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Individual Differences in the Three-Embedded Components of Working Memory and their Relation to Fluid Intelligence

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Abstract

Working memory (WM) capacity and fluid intelligence (Gf) have consistently been shown to be related, but it is unclear why. The Three-Embedded Components (3Cs) model of WM proposes the focus of attention (FA), representing a single attended memorandum, the region of direct access (RDA), representing memoranda bound to active context, and the activated part of long-term memory (aLTM), representing activated memoranda not bound to active context. This study examined the unity and diversity of WM. Bifactor analysis – which avoids previous analytical challenges of difference scores – was used to separate Common WM (i.e., common variance among the 3Cs; representing unity) from individual differences unique to each of the 3Cs (representing diversity); however, no variance unique to the FA could be identified. Furthermore, whereas Common WM correlated highly with WM capacity and Gf, only the aLTM but not the RDA correlated with WM capacity, and neither correlated with Gf. Psychometric network analysis was performed to additionally explore partial correlations among the manifest 3Cs, WM capacity, and Gf measures. Only WM capacity measures, but not 3Cs measures, consistently partially correlated with Gf. Taken together, these findings indicate that isolated individual components of WM cannot explain the WM-Gf relationship. Instead, the results suggest that only what is common across these components – and likely their interplay – underpins the relation between WM capacity and Gf, suggesting the whole of WM is greater than its parts.

Keywords: working memory, fluid intelligence, binding, bifactor analysis, network analysis

Individual Differences in the Three- Embedded Components of Working Memory and their Relation to Fluid Intelligence

Everyday tasks such as reading, writing, and cooking require working memory (WM). WM is a system with limited storage capacity for the active maintenance and manipulation of information in the service of cognition. Individual differences in WM capacity (WMC) have been shown to predict a wide range of outcomes such as academic achievement (e.g., Alloway & Alloway, 2010), reading comprehension (e.g., Daneman & Carpenter, 1980), executive functions (e.g., Friedman et al., 2008), and fluid intelligence (Gf; Kyllonen & Christal, 1990).

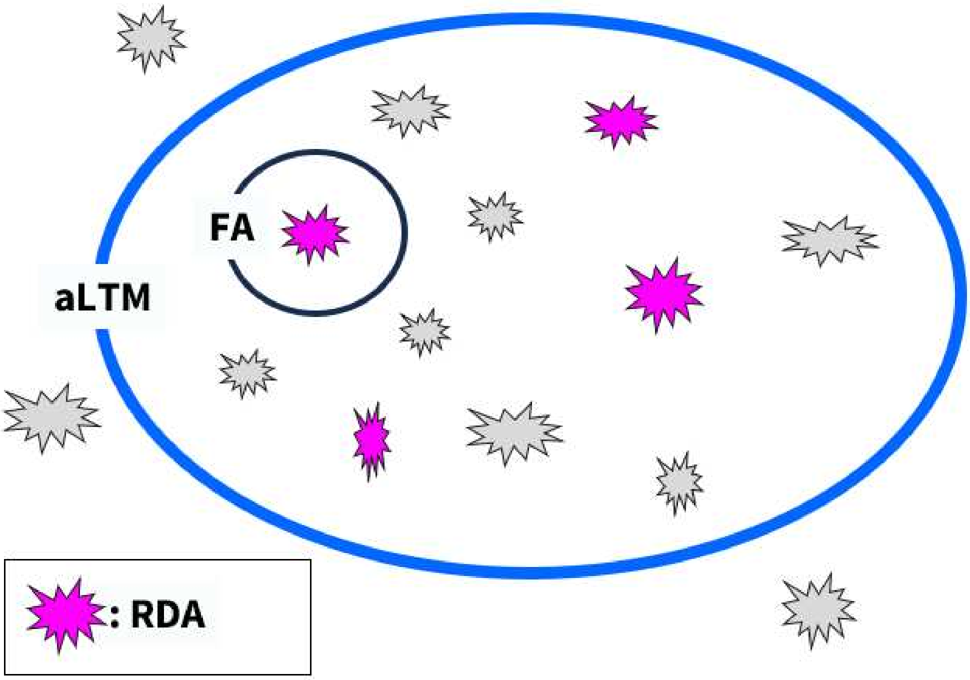
However, it is still not fully understood *why* individual differences in WMC and cognitive ability constructs, like Gf, are so strongly related. Previous research investigating individual differences in the structure of WM and its relation to Gf has predominantly conceptualized WM as a unitary construct, often assessed by complex span tasks (Daneman & Carpenter, 1980) which draw primarily on the simultaneous maintenance and manipulation of information (Oberauer et al., 2000; Oberauer et al., 2003). Experimental research, however, suggests that WM consists of multiple components, culminating in the Three-Embedded Components (3Cs) model of WM (Oberauer, 2009; Oberauer et al., 2007). The present study bridges these past differential and experimental approaches by examining the unity and diversity of individual differences in these theoretical components derived from experimental research. Moreover, the current study examines how these components are related to Gf, thereby offering insights into the mechanisms and functions shared between WM and Gf and advancing understanding of the source of individual differences in cognitive capacity limits.

Three Embedded Components of Working Memory

The 3Cs model is an activation-based model extending Cowan's (1988, 1999) Embedded-Processes model. In activation-based models, memory contents, or representations, vary in their amount of activation such that contents with more activation are more readily accessible in the present moment. The 3Cs model distinguishes between the activated part of long-term memory (aLTM), the region of direct access (RDA), and the focus of attention (FA; see Figure 1). The aLTM comprises representations in long-term memory that are relevant to the current task. A subset of these representations is available in the RDA, where they are bound to the present context in a mental space and can be integrated into new structures. Finally, the FA selects a single representation or chunk of information currently in the RDA that can then be processed in the present moment. For example, to solve “2 + 4”, the number “2” is first encoded, which spreads activation to other related long-term memory representations (e.g., other numbers). In the RDA, each element of the operation (i.e., “2”, “+”, and “4”) is bound to its respective current context (i.e., their positions or roles; e.g., first addend, operator, and second addend). Using the context as a retrieval cue, the FA then selects and processes each of these representations and performs the addition to retrieve the sum (“6”).

Figure 1

Illustration of The Three-Embedded Components Model of Working Memory



Note. Grey and pink stars signify long-term memory representations. Stars within the blue oval correspond to representations currently activated above a baseline and, thus, are part of the activated part of long-term memory. Pink stars correspond to a subset of representations in the region of direct access that are immediately accessible and bound to the current context (bindings to a mental space, not depicted here). Using the binding to the mental space as a cue, the focus of attention (black oval) selects a single representation that can be processed. aLTM = activated part of long-term memory; RDA = region of direct access; FA = focus of attention.

While the capacity of the aLTM is presumed to be unlimited, the capacity of the RDA is thought to be limited to about 3-5 chunks of information (Cowan, 2010). The binding hypothesis proposes that this capacity limit arises from interference between bindings of representations to their contexts in mental space, which also limits the complexity of structural representations. This complexity is a key requirement for successfully solving Gf tasks and, therefore, may explain the relationship between WM and Gf (Oberauer et al., 2007).

Experimental evidence supports the idea that WMC represents a limitation on the number of concurrently maintained bindings of contents to their context. For example, when presented with an array of stimuli and their positions to memorize, participants are more likely to make *binding* errors, in which stimuli from the probed array are recalled in incorrect positions, rather than *item* errors, where items that were not previously shown are incorrectly recalled (Bartsch & Oberauer, 2023; Henson et al., 1996; Pertzov et al., 2012). In other words, people may forget the bindings but still remember the contents. Moreover, as set size increases and surpasses the capacity of WM, the proportion of binding errors to item errors increases (Bartsch & Oberauer, 2023; Oberauer, 2019), meaning that people are increasingly more likely to forget bindings than contents with increasing set sizes. Furthermore, evidence from a correlational study showed that individual differences in a binding factor was perfectly correlated with a general WMC factor, which was interpreted as evidence in favor of the binding hypothesis (Wilhelm et al., 2013). However, in this study, binding performance was assessed as accuracy across all conditions and, hence, confounded general maintenance with interference between bindings.

There is also evidence suggesting that binding is essential to Gf. For example, performance on a simple relational representation task, that has no memory demands and only requires matching identical bindings, correlated with Gf tasks as highly as the Gf tasks correlated with each other. Moreover, the relational representation task highly loaded onto a Gf factor (Chuderski, 2019). These findings suggest that binding is so integral to Gf that simply mentally representing bindings may be all that is required for measuring Gf. Further evidence, although somewhat more indirect, comes from a study that showed that completing a secondary task with higher WM load (random-number generation vs. articulatory suppression) reduced performance on Gf measures (Schubert et al., 2023). This between-participants effect of secondary task performance was mediated by parameters reflecting the building and maintenance of bindings and the filtering of irrelevant information estimated with a computational model fitted to data from a separate WM task. However, the study design did not allow for evaluating the relative relations of individual differences in the theoretical components of WM to Gf.

The Current Study

The purpose of the current study was to investigate individual differences in the 3Cs and how they relate to WMC, as assessed with traditional complex span tasks, and Gf. We used structural-equation modeling to identify the common and unique variance associated with individual differences in each of the 3Cs and related them to a WMC and a Gf factor. We assessed the 3Cs with tasks that have previously been successful in experimentally demonstrating the functions of the 3Cs. Each of the tasks comprised a baseline condition to account for general WM maintenance, and an experimental condition drawing on the processes unique to the respective component. By computing the difference in performance between these two conditions, it is possible to isolate the variance unique to each of the components. However, difference scores can result in low reliability (Hedge et al., 2018), especially when the two conditions are highly correlated (Draheim et al., 2019). To avoid such problems related to difference scores, we used bifactor analysis in which we specified a common latent factor (henceforth referred to as *Common WM*) – representing the unity of WM components – and orthogonal factors to capture the component-specific variance – representing their diversity (for an overview of this approach applied to executive functions, see Miyake & Friedman, 2012). Isolating common and specific variance allows for examining how individual differences in the 3Cs uniquely relate to WMC and Gf.

To preview the results, a FA factor could not be established, the RDA factor did not have significant variance, the fit of the measurement model was not acceptable, and none of the 3Cs was uniquely related to Gf. Therefore, we additionally performed psychometric network analysis to explore relations between measures without assuming specific latent variables. Psychometric networks represent partial correlations between all observed variables and indicate the direct, unique association between cognitive processes represented at task-level while controlling for all other variables in the same network. Compared to the latent-factor approach, the network approach emphasizes patterns of conditional dependencies among observed task measures rather than relying on assumed latent factors of cognitive abilities. This makes psychometric network analysis particularly suitable for exploring specific associations among cognitive processes at a more granular level. The network analysis supported the findings from the SEM – none of the measures operationalizing the 3Cs uniquely related to Gf.

Method

Participants

We aimed at testing 200 young adults. Due to an experimenter error, one participant completed 25% of the tasks twice and was, thus, replaced by an additionally tested participant. Two participants were excluded because they indicated they did not follow instructions during testing. Thus, the sample consisted of $N = 198$ participants (155 women, 43 men, 0 non-binary or undisclosed gender) between 18 and 35 years of age ($M = 23.39$ years, $SD = 4.00$). Most participants were students at a Swiss university (82%, with 49% of them being students of psychology) and held a secondary school degree (i.e., Matur or Abitur, 69%) or university degree (25%). All participants self-reported to be German native speakers or highly proficient in German, had normal or corrected-to-normal vision, no color blindness, no current psychiatric or neurological disorders, and no psychotropic drug use. Participants were reimbursed with either CHF 50 or course credits. The experimental protocol was approved by the institutional review board at the University of Zurich. All participants gave written consent to taking part in the study and were debriefed upon completion of testing.

Materials and Procedure

Each general task paradigm was administered with four specific tasks, comprising different materials (numerical, verbal, visual, and spatial). Tasks were administered in the same order for all participants (see Table A1 in the Appendix for the task order) over the course of 5 hours with four breaks of about 10 min each. All tasks were preceded by two practice trials each.

Two Lists

The two-lists tasks were designed to assess retrieval of memoranda from the aLTM. Participants were asked to memorize two subsequently presented lists of items, with the lists being separated by a 2000 ms gap. Each item was presented for 400 ms in a row of boxes, with the number of boxes corresponding to the set size. Presentation of memoranda was interleaved by 100 ms intervals. Next, participants were asked to recall the items in their correct serial order, first for the most recently presented (*inner*) list and then for the list that was presented at the beginning of the trial (*outer* list). The set size of the inner list remained constant (4 items), whereas the set size of the outer list ranged from 2 to 4 items (except for the numerical variant, for which it ranged from 3 to 5). Stimuli were digits (1-9; numerical variant), letters (B, F, G, K, N, T, R, D; verbal variant), arrows (8 directions; spatial variant), and colored stars (8 colors; visual variant). For the numerical, verbal, and spatial variants, participants input their responses for recall using the corresponding keys on a keyboard. For the spatial variant, the numbers 1-9 on the number pad of a keyboard represented the directions of the arrows (i.e., the number 4 represented left, the number 8 represented up, the number 6 represented right, the number 2 represented down, etc.). For the visual variant, all colored stars were presented on the bottom of the screen, and participants clicked on the star to select their response. The dependent variables for the two-list tasks were recall accuracy for the outer list (experimental condition) and recall accuracy for the inner list (baseline condition).

Binding (De Simoni & von Bastian, 2018)

This paradigm was designed to assess the ability to deal with interference among bindings in the RDA. Participants were instructed to memorize sequentially presented items with the context in which they were presented. Associated pairs were used for the numerical and verbal variants (Wilhelm et al., 2013), and local recognition tasks for the spatial and visual variants (Oberauer, 2005). Specifically, contents and contexts were numbers paired with symbols (numerical variant), nouns paired with verbs (verbal variant), colored triangles and their location in a 4 x 4 grid (spatial variant), and fractals and their serial position in a row of boxes (visual variant). Memoranda were presented for 1800 ms followed by a 200 ms blank interval (numerical and verbal variants) or 900 ms followed by a 100 ms blank interval (spatial and visual variants). In the subsequent recognition phase (separated from the memorization phase by a 500 ms interval), each association was randomly probed with the context given as cue. Participants were asked to indicate via keypress whether the probe matched the current context or not. Of the probes, 50% were targets (i.e., exact matches), 25% were distractors (i.e., not presented in the current trial), and 25% were lures (i.e., presented in the current trial but associated with a different context). Per task, participants completed 24 trials with set sizes varying from 3 to 5. The dependent variables for the binding tasks were accuracy in lures (experimental condition) and accuracy in targets (baseline condition).

Memory Updating (De Simoni & von Bastian, 2018)

The memory updating paradigm was designed to assess switching of the FA between objects in memory. Participants were asked to remember an initial set of simultaneously presented stimuli (500 ms times set size). In the following nine updating steps, those memoranda had to be updated corresponding to provided cues, and participants were instructed to enter the result of the updating operation and remember the result. In half of the 24 trials, a retro-cue presented for 500ms indicated which of the stimuli had to be updated next; otherwise, a blank interval of the same duration was presented[1]. Half of the updating steps were object switches (i.e., the to-be-updated stimulus was different from the one in the

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[1] Retro-cues were included in this design for an analysis that is not a part of the current study.

preceding updating step) and the other half were object repetitions (i.e., the to-be-updated stimulus was the same as in the preceding updating step). Set sizes ranged from 3-5 (numerical and spatial variant) or 2-4 (verbal and visual variant). In the numerical variant, memoranda were digits (1 - 9) that had to be updated according to simple arithmetic operations (e.g., +2) and participants had to remember the result of that operation. In the verbal variant, participants mentally moved letters (A - Z) backward or forward in the alphabet (e.g., +1; the maximum operation was +/- 3) and remembered the resulting letter. In the spatial variant, colored circles had to be mentally moved 1 cell up, down, left, or right in a 4 x 4 grid. In the visual variant, arrows had to be mentally rotated 45 degrees clockwise or counterclockwise. For the numerical, verbal, and visual tasks, participants input their responses for recall using the corresponding keys on a keyboard. For the visual variant, the numbers on a 3 x 3 number pad represented the directions of the arrows as in the spatial two-list task. For the spatial variant, participants clicked on a cell in a 4 x 4 grid to indicate their response. The dependent variables for the memory updating tasks were accuracy in object switches (experimental condition) and accuracy in object repetitions (baseline condition).

Complex Span

The complex span tasks were used as a traditional measure for assessing WMC. Memoranda were presented for 1000 ms each, interleaved by processing tasks that participants were instructed to complete as quickly and accurately as possible. Time for responding to the processing task was restricted to 3000 ms, with failures to respond being counted as incorrect. Afterwards, participants were instructed to recall the memoranda in correct serial order. Participants completed 12 trials with varying set sizes. The tasks and stimuli for the verbal and numerical complex span tasks were the same as those used in von Bastian and Eschen (2016). In the numerical variant, participants memorized 3-5 two-digit numbers and judged the correctness of simple equations (e.g., 2 + 3 = 4). In the verbal variant, participants memorized 5-7 letters, interleaved by lexical decisions (i.e., deciding whether a string of four characters constitutes a word). The task and stimuli for the spatial variant were the same as those used in Vergauwe et al. (2009). In the spatial variant, participants memorized 4-6 locations in a 5 x 5 grid, interleaved by deciding whether the long side of an L-formed shape was oriented horizontally or vertically. In the visual variant, participants memorized 2-4 Gabor patches and decided whether a horizontally presented bar would fit into the gap between two horizontally presented dots. For the numerical and verbal tasks, participants input their responses for recall using the corresponding keys on a keyboard. For the spatial variant, participants clicked on a cell in a 5 x 5 grid to indicate their response. For the visual variant, an array of 3 x 3 Gabor patches were presented, and participants clicked on the patches to indicate their response. The dependent variables for the complex span tasks were the proportion of accurately recalled items in correct serial order across trials (partial-credit scoring, see Conway et al., 2005).

Berlin-Intelligence Structure Test (BIS-4; Jäger, Süß, & Beauducel, 1997)

The K scale of the BIS-4 served to measure reasoning. The BIS model assumes a hierarchical structure of intelligence, with *g* on the top level and operational and content facets on the second level. The operational facet refers to the cognitive function demanded by a given task and comprises reasoning (i.e., the K scale), creativity, memory, and speed. The content facets include verbal, numerical, and figural-spatial materials. The K scale corresponds to reasoning factors in other models and matches Carroll's (1993) conceptualization of Gf. The K scale comprises 15 time-restricted pen-and-paper tasks (5 per content facet), preceded by a brief warm-up task (see Table A2 in the Appendix for a description of all included tasks). Completing the K scale takes about 1 hour. Performance was scored by summing the correct responses on each task then transforming these sums into

BIS points which are based on raw score distributions in the BIS norming sample. The BIS points were then summed across tasks for a final score.

Analysis

Statistical analyses were completed with RStudio (RStudio Team, 2024). Dependent variables were z-standardized prior to modeling. Latent-variable modeling was conducted using the "lavaan" package (Rosseel, 2012). Psychometric network analysis was conducted using the "qgraph" (Epskamp et al., 2012) and "psychonetrics" (Epskamp, 2020) packages.

Exclusions and Outlier Removal

A multi-step systematic outlier analysis was conducted. Due to the multivariate nature of our analyses and the large sample size, if a participant was determined to have an outlier score on any of the tasks, we excluded their data across all tasks. First, 15 participants were excluded for achieving less than 60% accuracy in the processing component of any of the complex span tasks. Next, data from 17 participants who scored below guess rate in any task other than the BIS-4 were removed. Guess rate for the binding task was indicated by a score of 0 on the discrimination parameter (d') from Signal Detection Theory (Stanislaw & Todorov, 1999). The data were then manually reviewed for patterns of fast response times (RTs), low accuracies, and repetitive answers, which resulted in the removal of one additional participant who appeared to switch the meaning of the response keys in the binding task. Finally, the Mahalanobis distance of two participants exceeded the critical value ($p < 0.001$), indicating that they were multivariate outliers, so those participants were excluded. The final sample consisted of $N = 163$ participants (129 women, 34 men) between 18 and 35 years ($M = 23.43$, $SD = 4.01$).

Boxplots revealed a cluster of participants with accuracies far below the interquartile range in the spatial variant of the updating task (Figure A1 in the appendix), so we removed this task from further analysis. We then recalculated Mahalanobis distances, which did not result in any change in participants that exceeded the critical value.

Latent-Variable Modeling

We specified orthogonal models of standardized loadings estimated with the maximum likelihood approach. Model fits were compared using the chi-square statistic (χ^2). When two models were not nested, the Bayesian information criterion (BIC; Schwarz, 1978) and Akaike's information criterion (AIC; Akaike, 1987) values were compared between models. Lower BIC and AIC values indicate better model parsimony in consideration to goodness-of-fit and the number of parameters. Model fit was also evaluated based on the comparative fit index (CFI), the root mean-squared error of approximation (RMSEA) and its 90% confidence interval (CI), and the standardized root mean-squared residual (SRMR). Acceptable fit is indicated by values above .90 for CFI (Hu & Bentler, 1999) and below .10 for RMSEA and SRMR (Kline, 2015). If CFI is greater than .95, RMSEA is less than .06, and SRMR is below .08, the model has good fit (Hu & Bentler, 1999). We consulted modification indices of the best-fitting model to further improve model fit.

Once we found the best-fitting, theoretically and statistically sound model, we used the model output to compute factor scores for each latent variable in the model. Using factor scores allowed us to add WMC and Gf as latent variables covarying with the weighted composites of the 3Cs without artificial shared variance being produced due to shared manifest variables.

Psychometric Network Modeling

In a psychometric network model, the network nodes represent the observed variables, and the edges represent the conditional dependent associations between pairs of connected nodes. All network models are estimated by modeling the variance-covariance matrix of the data in Gaussian graphical models (Epskamp et al., 2018). We grouped nodes by tasks and condition and only included significant edges ($\alpha = .01$).

Results

Data and scripts for running the analyses are available on the Open Science Framework (https://osf.io/d8r3z). Descriptive statistics and reliability coefficients for all tasks are presented in Table 1. Most tasks showed commonly accepted levels of reliability except for the inner list of the verbal two-list task and the lures of the numerical, visual, and spatial binding tasks. However, the 95% confidence intervals of all measures with low reliability, except for visual binding lures, included acceptable reliability levels. The repetition condition of the numerical updating task had problematically high kurtosis (Kline, 2015), so we performed arcsine transformation on this data which alleviated this concern. The minimum score on the numerical and spatial complex span tasks were low but, critically, recall accuracies were above chance and RTs were within a reasonable range. Prior to analysis, all variables were centered and *z*-transformed, after which they displayed a normal distribution. Zero-order task correlations are color-scaled in Figure 2 for visual clarity. The lowest 10% of correlations are primarily measures from the binding tasks, the verbal two-list task inner list, and the verbal BIS-4.

Table 1

Descriptive Statistics of Raw Scores

Task/condition	*M* (*SD*)	Min	Max	Kurtosis	Skew	Reliability [95% CI]
Two-List						
Numerical						
Outer	0.68 (0.17)	0.15	0.99	2.53	-0.28	0.87 [0.84, 0.90]
Inner	0.85 (0.09)	0.56	1.00	3.40	-0.72	0.74 [0.68, 0.79]
Verbal						
Outer	0.83 (0.12)	0.51	1.00	2.73	-0.75	0.79 [0.74, 0.84]
Inner	0.93 (0.06)	0.74	1.00	3.73	-1.02	0.59 [0.49, 0.67]
Visual						
Outer	0.48 (0.16)	0.17	0.93	2.68	0.45	0.83 [0.79, 0.87]

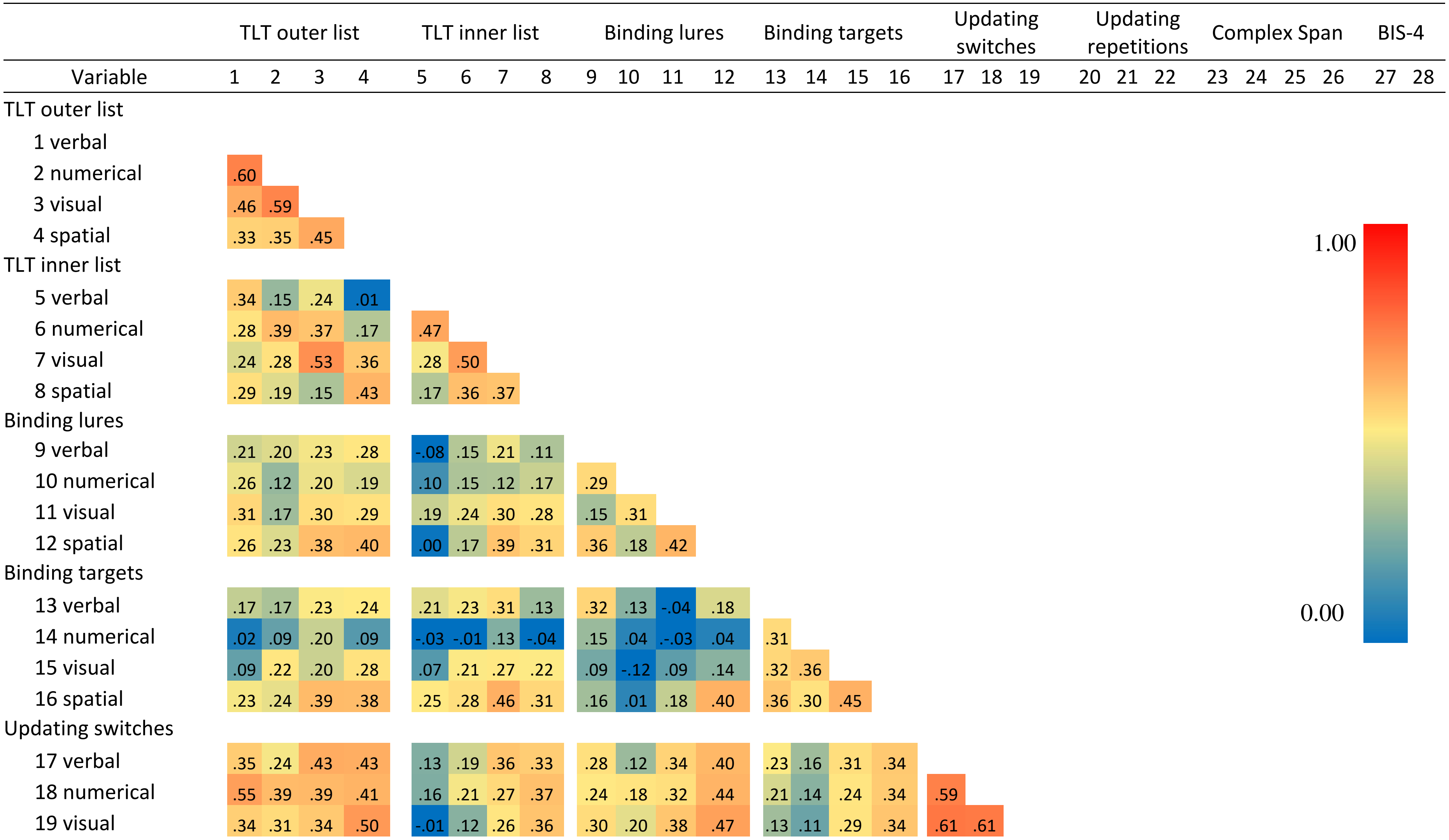
Inner	0.63 (0.14)	0.28	0.96	2.74	-0.18	0.79 [0.74, 0.83]
Spatial						
Outer	0.38 (0.12)	0.14	0.74	2.82	0.53	0.73 [0.67, 0.79]
Inner	0.60 (0.15)	0.22	0.89	2.42	-0.21	0.85 [0.81, 0.88]
Binding						
Numerical						
Lure	0.62 (0.14)	0.25	0.92	2.89	-0.21	0.54 [0.43, 0.63]
Target	0.73 (0.10)	0.44	0.96	2.96	-0.41	0.63 [0.54, 0.71]
Verbal						
Lure	0.71 (0.15)	0.29	1.00	2.59	-0.36	0.58 [0.58, 0.67]
Target	0.81 (0.09)	0.46	0.98	3.30	-0.43	0.64 [0.55, 0.71]
Visual						
Lure	0.71 (0.14)	0.29	0.96	2.90	-0.46	0.46 [0.34, 0.58]
Target	0.73 (0.11)	0.46	0.94	2.26	-0.31	0.63 [0.55, 0.71]
Spatial						
Lure	0.77 (0.13)	0.38	1.00	2.90	-0.64	0.59 [0.49, 0.68]
Target	0.81 (0.09)	0.48	1.00	3.43	-0.51	0.64 [0.55, 0.71]
Updating						
Numerical						
Switch	0.84 (0.09)	0.51	0.99	3.31	-0.78	0.81 [0.77, 0.85]
Repetition	1.34 (0.11)[a]	0.91[a]	1.57[a]	4.74[a]	-0.69[a]	0.73 [0.67, 0.79]
Verbal						
Switch	0.71 (0.14)	0.30	0.95	2.94	-0.69	0.87 [0.84, 0.90]
Repetition	0.88 (0.09)	0.53	1.00	4.84	-1.38	0.83 [0.79, 0.87]
Visual						
Switch	0.59 (0.18)	0.14	0.99	2.82	-0.41	0.92 [0.90, 0.94]
Repetition	0.85 (0.17)	0.18	1.00	7.94	-2.26	0.95 [0.93, 0.96]
Complex span						
Numerical	0.47 (0.16)	0.06	0.94	2.65	0.10	0.81 [0.76, 0.85]
Verbal	0.63 (0.16)	0.19	1.00	2.56	-0.27	0.83 [0.79, 0.87]
Visual	0.43 (0.14)	0.14	0.81	2.60	0.19	0.61 [0.52, 0.70]
Spatial	0.49 (0.19)	0.05	0.97	2.49	-0.02	0.83 [0.79, 0.87]
BIS-4						
Numerical	495.87 (33.10)	419	575	2.83	0.02	0.70 [0.62, 0.77]
Verbal	527.04 (36.01)	421	618	3.23	-0.23	0.73 [0.65, 0.79]
Figural	501.85 (29.34)	432	601	3.40	0.35	0.64 [0.55, 0.72]

Note. Dependent measures were proportion of correctly recalled items except for BIS4 which were scores in the Berlin Intelligence Structure Test 4. Reliabilities reflect Cronbach's α and its 95% confidence interval. CI = confidence interval; BIS-4 = K scale of the Berlin Intelligence-Structure Test 4.

[a] Arcsine transformed.

Figure 2

Color-Scaled Correlation Matrix



	TLT outer list				TLT inner list				Binding lures				Binding targets				Updating switches			Updating repetitions			Complex Span				BIS-4	
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
TLT outer list																												
1 verbal																												
2 numerical	.60																											
3 visual	.46	.59																										
4 spatial	.33	.35	.45																									
TLT inner list																												
5 verbal	.34	.15	.24	.01																								
6 numerical	.28	.39	.37	.17	.47																							
7 visual	.24	.28	.53	.36	.28	.50																						
8 spatial	.29	.19	.15	.43	.17	.36	.37																					
Binding lures																												
9 verbal	.21	.20	.23	.28	-.08	.15	.21	.11																				
10 numerical	.26	.12	.20	.19	.10	.15	.12	.17	.29																			
11 visual	.31	.17	.30	.29	.19	.24	.30	.28	.15	.31																		
12 spatial	.26	.23	.38	.40	.00	.17	.39	.31	.36	.18	.42																	
Binding targets																												
13 verbal	.17	.17	.23	.24	.21	.23	.31	.13	.32	.13	-.04	.18																
14 numerical	.02	.09	.20	.09	-.03	-.01	.13	-.04	.15	.04	.-.03	.04	.31															
15 visual	.09	.22	.20	.28	.07	.21	.27	.22	.09	-.12	.09	.14	.32	.36														
16 spatial	.23	.24	.39	.38	.25	.28	.46	.31	.16	.01	.18	.40	.36	.30	.45													
Updating switches																												
17 verbal	.35	.24	.43	.43	.13	.19	.36	.33	.28	.12	.34	.40	.23	.16	.31	.34												
18 numerical	.55	.39	.39	.41	.16	.21	.27	.37	.24	.18	.32	.44	.21	.14	.24	.34	.59											
19 visual	.34	.31	.34	.50	-.01	.12	.26	.36	.30	.20	.38	.47	.13	.11	.29	.34	.61	.61										

	TLT outer list				TLT inner list				Binding lures				Binding targets				Updating switches			Updating repetitions			Complex Span				BIS-4	
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
Updating repetitions																												
20 verbal	.20	.12	.27	.30	.13	.26	.34	.37	.23	.14	.29	.32	.23	.08	.31	.27	.78	.48	.47									
21 numerical	.25	.23	.19	.31	.01	.16	.17	.28	.23	.08	.17	.36	.19	.12	.14	.22	.38	.65	.46	.44								
22 visual	.34	.21	.21	.26	.05	.13	.14	.36	.25	.25	.32	.40	.09	.02	.24	.23	.51	.48	.78	.37	.35							
Complex Span																												
23 verbal	.46	.30	.30	.24	.19	.24	.14	.18	.04	.20	.18	.14	.06	.24	.20	.11	.27	.41	.26	.14	.23	.23						
24 numerical	.45	.36	.36	.37	.17	.20	.18	.12	.06	.13	.13	.20	.12	.13	.13	.25	.30	.42	.26	.16	.17	.10	.47					
25 visual	.33	.25	.38	.44	.12	.21	.33	.33	.31	.34	.26	.36	.21	.20	.21	.32	.42	.49	.48	.34	.30	.35	.23	.33				
26 spatial	.39	.37	.38	.44	.05	.26	.30	.41	.29	.11	.17	.42	.10	.13	.27	.38	.39	.44	.47	.35	.27	.37	.32	.38	.43			
BIS-4																												
27 verbal	.19	.09	.16	.08	.18	.17	.25	.21	.08	.10	.07	.06	.15	.10	.06	.16	.09	.21	.04	.05	.05	.13	.18	-.01	.21	.11		
28 numerical	.30	.28	.28	.33	.13	.28	.25	.34	.14	.10	.17	.15	.11	.11	.21	.14	.32	.30	.21	.22	.24	.22	.32	.17	.22	.37	.42	
29 figural	.23	.24	.21	.25	.06	.17	.17	.31	.18	.16	.13	.22	.05	.07	.10	.19	.15	.26	.28	.11	.15	.28	.11	.04	.31	.39	.36	.54

Note. TLT = two-list task; BIS-4 = K scale of the Berlin Intelligence Structure Test 4.

Structural-Equation Modeling

We conducted systematic model comparisons to find the best fitting model. Table 2 displays the fit statistics for each of the models in the order that they were tested. In Model 1, all experimental and baseline conditions loaded onto a latent variable capturing the commonality across all indicators of WM (Common WM). Furthermore, we correlated residual variances for each manifest variable derived from the same task (e.g., repetition and switch trials from the verbal updating task). Next, we stepwise added orthogonal factors manifested by the experimental condition variables to capture the variance specific to each theoretical WM component: aLTM (manifested by accuracy on outer-list trials in the two-list tasks; Model 2), RDA (manifested by accuracy on lure conditions of the binding tasks; Model 3), and FA (manifested by accuracy on object switches of the updating tasks; Model 4). Model comparisons showed that Model 4 had the best fit, but only two manifest variables significantly loaded onto the FA. Furthermore, while following modification indices applied to Model 4 improved model fit, none of the loadings onto the FA were significant. Therefore, Model 3 was retained over Model 4.

Modification indices for Model 3 suggested covarying the residual within-domain variance between baseline conditions from the same paradigm (i.e., verbal and numerical, and visual and spatial residual variance) to further improve model fit. We applied the suggested change because covarying domain-specific variance makes theoretical sense and has previously been reported in individual differences investigations of WM (e.g., Wilhelm et al., 2013; Model 3.1). We also tried specifying latent domain-specific variables for the baseline conditions, but this worsened model fit and rendered the model unacceptable. Modification indices additionally suggested to covary the residual variance between the baseline conditions on the spatial two-list task and visual updating task and the experimental conditions of these tasks. In hindsight, this seemed plausible because these two tasks both required participants to indicate the direction of an arrow using the 3 x 3 number pad of the keyboard (i.e., number 5 was the center, 2 was down, 8 was up, etc.). Therefore, we decided to covary their error variances (Model 3.2; Figure 3). No further recommendations from modification indices were deemed theoretically justifiable, so we used Model 3.2 as our measurement model.

Table 2

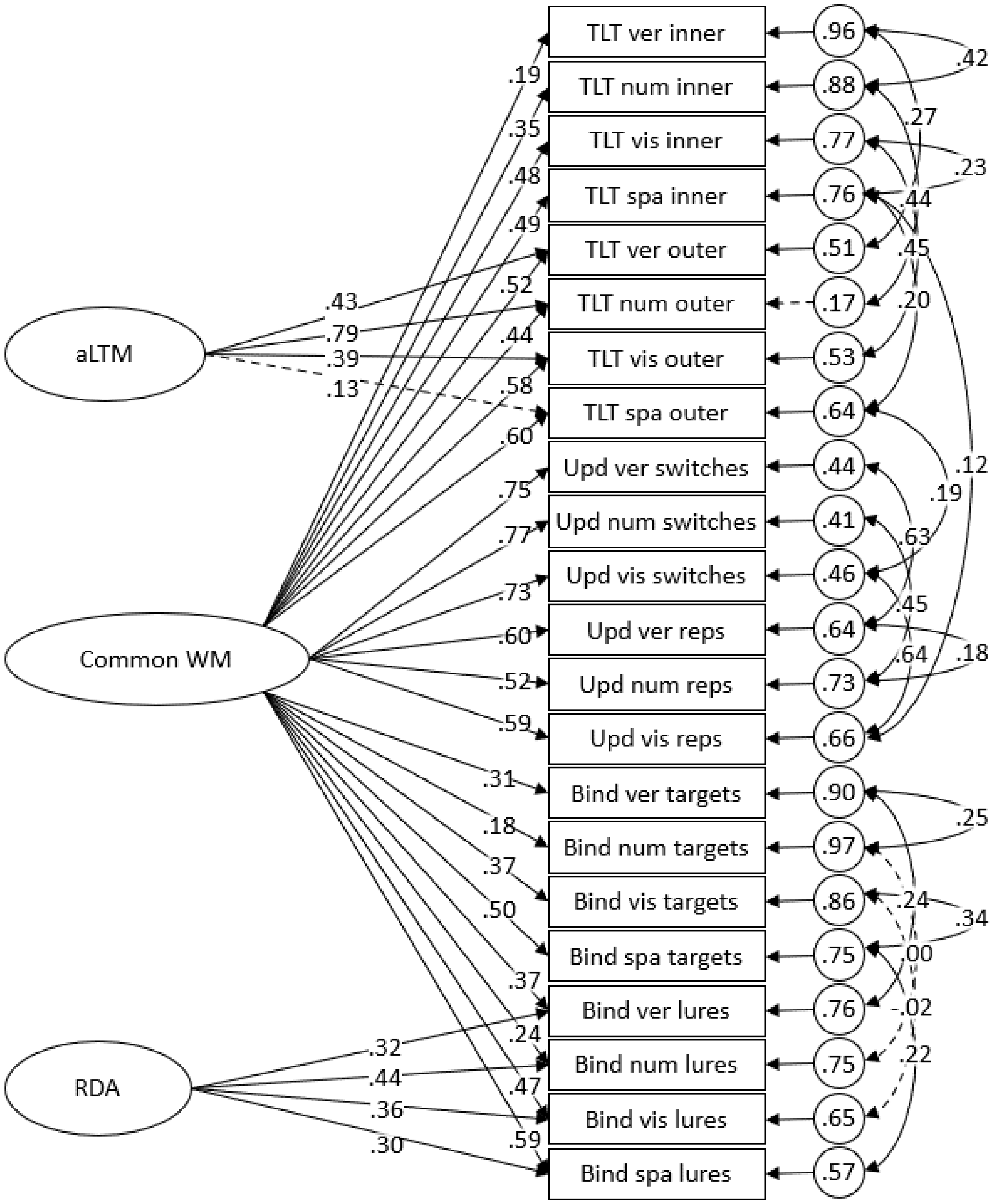
Model Fits from Structural-Equation Modeling

Model	χ^2(df)	CFI	RMSEA	SRMR	AIC	BIC	*p*-value
Model 1	550.87(198)	.76	.10 [.09, .11]	.09	9124.65	9294.81	-
Model 2	469.18(194)	.81	.09 [.08, .10]	.08	9050.96	9233.49	<.001
Model 3	450.83(190)	.82	.09 [.08, .10]	.08	9040.61	9235.52	.002
Model 4	441.33(187)	.83	.09 [.08, .10]	.08	9037.11	9241.30	.033
Model 3.1	366.22(185)	.88	.08 [.07, .09]	.08	8966.00	9176.38	<.001
Model 3.2	350.43(183)	.89	.07 [.06, .09]	.08	8954.21	9170.78	.001

Note. Model 3 was determined to fit better than Model 4 due to insignificant loadings onto the FA. Values in brackets represent the 90% confidence interval. The *p*-value represents the significance of $\Delta\ \chi^2$ between the model and the prior-most best fitting model (e.g., Models 4 and 3.1 are compared to Model 3). $\alpha = .05$.

Figure 3

Measurement Model (Model 3.2)



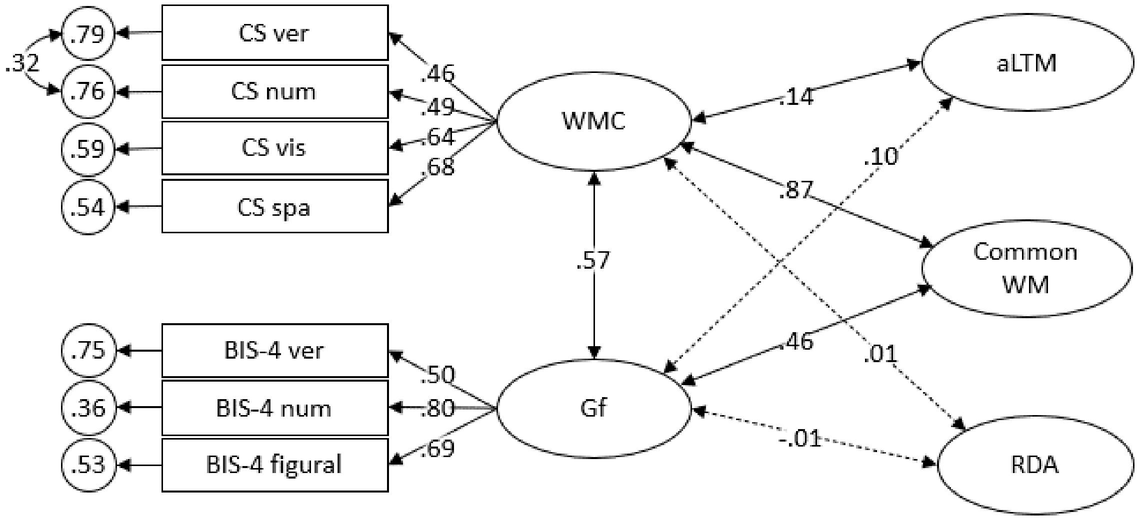
Note. Solid lines represent significant loadings (α = .05). Dashed lines represent non-significant loadings. aLTM = activated part of long-term memory; RDA = region of direct access; FA = focus of attention; TLT = two-list; Bind = binding; Upd = updating; Ver = verbal; Num = numerical; Vis = visual; Spa = spatial; Reps = repetitions.

In Model 3.2 all loadings were significant except the spatial experimental condition loading onto aLTM. Also, all error variance correlations were significant except between numerical binding lures and targets and visual binding lures and targets. We continued to specify the non-significant correlations and loadings for consistency across tasks. Importantly, the variance of the RDA in an unstandardized version of the model was not significant.

We computed weighted composites of the latent variables of Model 3.2 using their factor scores and added WMC and Gf latent variables to correlate with each other and with the weighted composites. Model fit was not acceptable, $\chi^2(31) = 72.90$, CFI = 0.89, RMSEA = 0.09 [90% CI: 0.06, 0.12], SRMR = 0.07. We consulted modification indices and covaried the residual variance between the verbal and numerical complex span tasks. The model fit became acceptable, $\chi^2(30) = 57.95$, CFI = 0.93, RMSEA = 0.08 [90% CI: 0.05, 0.11], SRMR = 0.07. No further modification indices seemed theoretically justifiable, so we continued analysis with this model (see Figure 4). We found significant positive correlations between WMC and Gf, Common WM and WMC, and Common WM and Gf. The correlations with Common WM are expected because Common WM represents shared variance among WM tasks and, therefore, should be highly correlated with WMC and variables highly correlated with WMC, like Gf. The only other significant correlation we found was between aLTM and WMC. The RDA did not significantly correlate with WMC or Gf. This is unsurprising given that the RDA did not have significant variance.

Figure 4

Model 3.2 with WMC and Gf



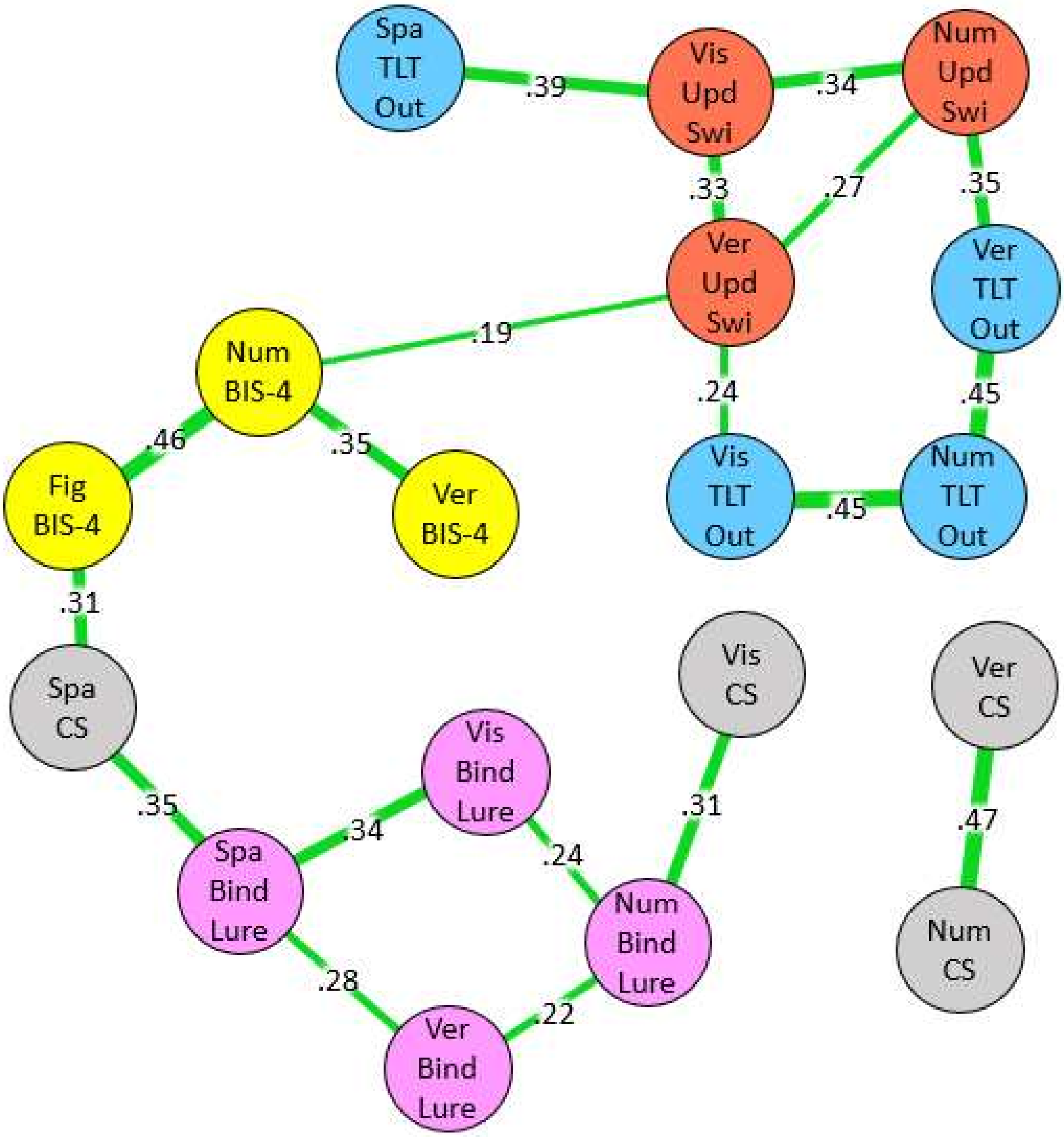
Note. Solid lines represent significant loadings (α = .05). Dashed lines represent non-significant loadings. aLTM = activated part of long-term memory; RDA = region of direct access; WMC = working memory capacity; Gf = fluid intelligence; CS = complex span task. BIS-4 = Berlin Intelligence Structure K-scale; WM = Working Memory; Ver = verbal; Num = numerical; Vis = visual; Spa = spatial.

Psychometric Network Analysis

Figure 5 illustrates the psychometric network model comprising all experimental conditions of the 3Cs alongside WMC and Gf. It was not necessary to include the baseline conditions to isolate the variance of interest, because partial correlations reveal the unique relationships between variables such that only the processes unique to each variable (i.e., the variance of interest) underlie the observed relationships. With some exceptions, nodes from the same tasks clustered together and shared significant edges. The BIS-4 nodes had few significant edges. Numerical BIS-4 shared an edge with the verbal updating switch node, and figual BIS-4 shared an edge with the spatial complex span node. The numerical and verbal complex span nodes shared a significant edge only with each other and were separated from the rest of the model which may reflect overlapping verbal-numerical domains. Similarly, many of the largest edges were between same-domain nodes (e.g., spatial and visual tasks), so these edges may reflect overlapping stimuli domains rather than common cognitive processes of interest.

Figure 5

Psychometric Network Analysis with all Variables as Nodes



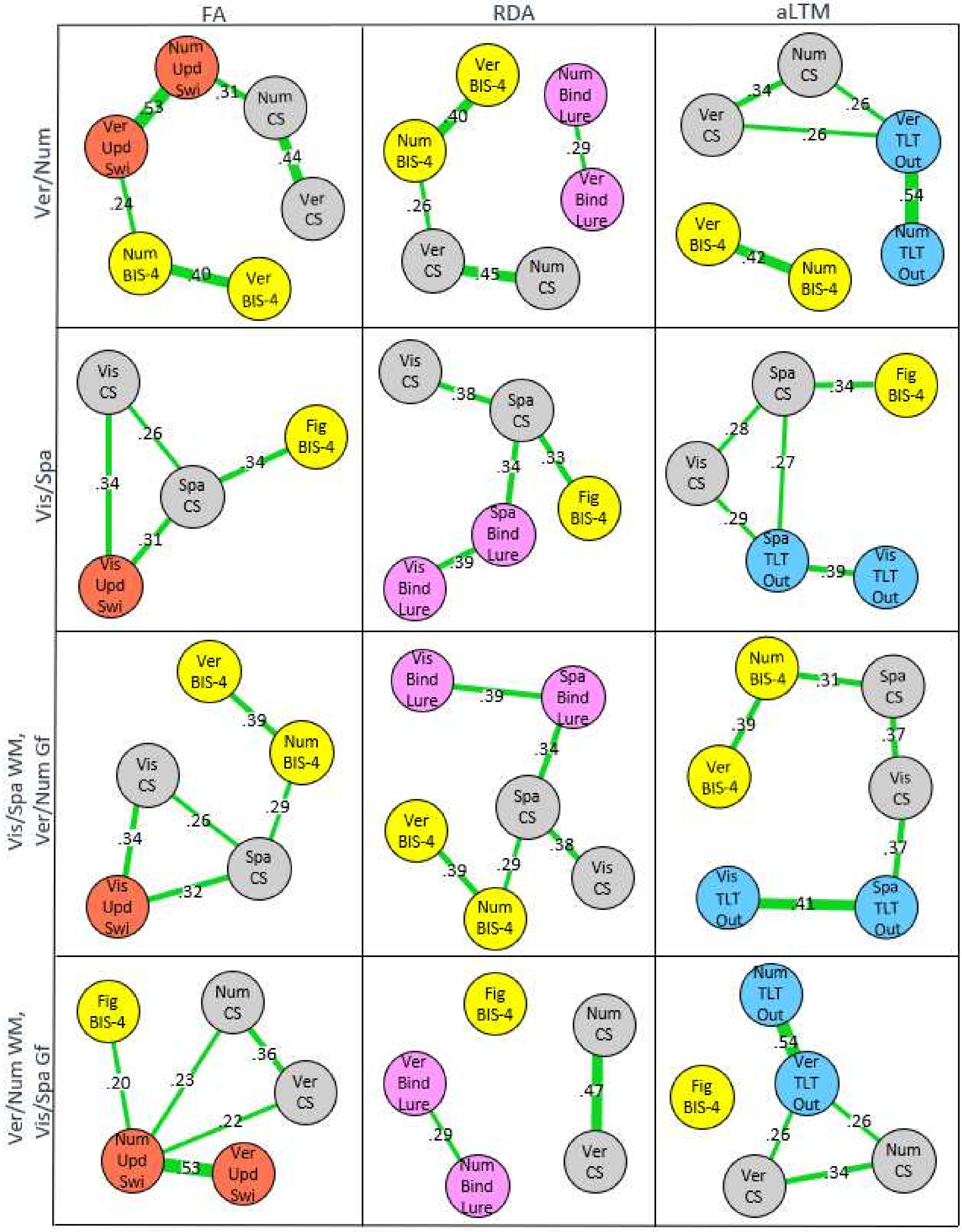
Note. Edges significant at $p < .01$. Num = numerical; Ver = verbal; Spa = spatial; Vis = visual; Upd = updating task; Bind = binding task; TLT = two-list task; CS = complex span; BIS-4 = Berlin Intelligence Structure K-scale; Swi = switch; Out = outer.

To reduce the influence of domain-specific relations, we ran separate exploratory models for each of the 3Cs and stimulus domains. Specifically, each model included complex span, BIS-4, and either the updating, binding, or two-list task nodes. Also, the models either used verbal-numerical nodes, visual-spatial nodes, or differentiated domains of the complex span and 3Cs nodes and BIS-4 nodes. By running multiple network models, we can visually compare the influence of different nodes, groups, and domains on the network to better understand the underlying relationships when all nodes are included.

Figure 6 shows a 4 x 3 matrix of network models, crossing the stimulus domains (rows) and the 3Cs (columns). In these models, visual-spatial complex span nodes, in particular spatial complex span, emerged as the only non-BIS-4 nodes to be uniquely related to verbal-numerical BIS-4 nodes. Moreover, complex span nodes bridged the verbal-numerical BIS-4 nodes and the visual-spatial 3Cs nodes. The same pattern emerged when we included all visual-spatial 3Cs and complex span nodes and the verbal-numerical BIS-4 nodes (Figure 7a). The only verbal-numerical node that uniquely related to visual-spatial BIS-4 was the numerical updating node. However, this relationship disappeared when all verbal-numerical 3Cs and complex span nodes and the visual-spatial BIS-4 were included, in which case no nodes shared a unique relationship with BIS-4 (Figure 7b). These findings are consistent with the results from the bifactor analysis and suggest that the 3Cs have only weak if any relationships with Gf that cannot be explained by domain-specificity and WMC.

Figure 6

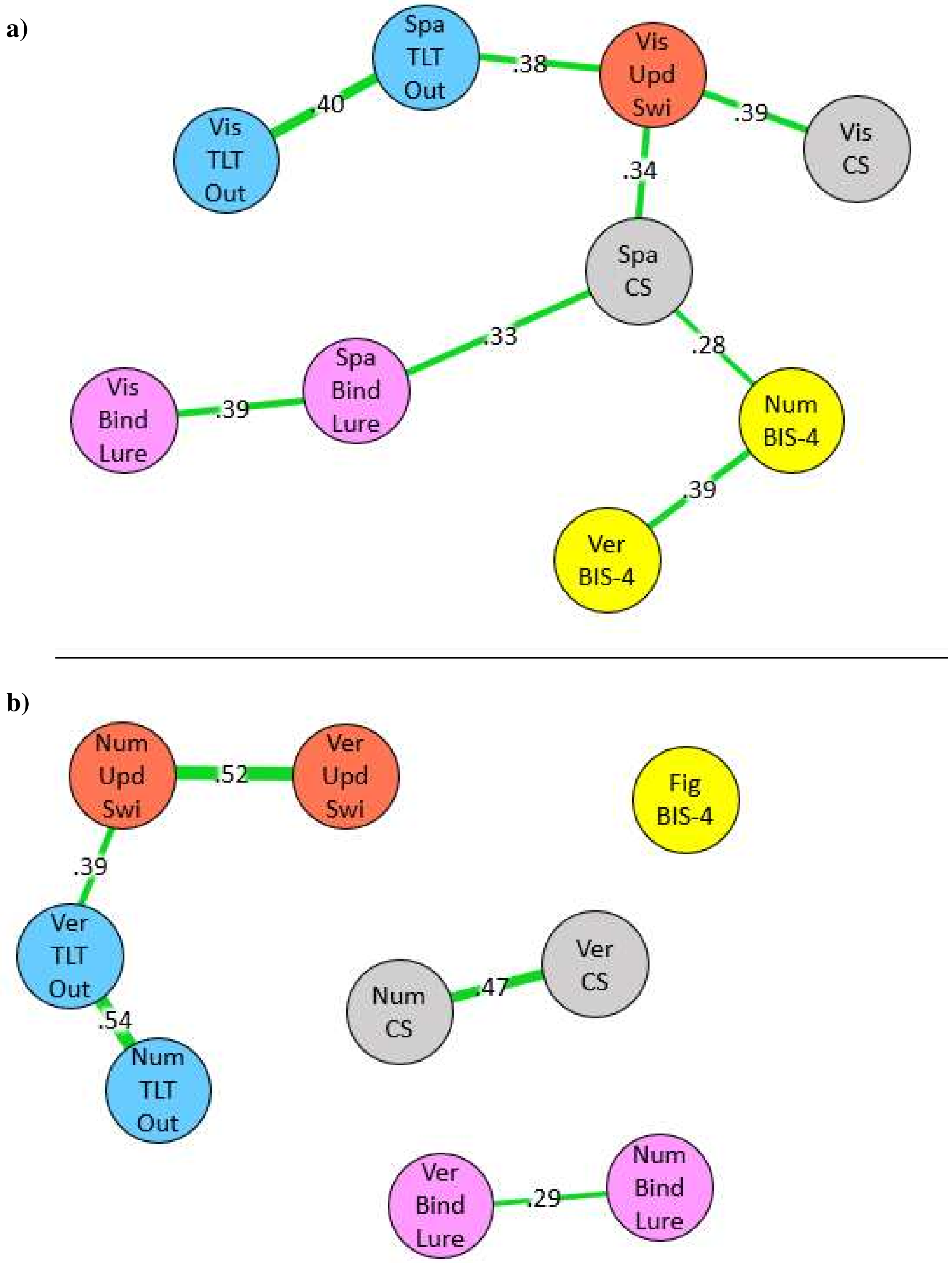
Matrix of Network Analyses by Domain and Embedded Component



Note. Edges significant at $p < .01$. FA = focus of attention; RDA = region of direct access; aLTM = activated part of long-term memory; WM = working memory; Gf = fluid intelligence; Num = numerical; Ver = verbal; Spa = spatial; Vis = visual; Fig = figural; Upd = updating task; Bind = binding task; TLT = two-list task; CS = complex span; BIS-4 = Berlin Intelligence Structure K-scale; Swi = switch; Out = outer.

Figure 7

Network Analyses with Differentiated Domains



Note. Edges significant at $p < .01$. Num = numerical; Ver = verbal; Spa = spatial; Vis = visual; Fig = figural; Upd = updating task; Bind = binding task; TLT = two-list task; CS = complex span; BIS-4 = Berlin Intelligence Structure K-scale. Swi = switch; Out = outer.

Discussion

This study investigated individual differences in the 3Cs of WM (as derived from past experimental work; Oberauer et al., 2007) and how they relate to general WMC (as measured by complex span tasks) and Gf. We used bifactor analysis to establish a Common WM factor, with loadings from all WM task conditions, and orthogonal 3Cs-specific factors by isolating variance specific to the experimental conditions. As expected, Common WM, which represents the commonalities of all WM tasks and conditions, was highly correlated with WMC and Gf. In contrast, individual differences in the aLTM were significantly related only to WMC but not Gf. Moreover, individual differences specific to the RDA were not significantly related to either WMC or Gf. However, variance of the RDA-specific factor was not significant (p = .106) and, thus, unlikely to explain individual differences in WMC and Gf. Finally, no FA-specific factor could be identified.

It is possible that we were unable to establish substantial individual differences in the RDA-specific and FA-specific factors because the experimental conditions of these tasks simply share too much common variance with performance on other WM tasks; in other words, the experimental effects in binding and focus-switching may be too small for assessing individual differences (for a similar discussion related to the assessment of individual differences in attentional control, see von Bastian et al., 2020). To examine unique relationships between the experimental conditions of all 3Cs, WMC, and Gf without the need to identify factor-specific variance, we used psychometric network analysis. Consistent with the bifactor analysis, none of the variables reflecting the FA, RDA, or aLTM partially correlated with Gf variables above and beyond the variance common to the 3Cs. In most cases, only performance in the spatial complex span task was uniquely related to Gf. Therefore, the 3Cs did not explain the WMC-Gf relationship.

Taken together, the results speak against the hypothesis that WM and Gf are related through the necessity to resolve interference arising from bindings. The results further suggest that neither resolving interference nor attentional processes for switching attention between different representations underpin individual differences in WMC. Instead, Common WM and, to a lesser extent, the aLTM are most strongly related to Gf. Furthermore, the results of the psychometric network analysis suggest that none of the 3Cs explains the relationship between WMC and Gf; rather, performance in complex span tasks – which draw on all 3Cs – show the strongest unique partial correlation with Gf.

The Unity and Diversity of WM

The present study allowed for examining the unity and diversity of WM in the context of the 3Cs theoretical framework. The findings suggest that WM performance across a range of different paradigms exhibits mostly unity, that is, variance reflecting commonality across tasks captured by the latent Common WM factor. In contrast, we observed limited diversity, that is, variance specific to processes above and beyond what is captured by the Common WM factor. These results suggest little reliable individual differences in how people resolve interference from no-longer relevant bindings (Ecker et al., 2014; Oberauer et al., 2007; Rey-Mermet et al., 2020; Singh et al., 2018) and shift attention between representations in WM, questioning whether these abilities constitute stable traits above and beyond mechanistic cognitive functions.

Establishing latent factors that isolate variance specific to executive processes above and beyond the maintenance of goals and representations is challenging. For example, past research similarly demonstrated little to no individual differences specific to updating of WM representations (Frischkorn et al., 2022) and inhibitory control (Friedman et al., 2008), with the high commonality between tasks assessing general WM not leaving sufficient variance to be explained by these more specific processes. A few studies successfully extracted latent factors of removal of no-longer relevant bindings in WM – a construct conceptually different but similar to the ability to resolving interference from no-longer relevant bindings (Rey-Mermet et al., 2020; Singh et al., 2018). However, these studies used difference scores rather than a bifactor analytical approach. The use of difference scores has been criticized for decreasing the amount of systematic variance while increasing the proportion of error variance and resulting in low convergent validity (for a review see Draheim et al., 2019).

Importantly, the inability to establish a latent FA-specific factor does not imply that the FA generally does not exist as a WM function. Indeed, there is ample evidence from experimental work supporting a single-item FA. Specifically, the bottleneck of information processing limits the information that can be processed at any given time to one representation (Oberauer, 2002; Oberauer & Göthe, 2006; for a review of the bottleneck, see Pashler, 1994) such that switching between representations in memory (switch costs) increases response time in processing tasks (McElree, 1998), and switch costs increase with the number of stored representations (Oberauer, 2002). Similarly, the non-significant variance of the RDA-specific factor does not contradict the existence of interference between bindings in WM; consistent with previous data from similar paradigms (Fandakova et al., 2014; Lin & Oberauer, 2019; Oberauer, 2005, 2008; von Bastian & Eschen, 2016; von Bastian & Oberauer, 2013) performance was consistently lower for items high in interference (i.e., lures) than for trials low in interference (i.e., targets). However, our results suggest that resolving interference may be a mechanism of WM that functions similarly across people rather than a structural feature exhibiting individual differences. At first glance, these conclusions seem to contradict previous work suggesting that binding and similar concepts, such as relational integration (Chuderski, 2014; Oberauer et al., 2008), predict Gf. Critically, however, these previous studies did not isolate variance specific to resolving the *interference* arising from no-longer relevant bindings. Most of the variance captured by the latent factors in these past studies representing binding and relational integration is likely akin to that captured by the Common WM factor in the present study.

Only variance specific to the activated part of long-term memory significantly related to WMC, which is consistent with a growing body of literature suggesting strong links between WM and LTM (Bartsch & Oberauer, 2023; Camos et al., 2019; Forsberg et al., 2022, 2023; Loaiza & Souza, 2024; Mızrak & Oberauer, 2022). Individual differences specific to the aLTM may relate to those in WMC because people with higher WMC may be better able to make efficient use of the limited capacity of WM, for example through offloading and retrieving representations to and from aLTM with fewer errors (Bartsch & Shepherdson, 2022) which reserves more space in their WMC.

The Relationship between Working Memory and Fluid Intelligence

As expected, we found a strong correlation between WMC and Gf, which is consistent with the wider literature (Ackerman et al., 2005; De Simoni & von Bastian, 2018; Kane et al., 2005; Oberauer et al., 2008). However, none of the 3Cs significantly related to Gf; instead, only Common WM and/or WMC were related to Gf. Moreover, the network models consistently suggested a unique relation between WMC and Gf nodes, in particular the spatial complex span task and the numerical BIS-4. This is not the first time that performance in spatial (complex) span tasks emerged as especially predictive of cognitive abilities, including domain-general Gf (Kane et al., 2004) and spatial reasoning (Miyake et al., 2001; Shah & Miyake, 1996), possibly because they afford fewer individual differences in strategic approach and, thus, exhibit better psychometric properties (Navarro et al., 2023).

We expected to see significant associations between the RDA-specific factor with both WMC and Gf in the bifactor analysis, and the binding lure nodes to mediate the variables reflecting WMC and Gf in the psychometric network models according to evidence implicating binding interference in individual differences in WMC and Gf (Bartsch &

Oberauer, 2023; Oberauer, 2005, 2019; Oberauer et al., 2007; Oberauer et al., 2008; Wilhelm et al., 2013). However, neither analytical approach provided evidence for such associations, which speaks against a critical role of the ability to resolve interference from no-longer relevant bindings in explaining the relation between individual differences in WMC and Gf.

An alternative explanation in the literature for the WMC-Gf relationship is the attention-control hypothesis (Burgoyne & Engle, 2020; Engle, 2002; Shipstead & Engle, 2013), which proposes that an overarching attention control ability governs both maintenance of representations and disengagement from no-longer relevant information. Whereas maintenance is primarily required in WMC tasks, disengagement contributes more strongly to performance in tasks assessing Gf. The proposed reason for this latter relationship is that disengaging from inaccurate or untenable hypotheses is necessary for arriving at accurate conclusions to solve novel reasoning problems. Although we did not design the present study to directly investigate the maintenance-disengagement model, our findings can still be interpreted in its context. According to this model, in the bifactor analysis, we would have expected to see Common WM to be more strongly related to WMC than Gf, and variance specific to the FA – and perhaps also the RDA, given its focus on resolving interference – to be related more strongly to Gf than WMC. In the psychometric network analysis, we would have expected the respective FA and RDA nodes to *mediate* the associations between the variables reflecting WMC and Gf. However, our results did not show these patterns and, therefore, do not support the maintenance-disengagement model.

Another alternative hypothesis as to why WMC and Gf are related arises from the dual-component model (Unsworth, 2016; Unsworth & Engle, 2007), which distinguishes a capacity-limited primary memory component with highly activated representations from a secondary memory component where representations are maintained over the longer-term. In ongoing cognitive tasks, representations exceeding primary memory capacity are moved to secondary memory, and attentional control processes serve to maintain activation of primary memory representations and retrieval of secondary memory representations to primary memory through a cue-dependent search mechanism. All three of these processes are thought to underpin individual differences in WMC that are predictive of Gf, including secondary memory. Individual differences in secondary memory have been shown to relate to Gf independent of WMC (Unsworth, 2010; Unsworth, Brewer, & Spillers, 2009; Unsworth & Spillers, 2010; Wilhelm et al., 2013), and in one study controlling for individual differences in Gf and secondary memory, WMC no longer predicted Gf at all (Mogle et al., 2008). Moreover, a recent individual differences study (Robison et al., 2024) demonstrated that, together, the latent factors representing primary memory, secondary memory, and attentional control fully mediated the relation between WMC and Gf, but not each on their own. This appears inconsistent with the present study, where only the aLTM-specific factor, but not the RDA-specific factor, was related to only WMC but not Gf, and none of the aLTM, RDA, or FA-related nodes were consistently related to Gf. Different from our study, however, Robison et al. (2024) did not isolate variance arising from the three processes, and, thus, did not reflect the same, more process-pure variance as the 3Cs-specific factors in our study. Indeed, in an additional analysis, Robison et al. reported that all three processes loaded on a hierarchical factor which was related to both WMC and Gf. Hence, the variance in the latent factors for primary memory, secondary memory, and attention-control that was shared with WMC and Gf was likely akin to the variance captured by our Common WM factor.

So, what does the Common WM factor in the present study represent? Given that variance *specific* to attention shifts, dealing with interference, and retrieval from LTM were accounted for by the variables reflecting the FA, RDA, and aLTM, respectively, the most likely interpretation of what Common WM represents is the domain-general, short-term maintenance of representations of task-relevant goals, context, and information, and the relations between them. The strong relation between Common WM and Gf is consistent with other, previous findings demonstrating maintenance of information as the primary source of individual differences in WM and Gf (e.g., Chuderski et al., 2012; Cowan et al., 2006; Frischkorn et al., 2022).

Consequently, a version of the binding hypothesis emphasizing *maintenance* of bindings is still tenable in light of the present results. Binding interference has been argued to limit the complexity of structural representations, which limits Gf (Oberauer et al., 2008; Oberauer, 2009). Whereas the present results speak against a critical role of interference, the number of structural representations, formed through bindings, may still limit WMC. The process of integrating multiple bindings into more complex structures has been referred to as relational integration, which can be measured with tasks requiring the rapid integration of separately presented information. For example, in monitoring (occasionally also referred to as coordination) tasks (e.g., Himi et al., 2023; Oberauer et al., 2003; von Bastian & Oberauer, 2013) participants are shown a 3 x 3 grid of stimuli which change over a regular interval. Participants are asked to indicate when some condition is met between the stimuli across the rows, columns, or diagonals of the grid. Performance in the monitoring task has been shown to be more strongly related to Gf more than other WM facets and cognitive abilities, specifically storage and processing (Chuderski, 2014; Oberauer et al., 2008), attention control, and short-term memory (Chuderski, 2014). Other operationalizations of relational integration include tasks where participants are asked to infer relational conclusions based on sequentially presented statements (e.g., Oberauer, 1993; von Bastian et al., 2013; von Bastian & Oberauer, 2013). Even more barebones operationalizations, in which participants merely compare relational statements (e.g., “A/B” to “A\B”), have been shown to be predictive of Gf (Chuderski, 2019). However, it is yet unclear to what extent these different types of tasks assess a common relational integration or binding ability, and to what extent they draw on other processes such as attention control and sustained attention.

Compared to the binding hypothesis, the current results are more consistent with process-overlap theory which may explain why complex span as a WMC node largely consistently bridged 3Cs-specific and Gf nodes rather than the reverse, as would be expected by other accounts. Process-overlap theory proposes that cognitive abilities are related to the extent that they depend on the same domain-general, overlapping processes (Kovacs & Conway, 2016). According to process-overlap theory, the reason that WM and Gf are related is because they both tap some of the same cognitive processes. In other words, no individual cognitive ability can explain the WM-Gf relationship, but multiple abilities tapped by both WM and Gf account for the overall relationship. Accordingly, WMC nodes may have partially correlated with Gf when none of the 3Cs-specific nodes did because performance in the complex span tasks draws on multiple cognitive processes simultaneously. Since the RDA-specific and aLTM-specific latent factors in the bifactor analyses represented process-specific variance, they overlapped only to a small or no extent with WMC and Gf. In contrast, the strong relations between Common WM and WMC and Gf suggest that Common WM captured domain-general processes which overlap with those of WMC and Gf. This is consistent with previous findings, like those of Wilhelm et al. (2013) and Robison et al. (2024), which did not isolate WM process-specific variance and found that different WM facets strongly related to WM. It is also consistent with previous investigations of individual differences in WM and Gf that have not consistently found a singular cognitive mechanism to fully explain the WM-Gf relationship, with evidence that individual differences in secondary memory (Mogle et al., 2008; Unsworth, 2010; Unsworth et al., 2009; Unsworth & Spillers, 2010; Wilhelm et al., 2013), binding (Bateman & Birney, 2019; Chuderski, 2014; Oberauer, 2005; Oberauer et al., 2008; Schubert et al., 2023), attention control (Schubert et al., 2023;

Unsworth & Spillers, 2010), WM updating (Friedman et al., 2006), short-term memory (Colom et al., 2008), and processing speed (Ackerman et al., 2002; Frischkorn et al., 2019; Schmitz & Wilhelm, 2016) are capable of explaining the WM-Gf relationship only to some extent. These findings and those from the current study represent a growing body of evidence supporting process overlap theory.

Limitations

One limitation of this study is its homogenous sample, which consisted largely of young adults studying at a Swiss university. Hence, the results are not generalizable to other populations from other demographic backgrounds. The 3Cs model and most other models of cognitive abilities were developed in Western, educated, industrialized, rich, and democratic ("WEIRD") societies which limits their generalizability to most of the human population (Henrich et al., 2010) and can perpetuate harmful colonialist frameworks of human-participants research. Future research must focus on the development of cognitive models that more directly consider representation of the human population.

Another limitation of this study is that most of the binding task variables had below acceptable reliability coefficients which suggests that these tasks have not sufficiently measured the variables of interest. However, for all but one of these variables the 95% confidence interval of their reliability coefficients fell within the commonly acceptable range. Moreover, all binding task variables significantly loaded to similar degrees onto Common WM and RDA and clustered together in the network analysis – suggesting that they measured the same variables to a similar degree.

One final limitation is that the spatial updating task could not be included in the analysis due to irreconcilable outliers. It is possible that if a variable representing spatial FA were included in the analyses, then this variable could have considerably changed the outcome of the network analysis by mediating WMC and Gf variables. Indeed, the spatial domain of WMC in particular connected Common WM and Gf. Spatial WMC could contain variance pertaining to spatial FA which could be why spatial WMC connected Common WM and Gf.

Conclusion

This study investigated individual differences in the 3Cs of WM and their relation to WMC and Gf. Through bifactor analysis and psychometric network analysis, shared and unique variance among WM were separated into Common WM and each of the 3Cs – allowing for the investigation of the unity and diversity of WM. While Common WM correlated highly with both WMC and Gf, of the 3Cs only the aLTM correlated with WMC and none of them correlated with Gf. In fact, only the aLTM was identified with significant variance. In a network analysis of the 3Cs, WMC, and Gf, none of the variables representing the 3Cs consistently mediated WMC and Gf variables. Instead, spatial complex span consistently directly related to numerical BIS-4. Thus, apart from aLTM for which there is a growing body of evidence showing its connection with WM and Gf, individual differences in the 3Cs are minimal and do not contribute to the relationship between WMC and Gf.

Taken together, the findings of the present study do not support theoretical views that emphasize a critical role of managing binding interference (Oberauer et al., 2007) or disengaging from no-longer relevant information in WM (Shipstead et al., 2016). Instead, more consistent with the dual-component model (Unsworth, 2016) and process-overlap theory (Kovacs & Conway, 2016), the present results suggest that the *whole is greater than its parts* when it comes to the predictive power of WM for Gf.

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Appendix A

Table A1

Order of Task Administration

Block	Paradigm	Material
1	BIS reasoning	numerical, figural, and verbal intermixed
2	Updating	spatial
	Binding	numerical
	Two-lists	visual
	Complex span	verbal
3	Complex span	numerical
	Updating	visual
	Binding	verbal
	Two-lists	spatial
4	Binding	spatial
	Two-lists	numerical
	Complex span	visual
	Updating	verbal
5	Two-lists	verbal
	Complex span	spatial
	Updating	numerical
	Binding	visual

Note. Between each block was a 10-min break.

Table A2

Tasks Included in the K scale of the Berlin Intelligence Structure Test (BIS-4).

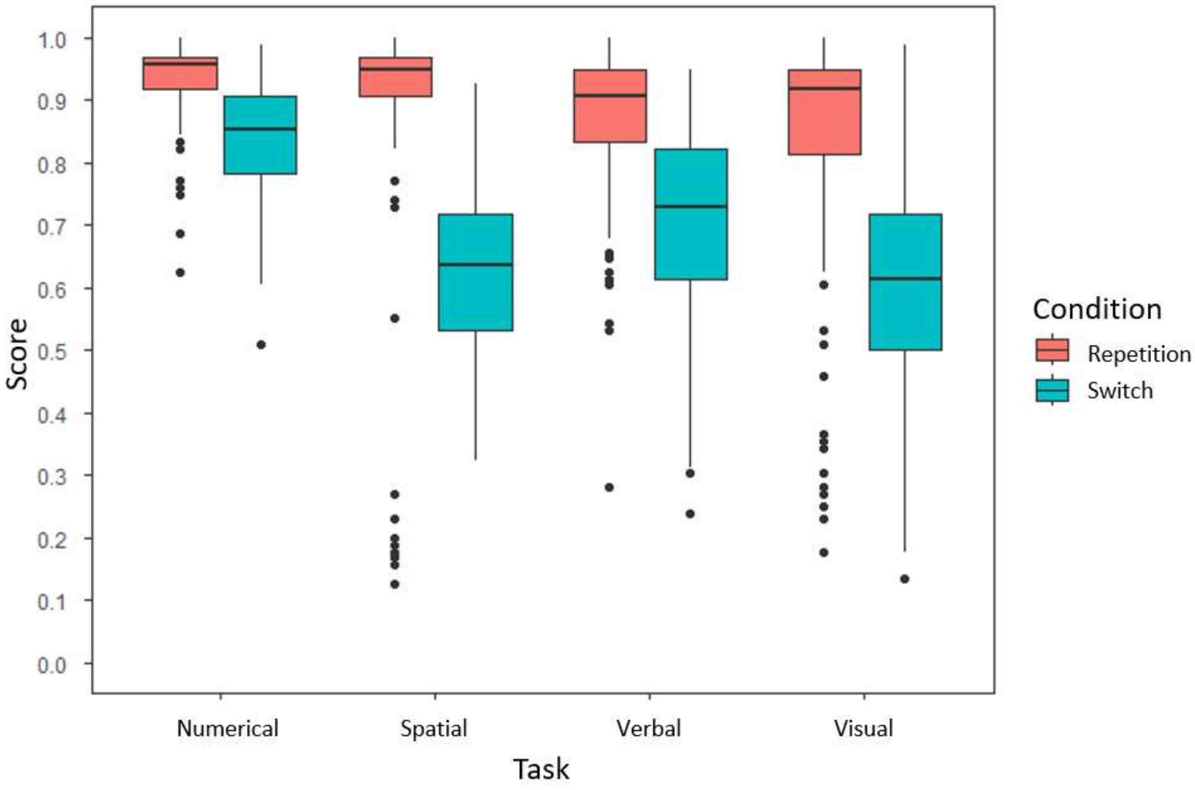
Task	Description	Content
UW: Word completion (warm-up)	Complete the missing letters in a given list of words.	Verbal
FA: Figure completion	Identify which bigger shape can be composed of a set of shapes.	Figural
RD: Mathematical thinking	Solve mathematical word problems.	Numerical
SV: Drawing conclusions	Determine whether conclusions follow logical from a given statement.	Verbal
WS: Word relationships	Identify the underlying relationship between a series of words and select the one that deviates.	Verbal
TL: Understanding tables	Relate and integrate the information presented in a table.	Numerical
ZN: Digit series	Identify the logical pattern underlying a series of digits and add the next digit to complete it.	Numerical
AN: Figural analogies	Identify the underlying relationship between two figures to complete an analogous pair of figures.	Figural
WA: Word analogies	Identify the underlying relationship between two words to complete an analogous pair of words.	Verbal
TM: Fact vs. opinion	Identify statements as being facts or opinions.	Verbal
SC: Estimation	Estimate the results of complex equations.	Numerical
CH: Charkow	Identify the logical pattern underlying a series of figures and complete it.	Figural
SL: Syllogisms	Determine whether a conclusion follows logically from two premises.	Verbal

AW: Paper folding	Identify which shape can be derived from folding a paper with specific patterns.	Figural
BR: Letter series	Identify the logical pattern underlying a series of letters and add the next letter to complete it.	Numerical
BG: Bongard	Derive the common denominator of groups of objects and classify new exemplars accordingly.	Figural

Note. The BIS-4 K scale measures reasoning across three content facets. The first task served as warm-up and was not analyzed.

Figure A1

Boxplot of Updating Paradigm Scores Including the Spatial Task



Note. Even though all of the updating tasks had scores well below the interquartile range, we only decided to remove the spatial updating task because the low scores are clustered rather than spread.