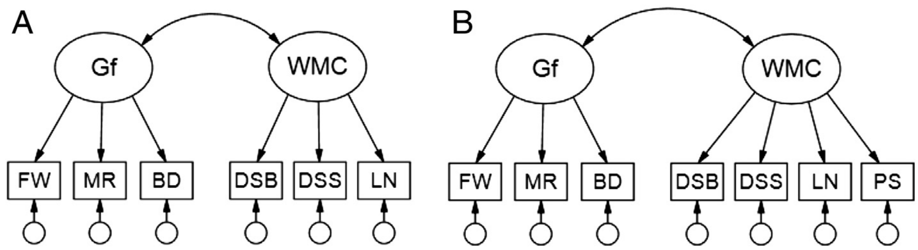

Fig. 1. Correlated two-factor models tested in this investigation (A: excluding PS; B: including PS; PS = Picture Span).

estimate the strength of the g_f and WMC latent variables, independently of their shared variance, the correlated two-factor model analyses were supplemented with corresponding bifactor models (Gustafsson & Balke, 1993; see Fig. 2). Consistent with Gignac (2014a), the strength of the nested WMC and g_f latent variables was estimated via omega specific (ω_s; Gignac, Palmer, & Stough, 2007; Reise, 2012). ω_s is the sum of the squared standardized loadings associated with a nested factor divided by the total variance associated with the indicators used to define the corresponding nested factor. Values can range from .00 to 1.0 with larger values indicative of a stronger factor.

As per Gignac (2014a), in order to test the hypothesis that the nested WMC and g_f latent variables were associated with equal ω_s estimates, a bootstrapped sampling distribution of the difference in WMC and g_f ω_s values was estimated via 1000 parametric bootstrapped replications within Amos 21. It will be noted that the bifactor model in panel A (Fig. 2) is not identified based upon conventional scaling specifications (Zinbarg, Revelle, & Yovel, 2007). Consequently, in addition to constraining the latent variable variances to one, the MR and LN common factor loadings were constrained to equality to achieve model identification. Such a strategy was considered defensible, in the event that the model with the equality constraints did not result in a poor-fitting model. To help ensure comparability of results, the bifactor model depicted in panel B retained the same equality constraints included in the bifactor model depicted in panel A.

Finally, in order to replicate the observation that g_f is a better indicator of g than WMC (Gignac, 2014a), a hybrid higher-order model was tested. As can be seen in Fig. 3, four first-order factors were specified to have as close a correspondence to the factors described within the Cattell–Horn–Carroll model of abilities (Carroll, 2003).

The g_f factor was defined by MR, FW, and BD. WMC was defined by DSB, DSS, LN, and PS. Arithmetic (AR) and Digit Span Forward (DSF) were included in the model as a direct indicators of g. Finally, processing speed (g_s) was defined by Symbol Search (SS), Coding (CD), and Cancellation (CA). The SI, VP, PC, DSF and AR subtests were included in the model as direct indicators of g to help create a broad g factor. As per Gignac (2014a), in order to test the null hypothesis that the g_f and WMC latent variables would be associated with equal second-order factor g loadings, a bootstrapped sampling distribution of the difference in WMC and g_f second-order factor g loadings (Δg) was estimated via 1000 parametric bootstrapped replications within Amos 21 (see Gignac, 2014a, for further details relevant to testing statistically the difference between two standardized factor loadings). Finally, for the purposes of robustness, the hybrid higher-order model was re-tested with the inclusion of SI as an indicator of g_c and VP as an indicator of g_f. As VP and BD are very similar tests and indicators of visual spatial ability according to the WISC-V (Wechsler, 2014b) technical manual, the modified hybrid higher-order model included a covariance term between the VP and BD subtest residuals.

3. Results

As a well-fitting correlated two-factor model does not necessarily preclude the plausibility of a well-fitting, simpler, single-factor model, the first model tested in this investigation was a single-factor model (three g_f indicators and three WMC indicators), which was not found to be acceptably well-fitting, $\chi^2(9, N = 2200) = 306.92$, $p < .001$, CFI = .925, TLI = .875, RMSEA = .123, SRMR = .052. Next, the correlated two-factor model was tested and found to be well-fitting, $\chi^2(8, N = 2200) = 10.68$, $p = .221$, CFI = .999, TLI = .999, RMSEA = .012, SRMR = .009. Furthermore, the correlation between the g_f and WMC latent variables was estimated at $r = .76$ ($r^2 = .58$), $p < .001$, with 95% CIs equal to .72 and .79. Thus, as the upper bound did not intersect with 1.0, the factorial distinction between WMC and g_f may be considered plausible. As can be seen in Table 1 (left-hand side), the WMC and g_f latent variable correlation was very consistent across the age groups (range: .75 to .78).

To examine the question of WMC and g_f factorial uniqueness more directly, the corresponding bifactor model was tested and found to be well-fitting, $\chi^2(4, N = 2200) = 5.85$, $p = .211$, CFI = 1.00, TLI = .998, RMSEA = .015, SRMR = .005. As can be seen in Table 2 (left-hand side), all of the factor loadings were positive and statistically significant. For the total sample, the nested WMC and g_f latent variables were associated with ω_s estimates of .24 and .13, respectively. The difference between the two ω_s estimates was found to be statistically significantly ($\Delta\omega_s = .11$, $p = .02$). Across the age groups, nearly all of the ω_s estimates were positive and statistically significant, with the exception of the 10 to 11 years age group, which yielded a relatively small and non-significant g_f ω_s value (see Table 3; left-hand side). The 10 to 11 age group was also associated with a g_f vs WMC statistically significant difference in ω_s values ($\Delta\omega_s = -.24$, $p = .02$).

Next, the same series of analyses were conducted with the inclusion of the Picture Span subtest as an indicator of WMC. Based on the total sample, the correlated two-factor model was found to be well-fitting, $\chi^2(13, N = 2200) = 5.85$, $p = .003$, CFI = .996, TLI = .994, RMSEA = .025, SRMR = .014. Furthermore, the WMC and g_f latent variable correlation was estimated at .77, $p < .001$ (95% CI: .74/.80).

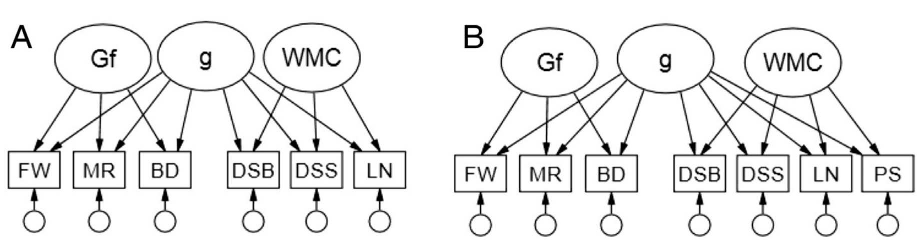

Fig. 2. Bifactor models tested in this investigation (A: excluding Picture Span; B: including Picture Span).

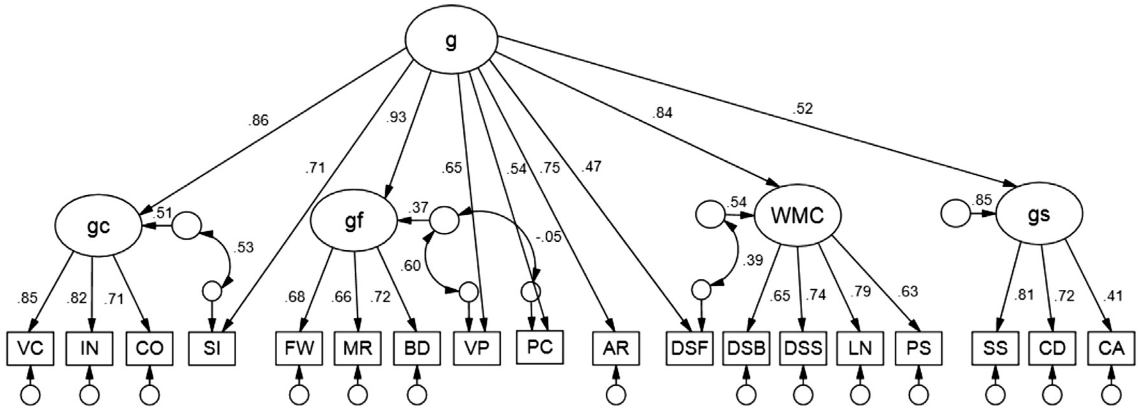

Fig. 3. Hybrid higher-order model depicting the association between relatively pure Cattell–Horn–Carroll WISC-V first-order factors and g (N = 2200).

Thus, only slightly larger than the correlation of .76, based on the correlated two-factor model that excluded PS as an indicator. Again, the correlations were largely consistent across the age groups (see Table 1; right-hand side). Next, the corresponding bifactor model was tested and found to be well-fitting, $\chi^2(8, N = 2200) = 14.50$, $p = .070$, CFI = .999, TLI = .996, RMSEA = .019, SRMR = .008. As can be seen in Table 3 (right-hand side), for the total sample, all of the subtest factor loadings were positive and statistically significant ($p < .05$). Finally, as can be seen in Table 3, for the total sample, the WMC and g_f latent variables were associated with ω_s of .21 and .13, respectively, which was not found to be statistically significantly different ($\Delta\omega_s = .07$, $p = .15$). Thus, the strength of the nested WMC latent variable reduced somewhat from .24 to .21 with the addition of the PS indicator to the model.

In the last series of analyses, a hybrid higher-order model was tested to determine whether g_f was a more substantial loader on g than WMC. The model fit well: $\chi^2(127, N = 2200) = 491.54$, $p < .001$, CFI = .978, TLI = .974, RMSEA = .036, SRMR = .026. Furthermore, as can be seen in Fig. 3, g_f and WMC were associated with second-order loadings of $\lambda = .93$ ($\lambda^2 = .86$) and $\lambda = .84$ ($\lambda^2 = .71$), respectively. The difference in loadings of .09 was found to be statistically significant ($p = .001$; 95% CI: .06/.13), suggesting that g_f was a stronger indicator of g than WMC.[1] Although a factor loading difference of .09 may be considered small, when expressed in terms of percentage of variance shared with g, the difference between g_f ($.93^2 = 86\%$) and WMC ($.84^2 = 71\%$) may be considered more appreciable (i.e., 86%–71% = 15%). The results were observed to be robust to the inclusion of SI as an indicator of g_c and VP as an indicator of g_f within a modified hybrid higher-order model (second-order loadings: $\lambda g_f = .92$, $\lambda_{WMC} = .85$; $\Delta\lambda = .07$, $p < .001$; $\lambda^2 g_f = .85$, $\lambda^2_{WMC} = .72$, $\Delta\lambda^2 = .13$; full results available upon request). Across ages, however, it will be noted that the statistical superiority of g_f did not emerge until the ages of 10 to 11, with little numerical differences in second-order g_f and WMC loadings associated with the 6 to 7 and 8 to 9 age groups (see Table 4).

Finally, it will be noted that there was no evidence to suggest that the g_f and WMC first-order factor residuals should be allowed to covary. First, the modification index associated with the g_f and WMC first-order factor residuals was estimated at only 1.43. Correspondingly, the addition of a covariance link between the g_f and WMC first-order factor residuals yielded a non-significant coefficient ($-.10$, $p = .152$). Finally, the product of the g_f and WMC second-order g loadings ($.93 * .84 = .78$) corresponded nearly exactly to their corresponding correlated two-factor latent variable model correlation ($r = .76$), which suggested further that the entirety of the shared variance between g_f and WMC was mediated by g.

4. Discussion

The results of this investigation based on children suggest that WMC and g_f share closer to 60% of their true score variance ($r^2 = .58$), in close agreement with the results reported by Gignac (2014a) in adults ($r^2 = .59$). Given the recent focus on the importance of replication in psychological research (Ledgerwood, 2014), such a close correspondence in the results between two studies may be considered noteworthy. The magnitude of the association between WMC and g_f changed only trivially with the addition of the PS subtest to the model as an indicator of WMC ($r^2 = .59$). Thus, Gignac's (2014a) contention that WMC and g_f share closer to 60% of their true score variance may be considered in a robust position. As per Gignac (2014a), there was also evidence to suggest that both WMC and g_f were associated with unique true score variance (i.e., ω_s). Thus, they are very likely not isomorphic constructs, in contrast to some suggestions (Blair, 2006).

Precisely why g_f and WMC share such a large amount of true score variance remains an active area of research (Conway & Kovacks, 2013). Some contend that the association is fundamental in nature (Carpenter et al., 1990; Fry & Hale, 1996; Oberauer et al., 2007). Others, however, have suggested that the association may not be particularly special. For example, based on running memory type tasks, Salthouse and Pink (2008) and Salthouse (2014) failed to observe a positive association between working memory item difficulty and g_f. Stated alternatively, working memory items which were more cognitively demanding were not observed to predict individual differences in fluid intelligence any better than simpler working memory items. Consequently, Salthouse (2014) concluded that the principal reason

Table 1
g_f by WMC latent variable correlations across age groups (including and excluding PS).

Age	Excluding PS		Including PS	
	r	95% CI	r	95% CI
6–7	.78	.69/.86	.77	.74/.80
8–9	.75	.65/.83	.76	.67/.83
10–11	.76	.67/.83	.75	.67/.82
12–13	.77	.69/.84	.81	.73/.87
14–16	.76	.69/.81	.76	.70/.82
6–16	.76	.72/.79	.77	.74/.80

Note. PS = Picture Span.

[1] As the results associated with higher-order modeling can sometimes be difficult to interpret (Gignac, 2014b; Molenaar, Dolan, Wicherts, & van der Maas, 2010), a bifactor model was also tested with direct links between a first-order general factor and nested first-order Verbal Comprehension, Perceptual Reasoning, Working Memory, and Processing Speed index factors. The model was found to be well-fitting: $\chi^2(118, N = 2{,}200) = 413.08$, $p < .001$, CFI = .982, TLI = .977, RMSEA = .034, SRMR = .023. Furthermore, the MR, FW, BD subtests were associated with a mean g loading of .633. By contrast, the DSB, DSS, LN, and PS subtests were associated with a mean g loading of .595. Thus, the bifactor results corroborated the hybrid higher-order model results, suggesting that the g_f subtests were associated with higher levels of g saturation.

Table 2
Completely standardized factor loadings associated with the g_f and WMC bifactor model.

	Excluding − PS			Including − PS		
	g	g_f	WMC	g	g_f	WMC
FW	.63	.27		.62	.29	
MR	.65	.23		.65	.24	
BD	.59	.36		.59	.36	
DSB	.55		.32	.56		.32
DSS	.62		.43	.62		.41
LN	.65		.65	.65		.46
PS	–	–	–	.58		.23

Note. $N = 2200$; all loadings were statistically significant ($p < .001$).

Table 4
Higher-order model fit statistics and standardized second-order factor loadings.

Age	Fit statistics/indices					Second-order loadings				g_f vs. WMC	
	χ^2	SRMR	RMSEA	TLI	CFI	g_c	g_f	WMC	g_s	Δ	p
6–7	252.21	.041	.050	.943	.953	.82	.89	.91	.56	−.02	.679
8–9	174.38	.035	.031	.979	.983	.85	.89	.87	.57	.01	.827
10–11	206.15	.034	.040	.968	.974	.82	.93	.82	.51	.11	.021
12–13	216.55	.037	.042	.969	.974	.89	.96	.84	.55	.12	.037
14–16	270.06	.034	.043	.967	.973	.89	.95	.81	.50	.15	.012
6–16	491.04	.026	.036	.974	.978	.86	.93	.84	.52	.09	.001

Note. Across all ages, $df = 127$; Δ = difference in g_f and WMC standardized factor loadings; p = bootstrapped based p value;

WMC and g_f are related may be simply because of the novelty associated with the items, rather than some fundamentally shared process. Additionally, Mogle, Lovett, Stawski, and Sliwinski (2008) examined the inter-associations between processing speed, primary memory, WMC, secondary memory, and g_f in a sample of 384 university students. From a bivariate perspective, WMC was found to correlate with g_f at .42. However, in their final model, Mogle et al. regressed g_f onto the four latent memory variables and found that WMC did not have a unique effect on g_f. Mogle et al. concluded (p. 1076):

> "The current findings … suggest the need for a reframing of claims that the relationship between WMC and fluid intelligence is unique to these constructs…. On the contrary, it appears that all of the memory tasks used in this study incorporate, to some degree, the processes that underlie the relationships of WMC to fluid intelligence."

Based on the results of this investigation, Mogle et al.'s conclusion should probably be generalised beyond "memory tasks." Specifically, it may be suggested that the "processes" that underlie the association between WMC and g_f are incorporated, to some degree, across all cognitive ability tasks, that is, g. Furthermore, WMC and g_f do not appear to share variance above and beyond that which can be accounted for by g, as there was no evidence to suggest that their first-order factor residuals were correlated within the second-order factor model of intelligence tested in this investigation. Thus, WMC and g_f may be suggested to share a substantial amount of variance, simply because they incorporate a substantial amount of the elements fundamental to g.

It will be noted that both WMC and g_f were observed to be the two most substantial indicators of g in this investigation, consistent with Gignac's (2014a) investigation of the WAIS-IV and other investigations (e.g., Benson, Hulac, & Kranzler, 2010; Watkins, 2010). Consequently, perhaps from this perspective, WMC and g_f may be regarded as special. As per Gignac (2014a), g_f was observed in this investigation to be a more substantial indicator of g than WMC. Furthermore, the magnitude of the difference was very similar ($\Delta g^2 = 15\%$ vs. $\Delta g^2 = 17\%$). However, in contrast to Gignac (2014a), the difference was not completely consistent across age groups. In the youngest age groups of this investigation (ages 6 to 7 and 8 to 9 years), the difference between the WMC and g_f second-order loadings was numerically very small and non-significant statistically. However, across all age groups, it was noted that the WMC second-order g loading was observed to reduce in magnitude, whereas the g_f second-order g loading was observed to increase in magnitude. Unfortunately, testing such trends statistically (via, say, multi-group confirmative factor analysis or moderated factor analysis) was not possible as it would require access to the raw (unscaled) data, which is not available from the test publisher.

However, in a comprehensive higher-order model analysis of the Woodcock–Johnson-III raw data (Woodcock, McGrew, & Mather, 2001) normative sample (ages: 4 to 80 years; $N = 6273$), Tucker-Drob (2009) found evidence for ability differentiation, but not age differentiation, which was considered a perplexing observation, as cognitive capacity increases across the ages of 4 to 25 years in humans. It is worth noting, however, that Molenaar et al. (2010) detailed a number of distinctly different circumstances under which second-order loadings may be observed to change in magnitude, which can make interpretations of higher-order model solutions rather difficult. In light of the above, we offer here only as a speculative suggestion that WMC may increasingly differentiate itself from g, to some degree, from ages 6 to 9, whereas g_f may de-differentiate itself from g, to some degree, across the same age span. In contrast to the higher-order model results, the simpler bivariate association between WMC and g_f appears to be largely constant across the ages of 6 to 16, an effect also observed in adults (Gignac, 2014a). The strength of the g factor also appears to be consistent across a wide age span (Gignac, 2014b).

4.1. Limitations

The validity of the interpretation of the results reported in this investigated are limited to the extent that the associations between the variables are linear. There is some evidence to suggest that to be the case, at least in adults, via bifactor modeling (Gignac & Weiss, in press; see Reynolds, 2013, for a contrasting view in children via higher-order modeling). For the purposes of greater test heterogeneity, a model which included a verbal measure of g_f may be considered a useful future investigation. However, the fact that the addition of a spatial measure of WMC to the model had virtually no effect on the magnitude of the

Table 3
Fluid Intelligence (g_f) and WMC omega specific estimates across age groups.

Age	Excluding Picture Span						Including Picture Span					
	WMC		g_f				WMC		g_f			
	ω	95% CI	ω	95% CI	$\Delta\omega$	p	ω	95% CI	ω	95% CI	$\Delta\omega$	p
6–7	.21	.09/.32	.22	.39/*	−.01	.49	.17	.02/.29	.14	*/.23	.02	.54
8–9	.19	.06/.28	.20	.26/.31	−.01	.91	.15	.03/.25	.20	.25/.30	−.05	.58
10–11	.29	.18/.43	.05	−.40/.17	.24	.02	.30	.19/.47	.08	−.57/.20	.22	.03
12–13	.22	.09/.30	.15	.18/.25	.07	.51	.17	.06/.26	.14	.04/.26	.03	.67
14–16	.22	.13/.32	.15	.24/.23	.07	.28	.23	.14/.33	.14	.15/.22	.08	.21
6–16	.24	.18/.28	.13	.27/.18	.11	.02	.21	.15/.26	.13	.28/.19	.07	.15

Note. $\Delta\omega$ = difference between WMC and g_f ω values; p = bootstrapped based p value; * could not be estimated.

association between WMC and g_f would suggest that shared modality variance has little impact on the association. Also, it should be acknowledged that highly regarded WMC measures such as operation span and reading span were not included in this investigation. Finally, it is possible that an even more comprehensive representation of g than that modeled in this investigation may help identify a unique association between g_f and WMC. For example, the addition of a quantitative reasoning first-order factor (g_q) and/or a long-term retrieval first-order factor (g_{lr}) to the model tested in this investigation may help the g_f and WMC first-order factors distinguish themselves in such a way that they become associated uniquely.

5. Conclusion

The association between WMC and g_f is almost undoubtedly large; however, based on the results of this investigation, it is arguably not unique. Other approaches to the evaluation of this question may be identified, and we encourage researchers to do so. We conclude with the observation that the association between WMC and g_c is discussed in the literature only very rarely by cognitive scientists, despite the fact that it is also very substantial (Gignac, 2014a: $r = .66$; this investigation: $r = .70$). Researchers are encouraged to explore the significance and possible mechanistic implications of such a robust observation, even if it implies the plausibility of an (as yet) largely atheoretical g factor.

References

Arbuckle, J.L. (2012). *Amos (Version 21.0)*. Chicago: IBM SPSS.

Benson, N., Hulac, D.M., & Kranzler, J.H. (2010). Independent examination of the Wechsler Adult Intelligence Scale — Fourth Edition (WAIS-IV): What does the WAIS-IV measure? *Psychological Assessment*, *22*, 121–130. http://dx.doi.org/10.1037/a0017767.

Blair, C. (2006). How similar are fluid cognition and general intelligence? A developmental neuroscience perspective on fluid cognition as an aspect of human cognitive ability. *Behavioral and Brain Sciences*, *29*, 109–125. http://dx.doi.org/10.1017/S0140525X06009034.

Canivez, G.L., & Watkins, M.W. (2015). Review of the Wechsler Intelligence Scale for Children — Fifth Edition: Critique, commentary, and independent analyses. In A.S. Kaufman, S.E. Raiford, & D.L. Coalson (Eds.), *Intelligent testing with the WISC-V*. Hoboken, NJ: Wiley (in press).

Carpenter, P.A., Just, M.A., & Shell, P. (1990). What one intelligence test measures: A theoretical account of the processing in the Raven Progressive Matrices Test. *Psychological Review*, *97*, 404–431. http://dx.doi.org/10.1037/0033-295X.97.3.404.

Carroll, J.B. (2003). The higher-stratum structure of cognitive abilities: Current evidence supports g and about ten broad factors. In H. Nyborg (Ed.), *The scientific study of general intelligence: Tribute to Arthur R. Jensen* (pp. 5–21). New York, NY: Pergamon.

Conway, A.R.A., & Kovacks, K. (2013). Individual differences in intelligence and working memory: A review of latent variable models. In B.H. Ross (Ed.), *The psychology of learning and motivation* (pp. 233–270). San Diego, CA: Academic Press.

Fry, A.F., & Hale, S. (1996). Processing speed, working memory, and fluid intelligence: Evidence for a developmental cascade. *Psychological Science*, *7*, 237–241. http://dx.doi.org/10.1111/j.1467-9280.1996.tb00366.x.

Gignac, G.E. (2008). Higher-order models versus bifactor modes: g as superordinate or breadth factor? *Psychology Science Quarterly*, *50*, 21–43.

Gignac, G.E. (2014a). Fluid intelligence shares closer to 60% of its variance with working memory capacity and is a better indicator of general intelligence. *Intelligence*, *47*, 122–133. http://dx.doi.org/10.1016/j.intell.2014.09.004.

Gignac, G.E. (2014b). Dynamic mutualism versus g factor theory: An empirical test. *Intelligence*, *42*, 89–97. http://dx.doi.org/10.1016/j.intell.2013.11.004.

Gignac, G.E., Palmer, B., & Stough, C. (2007). A confirmatory factor analytic investigation of the TAS-20: Corroboration of a five-factor model and suggestions for improvement. *Journal of Personality Assessment*, *89*, 247–257. http://dx.doi.org/10.1080/00223890701629730.

Gignac, G.E., & Watkins, M.W. (2013). Bifactor modeling and the estimation of model-based reliability in the WAIS-IV. *Multivariate Behavioral Research*, *48*, 639–662. http://dx.doi.org/10.1080/00273171.2013.804398.

Gignac, G.E., & Weiss, L.G. (2015). Digit span is (mostly) related linearly to general intelligence: Every extra bit of span counts. *Psychological Assessment* (in press).

Goldstein, G. (2008). Intellectual evaluation. In M. Hersen, & A.M. Gross (Eds.), *Handbook of clinical psychology: Adults, Vol. 1*. (pp. 395–415). Hoboken, NJ: Wiley.

Gustafsson, J.E., & Balke, G. (1993). General and specific abilities as predictors of school achievement. *Multivariate Behavioral Research*, *28*, 407–434. http://dx.doi.org/10.1207/s15327906mbr2804_2.

Juan-Espinoza, M., Cuevas, L., Escorial, S., & Garcia, L.F. (2006). Testing the indifferentiation hypothesis during childhood, adolescence, and adulthood. *Journal of Genetic Psychology*, *167*, 5–15. http://dx.doi.org/10.3200/GNTP.167.1.5-15.

Kane, M.J., Hambrick, D.Z., & Conway, A.R. (2005). Working memory capacity and fluid intelligence are strongly related constructs: Comment on Ackerman, Beier, and Boyle (2005). *Psychological Bulletin*, *131*, 65–71. http://dx.doi.org/10.1037/0033-2909.131.1.66.

Ledgerwood, A. (2014). Introduction to the special section on advancing our methods and practices. *Perspectives on Psychological Science*, *9*, 275–277. http://dx.doi.org/10.1177/1745691614529448.

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. http://dx.doi.org/10.1111/j.1467-9280.2008.02202.x.

Molenaar, D., Dolan, C.V., Wicherts, J.M., & van der Maas, H.L. (2010). Modeling differentiation of cognitive abilities within the higher-order factor model using moderated factor analysis. *Intelligence*, *38*, 611–624. http://dx.doi.org/10.1016/j.intell.2010.09.002.

Oberauer, K., Su, H. -M., Wilhelm, O., & Sander, N. (2007). Individual differences in working memory capacity and reasoning ability. In A.R.A. Conway, C. Jarrold, M.J. Kane, A. Miyake, & J.N. Towse (Eds.), *Variation in working memory* (pp. 21–48). New York, NY: Oxford University Press.

Reise, S.P. (2012). The rediscovery of bifactor measurement models. *Multivariate Behavioral Research*, *47*, 667–696. http://dx.doi.org/10.1080/00273171.2012.715555.

Reynolds, M.R. (2013). Interpreting the *g* loadings of intelligence test composite scores in light of Spearman's law of diminishing returns. *School Psychology Quarterly*, *28*, 63–76. http://dx.doi.org/10.1037/spq0000013.

Salthouse, T.A. (2014). Relations between running memory and intelligence. *Intelligence*, *43*, 1–7. http://dx.doi.org/10.1016/j.intell.2013.12.002.

Salthouse, T.A., & Pink, J.E. (2008). Why is working memory related to fluid intelligence? *Psychonomic Bulletin & Review*, *15*, 364–371. http://dx.doi.org/10.3758/PBR.15.2.364.

Sattler, J.M., & Ryan, J.J. (2009). *Assessment with the WAIS-IV*. San Diego, CA: Jerome M. Sattler.

Tucker-Drob, E.M. (2009). Differentiation of cognitive abilities across the life span. *Developmental Psychology*, *45*, 1097–1118. http://dx.doi.org/10.1037/a0015864.

Watkins, M.W. (2010). Structure of the Wechsler Intelligence Scale for Children — Fourth Edition among a national sample of referred students. *Psychological Assessment*, *22*, 782–787. http://dx.doi.org/10.1037/a0020043.

Wechsler, D. (2008). *Wechsler Adult Intelligence Scale — Fourth Edition*. San Antonio, TX: Pearson Assessment.

Wechsler, D. (2014a). *Wechsler Intelligence Scale for Children — Fifth Edition*. San Antonio, TX: Pearson Assessment.

Wechsler, D. (2014b). *Wechsler Intelligence Scale for Children — Fifth Edition: Technical and interpretive manual*. San Antonio, TX: Pearson Assessment.

Woodcock, R.W., McGrew, K.S., & Mather, N. (2001). *Woodcock–Johnson III tests of cognitive abilities*. Itasca, IL: Riverside.

Zinbarg, R.E., Revelle, W., & Yovel, I. (2007). Estimating ω_h for structures containing two group factors: Perils and prospects. *Applied Psychological Measurement*, *31*, 135–157. http://dx.doi.org/10.1177/0146621606291558.