



University of Sheffield

Relationships Between Common Factors of Fluid Cognition

William Frederick Garvey

A thesis submitted in partial fulfilment of the requirements
for the degree of Doctor of Philosophy.

School of Psychology
Faculty of Science
The University of Sheffield

Submitted 25th March 2026

THESIS ABSTRACT

Understanding the source of the positive correlation between working memory capacity (WMC) and fluid intelligence (Gf) could benefit those who struggle in daily life. The binding hypothesis posits that WMC and Gf are jointly limited by the number of bindings in working memory (WM), but the mechanisms of binding are unclear. The processing speed theory proposes that fluid cognition declines in older age due to a processing speed bottleneck. However, components of processing speed may differentially relate to fluid cognition across adulthood. This thesis advances understanding of the WM-Gf overlap using methods to partition variance of underlying mechanisms.

Chapter 2 investigated the Three-Embedded Components (3Cs) model of WM using bi-factor analysis and psychometric network analysis to investigate the partial correlations between indicators of the 3Cs, WMC, and Gf. The isolated components of WM could not uniquely explain the WMC-Gf relationship. Instead, the common variance shared across these components underpins the relation between WMC and Gf.

Chapter 3 examined diverse conceptualizations of binding via structural equation modelling. Item-to-item and item-to-location binding were best represented by a single *binding maintenance* latent variable. This loaded onto a higher-order binding factor that was statistically indistinguishable from Gf, highlighting the importance of binding maintenance and revealing process-general binding is isomorphic with Gf.

Chapter 4 investigated cognitive dedifferentiation in a cross-sectional sample (ages 18–85). Age-weighted models estimated non-linear partial correlations between WMC, Gf, and processing speed components. The partial correlation between WMC and Gf increased to near unity in older adulthood regardless of processing speed, suggesting speed is not solely responsible for cognitive dedifferentiation.

Ultimately, no single ability could completely account for the WM-Gf relationship. Binding maintenance captured a substantial proportion of their shared variance. These findings challenge single-mechanism theories of fluid cognition and highlight the utility of network models in mapping cognitive relationships.

ACKNOWLEDGEMENTS

I firmly believe that – through a beautiful, phenomenally complex chain of cause and effect – everyone I have ever met and many that I haven’t have contributed to this thesis. As such, I cannot possibly thank everyone by name, but I will say, “Thank you everyone!”.

Over the past few weeks some specific people have come to mind that I would like to specifically acknowledge. First and foremost, I have to thank my supportive, knowledgeable, and all-around-wonderful supervisors, Claudia and Alicia.

Second, I would like to thank my family, especially Mom, Dad, Francine, Matthew, Brian, Aleckz, Rebecca, Dale, Aunt Becky, Uncle Bill, and Aunt Sandy. Also, thank you to Connor, Jack, Haris, Carolina, Max, Sam, Alice, Shawn, Grace, and Jake.

I have also received incredible support in the *School of Psychology* from staff and colleague/dear friends, including but not limited to: the wonderful past and present members of CAPLab (including João) who are the best academic family a man could ask for, the Squid People, Ellie, Dom, Hazel, Rosemary, Myles, Anna, Sonia, Anton, Molly, Liam, Heather, Ankita, Luthfi, Luke, Beatrix, Hannes, Jane, Claire, Karen, and Dirk.

I have also received a fantastic boost in oxytocin production with the addition of my precious cuddly cat Blossom.

Thank you to those who have kept music an active part of my life, including Make Noise Studio, AKOD, and my band mates, and those who have brought baseball back into my life, the Sheffield Bruins and Kodiaks.

Of course this work would not be possible without my collaborators Han, Andy, Alon, and the Co-TraiLs team; my research assistants Michal, Aysin, and Rowan; and my reviewers and examiners. Special shout out as well to the brilliant psychologists I have met at conferences during this time, especially those at Parcevall Hall.

If you feel like you should have been mentioned, you’re probably right! Thank you so much!

DECLARATION AND NOTES ON INCLUSION OF PUBLISHED WORK

I, William Frederick Garvey, confirm that this thesis is my own work. I am aware of the University's Guidance on the Use of Unfair Means (www.sheffield.ac.uk/ssid/unfair-means).

This thesis is in a publication format and contains the following published work:

Chapter 2: Research presented in this chapter is currently under review and the preprint is available online on the Open Science Framework.

Garvey, W. F., Hao, H., Conway, A., Forsberg, A., & von Bastian, C. C. (2026). *Individual differences in the three embedded components of working memory and their relation to fluid intelligence*. PsyArXiv. https://doi.org/10.31234/osf.io/2tf4n_v1

Findings from this thesis have been presented in the following conferences:

Chapter 2:

Garvey, W. F., Forsberg, A., & von Bastian, C. C. (2025). *The relationship between working memory and fluid intelligence* [Spoken session]. University of Sheffield School of Psychology Postgraduate Conference 2025, Sheffield, UK.

Garvey, W. F., Hao, H., Conway, A., Forsberg, A., & von Bastian, C. C. (June 25th, 2025). *Individual differences in the three-embedded components of working memory and their relation to fluid intelligence* [Spoken session]. Annual Working Memory Discussion Meeting at Parcevall Hall, Appletreewick, UK.

Garvey, W. F., Forsberg, A., & von Bastian, C. C. (April 30th, 2024). *Fluid intelligence and the three-embedded-components model of working memory: A latent-variable analysis* [Poster session]. University of Sheffield Science Graduate School Research Showcase Event 2024, Sheffield, UK.

Garvey, W. F., Forsberg, A., & von Bastian, C. C. (June 26, 2024). *Can individual differences in the three embedded components explain the working memory - fluid intelligence relationship?* [Poster session]. 4th International Conference on Working Memory, Leeds, UK.

Garvey, W. F., Forsberg, A., & von Bastian, C. C. (2023). *How well do the three embedded components of working memory account for the reasoning and working memory relationship? A latent-variable analysis* [Poster session]. 23rd Conference of the European Society for Cognitive Psychology (ESCOP), Porto, Portugal. <https://doi.org/10.17605/OSF.IO/9DYQE>

Garvey, W.F., Forsberg, A., & von Bastian, C. C. (2023). *Working memory and fluid intelligence: Can the three embedded components explain their relationship? A latent variable analysis* [Spoken session]. Psychonomic Society 64th Annual Meeting, San Francisco, California, USA.

Chapter 3:

Garvey, W. F., Forsberg, A., & von Bastian, C. C. (2025). *The relationship between working memory and fluid intelligence* [Spoken session]. University of Sheffield School of Psychology Postgraduate Conference 2025, Sheffield, UK.

Garvey, W. F., Zivony, A., Forsberg, A., & von Bastian, C. C. (2025). *The unity and diversity of binding and its relation to fluid intelligence* [Poster session]. 24th Conference of the European Society for Cognitive Psychology (ESCoP), Sheffield, UK.

CONTENTS

THESIS ABSTRACT	i
ACKNOWLEDGEMENTS	ii
DECLARATION AND NOTES ON INCLUSION OF PUBLISHED WORK	iii
CONTENTS	iv
LIST OF TABLES	vii
LIST OF FIGURES	viii
LEGEND.....	x
CHAPTER 1 General Introduction	1
1.1 Working Memory and Fluid Intelligence.....	2
1.2 Binding.....	3
1.3 Processing Speed	5
1.4 Construct Isolation	8
1.5 Aims of this Thesis	11
CHAPTER 2 Individual Differences in The Three-Embedded Components of Working Memory and their Relation to Fluid Intelligence	12
2.1 Introduction.....	14
2.1.1 Three Embedded Components of Working Memory	14
2.1.2 The Current Study	17
2.2 Method	18
2.2.1 Participants.....	18
2.2.2 Materials and Procedure	18
2.2.3 Analysis.....	26
2.3 Results	28
2.3.1 Structural Equation Modeling	32
2.3.2 Psychometric Network Analysis	36
2.4 Discussion	41
2.4.1 The Unity and Diversity of WM	42
2.4.2 The Relationship between Working Memory and Fluid Intelligence.....	44

2.4.3 Limitations	49
2.5 Conclusion	50
CHAPTER 3 Processing and Maintaining Relations: The Central Role of Binding in Fluid Intelligence.....	
3.1 Introduction.....	53
3.1.1 Binding Abilities	53
3.1.2 The Current Study	55
3.2 Method	56
3.2.1 Participants.....	56
3.2.2 Materials and Procedure.....	57
3.2.3 Analysis.....	67
3.3 Results	69
3.3.1 Structural Equation Modelling	71
3.3.2 Psychometric Network Analysis	76
3.4 Discussion	77
3.4.1 The Diversity of Binding.....	78
3.4.2 Binding and Fluid Intelligence	80
3.4.3 Strengths, Limitations, and Future Directions.....	81
3.5 Conclusion	83
CHAPTER 4 Dedifferentiation and Bottlenecks of Processing Speed Components: An Age-Weighted Latent Network Analysis.....	
4.1 Introduction.....	86
4.1.1 The Current Study	89
4.2 Method	90
4.2.1 Participants.....	91
4.2.2 Materials.....	91
4.2.3 Analysis.....	95
4.3 Results	100
4.3.1 Age-Weighted Model Fits.....	104
4.3.2 Age-Weighted Factor Loadings	106
4.3.3 Dedifferentiation	107

4.3.3 Bottlenecks	109
4.4 Discussion	112
4.4.1 Strengths and Limitations.....	116
4.5 Conclusion.....	117
CHAPTER 5 General Discussion.....	119
5.1 Summary of Findings.....	120
5.2 Common Factors of Fluid Cognition	122
5.3 Strengths, Limitations, and Future Directions	125
5.4 Conclusion.....	127
REFERENCES.....	128
APPENDIX A.....	149
APPENDIX B.....	152
APPENDIX C.....	153

LIST OF TABLES

Table 2.1: <i>Descriptive Statistics of Raw Scores</i>	28
Table 2.2: <i>Model Fits from Structural Equation Modeling</i>	33
Table 3.1: <i>Descriptive Statistics of Raw Scores after Outlier Removal</i>	70
Table 3.2: <i>Confirmatory Factor Analysis Model Fits</i>	73
Table 4.1: <i>Task Descriptions</i>	92
Table 4.1: <i>Descriptive Statistics</i>	100
Table A1: <i>Order of Task Administration (Chapter 2)</i>	149
Table A2: <i>Tasks Included in the K scale of the Berlin Intelligence-Structure Test 4</i>	149
Table B1: <i>Order of Task Administration (Chapter 3)</i>	152

LIST OF FIGURES

Figure 2.1: <i>Illustration of The Three-Embedded Components Model of Working Memory</i>	15
Figure 2.2: <i>Example Two-List Task Trial</i>	20
Figure 2.3: <i>Example Binding Task Trials</i>	21
Figure 2.4: <i>Example Updating Task Trials</i>	23
Figure 2.5: <i>Example Complex Span Task Trials</i>	25
Figure 2.6: <i>Color-Scaled Correlation Matrix</i>	30
Figure 2.7: <i>Measurement Model (Model 3.2)</i>	34
Figure 2.8: <i>Model 3.2 with WMC and Gf</i>	35
Figure 2.9: <i>Psychometric Network Analysis with all Variables as Nodes</i>	37
Figure 2.10: <i>Matrix of Network Analyses by Domain and Embedded Component</i>	39
Figure 2.11: <i>Network Analyses with Differentiated Domains</i>	40
Figure 3.1: <i>Selection of Arrows, Fractals, and Symbols Stimuli</i>	58
Figure 3.2: <i>Local Recognition Tasks</i>	59
Figure 3.3: <i>Associated Pairs Tasks</i>	60
Figure 3.4: <i>Example Trials of the Monitoring Paradigm</i>	61
Figure 3.5: <i>Example Trials from the Relational Representation Paradigm</i>	63
Figure 3.6: <i>Trial Diagram of the Rapid Serial Visual Presentation Paradigm</i>	64
Figure 3.7: <i>Raven’s Advanced Progressive Matrices Example</i>	65
Figure 3.8: <i>Paper Folding Task Example</i>	66
Figure 3.9: <i>Locations Task Example</i>	67
Figure 3.10: <i>Color-Scaled Correlation Matrix</i>	71
Figure 3.11: <i>Baseline Structural Equation Model</i>	72
Figure 3.12: <i>Baseline Model with Binding Maintenance</i>	74
Figure 3.13: <i>Confirmatory Factor Analysis with Binding Fixed to Fluid Intelligence</i>	76
Figure 3.14: <i>Latent Network Model of the Best-Fitting Model</i>	77

Figure 4.1: Processing Speed as a Bottleneck of Cognitive Abilities	86
Figure 4.2: Continuous Reproduction Task	95
Figure 4.3: Choice Reaction Time Task	95
Figure 4.4: Letter Sets Task Example	96
Figure 4.5: Everyday Problems Test Example.....	97
Figure 4.6: Color-Scaled Correlation Matrix	101
Figure 4.7: Performance Trends Across Age	103
Figure 4.8: Baseline Confirmatory Factor Analysis.....	104
Figure 4.9: Effective Sample Size by Age	105
Figure 4.10: Model Fits by Age	106
Figure 4.11: Factor Loadings by Age	107
Figure 4.12: Global Connectivity by Age and Model	109
Figure 4.13: Network Edges (Panel A) and Node Strength (Panel B) by Age and Model	111
Figure A1: Boxplot of Updating Paradigm Scores Including the Spatial Task.....	151
Figure C1: Latent Network Model Factor Loadings by Age.....	153

LEGEND

3Cs	Three-Embedded Components
AIC	Akaike's information criterion
aLTM	Activated part of long-term memory
awLNM	Age-weighted latent network model
BCFA	Bayesian confirmatory factor analysis
BIC	Bayesian information criterion
BIS-4	Berlin Intelligence-Structure Test 4
CFA	Confirmatory factor analysis
CFI	Comparative fit index
CI	Confidence interval
CRT	Choice reaction time
ELPD	Expected log predictive density
FA	Focus of attention
Gf	Fluid intelligence
N_{eff}	Effective sample size
RAPM or RAPM-SF	Raven's Advanced Progressive Matrices – Short Form
RDA	Region of direct access
RMSEA	Root mean-squared error of approximation
RSVP	Rapid serial visual presentation
RT	Response time
SRMR	Standardized root mean-squared residual
STAC-r	Scaffolding Theory of Aging and Cognition (revised)
TLT	Two-list task
WEIRD	Western, educated, industrialized, rich, and democratic
WM	Working memory
WMC	Working memory capacity

CHAPTER 1

General Introduction

1.1 Working Memory and Fluid Intelligence

Everyday functioning requires fluid cognition, which is adaptable mental processing that does not rely on previously acquired knowledge or experience. Individuals differ in their ability to perform fluid cognitive tasks. Two essential fluid cognitive abilities in which individuals differ are working memory (WM), a system with limited storage capacity for the active maintenance and manipulation of information in the service of cognition, and fluid intelligence (Gf), the ability to reason and solve novel problems. WM is essential for any task that requires following multistep instructions (e.g., Jaroslawska et al., 2016), such as cooking, navigating, or using a smartphone, as well as for reading comprehension (Carretti et al., 2009; Daneman & Merikle, 1996) and emotion regulation (Schmeichel et al., 2008). Gf is essential for tasks that involve learning and pattern recognition, such as motor learning (e.g., Apšvalka et al., 2019) and navigating unfamiliar technology (Czaja et al., 2006). WM and Gf are both predictive of early skill acquisition in children (Alloway & Alloway, 2010) and academic success in adults (Engle et al., 1999). As essential as WM and Gf are, much is yet to be understood about how they function. A deeper understanding of the mechanisms of WM and Gf may reveal targets for training, compensatory strategies, or other means to support those who struggle with daily functioning or academic success.

WM capacity (WMC) and Gf can be measured as latent constructs using latent-variable analysis in which they are not directly observed but representative of the shared variance among measures operationalizing WMC and Gf, respectively. By defining WMC and Gf as latent constructs, measurement error pertaining to variables that are not relevant to WMC or Gf can be separated from the variance that does define WMC and Gf, allowing more pure estimates of these constructs. Using this technique, WMC and Gf are found to be highly correlated (e.g., Kyllonen & Christal, 1990) but distinct abilities (Engle et al., 1999). One way of understanding the vital mechanisms of fluid cognition is by investigating their shared variance which may reveal shared underlying mechanisms (common factors).

An early proposal for a mechanism shared between WM and Gf was attention control, the ability to direct attention and ignore external or internal distractors during goal-

directed behavior (Engle, 2002). The more recently refined disengagement hypothesis proposes that attention control supports the maintenance of representations in WM and the disengagement from irrelevant information and false hypotheses to the benefit of Gf (Burgoyne & Engle, 2020; Shipstead & Engle, 2013). A recent mega-analysis pooling data across multiple studies was able to identify attention control as a latent factor that correlated with WMC (Unsworth et al., 2020). However, many studies find weak correlations between measures of attention control (Keye et al., 2009; Rey-Mermet et al., 2018; Shilling et al., 2002; von Bastian et al., 2020). Moreover, when influences of processing speed are accounted for in measures of attention control, these measures do not significantly correlate with WMC or Gf (Rey-Mermet et al., 2019). Due to this inconsistent evidence for the identity of attention control as a latent factor, the plausibility that attention control is a common factor of WMC and Gf is questionable.

1.2 Binding

An alternative mechanism that has been proposed to be shared between WM and Gf is binding, the ability to link representations of information to their contexts. The binding hypothesis proposes that both WM and Gf are limited by the number of bindings that can be concurrently maintained in WM (Oberauer et al., 2008; Oberauer, 2009). Accordingly, when recalling items and their locations, participants are more likely to make binding errors in which items are recalled in the incorrect location, than item errors, where items that were not previously shown are erroneously recalled (Bartsch & Oberauer, 2023; Henson et al., 1996; Pertzov et al., 2012). Moreover, as demand on WMC increases, the proportion of binding errors to item errors increases (Bartsch & Oberauer, 2023; Oberauer, 2019). This pattern of findings suggests that the ability to maintain bindings rather than individual item representations is the primary limiting factor of WMC.

The binding hypothesis further specifies that Gf is limited by the complexity of structural representations of information built by integrating bindings into argument slots in a process called relational integration (Oberauer et al., 2008; Oberauer, 2009). These structural representations consist of the relations between elements allowing for the

GENERAL INTRODUCTION

comparison and application of relations to novel problems which is proposed to be necessary for different types of reasoning, including inductive (Klauer, 1996) and deductive reasoning (Goodwin & Johnson-Laird, 2005). Thus, greater capacity for bindings allows for more complex relational integration which allows for solving more complex Gf problems (Oberauer et al., 2007, 2008). Indeed, individual differences in relational integration have been shown to predict Gf at least as well as traditional storage and processing measures of WM (Oberauer et al., 2008) and explain variance in Gf that traditional WM tasks (specifically, complex span and *n*-back tasks) cannot (Chuderski, 2014), suggesting that relational integration, relative to other WM mechanisms, is crucial to Gf.

The binding hypothesis can further be understood within the framework of the Three-Embedded Components (3Cs) model of WM (Oberauer et al., 2007; Oberauer, 2009). In the 3Cs model, mental representations vary in their amount of activation such that representations with higher activation are more readily accessible than representations with lower activation. The level of activation is dependent on both perceptual input and the spread of activation from associated representations, both of which contribute to the expected relevance of the representations. These representations are selected by the focus of attention (FA) which represents active thought. Although only one representation can be selected by the FA at a time, this representation can be updated with representations that are readily accessible from the region of direct access (RDA). Binding and relational integration occur in the RDA. All representations that have a level of activation above that of long-term memory are in the activated part of long-term memory (aLTM) which includes the RDA along with representations that are less active than those in the RDA. According to the binding hypothesis, WMC and Gf are both dependent on the RDA, because representations in the RDA are bindings (the maximum of which is WMC) within structural representations (the complexity of which underlies Gf). The RDA is therefore limited by the same mechanism that limits WMC and Gf, but what is this mechanism?

It has been proposed that the mechanism which limits number of bindings that can be concurrently maintained in WM is binding interference (Oberauer, 2009; Oberauer et al.,

2016) or, more specifically, retrieval competition, in which representations are more difficult to retrieve because multiple representations have related contexts, and representational interference, in which readily accessible representations mutually degrade each other (Oberauer, 2009). In either case, binding interference occurs when representations cannot be matched to the correct context. However, some specifications of the binding hypothesis do not label interference as the limiting mechanism (Oberauer, 2019; Wilhelm et al., 2013). Instead, the general ability to establish and maintain bindings is proposed to limit WMC (Oberauer, 2019).

The mechanisms of binding and their influence on WM and Gf are still a matter of discussion. Some research has found that, in contrast to the complexity of structural representations underlying individual differences in Gf, the simple ability to establish relations between representations accounts for a substantial amount of the variance in Gf (Chuderski, 2019, 2022; Jastrzębski et al., 2020). Chuderski (2019) demonstrated that, when given the instruction to match pairs of stimuli separated by a slash to the exact same pairs, participants' performances were highly predictive of Gf. Interestingly, this effect disappeared when the slashes between the pairs were removed, leading Chuderski (2019) to suggest that the slashes acted as the relation between the stimuli; when the slashes were removed, the pairs could be represented as single representations rather than relations and were, thus, unrelated to Gf. Chuderski (2022) presents the counter-intuitive idea that the majority of individual differences in Gf pertain to the simple ability to represent relations rather than the complexity of structural representations. Questions, therefore, persist about the specific mechanisms of binding and whether and how they could be considered common factors of fluid cognition.

1.3 Processing Speed

While binding appears to be a promising explanatory mechanism for the WM-Gf relationship, the majority of this research has focused on young adults (Hofer & Sliwinski, 2001). This is a critical gap considering that fluid cognitive abilities, such as WM and Gf, are well-established to decline and differentiate in older age even in participants without

symptoms of pathological diseases (Tucker-Drob et al., 2019; Verhaeghen & Salthouse, 1997). Older adults would, thus, especially benefit from an understanding of mechanisms that could support their cognition during cognitive decline (e.g., Naveh-Benjamin, 2000). Moreover, middle-aged adults are often overlooked in cognitive research, leaving much to be understood about how WM, Gf, and their underlying mechanisms change from young adulthood and into older adulthood (Lachman, 2004). In terms of explanatory mechanisms of WM and Gf in older-adulthood, much more is known about processing speed than binding.

Alongside binding and attention control, processing speed (the efficiency of information processing) is another mechanism hypothesized to play an important role in both WM and Gf (e.g., Frischkorn et al., 2019; Schubert et al., 2017, 2018; Sheppard & Vernon, 2008), especially in older age (Verhaeghen & Salthouse, 1997). In particular, the Processing Speed Theory posits that processing speed acts as a functional bottleneck that limits fluid cognitive abilities such that, as processing speed declines in older age, fluid cognitive abilities become capped by limitations of processing speed (Salthouse, 1996). Indeed, processing speed has been shown to mediate the relationship between age and both WM (Salthouse & Babcock, 1991) and Gf (Hertzog, 1989; Lindenberger et al., 1993) as well as episodic memory (Hultsch et al., 1990) and visuospatial processing (Salthouse, 1994).

The Processing Speed Theory specifically postulates two distinct mechanisms in which processing speed limits cognitive performance: the simultaneity mechanism and the limited time mechanism (Salthouse, 1996). According to the simultaneity mechanism, limited processing speed causes cognitive operations to fail because decay or displacement causes representations in WM to degrade over time. If processing speed is not sufficient between cognitive operations, then representations utilized in one operation degrade before they can be used in the next operation. Also, the limited time mechanism explains that cognitive performance is limited by processing speed because cognitive operations that must be performed sequentially suffer when speed is necessary or time is limited in any of the cognitive operations. If one cognitive operation fails to be completed in time, the remaining operations also fail.

One challenge of the Processing Speed Theory that requires further consideration is that different components of processing speed (such as perceptual speed, information accumulation time, decision time, response bias, speed-accuracy tradeoff, and motor response time) exhibit different relationships with age and fluid cognition (e.g., [Theisen et al., 2021](#)). Without understanding age-related individual differences across processing speed components, the Processing Speed Theory cannot claim that processing speed, generally, rather than any of its specific components, influences age-related changes in cognitive abilities. Previous research has used different tasks to approximate some of the distinct components of processing speed. For example, [Salthouse \(1993\)](#) measured motor response time using tasks that require minimal processing, such as copying numbers and letters or drawing lines, and perceptual speed using tasks that also involve minimal processing but more processing than the motor-response-time tasks, such as mathematically adding 1 to a given number. Using these tasks Salthouse (1993) found that perceptual speed accounted for significantly more of the age-related variance in WM and Gf than motor response time. However, tasks like these which Salthouse and colleagues employed to differentiate processing speed components are problematic, because they largely rely on face validity to determine whether they measure what they purport to measure and will inherently be influenced by multiple processing speed components due to their interrelated nature.

Computational modelling is another method that has been used to disentangle processing speed components. The drift-diffusion model is one such model which works by utilizing the probability distributions of both response accuracy and response time from two-alternative forced-choice tasks ([Ratcliff, 1978](#)). The model operates on the assumption that evidence accumulation is a noisy process, so a normal distribution of random noise is applied to an approximation of evidence accumulation estimated from the accuracy and response time distributions. Evidence accumulation typically begins in the middle of the two choices from the two-alternative forced-choice task but may also favor one choice depending on anticipated or estimated response bias. A decision is made when evidence accumulation surpasses a specific threshold. The distance between the starting point and this threshold is

known as the boundary separation, which represents the individual's speed-accuracy tradeoff (i.e., a wider boundary requires more evidence and prioritizes accuracy over speed). The drift-diffusion model can provide estimates of the starting point (response bias), drift rate (the speed of evidence accumulation), boundary separation (speed-accuracy tradeoff), and non-decision time (a composite of all other non-decisional process) among other parameters, such as inter-trial variability ([Ratcliff, 1978](#); [for an introduction to diffusion modelling, see Voss et al., 2013](#)).

The drift-diffusion model has been used to analyze the role of processing speed components in age-related changes in cognitive abilities and differential relations have been found between the different components. Whereas, drift rate has been more often associated with Gf ([Schmiedek et al., 2007](#); [Schmitz & Wilhelm, 2016](#); [Schubert, Nunez, et al., 2019](#)), non-decision time has been found to increase in older age and mediate the relationship between age and Gf, suggesting that slower non-decisional processing substantially contributes to lower Gf in older adults ([Schubert, Hagemann, et al., 2019](#); [von Krause et al., 2020](#)). Moreover, older adults have been found to exhibit higher boundary separation indicative of higher prioritization of accuracy over speed ([Theisen et al., 2021a](#)). The role of process speed in cognitive ageing, thus, becomes more complex when distinct components of processing speed are considered.

Ultimately, Salthouse's ([1996](#)) Processing Speed Theory provides a framework for age-related cognitive decline, but the distinct influences of diverse processing speed components require further research to obtain a more complete understanding for the role of processing speed in fluid cognition across age. In addition to drift-diffusion modelling, techniques which separate the unique and shared variance of cognitive abilities will be useful for determining which *exact* cognitive abilities constitute common factors of fluid cognition.

1.4 Construct Isolation

To determine the extent that individual differences in one mechanism, such as binding or drift rate, underlie individual differences in higher-order abilities, such as WM and Gf, the unique variance of these mechanisms should be separated from the variance

GENERAL INTRODUCTION

shared with adjacent mechanisms. Given the ubiquitous overlap among fluid cognitive abilities (Carroll, 1993; Kovacs & Conway, 2016; Spearman, 1904), even a task carefully designed to isolate a specific mechanism will inevitably suffer from task impurity and be influenced by proximal cognitive processes. Especially if mechanisms under investigation are theorized to be part of the same higher-order ability, to understand the unique variances of these mechanisms, their shared variance should be statistically controlled. Traditional latent-variable analysis can accomplish this to some extent. If at least three diverse measures are used to indicate the mechanism of interest, structural equation modeling separates random measurement error from systematic variance (Kline, 2015). However, a latent variable captures *all* systematic variance shared among its indicators. If multiple of the same cognitive abilities are represented in each of the indicators, the latent variable would be a composite of each of those abilities rather than a pure measure of the ability of interest.

One method for separating variance between different cognitive abilities that are present in the same indicators is bifactor analysis. In bifactor analysis, indicator variables load onto at least two latent variables such that systematic variance can be further specified. These latent variables are defined by the measures that manifest them. For example, Friedman et al. (2008; 2011) investigated the unique and shared variance among executive functions: updating, shifting, and inhibition. Measures that were designed to measure updating loaded onto the updating-specific factor and those that were designed to measure shifting loaded onto the shifting-specific factor. Additionally, updating, shifting, and inhibition indicators all loaded onto one latent variable representing the variance shared among all of these executive functions and the entirety of the systematic variance from the inhibition tasks. With this approach the variance common to all of the executive functions was found to be isomorphic with inhibition, indicating that inhibition relies heavily on processes that are also required for updating and shifting (Friedman et al., 2008, 2011). Bifactor analysis thus revealed a key finding of theoretical significance for executive functioning by disentangling systematic variance. Regarding common factors of fluid cognitive abilities,

GENERAL INTRODUCTION

the use of bi-factor analysis could uncover mechanisms whose unique variance can explain a substantial amount of covariance in fluid cognition.

Another approach which allows for the investigation of how multiple distinct cognitive mechanisms directly interact is network analysis. Although traditionally used to study complex systems across physics, biology, and sociology, network analysis has recently emerged as a method for understanding the complex structures inherent in cognitive psychology (Borsboom et al., 2021). In psychometric network models, researchers estimate regularized partial correlations to map the conditional dependencies between variables. This reveals the direct, unique associations (partial correlations) between constructs when all other variables in the model are statistically controlled. Furthermore, these models are typically undirected, requiring no a priori specification of causality. To account for measurement error, these networks can be integrated with traditional structural equation modeling via latent network analysis (Epskamp et al., 2017). With this approach, the nodes in the network are latent variables rather than manifest tasks.

The use of psychometric network analysis could reveal crucial structural information about fluid cognition. For example, network models were recently used to investigate the unity and diversity of executive functions (Karr et al., 2022), similar to the research objectives of Friedman et al. (2008, 2011) discussed earlier. Karr et al. (2022) investigated inhibition, shifting, and WM between age groups ranging from 3-6 years to 65-85 years. They found that the partial correlations shared with shifting increased from childhood and into adulthood while the partial correlations shared with inhibition and WM decreased. Moreover, the partial correlations between WM and inhibition were small or non-significant from adolescence to older adulthood while their partial correlations with shifting increased or remained stable. These findings lead Karr et al. to suggest that shifting mediates the relationship between inhibition and WM – a finding of potential theoretical significance to the structure of fluid cognition. Thus, both network analysis and bi-factor analysis can reveal theoretically impactful information on the structure of fluid cognition, such as common factors.

1.5 Aims of this Thesis

The aim of this PhD thesis is to advance understanding of the overlap between WM and Gf and how it changes across adulthood. To achieve this, the current research used statistical methods that extract shared variance among cognitive abilities to isolate unique variances specific to their underlying mechanisms.

To this end, Chapter 2 directly assessed the binding hypothesis by investigating the shared and unique variance within the 3Cs model of WM and evaluating how these specific components and their shared variance relate to Gf. Building upon these initial findings, Chapter 3 broadened the investigation of the binding mechanism by estimating the shared and unique variances across abilities that involve binding to some extent (e.g., relational integration and relational representation). We then compared the variance unique to each ability to Gf using latent network analysis. To further understand the WM-Gf relationship across adulthood and the role of distinct processing speed components in fluid cognition, Chapter 4 examined the partial correlations that processing speed and its underlying computational components share with attention control, WM, and Gf across the adult lifespan. Finally, Chapter 5 reviews and synthesizes the findings from the preceding chapters in the context of the relevant literature and theories. It also discusses the value of the methods employed in this thesis and make recommendations for future research.

CHAPTER 2

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

W. Fred Garvey¹	Conceptualization, Data Curation, Formal Analysis, Software, Methodology, Visualization, Writing - Original Draft & Editing
Han Hao²	Formal Analysis, Software, Writing - Review & Editing
Andrew Conway³	Writing - Review & Editing
Alicia Forsberg¹	Conceptualization, Methodology, Supervision, Writing - Review & Editing
Claudia C. von Bastian¹	Conceptualization, Data Curation, Funding Acquisition, Investigation, Methodology, Project Administration, Resources, Software, Supervision, Writing - Review & Editing

¹University of Sheffield, ²Tarleton State University, ³New Mexico State University

Research presented in this chapter is currently under review and the preprint is available online on the Open Science Framework:

Garvey, W. F., Hao, H., Conway, A., Forsberg, A., & von Bastian, C. C. (2026). *Individual differences in the three embedded components of working memory and their relation to fluid intelligence*. PsyArXiv. https://doi.org/10.31234/osf.io/2tf4n_v1

Findings from this chapter have been presented at the following conferences:

Garvey, W. F., Forsberg, A., & von Bastian, C. C. (2025). *The relationship between working memory and fluid intelligence* [Spoken session]. University of Sheffield School of Psychology Postgraduate Conference 2025, Sheffield, UK.

Garvey, W. F., Hao, H., Conway, A., Forsberg, A., & von Bastian, C. C. (June 25th, 2025). *Individual differences in the three-embedded components of working memory and their relation to fluid intelligence* [Spoken session]. Annual Working Memory Discussion Meeting at Parcevall Hall, Appletreewick, UK.

Garvey, W. F., Forsberg, A., & von Bastian, C. C. (April 30th, 2024). *Fluid intelligence and the three-embedded-components model of working memory: A latent-variable analysis* [Poster session]. University of Sheffield Science Graduate School Research Showcase Event 2024, Sheffield, UK.

Garvey, W. F., Forsberg, A., & von Bastian, C. C. (June 26, 2024). *Can individual differences in the three embedded components explain the working memory - fluid intelligence relationship?* [Poster session]. 4th International Conference on Working Memory, Leeds, UK.

Garvey, W. F., Forsberg, A., & von Bastian, C. C. (2023). *How well do the three embedded components of working memory account for the reasoning and working memory relationship? A latent-variable analysis* [Poster session]. 23rd Conference of the European Society for Cognitive Psychology (ESCOP), Porto, Portugal. <https://doi.org/10.17605/OSF.IO/9DYQE>

Garvey, W.F., Forsberg, A., & von Bastian, C. C. (2023). *Working memory and fluid intelligence: Can the three embedded components explain their relationship? A latent variable analysis* [Spoken session]. Psychonomic Society 64th Annual Meeting, San Francisco, California, USA.

2.1 Introduction

Everyday tasks such as reading, writing, and cooking require 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 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 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, 2003). Experimental research, however, suggests that WM consists of multiple components, culminating in the 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.

2.1.1 Three Embedded Components of Working Memory

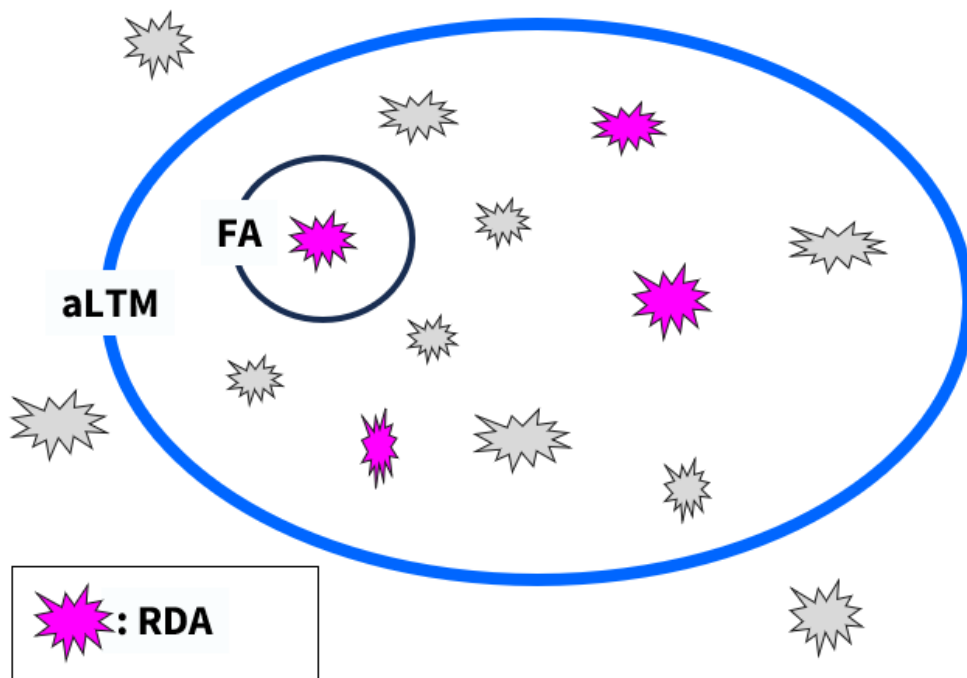
The 3Cs model is an activation-based model extending Cowan's (1988, 1999) Embedded-Processes model. In activation-based models, memory contents, or representations, vary in their amount of activation such that contents with more activation are more readily accessible in the present moment. The 3Cs model distinguishes between the aLTM, RDA, and FA (see Figure 2.1). 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

THREE-EMBEDDED COMPONENTS INDIVIDUAL DIFFERENCES

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 2.1

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.

2.1.2 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 structural equation model – none of the measures operationalizing the 3Cs uniquely related to Gf.

2.2 Method

2.2.1 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.

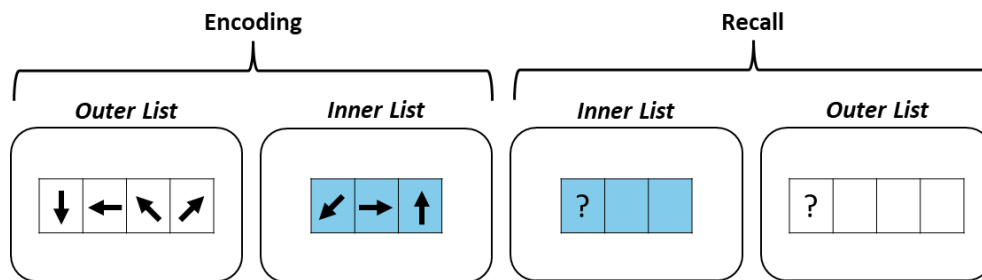
2.2.2 Materials and Procedure

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 Appendix A 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.

2.2.2.1 Two Lists

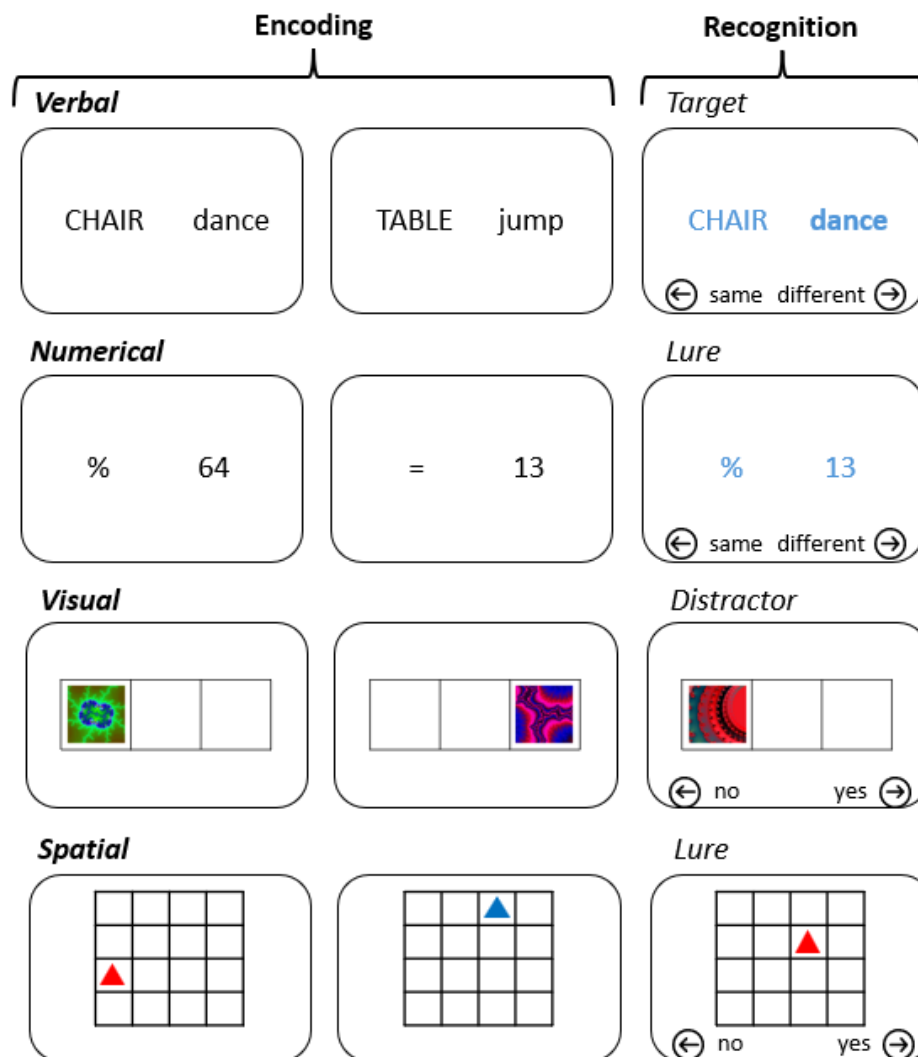
The two-lists tasks were designed to assess retrieval of memoranda from the aLTM (see Figure 2.2 for an illustration). Participants were asked to memorize two subsequently presented lists of items, with the lists being separated by a 2000 ms gap. Each item was presented for 400 ms in a row of boxes, 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).

Figure 2.2*Example Two-List Task Trial*

Note. The spatial variant is depicted. Stimuli and probes were presented sequentially left-to-right starting with the outer list and then the inner list. Numerical, verbal, and visual two-list tasks differ in set size and stimuli.

2.2.2.2 Binding (De Simoni & von Bastian, 2018)

This paradigm was designed to assess the ability to deal with interference among bindings in the RDA (see Figure 2.3 for an example). 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).

Figure 2.3*Example Binding Task Trials*

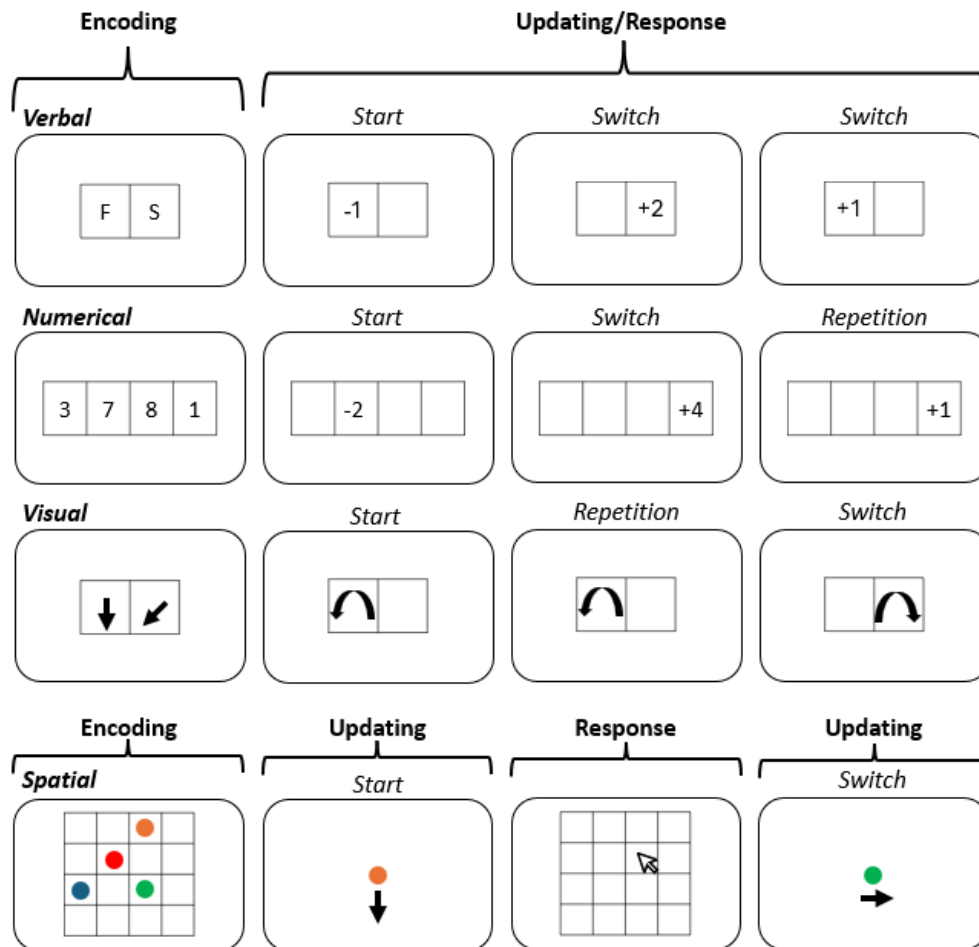
Note. Examples depicted differ from actual trials in set size and language (tasks were in German). Examples of targets, lures, and distractors are depicted.

2.2.2.3 Memory Updating (De Simoni & von Bastian, 2018)

The memory updating paradigm was designed to assess switching of the FA between objects in memory (see Figure 2.4). 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 presented¹. Half of the updating steps were object switches (i.e., the to-be-updated stimulus was different from the one in the 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 - H) 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).

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

Figure 2.4*Example Updating Task Trials*

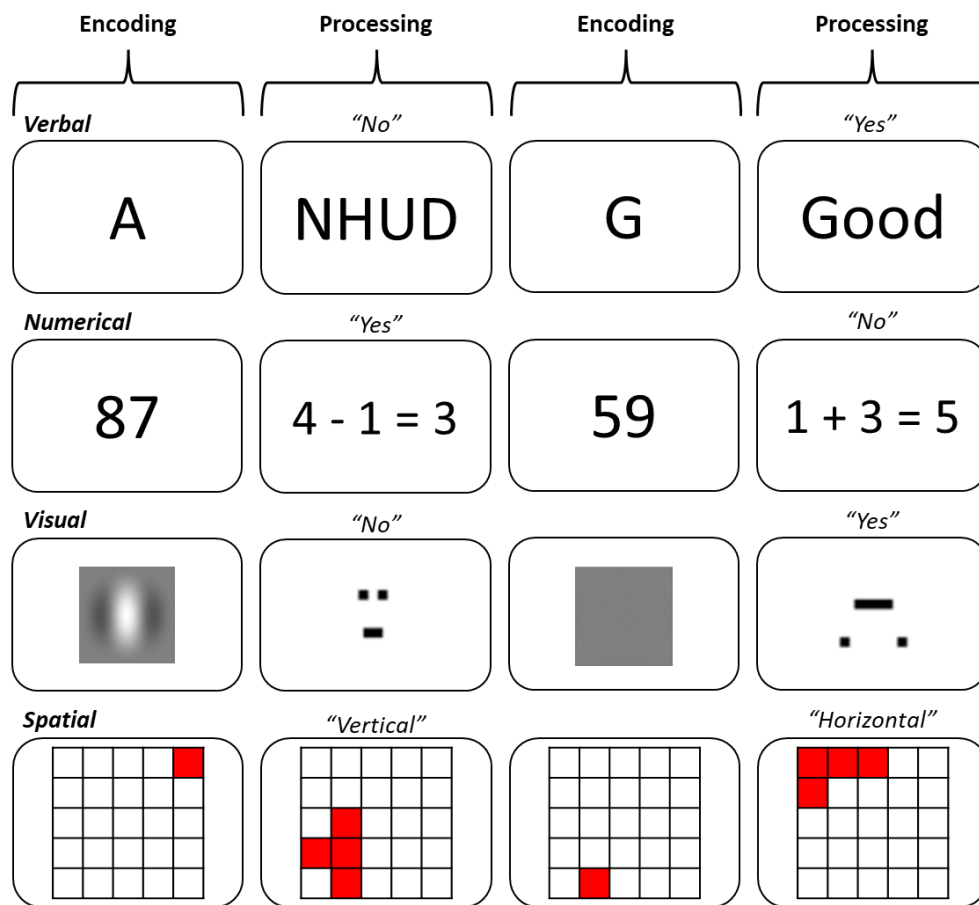
Note. Examples depicted differ from actual trials in number of updating operations. In the verbal, numerical, and visual variants participants input their responses using a keyboard while the updating operation was displayed. In the spatial variant, participants input their responses by clicking on grid cells after the updating operation was displayed. Object switches and repetitions are presented.

2.2.2.4 Complex Span

The complex span tasks were used as a traditional measure for assessing WMC (see Figure 2.5). 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

THREE-EMBEDDED COMPONENTS INDIVIDUAL DIFFERENCES

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).

Figure 2.5*Example Complex Span Task Trials*

Note. The recall phase is not depicted. Actual trials had larger set sizes and were in German. The correct responses to the processing operations are depicted.

2.2.2.5 Berlin-Intelligence Structure Test (BIS-4; Jäger et al., 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 Appendix A 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.

2.2.3 Analysis

Statistical analyses were completed with R (R Core Team, 2024) and RStudio (Posit 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.

2.2.3.1 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 Appendix A), 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.

2.2.3.2 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.

2.2.3.3 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 ($p < .01$).

Data and scripts for running the analyses are available on the Open Science Framework (<https://osf.io/d8r3z>). This study was not preregistered.

2.3 Results

Descriptive statistics and reliability coefficients for all tasks are presented in Table 2.1. 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 2.6 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 2.1

Descriptive Statistics of Raw Scores

Task/condition	<i>M (SD)</i>	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]

THREE-EMBEDDED COMPONENTS INDIVIDUAL DIFFERENCES

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]

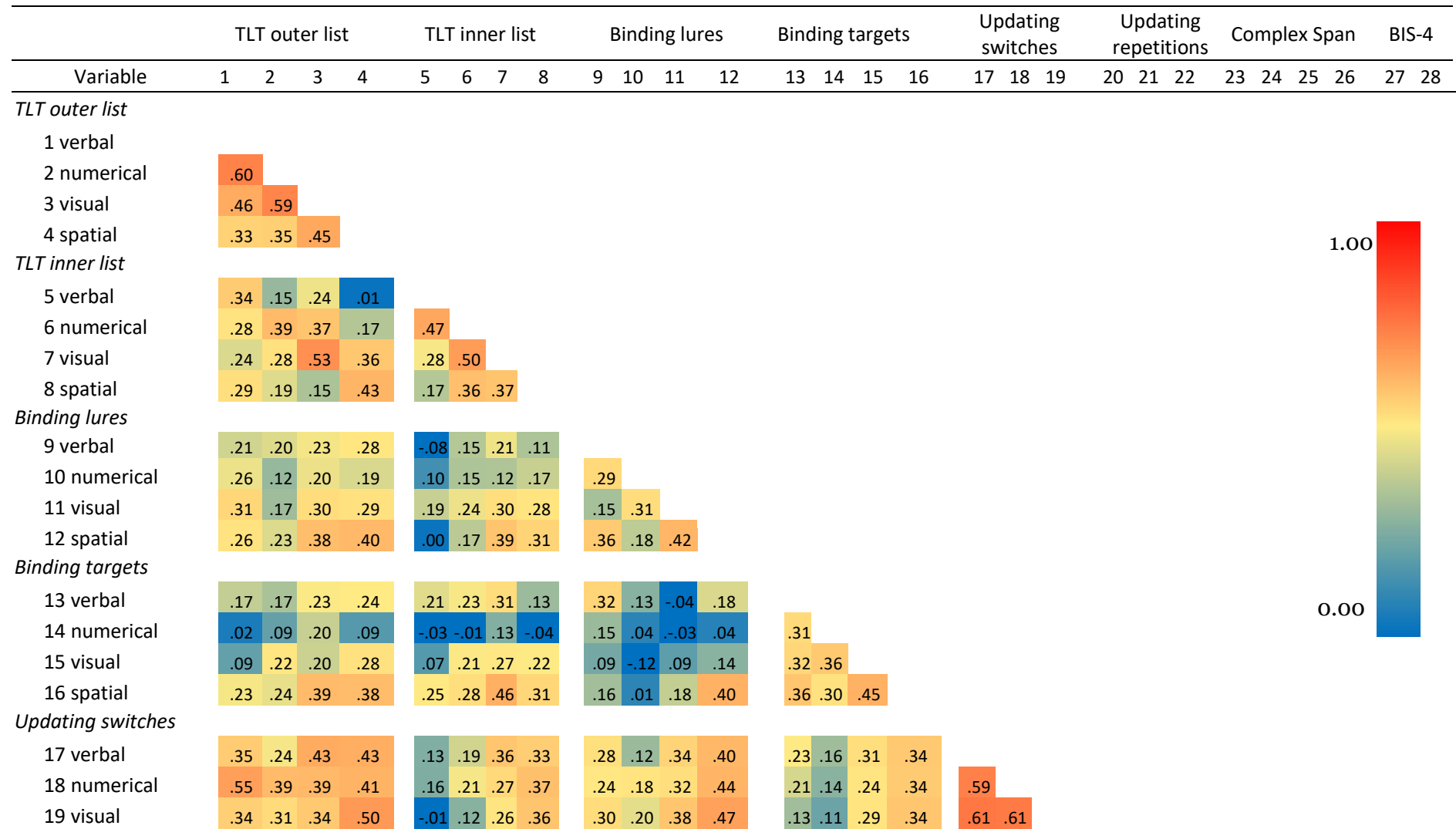
Note. Dependent measures were proportion of correctly recalled items except for BIS-4 which were scores in the Berlin Intelligence-Structure Test 4. Reliabilities reflect Cronbach's α and its 95% confidence interval. CI = confidence interval; BIS-4 = K scale of the Berlin Intelligence-Structure Test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

^a Arcsine transformed.

THREE-EMBEDDED COMPONENTS INDIVIDUAL DIFFERENCES

Figure 2.6

Color-Scaled Correlation Matrix



THREE-EMBEDDED COMPONENTS INDIVIDUAL DIFFERENCES

	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.

2.3.1 Structural Equation Modeling

We conducted systematic model comparisons to find the best fitting model. Table 2.2 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 2.7). No further recommendations from

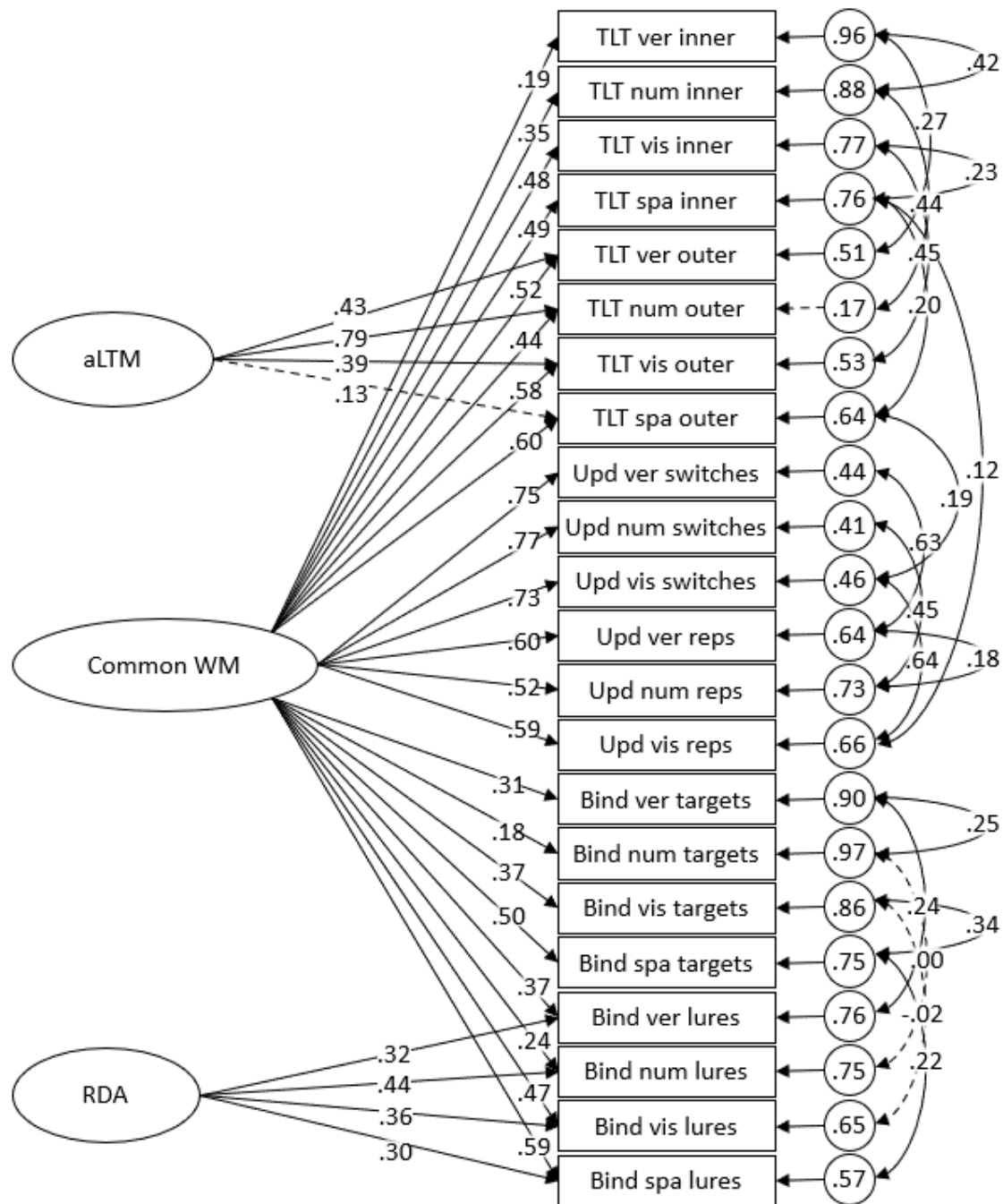
modification indices were deemed theoretically justifiable, so we used Model 3.2 as our measurement model.

Table 2.2

Model Fits from Structural Equation Modeling

Model	$\chi^2(df)$	CFI	RMSEA	SRMR	AIC	BIC	<i>p</i> -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 2.7*Measurement Model (Model 3.2)*

Note. Solid lines represent significant loadings ($p < .05$). 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

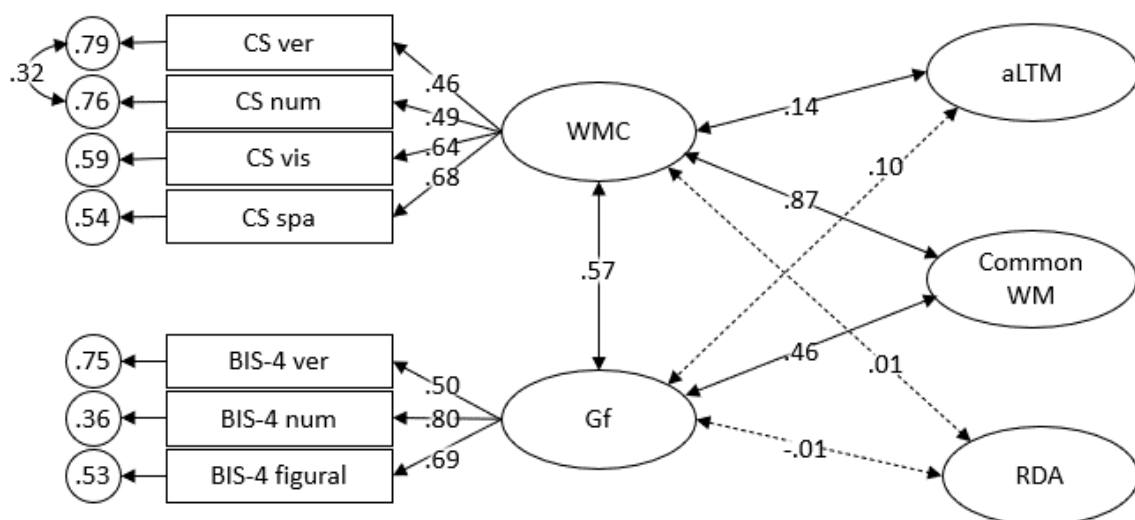
specify the non-significant correlations and loadings for consistency across tasks.

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 2.8). 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 2.8

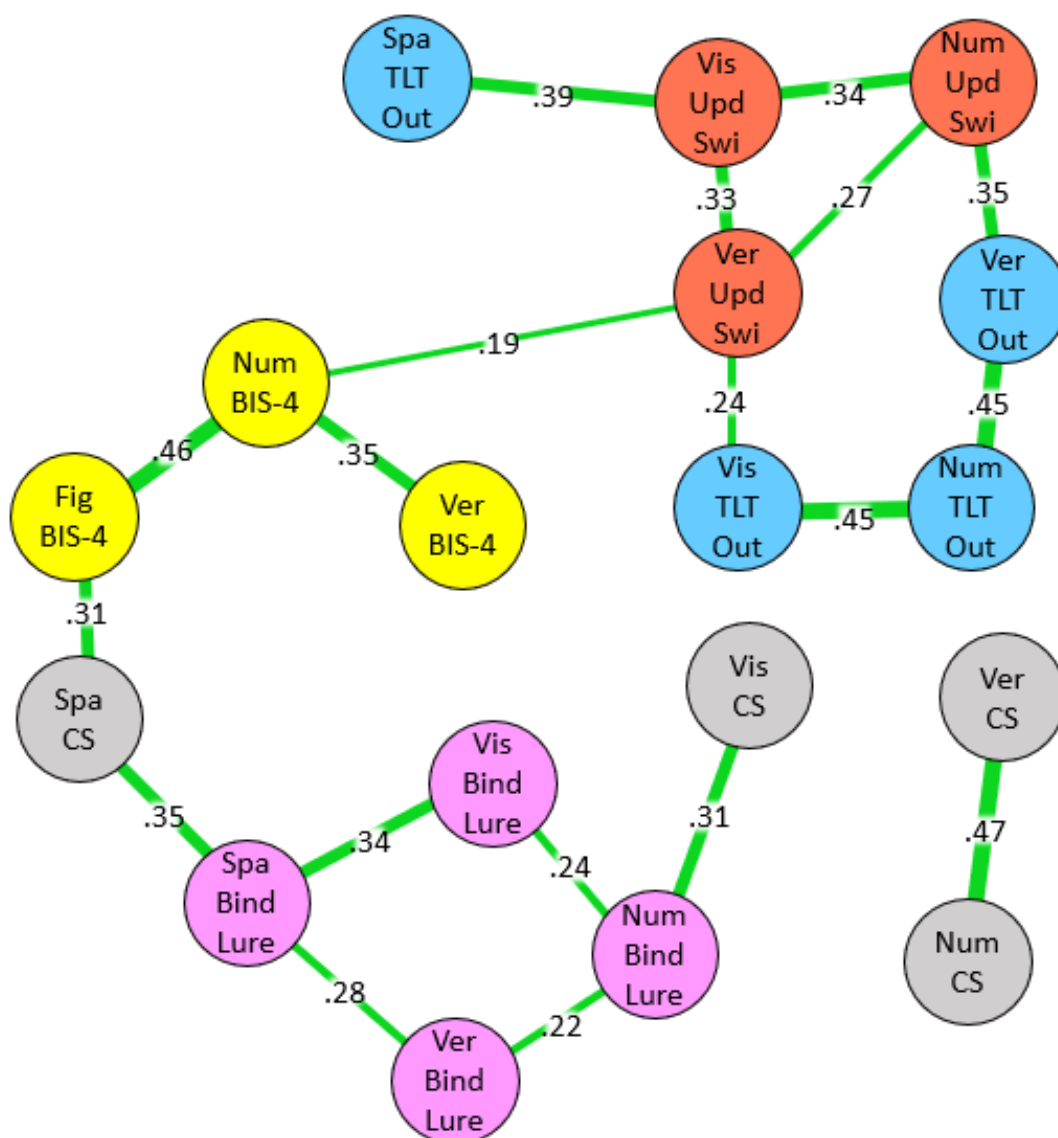
Model 3.2 with WMC and Gf



Note. Solid lines represent significant loadings ($p < .05$). 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.

2.3.2 Psychometric Network Analysis

Figure 2.9 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 figural 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.

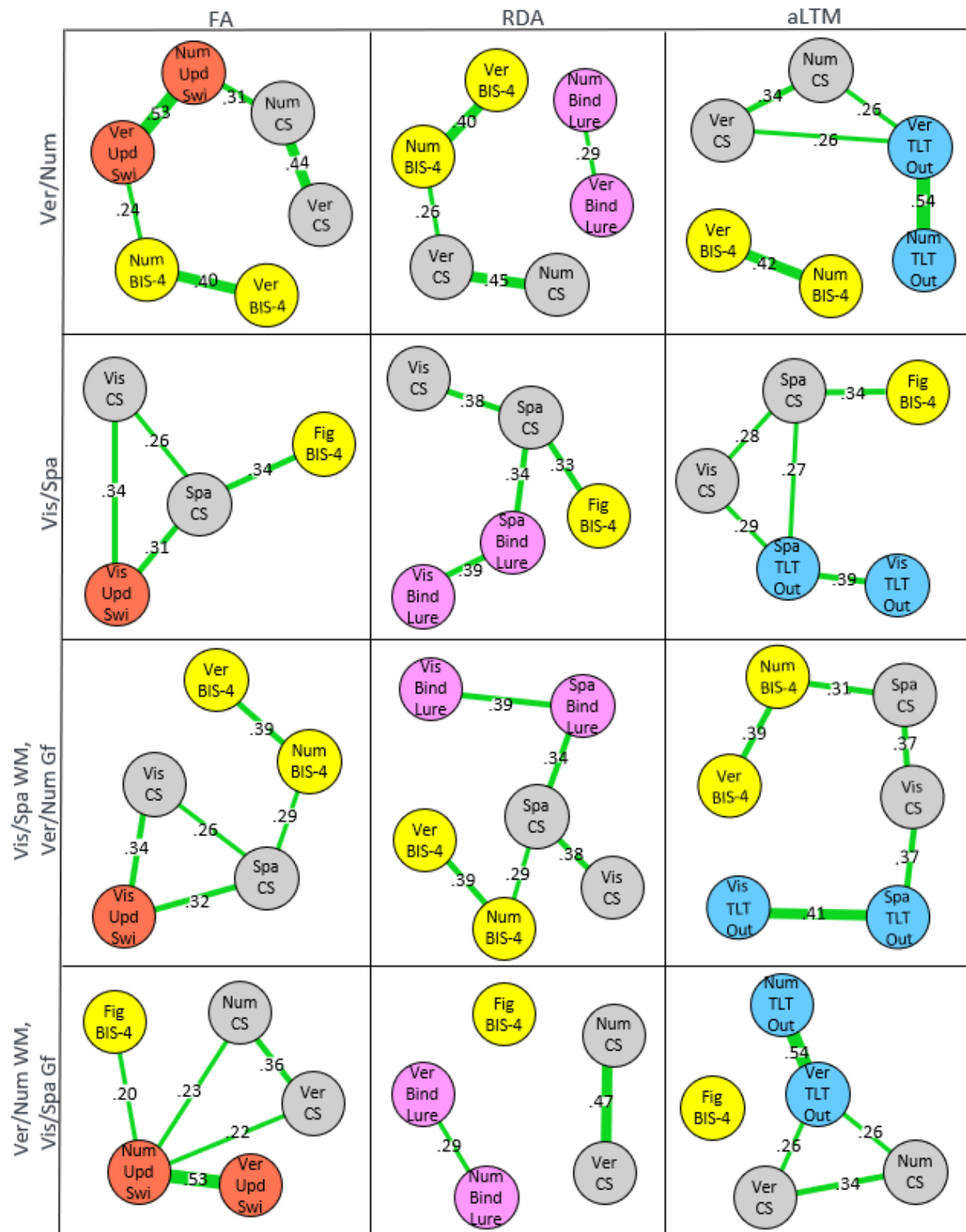
Figure 2.9*Psychometric Network Analysis with all Variables as Nodes*

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 2.10 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 2.11A). 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 2.11B). 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.

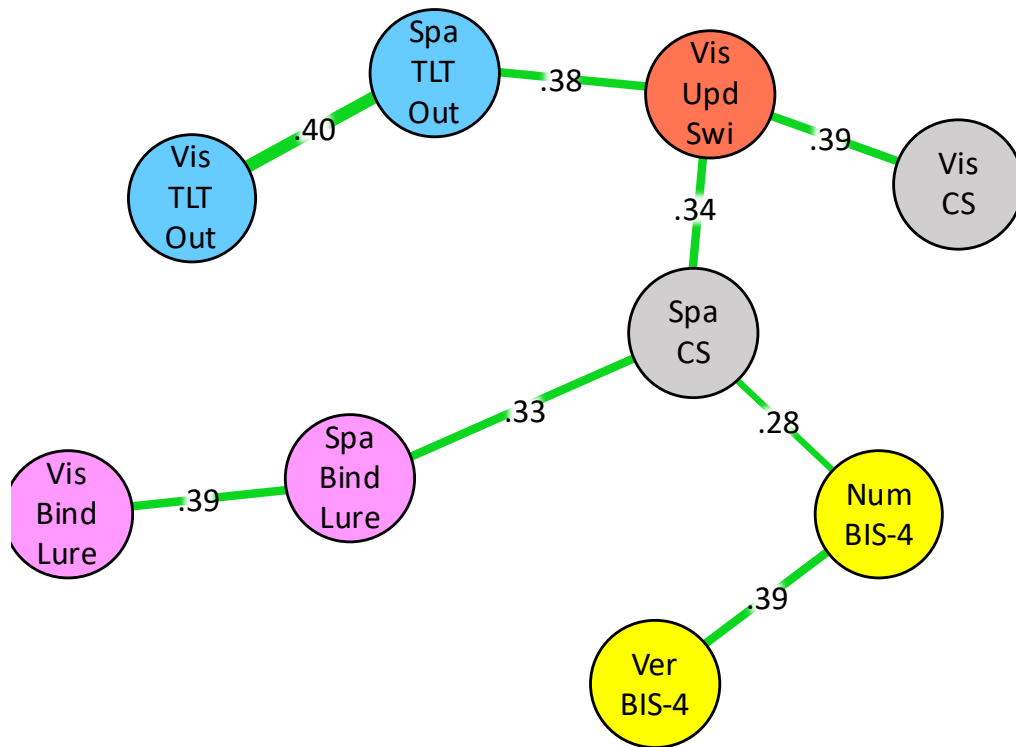
Figure 2.10*Matrix of Network Analyses by Domain and Embedded Component*

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.

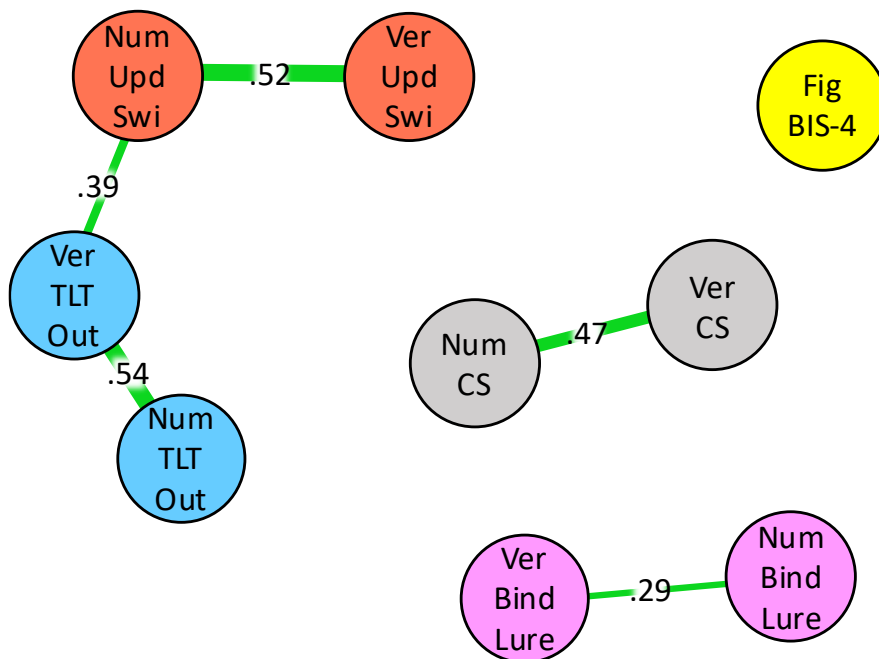
Figure 2.11

Network Analyses with Differentiated Domains

A)



B)



Note. Panel A includes verbal and numerical BIS-4 and visual and spatial complex span, binding, updating, and two-list tasks. Panel B includes figural BIS-4 node and verbal and numerical complex span, binding, updating, and two-list tasks. 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.

2.4 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.

2.4.1 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 attention 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, 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 long-term memory (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.

2.4.2 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, 2018a; 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 disengagement 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 WM 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 et al., 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 long-term memory 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 theories like process-overlap theory or common cause theory which emphasize domain-general variance, rather than specific mechanisms in explaining the WMC-Gf relationship. 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, no individual cognitive ability can explain the WM-Gf relationship, but multiple abilities tapped by both WM and Gf account for the overall relationship. In the current study, 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 relationships observed between Common WM, WMC, and Gf suggest that Common WM captured domain-general processes which overlap with those of WMC and Gf.

Alternatively, the current pattern of findings can be explained through the lens of common cause theory, which posits that general intelligence (g) drives performance across all cognitive tasks. Under this framework, the correlation between cognitive measures indicates the extent to which the measures reflect g (Spearman, 1904). Alongside g , common

cause theory specifies that task performance is driven by task-specific factors (s) that are independent of g . Like process-overlap theory, common cause theory predicts that broader measures relate more strongly to Gf. However, the mechanism differs: in common cause theory, process-general measures are highly reflective of g . Any measure that is not a pure representation of g would not completely account for relationships between cognitive abilities. Thus, the 3Cs-specific variables did not relate to Gf because they were highly process-specific (reflecting s), whereas Common WM related strongly because it was process-general (reflecting g). Furthermore, the network analyses could not mathematically control for g , because g is an unmeasured underlying cause rather than a distinct node. Hence, the finding that WMC mediated the 3Cs and Gf in the network model could reflect unaccounted-for variance in g and shared specific variance (i.e., s).

Both process-overlap theory and common cause theory are consistent with previous literature on the overlap between cognitive functions. For instance, [Wilhelm et al. \(2013\)](#) and Robison et al. (2024) did not isolate WM process-specific variance and found that different WM facets strongly related to WM. In accordance with both process-overlap theory and common cause theory, the process-generalities of these WM measures accounts for their relationship with the general WM factors. Similarly, a wide-range of specific mechanisms, including 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), have all been found to partially explain the WM-Gf relationship. Both theories would predict that these mechanisms only partially explain the overlap. According to process-overlap theory, previously investigated mechanisms represent only a fraction of the many processes responsible for the WM-Gf overlap. According to common cause theory, these specific mechanisms capture only a portion of the true underlying g factor.

2.4.3 Limitations

One limitation of this study is its homogenous sample, which consisted largely of young adults studying at a Swiss university. University students have been found to score better on assessments of Gf and executive functioning compared to non-university students (Guerra-Carrillo et al., 2017). If the RDA (the capacity to resolve binding interference) contributes to individual differences in Gf, then a sample with above average Gf may have minimal variability in RDA. Consequently, the non-significant variance found in RDA may be the direct result of the homogeneity and education of the sample. Hence, the results are not generalizable to other populations from other demographic backgrounds. Moreover, 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.

2.5 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 the 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 specific mechanisms, like managing binding interference (Oberauer et al., 2007) or disengaging from no-longer relevant information in WM (Shipstead et al., 2016). Instead, more consistent with frameworks that emphasize domain-general, such as the dual-component model (Unsworth, 2016), process-overlap theory (Kovacs & Conway, 2016), and common cause theory (Spearman, 1904), the present results suggest that domain-general variance, rather than highly specific mechanistic parts, drives the predictive power of WM for Gf.

CHAPTER 3

Processing and Maintaining Relations: The Central Role of Binding in Fluid Intelligence

W. Fred Garvey¹	Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Project Administration, Software, Visualization, Writing – Original Draft & Editing
Alon Zivony¹	Conceptualization, Methodology, Resources, Writing - Review & Editing
Alicia Forsberg¹	Conceptualization, Methodology, Supervision, Writing - Review & Editing
Claudia C. von Bastian¹	Conceptualization, Methodology, Resources, Software, Supervision, Writing - Review & Editing

¹*University of Sheffield*

Findings from this chapter have been presented at the following conferences:

Garvey, W. F., Forsberg, A., & von Bastian, C. C. (2025). *The relationship between working memory and fluid intelligence* [Spoken session]. University of Sheffield School of Psychology Postgraduate Conference 2025, Sheffield, UK.

Garvey, W. F., Zivony, A., Forsberg, A., & von Bastian, C. C. (2025). *The unity and diversity of binding and its relation to fluid intelligence* [Poster session]. 24th Conference of the European Society for Cognitive Psychology (ESCoP), Sheffield, UK.

3.1 Introduction

A central goal in cognitive psychology is to understand the mechanisms that underlie Gf, the ability to reason and solve novel problems. Gf is strongly related to WMC (Kyllonen & Christal, 1990), which is the capacity of a system for maintaining and manipulating a limited amount of information for ongoing cognitive processing. One WM mechanism that has been proposed to be vital for Gf is binding, the linking of representations of information to their context (e.g., remembering which colleague asked for which type of coffee). According to the binding hypothesis, WM and Gf are jointly limited by binding interference in which WM representations cannot be matched to the correct context (Oberauer et al., 2007). Indeed, evidence shows that as WMC is surpassed, binding errors are more likely to occur than item errors; errors occur due to content being bound to the incorrect context rather than items being recalled that were not previously shown (Bartsch & Oberauer, 2023; Henson et al., 1996; Pertzov et al., 2012). However, recent research found a lack of individual differences specific to the ability to manage binding interference (Garvey et al., 2026). While the ability to manage binding interference may not be vital to Gf, other abilities pertaining to binding, *binding abilities*, have some conceptual and, possibly, mechanistic overlap which would be useful for pinpointing the individual differences that *are* fundamental to Gf. Therefore, the purpose of this study is to investigate binding abilities, namely item-to-location binding, item-to-item binding, relational integration, relational representation, and temporal binding, to determine the extent of their overlap and their relation to Gf.

3.1.1 Binding Abilities

Item-to-location and item-to-item binding differ in the context to which items are bound (i.e., locations and items, respectively). Item-to-location binding is typically operationalized with the local recognition task in which participants are sequentially shown items in different locations and then indicate whether probes represent the same items in the same locations (Oberauer, 2003). Item-to-item binding is typically operationalized with the associated pairs task in which participants are sequentially shown pairs of items and then indicate whether probes represent the same pairs that were previously shown (e.g., Wilhelm

et al., 2013). Shared variance between local recognition and associated pairs task performance has been used in past research to indicate latent binding (De Simoni & von Bastian, 2018b; Garvey et al., 2026), but there may be substantial distinct variance between item-to-location and item-to-item binding. Indeed, it may be that Garvey et al. (2026) was unable to find significant individual differences in the ability to manage binding interference because this ability was indicated by shared variance in local recognition and associated pairs tasks. If individual differences in the ability to manage binding interference are distinct between item-to-location bindings and item-to-item bindings, then this ability would not be represented in their shared variance. The use of two meaningful items in the associated pairs task inherently provides greater semantic richness than an item-location binding. Since semantic richness is theorized to facilitate retrieval from long-term memory (Brady et al., 2013; Konkle et al., 2010), the associated pairs paradigm may utilize long-term memory more than the local recognition paradigm which may substantially differentiate individual differences in item-to-item from item-to-location bindings.

Relational integration is the ability to bind information into structural representations, such as a schema or cognitive coordinate system. According to the binding hypothesis, the individual differences in the complexity of structural representations underlies individual differences in Gf. Indeed, relational integration has been found to predict Gf better than other cognitive abilities, namely storage and processing (Chuderski, 2014; Oberauer et al., 2008), attention control, and short-term memory (Chuderski, 2014). However, relational representation also relates to Gf but only requires the mental representation of connections between individual stimuli rather than the complex structural representations built by relational integration (Chuderski, 2019). It may be that findings pertaining to relational integration are actually indicative of individual differences in relational representation. Indeed, relational integration is typically operationalized with monitoring tasks. In these tasks, participants are shown a grid of stimuli which changes periodically and instructed to respond when a specific pattern emerges across the grid. Accurate responding is thought to require the integration of information into a common

cognitive coordinate system. However, performance in the monitoring task may be confounded by relational representation or other binding abilities, so it is unclear whether the relationship between relational integration and Gf is an effect of these confounds.

Much is still unknown about relational representation as well. Chuderski (2019) introduced the relational representation task which has low complexity and minimal memory demands; participants are tasked with finding exact copies of pairs of stimuli separated by forward or backward slashes. Accuracy in the relational representation task has been found to load highly onto Gf and correlate with established Gf tasks as highly as these tasks correlate with each other. However, performance in this task may be confounded by relational integration or other binding abilities. Moreover, to the best of our knowledge, no studies have controlled for stimulus-specificity and measurement error in the measurement of relational representation, so the magnitude of the relationship between relational representation and Gf is questionable.

Another binding ability that warrants differential investigation is temporal binding – the ability to bind stimuli that rapidly appear. Temporal binding is typically measured with the rapid serial visual presentation (RSVP) task in which participants are shown images presented sequentially in 50- to 250-ms intervals. Participants indicate which of these images they saw in a box. Binding errors often occur in which the item directly after the target item is erroneously perceived inside of the box (Botella et al., 2001; Chun, 1997; Zivony & Eimer, 2023). These binding errors may be a result of the same capacity that causes binding errors in associated pairs and local recognition tasks. Individual differences in temporal binding have not been the topic of much investigation with the exception of a recent study reporting that WMC is predictive of temporal binding only when participants were allowed to rehearse (Zhao & Vogel, 2025). It remains unclear, however, the extent that temporal binding is related to other binding abilities and Gf.

3.1.2 The Current Study

The goal of this study was to determine the extent that five binding abilities – item-to-location binding, item-to-item binding, relational integration, relational representation, and

temporal binding – overlap and how they relate to Gf. We compared latent-variable models beginning with a model which has six correlated latent variables representing each ability and Gf. We systematically modified each model by reducing the number of latent variables until further reductions did not improve model fit. We also used latent-variable network analysis to uncover the unique relationships between these variables. We expected to find that each ability significantly relates to each other and to Gf, but we had no prediction for the magnitude of their overlap.

3.2 Method

This study was pre-registered on the Open Science Framework (<https://osf.io/dgckf>).

3.2.1 Participants

A total of 201 young adults were recruited from Sheffield, England through Sona Systems, posters, social media advertisements, and word of mouth. Participants were included if they indicated that they were young adults (18-30 years old, inclusive), fluent in English, had normal or corrected-to-normal vision (color vision was tested using the Ishihara test), and did not have ongoing psychiatric/neurological disorders or psychotropic drug use. Participants were compensated with a £25 gift card, course credits, or a mix of both. Ethical approval for this study was received from the University of Sheffield's Ethics Review Committee administered by the School of Psychology.

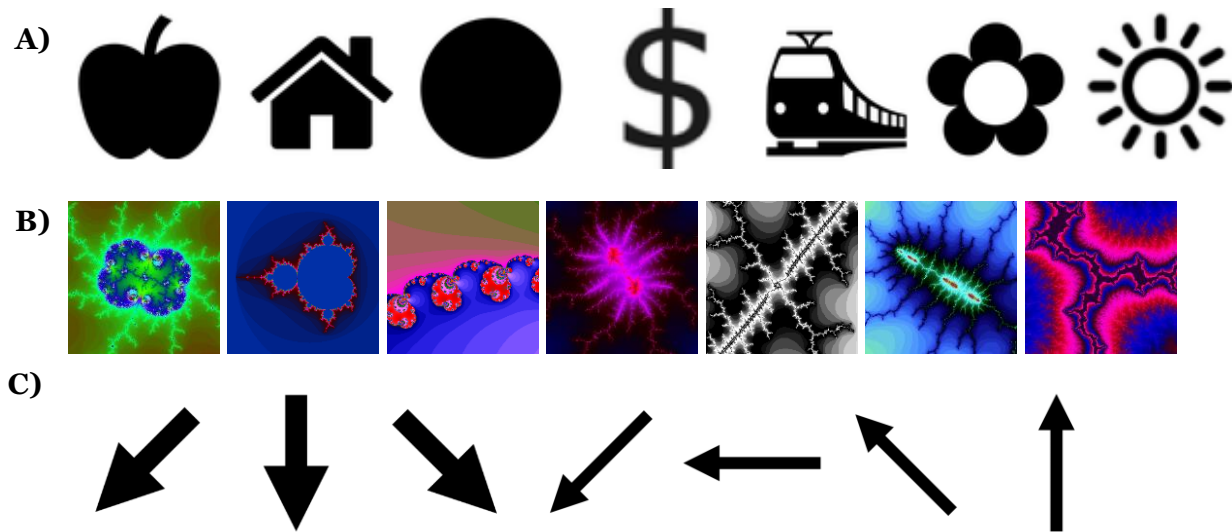
The data were cleaned by excluding participants with incomplete protocols ($n = 3$), data loss ($n = 2$), unmet inclusion criteria ($n = 6$), duplicate task completion ($n = 2$), or incorrect task order ($n = 1$); 187 participants remained. Participants were also excluded when their response patterns suggested disingenuous effort ($n = 10$; see Analysis for details) or if their data were identified as multivariate outliers as per Mahalanobis Distance ($n = 3$).

The final sample consisted of 174 participants. Participants were mostly young (range 18 to 30 years, $M_{\text{age}} = 21.29$ years, $SD_{\text{age}} = 3.16$), female (115 female, 58 male, 1 non-binary, 2 undisclosed), university students (83%), and White (66%) or Asian (22%). Most participants had further education (96%). Additionally, participants indicated their socioeconomic status using the MacArthur Scale of Subjective Social Status which has a minimum value of 1 for

those “worst off” in society and a maximum value of 10 for those “best off” in society (Adler et al., 2000). Participants’ socioeconomic status was moderate to above moderate ($M = 6.16$, $SD = 1.31$). We departed from the pre-registration here by not collecting information on the employment status.

3.2.2 Materials and Procedure

After providing informed consent and completing the Ishihara test, participants completed three visuospatial variants of local recognition, associated pairs, monitoring, relational representation, RSVP, and Gf tasks. Each paradigm (apart from Gf) used the same three sets of stimulus materials (i.e., arrows, symbols, and fractals), one for each task variant. The symbols were a selection of those used in the figural-icon tasks of [Himi et al. \(2023\)](#). The fractals were a selection of those used in the binding tasks of previous work (von Bastian & Oberauer, 2013). The arrows were created to point in 1 of 8 unique directions evenly divisible by 45 degrees and to be either long and thin or short and wide (see Figure 3.1 for selections from each stimulus set). To minimize individual differences due to task order effects, tasks were administered in the same order for all participants, which is common practice in individual differences research (Appendix B for the task order). Completing all tasks took 2.5-3 hr with two designated breaks of no set duration. We deviated from the pre-registration (which specified two 10-min breaks) to increase participant comfort. Data were collected in groups of up to seven participants.

Figure 3.1*Selection of Arrows, Fractals, and Symbols Stimuli*

Note. Panel A: A selection of stimuli from the symbols task variants. Panel B: A selection of stimuli from the fractals task variants. Panel C: A selection of stimuli from the arrows task variants.

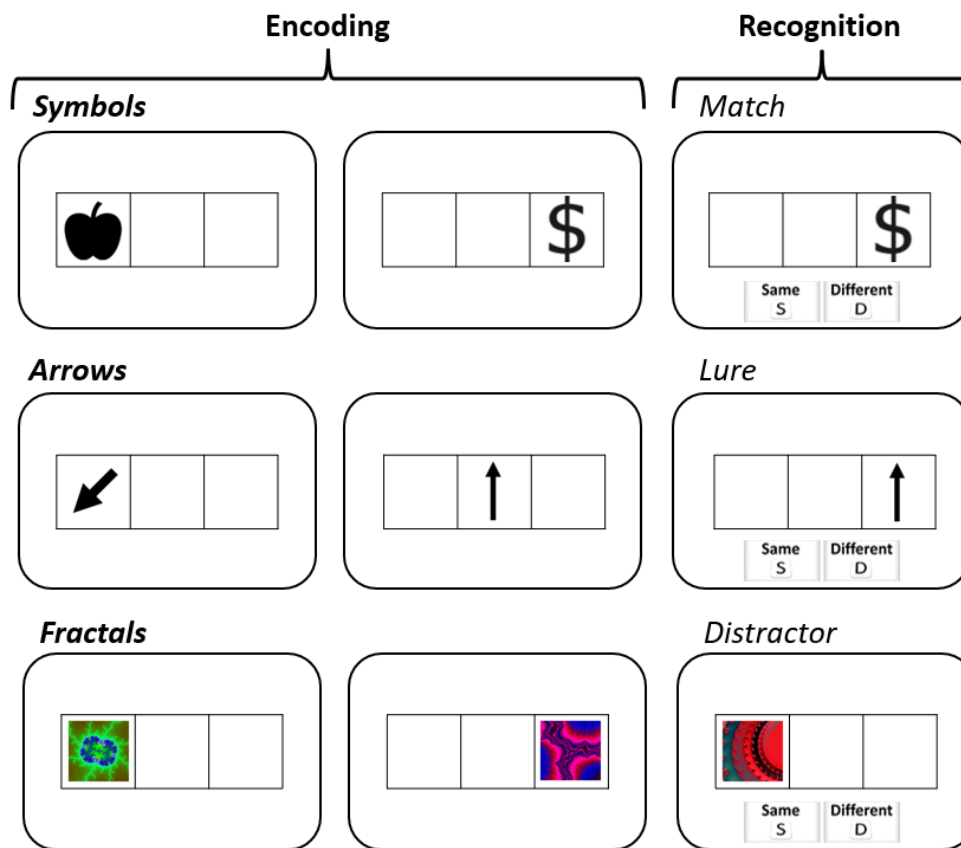
3.2.2.1 Local Recognition (Oberauer, 2003; see also, De Simoni & von Bastian, 2018)

Participants were asked to memorize stimuli presented in a row of boxes the number of which corresponded to the trial set size on a computer screen (see Figure 3.2 for an illustration). In the memorization phase, each box contained one stimulus presented in random order one at a time for 500 ms with a 200 ms interstimulus interval. Once all memoranda in the trial were presented, probes were presented in pseudorandom order (explained below) in each box until participants indicated via key press whether the probe matched the stimulus presented in the box during the memorization phase (“S” for a match, “D” for no match). Of the probes, 50% were matches, 25% were distractors (i.e., not presented in the current trial), and 25% were lures (i.e., presented in the current trial but in a different box). Stimuli selection was pseudorandom. No memoranda or probes repeated in a trial, and they were equally distributed (± 2) across temporal order and serial position. Probe types were equally distributed across stimuli (± 2), temporal order (± 1), and serial position (± 1). Temporal order and serial position were also cross-balanced. There were three practice trials and 20 test trials with set sizes ranging from 3-6 such that each set size

occurred five times across the test trials. To distinguish binding memory from item memory, the dependent variable was the discrimination parameter, d' , from signal detection theory (Stanislaw & Todorov, 1999) in which false alarms were specific to lures: $d' = z(H) - z(F_L)$, where $z(H)$ is z-transformed hit rate (correct identification of matches) and $z(F_L)$ is z-transformed false alarms to lures (incorrect identification of a lure trial as a match).

Figure 3.2

Local Recognition Tasks



Note. Examples depicted differ from actual trials in that one stimulus was shown per box. Examples of match, lures, and distractor trials are shown for the symbols, arrows, and fractals task variants, respectively.

3.2.2.2 Associated Pairs (Garvey et al., 2026; Wilhelm et al., 2013)

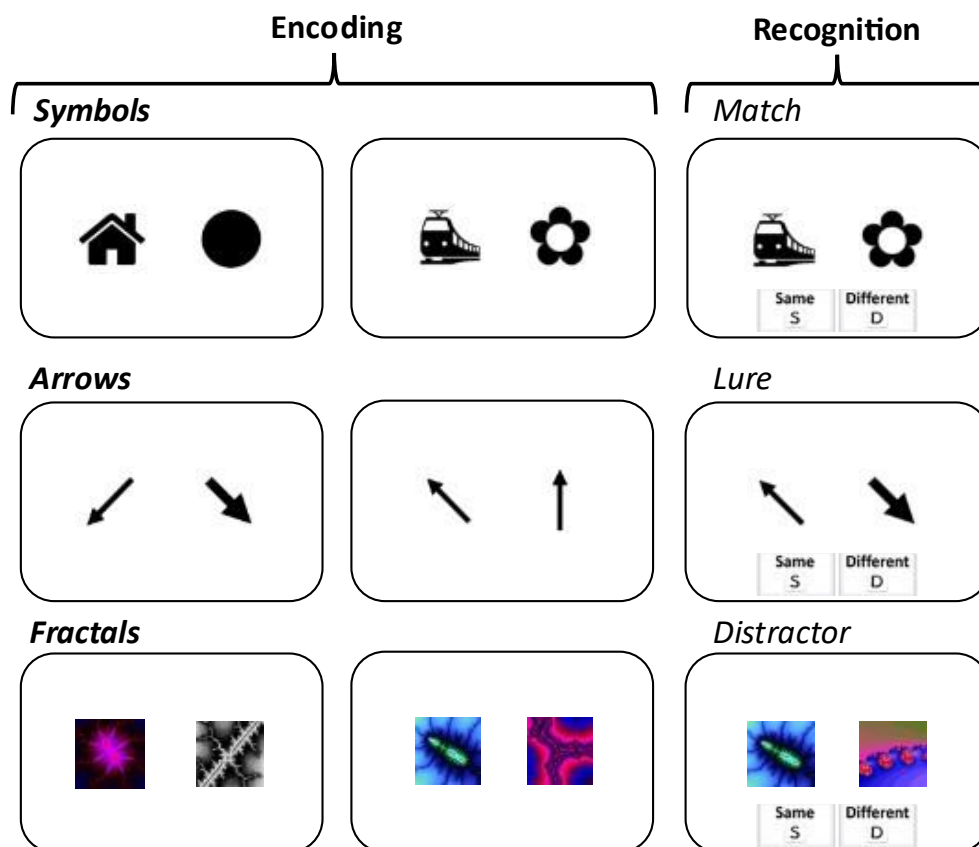
Participants were asked to memorize pairs of stimuli presented one at a time for 1000 ms each with a 200-ms inter-stimulus interval (see Figure 3.3 for examples). Arrows that point in the same direction were not paired. Once all memoranda were presented in the trial, probes were presented until participants indicated via key press whether the probes matched the pairs presented in the trial ("S" for a match, "D" for no match). Of the probes, 50% were

PROCESSING AND MAINTAINING RELATIONS

matches, 25% were distractors (i.e., half of the pair was not presented in the current trial), and 25% were lures (i.e., both stimuli in the pair were presented in the current trial but in a different pair). Stimuli selection was pseudorandom. No memoranda were repeated in a trial. Memoranda occurred with equal frequency across temporal order (+/- 3) and position (left or right half of a pair; +/- 1). Probe types were equally distributed (+/- 2) across stimuli and temporal order. Stimuli were also balanced across pairs such that no pairing occurred more than twice. The temporal order of the memoranda and probes were also distributed such that the temporal order of the memoranda was unrelated to a probe type. The distractors were balanced such that the left or right half of the pair was the distractor stimulus with equal frequency. There were three practice trials and 20 test trials with set sizes ranging from 3-6 such that each set size occurred 5 times across the test trials. The dependent variable was d' calculated the same as in the local recognition paradigm.

Figure 3.3

Associated Pairs Tasks



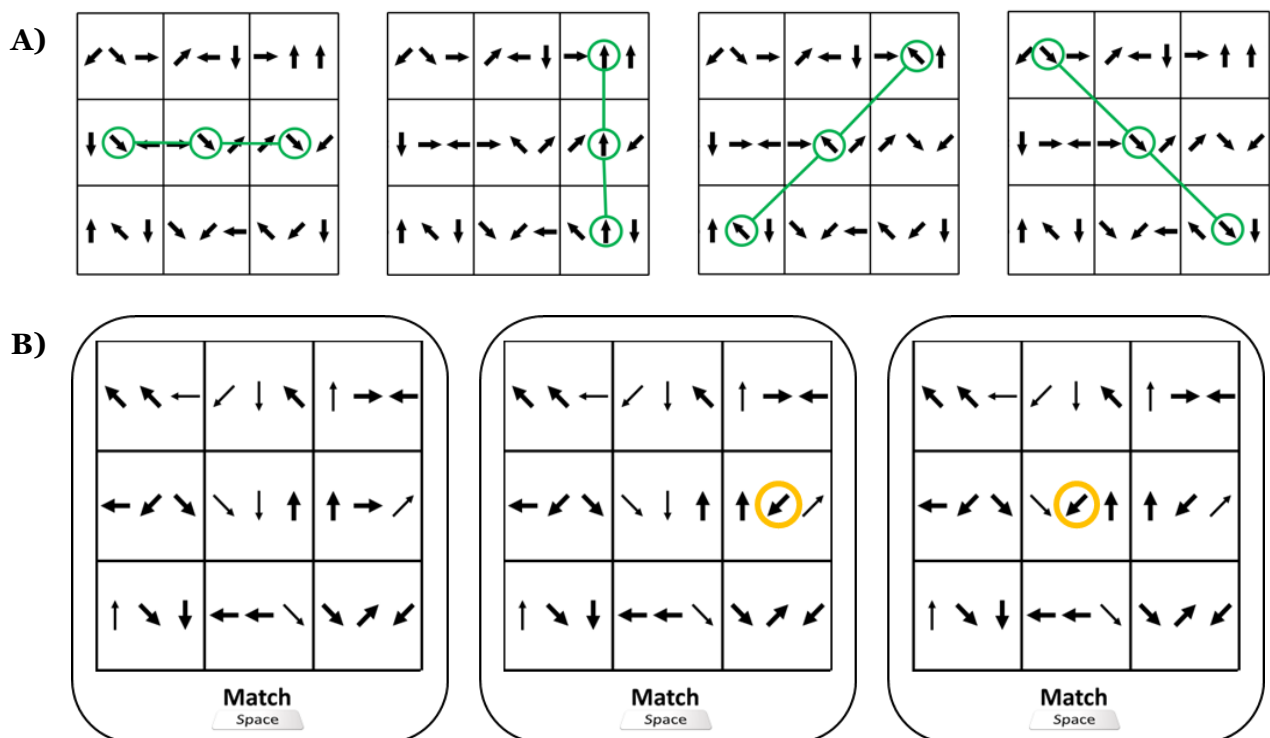
Note. The examples depicted differ from the actual trials in that the smallest set size was 3. The symbols, arrows, and fractals variants are shown along with target, lure, and distractor trial types.

3.2.2.3 Monitoring (Oberauer *et al.*, 2003; von Bastian & Oberauer, 2013)

Participants were presented with a 3 x 3 grid. In each cell of the grid, three stimuli were shown in one row (see Figure 3.4). One stimulus changed every 2000 ms. Participants were instructed to respond by pressing the space bar when the central stimuli in three connected cells (a row, column, or diagonal) were identical. The critical relation appeared every 3-9 stimulus changes. Participants completed 12 practice trials and 112 test trials. Stimuli were pseudorandom such that each stimulus was part of a match an equal number of times (± 2), and matches were equally distributed (± 1) across each row, column, and diagonal. The dependent variable was d' calculated the same as in the local recognition and associated pairs paradigms.

Figure 3.4

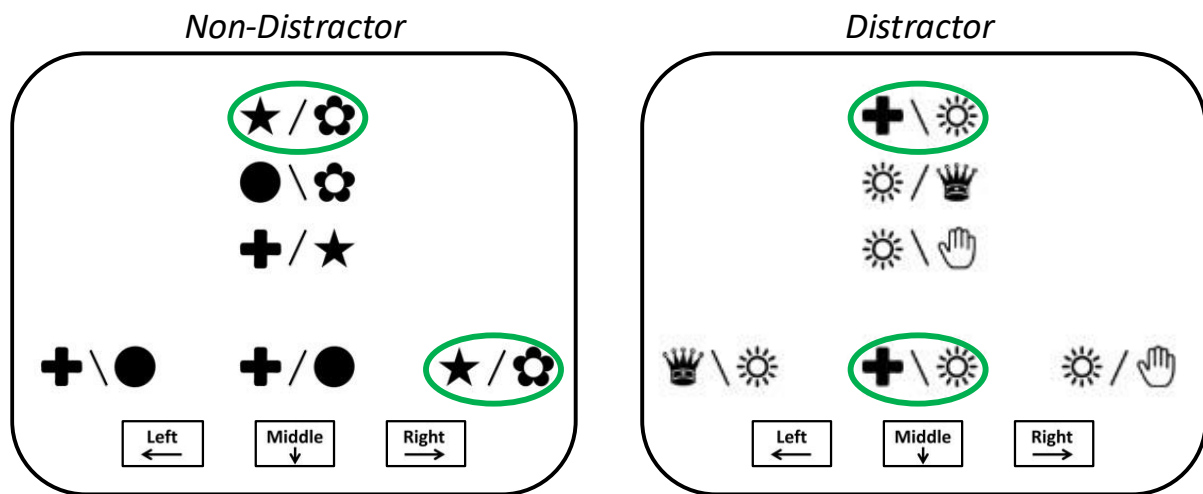
Example Trials of the Monitoring Paradigm



Note. The green and orange circles and lines were not shown to participants. Green indicates a match. Orange indicates a stimulus change. Panel A: A selection of match conditions. Horizontal and vertical matches could occur in any row or column, respectively. Panel B: An example of sequential trials. A match occurs in the example on the right across the middle row.

3.2.2.4 Relational Representation (Chuderski, 2019)

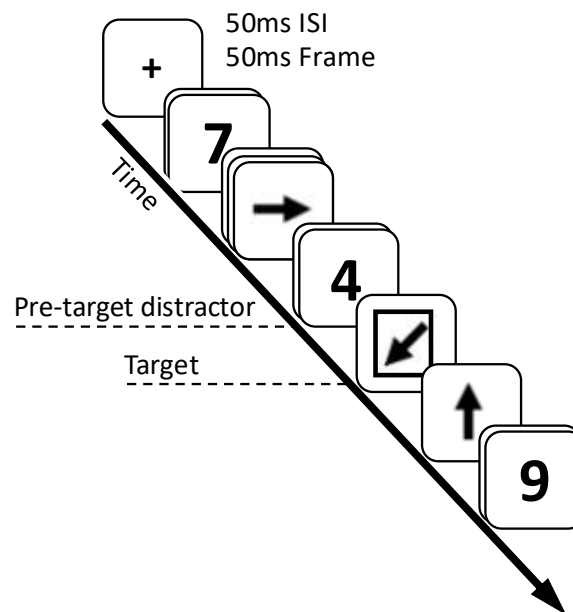
Participants were presented with three pairs of stimuli arranged vertically (see Figure 3.5). The stimuli within the pairs were separated by either a forward or a backward slash. Below these stimuli were three other pairs of stimuli arranged horizontally that were also separated by either a forward or backward slash. Participants were given the same instructions as in Chuderski (2019): “choose the one and only pair below that is the same as one pair above, meaning that both pairs include the same [arrows/symbols/images] in the same order and the slash is slanted in the same direction. If the [arrows/symbols/images] order or the slash direction differs, then the pairs differ as well”. Participants selected their responses by pressing the left, down, or right arrow key corresponding to the response option on the left, middle, or right, respectively. There were five practice trials and 100 test trials. Half of the test trials were distractor trials in which both incorrect options matched one stimulus element from the correct pair (excluding the slash). In non-distractor trials, the incorrect options did not match any stimuli from the correct option (excluding the slash). Stimuli were pseudorandom such that no stimulus was substantially more likely than any other to occur in any position and across the trials. Also, the correct response options occurred with equal frequency (+/- 1) and corresponded to the top, middle, or bottom stimulus pairs with equal frequency (+/- 1). The dependent variable was accuracy (proportion of correct responses).

Figure 3.5*Example Trials from the Relational Representation Paradigm*

Note. The green ovals show the matching pairs and were not shown to participants. The example on the left is a non-distractor trial, and the example on the right is a distractor trial.

3.2.2.4 RSVP (Zivony & Eimer, 2023)

Participants were presented with eight target and eight distractor stimuli over 10-14 frames per trial (see Figure 3.6). Each trial presented stimuli without repetition from the target category and distractor category. Symbols, fractals, and arrows were target categories and letters, multicolored grids, and digits were the respective distractor categories. The stimuli were presented for 50 ms each with 50-ms inter-stimulus intervals. One of the stimuli from the target category was surrounded by a box, designating it as the target. The target appeared in either the eighth, tenth, or twelfth frame and was followed by two frames. The target was always preceded by a stimulus from the distractor category and followed by a stimulus from the target category. After all stimuli of a trial were presented, participants were asked to select the stimulus they saw in the box from the eight target category stimuli. There were five practice trials and 50 test trials. The stimuli were presented in pseudorandom order such that each stimulus was the target stimulus with equal frequency (± 2). The dependent variable was accuracy (proportion of correct responses).

Figure 3.6*Trail Diagram of the Rapid Serial Visual Presentation Paradigm*

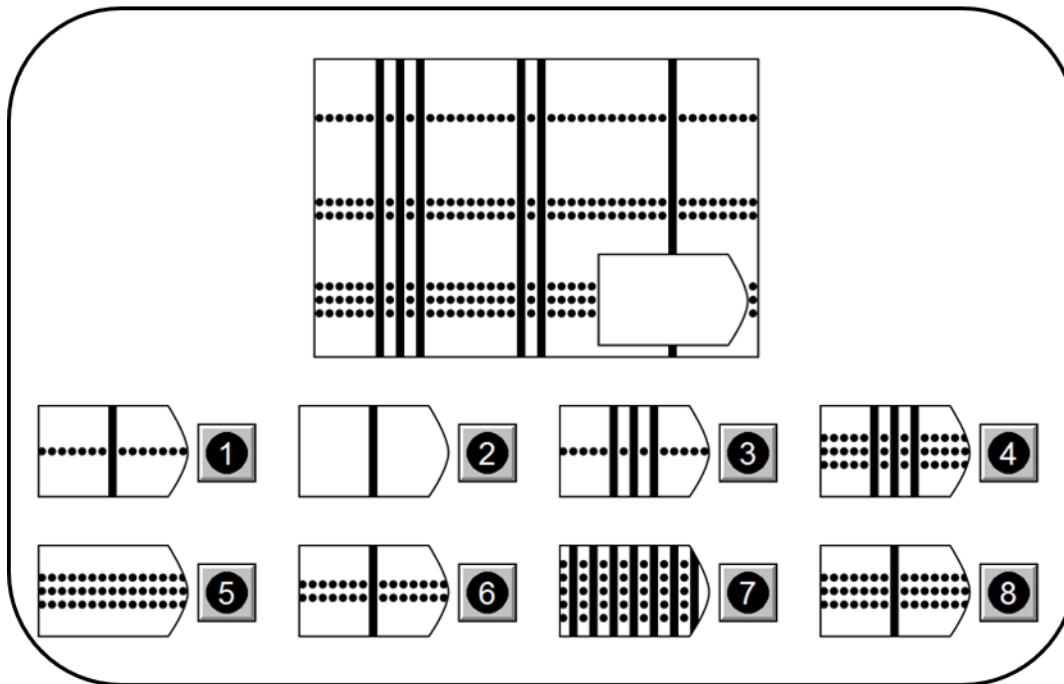
Note. ISI = inter-stimulus interval.

3.2.2.5 Fluid Intelligence

We used three different tasks which have all been successfully used in previous literature to measure Gf: the Raven's Advanced Progressive Matrices – Short Form (RAPM; Arthur & Day, 1994; also see Arthur et al., 1999), the paper folding task (Ekstrom et al., 1976), and the locations task (Ekstrom et al., 1976). In the RAPM, participants are presented with a 3 x 3 array with figures in each cell except for the bottom-right (see Figure 3.7). The participants' task is to recognize the pattern left-to-right and top-to-down in the array to determine which figure belongs in the missing cell and select it from eight options by selecting the corresponding number from 1 to 8 on a keyboard. Participants are given 15 min to solve up to 12 problems with progressive difficulty.

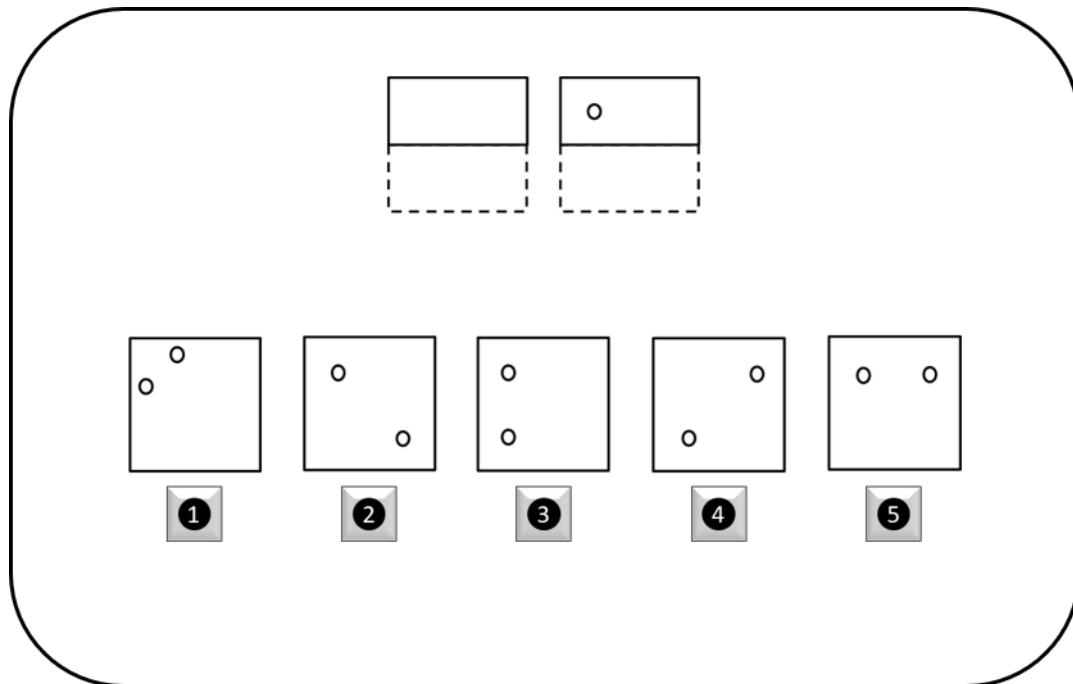
Figure 3.7

Raven's Advanced Progressive Matrices Example



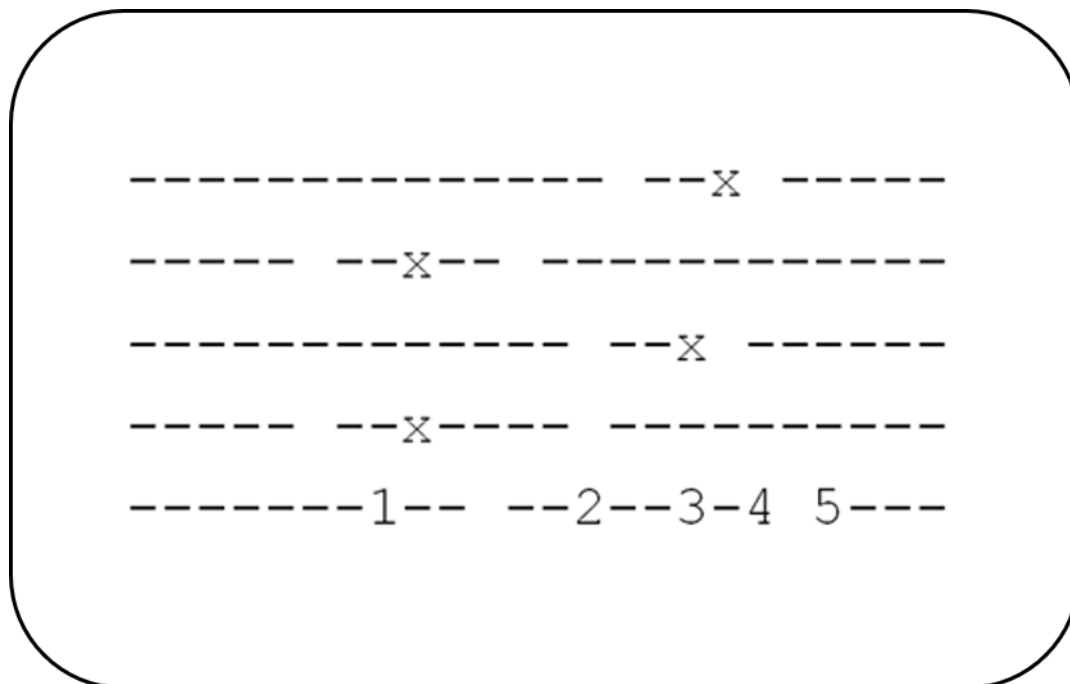
Note. The correct answer is 8, because the bottom row of figures consistently has three rows of dots while the right column consistently has 1 vertical line splitting the dots.

In the paper folding task, participants are presented with images of a piece of paper being folded 1-3 times then punctured with 1-2 holes (see Figure 3.8). The participants' task is to select 1 of 5 images that shows the hole(s) in the correct place on the paper if it were unfolded by selecting the corresponding number from 1 to 5 on a keyboard. The paper folding task is split into two blocks. In each block, participants are given 3 min to complete up to 10 problems with progressive difficulty.

Figure 3.8*Paper Folding Task Example*

Note. The correct answer is 3, because the paper was folded across the horizontal midline and then a whole was punched on the left side. When unfolded the paper would then have two holes in a vertical line on the left side.

In the locations task, participants are presented with five rows with a variable number of dashes separated into a variable number of groups in each row (see Figure 3.9). In the top four rows, one of the dashes is replaced with an “x” following a certain pattern, and the participants’ task is to recognize this pattern to decide where the “x” should be placed in the bottom row out of a possible five options by selecting the corresponding number from 1 to 5 on a keyboard. The locations task is split into two blocks. In each block, participants are given 6 min to complete up to 14 problems with progressive difficulty. The dependent variable for each of these tasks was the proportion of correct responses out of the total number of possible problems.

Figure 3.9*Locations Task Example*

Note. The correct answer is 2, because each row contains an *x* in place of the third dash from the left in the second group of dashes. Option 2 corresponds to the third dash from the left in the second group of dashes.

3.2.3 Analysis

Statistical analyses were performed with R (R Core Team, 2024) and RStudio (Posit team, 2024). Except for the Mahalanobis Distance cutoff, *p*-values below .05 were considered significant. Data cleaning deviated from the preregistration which stated that we would calculate guess rate to exclude participants and winsorize data². Instead, participants' response patterns for a task were examined if they scored below the lower quartile in that task. These participants with RTs < 300 ms in more than 25% of the trials of the local recognition, associated pairs, and relational representation tasks; with streaks of 20 or more repetitive responses in any task; with false alarm rate > 50% in any monitoring task; and with

²We elected to not remove or winsorize the data of participants who scored below guess rate because more than half of the participants would have been affected and, in hindsight, we could more accurately determine which participants should be excluded for disingenuous effort (the main concern) by examining the raw data.

RTs < 2000 ms in any of the Gf tasks were excluded³. Mahalanobis Distances were then calculated for each participant to identify multivariate outliers. Participants whose Mahalanobis Distance exceeded the critical value ($p < .001$) were excluded. The dependent variables for each task were then examined for normality in distribution based on skew and kurtosis indices and then z-transformed. If the absolute value of a skew index was above 3.0 or the absolute value of a kurtosis was greater than 10.0 (Kline, 2015), we used appropriate transformations to approach normal distributions.

3.2.3.1 Latent-Variable Modeling

Confirmatory factor analysis was performed, and model fits were estimated using the “lavaan” package (Rosseel, 2012) and the maximum likelihood approach and based on the confirmatory fit index (CFI), root mean squared error of approximation (RMSEA), and standardized root mean squared residual (SRMR). CFI values above .95, RMSEA values below .06, and SRMR values below .08 were considered good fit (Hu & Bentler, 1999). CFI values above .90 (Hu & Bentler, 1999), RMSEA values below .10, and SRMR values below .10 (Kline, 2015) were considered acceptable fit. Nested models were compared using the chi-square statistic (χ^2).

To determine the extent of the overlap between binding abilities, we used a stepwise model comparison approach beginning with the baseline structural equation model where indicators loaded onto their respective paradigm-specific latent factors. In each subsequent step, we identified the two latent factors with the strongest correlation and tested a nested model in which these factors merged into a single factor. We compared this simplified model to the baseline model or the comparison model. If merging the factors did not significantly worsen model fit, we retained the model as the comparison model. If the fit significantly worsened, we tested the pair of factors with the next highest correlation. This process continued until no further factors could be combined without significant loss of fit. We also

³The main findings do not differ if these participants are retained in the analysis.

explored a model in which each paradigm-specific latent factor loaded onto a higher-order latent factor.

For each comparison model, we further investigated the change in model fit from the most recent comparison model using Bayesian confirmatory factor analysis (BCFA). We used leave-one-out cross-validation estimates to compare the expected log predictive density (ELPD). If the difference in ELPD between two models is more than twice its standard error, the difference is interpreted as reliable. To run BCFA we used “blavaan” package utilizing the Stan sampler (Merkle et al., 2021) with three Markov-Chain Monte-Carlo chains, 500 warm-up iterations, and 1000 sampling iterations.

3.2.3.2 Latent-Network Modelling

Latent network analysis was performed on the best-fitting model. In a latent network model, network nodes represent latent variables, and edges represent the conditional dependent associations between pairs of connected nodes. All network models are estimated by modelling the variance-covariance matrix of the data in Gaussian graphical models (Epskamp et al., 2018). Models were estimated using the Maximum Likelihood approach using the “qgraph” (Epskamp et al., 2012) and “psychonetrics” (Epskamp, 2020) packages. A threshold of $r_{xy,z} > 0.10$ was applied to edges for visual clarity.

3.3 Results

Descriptive statistics and reliability coefficients of all tasks are presented in Table 3.1. The reliability of the local recognition, associated pairs, and monitoring tasks were estimated using a stratified split-half approach corrected with the Spearman-Brown prophecy formula in which trials were split into two halves balanced to ensure an equal distribution of trial types (matches and lures). The reliabilities of the other tasks were assessed with Cronbach’s α . Most tasks showed acceptable reliability, apart from the local recognition and associated pairs tasks. Given the non-linearity of d' , performance extremes, especially low scores, disproportionately influence split-half reliability estimates. Indeed, when accuracy was used as the dependent variable in the associated pairs and local recognition task, split-half reliability increased to 0.54 and 0.63 for the fractals and arrows local recognition tasks,

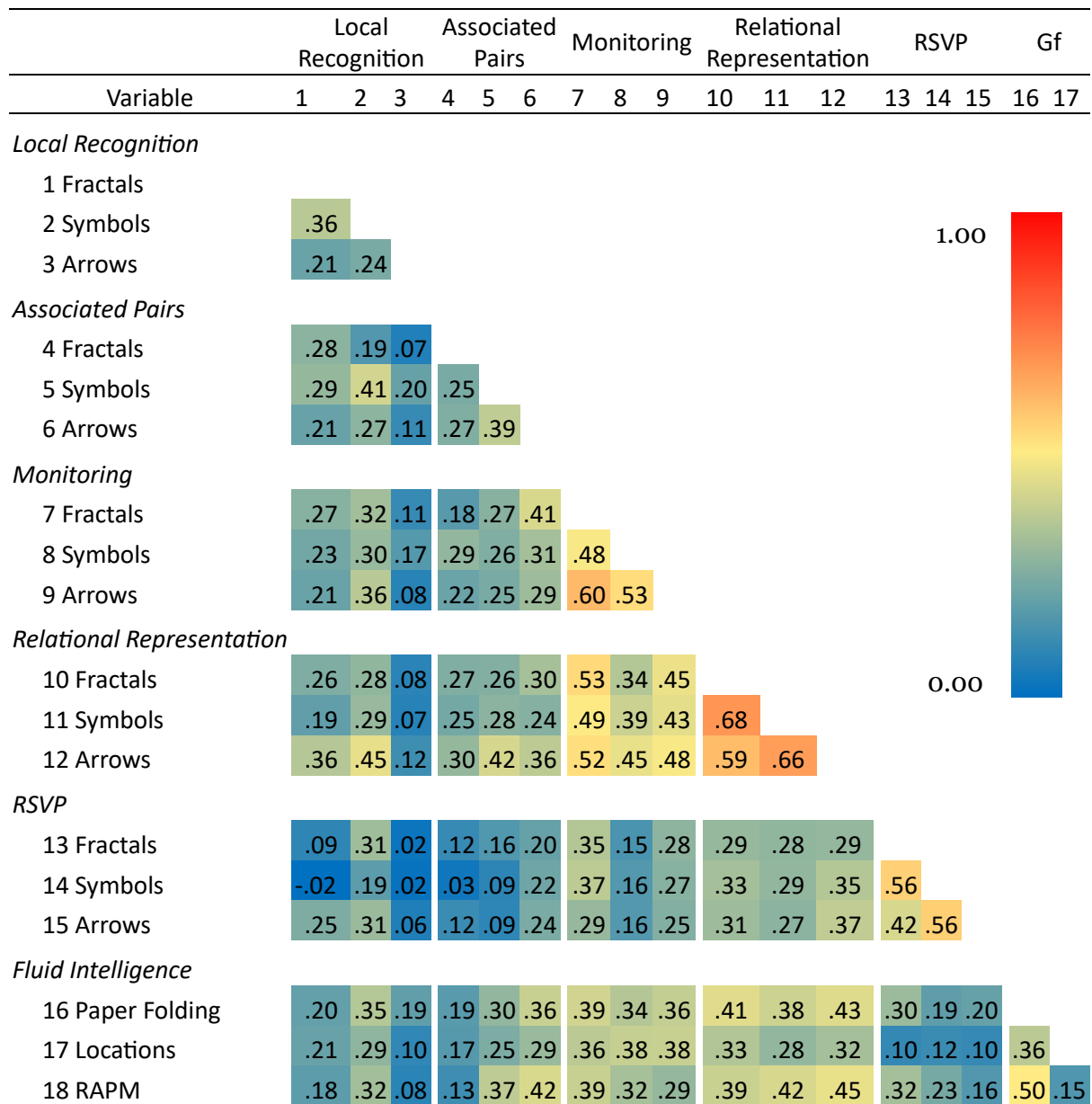
respectively. Split-half reliability also increased to 0.54 for the symbols and arrows associated pairs tasks. Reliability remained especially low for the fractals associated pairs task ($r = 0.24$), suggesting measurement instability. The kurtosis and skewness of all tasks were acceptable. Prior to analysis, all dependent variables were centered and z-transformed, after which all variables were normally distributed. Zero-order task correlations of the final data are color-scaled in Figure 3.10 for visual clarity.

Table 3.1

Descriptive Statistics of Raw Scores after Outlier Removal

Task	<i>M (SD)</i>	Min	Max	Kurtosis	Skew	Reliability
<i>Local Recognition</i>						
Fractals	0.82 (0.49)	-0.20	2.47	3.41	0.58	0.50
Symbols	1.06 (0.56)	-0.31	3.37	4.42	0.76	0.64
Arrows	0.91 (0.46)	-0.76	2.05	4.20	-0.61	0.43
<i>Associated Pairs</i>						
Fractals	0.42 (0.41)	-1.03	1.70	3.42	0.10	0.25
Symbols	0.99 (0.58)	-0.39	2.94	3.09	0.21	0.51
Arrows	0.52 (0.44)	-0.47	1.75	3.03	0.23	0.47
<i>Monitoring</i>						
Fractals	3.28 (0.75)	1.09	4.47	2.47	-0.42	0.67
Symbols	2.90 (0.86)	0.40	4.47	2.83	-0.37	0.67
Arrows	2.87 (0.79)	0.75	4.47	2.47	-0.21	0.69
<i>Relational Representation</i>						
Fractals	0.91 (0.06)	0.66	1.00	4.47	-1.12	0.81
Symbols	0.92 (0.06)	0.65	0.99	6.16	-1.69	0.84
Arrows	0.81 (0.10)	0.47	0.99	3.21	-0.59	0.87
<i>RSVP</i>						
Fractals	0.51 (0.23)	0.00	0.94	2.33	-0.31	0.93
Symbols	0.76 (0.17)	0.04	0.98	6.56	-1.56	0.89
Arrows	0.43 (0.20)	0.06	0.92	2.20	0.21	0.91
<i>Fluid Intelligence</i>						
Paper Folding	0.68 (0.18)	0.20	1.00	2.34	-0.21	0.77
Locations	0.52 (0.17)	0.14	0.86	2.16	0.08	0.77
RAPM	0.53 (0.22)	0.00	1.00	2.64	-0.18	0.71

Note. The local recognition, associated pairs, and monitoring tasks dependent measures were d' and reliability coefficients were split-half reliabilities corrected with the Spearman-Brown Prophecy formula. For all other tasks, the dependent measures were the proportion correct and the reliability coefficients were Cronbach's α . RSVP = rapid serial visual presentation; RAPM = Raven's Advanced Progressive Matrices – Short Form.

Figure 3.10*Color-Scaled Correlation Matrix*

Note. RSVP = rapid serial visual presentation; Gf = fluid intelligence; RAPM = Raven's Advanced Progressive Matrices – Short Form.

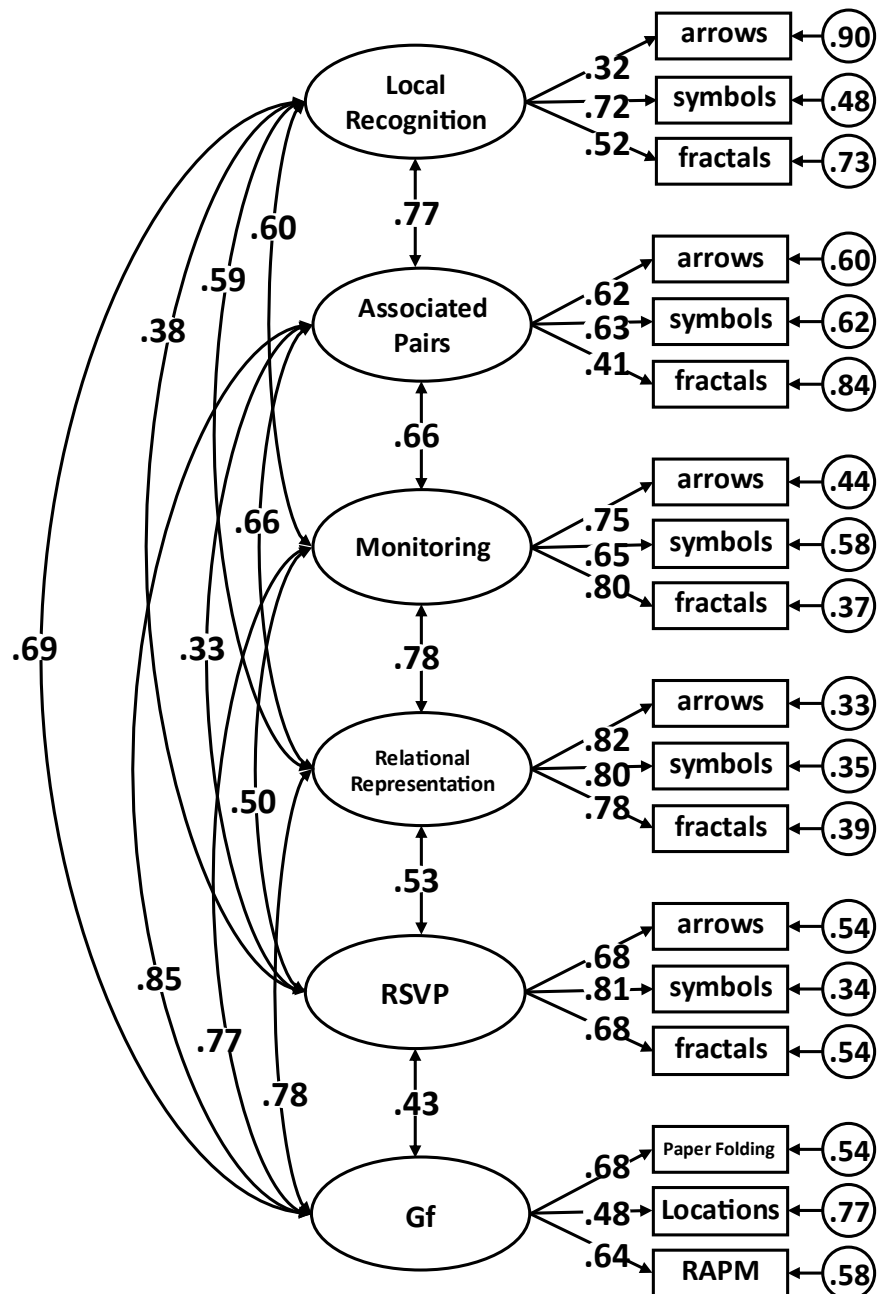
3.3.1 Structural Equation Modelling

We began with a model in which each latent variable was indicated by the arrows, fractals, and symbols variants of each paradigm for the binding abilities, or paper folding, locations, and RAPM for Gf, respectively (see Figure 3.11). This model had good fit $\chi^2(120) = 1684.91$, CFI = 0.96, RMSEA = 0.05 [90% CI: 0.03, 0.06], SRMR = 0.05. All correlations were significant and in the expected direction. Next, we systematically compared models in

which we combined the latent binding factors. Table 3.2 shows the fits for each of these models.

Figure 3.11

Baseline Structural Equation Model



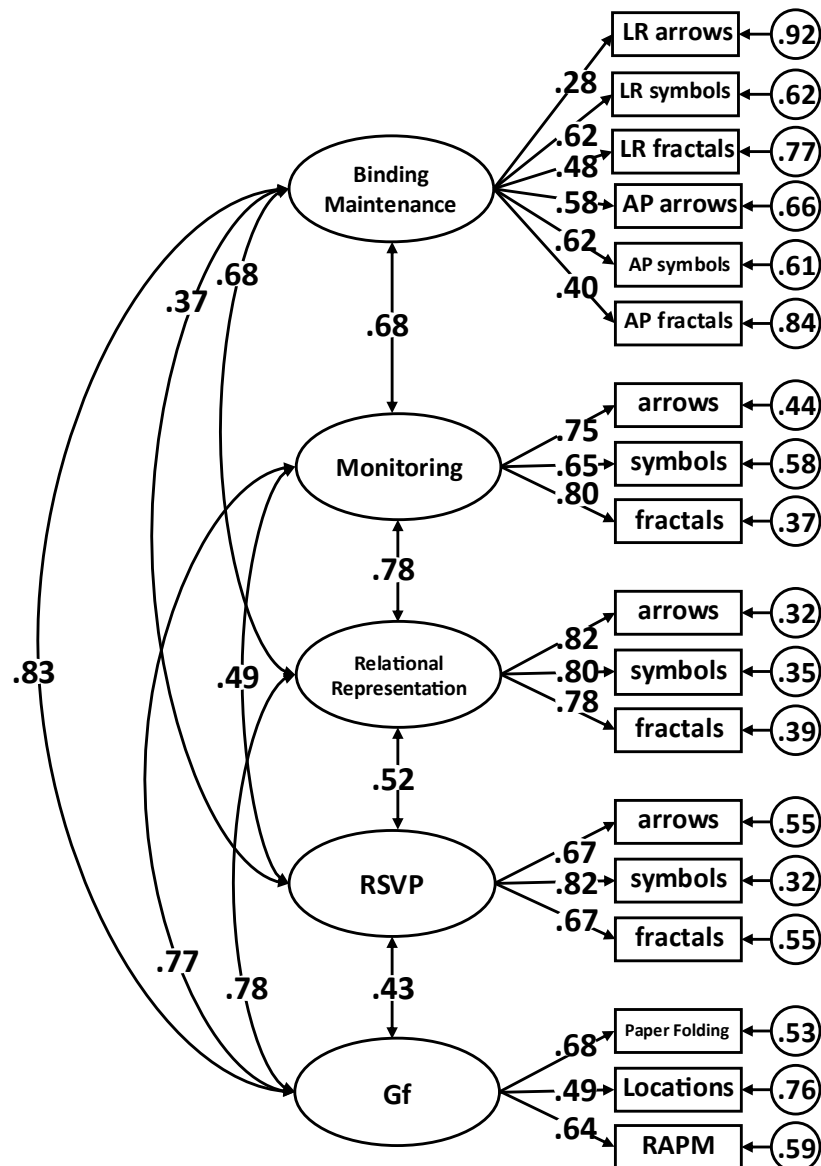
Note. All depicted relationships are significant ($p < .05$). RSVP = rapid serial visual presentation; Gf = fluid intelligence; RAPM = Raven's Advanced Progressive Matrices – Short Form.

Table 3.2*Confirmatory Factor Analysis Model Fits*

Model	χ^2 (df)	CFI	RMSEA	SRMR	AIC	BIC	$\Delta \chi^2$ <i>p</i> -value
*Baseline	164.91 (120)	.96	.05 [.03, .06]	.05	7982.70	8143.81	-
RR + M	200.28 (125)	.92	.06 [.04, .07]	.06	8008.07	8153.38	< .001
*LR + AP (BM)	172.06 (125)	.95	.05 [.03, .06]	.06	7979.85	8125.17	.199
BM + RR	217.28 (129)	.91	.06 [.05, .08]	.06	8017.07	8149.75	< .001
BM + M	209.70 (129)	.92	.06 [.04, .07]	.06	8009.49	8142.17	< .001
RR + RSVP	256.29 (129)	.87	.08 [.06, .09]	.07	8056.08	8188.76	< .001
M + RSVP	256.84 (129)	.87	.08 [.06, .09]	.07	8056.63	8189.31	< .001
BM + RSVP	264.90 (129)	.86	.08 [.06, .09]	.07	8064.69	8197.37	< .001

Note. Each model following the comparison models are nested by combining latent factors indicated by the name of the model (e.g., “RR + M” is “Baseline” with the relational representation and monitoring factors combined). Values in brackets represent the 90% confidence interval. The *p*-value represents the significance of $\Delta \chi^2$ between the model and the comparison model. RR = relational representation; M = monitoring; LR = local recognition; AP = associated pairs; BM = binding maintenance; RSVP = rapid serial visual presentation. *Comparison model.

The only model which increased parsimony without significantly sacrificing fit combined local recognition and associated pairs (see Figure 3.12). We labeled the combined latent factor *binding maintenance*, because these are the only two binding paradigms that substantially involved WM maintenance. BCFA revealed that the binding maintenance had better predictive accuracy over the baseline model, $\Delta \text{ELPD} = -21.34$, $SE = 4.26$.

Figure 3.12*Baseline Model with Binding Maintenance*

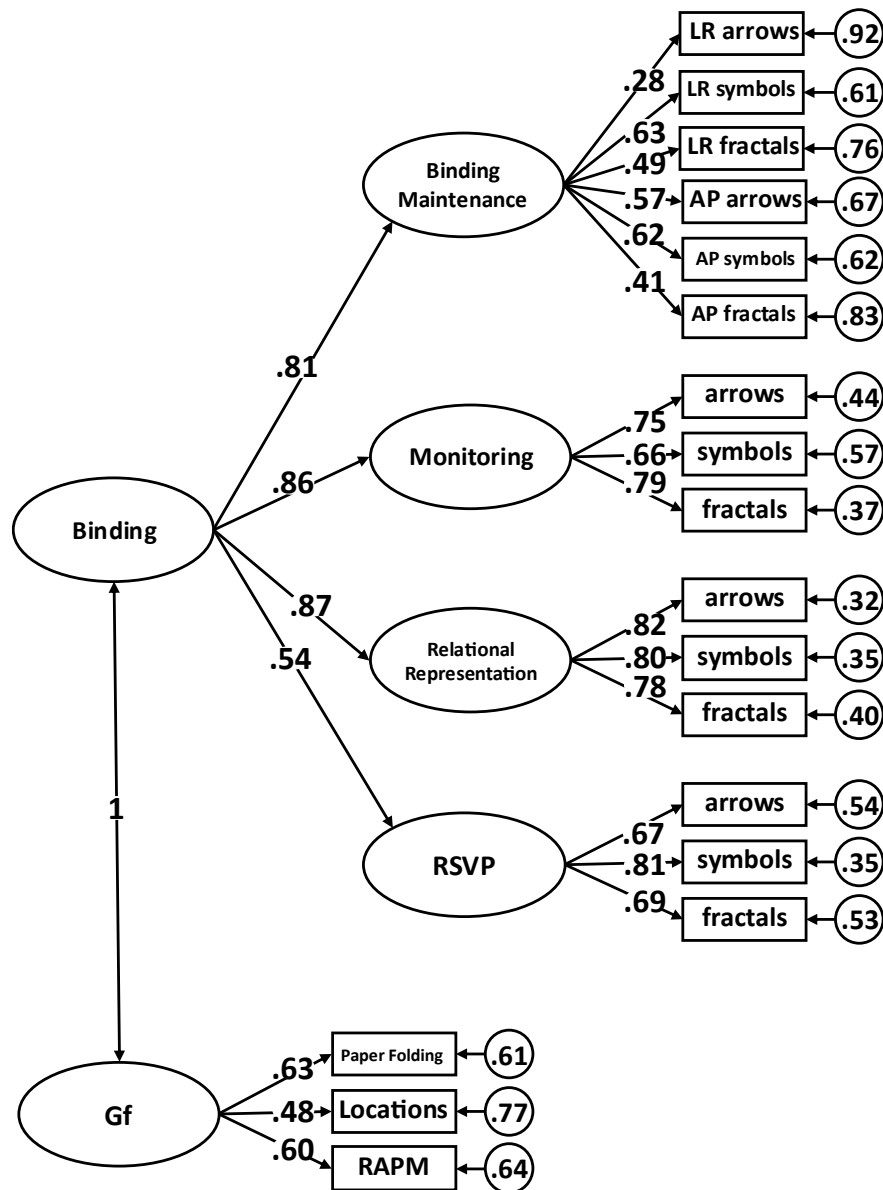
Note. All depicted relationships are significant ($p < .05$). LR = local recognition; AP = associated pairs; RSVP = rapid serial visual presentation; Gf = fluid intelligence; RAPM = Raven's Advanced Progressive Matrices – Short Form.

Due to the high correlations between binding abilities, we loaded these factors onto a second-order latent factor which we labeled *Binding*. This model increased parsimony without significantly worsening model fit, $\Delta\chi^2(5) = 6.06$, $p = .30$, and had good model fit $\chi^2(130) = 182.35$, CFI = 0.95, RMSEA = 0.05 [90% CI: 0.03, 0.06], SRMR = 0.06. The difference in predictive accuracy between these models was shown with BCFA to not be significant, $\Delta\text{ELPD} = -3.42$, $SE = 3.08$. The loadings onto Binding were high with relational

PROCESSING AND MAINTAINING RELATIONS

representation $\lambda = .88$, monitoring $\lambda = .87$, binding maintenance $\lambda = .80$, and RSVP $\lambda = .55$. To determine whether any of the Binding first-order factors underpinned the shared variance between binding abilities, we ran four additional models. In each model, the loading of a single binding ability onto the Binding factor was individually fixed to 1. However, each of these models had significantly worse fit, so they were not retained.

The correlation between Binding and Gf was high ($r = .90$), so we fixed their correlation to 1 (see Figure 3.13). This modification increased parsimony without significantly worsening model fit, $\Delta \chi^2(1) = 1.80$, $p = .18$. The resulting model fit the data well, $\chi^2(131) = 181.35$, CFI = 0.95, RMSEA = 0.05 [90% CI: 0.03, 0.06], SRMR = 0.06, and was retained. BCFA indicated that the models were statistically indistinguishable in terms of predictive accuracy, $\Delta \text{ELPD} = -0.21$, $SE = 2.50$, indicating that Binding was indistinguishable from Gf.

Figure 3.13*Confirmatory Factor Analysis with Binding Fixed to Fluid Intelligence*

Note. Solid lines represent significant loadings ($p < .05$). Dashed lines represent non-significant loadings. LR = local recognition; AP = associated pairs; RSVP = rapid serial visual presentation; Gf = fluid intelligence; RAPM = Raven's Advanced Progressive Matrices – Short Form.

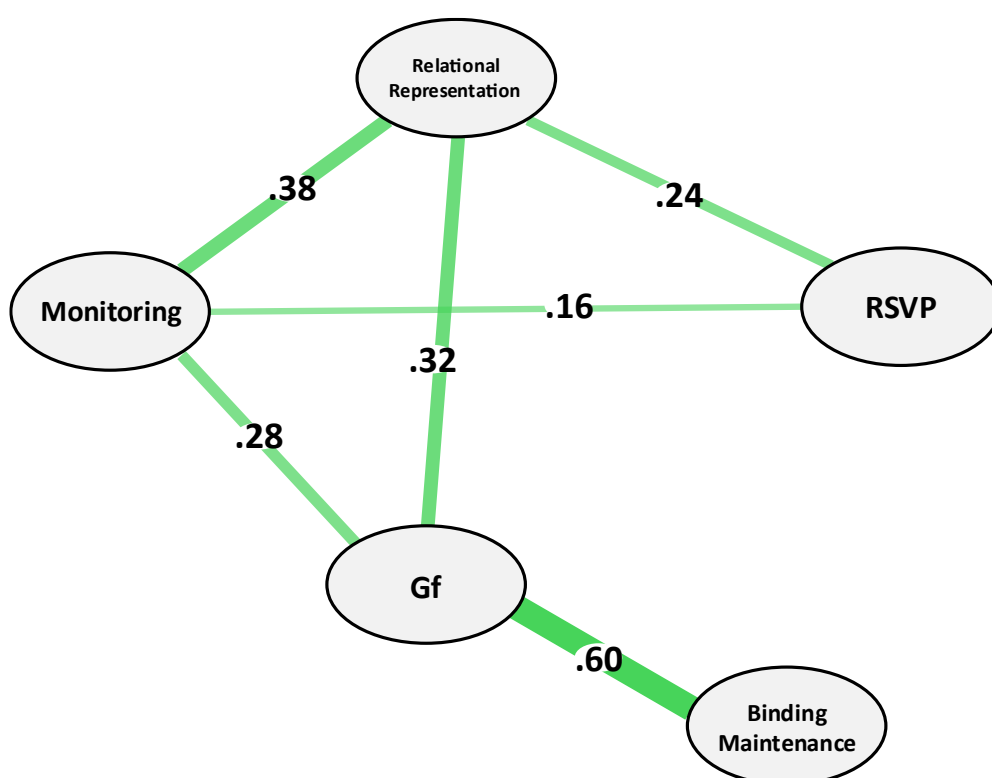
3.3.2 Psychometric Network Analysis

To examine the conditional dependencies of each binding ability with Gf, we specified a latent network model of the best-fitting model without second-order latent variables which is the binding maintenance model (Figure 3.14). The latent network model revealed conditional dependencies between Gf and binding maintenance, relational representation,

and monitoring but not between Gf and RSVP. The partial correlation between binding maintenance and Gf was approximately double the magnitude of the partial correlations linking Gf to relational representation and monitoring. Moreover, binding maintenance did not substantially directly relate to any of the other binding abilities – indicating that the correlation between binding maintenance and the other binding abilities were accountable by a shared variable.

Figure 3.14

Latent Network Model of the Best-Fitting Model



Note. For visual clarity the model does not show partial correlations $< .10$. Gf = fluid intelligence; RSVP = rapid serial visual presentation.

3.4 Discussion

This study investigated variance shared between binding abilities (item-to-location binding, item-to-item binding, relational integration, relational representation, and temporal binding) and how they relate to Gf. Only item-to-location binding and item-to-item binding were found to be represented by one latent variable which we called binding maintenance, suggesting that the distinction between these abilities is minimal and questioning whether they represent distinct abilities. Moreover, binding maintenance and the other binding

abilities shared significant variance, indicating the presence of a process-general ability which we labeled Binding. Statistically, Binding was isomorphic with Gf, suggesting that it is crucial to Gf or vice versa. Complementing this, network analysis revealed that binding maintenance, relational representation, and relational integration each had direct, unique associations with Gf, indicating that each of the binding abilities apart from temporal binding were uniquely predictive of Gf.

3.4.1 The Diversity of Binding

3.4.1.1 Binding Maintenance

Binding maintenance is interpreted here as the ability to store, maintain, and recognize bindings in WM, because local recognition and associated pairs tasks are both heavily dependent on these processes. This interpretation is supported by the network analysis in which binding maintenance had the strongest unique relationship with Gf compared to any of the other binding abilities. This unique relationship with Gf likely parallels the well-established strong relationship between WM and Gf (e.g., Kyllonen & Christal, 1990); because maintenance is a fundamental mechanism of WM, a factor representing the maintenance of bindings would likely overlap with Gf. Binding maintenance also did not have unique relationships with any of the other binding abilities, indicating that their relationships were mediated by Gf. Importantly, this does not imply that the other binding abilities (such as relational integration and representation) are not WM mechanisms. Rather, as indicated by the isomorphism between Binding and Gf, the amount of shared variance between binding abilities and Gf is so substantial that Gf was capable of mediating the relationship between different WM mechanisms.

Although item-to-item and item-to-location binding differ in the semantic richness of binding contexts, and semantic richness is evidenced to facilitate retrieval from long-term memory (Brady et al., 2013; Konkle et al., 2010), they were still best represented by binding maintenance. This finding can be explained by variance in performance that is attributed to semantic richness being minimal compared to the shared variance due to binding maintenance. Indeed, the stimuli sets of each task varied in semantic richness. Although the

use of two stimuli per memoranda may double the semantic richness compared to one stimulus per memoranda, semantic richness is likely often not additive. For example, fractals are colorful meaningless stimuli from which meaning may be interpreted from figures in the colors, but providing two fractals would not necessarily provide twice the amount of meaning. Hence, there may not be much additional influence from long-term memory in item-to-item binding compared to item-to-location binding if the items are not semantically rich.

3.4.1.2 Relational Representation, Integration, and Perception

Relational representation and relational integration abilities exhibited remarkably strong relationships with Gf, other binding abilities, and the process-general Binding factor. Supporting the findings from Chuderski (2019), relational representation was identifiable as a latent factor across tasks using diverse visual and spatial stimuli and was highly correlated with Gf. Thus, Chuderski's (2019) conclusion that single trivial bindings are critical for Gf is supported by the current study which further shows that the process-general Binding ability (discussed below) is especially critical. Moreover, relational representation directly related to Gf in the network analysis, indicating that their relationship is not entirely underlined by other binding abilities (although their direct relationship was smaller [from $r = .78$ to $r_{xy.z} = .32$]).

Relational representation was also directly related to relational integration which was also directly related to Gf. The direct relationship between relational representation and relational integration may indicate that either relational representation is required for relational integration or relational representation is a simple form of relational integration. It may be that integrating bindings into structural representations requires the ability to represent and compare bindings before they can be integrated. However, this possibility would mean that the direct relationship that Gf shared with relational representation and relational integration was not due to relational representation or relational integration, respectively, nor could it be due to relational integration, temporal binding, or binding maintenance. Instead, the direct relationship between relational representation and Gf would

necessarily be a confounding ability, such as attention control. Another possible explanation for the direct relationship between relational representation and relational integration is that both abilities tap some third ability, such as attention control. In this scenario, the direct relationships relational representation and relational integration have with Gf would likely be due to the abilities that they were designed to operationalize. Regardless, the high zero-order correlation between both relational representation and relational integration and Gf are likely indicative of some shared variance of relational representation and relational integration, respectively.

Finally, temporal binding ability was included to determine whether temporal binding was distinct from other binding measures and related to Gf. The results show that temporal binding does share significant variance with other binding abilities, suggesting that it relies on some of the same mechanisms as these abilities. However, temporal binding loaded less onto Binding relative to the other binding abilities, and in the network analysis, it did not directly relate to Gf but indirectly via relational representation and monitoring. Temporal binding, therefore, *mostly* depends on mechanism unrelated to other binding abilities which is indicative of the distinction between perceptual and WM abilities.

3.4.2 Binding and Fluid Intelligence

Although Binding was isomorphic with Gf, some speculation is required in determining what ability Binding represents. Definitively, Binding is the shared variance between binding maintenance, monitoring, relational representation, and RSVP tasks. Each of these tasks involves bindings between content and context in some form but vary in how these bindings are utilized. In the local recognition and associated pairs tasks, bindings must be maintained and recognized. In the monitoring task, bindings must be integrated and updated to identify a specific pattern. In the relational representation task, bindings must be compared to select identical bindings, and in the RSVP task, bindings must be formed quickly to bind the correct item with the cue. The most apparent common thread across these tasks is the ability to form and make use of bindings in a goal-directed manner, so this is likely what Binding represents.

The overlap between Binding and Gf suggests interdependence between the abilities, partially supporting conceptualizations/theories of Gf or complex reasoning in which Gf depends on bindings, such as the binding hypothesis (Oberauer, 2009), the relational representation account (Chuderski, 2022), and Relational Complexity Theory (Andrews et al., 2003; Andrews & Halford, 1998). Importantly however, binding maintenance, relational representation, and relational integration each correlated with Gf independently of each other – indicating that none of these specific binding abilities could completely account for individual differences in Gf. Rather, the more process-general Binding was isomorphic with Gf. Therefore, versions of the binding hypothesis that state that binding interference (Oberauer, 2009) or binding maintenance (Garvey et al., 2026) underlie individual differences in Gf are not supported. The current findings expand upon the relational representation account by suggesting that it is not the ability to *represent* relations that underlies Gf but the ability to *use* bindings in pursuit of a goal that predicts Gf over and above relational representation. Relational Complexity Theory is also partially supported in that the use of bindings but not the complexity of these bindings were found to be crucial to Gf. The complexity of bindings were not varied in any task, yet Binding and Gf were statistically indistinguishable.

3.4.3 Strengths, Limitations, and Future Directions

The use of the monitoring task to operationalize relational integration may be considered a limitation because its face validity is debatable; it may require attention control and sustained attention to some extent. However, its high correlation with established binding abilities strongly supports its construct validity. To definitively establish its operational validity, future research should evaluate the monitoring paradigm alongside established relational integration tasks, such as those from von Bastian and Oberauer (2013; see also, Oberauer, 1993, and von Bastian et al., 2013).

One strength of this study was the use of the same sets of visual/spatial stimuli for each binding paradigm. Using the same stimuli sets allowed us to focus the shared variance on paradigm-specific mechanisms (the binding abilities) and pre-emptively remove error

variance due to stimulus-specific variance that might have otherwise varied between paradigms. Furthermore, each stimulus set was chosen to differ meaningfully from each other to mitigate the influence of specific task strategies (e.g., verbal labelling). The fractals were meaningless, colorful, and visually complex. The arrows were more meaningful, black-and-white, and less complex than the fractals but were identical to each other apart from orientation and thickness. The symbols were the most meaningful, black-and-white, and less visually similar than the arrows. These considerations likely contributed to the strong correlations, high factor loadings, and good model fits observed in the structural equation models.

However, using the same sets of stimuli for each paradigm and using only visual/spatial Gf tasks can also be a limitation. It is possible that shared method variance artificially inflated factor loadings and the correlations between the latent factors. Additionally, because we only used visual/spatial tasks, we cannot definitively conclude that the present results extend to verbal/numerical domains. While some research suggests that WMC is largely domain-general (e.g., Vergauwe et al., 2022), future research should use a broader array of stimulus domains to investigate the domain-general nature of the Binding-Gf isomorphism.

Future research should also investigate a wider array of binding abilities, such as feature binding (the perceptual integration of object properties like color and shape) and action binding (the linking of a stimulus to a specific motor response). Because feature binding is a highly perceptual ability, it may have substantial overlap with temporal binding. Conversely, action binding may share mechanisms with the monitoring task, as successful monitoring requires participants to identify a complex constellation of information and actively bind it to a specific response. Investigating individual differences in feature binding and action binding alongside other binding abilities could further clarify the specific mechanisms driving fluid cognition.

Future research should also include a more diverse sample. Indeed, our results may not be fully generalizable due to the use of a relatively homogenous sample of mostly young

university students. The convenience sample of university students is a long-standing trend in psychological research that may be severely limiting generalizability. University students may have more strategy-use and familiarity with cognitive tasks compared to the broader population, possibly resulting in inflated correlations in cognitive task performance among this sample. Future research must use more diverse samples from countries that are not Western, educated, industrialized, rich and democratic (“WEIRD”; Henrich et al., 2010) in order to develop an understanding of cognitive functioning that is representative of humanity and does not perpetuate harmful colonialist mindsets.

Finally, based on the isomorphic relationship between Binding and Gf observed in this study, future research should carefully consider their definitions and measurements of Gf. The current findings suggest that Gf can be effectively captured using basic relational tasks that require little to no complex problem-solving, which aligns with previous work by Chuderski (2019, 2022) and Bateman and Birney (2019). While traditional Gf paradigms (e.g., RAPM) are rigorously validated and highly effective measures of Gf, they may partially obscure the underlying mechanisms of Gf. By contrast, simpler binding tasks may isolate the underlying mechanisms of Gf more precisely. If simpler tasks do not subjectively appear to capture reasoning ability, it raises an important question for the field to consider: must the measurement and definition of Gf require reasoning ability, or should it be measured and defined by its underlying mechanisms? Whether or not binding abilities represent these mechanisms is not certain, but the current and past findings (Bateman & Birney, 2019; Chuderski, 2022; Jastrzębski et al., 2020) suggest this possibility.

3.5 Conclusion

This study investigated the shared and unique variance between item-to-location binding, item-to-item binding, relational integration, relational representation, and temporal binding and how they relate to Gf. We found significant overlap between binding abilities, but only item-to-item and item-to-location binding were best modelled as one ability, binding maintenance, which appears to represent the storage, maintenance, and retrieval of bindings. Moreover, the shared variance between binding maintenance and the other binding

PROCESSING AND MAINTAINING RELATIONS

abilities was well-represented by a process-general ability which seems to represent the ability to form and use bindings in a goal-directed manner. This shared variance was statistically indistinguishable from Gf while each individual binding ability (apart from temporal binding) uniquely related to Gf in a latent network analysis. Taken together, these results indicate that, more so than any specific binding ability, the general ability to form and use bindings towards an objective is crucial to Gf or vice versa.

CHAPTER 4

Dedifferentiation and Bottlenecks of Processing Speed Components: An Age-Weighted Latent Network Analysis

W. Fred Garvey¹	Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Software, Visualization, Writing – Original Draft & Editing
Alice Reinhartz²	Investigation, Methodology, Project Administration
Eleanor Hyde¹	Data Curation, Investigation, Project Administration
Shuangke Jiang³	Investigation, Project Administration
Tilo Strobach²	Conceptualization, Funding Acquisition, Methodology, Project Administration
Sylvie Belleville^{4, 5}	Conceptualization, Funding Acquisition, Methodology, Project Administration
Alicia Forsberg¹	Conceptualization, Methodology, Supervision, Writing - Review & Editing
Claudia C. von Bastian¹	Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Methodology, Project Administration, Software, Supervision, Writing - Review & Editing

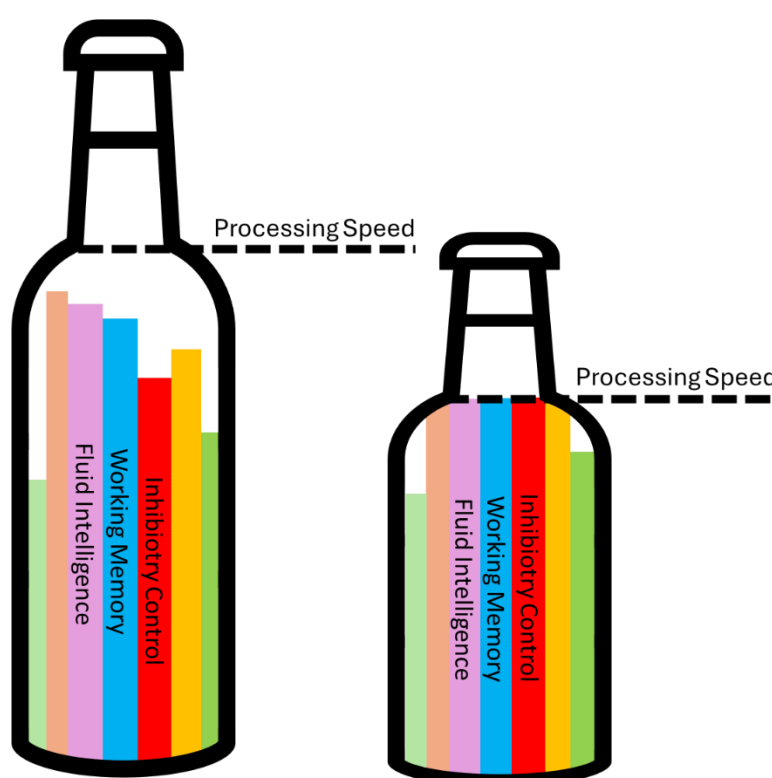
¹University of Sheffield, ²Medical School Hamburg, ³University of Zurich, ⁴Centre de Recherche de L'Institut Universitaire de Gériatrie de Montréal, ⁵Université de Montréal

4.1 Introduction

Understanding the mechanisms underlying cognitive ageing is vital for supporting the ageing global population (Bloom et al., 2015). It is well established from meta-analyses of both cross-sectional (Verhaeghen & Salthouse, 1997) and longitudinal (Tucker-Drob et al., 2019) research that fluid cognitive abilities are negatively correlated with age independent of pathology (e.g., Salthouse, 2004, 2009). Distinct cognitive abilities are sometimes shown to increasingly correlate in older age and become indistinguishable, a phenomenon called dedifferentiation (La Fleur et al., 2018). Cognitive decline and dedifferentiation may both be the result of a bottleneck, in which the decline in one ability constrains other abilities resulting in decreased performance and increased correlation (see Figure 4.1). If identified, this bottleneck could be a target for cognitive training and influential to models of WM.

Figure 4.1

Processing Speed as a Bottleneck of Cognitive Abilities



Note. Fluid intelligence, working memory, and attention control are examples of cognitive abilities that cannot surpass a threshold determined by the processing speed bottleneck. If

the threshold is high (left), cognitive abilities are less related. If the threshold is low (right) cognitive abilities are more related due to a shared limitation (i.e., processing speed).

Processing speed has been proposed to be a functional bottleneck driving cognitive decline (Salthouse, 1996). Indeed, processing speed has been found to mediate the relationships between age and cognitive abilities, including Gf (Hertzog, 1989; Lindenberger et al., 1993), WMC (Salthouse & Babcock, 1991), episodic memory (Hultsch et al., 1990), and visuospatial processing (Salthouse, 1994). Processing speed has also been shown to share significant variance with attention control, likely because traditional attention control tasks (e.g., the Stroop paradigm) are highly reliant on response times (Salthouse & Mein, 1995a). If processing speed is primarily responsible for cognitive decline because it is a bottleneck, it logically follows that it would also drive cognitive dedifferentiation; as the bottleneck tightens across adulthood, diverse fluid abilities would be uniformly constrained by this single mechanism, forcing them to become highly correlated. However, a recent meta-analysis has revealed that a higher-order factor can account for an equivalent amount of variance in cognitive ageing among numerous cognitive abilities, including processing speed, suggesting that processing speed is equally affected by cognitive ageing rather than being a bottleneck driving decline and dedifferentiation (Tucker-Drob et al., 2019).

The effects of processing speed in cognitive decline and dedifferentiation thus remain unclear: is it a bottleneck, or does it co-decline alongside other abilities as part of a global ageing factor? Resolving this ambiguity requires further investigation of the underlying components of processing speed. Traditional measures of processing speed (typically reaction time in elementary cognitive tasks) are often confounded by individual differences in variables such as motor response execution, the speed of information accumulation, and the speed-accuracy tradeoff. Although past research has differentiated between these processing speed components by measuring the shared variance between different sets of tasks (e.g., Salthouse, 1993, 1994), this approach is problematic. Even with latent-variable analysis, systematic measurement errors, such as the motor demands inherent in most timed tasks, can reduce measurement purity.

The drift-diffusion model addresses these challenges. This computational model incorporates response time and accuracy distributions to estimate processing speed components (Ratcliff, 1978). The model estimates drift rate (the rate of evidence accumulation), boundary separation (the amount of evidence necessary before a decision is made, reflecting the speed-accuracy tradeoff), and non-decision time (a composite measure of the speed of stimulus encoding and motor response) among other parameters (Ratcliff, 1978; for an introduction to diffusion modelling, see Voss et al., 2013). A recent meta-analysis has shown that boundary separation and non-decision time are higher in older age groups, indicating that older adults favor accuracy over speed and have slower stimulus encoding and/or motor response (Theisen et al., 2021b). Age-related changes in drift rate are task-specific, decreasing in perceptual tasks and memory tasks but increasing in lexical decision tasks in older age (Dully et al., 2018; Theisen et al., 2021b). Of these parameters, only non-decision time has been found to consistently mediate the relationship between age and cognitive abilities, specifically Gf, suggesting that slower stimulus encoding and/or response execution substantially contributes to lower Gf in older adults (Schubert, Hagemann, et al., 2019b; von Krause et al., 2020). Research has yet to address whether these components act as bottlenecks driving cognitive decline and dedifferentiation.

An analysis of the effects of processing speed components on cognitive ageing requires several methodological considerations. A recent meta-analysis revealed that dedifferentiation increases exponentially with age (Tucker-Drob et al., 2019), so investigations of potential cognitive bottlenecks underlying ageing effects would be strengthened with approaches that permit observations of non-linear relationships. Models typically include age as either a continuous covariate or a categorical variable. However, these approaches obscure dynamic structural changes in fluid cognition; treating age as a linear covariate assumes that the relationships between cognitive constructs remain fixed across adulthood, while splitting age into (sometimes arbitrary) categorical groups obscures the trajectory of relationships between cognitive abilities. One alternative approach is local structural equation modelling in which age is used as a continuous weighting parameter

allowing the comparison of models across age (Hildebrandt et al., 2016). While this approach does permit the visualization of non-linear changes in relationships between cognitive abilities with age, it depends on a priori assumptions of structural relationships, the interpretations for which are dependent on goodness-of-fit of models that are vulnerable to equivalent model fallacies and unmeasured confounding variables (Kline, 2015). For example, a structural model hypothesizing that processing speed constrains WMC can have the exact same mathematical fit as a model hypothesizing the reverse. Furthermore, both models might appear perfectly valid even if their correlation is actually driven entirely by a third, unmeasured confounding variable—such as neurobiological degradation. In such cases, traditional structural models can falsely confirm a direct bottleneck effect where none actually exists.

4.1.1 The Current Study

The purpose of this study is to investigate the changing relationships between cognitive abilities across adulthood. We used age-weighted latent network models (awLNMs) which allowed us to treat age as a continuous variable, observe non-linear changes in a cross-sectional sample, and avoid limitations of structural equation modelling (for a similar analysis, see [Menu et al., 2024](#)). Moreover, we investigated the influence of distinct processing speed components estimated using the drift-diffusion model: drift rate, boundary separation, and non-decision time. To prevent multicollinearity, we specified four distinct network models: one containing a general processing speed factor, and three separate models substituting the general factor for each processing speed component.

WMC and Gf were included because these are highly related abilities (Kyllonen & Christal, 1990) influential to daily functioning with previous research suggesting that their age-related decline is mediated by processing speed (Hertzog, 1989; Lindenberger et al., 1993; Salthouse & Babcock, 1991). Attention control was also included, because it has been shown to share substantial variance with processing speed (Salthouse & Mein, 1995a) and has been theorized to underlie the relationship between WMC and Gf (Engle, 2018). By

including attention control alongside processing speed, we can observe their unique contributions to WMC and Gf across adulthood.

In line with evidence showing cognitive dedifferentiation, we expected to find that the global connectivity⁴, which reflects the aggregate zero-order correlations within a model, increases from younger adulthood to older adulthood. This would indicate that cognitive abilities become more interconnected in older age. To identify structural bottlenecks, we also compared node strength⁵, which is the sum of absolute values of the partial correlations between variables, between cognitive abilities within each age-weighted model. Changes in abilities with higher node strength have more influence on the interconnectivity of a model (Robinaugh et al., 2016). Based on the evidence showing that processing speed can mediate age-related decline in various cognitive abilities (e.g., Salthouse, 1996), we expected to find that processing speed and at least one of its components has higher node strength than WMC, Gf, and attention control in older adulthood.

4.2 Method

The data used in this study were collected as part of a project described in von Bastian et al (2022). Data were collected in the UK, Germany, and Canada, and the tasks were administered in English, German, and French in each respective country. This study was pre-registered on Open Science Framework (<https://osf.io/b4uzp>) after data were collected but before the present analyses were conducted.

⁴The pre-registration specified “global strength” rather than “global connectivity”, but the measurement remains unchanged. We decided to use a different term to avoid confusion, because global strength is typically measured as the aggregate absolute values of the *partial* correlations in a network.

⁵The pre-registration stated that we would measure the expected influence to determine the influence of a variable within a model. The difference between expected influence and node strength is that node strength takes the absolute value of the partial correlations whereas the expected influence takes the untransformed partial correlation. We decided to use node strength because we were interested in the magnitude of the variance explained by each variable regardless of the directionality of the associations.

4.2.1 Participants

The sample included 424 adults aged 18–85 years ($M_{age} = 48.92$ years, $SD_{age} = 18.52$; 274 women, 197 men, 4 undisclosed). Less than half of the participants had a bachelor's degree ($n = 188$) and 81 of those had postgraduate degrees. After data cleaning procedures (described below), 366 participants remained, aged 18–85 years ($M_{age} = 48.26$ years, $SD_{age} = 18.34$; 209 women, 154 men, 3 undisclosed). Of these, 151 held bachelor's degrees and 68 held postgraduate degrees. Participants also completed the Montreal Cognitive Assessment and were excluded if their scores indicated mild cognitive impairment. Additional details on participant inclusion can be found in (von Bastian et al., 2022).

4.2.2 Materials

In von Bastian et al. (2022) participants completed WM, Gf, attention control, and processing speed tasks before and after a series of training sessions. We used the pre-training data from the choice reaction time (CRT; drawings, shapes, and numbers), continuous reproduction, updating, binding, Stroop, Go/No-Go, Simon, Raven's Advanced Progressive Matrices - Short-Form (RAPM - SF), Paper Folding, Letter Sets, and Everyday Problems Test tasks. Table 4.1 describes and lists the details of the tasks included in the present study.

BOTTLENECKS OF PROCESSING SPEED COMPONENTS

Table 4.1

Task Descriptions

Measure	Task	Number of trials	Timing	Dependent variable
<i>Working Memory</i>				
Binding (Oberauer, 2005)	Memorize 3-5 colored triangles and their locations in a 4 x 4 grid. Recognize whether probes are the correct color in the correct location. Probes may be targets (i.e., correct color in correct location) or lures (i.e., color in incorrect location).	6 practice trials; 2 blocks of 12 trials each (8 trials per set size) 50% target probes, 50% lure probes	900 ms presentation time; 100 ms post-presentation blank interval; 100 ms post-trial blank interval	d' : the difference between z-transformed hit rates to target probes and z-transformed false alarm rates to lure probes
Updating (Miyake et al., 2000)	Memorize single digits presented in 3 boxes. Recall the most recent digits presented after 0, 3, or 6 substitutions.	3 practice trials; 2 blocks of 9 test trials each (6 trials per number of substitutions)	3750 ms initial presentation; 1250 ms substitution presentation; 250 ms blank ISI; 100 ms blank ITI	Proportion correct
Continuous Reproduction (Fougnie & Alvarez, 2011)	Memorize the orientation of 5 isosceles triangles then reproduce the orientation of a select triangle (see Figure 4.2).	10 practice trials; 2 blocks of 50 test trials each	500 ms pre-trial fixation cross; 1200 ms presentation time; 900 ms retention interval	Capacity or precision estimated using the standard mixture model or the swap-model, whichever resulted in better model fit
<i>Attention control</i>				
Stroop (Salthouse & Meinz, 1995b)	Indicate how many digits are presented simultaneously in the center of the screen. The number of digits may match their value (congruent trials) or mismatch their value (incongruent trials).	12 practice trials; 2 blocks of 144 test trials each (216 congruent trials, 72 incongruent trials)	100 ms blank ITI	Congruency effect: the difference in log-transformed RTs to correct responses between incongruent and congruent trials

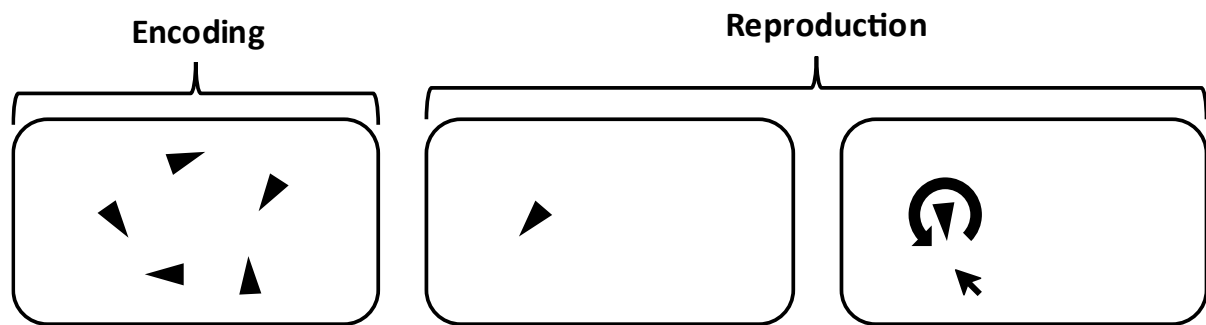
BOTTLENECKS OF PROCESSING SPEED COMPONENTS

Go/No-Go (Chuderski et al., 2012)	Press space if a square appears (“go” trials”). Withhold response if a diamond appears (“no-go” trials).	12 practice trials; 2 blocks of 144 test trials each (216 go trials, 72 no-go trials)	250 ms fixation cross; 2000 ms presentation time (or until a response)	d' : the difference between z-transformed hit rates to go trials and z-transformed false alarm rates to no-go trials
Simon (Simon, 1969)	Press A for green circles or L for red circles. The circles may be on the left or right side of the screen. Green circles on the left and red circles on the right are congruent trials. Others are incongruent.	12 practice trials; 2 blocks of 144 test trials each (216 congruent trials, 72 incongruent trials)	250 ms fixation cross	Congruency effect: the difference in log-transformed RTs to correct responses between incongruent and congruent trials
<i>Processing Speed</i>				
Drawings	Press A or L keys to classify drawings as “animals” or “objects” for two blocks then “smaller or larger than a football” for two blocks (see Figure 4.3A).	5 practice trials; 4 blocks of 80 test trials each	100 ms blank ISI; 150 ms ISI with classification cue	Negated RT to correct responses after removing 3 median absolute deviations above and below the median RT
Numbers	Press A or L keys to classify numbers as “divisible by 2 or not” for two blocks then “smaller or greater than 5” for two blocks (see Figure 4.3B).	5 practice trials; 4 blocks of 80 test trials each	100 ms blank ISI; 150 ms ISI with classification cue	Negated RT to correct responses after removing 3 median absolute deviations above and below the median RT
Shapes	Press A or L keys to classify shapes as “blue or green” for two blocks then “curvy or spiky” for two blocks (see Figure 4.3C).	5 practice trials; 4 blocks of 80 test trials each	100 ms blank ISI; 150 ms ISI with classification cue	Negated RT to correct responses after removing 3 median absolute deviations above and below the median RT
<i>Fluid Intelligence</i>				
RAPM-SF (Arthur & Day, 1994; Arthur et	Identify the missing element in a grid that completes a pattern which precedes	2 practice trials; 12 test trials	15 min overall time limit	Proportion correct out of 12

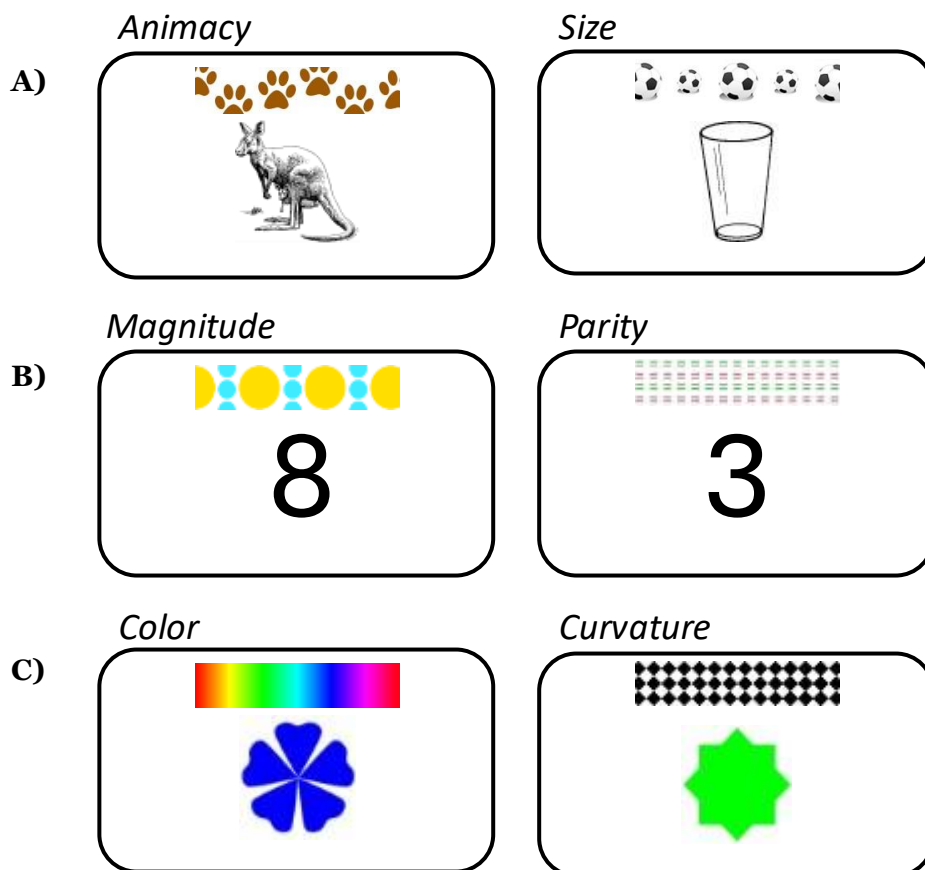
BOTTLENECKS OF PROCESSING SPEED COMPONENTS

<u>al., 1999; Raven, 1990)</u>	left-to-right and top-down in the grid (see Figure 3.7).			
Letter Sets (Ekstrom et al., 1976)	Identify the set of 4 letters from 5 sets that does not follow the pattern of the other sets (see Figure 4.4).	2 practice trials; 15 test trials	7 min overall time limit	Proportion correct out of 15
Paper Folding (Ekstrom et al., 1976)	Indicate where holes would appear in an unfolded piece of paper after having been folded and hole punched (see Figure 3.8).	1 practice trial; 2 blocks of 10 test trials each	3 min per block	Proportion correct out of 20
EPT (Reinhartz et al., 2026)	Choose the correct response to solve tasks resembling problems from everyday life, such as dosing medicine (see Figure 4.5).	1 practice trials; 14 test trials	1.5 min per trial	Proportion correct

Note. d' = discrimination parameter (Stanislaw & Todorov, 1999); ISI = inter-stimulus interval; ITI = inter-trial interval; RT = response time; RAPM-SF = Raven's Advanced Progressive Matrices – Short Form; EPT = Everyday Problems Test.

Figure 4.2*Continuous Reproduction Task*

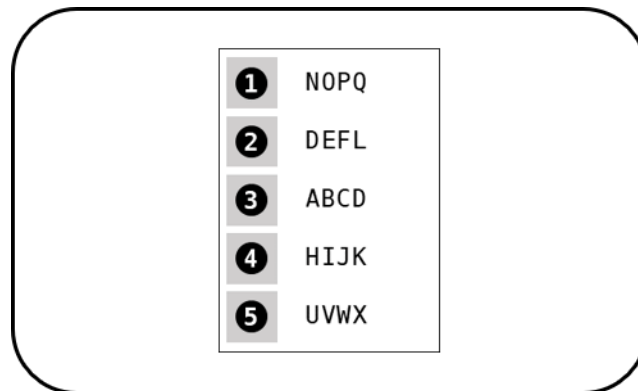
Note. After encoding, participants are given one triangle from the encoding phase whose orientation they need to reproduce by rotating the triangle with the mouse and clicking to input their response.

Figure 4.3*Choice Reaction Time Tasks*

Note. For each example, the symbol above the image or number indicates the relevant dimension (i.e., animacy or size, magnitude or parity, color or curvature). Panel A: Drawings CRT. Participants indicate whether the image is an animal or an object (left) or smaller or larger than a football (right). Panel B: Numbers CRT. Participants indicate whether the number is smaller or greater than 5 (left) or divisible by 2 (right). Panel C: Shapes CRT. Participants indicate whether the shape is blue or green (left) or curvy or spiky (right).

Figure 4.4

Letter Sets Task Example



Note. The correct answer would be option 2, because every other option has letters in sequential alphabetical order.

Figure 4.5

Everyday Problems Test Example

<i>Example Question:</i>	Which ingredient is mixed with the sour milk? 1. Flour 2. Shortening 3. Soda 4. Salt						
<i>Information:</i>	SOUR MILK BISCUITS <table style="width: 100%; border: none;"> <tr> <td style="width: 50%;">250g flour</td> <td style="width: 50%;">2 tablespoons shortening</td> </tr> <tr> <td>3 teaspoons baking powder</td> <td>½ teaspoon soda</td> </tr> <tr> <td>1 teaspoon salt</td> <td>120ml sour milk</td> </tr> </table> Sift flour, baking powder, and salt together. Rub in shortening with finger tips. Mix soda and sour milk. Add slowly to first mixture and mix to a soft dough. Roll out on slightly floured board to 1cm thickness. Cut with a biscuit cutter. Bake in oven at 230°C for 10 to 15 minutes. Yields 12 biscuits.	250g flour	2 tablespoons shortening	3 teaspoons baking powder	½ teaspoon soda	1 teaspoon salt	120ml sour milk
250g flour	2 tablespoons shortening						
3 teaspoons baking powder	½ teaspoon soda						
1 teaspoon salt	120ml sour milk						

Note. The correction response is option 3 (“Soda”), because the instructions explicitly state “Mix soda and sour milk.”

4.2.3 Analysis

Statistical analyses and data cleaning were performed with R (R Core Team, 2024) and RStudio (Posit team, 2024). Dependent variables were z-standardized prior to modelling. We used the “lavaan” package (Rosseel, 2012) for latent-variable modelling, the “lvnet” package (Epskamp et al., 2017) for latent network modelling, and the “qgraph” package (Epskamp et al., 2012) for calculating node strength.

To determine the more statistically valid indicator of WM from the continuous reproduction task, we compared model fits of the swap-model and the standard mixture

GENERAL DISCUSSION

model. The swap-model was found to have better predictive accuracy as indicated by lower Akaike Information Criterion (AIC), $\Delta AIC = 1082.00$, and significantly better fit, $\chi^2(366) = 1084.00$, $p < .001$, so capacity (P_t) was used as a measure of WM.

4.2.3.1 Data Cleaning

We excluded participants if they did not complete all the pre-training tasks or if their dependent variables could not be calculated (i.e., because they scored 0 on incongruent trials of the Stroop task or the drift-diffusion model did not converge for them [$\hat{R} > 1.05$]; $n = 45$). Mahalanobis Distances were then calculated for each participant, and those that exceeded the critical value with $p < .001$ were excluded ($n = 13$). We then examined the dependent variables for each task, and the drift-diffusion model parameter estimates, for normality. If the absolute value of a skew index was above 3.0 or the absolute value of a kurtosis was greater than 10.0, we used appropriate transformations to approach normal distributions following recommendations from Kline (2015).

4.2.3.2 Latent-Variable Modelling

We began with a baseline confirmatory factor analysis (CFA) model to observe the relationships between latent constructs before segregating models by age. We specified latent variables of WMC, attention control, Gf, and processing speed for CFA and awLNMs, henceforth referred to as *processing speed models*. WMC and attention control were indicated by three tasks each (updating, binding, continuous reproduction; and Go/No-Go, Stroop, Simon). Gf was indicated by performance on the RAPM – SF, Paper Folding, Letter Sets, and Everyday Problems Test, which has previously correlated well with Gf in this dataset (Reinhartz et al., 2026). Processing speed was indicated by *negated* response time (where higher values represent faster processing) in the drawings, numbers, and shapes CRTs.

Fits of the CFA and awLNMs were inspected with comparative fit index (CFI) values $\geq .95$, root mean square error of approximation (RMSEA) and its 90% confidence interval (CI) $\leq .06$, and standardized root mean square residual (SRMR) $\leq .08$ indicating good fit (Hu & Bentler, 1999), while CFI $\geq .90$, RMSEA $\leq .10$, and SRMR $\leq .10$ indicated acceptable

fit (Kline, 2015). CFA model fits were first inspected to check the validity of the models' specifications, so any model convergence issues were addressed before awLNM.

4.2.3.3 Age-Weighted Latent Network Modelling

To calculate weighted values, we applied a Gaussian kernel function with a bandwidth parameter of 2 to each focal point (ages 20 to 83). The resulting 61 sets of weights were applied to the observed data to calculate weighted covariance matrices and age-specific effective sample sizes (N_{eff}) which we used to calculate model fits and statistical significance. To avoid computational errors that are equivalent to dividing by zero, we applied a negligible ridge constant (1×10^{-5}) to the diagonal of the covariance matrix whenever the matrix was mathematically unstable (i.e., possessed eigenvalues near or below zero). The weighted covariance matrices were applied to the models to generate each of the 61 awLNMs via the maximum likelihood approach.

As an indication of the relatedness of cognitive abilities, global connectivity was calculated for each awLNM as the sum of the absolute values of the zero-order correlations between latent variables. We used Monte Carlo simulations (5000 iterations) and Cohen's d to compare the global connectivity between the youngest and oldest groups for each model. To investigate the change in influence of the constructs in the models across age, the node strength was calculated for each latent variable as the sum of the absolute values of the partial correlations with that variable.

4.2.3.4 Drift-Diffusion Modelling

To investigate the influence of specific processing speed components, we substituted the processing speed variable from the processing speed models (except the baseline model) with individual processing speed components estimated from the drift-diffusion model (drift rate, boundary separation, and non-decision time). We ran the analyses once for each component to isolate their specific relationships with the other cognitive abilities. Each component was specified in the models as a single-indicator latent variable with residual variance fixed to zero. We refer to these models as *drift rate models*, *boundary separation models*, and *non-decision time models*, respectively. By pooling trials across the three CRT

tasks, we tripled the number of trials per participant, improving model convergence and parameter estimation (Ratcliff & Childers, 2015) while minimizing measurement error. This approach assumes the estimates are robust which is supported by previous individual differences investigations of processing speed parameters (e.g., Ratcliff et al., 2010).

Drift rate, boundary separation, and non-decision time were estimated using the hierarchical drift-diffusion model (Pan et al., 2025; Wiecki et al., 2013) with the starting point z fixed at 0.5, assuming no prior bias toward either response option. Posterior distributions were approximated using four Markov Chain Monte Carlo chains, each drawing 20,000 samples with the first 5,000 discarded as burn-in. Non-decision time estimates were negated so that higher values represented faster response times.

4.3 Results

Descriptive statistics and reliability coefficients for indicators are presented in Table 4.2. Most measures showed acceptable reliability except for the Everyday Problems Test which we decided to retain for having similar correlations and loadings with other Gf indicators (described below). The updating task had problematically high kurtosis and skew (Kline, 2015), so we performed arcsine transformation on these data which alleviated this concern. All dependent variables were centered and z-transformed prior to analysis to normalize the distribution. Zero-order correlations of dependent variables are color-scaled in Figure 4.6 for visual clarity. Most of the lowest correlations were shared with attention control tasks. As expected, most of the highest correlations were between indicators of the same ability, except for the attention control indicators which had higher correlations with boundary separation and drift rate than each other.

Table 4.2

Descriptive Statistics

Task/Component	DV	<i>M (SD)</i>	Min	Max	Kurtosis	Skew	Reliability
<i>Working Memory</i>							
Binding	d'	1.51 (0.92)	-1.38	4.43	3.16	0.20	0.91
Updating	PC	1.42 (0.20) ^a	0.67 ^a	1.57 ^a	5.67 ^a	-1.67 ^a	0.94

GENERAL DISCUSSION

Continuous reproduction	P_t	0.37 (0.20)	0.00	0.88	2.47	0.30	0.68
<i>Attention control</i>							
Stroop	CE	-0.16 (0.07)	-0.35	0.11	3.48	0.06	0.61
Go/No-Go	d'	4.20 (0.57)	2.07	5.29	3.72	-0.39	0.79
Simon	CE	-0.17 (0.08)	-0.46	0.00	3.66	-0.60	0.80
<i>Processing Speed</i>							
Drawings	RT	636.11 (100.54)	441.37	1027.66	3.47	0.68	1.00
Numbers	RT	584.45 (88.32)	387.10	865.29	3.07	0.46	1.00
Shapes	RT	554.99 (87.92)	376.18	837.07	3.10	0.59	1.00
Drift rate	ν	4.35 (1.45)	0.94	7.47	2.05	-0.31	-
Boundary separation	a	3.31 (1.46)	0.95	6.86	1.92	-0.12	-
Non-decision time	t_o	-0.23 (0.08)	-0.49	-0.06	3.21	-0.60	-
<i>Fluid Intelligence</i>							
RAPM - SF	PC	0.48 (0.22)	0.00	1.00	2.36	0.07	0.71
Letter sets	PC	0.58 (0.16)	0.07	0.93	2.98	-0.49	0.63
Paper folding	PC	0.51 (0.21)	0.10	1.00	2.24	0.07	0.82
EPT	PC	0.68 (0.17)	0.21	1.00	2.69	-0.44	0.58

Note. Response times were measured in milliseconds, were negated, and were calculated from correct responses. Non-decision time was negated. Reliabilities reflect odd-even split-half reliability for all tasks except the updating and fluid intelligence tasks which reflect Cronbach's α . DV = dependent variable; CI = confidence interval; d' = discrimination parameter; P_t = Probability of target; CE = congruency effect; RT = Response time; ν = drift rate; a = boundary separation; t_o = non-decision time; RAPM - SF = Raven's Advanced Progressive Matrices - Short-Form; PC = proportion correct; EPT = Everyday Problems Test. ^a Arcsine transformed.

Figure 4.6

Color-Scaled Correlation Matrix

Task/Component	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
<i>Working memory</i>															
1 Binding														1.00	
2 Updating															
3 Continuous reproduction															
<i>Attention control</i>															

GENERAL DISCUSSION

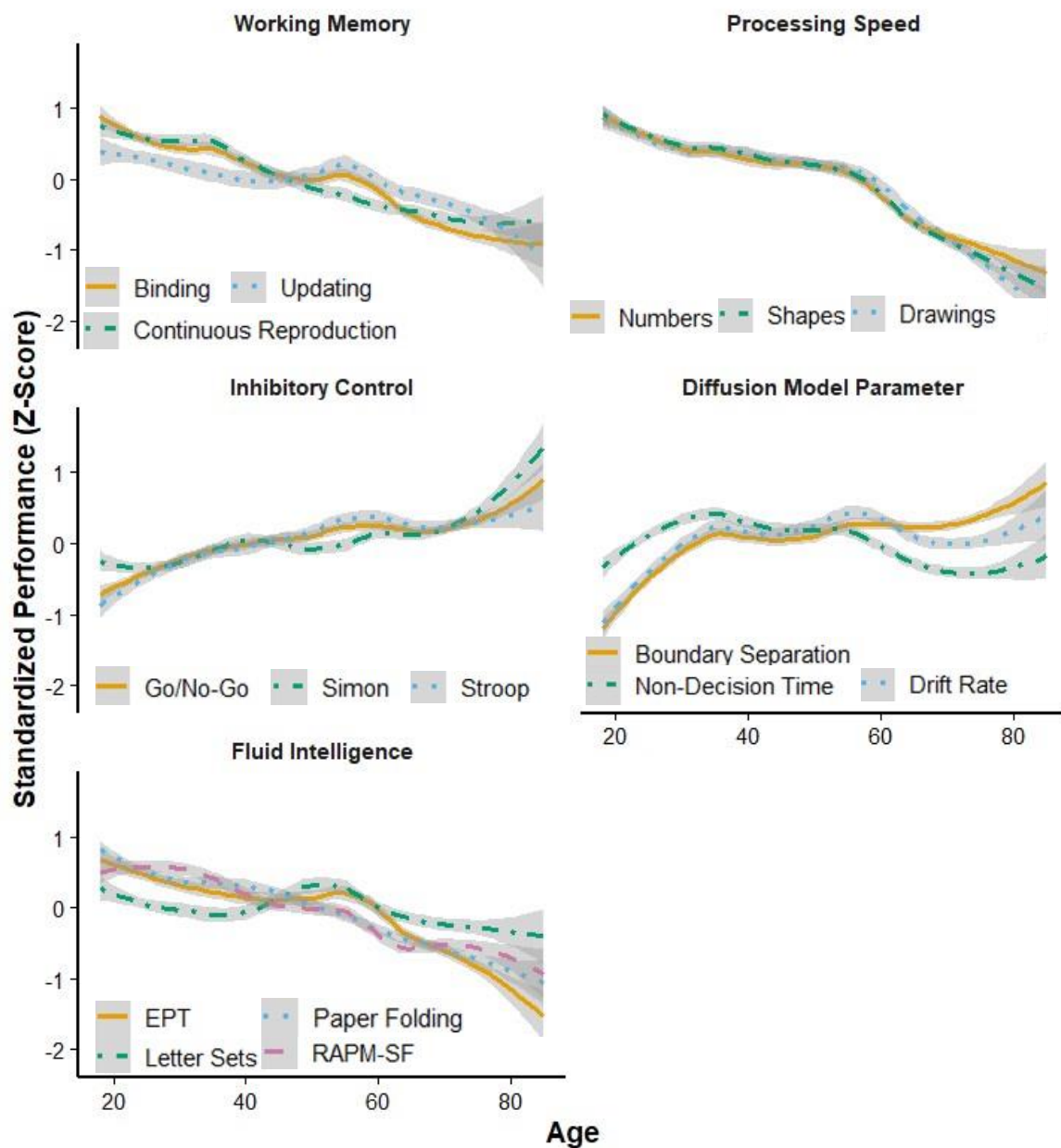
4 Go/No-Go	.02	.09	.03																
5 Simon	.08	.15	.08	.27															
6 Stroop	-.13	-.08	-.14	.26	.30														
<i>Processing speed</i>																			
7 Drawings	.49	.37	.42	-.16	.00	-.23													
8 Numbers	.45	.32	.39	-.15	.01	-.21	.88												
9 Shapes	.46	.35	.39	-.20	-.01	-.24	.91	.90											-1.00
10 Boundary separation	-.08	-.05	-.04	.32	.20	.29	-.23	-.31	-.30										
11 Drift Rate	.11	.12	.12	.35	.28	.26	.14	.07	.07	.85									
12 Non-decision time	.20	.12	.19	.10	.03	.03	.29	.22	.26	.74	.68								
<i>Fluid Intelligence</i>																			
13 EPT	.48	.40	.42	-.01	-.05	-.13	.40	.38	.40	-.12	.05	-.11							
14 Letter sets	.42	.46	.31	.12	.04	-.05	.25	.22	.22	-.03	.09	-.04	.41						
15 Paper folding	.49	.41	.46	-.14	-.04	-.23	.37	.32	.35	-.13	-.02	-.09	.51	.41					
16 RAPM-SF	.50	.44	.49	-.07	.00	-.14	.37	.37	.37	-.19	-.04	-.05	.54	.42	.54				

Note. CR = continuous reproduction; EPT = Everyday Problems Test; RAPM-SF = Raven's Advanced Progressive Matrices – Short-Form.

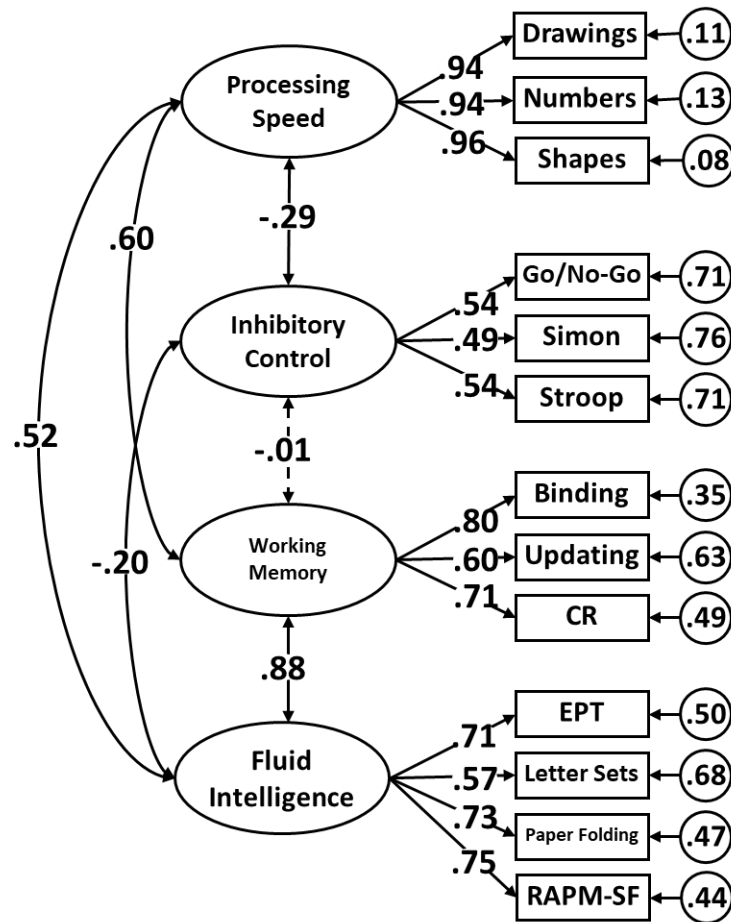
Performance trends for each measure are plotted across age in Figure 4.7, and the baseline CFA is shown in Figure 4.8. Most of the processing speed, WM, and Gf measures decreased in older age with the exception of Letter Sets which increased in middle age and then returned to baseline performance. Non-decision time showed a similar pattern to Letter Sets but peaked earlier. Boundary separation, drift rate, and, surprisingly, attention control measures increased in older age. Furthermore, the baseline CFA revealed that attention control negatively correlated with both Gf and processing speed, and the model exhibited good fit, $\chi^2(59) = 126.93$, CFI = 0.97, RMSEA = 0.06 [90% CI: 0.04, 0.07], SRMR = 0.06.

Figure 4.7

Performance Trends Across Age



Note. Shaded area represents 95% confidence interval. EPT = Everyday Problems Test; RAPM-SF = Raven's Advanced Progressive Matrices – Short Form.

Figure 4.8*Baseline Confirmatory Factor Analysis*

Note. Solid lines represent significant loadings ($p < .05$). Dashed lines represent non-significant loadings. CR = continuous reproduction; EPT = Everyday Problems Test; RAPM-SF = Raven's Advanced Progressive Matrices – Short Form.

4.3.1 Age-Weighted Model Fits

N_{eff} ranged from 61.77 at age 83 to 164.09 at age 59, indicating that models have more statistical power in middle age relative to younger and older age (see Figure 4.9). CFA models did not converge for all ages when attention control was included as a latent variable. Specifically, CFA processing speed models did not converge between ages 20-27 and 60-83, CFA drift rate and boundary separation models did not converge between ages 65-83, and non-decision time models did not converge between ages 63-83. We investigated models using separate age groups of 18-30, 31-64, and 65-85 in an attempt to achieve model convergence, but the Stroop task did not significantly load onto attention control in the oldest age group. All age-weighted models converged when the attention control ability was

GENERAL DISCUSSION

removed. Previous research suggests that dedifferentiation becomes evident in the oldest age range (de Frias et al., 2007; Ghisletta & Lindenberger, 2003; Hülür et al., 2015; Schaie et al., 1998), so we decided to prioritize maintaining the oldest age range over attention control and proceeded with the analyses without attention control. CFA and LNM model fits were then mathematically identical because three latent variables were included which causes LNM saturation (Epskamp et al., 2017). Model fits ranged from acceptable to good across age, peaking at CFI = 1.00 and RMSEA = 0.00 from age 52 across models, likely a result of high interconnectivity between latent variables in older age groups (see Figure 4.10).

Figure 4.9

Effective Sample Size by Age

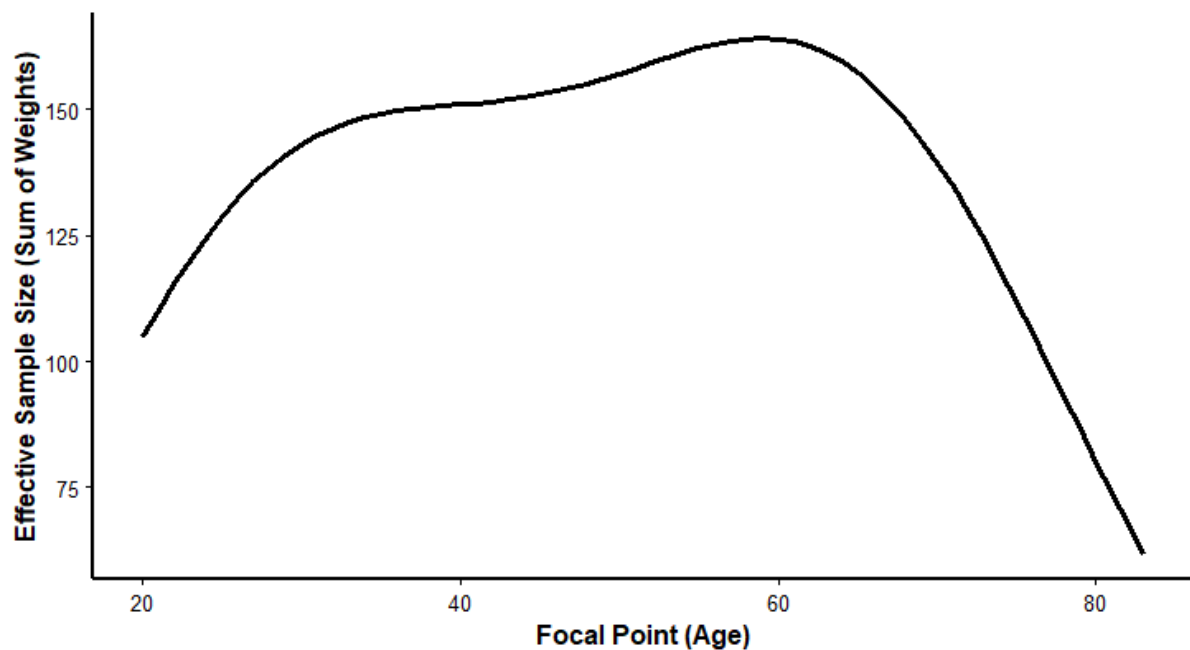
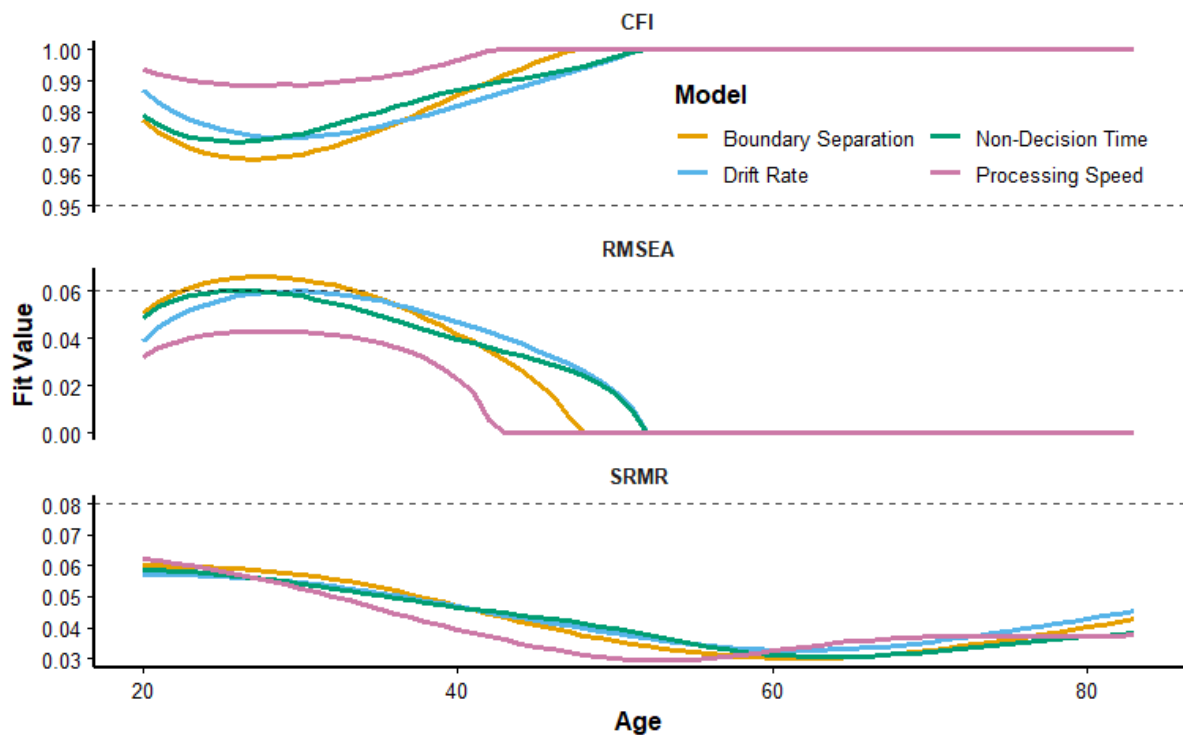


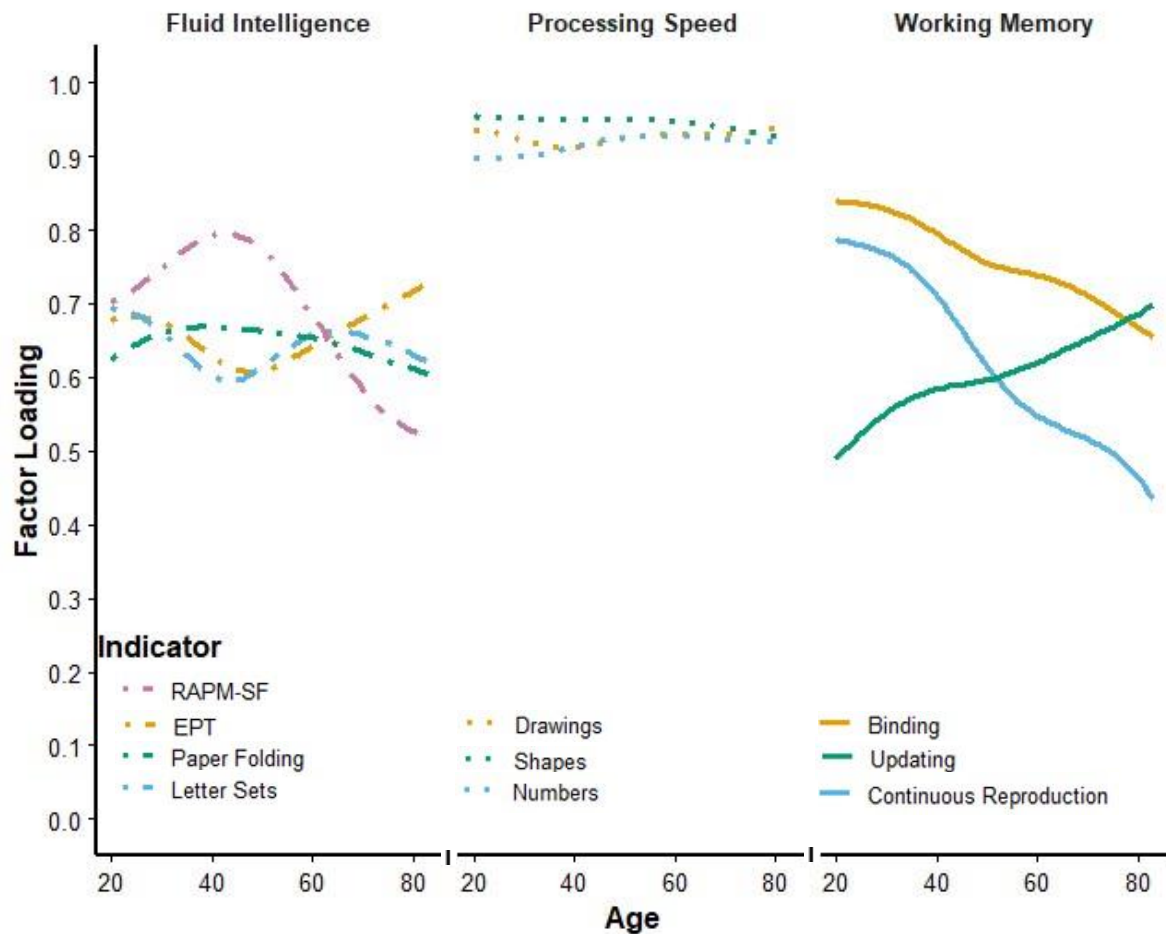
Figure 4.10*Model Fits by Age*

Note. Dotted lines indicate cutoff for good fit. Confirmatory factor analysis and latent network model fits are mathematically identical. CFI = comparative fit index; RMSEA = root mean squared error of approximation; SRMR = standardized root mean square residual.

4.3.2 Age-Weighted Factor Loadings

CFA factor loadings for the processing speed models are displayed in Figure 4.11.

Some change is prevalent in the factor loadings on Gf and WMC. In particular, the RAPM-SF loadings trend as an increase in middle age then decrease in older age, whereas the Everyday Problems Test and Letter Sets trend as a decrease in middle age and increase in older age. For WMC, the updating loading trends upward from young adulthood to older adulthood while continuous reproduction and binding trend downward. These apparent changes in loading magnitudes are indicative of changes in either the identification or the functioning of the latent construct. For example, the increase in the loading of the updating variable onto WM indicates that updating ability either becomes more consequential to WMC or more reliant on WMC in older age. LNM factor loadings exhibit the same trends (see Appendix C).

Figure 4.11*Factor Loadings by Age*

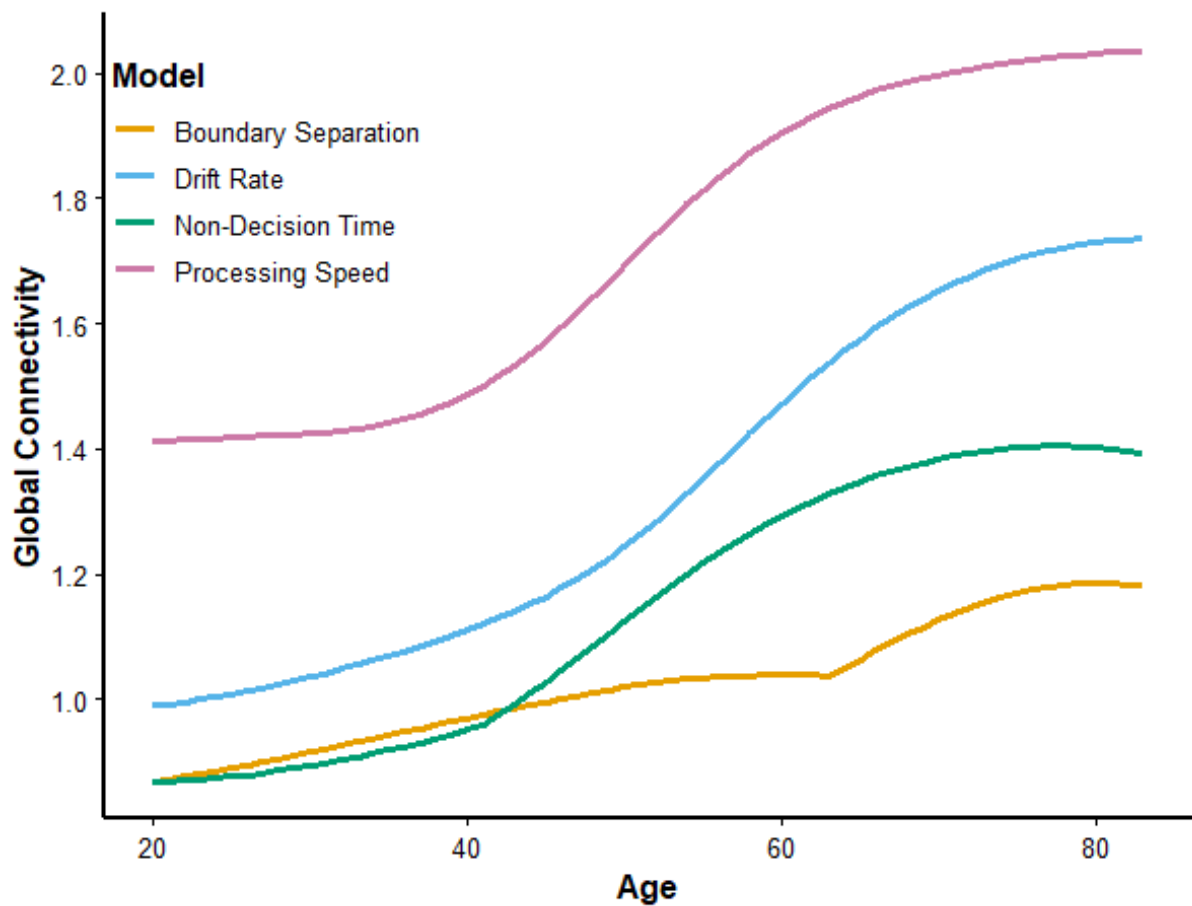
Note. The drift rate, boundary separation, and non-decision time models are identical, because the processing speed components are single-factor indicators and thus each have single loadings of 1. RAPM-SF = Raven's Advanced Progressive Matrices-Short Form; EPT = Everyday Problems Test.

4.3.3 Dedifferentiation

Figure 4.12 shows global connectivity, which is the sum of the absolute value of zero-order correlations, for each model. Higher global connectivity is indicative of a more interconnected, less differentiated model. Global connectivity appeared to increase from the youngest to the oldest focal point in the processing speed model, but Monte Carlo simulations revealed that this increase was not significant, $M_{diff} = 0.62$, 95% CI [-0.03, 1.24], $d = 2.68$. However, global connectivity significantly increased in the drift rate, $M_{diff} = 0.70$, 95% CI [0.08, 1.30], $d = 3.10$, and non-decision time models, $M_{diff} = 0.50$, 95% CI [0.02, 1.08], $d = 2.56$, but not the boundary separation model, $M_{diff} = 0.35$, 95% CI [-0.09, 0.89], d

GENERAL DISCUSSION

= 1.99. Differences in magnitude of global connectivity between models only reflect differences in the correlations WM and Gf share with processing speed or its components, because the zero-order correlations between WM and Gf change minimally between models. Processing speed having the highest global connectivity across age is therefore a reflection of processing speed having a higher correlation with WM and Gf than processing speed components. Although we did not find a significant effect of dedifferentiation in the processing speed model (likely due to small N_{eff} in the youngest and oldest focal points), the presence of an effect in the drift rate and non-decision time models indicates that dedifferentiation is occurring among components of processing speed. The following analyses were conducted to determine whether dedifferentiation was driven by components of processing speed.

Figure 4.12*Global Connectivity by Age and Model*

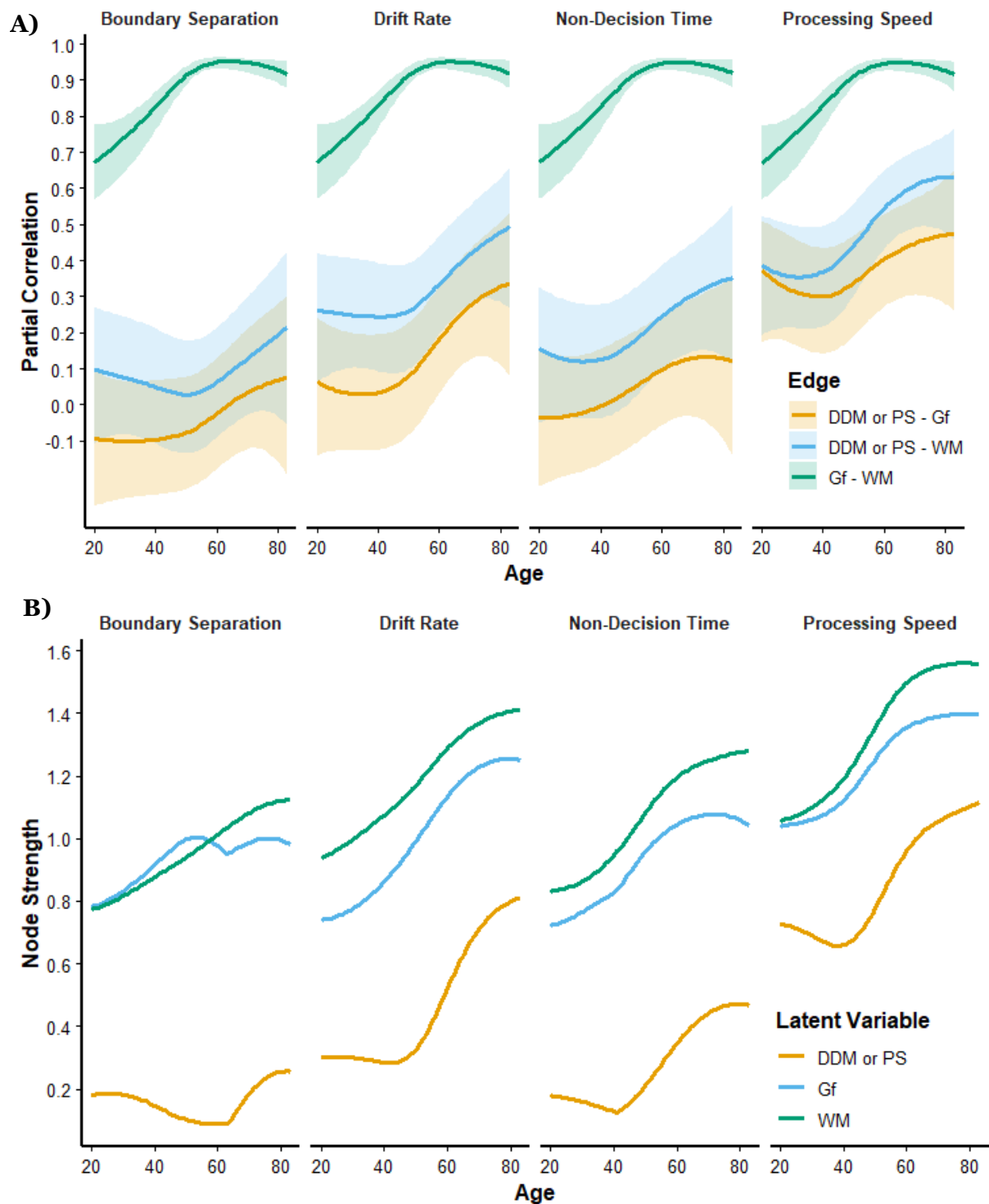
Note. Global connectivity was calculated as the sum of the absolute value of zero-order correlations between nodes in the corresponding network model. Only drift rate and non-decision time models exhibited significant increases in global connectivity estimated from Monte Carlo simulations.

4.3.3 Bottlenecks

LNM edges (partial correlations) are shown in Figure 4.13a and indicate the correlation between latent constructs when controlling for the influence of every other construct in the model. Node strengths are shown in Figure 4.13b and are the sums of the absolute values of the edges per construct. A construct with higher node strength has more influence on the edges between constructs in the model. If any of the processing speed components completely account for dedifferentiation, we would expect to find higher node strength in the processing speed components compared to WMC and Gf in older ages. We would also expect to find a flat edge between WMC and Gf across age, because changes in the

GENERAL DISCUSSION

relationship between WMC and Gf would be completely dependent on processing speed components. Instead, WMC and Gf showed the highest node strength across age and increasingly related to each other into older age, indicating that processing speed components could not completely account for dedifferentiation in these models. Node strength appeared to increase across age for processing speed, drift rate, and non-decision time but did not surpass WMC or Gf at any point. Thus, node strength appeared to increase for *every* construct in the processing speed, drift rate, and non-decision time models, indicating that WMC, Gf, general processing speed, and specific processing speed components (except boundary separation) all became more influential in these models in older age. While this pattern of results is indicative of dedifferentiation, it further suggests that some factor besides WMC, Gf, general processing speed, drift, and non-decision time is responsible for this dedifferentiation.

Figure 4.13*Network Edges (Panel A) and Node Strength (Panel B) by Age and Model*

Note. Shaded regions represent 95% confidence intervals. DDM or PS = either a drift-diffusion model parameter or processing speed depending on the model; Gf = fluid intelligence; WM = working memory.

4.4 Discussion

This study investigated the changing relationships between cognitive abilities throughout adulthood, addressing the question of whether processing speed or its underlying components are functional bottlenecks that drive dedifferentiation. We used drift-diffusion modelling to disentangle variables that underlie measures of general processing speed, specifically the rate of evidence accumulation (drift rate), speed-accuracy tradeoff (boundary separation), and time spent on decisional processes (non-decision time). We systematically included general processing speed or these processing speed components in LNMs along with measures of WM and Gf which allowed us to model the interconnectivity between these cognitive constructs and estimate the influence of these constructs on their interconnectivity without a priori specification of mediator variables. We used age-weighting to identify non-linear shifts in these models in a non-pathological cross-sectional sample of adults from 18 to 85. Attention control was not identifiable in older age groups, so it was not included in the main analyses.

The current results show significant dedifferentiation in the drift rate and non-decision time models and a trend of dedifferentiation in the processing speed and boundary separation models that were not attenuated by processing speed or processing speed components. In all of the models, the partial correlation between WM and Gf increased until age 61 to near unity, and at no point did processing speed or the processing speed components have higher node strength than WM and Gf, indicating that they did not have more influence on the interconnectivity within these models than WM and Gf did. Moreover, the node strength appeared to increase for every construct except, perhaps, boundary separation. Thus, the current results suggest that dedifferentiation is not caused by a bottleneck of processing speed or the processing speed components but another factor that was not modelled.

The factor driving dedifferentiation may not be a cognitive ability but the direct result of cognitive/neurological ageing which manifests as a general factor in statistical models. The common cause hypothesis posits that this general factor underlies dedifferentiation

GENERAL DISCUSSION

rather than any specific bottleneck (Baltes & Lindenberger, 1997; Tucker-Drob et al., 2019). Indeed, a recent meta-analysis supports the common cause hypothesis, showing that a general factor accounts for an equivalent amount of variance in cognitive ageing across different cognitive abilities (Tucker-Drob et al., 2019). The current study is the first to include processing speed components identified with the drift-diffusion model in an investigation of dedifferentiation, and the results show that age-related individual differences in these components do not underlie dedifferentiation. Moreover, as evidenced by the increased node strength of drift rate, non-decision time, and, to a lesser extent, boundary separation, these processing speed components were also subject to dedifferentiation – increasing in their relation to other cognitive constructs. Because all of the included cognitive constructs increased in interdependence with no single ability underlying this change, the current results support the common cause hypothesis.

Notably, the age-related changes in drift rate and non-decision time from the current study are not entirely consistent with those from the literature. In a recent meta-analysis, Theisen et al. (2021) investigated findings of age-related changes in drift-diffusion model parameter estimates and classified the tasks that studies have employed as perceptual (visual discrimination), lexical decision (word discrimination), or memory-based. Although the three tasks used to estimate drift-diffusion model parameters in the current study align with their 'perceptual' classification, our finding that drift rate *increased* in older age contrasts with their conclusion that perceptual drift rates are lower in older age. The discrepancy in these findings may be because drift rate is more task-specific than the task classifications used in Theisen et al. (2021). Indeed, in a study investigating the shared variance between drift rate estimates from 18 different tasks, Lerche et al. (2020) found interindividual differences in *content*-specific drift rates. Moreover, a review of evidence from 14 studies concluded that the associations between drift rate and age were task-dependent (Dully et al., 2018). Thus, the contrast in the relationship between age and drift rate reported in this study compared to others (Theisen et al., 2021) is emblematic of the specificity of drift rate. Regarding non-decision time, the literature more consistently finds that it increases in older

GENERAL DISCUSSION

age (Dully et al., 2018; Theisen et al., 2021), but the current study found a non-linear, bell-shaped trajectory indicating that the speed of non-decisional processes increased between young and middle adulthood and then decreased in older age. Much of past research has used categorical comparisons of younger and older adults, including the meta-analysis of Theisen et al. (2021), so non-linear effects of mid-life fluctuations in processing speed components may have been obscured. Depending on the chosen range for categorical binning (which is often arbitrary), traditional cross-sectional models may average out mid-life fluctuations into young and older adulthood, such that non-decision time appears to increase from young to older adulthood rather than the non-linear trend reported here. However, this finding should be interpreted with caution because of the lower N_{eff} in younger and older focal points. Future research should consider the possibility of a non-linear relationship between non-decision time and age. Indeed, as non-decision time is a composite measure consisting of all non-decisional processes, such as encoding, memory retrieval, or response execution, it would be surprising if each of these variables slowed at the same rate. Moreover, if compensatory strategies are implemented as non-decision time slows, then non-decision time may appear to become quicker as the strategies are integrated and developed.

While past studies have shown that processing speed (e.g., Verhaeghen & Salthouse, 1997) and non-decision time (Schubert, Hagemann, et al., 2019b; von Krause et al., 2020) mediate age-related *declines* in cognitive performance, the current results suggest that neither general processing speed nor specific processing speed components drive the *relationships* between these abilities. Although the current results were based on a cross-sectional analysis and must be interpreted with caution, this pattern of results can be explained by the Scaffolding Theory of Aging and Cognition (STAC-r) which explains that, as processing speed declines, cognition become more reliant on domain-general mechanisms, such as compensatory strategies (Park & Reuter-Lorenz, 2009; Reuter-Lorenz & Park, 2014). STAC-r is supported by causal evidence using transcranial magnetic stimulation showing that dedifferentiation of functional networks and, thus, the utilization of shared networks, is

GENERAL DISCUSSION

essential for maintaining performance in older age but not younger age (Rossi et al., 2004). It is possible, therefore, that dedifferentiation is a consequence of decreases in processing speed, but processing speed does not statistically underlie dedifferentiation because the usage of domain-general mechanisms increases. Dedifferentiation could therefore be a result of two simultaneous cognitive shifts: a decline in processing speed and an increase in usage of domain-general mechanisms. In other words, processing speed may drive the decline in cognitive abilities, but resultant domain-general compensatory mechanisms account for (more) of the dedifferentiation in cognitive abilities.

Boundary separation has been proposed to be a deliberate compensatory strategy such that older adults choose to prioritize accuracy over speed (Ratcliff et al., 2006; Starns & Ratcliff, 2010). It may, therefore, be expected under the assumptions of the above argument that boundary separation significantly contributes to dedifferentiation, but it was not found to significantly contribute to the relationship between cognitive abilities in the current study. This apparent contradiction can be explained by the possibility that many domain-general mechanisms increase in their influence on cognition in older age such that no single mechanism could be identified as the singular driving force of dedifferentiation. Rather, each domain-general mechanism contributes to a small amount of the overall change in covariance.

This interpretation of the current results aligns with process-overlap theory (Kovacs & Conway, 2016) which posits that general intelligence emerges from the shared recruitment of executive processes, rather than a single ability. Indeed, attempts to isolate domain-specific variance of cognitive abilities from domain-general variance have mostly proven detrimental to their covariance with Gf (Garvey et al., 2026). Extensive domain-generality across many cognitive abilities can manifest as a common factor which could be interpreted as general intelligence in one context or the common cause of dedifferentiation in another. Either way, domain-generality rather than any specific cognitive ability underlies the pattern of observed relationships. Thus, in the current study, the finding that processing speed

GENERAL DISCUSSION

components cannot completely explain dedifferentiation could be because no specific ability underlies dedifferentiation.

One criticism of the common cause hypothesis and process-overlap theory, is that it can be difficult to design a study that could disprove them (see [Colom et al., 2016](#)). One route is the use of bi-factor analysis or network analysis to separate task-specific from domain-general variance (e.g., Garvey et al., 2026). If task-specific variance is found to account for a substantial amount of variance in dedifferentiation, for example, then any identifiable underlying components of that task could further be separated into their specific variances. If these variances also account for a substantial amount of variance in dedifferentiation, then any further identifiable underlying components could be investigated and so forth until either the specific variance does not relate to dedifferentiation or no further underlying components can be identified. If even the most nested component is found to substantially relate to dedifferentiation, then the common cause hypothesis would need to consider the implications of said component.

4.4.1 Strengths and Limitations

The lack of statistical power in older ages may have heightened the instability of attention control. We were unable to include attention control in the main analyses to examine its influence on dedifferentiation, because it could not be identified in any of the models in older age groups. Other research has also struggled to identify attention control as a latent variable (Hull et al., 2008; Rey-Mermet et al., 2018; von Bastian et al., 2020), especially in older ages (Miyake & Friedman, 2012). We can, however, make some observations about attention control from our data. Surprisingly, the baseline CFA revealed a negative relationship between attention control and both processing speed and Gf along with no relationship with WM, even though attention control is typically positively correlated with each of these abilities (Friedman & Miyake, 2017; Salthouse, 1996; Unsworth & Spillers, 2010). The current results are likely influenced by the instability of attention control in older age. It is possible that attention control was unstable due to dedifferentiation and/or contributed to dedifferentiation in other abilities.

This study had a relatively diverse sample with data collected from three different countries in three different languages. It also had an ideal age range (18-85) for the current analysis, because previous research has shown that dedifferentiation becomes most evident from age 65 (de Frias et al., 2007; Ghisletta & Lindenberger, 2003; Hülür et al., 2015; Schaie et al., 1998). Using older age groups always comes with the risk of pathological influences, but this study accounted for this possibility by administering the Montreal Cognitive Assessment and excluding participants whose scores indicated mild cognitive impairment. Importantly, this sample still suffers from a reliance on participants that are Western, educated, industrialized, rich and democratic (“WEIRD”; Henrich et al., 2010), potentially limiting the generalizability of the present findings.

This study benefited from the use of age-weighted latent network analysis. This approach allowed us to model non-linear changes in model estimates including fit, partial correlations, and factor loadings from a cross-sectional sample without a priori specification of directional relationships that can be prone to equivalent model fallacies and confounding variables (Kline, 2015). The use of age-weighting increases the N_{eff} per age, but this study is still limited by sample size. The effective sample sizes at the tail ends of the age distribution were low enough to create concern regarding statistical power. Hence, processing speed and its components may yet contribute to dedifferentiation to a small degree that the current study was underpowered to detect.

4.5 Conclusion

The current study shows that dedifferentiation is not caused by a processing speed bottleneck or a bottleneck of drift rate, boundary separation, or non-decision time. Using age-weighted latent network analysis, we were able to visualize non-linear interconnectivity between WM, Gf, processing speed, and processing speed components and the influence of these components on their interconnectivity from ages 18-85. We found evidence for significant dedifferentiation in drift rate and non-decision time models. We also found that WM and Gf do not become dependent on processing speed or processing speed components as dedifferentiation occurs. The results, thus, do not support processing speed as a

GENERAL DISCUSSION

bottleneck. Future research would benefit from a study designed to test a falsifiable version of the common-cause hypothesis.

CHAPTER 5

General Discussion

5.1 Summary of Findings

The aim of this thesis was to advance understanding of the overlap between WM and Gf and how it changes across adulthood. In particular, we investigated the binding hypothesis in the context of the 3Cs model of WM, the generality of binding and its relationship to Gf, and the bottleneck of processing speed. Across three studies, we utilized methods that isolated variance of interest and the partial correlations between WMC, Gf, binding abilities, processing speed, and processing speed components.

Chapter 2 investigated the binding hypothesis in the context of the 3Cs model. We found that variance specific to each of the components of the 3Cs model had only small or non-significant relationships with WMC and Gf, but the variance shared among these components was highly related to both WMC and Gf. We were unable to establish substantial individual differences in the RDA-specific and FA-specific factors, and none of the variables reflecting the FA, RDA, or aLTM partially correlated with Gf variables above and beyond the variance common to the 3Cs. Instead, the variance shared among the 3Cs highly related to WMC and Gf. As the RDA-specific factor represented individual differences in managing binding interference, the finding that individual differences in the RDA were not significant or related to WMC or Gf is evidence against the proposal that binding interference limits WMC and Gf. However, individual differences in other abilities pertaining to binding may yet be vital to the WMC-Gf relationship. Moreover, the paradigms that operationalized the RDA differed in a way that may have lessened their shared variance: one paradigm used item-to-location binding and the other used item-to-item binding.

Chapter 3 investigated these possibilities by estimating the shared variance among binding abilities (item-to-location binding, item-to-item binding, relational integration, relational representation, and temporal binding) and evaluating their zero-order and partial correlations with Gf. Item-to-location binding and item-to-item binding were found to best be represented by one latent variable, termed *binding maintenance*. We interpreted this variable to represent the ability to store, maintain, and recognize bindings in WM, because the local recognition and associated pairs tasks are both especially dependent on these

GENERAL DISCUSSION

processes. Furthermore, all evaluated binding abilities shared significant variance representative of a higher-order latent variable (Binding). This variable appears to represent the ability to form and make use of bindings in a goal-directed manner, because each of its indicators involves content-context mechanisms but vary in how they are utilized.

Gf and Binding were statistically indistinguishable. Moreover, each of the binding abilities, except for temporal binding, shared a partial correlation with Gf, indicating that they each had unique variance shared with Gf. Thus, the process-general Binding ability *and* its underlying WM mechanisms were predictive of Gf. Temporal binding was indirectly correlated with Gf via relational representation and relational integration which may be indicative of the distinction of temporal binding as a perceptual mechanism and the other binding abilities as WM mechanisms. Binding maintenance showed the strongest partial correlation with Gf compared to any of the other binding abilities. Furthermore, binding maintenance only indirectly related to the other binding abilities via Gf. This finding is indicative of two key points: the substantial amount of shared variance between binding abilities and Gf, and the distinctness of the binding maintenance-Gf relationship. Overall, Chapter 3 clarified that process-general Binding and process-specific binding, especially binding maintenance, are integral to Gf. This contrasts the finding from Chapter 2 that individual differences in managing binding interference are not as influential to Gf as previously hypothesized.

Chapters 2 and 3 only investigated the WM-Gf relationship in young adults, so Chapter 4 investigated partial correlations between WMC and Gf from younger to older adulthood. We investigated the bottleneck of processing speed that is proposed by the processing speed theory to underlie age-related decline in cognitive abilities (Salthouse, 1996) and may additionally drive cognitive dedifferentiation (the age-related increase in correlation between fluid cognitive abilities, such as WMC and Gf). We examined whether the age-related change in partial correlations between WMC and Gf was attenuated by processing speed or its constituent components as estimated by the drift-diffusion model (drift rate, boundary separation, and non-decision time). We found that the partial

correlation between WMC and Gf increased in older age to near unity independent of processing speed or any of its components, suggesting that neither processing speed nor its components are bottlenecks driving dedifferentiation.

5.2 Common Factors of Fluid Cognition

None of the 3Cs, individual binding abilities, processing speed, or processing speed components were found to account for individual differences in WMC, Gf, or the relationship between WM and Gf. However, Chapters 2 and 3 collectively suggest that maintenance and, possibly, binding maintenance are highly predictive of Gf. Specifically, in Chapter 2 the shared variance among the 3Cs was significantly correlated with WMC and Gf, whereas none of the component-specific factors significantly correlated with Gf. In other words, only what was shared between the components significantly correlated with WMC and Gf. Based on consideration of what cognitive processes are shared among the tasks used to operationalize the 3Cs, their shared variance most likely represents the domain-general, short-term maintenance of representations of task-relevant goals, context, and information, and the relations between them. Moreover, in Chapter 3, binding maintenance highly correlated with Gf, and the magnitude of their partial correlation was about twice that which Gf shared with any other binding ability. Together, these chapters align with previous findings that maintenance is a primary source of individual differences in WMC and Gf (e.g., [Chuderski et al., 2012](#); [Cowan et al., 2006](#); [Frischkorn et al., 2022](#)).

Consequently, this strong evidence for maintenance requires a reconsideration of other proposed mechanisms, particularly binding interference. Whereas previous models have proposed that binding interference simultaneously limits WMC and Gf (Oberauer, 2009; Oberauer et al., 2016), Chapter 2 found no significant individual differences in the ability to manage binding interference. Given the robust, unique relationship between binding maintenance and Gf observed in Chapter 3, the present findings suggest that individual differences in basic maintenance provides a better fit to the data of the WMC-Gf relationship than binding interference.

Second, these findings challenge existing assumptions regarding the complexity of representations. The binding hypothesis (Oberauer et al., 2007) and theories such as Relational Complexity Theory (Andrews et al., 2003; Andrews & Halford, 1998) posit that the complexity of structural representations is what underlies Gf. However, Chapter 3 found that individual differences in relational integration (the ability to build structural representations) were remarkably similar to relational representation (the ability to represent relatively simple relations) in their partial correlations with Gf. Furthermore, the shared variance among these binding abilities was statistically indistinguishable from Gf. Importantly, the complexity of bindings was not experimentally manipulated in any task in Chapter 3. The fact that the variance of Gf could be perfectly captured without requiring explicitly complex task demands suggests that the necessity of complex structural representations is overemphasized in current cognitive theories. Instead, the present findings support Chuderski's (2022) proposal that the ability to represent and process simple relations in a valid and robust way is more critical for operationalizing Gf than the complexity of the tasks themselves.

Chapter 4 alternatively investigated the role of processing speed and its constituent components in the relationship between WMC and Gf across age; however, neither processing speed nor its constituent components could explain the relationship between WMC and Gf at any age. Instead, these results are consistent with the common cause hypothesis that a general factor underlies dedifferentiation (Baltes & Lindenberger, 1997; Tucker-Drob et al., 2019). This general factor may reflect neurobiological decline, such as systemic degradation at the neuronal level, that simultaneously drives down multiple fluid cognitive abilities and increases their correlation. However, cognitive dedifferentiation also accompanies an increased spread of activation in more diverse brain areas that appear to improve task performance (see Park & Reuter-Lorenz, 2009). Thus, neurobiological decline does not appear to be the sole mechanism representing the general factor of dedifferentiation. Instead, as theorized in STAC-r, the decline in cognitive performance may accompany increased usage of compensatory mechanisms (Park & Reuter-Lorenz, 2009;

Reuter-Lorenz & Park, 2014). Moreover, boundary separation may be a compensatory mechanism as some researchers have theorized (Ratcliff et al., 2006; Starns & Ratcliff, 2010), but the current findings do not support this – boundary separation had no measurable impact on the WM-Gf relationship. It may be that boundary separation is one of many compensatory mechanisms which, on its own, contributes little to the WM-Gf relationship.

Taken together, we were unable to establish any single mechanism as the key source of WMC-Gf overlap, possibly because there is no such single, underlying mechanism. Instead, process-overlap theory (Kovacs & Conway, 2016) and sampling theory (Thomson, 1916) propose that the correlation between cognitive abilities is a result of a multitude of shared mechanisms, not just one. Accordingly, the reason that WMC and Gf overlap is because they both tap multiple of the same cognitive processes. The reason that none of the 3Cs in Chapter 2 significantly related to Gf after their specific variance was partitioned from their shared variance may be because any highly specific WM mechanisms have little or no overlap with Gf. In other words, the mechanisms were too specific to be related to Gf. In contrast, maintenance (the process-general measure in Chapter 2) and Binding (the process-general measure in Chapter 3) were both highly related to Gf. This would be expected to some extent under process-overlap theory and sampling theory, because the more general a measure is, the more likely it is to tap processes that overlap with Gf. Furthermore, the finding from Chapter 4 that neither processing speed nor any of its specific components could explain dedifferentiation could be because no single ability can explain dedifferentiation. Instead, process-overlap theory and sampling theory would predict that dedifferentiation is the result of an age-related increase in the proportion of cognitive processes that WMC and Gf both tap. This possibility aligns with evidence that a larger spread of brain activity accompanies dedifferentiation (Park & Reuter-Lorenz, 2009); if this spread of activation is indicative of more mechanisms being utilized, there would likely be more overlapping processes contributing to fluid cognition.

Alternatively, the current pattern of findings could be explained as an effect of general intelligence (g) in accordance with the common cause theory (Spearman, 1904). Common cause theory posits that performance on cognitive tasks is driven, at least partially, by a single latent factor, g . While conceptually distinct, models of process-overlap theory and sampling theory are statistically equivalent to common cause models; therefore, the current findings can also be interpreted in a common cause framework. Accordingly, the reason that none of the 3Cs-specific variables related to Gf in Chapter 2 is because these variables were too specific to reflect g . Also, the reason that neither processing speed nor any of its specific components could explain dedifferentiation in Chapter 4 was because these measures are not highly reflective of g . Process-general variables (e.g., maintenance and Binding) are highly reflective of g and are, thus, highly related to Gf.

5.3 Strengths, Limitations, and Future Directions

One limitation of this thesis is the lack of any latent variable of attention control. Like binding, attention control is hypothesized to explain the WMC-Gf relationship because both WMC and Gf are dependent on attention control. Specifically, the disengagement hypothesis proposes that attention control supports the maintenance of representations in WM and the disengagement from irrelevant information and false hypotheses to the benefit of Gf (Burgoyne & Engle, 2020; Shipstead & Engle, 2013). It would have been useful to establish a latent measure of attention control to further understand the significance of maintenance that this thesis has established. However, Chapters 2 and 4 did include some measures of attention control.

In Chapter 2, the FA pertained to the ability to select representations from WM, which according to the disengagement hypothesis, supports their maintenance. As such, we would have expected to see the shared variance among the 3Cs 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

GENERAL DISCUSSION

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.

In Chapter 4, we intended to include a latent variable of attention control in the main analysis, but this latent variable could not be established in older age groups. Other research has also struggled to identify attention control as a latent variable (Hull et al., 2008; Rey-Mermet et al., 2018; von Bastian et al., 2020), especially in older ages (Miyake & Friedman, 2012). Surprisingly, the baseline CFA (aggregated across age) revealed a negative relationship between attention control and both processing speed and Gf along with no relationship with WMC, even though attention control is typically positively correlated with each of these abilities (Friedman & Miyake, 2017; Salthouse, 1996; Unsworth & Spillers, 2010). This finding may be influenced by the lack of stability of attention control across age groups, but also speaks to the findings that question the plausibility of attention control as a common factor of WM and Gf.

One methodological strength of this thesis was the use of network analysis along with latent-variable modeling to uncover relationships that are often overlooked. By estimating relationships while statistically accounting for all other variables without a priori defined structures, this approach revealed patterns of relationships that traditional models often obscure. For example, the network analysis in Chapter 3 revealed an unexpected pathway between temporal binding and Gf, via relational representation. Moreover, binding maintenance was found to only relate to the other binding abilities via Gf – a surprising finding given that these binding abilities were all assumed to be related due to their usage of bindings, not Gf.

Future research should continue to utilize psychometric network models to explore and test precise models of cognitive abilities. The recent development of confirmatory network modeling, for instance, now provides a method to rigorously test precisely defined structural networks (Du et al., 2025; Epskamp et al., 2017). Because psychometric network models can map complex webs of partial correlations between cognitive abilities – differentiating unique, direct relationships from indirect relationships while controlling for

the entire measured system – these models permit complex specifications necessary to more accurately represent the complexity of human cognition. Moreover, psychometric network models are uniquely suited to investigate systematicity, the efficiency with which the cognitive system functions, by estimating metrics, such as network density or global connectivity, which are representative of system-wide efficiency. These methods are similar to those from Chapter 4 that were used to measure dedifferentiation which provided an indication of system interconnectivity. Current common approaches focus on individual cognitive abilities and their relationships, but examining system-wide interactions may be crucial for advancing theories of cognition.

5.4 Conclusion

The aim of this PhD thesis was to advance understanding of the overlap between WM and Gf and how it changes across adulthood using methods that extract shared variance among cognitive abilities to isolate unique variances specific to their underlying mechanisms. Across three studies, we found no single ability that, when isolated, could account for the relationship between WM and Gf in younger adulthood through to older adulthood; however, maintenance and Binding emerged as powerful predictors of WMC and Gf. The shared variance among the 3Cs of WM was highly related to WMC and Gf, but none of the variance specific to the individual components were related to Gf. While individual differences in binding interference were limited, other binding abilities, especially binding maintenance, were found to be strongly correlated with Gf. Moreover, each binding ability (apart from temporal binding) uniquely related to Gf in a latent network analysis, while their shared variance was statistically indistinguishable from Gf. In an examination of the relationship between WM and Gf from younger adulthood into older adulthood, processing speed, drift rate, non-decision time, and boundary separation were unable to account for the increase in the partial correlation between WMC and Gf. Collectively, the research presented challenges single-mechanism theories of fluid cognition and highlights the utility of network models in mapping cognitive relationships.

REFERENCES

- Ackerman, P. L., Beier, M. E., & Boyle, M. D. (2002). Individual differences in working memory within a nomological network of cognitive and perceptual speed abilities. *Journal of Experimental Psychology: General*, 131(4), 567.
- Ackerman, P. L., Beier, M. E., & Boyle, M. O. (2005). Working memory and intelligence: The same or different constructs? *Psychological Bulletin*, 131(1), 30. <https://doi.org/10.1037/0033-2909.131.1.30>
- Adler, N. E., Epel, E. S., Castellazzo, G., & Ickovics, J. R. (2000). Relationship of subjective and objective social status with psychological and physiological functioning: Preliminary data in healthy, White women. *Health Psychology*, 19(6), 586–592. <https://doi.org/10.1037/0278-6133.19.6.586>
- Akaike, H. (1987). Factor analysis and AIC. *Psychometrika*, 52(3), 317–332. <https://doi.org/10.1007/BF02294359>
- Alloway, T. P., & Alloway, R. G. (2010). Investigating the predictive roles of working memory and IQ in academic attainment. *Journal of Experimental Child Psychology*, 106(1), 20–29. <https://doi.org/10.1016/j.jecp.2009.11.003>
- Andrews, G., & Halford, G. S. (1998). Children's ability to make transitive inferences: The importance of premise integration and structural complexity. *Cognitive Development*, 13(4), 479–513. [https://doi.org/10.1016/S0885-2014\(98\)90004-1](https://doi.org/10.1016/S0885-2014(98)90004-1)
- Andrews, G., Halford, G. S., Bunch, K. M., Bowden, D., & Jones, T. (2003). Theory of Mind and Relational Complexity. *Child Development*, 74(5), 1476–1499. <https://doi.org/10.1111/1467-8624.00618>
- Apšvalka, D., Cross, E. S., & Ramsey, R. (2019). Fluid intelligence and working memory support dissociable aspects of learning by physical but not observational practice. *Cognition*, 190, 170–183. <https://doi.org/10.1016/j.cognition.2019.04.015>
- Arthur, W., & Day, D. V. (1994). Development of a Short form for the Raven Advanced Progressive Matrices Test. *Educational and Psychological Measurement*, 54(2), 394–403. <https://doi.org/10.1177/0013164494054002013>

GENERAL DISCUSSION

- Arthur Jr., W., Tubre, T. C., Paul, D. S., & Sanchez-Ku, M. L. (1999). College-Sample Psychometric and Normative Data on a Short Form of the Raven Advanced Progressive Matrices Test. *Journal of Psychoeducational Assessment, 17*(4), 354–361.
<https://doi.org/10.1177/073428299901700405>
- Baltes, P. B., & Lindenberger, U. (1997). Emergence of a powerful connection between sensory and cognitive functions across the adult life span: A new window to the study of cognitive aging? *Psychology and Aging, 12*(1), 12.
- Bartsch, L. M., & Oberauer, K. (2023). The contribution of episodic long-term memory to working memory for bindings. *Cognition, 231*, 105330.
<https://doi.org/10.1016/j.cognition.2022.105330>
- Bartsch, L. M., & Shepherdson, P. (2022). Chunking, boosting, or offloading? Using serial position to investigate long-term memory's enhancement of verbal working memory performance. *Attention, Perception, & Psychophysics*. <https://doi.org/10.3758/s13414-022-02625-w>
- Bateman, J. E., & Birney, D. P. (2019). The link between working memory and fluid intelligence is dependent on flexible bindings, not systematic access or passive retention. *Acta Psychologica, 199*, 102893. <https://doi.org/10.1016/j.actpsy.2019.102893>
- Bloom, D. E., Canning, D., & Lubet, A. (2015). Global Population Aging: Facts, Challenges, Solutions & Perspectives. *Daedalus, 144*(2), 80–92. https://doi.org/10.1162/DAED_a_00332
- Borsboom, D., Deserno, M. K., Rhemtulla, M., Epskamp, S., Fried, E. I., McNally, R. J., Robinaugh, D. J., Perugini, M., Dalege, J., Costantini, G., Isvoranu, A.-M., Wysocki, A. C., Van Borkulo, C. D., Van Bork, R., & Waldorp, L. J. (2021). Network analysis of multivariate data in psychological science. *Nature Reviews Methods Primers, 1*(1).
<https://doi.org/10.1038/s43586-021-00055-w>
- Botella, J., Barriopedro, M., & Suero, M. (2001). A model of the formation of illusory conjunctions in the time domain. *Journal of Experimental Psychology: Human Perception and Performance, 27*(6), 1452.

GENERAL DISCUSSION

- Brady, T. F., Konkle, T., Gill, J., Oliva, A., & Alvarez, G. A. (2013). Visual Long-Term Memory Has the Same Limit on Fidelity as Visual Working Memory. *Psychological Science*, 24(6), 981–990. <https://doi.org/10.1177/0956797612465439>
- Burgoyne, A. P., & Engle, R. W. (2020). Attention Control: A Cornerstone of Higher-Order Cognition. *Current Directions in Psychological Science*, 29(6), 624–630. <https://doi.org/10.1177/0963721420969371>
- Camos, V., Mora, G., Oftinger, A.-L., Mariz Elsig, S., Schneider, P., & Vergauwe, E. (2019). Does semantic long-term memory impact refreshing in verbal working memory? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 45(9), 1664–1682. <https://doi.org/10.1037/xlm0000657>
- Carretti, B., Borella, E., Cornoldi, C., & De Beni, R. (2009). Role of working memory in explaining the performance of individuals with specific reading comprehension difficulties: A meta-analysis. *Learning and Individual Differences*, 19(2), 246–251. <https://doi.org/10.1016/j.lindif.2008.10.002>
- Carroll, J. B. (1993). *Human Cognitive Abilities: A Survey of Factor-Analytic Studies*. Cambridge University Press.
- Chuderski, A. (2014). The relational integration task explains fluid reasoning above and beyond other working memory tasks. *Memory & Cognition*, 42(3), 448–463.
- Chuderski, A. (2019). Even a single trivial binding of information is critical for fluid intelligence. *Intelligence*, 77, 101396. <https://doi.org/10.1016/j.intell.2019.101396>
- Chuderski, A. (2022). Fluid Intelligence Emerges from Representing Relations. *Journal of Intelligence*, 10(3), 51. <https://doi.org/10.3390/jintelligence10030051>
- Chuderski, A., Taraday, M., Nęcka, E., & Smoleń, T. (2012). Storage capacity explains fluid intelligence but executive control does not. *Intelligence*, 40(3), 278–295. <https://doi.org/10.1016/j.intell.2012.02.010>
- Chun, M. M. (1997). Temporal binding errors are redistributed by the attentional blink. *Perception & Psychophysics*, 59(8), 1191–1199. <https://doi.org/10.3758/BF03214207>

GENERAL DISCUSSION

- Colom, R., Abad, F. J., Quiroga, M. Á., Shih, P. C., & Flores-Mendoza, C. (2008). Working memory and intelligence are highly related constructs, but why? *Intelligence*, 36(6), 584–606.
<https://doi.org/10.1016/j.intell.2008.01.002>
- Colom, R., Chuderski, A., & Santarnecchi, E. (2016). Bridge Over Troubled Water: Commenting on Kovacs and Conway's Process Overlap Theory. *Psychological Inquiry*, 27(3), 181–189.
<https://doi.org/10.1080/1047840x.2016.1181513>
- Conway, A. R. A., Kane, M. J., Bunting, M. F., Hambrick, D. Z., Wilhelm, O., & Engle, R. W. (2005). Working memory span tasks: A methodological review and user's guide. *Psychonomic Bulletin & Review*, 12(5), 769–786. <https://doi.org/10.3758/bf03196772>
- Cowan, N. (1988). Evolving conceptions of memory storage, selective attention, and their mutual constraints within the human information-processing system. *Psychological Bulletin*, 104, 163–191. <https://doi.org/10.1037/0033-2909.104.2.163>
- Cowan, N. (1999). An Embedded-Processes Model of Working Memory. In A. Miyake & P. Shah (Eds.), *Models of Working Memory: Mechanisms of Active Maintenance and Executive Control* (pp. 62–101). Cambridge University Press.
- Cowan, N. (2010). The Magical Mystery Four. *Current Directions in Psychological Science*, 19(1), 51–57. <https://doi.org/10.1177/0963721409359277>
- Cowan, N., Fristoe, N. M., Elliott, E. M., Brunner, R. P., & Saults, J. S. (2006). Scope of attention, control of attention, and intelligence in children and adults. *Memory & Cognition*, 34(8), 1754–1768. <https://doi.org/10.3758/bf03195936>
- Czaja, S. J., Charness, N., Fisk, A. D., Hertzog, C., Nair, S. N., Rogers, W. A., & Sharit, J. (2006). Factors predicting the use of technology: Findings from the center for research and education on aging and technology enhancement (create). *Psychology and Aging*, 21(2), 333–352.
<https://doi.org/10.1037/0882-7974.21.2.333>
- Daneman, M., & Carpenter, P. A. (1980). Individual differences in working memory and reading. *Journal of Verbal Learning and Verbal Behavior*, 19(4), 450–466.
[https://doi.org/10.1016/S0022-5371\(80\)90312-6](https://doi.org/10.1016/S0022-5371(80)90312-6)

GENERAL DISCUSSION

- Daneman, M., & Merikle, P. M. (1996). Working memory and language comprehension: A meta-analysis. *Psychonomic Bulletin & Review*, 3(4), 422–433.
<https://doi.org/10.3758/BF03214546>
- de Frias, C. M., Dixon, R. A., & Strauss, E. (2009). Characterizing executive functioning in older special populations: From cognitively elite to cognitively impaired. *Neuropsychology*, 23(6), 778–791. <https://doi.org/10.1037/a0016743>
- de Frias, C. M., Lövdén, M., Lindenberger, U., & Nilsson, L.-G. (2007). Revisiting the dedifferentiation hypothesis with longitudinal multi-cohort data. *Intelligence*, 35(4), 381–392.
<https://doi.org/10.1016/j.intell.2006.07.011>
- De Simoni, C., & von Bastian, C. C. (2018a). Working memory updating and binding training: Bayesian evidence supporting the absence of transfer. *Journal of Experimental Psychology: General*, 147(6), 829. <https://doi.org/10.1037/pag0000206>
- De Simoni, C., & von Bastian, C. C. (2018b). Working memory updating and binding training: Bayesian evidence supporting the absence of transfer. *Journal of Experimental Psychology: General*, 147(6), 829–858. <https://doi.org/10.1037/xge0000453>
- Draheim, C., Mashburn, C. A., Martin, J. D., & Engle, R. W. (2019). Reaction time in differential and developmental research: A review and commentary on the problems and alternatives. *Psychological Bulletin*, 145(5), 508.
- Du, X., Skjerdingsstad, N., Freichel, R., Ebrahimi, O. V., Hoekstra, R. H. A., & Epskamp, S. (2025). Moving from exploratory to confirmatory network analysis: An evaluation of structural equation modeling fit indices and cutoff values in network psychometrics. *Psychological Methods*. <https://doi.org/10.1037/met0000760>
- Dully, J., McGovern, D. P., & O'Connell, R. G. (2018). The impact of natural aging on computational and neural indices of perceptual decision making: A review. *Behavioural Brain Research, SI: MCC 2016*, 355, 48–55. <https://doi.org/10.1016/j.bbr.2018.02.001>
- Ecker, U. K. H., Lewandowsky, S., & Oberauer, K. (2014). Removal of information from working memory: A specific updating process. *Journal of Memory and Language*, 74, 77–90.
<https://doi.org/10.1016/j.jml.2013.09.003>

GENERAL DISCUSSION

- Ekstrom, R. B., French, J. W., Harman, H. H., & Dermen, D. (1976). Manual for kit of factor-referenced tests. *Princeton, NJ: Educational Testing Service*, 586, 1989–1995.
- Engle, R. W. (2002). Working Memory Capacity as Executive Attention. *Current Directions in Psychological Science*, 11(1), 19–23. <https://doi.org/10.1111/1467-8721.00160>
- Engle, R. W. (2018). Working Memory and Executive Attention: A Revisit. *Perspectives on Psychological Science*, 13(2), 190–193. <https://doi.org/10.1177/1745691617720478>
- Engle, R. W., Tuholski, S. W., Laughlin, J. E., & Conway, A. R. A. (1999). Working memory, short-term memory, and general fluid intelligence: A latent-variable approach. *Journal of Experimental Psychology: General*, 128(3), 309–331. <https://doi.org/10.1037/0096-3445.128.3.309>
- Epskamp, S. (2020). *Psychonetrics: Structural equation modeling and confirmatory network analysis* [Computer software].
- Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, 50(1), 195–212. <https://doi.org/10.3758/s13428-017-0862-1>
- Epskamp, S., Cramer, A. O., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software*, 48, 1–18.
- Epskamp, S., Rhemtulla, M., & Borsboom, D. (2017). Generalized Network Psychometrics: Combining Network and Latent Variable Models. *Psychometrika*, 82(4), 904–927. <https://doi.org/10.1007/s11336-017-9557-x>
- Fandakova, Y., Sander, M. C., Werkle-Bergner, M., & Shing, Y. L. (2014). Age Differences in Short-Term Memory Binding Are Related to Working Memory Performance Across the Lifespan. *Psychol Aging*, 29(1), 140–149. <https://doi.org/10.1037/a0035347>
- Forsberg, A., Guitard, D., Adams, E. J., Pattanakul, D., & Cowan, N. (2022). Children’s long-term retention is directly constrained by their working memory capacity limitations. *Developmental Science*, 25(2). <https://doi.org/10.1111/desc.13164>

GENERAL DISCUSSION

- Forsberg, A., Guitard, D., Adams, E. J., Pattanakul, D., & Cowan, N. (2023). Working Memory Constrains Long-Term Memory in Children and Adults: Memory of Objects and Bindings. *Journal of Intelligence*, 11(5), 94. <https://doi.org/10.3390/jintelligence11050094>
- Fougnie, D., & Alvarez, G. A. (2011). Object features fail independently in visual working memory: Evidence for a probabilistic feature-store model. *Journal of Vision*, 11(12), 3–3.
- Friedman, N. P., & Miyake, A. (2017). Unity and diversity of executive functions: Individual differences as a window on cognitive structure. *Cortex, Is a “Single” Brain Model Sufficient?*, 86, 186–204. <https://doi.org/10.1016/j.cortex.2016.04.023>
- Friedman, N. P., Miyake, A., Corley, R. P., Young, S. E., Defries, J. C., & Hewitt, J. K. (2006). Not All Executive Functions Are Related to Intelligence. *Psychological Science*, 17(2), 172–179. <https://doi.org/10.1111/j.1467-9280.2006.01681.x>
- Friedman, N. P., Miyake, A., Robinson, J. L., & Hewitt, J. K. (2011). Developmental trajectories in toddlers’ self-restraint predict individual differences in executive functions 14 years later: A behavioral genetic analysis. *Developmental Psychology*, 47(5), 1410–1430. <https://doi.org/10.1037/a0023750>
- Friedman, N. P., Miyake, A., Young, S. E., Defries, J. C., Corley, R. P., & Hewitt, J. K. (2008). Individual differences in executive functions are almost entirely genetic in origin. *Journal of Experimental Psychology: General*, 137(2), 201–225. <https://doi.org/10.1037/0096-3445.137.2.201>
- Frischkorn, G. T., Schubert, A.-L., & Hagemann, D. (2019). Processing speed, working memory, and executive functions: Independent or inter-related predictors of general intelligence. *Intelligence*, 75, 95–110. <https://doi.org/10.1016/j.intell.2019.05.003>
- Frischkorn, G. T., Von Bastian, C. C., Souza, A. S., & Oberauer, K. (2022). Individual differences in updating are not related to reasoning ability and working memory capacity. *Journal of Experimental Psychology: General*, 151(6), 1341.
- Garvey, W. F., Hao, H., Conway, A., Forsberg, A., & von Bastian, C. C. (2026). *Individual differences in the three embedded components of working memory and their relation to fluid intelligence*. PsyArXiv. https://doi.org/10.31234/osf.io/2tf4n_v1

GENERAL DISCUSSION

- Ghisletta, P., & Lindenberger, U. (2003). Static and Dynamic Longitudinal Structural Analyses of Cognitive Changes in Old Age. *Gerontology*, 50(1), 12–16.
<https://doi.org/10.1159/000074383>
- Goodwin, G. P., & Johnson-Laird, P. N. (2005). Reasoning about relations. *Psychological Review*, 112(2), 468–493. <https://doi.org/10.1037/0033-295X.112.2.468>
- Guerra-Carrillo, B., Katovich, K., & Bunge, S. A. (2017). Does higher education hone cognitive functioning and learning efficacy? Findings from a large and diverse sample. *PLOS ONE*, 12(8), e0182276. <https://doi.org/10.1371/journal.pone.0182276>
- Hedge, C., Powell, G., & Sumner, P. (2018). The reliability paradox: Why robust cognitive tasks do not produce reliable individual differences. *Behavior Research Methods*, 50(3), 1166–1186.
<https://doi.org/10.3758/s13428-017-0935-1>
- Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *Behavioral and Brain Sciences*, 33(2–3), 61–83. <https://doi.org/10.1017/s0140525x0999152x>
- Henson, R. N. A., Norris, D. G., Page, M. P. A., & Baddeley, A. D. (1996). Unchained Memory: Error Patterns Rule out Chaining Models of Immediate Serial Recall. *The Quarterly Journal of Experimental Psychology*, 49(1), 80–115. <https://doi.org/10.1080/713755612>
[info:doi/10.1080/713755612](https://doi.org/10.1080/713755612)
- Hertzog, C. (1989). Influences of cognitive slowing on age differences in intelligence. *Developmental Psychology*, 25(4), 636–651. <https://doi.org/10.1037/0012-1649.25.4.636>
- Hildebrandt, A., Lüdtke, O., Robitzsch, A., Sommer, C., & Wilhelm, O. (2016). Exploring Factor Model Parameters across Continuous Variables with Local Structural Equation Models. *Multivariate Behavioral Research*, 51(2–3), 257–258.
<https://doi.org/10.1080/00273171.2016.1142856>
- Himi, S. A., Stadler, M., von Bastian, C. C., Bühner, M., & Hilbert, S. (2023). Limits of near transfer: Content- and operation-specific effects of working memory training. *Journal of Experimental Psychology: General*, 152(5), 1305–1333. <https://doi.org/10.1037/xge0001328>

GENERAL DISCUSSION

- Hofer, S. M., & Sliwinski, M. J. (2001). Understanding Ageing: An Evaluation of Research Designs for Assessing the Interdependence of Ageing-Related Changes. *Gerontology*, 47(6), 341–352. <https://doi.org/10.1159/000052825>
- Hu, L.-T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55. <https://doi.org/10.1080/10705519909540118>
- Hull, R., Martin, R. C., Beier, M. E., Lane, D., & Hamilton, A. C. (2008). Executive function in older adults: A structural equation modeling approach. *Neuropsychology*, 22(4), 508–522. <https://doi.org/10.1037/0894-4105.22.4.508>
- Hultsch, D. F., Hertzog, C., & Dixon, R. A. (1990). Ability correlates of memory performance in adulthood and aging. *Psychology and Aging*, 5(3), 356–368. <https://doi.org/10.1037/0882-7974.5.3.356>
- Hülür, G., Ram, N., Willis, S. L., Schaie, K. W., & Gerstorf, D. (2015). Cognitive dedifferentiation with increasing age and proximity of death: Within-person evidence from the Seattle Longitudinal Study. *Psychology and Aging*, 30(2), 311–323. <https://doi.org/10.1037/a0039260>
- Jäger, A. O., Süß, H.-M., & Beauducel, A. (1997). *Berliner Intelligenzstruktur-Test: BIS-Test*.
- Jaroslawska, A. J., Gathercole, S. E., Allen, R. J., & Holmes, J. (2016). Following instructions from working memory: Why does action at encoding and recall help? *Memory & Cognition*, 44(8), 1183–1191. <https://doi.org/10.3758/s13421-016-0636-5>
- Jastrzębski, J., Ociepka, M., & Chuderski, A. (2020). Fluid reasoning is equivalent to relation processing. *Intelligence*, 82, 101489. <https://doi.org/10.1016/j.intell.2020.101489>
- Kane, M. J., Hambrick, D. Z., & Conway, A. R. A. (2005). Working Memory Capacity and Fluid Intelligence Are Strongly Related Constructs: Comment on Ackerman, Beier, and Boyle (2005). *Psychological Bulletin*, 131(1), 66–71. <https://doi.org/10.1037/0033-2909.131.1.66>
- Kane, M. J., Hambrick, D. Z., Tuholski, S. W., Wilhelm, O., Payne, T. W., & Engle, R. W. (2004). The Generality of Working Memory Capacity: A Latent-Variable Approach to Verbal and

GENERAL DISCUSSION

- Visuospatial Memory Span and Reasoning. *Journal of Experimental Psychology: General*, 133(2), 189–217.
- Karr, J. E., Rodriguez, J. E., Goh, P. K., Martel, M. M., & Rast, P. (2022). The unity and diversity of executive functions: A network approach to life span development. *Developmental Psychology*, 58(4), 751.
- Keye, D., Wilhelm, O., Oberauer, K., & Ravenzwaaij, D. (2009). Individual differences in conflict-monitoring: Testing means and covariance hypothesis about the Simon and the Eriksen Flanker task. *Psychological Research Psychologische Forschung*, 73(6), 762–776.
<https://doi.org/10.1007/s00426-008-0188-9>
- Klauer, K. J. (1996). Teaching inductive reasoning: Some theory and three experimental studies. *Learning and Instruction*, 6(1), 37–57. [https://doi.org/10.1016/S0959-4752\(96\)80003-X](https://doi.org/10.1016/S0959-4752(96)80003-X)
- Kline, R. B. (2015). *Principles and Practice of Structural Equation Modeling*. Guilford Publications.
- Konkle, T., Brady, T. F., Alvarez, G. A., & Oliva, A. (2010). Scene Memory Is More Detailed Than You Think: The Role of Categories in Visual Long-Term Memory. *Psychological Science*, 21(11), 1551–1556. <https://doi.org/10.1177/0956797610385359>
- Kovacs, K., & Conway, A. R. A. (2016). Process Overlap Theory: A Unified Account of the General Factor of Intelligence. *Psychological Inquiry*, 27(3), 151–177.
<https://doi.org/10.1080/1047840x.2016.1153946>
- Kyllonen, P. C., & Christal, R. E. (1990). Reasoning ability is (little more than) working-memory capacity?! *Intelligence*, 14(4), 389–433. [https://doi.org/10.1016/S0160-2896\(05\)80012-1](https://doi.org/10.1016/S0160-2896(05)80012-1)
- La Fleur, C.-G., Meyer, M. J., & Dodson, C. (2018). Exploring Dedifferentiation Across the Adult Lifespan. *Psychology and Aging*, 33(5), 855–870. <https://doi.org/10.1037/pag0000274>
- Lachman, M. E. (2004). Development in Midlife. *Annual Review of Psychology*, 55(Volume 55, 2004), 305–331. <https://doi.org/10.1146/annurev.psych.55.090902.141521>
- Lerche, V., von Krause, M., Voss, A., Frischkorn, G. T., Schubert, A.-L., & Hagemann, D. (2020). Diffusion modeling and intelligence: Drift rates show both domain-general and domain-

GENERAL DISCUSSION

specific relations with intelligence. *Journal of Experimental Psychology: General*, 149(12), 2207.

Lin, H.-Y., & Oberauer, K. (2019). How to Say No in Recognition Tests of Visual Working Memory: Testing Unidimensional and Two-Dimensional Models With Continuous or Discrete Memory States. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, 45(12), 2123–2146. <https://doi.org/10.1037/xlm0000700>

Lindenberger, U., Mayr, U., & Kliegl, R. (1993). Speed and intelligence in old age. *Psychology and Aging*, 8(2), 207–220. <https://doi.org/10.1037/0882-7974.8.2.207>

Loaiza, V. M., & Souza, A. S. (2024). Active maintenance in working memory reinforces bindings for future retrieval from episodic long-term memory. *Memory & Cognition*, 52(8), 1999–2021. <https://doi.org/10.3758/s13421-024-01596-7>

McElree, B. (1998). Attended and Non-Attended States in Working Memory: Accessing Categorized Structures. *Journal of Memory and Language*, 38(2), 225–252. <https://doi.org/10.1006/jmla.1997.2545>

Menu, I., Borst, G., & Cachia, A. (2024). Latent network analysis of executive functions across development. *Journal of Cognition*, 7(1), 31. <https://doi.org/10.5334/joc.355>

Merkle, E. C., Fitzsimmons, E., Uanhoro, J., & Goodrich, B. (2021). Efficient Bayesian Structural Equation Modeling in Stan. *Journal of Statistical Software*, 100, 1–22. <https://doi.org/10.18637/jss.v100.i06>

Miyake, A., & Friedman, N. P. (2012). The nature and organization of individual differences in executive functions: Four general conclusions. *Current Directions in Psychological Science*, 21(1), 8–14. <https://doi.org/10.1177/0963721411429458>

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The Unity and Diversity of Executive Functions and Their Contributions to Complex “Frontal Lobe” Tasks: A Latent Variable Analysis. *Cognitive Psychology*, 41(1), 49–100. <https://doi.org/10.1006/cogp.1999.0734>

GENERAL DISCUSSION

- Miyake, A., Friedman, N. P., Rettinger, D. A., Shah, P., & Hegarty, M. (2001). How are visuospatial working memory, executive functioning, and spatial abilities related? A latent-variable analysis. *Journal of Experimental Psychology: General*, 130(4), 621.
- Mızrak, E., & Oberauer, K. (2022). Working memory recruits long-term memory when it is beneficial: Evidence from the Hebb effect. *Journal of Experimental Psychology: General*, 151(4), 763–780. <https://doi.org/10.1037/xge0000934>
- 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(11), 1071–1077. <https://doi.org/10.1111/j.1467-9280.2008.02202.x>
- Navarro, E., Hao, H., Rosales, K. P., & Conway, A. R. A. (2023). An item response theory approach to the measurement of working memory capacity. *Behavior Research Methods*, 56(3), 1697–1714. <https://doi.org/10.3758/s13428-023-02115-3>
- Naveh-Benjamin, M. (2000). Adult age differences in memory performance: Tests of an associative deficit hypothesis. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 26(5), 1170–1187. <https://doi.org/10.1037/0278-7393.26.5.1170>
- Oberauer, K. (1993). Die Koordination kognitiver Operationen—Eine Studie über die Beziehung zwischen Intelligenz und "working memory.". *Zeitschrift Für Psychologie Mit Zeitschrift Für Angewandte Psychologie*.
- Oberauer, K. (2002). Access to information in working memory: Exploring the focus of attention. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 28(3), 411.
- Oberauer, K. (2003). Understanding serial position curves in short-term recognition and recall. *Journal of Memory and Language*, 49(4), 469–483. [https://doi.org/10.1016/S0749-596X\(03\)00080-9](https://doi.org/10.1016/S0749-596X(03)00080-9)
- Oberauer, K. (2005). Binding and Inhibition in Working Memory: Individual and Age Differences in Short-Term Recognition. *Journal of Experimental Psychology: General*, 134(3), 368–387. <https://doi.org/10.1037/0096-3445.134.3.368>

GENERAL DISCUSSION

- Oberauer, K. (2008). How to say no: Single- and dual-process theories of short-term recognition tested on negative probes. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 34(3), 439–459. <https://doi.org/10.1037/0278-7393.34.3.439>
- Oberauer, K. (2009). Design for a Working Memory. In *The Psychology of Learning and Motivation: Advances in Research and Theory* (51st ed., pp. 45–100). Elsevier.
- Oberauer, K. (2019). Working Memory Capacity Limits Memory for Bindings. *Journal of Cognition*, 2(1), 40. <https://doi.org/10.5334/joc.86>
- Oberauer, K., Farrell, S., Jarrold, C., & Lewandowsky, S. (2016). What limits working memory capacity? *Psychological Bulletin*, 142(7), 758.
- Oberauer, K., & Göthe, K. (2006). Dual-task effects in working memory: Interference between two processing tasks, between two memory demands, and between storage and processing. *European Journal of Cognitive Psychology*, 18(4), 493–519. <https://doi.org/10.1080/09541440500423038>
- Oberauer, K., Süß, H. M., Schulze, R., Wilhelm, O., & Wittmann, W. W. (2000). Working memory capacity—Facets of a cognitive ability construct. *Personality and Individual Differences*, 29(6), 1017–1045. [https://doi.org/10.1016/S0191-8869\(99\)00251-2](https://doi.org/10.1016/S0191-8869(99)00251-2)
- Oberauer, K., Süß, H.-M., Wilhelm, O., & Sander, N. (2007). Individual differences in working memory capacity and reasoning ability. *Variation in Working Memory*, 49–75.
- Oberauer, K., Süß, H.-M., Wilhelm, O., & Wittman, W. W. (2003). The multiple faces of working memory: Storage, processing, supervision, and coordination. *Intelligence*, 31(2), 167–193. [https://doi.org/10.1016/S0160-2896\(02\)00115-0](https://doi.org/10.1016/S0160-2896(02)00115-0)
- Oberauer, K., Süß, H.-M., Wilhelm, O., & Wittmann, W. W. (2008). Which working memory functions predict intelligence? *Intelligence*, 36(6), 641–652. <https://doi.org/10.1016/j.intell.2008.01.007>
- Pan, W., Geng, H., Zhang, L., Fengler, A., Frank, M. J., Zhang, R.-Y., & Chuan-Peng, H. (2025). dockerHDDM: A User-Friendly Environment for Bayesian Hierarchical Drift-Diffusion Modeling. *Advances in Methods and Practices in Psychological Science*, 8(1), 25152459241298700. <https://doi.org/10.1177/25152459241298700>

GENERAL DISCUSSION

- Park, D. C., & Reuter-Lorenz, P. (2009). The Adaptive Brain: Aging and Neurocognitive Scaffolding. *Annual Review of Psychology*, 60(Volume 60, 2009), 173–196.
<https://doi.org/10.1146/annurev.psych.59.103006.093656>
- Pashler, H. (1994). Dual-task interference in simple tasks: Data and theory. *Psychological Bulletin*, 116, 220–244. <https://doi.org/10.1037/0033-2909.116.2.220>
- Pertzov, Y., Dong, M. Y., Peich, M.-C., & Husain, M. (2012). Forgetting What Was Where: The Fragility of Object-Location Binding. *PLOS ONE*, 7(10), e48214.
<https://doi.org/10.1371/journal.pone.0048214>
- Posit team. (2024). *RStudio: Integrated Development Environment for R* [Computer software]. Posit Software, PBC. <http://www.posit.co/>
- R Core Team. (2024). *R: A Language and Environment for Statistical Computing* [Computer software]. R Foundation for Statistical Computing. <https://www.R-project.org/>
- Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, 85(2), 59.
- Ratcliff, R., & Childers, R. (2015). Individual differences and fitting methods for the two-choice diffusion model of decision making. *Decision*, 2(4), 237–279.
<https://doi.org/10.1037/dec0000030>
- Ratcliff, R., Thapar, A., & McKoon, G. (2006). Aging and individual differences in rapid two-choice decisions. *Psychonomic Bulletin & Review*, 13(4), 626–635.
<https://doi.org/10.3758/bf03193973>
- Ratcliff, R., Thapar, A., & McKoon, G. (2010). Individual differences, aging, and IQ in two-choice tasks. *Cognitive Psychology*, 60(3), 127–157. <https://doi.org/10.1016/j.cogpsych.2009.09.001>
- Raven, J. (1990). *Advanced Progressive Matrices: Sets I, II*. Oxford Psychologists Press.
- Reinhartz, A., Strobach, T., Hyde, E., Jiang, S., Jacobsen, T., Belleville, S., & von Bastian, C. (2026). *The 14-Item Everyday Problems Test (EPT-14): A Revised Assessment Tool for Problem Solving in an Everyday Context* [Manuscript submitted for publication].
- Reuter-Lorenz, P. A., & Park, D. C. (2014). How Does it STAC Up? Revisiting the Scaffolding Theory of Aging and Cognition. *Neuropsychology Review*, 24(3), 355–370.
<https://doi.org/10.1007/s11065-014-9270-9>

GENERAL DISCUSSION

Rey-Mermet, A., Gade, M., & Oberauer, K. (2018). Should we stop thinking about inhibition?

Searching for individual and age differences in inhibition ability. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 44(4), 501–526.

<https://doi.org/10.1037/xlm0000450>

Rey-Mermet, A., Gade, M., Souza, A. S., von Bastian, C. C., & Oberauer, K. (2019). Is executive

control related to working memory capacity and fluid intelligence? *Journal of Experimental Psychology: General*, 148(8), 1335–1372. <https://doi.org/10.1037/xge0000593>

Rey-Mermet, A., Singh, K. A., Gignac, G. E., Brydges, C. R., & Ecker, U. K. H. (2020). Interference control in working memory: Evidence for discriminant validity between removal and

inhibition tasks. *PLOS ONE*, 15(12), e0243053. <https://doi.org/10.1371/journal.pone.0243053>

Robinaugh, D. J., Millner, A. J., & McNally, R. J. (2016). Identifying Highly Influential Nodes in the Complicated Grief Network. *Journal of Abnormal Psychology*, 125(6), 747–757.

<https://doi.org/10.1037/abn0000181>

Robison, M. K., Miller, A. L., Wiemers, E. A., Ellis, D. M., Unsworth, N., Redick, T. S., & Brewer, G. A. (2024). What makes working memory work? A multifaceted account of the predictive power of working memory capacity. *Journal of Experimental Psychology: General*, 153(9), 2193.

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, 48, 1–36.

Rossi, S., Miniussi, C., Pasqualetti, P., Babiloni, C., Rossini, P. M., & Cappa, S. F. (2004). Age-related functional changes of prefrontal cortex in long-term memory: A repetitive transcranial magnetic stimulation study. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, 24(36), 7939–7944. <https://doi.org/10.1523/JNEUROSCI.0703-04.2004>

Salthouse, T. A. (1993). Speed mediation of adult age differences in cognition. *Developmental Psychology*, 29(4), 722–738. <https://doi.org/10.1037/0012-1649.29.4.722>

Salthouse, T. A. (1994). The nature of the influence of speed on adult age differences in cognition. *Developmental Psychology*, 30(2), 240–259. <https://doi.org/10.1037/0012-1649.30.2.240>

GENERAL DISCUSSION

- Salthouse, T. A. (1996). The processing-speed theory of adult age differences in cognition. *Psychological Review*, 103(3), 403.
- Salthouse, T. A. (2004). What and When of Cognitive Aging. *Current Directions in Psychological Science*, 13(4), 140–144. <https://doi.org/10.1111/j.0963-7214.2004.00293.x>
- Salthouse, T. A. (2009). When does age-related cognitive decline begin? *Neurobiology of Aging*, 30(4), 507–514. <https://doi.org/10.1016/j.neurobiolaging.2008.09.023>
- Salthouse, T. A. (2017). Shared and unique influences on age-related cognitive change. *Neuropsychology*, 31(1), 11.
- Salthouse, T. A., & Babcock, R. L. (1991). Decomposing adult age differences in working memory. *Developmental Psychology*, 27(5), 763–776. <https://doi.org/10.1037/0012-1649.27.5.763>
- Salthouse, T. A., & Meinz, E. J. (1995a). Aging, Inhibition, Working Memory, and Speed. *The Journals of Gerontology: Series B*, 50B(6), P297–P306. <https://doi.org/10.1093/geronb/50B.6.P297>
- Salthouse, T. A., & Meinz, E. J. (1995b). Aging, Inhibition, Working Memory, and Speed. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 50B(6), P297–P306. <https://doi.org/10.1093/geronb/50b.6.p297>
- Schaie, K. W., Maitland, S. B., Willis, S. L., & Intrieri, R. C. (1998). Longitudinal invariance of adult psychometric ability factor structures across 7 years. *Psychology and Aging*, 13(1), 8–20. <https://doi.org/10.1037/0882-7974.13.1.8>
- Schmeichel, B. J., Volokhov, R. N., & Demaree, H. A. (2008). Working memory capacity and the self-regulation of emotional expression and experience. *Journal of Personality and Social Psychology*, 95(6), 1526–1540. <https://doi.org/10.1037/a0013345>
- Schmiedek, F., Oberauer, K., Wilhelm, O., Süß, H.-M., & Wittmann, W. W. (2007). Individual differences in components of reaction time distributions and their relations to working memory and intelligence. *Journal of Experimental Psychology: General*, 136(3), 414.
- Schmitz, F., & Wilhelm, O. (2016). Modeling Mental Speed: Decomposing Response Time Distributions in Elementary Cognitive Tasks and Correlations with Working Memory

GENERAL DISCUSSION

- Capacity and Fluid Intelligence. *Journal of Intelligence*, 4(4), 13.
<https://doi.org/10.3390/jintelligence4040013>
- Schubert, A.-L., Hagemann, D., & Frischkorn, G. T. (2017). Is general intelligence little more than the speed of higher-order processing? *Journal of Experimental Psychology: General*, 146(10), 1498.
- Schubert, A.-L., Hagemann, D., Frischkorn, G. T., & Herpertz, S. C. (2018). Faster, but not smarter: An experimental analysis of the relationship between mental speed and mental abilities. *Intelligence*, 71, 66–75. <https://doi.org/10.1016/j.intell.2018.10.005>
- Schubert, A.-L., Hagemann, D., Löffler, C., & Frischkorn, G. T. (2019a). Disentangling the Effects of Processing Speed on the Association between Age Differences and Fluid Intelligence. *Journal of Intelligence*, 8(1). <https://doi.org/10.3390/jintelligence8010001>
- Schubert, A.-L., Hagemann, D., Löffler, C., & Frischkorn, G. T. (2019b). Disentangling the Effects of Processing Speed on the Association between Age Differences and Fluid Intelligence. *Journal of Intelligence*, 8(1). <https://doi.org/10.3390/jintelligence8010001>
- Schubert, A.-L., Löffler, C., Sadus, K., Göttmann, J., Hein, J., Schröer, P., Teuber, A., & Hagemann, D. (2023). Working memory load affects intelligence test performance by reducing the strength of relational item bindings and impairing the filtering of irrelevant information. *Cognition*, 236, 105438. <https://doi.org/10.1016/j.cognition.2023.105438>
- Schubert, A.-L., Nunez, M. D., Hagemann, D., & Vandekerckhove, J. (2019). Individual Differences in Cortical Processing Speed Predict Cognitive Abilities: A Model-Based Cognitive Neuroscience Account. *Computational Brain & Behavior*, 2(2), 64–84.
<https://doi.org/10.1007/s42113-018-0021-5>
- Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, 461–464.
- Shah, P., & Miyake, A. (1996). The separability of working memory resources for spatial thinking and language processing: An individual differences approach. *Journal of Experimental Psychology: General*, 125(1), 4.

GENERAL DISCUSSION

- Sheppard, L. D., & Vernon, P. A. (2008). Intelligence and speed of information-processing: A review of 50 years of research. *Personality and Individual Differences*, 44(3), 535–551.
<https://doi.org/10.1016/j.paid.2007.09.015>
- Shilling, V. M., Chetwynd, A., & Rabbitt, P. M. A. (2002). Individual inconsistency across measures of inhibition: An investigation of the construct validity of inhibition in older adults. *Neuropsychologia*, 40(6), 605–619. [https://doi.org/10.1016/S0028-3932\(01\)00157-9](https://doi.org/10.1016/S0028-3932(01)00157-9)
- Shipstead, Z., & Engle, R. W. (2013). Interference within the focus of attention: Working memory tasks reflect more than temporary maintenance. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 39(1), 277–289. <https://doi.org/10.1037/a0028467>
- Shipstead, Z., Harrison, T. L., & Engle, R. W. (2016). Working memory capacity and fluid intelligence. *Perspectives on Psychological Science*, 11(6), 771–799.
<https://doi.org/10.1177/1745691616650647>
- Simon, J. R. (1969). Reactions toward the source of stimulation. *Journal of Experimental Psychology*, 81(1), 174–176. <https://doi.org/10.1037/h0027448>
- Singh, K. A., Gignac, G. E., Brydges, C. R., & Ecker, U. K. H. (2018). Working memory capacity mediates the relationship between removal and fluid intelligence. *Journal of Memory and Language*, 101, 18–36. <https://doi.org/10.1016/j.jml.2018.03.002>
- Spearman, C. (1904). General intelligence objectively determined and measured. *The American Journal of Psychology*, 15(2), 201–292.
- Stanislaw, H., & Todorov, N. (1999). Calculation of signal detection theory measures. *Behavior Research Methods, Instruments, & Computers*, 31(1), 137–149.
<https://doi.org/10.3758/bf03207704>
- Starns, J. J., & Ratcliff, R. (2010). The effects of aging on the speed–accuracy compromise: Boundary optimality in the diffusion model. *Psychology and Aging*, 25(2), 377–390.
<https://doi.org/10.1037/a0018022>
- Theisen, M., Lerche, V., von Krause, M., & Voss, A. (2021a). Age differences in diffusion model parameters: A meta-analysis. *Psychological Research*, 85(5), 2012–2021.
<https://doi.org/10.1007/s00426-020-01371-8>

GENERAL DISCUSSION

- Theisen, M., Lerche, V., von Krause, M., & Voss, A. (2021b). Age differences in diffusion model parameters: A meta-analysis. *Psychological Research*, 85(5), 2012–2021.
<https://doi.org/10.1007/s00426-020-01371-8>
- Thomson, G. H. (1916). A Hierarchy without a General Factor. *British Journal of Psychology*, 8(3), 271–281.
- Tucker-Drob, E. M., Brandmaier, A. M., & Lindenberger, U. (2019). Coupled cognitive changes in adulthood: A meta-analysis. *Psychological Bulletin*, 145(3), 273.
- Unsworth, N. (2010). On the division of working memory and long-term memory and their relation to intelligence: A latent variable approach. *Acta Psychol (Amst)*, 134(1), 16–28.
<https://doi.org/10.1016/j.actpsy.2009.11.010>
- Unsworth, N. (2016). The Many Facets of Individual Differences in Working Memory Capacity. In B. H. Ross (Ed.), *Psychology of Learning and Motivation* (Vol. 65, pp. 1–46). Academic Press.
- Unsworth, N., Brewer, G. A., & Spillers, G. J. (2009). There's more to the working memory capacity—Fluid intelligence relationship than just secondary memory. *Psychonomic Bulletin & Review*, 16(5), 931–937. <https://doi.org/10.3758/pbr.16.5.931>
- Unsworth, N., & Engle, R. W. (2007). The nature of individual differences in working memory capacity: Active maintenance in primary memory and controlled search from secondary memory. *Psychological Review*, 114, 104–132. <https://doi.org/10.1037/0033-295X.114.1.104>
- Unsworth, N., Miller, A. L., & Robison, M. K. (2020). Are individual differences in attention control related to working memory capacity? A latent variable mega-analysis. *Journal of Experimental Psychology. General*. <https://doi.org/10.1037/xge0001000>
- Unsworth, N., & Spillers, G. J. (2010). Working memory capacity: Attention control, secondary memory, or both? A direct test of the dual-component model. *Journal of Memory and Language*, 62(4), 392–406. <https://doi.org/10.1016/j.jml.2010.02.001>
- Vergauwe, E., Barrouillet, P., & Camos, V. (2009). Visual and spatial working memory are not that dissociated after all: A time-based resource-sharing account. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 35(4), 1012–1028.
<https://doi.org/10.1037/a0015859>

GENERAL DISCUSSION

- Vergauwe, E., von Bastian, C. C., Kostova, R., & Morey, C. C. (2022). Storage and processing in working memory: A single, domain-general resource explains multitasking. *Journal of Experimental Psychology: General*, 151(2), 285–301. <https://doi.org/10.1037/xge0000895>
- Verhaeghen, P., & Salthouse, T. A. (1997). Meta-analyses of age–cognition relations in adulthood: Estimates of linear and nonlinear age effects and structural models. *Psychological Bulletin*, 122(3), 231–249. <https://doi.org/10.1037/0033-2909.122.3.231>
- von Bastian, C. C., Blais, C., Brewer, G. A., Gyurkovics, M., Hedge, C., Kałamała, P., Meier, M. E., Oberauer, K., Rey-Mermet, A., Rouder, J., Souza, A., Bartsch, L. M., Conway, A., Draheim, C., Engle, R., Friedman, N., Frischkorn, G., Gustavson, D., Koch, I., ... Wiemers, E. (2020). *Advancing the understanding of individual differences in attentional control: Theoretical, methodological, and analytical consideration*. PsyArXiv. <https://doi.org/10.31234/osf.io/x3b9k>
- von Bastian, C. C., & Eschen, A. (2016). Does working memory training have to be adaptive? *Psychological Research*, 80(2), 181–194. <https://doi.org/10.1007/s00426-015-0655-z>
- von Bastian, C. C., Langer, N., Jäncke, L., & Oberauer, K. (2013). Effects of working memory training in young and old adults. *Memory & Cognition*, 41(4), 611–624. <https://doi.org/10.3758/s13421-012-0280-7>
- von Bastian, C. C., & Oberauer, K. (2013). Distinct transfer effects of training different facets of working memory capacity. *Journal of Memory and Language*, 69(1), 36–58. <https://doi.org/10.1016/j.jml.2013.02.002>
- von Bastian, C. C., Reinhartz, A., Udale, R. C., Grégoire, S., Essounni, M., Belleville, S., & Strobach, T. (2022). Mechanisms of processing speed training and transfer effects across the adult lifespan: Protocol of a multi-site cognitive training study. *BMC Psychology*, 10(1). <https://doi.org/10.1186/s40359-022-00877-7>
- von Krause, M., Lerche, V., Schubert, A.-L., & Voss, A. (2020). Do Non-Decision Times Mediate the Association between Age and Intelligence across Different Content and Process Domains? *Journal of Intelligence*, 8(3), 33. <https://doi.org/10.3390/jintelligence8030033>

GENERAL DISCUSSION

- Voss, A., Nagler, M., & Lerche, V. (2013). Diffusion models in experimental psychology: A practical introduction. *Experimental Psychology*, 60(6), 385.
- Wiecki, T. V., Sofer, I., & Frank, M. J. (2013). HDDM: Hierarchical Bayesian estimation of the Drift-Diffusion Model in Python. *Frontiers in Neuroinformatics*, 7.
<https://doi.org/10.3389/fninf.2013.00014>
- Wilhelm, O., Hildebrandt, A., & Oberauer, K. (2013). What is working memory capacity, and how can we measure it? *Frontiers in Psychology*, 4, 433.
- Zhao, C., & Vogel, E. K. (2025). Working memory and attentional control abilities predict individual differences in visual long-term memory tasks. *Journal of Memory and Language*, 144, 104665. <https://doi.org/10.1016/j.jml.2025.104665>
- Zivony, A., & Eimer, M. (2023). The temporal dynamics of selective attention are reflected by distractor intrusions. *Scientific Reports*, 13(1). <https://doi.org/10.1038/s41598-022-26902-8>

APPENDIX A

Table A1*Order of Task Administration (Chapter 2)*

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 4*

Task	Description	Content
UW: Word completion (warm-up)	Complete the missing letters in a given list of words.	Verbal

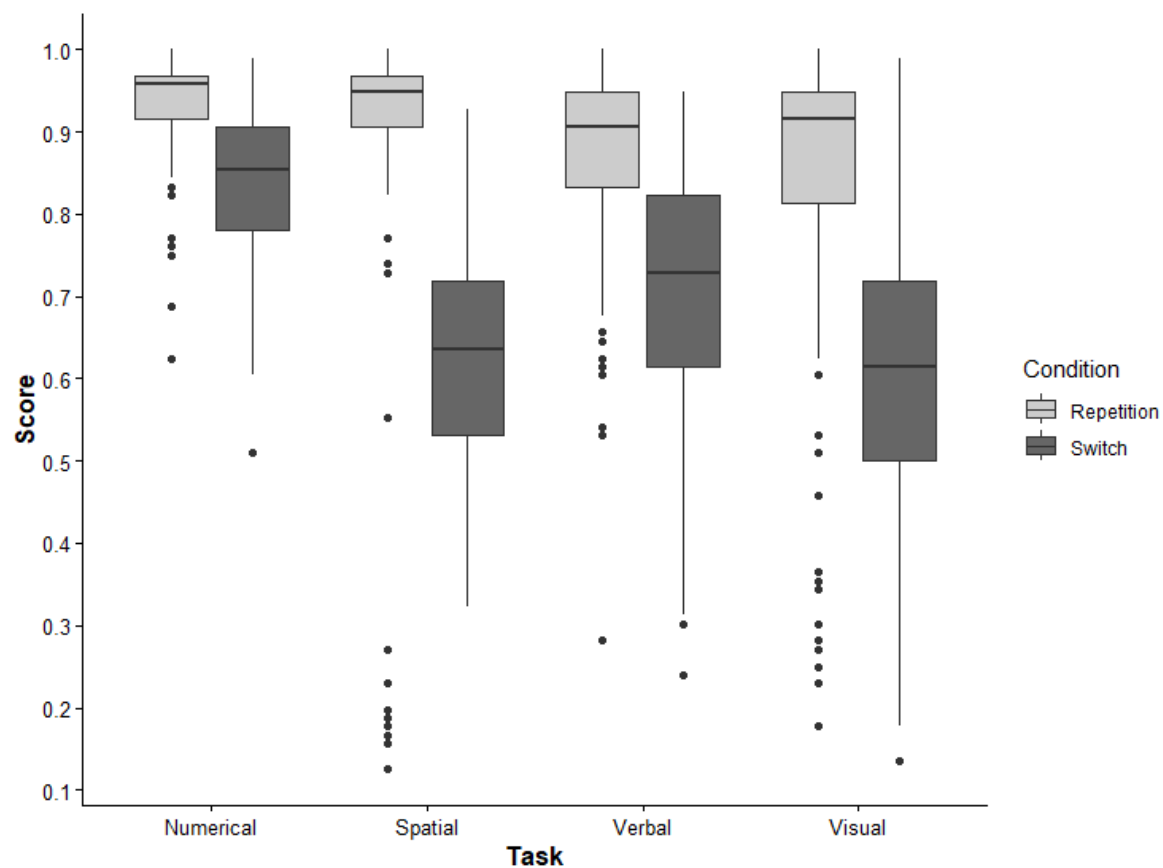
GENERAL DISCUSSION

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 logically 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 Berlin Intelligence-Structure Test 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.

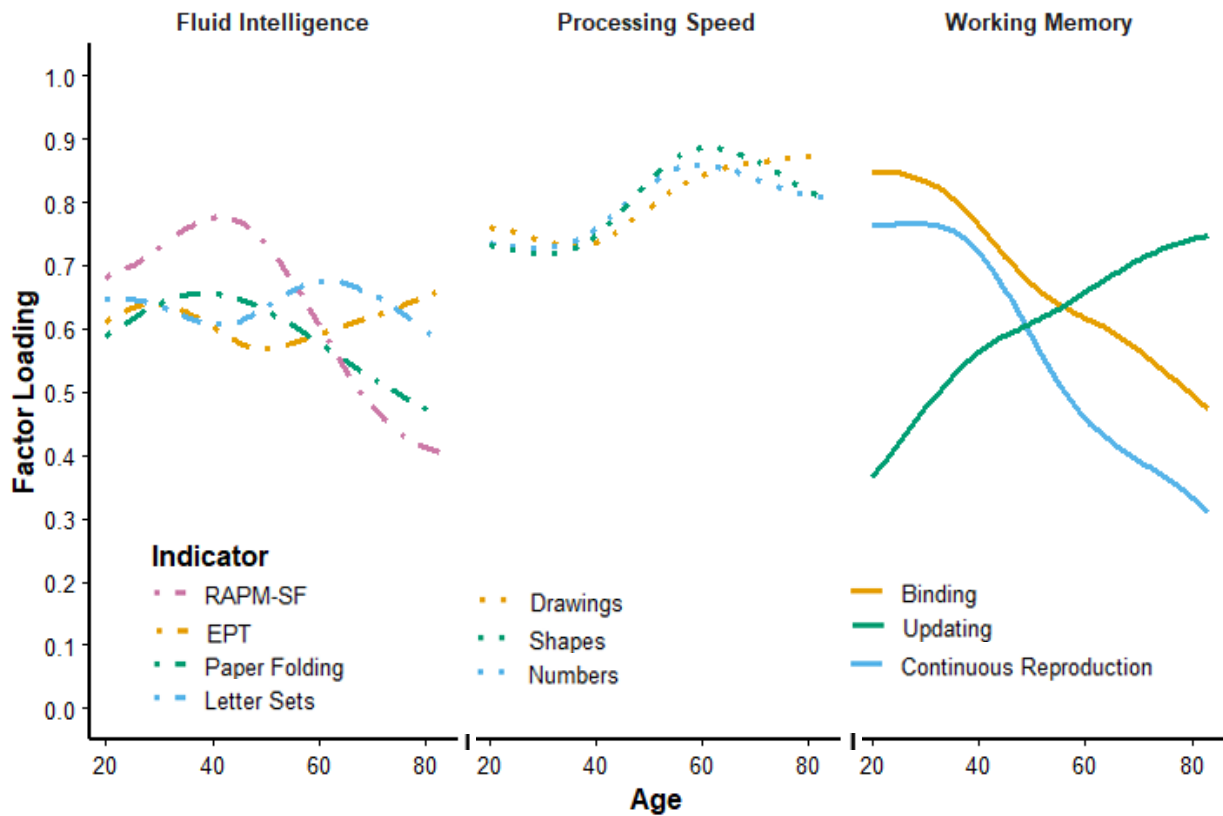
APPENDIX B

Table B1*Order of Task Administration (Chapter 3)*

Block	Paradigm	Material
1	RSVP	Fractals
	Local Recognition	Arrows
	Monitoring	Symbols
	Gf	Locations
	Relational Representation	Fractals
	Associated Pairs	Arrows
2	RSVP	Symbols
	Local Recognition	Fractals
	Monitoring	Arrows
	Gf	Paper Folding
	Relational Representation	Symbols
	Associated Pairs	Fractals
3	RSVP	Arrows
	Local Recognition	Symbols
	Monitoring	Fractals
	Gf	RAPM
	Relational Representation	Arrows
	Associated Pairs	Symbols

Note. Between each block was a break. RSVP = rapid serial visual presentation; Gf = fluid intelligence; RAPM = Raven's Advanced Progressive Matrices – Short Form.

APPENDIX C

Figure C1*Latent Network Model Factor Loadings by Age*

Note. The drift rate, boundary separation, and non-decision time models are identical, because the processing speed components are single-factor indicators and thus each have single loadings of 1. RAPM-SF = Raven's Advanced Progressive Matrices-Short Form; EPT = Everyday Problems Test.