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The Structure of Working Memory: A Review and New View of Psychometric Models

Kevin Pablo Rosales
Claremont Graduate University

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Kevin P. Rosales

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Approval of the Dissertation Committee

This dissertation has been duly read, reviewed, and critiqued by the committee listed below, which hereby approves the manuscript of Kevin P. Rosales as fulfilling the scope and quality of requirements for meriting the degree of Doctor of Philosophy in Psychology.

Andrew A.R.A Conway, Chair

New Mexico State University

Professor of Psychology

Kathy Pezdek

Claremont Graduate University

Professor of Psychology

Gabriel I. Cook

Claremont McKenna College

Associate Professor of Psychology

Kristof Kovacs

Eötvös Loránd University

Professor of School Psychology

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Abstract

Beginning in the 1970s, a great deal of research in cognitive psychology, developmental psychology, psychometrics, and cognitive neuroscience has investigated the structure and function of working memory (WM), defined as the ability to actively maintain and manipulate information in the service of complex cognition (Baddeley & Hitch, 1974). It is well established that WM is a limited capacity system and individual differences in WM capacity are strongly associated with important cognitive abilities and outcomes, such as general intelligence (Engle et al., 1999) and academic achievement (Swanson & Berninger, 1996; Ramirez et al., 2013). For this reason, WM is a central component in most general theories and models of cognition. However, over the years, different researchers have proposed different definitions of WM. This is problematic because researchers who adopt different definitions of WM also tend to administer different kinds of tasks to measure WM capacity, which has produced a pattern of inconsistent results reported throughout the literature. This inconsistency has led to a lack of a consensus in the field regarding how to measure WM capacity and how to determine the "best" psychometric model of the structure of WM capacity. If we look to the most prominent contemporary theories of WM, both cognitive and psychometric, we can identify several different components of WM function that are thought to contribute to individual differences in WM capacity. These include attention control (Engle, 2002), verbal and spatial temporary

memory storage (Kane et al., 2004), and episodic memory retrieval (Unsworth et al., 2014; Oberauer, 2009). Though these components have been shown to contribute to variation in WM capacity, there currently is not a comprehensive psychometric model of WM that includes all of these components. Moreover, most of the research on individual differences in WM capacity has been conducted using traditional latent variable modeling approaches (factor models), which are based on problematic assumptions (Borsboom et al., 2003). More recently, network analysis has emerged as an attractive alternative psychometric modeling approach to study individual differences in cognitive abilities (Kan et al., 2019). Network analysis does not rely on the same problematic assumptions required by latent variable models, and it is more compatible with recent theories of intelligence, namely, Process Overlap theory (POT) (Kovacs & Conway, 2016). POT proposes that broad cognitive abilities reflect multiple cognitive processes that are sampled in an overlapping manner across a range of cognitive tasks. This theoretical framework aligns well with network modeling where abilities are represented as an inter-connected network of multiple cognitive processes.Across two studies in this dissertation, we (1) compared network models to traditional latent variable models of WM capacity, with both types of models designed to include multiple components, namely, attention, verbal storage, spatial storage, and episodic memory retrieval and (2) tested the predictive validity of the models by estimating the correlation between WM capacity and fluid intelligence. The results show that a network model of WM fits the data just as well as a latent variable model, as predicted. However, we did not support the hypothesis that the network model of WM predicts fluid intelligence equally well as the latent variable model. Taken together, the current studies provide new insights into the psychometric structure of WM using the novel technique of network modeling. It is shown that a four-component network model of WM capacity is an accurate and comprehensive depiction of

WM. These results help to integrate cognitive models and psychometric models of WM, which is an important contribution to the field and has implications for research and practice in clinical and educational settings where measuring WM capacity effectively, and interpreting WM test scores properly, is of the utmost importance.

Dedication

This dissertation is dedicated to my parents, Jose, and Nuvia Rosales, and to the rest of my family, friends, and mentors. To my graduate advisor Andrew Conway, for his constant guidance and teachings that molded the scholar and researcher I am today. To all my additional mentors, Kathy Pezdek, Gabriel Cook, Kristof Kovacs, and Eugene Wong for their immense contributions to my learning and growth as a person and scholar. To my loved one, J.V. for the unending support you have cherished me with. Thank you all for all the unconditional support and guidance that you have provided to me. We have accomplished this unprecedented milestone together. Thank you to God for giving me the day-to-day strength and wisdom to persevere in this journey. This is also for the future generations of my family to come, that they may see this accomplishment as an inspiration and catalyst to achieve their own goals and aspirations. I am hopeful that this accomplishment shapes the future of those generations. Thank you for enduring this journey with me. We have closed this chapter of my professional and academic journey and now move onto the next.

With love,

Kevin

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The Structure of Working Memory: A Review and New View of Psychometric Models

Decades of research have examined the nature of working memory, which is a limited capacity system that allows for storage and processing of information in the face of distraction (Baddeley & Hitch, 1974). Importantly, working memory capacity predicts several real-world outcomes, such as reading comprehension (Daneman & Carpenter, 1980), mathematics performance (Ramirez et al., 2013), and writing ability (Swanson & Beringer, 1996), but is also associated with other important cognitive abilities like general intelligence (Kovacs & Conway, 2016) and fluid reasoning (Kyllonen & Christal, 1990).

Individual differences research has investigated the psychometric structure of working memory to understand its theoretical nature and predictive validity better. Here I will first (a) review leading theoretical perspectives on working memory, (b) review several psychometric models of working memory capacity, and (c) propose an alternative approach to understanding the psychometric structure of working memory via network modeling and (d) present two studies that test the psychometric structure of working memory via network modeling.

Working Memory

Conceptualizations of Working Memory

Research has established that working memory plays a central role in higher-order cognition and that working memory capacity is predictive of important real-world outcomes (Bailey, 2007; Borella et al., 2010; Duncan et al., 2007, & Gathercole et al., 2004). Problematic to the field, however, is that researchers have proposed different definitions of working memory. This has led to confusion in the field, and it has raised questions as to how to best measure working memory capacity. Researchers tend to adopt different notions of working memory, and in turn, administer different kinds of working memory tasks, which often produces inconsistent results. This inconsistency of conceptual definitions of WM has led to a lack of a consensus in the field as to what determines the "best" psychometric model of the structure of working memory. In other words, the best model for researcher A who adopts operational definition A of working memory may be different from the best model for researcher B who adopts operational definition B. To give some insight into this problem, a brief summary of how working memory has been distinguished from other constructs will be provided here in the introduction.

In the infancy of working memory research, several schools of thought used the terms working memory and short-term memory (primary memory) synonymously to refer to the same cognitive construct. However, numerous studies have consistently supported the hypothesis that working memory is distinct from short-term memory (Cantor et al., 1991; Engle et al., 1999; Kane et al., 2004; Conway et al., 2002; Cowan, 2008). This distinction has been achieved mainly through individual differences studies and factor analysis (also known as latent variable modeling). For example, Engle et al. (1999) submitted a battery of simple span tasks and complex span tasks to confirmatory factor analyses. They tested two models: (a) a single-factor model that accounts for variance in performance on all tasks and (b) a two-factor model where one factor reflects short-term memory and accounts for variance in simple span tasks, and the other factor reflects working memory and accounts for variance in complex span tasks. The two-factor model fit the data better than the one-factor model. This finding shows that, from a psychometric perspective, short-term memory and working memory are distinct constructs. Other studies have also provided evidence for the distinction between short-term memory and working memory on the basis of predictive validity. For example, Kane et al. (2004) reported that in a confirmatory factor analysis, a working memory factor predicted reasoning to a greater degree than a short-term memory factor (similarly based on complex span tasks and simple span tasks, respectively). Similar finding have been reported elsewhere (Conway et al., 2002; Cowan, 2008; Kane, Hambrick, & Conway, 2005).

Other lines of work have also focused on delineating the various definitions of working memory. Cowan (2017) provides a useful taxonomy of the various definitions currently found in the field. Specifically, Cowan proposes that there are nine different definitions of working memory. See Table 1 for a summary (adapted from Cowan, 2017). A taxonomy like this helps to clarify the numerous theories of working memory.

Table 1.

Cowan's taxonomy of working memory definitions

Definitions of Working Memory	
1. Computer WM (Laird, 2012)	A holding place for information to be used temporarily, with the possibility of many working memories being held concurrently
2. Life-planning WM (Miller et al., 1960)	A part of the mind that saves information about goals and subgoals needed to carry out ecologically useful actions
3. Multicomponent WM (Baddeley & Hitch, 1974)	A multicomponent system that holds information temporarily and mediates it use in ongoing mental activities
4. Recent-event WM (Olton et al., 1977)	A part of the mind that can be used to keep track of recent actions their consequences in order to allow sequences of behaviors to remain effective over time.
5. Storage and Processing WM (Daneman & Carpenter (1980)	A combination of temporary storage and the processing that acts upon it, with a limited capacity for the sum of storage and processing activities.
6. Generic WM (Cowan, 1988)	The ensemble of the mind that hold a limited amount of information temporarily in a heightened state of availability for use in ongoing information processing.
7. Long-term WM (Ericsson & Kintsch, 1995)	The use of cue and data-structure formation in long-term memory that allows the information

	related to an activity to be retrieved relatively easily after a delay.
8. Attention-control WM (Engle, 2002)	The use of attention to preserve information about goals and subgoals for ongoing processing and to inhibit distractions from those goals.
9. Inclusive WM (Unsworth & Engle, 2007)	The mental mechanisms that are needed to carry out a complex span task; it can include both temporary storage and long-term memory insofar as both of them require attention for the mediation of performance.

Note. Adapted from Cowan (2017).

Of the numerous concepts above, only a few have been formalized as cognitive theories or psychometric models of working memory. Specifically, definition #3, multicomponent WM, is associated with the multicomponent theory of working memory originally proposed by Baddeley & Hitch (1974). Definition #6, generic WM, is associated with the embedded processes theory of working memory proposed by Cowan (1988). Also, definition #8, attention-control WM, is associated with the psychometric model of working memory proposed by Engle (2002).

However, all of these theories/models fail to provide a comprehensive approach to the measurement of working memory capacity, hence, the need for a new and improved psychometric model. To preview the limitations of previous approaches, the Baddeley model fails to provide a detailed account of executive attention, and both the Cowan and Engle models fail to account for the role of domain-specific verbal and spatial storage and retrieval processes. It is shown here that definition #9, the inclusive WM approach by Unsworth, is the best definition to guide future research on the measurement of working memory capacity. Before expanding on this discussion, a review of the most prominent cognitive theories of working memory is presented.

Cognitive Theories of Working Memory

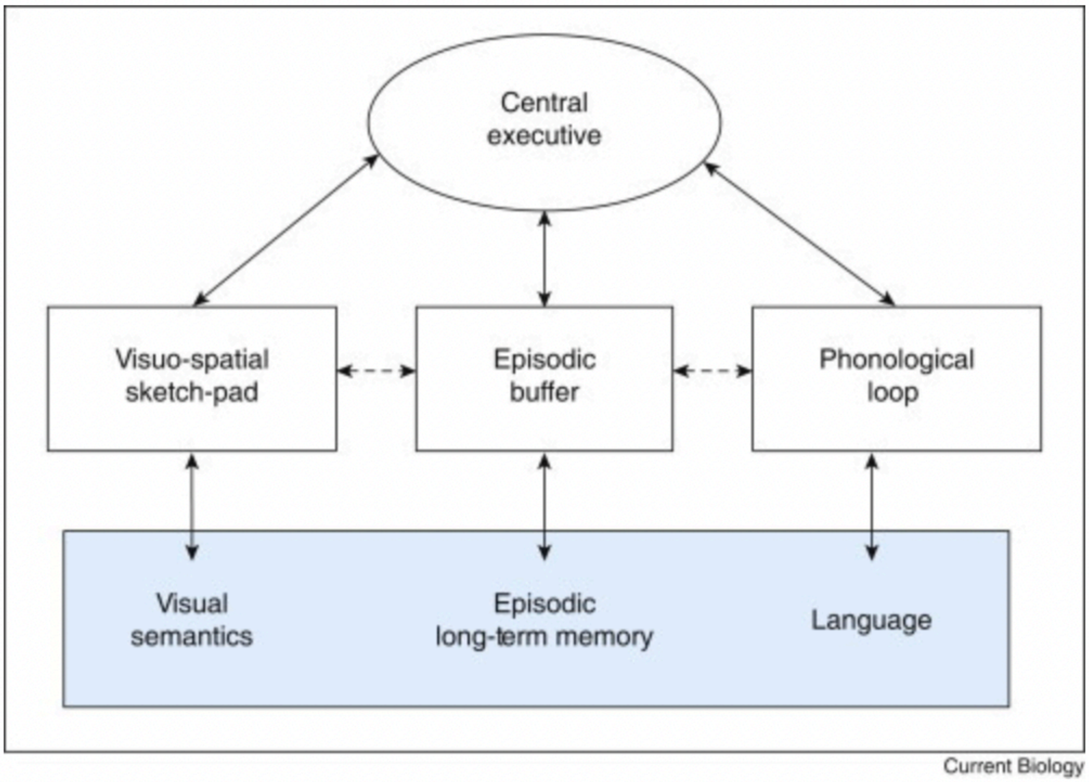
While there are several informal conceptualizations of working memory, there are actually very few formal cognitive theories of working memory. In other words, some conceptualizations of working memory have not been tested empirically while others have been tested and supported. Arguably, the two most influential formal theories of working memory are Baddeley's multicomponent model and Oberauer's cognitive process model (which is largely based on Cowan's embedded process model). An in-depth review of Baddeley and Oberauer's theories is presented here.

Baddeley's multicomponent model

In their seminal paper, Baddeley and Hitch (1974) proposed a cognitive system that can simultaneously process and store information while experiencing distraction. Baddeley and Hitch proposed a working memory system composed of a central executive and two storage buffers, the visuospatial sketchpad and phonological loop. The central executive serves as an attentional mechanism that helps to select and maintain information active in working memory. The visuospatial sketchpad is considered to be a storage buffer that maintains visual information and the phonological loop is considered to be a storage buffer that maintains auditory information. Later, Baddeley and colleagues revised their model to include an episodic buffer (Baddeley, 2000; see Figure 1). The episodic buffer allowed the model to account for the maintenance of multisensory information. This revision to the model was important given that the initial multicomponent model did not previously account for how multisensory information was processed. It is important to note here that a defining feature of Baddeley's model is the non-unitary nature of working memory. The idea of having multiple storage systems (or buffers) and a central executive implies that there are multiple mechanisms (components) involved in working memory task performance.

Figure 1

Baddeley's multicomponent model of WM (Baddeley, 2010)



Several lines of research support Baddeley's model. Evidence in support of the distinction between the phonological loop and visuospatial sketchpad stems from memory interference effects. Chein et al., (2011) tested the effects of interference on verbal and spatial recall in a study in which participants completed trials of a task that involved processing, storage, or both. (See Figure 2 for an illustration of the task design). The conditions that involved both processing and storage were manipulated by domain (verbal vs. spatial). The verbal storage conditions involved remembering letters while the spatial conditions involved remembering the positions of squares on a grid. On some of the trials, the domain of the processing component matched the domain of the storage component (e.g., verbal storage and verbal processing); on other trials the domain of the processing component did not match that of the storage component (e.g., verbal storage and spatial processing). The task demands (i.e., processing and storage components) outlined above are typical features of complex span working memory measures. The number of items recalled was the dependent variable. They found that verbal processing interfered with verbal storage more than spatial processing interfered with verbal storage. Likewise, spatial processing interfered more with spatial storage than verbal processing interfered with spatial storage. The results from Chein et al. (2011) are presented in Figure 3. Similar findings were reported by Shah and Miyake (1996). Taken together, the above findings are evidence for a dissociation between the verbal and spatial components of working memory, which map onto Baddeley's model as the phonological loop and visuospatial sketchpad, respectively.

Figure 2.

Chein et al. (2017) task design.

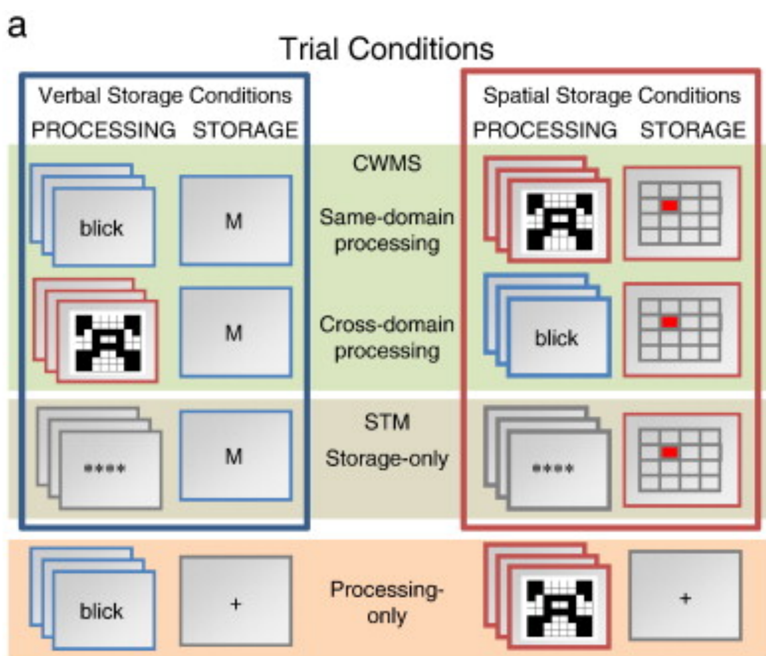
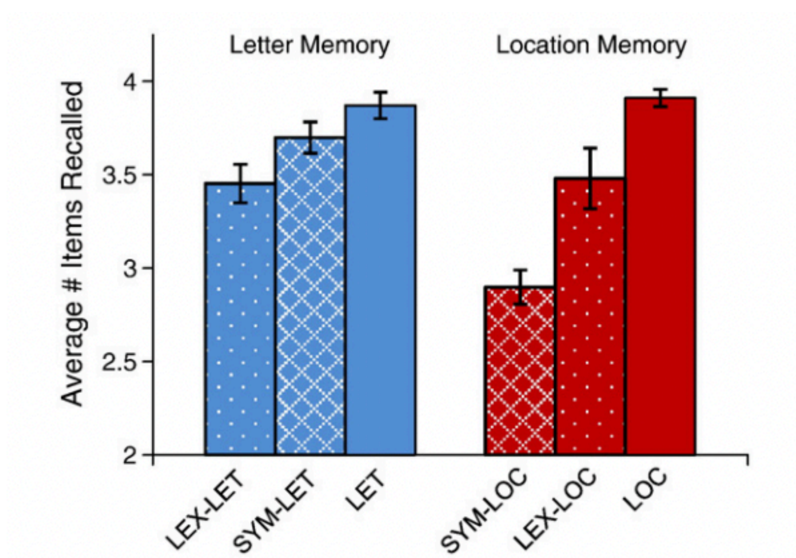


Figure 3

Chein et al. (2011) interference effect results.



Other evidence for the verbal and spatial storage distinction unique to Baddeley's model comes from neuropsychological studies. For example, Vallar & Baddeley (1984) showed that patients with impaired verbal short-term memory failed to encode and rehearse verbal information but successfully processed visual-spatial information. Moreover, other neuropsychological studies have reported dissociation effects that favor the verbal and spatial distinction. Baddeley et al. (1988) conducted a study in which children who had a speech-related learning disability showed increased difficulty acquiring new vocabulary compared to their typically developing peers. Importantly, no visual processing impairments were shown for either group. Similarly, Gathercole and Baddeley (1990a) tested non-word learning in groups of 5-year-old children were matched based on non-verbal ability. The children were shown toys that were given familiar names (e.g., Michael) or unfamiliar names (e.g., Peeton). Children with lower levels of verbal ability were worse at recalling new verbal information (non-words) than children who showed better verbal abilities. Importantly, the two groups did not differ on measures of visual processing. Taken together, these findings support Baddeley's model and the idea that separate domain-specific storage systems are key components of overall working memory functioning.

In addition to the research that distinguished between the verbal and spatial components of working memory, other lines of work have supported Baddeley's conceptualization of a domain-general central executive component that is critical for working memory functioning. Evidence for a domain-general central executive comes from individual difference studies of working memory capacity and the relationship between working memory capacity and other measures of cognitive performance. For example, across two experiments, Turner and Engle (1989) tested the domain-generality of working memory by correlating performance on span tasks with performance on tests of reading comprehension. The specific goal was to determine whether the correlation between span tasks and reading comprehension (i.e., correct number of questions answered after reading a passage) was due to domain-specific processes or domain-general processes. If the relationship between span task performance and reading comprehension was domain-specific, then the correlation between the span tasks and reading comprehension would change, such that the correlation would be highest for span tasks that contained a verbal processing component. However, if the relationship between the span tasks and reading comprehension is domain-general, then the correlations between the span tasks and reading comprehension would be similar, regardless of the type of processing component. The results showed that the correlation between working memory capacity and reading comprehension did not change as function of the type of processing task (i.e., arithmetic vs. reading). Notably, the correlation between working memory capacity and reading comprehension persisted even after controlling for quantitative skills. These findings provide evidence for the domain-general central executive component of working memory. Similar findings have been reported elsewhere (Conway & Engle, 1996; Conway et al., 2001; Engle, Cantor, & Carullo, 1992; Engle et al., 1999; Engle 2002).

The work discussed above provides experimental and correlational evidence for the multicomponent model of working memory proposed by Baddeley. It is important to note here that Baddeley's multicomponent model of working memory lends itself well to individual differences research that aims to understand the psychometric structure of working memory. Baddeley's model provides support for four distinct components of working memory: a central executive, a phonological loop, a visuospatial sketchpad, and an episodic buffer. In terms of psychometric structure, Baddeley's model is consistent with a four factor latent variable model, in which the four components (or factors) are roughly equivalent to attention control (central executive), verbal storage (phonological loop), spatial storage (visuospatial sketchpad), and episodic memory (episodic buffer), which have all been identified as distinct factors in psychometric models of cognitive abilities (Conway et al., 2002; Engle et al., 1999; Kane et al., 2004; Unsworth et al., 2014). Baddeley's model of working memory therefore not only provides a framework of working memory, but it also maps well onto a psychometric model of working memory capacity. This is insight is important for the purpose of the current paper where the goal is to establish a new and improved psychometric model of working memory capacity that includes the components mentioned above.

Baddeley's model of working memory offers a multicomponent view that is supported by numerous lines of evidence discussed above (i.e., interference studies, brain-lesion studies, individual differences). Though Baddeley's model provides a conceptualization of working memory and can potentially lend itself to uncovering a more accurate psychometric model of working memory, it does not provide a sufficiently accurate description of the central executive component of working memory. The empirical work conducted on Baddeley's model does not inform how the central executive functions, it does not identify the processes/mechanisms that constitute the central executive, and it does not explain various limitations of the central executive. It is now well established that executive function is not a unitary construct (Miyake et al., 2000), so failures of Baddeley's model to identify different central executive processes is a major limitation of the model. For example, Baddeley's model is incompatible with the influential unity/diversity theory of executive function, which is expressed as a psychometric model of individual differences and includes multiple executive processes (Friedman et al., 2006; Friedman et al., 2007; Miyake, 2000). The unity/diversity model has been supported by experimental (Healey & Miyake, 2009; Miyake & Shah, 1999) and neuropsychological evidence (Miyake et al., 2000; Friedman et al., 2011; Snyder et al., 2015). Specifically, Miyake (2000) proposed that executive function (central executive) consists of three distinct mechanisms: updating, task-switching, and inhibition. This finding supports a non-unitary concept of the central executive in working memory and calls into question Baddeley's unitary view of the central executive.

Oberauer's cognitive process model

Considering the limitations of Baddeley's model above, other researchers have sought to provide a more precise description of working memory and its components. In this section, Oberauer's theory of working memory is discussed, highlighting how this framework can help to inform a new and improved psychometric model of working memory capacity. Oberauer's model provides an account of domain-specific memory interference, consistent with Baddeley's view of domain-specific storage buffers. However, in Oberauer's model, interference effects arise from "representational interference" and "retrieval interference", not from different storage buffers as proposed in Baddeley's model. Representational interference is the result of active memory mechanisms whereas retrieval interference is the result of episodic memory mechanisms. Thus, Oberauer's model points to three different memory components: verbal storage, spatial storage, and episodic retrieval. In addition, the model points to a non-unitary view of attention by providing a more precise account of executive processes, i.e., inhibition, switching, and updating. A more detailed discussion of this model follows.

Oberauer (2009) proposed a cognitive processing model of working memory that is largely motivated by Cowan's "embedded processes" model of working memory (Cowan, 1988). Oberauer proposes six functions that allow working memory to operate optimally, and in turn, help to explain why WM capacity is predictive of higher-order cognitive abilities. The six functions are the ability to build and maintain new representations, the manipulation of structural representations, a general-purpose mechanism, rapid updating of structural representations, retrieval from long-term memory, and the transferring of information from working memory into long-term memory. For a description of each function please see Table 2 below.

Table 2.

Oberauer's Six Functions of Working Memory

Function	**Description**
Building and maintaining new representations	Binding elements like words and images into meaningful cognitive representations
Manipulation of structural representations	Selecting relevant information for a cognitive operation
General-purpose mechanism	Domain-general executive processes needed to create new structural representations
Rapid updating of structural representations	Updating the contents of WM
Retrieval from LTM	Accessing information from LTM that is relevant for the task goals
Transferring WM contents to LTM	Storing processed information from WM into LTM

Note. This table represents a brief description of the six functions of working memory proposed by Oberauer's cognitive model.

The next section discusses how Oberauer's model conceptualizes the structure of working memory.

The structure of working memory in Oberauer's model

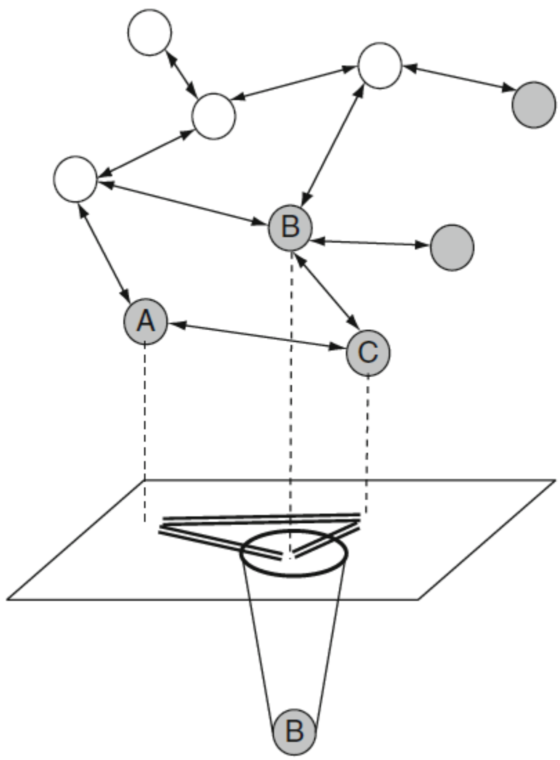
Oberauer's model makes a distinction between declarative and procedural working memory. The declarative part of working memory is responsible for making information available for processing while the procedural part of working memory is necessary for enacting the processing of cognitive operations. The focus here is on the declarative component because it is more relevant to the study of individual differences and psychometric models of working memory capacity.

Declarative working memory

In Oberauer's model, declarative working memory consists of active long-term memory (LTM), the region of direct access (DA), and the focus of attention (FOA) (see Figure 4). The active LTM component represents contents from long-term memory that are relevant for the current task at hand, the DA region is responsible for holding bindings accessible for processing in the FOA, and the FOA is responsible for keeping information active for the service of an ongoing complex task. The layers of declarative working memory can be conceptualized as a narrowing of the amount of information, from the outermost layer, LTM, to the innermost layer, the focus of attention. In other words, the focus of attention processes a more narrow and specific set of stimuli compared to LTM, which processes a broader set of stimuli.

Figure 4

Architecture of declarative working memory (Oberauer, 2009)



Active LTM

Representations in LTM that are not currently activated are depicted by the unshaded circles in Figure 4. In contrast, representations in LTM that are currently active are depicted by the shaded circles. Representations in LTM are activated through either sensory input or through spreading activation (Collins & Quillian, 1969) from other conceptually related representations.

Direct-access region

In Figure 4 above, the DA region is the plane where the shaded circles (active representations) are bounded together. The DA region is characterized as a subset of active mental representations that are available for rapid access. Additionally, the DA region binds these representations into a structure. The ability to do this requires the binding of content representations to context representations. For example, one can envision a chess player moving the pawn chess piece across the chess board. One is forming a new structure by binding the what (the pawn chess piece) to the where (position on the chess board). All of these pieces of information are activated as a cognitive representation that is maintained in the DA region. In sum, the DA region is a mechanism responsible for retaining active bindings between contents and contexts and forming new structures for the service of completing complex cognitive tasks.

Oberauer's model posits capacity limits of the DA region. The capacity limit is in the number of pieces of information that can be bounded together. This capacity limit arises from two sources: (a) representational interference and (b) retrieval competition. The first source of capacity limits, representational interference, is generated by contents of the DA region that interfere with and deteriorate each other to cause a decrement in performance. One example of this is the phonological similarity effect (Chow et al., 2016; Tehan et al., 2001; Copeland & Radvansky, 2001; Hitch et al., 1989). The phonological similarity effect is the finding that immediate serial recall is impaired when words within a list are phonologically similar compared to when they're phonologically dissimilar. For example, consider the sounds for the letters "c" and "d". These letters are phonologically similar, and this similarity is likely to cause representational interference during recall, and ultimately worse recall performance. On the other hand, the letters "k" and "n" are phonologically dissimilar and thus, do not cause representational interference during recall, and thus, leads to better recall performance (Chow et al., 2016).

The second source of capacity limits, retrieval competition, occurs when recall of stimuli from LTM competes with other similar stimuli during the retrieval process. Oberauer (2001) implemented a version of the Sternberg working memory task and showed that removing irrelevant information from working memory was more difficult (slower reaction times) when the irrelevant information (non-target words) was similar to the relevant information (target words). This was not the case when the irrelevant information was dissimilar to the relevant information that was to be remembered. Thus, the more competition that exists in working memory when retrieving a stimulus, the more impaired retrieval of information is overall.

Focus of attention

Another component of Oberauer's model is the focus of attention. This component is responsible for selecting specific representations or features of a representation and operating on these representations/features. Again, one can think of this through the chess example previously discussed. Consider a chess player who is contemplating several options for moving the queen. Out of the potential options, one move is more strategic and advantageous The chess player must shift features of the representation in and out of the focus of attention to consider each option and realize that one option is more advantageous. In this example, Oberauer's conceptualization of the focus of attention refers to its functionality of selecting relevant information for processing.

In summary, Oberauer's model of working memory consists of three components: active LTM, direct-access region, and the focus of attention. These three components work in conjunction to bind information in working memory, create new structures, and enact cognitive operations on them for the purpose of completing a complex task. According to this model, the ability to do all of this is what is measured in a working memory task. Importantly, Oberauer's model provides a more detailed description of working memory, especially in regard to the central executive component. Because of this, Oberauer's model of working memory lends itself well to other fields like neuroscience and psychometrics. This is the case because the concentric structure of working memory proposed by Oberauer's model is conceptually similar to models of working memory proposed by studies in neuroscience where working memory is also thought to operate via distinct layers (Beukers et al., 2021). Studies in these fields have corroborated Oberauer's findings. Converging evidence of this sort is a strength of Oberauer's theory of working memory. The next section will discuss empirical evidence in support of Oberauer's model of working memory.

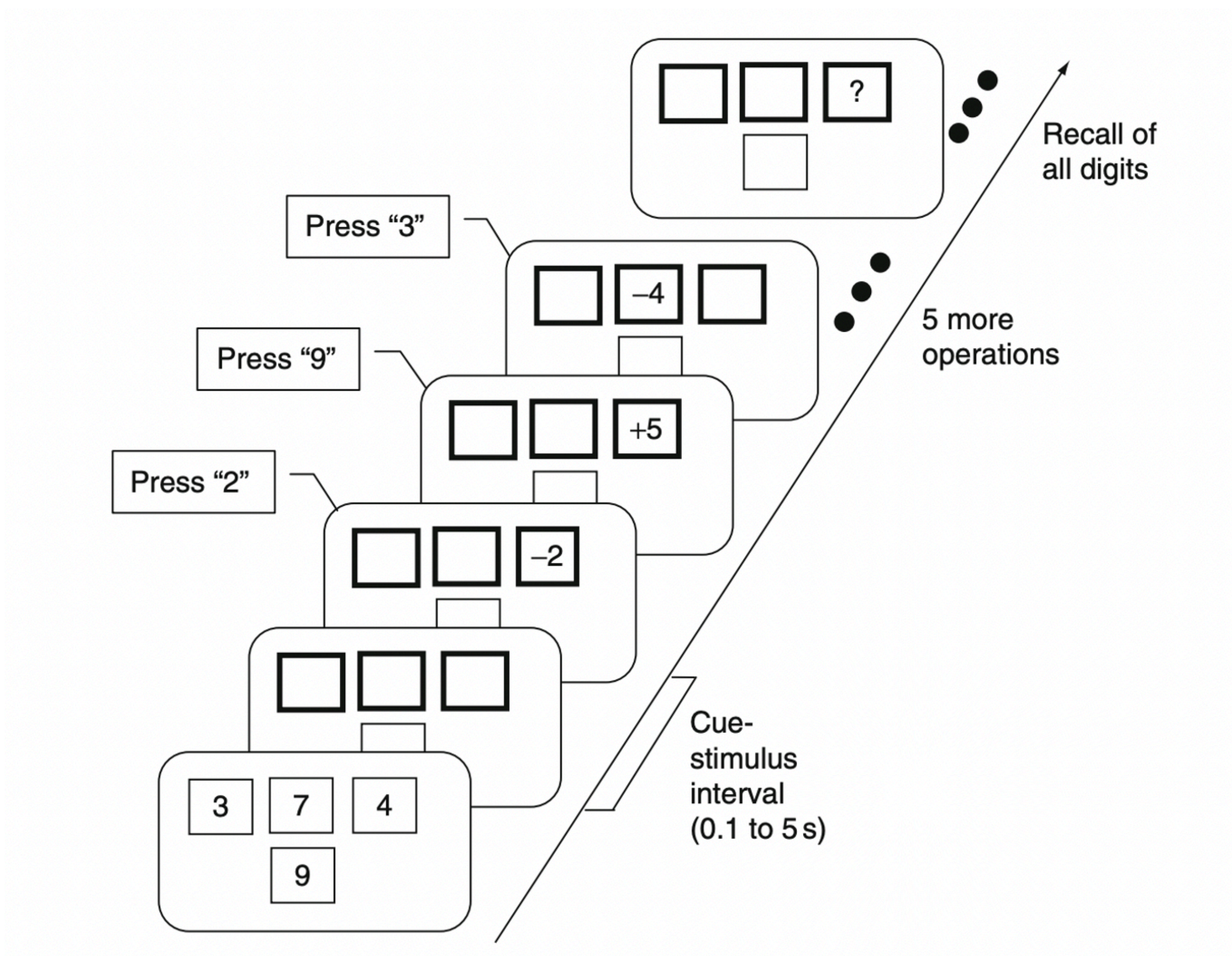
Evidence for Oberauer's model of working memory

Oberauer's model has been supported largely by experimental work. For example, in an influential paper, Oberauer (2002) explored the structure of working memory in two experiments using a memory-updating task originally designed by Salthouse et al. (1991). In Experiment 1, participants were asked to remember a series of digits that were presented in a 3x2 matrix on a computer screen (see Figure 5 below). These initial values were then updated according to arithmetic operations that were provided (e.g., "+4" or "-2"). After a total of 9 updating arithmetic operations on the initial values, participants were required to recall the final values. In the task, a key manipulation was that in some conditions the digits in both rows constantly changed (active condition), while in other conditions, one of the rows changed and the other row did not change (passive condition). Response times were slower in conditions with active sets than conditions with passive sets. This finding suggests that active sets are maintained in the limited capacity direct access region whereas passive sets can be maintained in active LTM. In other words, an active set needs to be in the direct access region because the task requires rapid access to the set for manipulation. In contrast, the static nature of the passive set means it does not require continuous maintenance and manipulation. This set of findings provide support for the distinction between active LTM and the region of direct access in Oberauer's model.

Further support for Oberauer's model comes from investigations of the focus of attention. Oberauer (2003) examined *object-switch costs* in the focus of attention. To do so, Oberauer (2003) utilized the same paradigm in Oberauer (2002), except that the task was modified so that arithmetic operations (e.g., "+3") were applied to either the same digit as in the previous trial or the arithmetic operation was applied to a different digit than the one in the previous trial. Response times were longer on trials where the arithmetic operation was applied to different digit than on trials where the arithmetic operation was applied to the same digit. According to Oberauer's model, object-switch costs can be interpreted as the time it takes for the focus of attention to bring new information into focus from the region of direct access. These findings provide evidence for how processes in the FOA impact information processing of working memory during complex tasks. In addition, Oberauer (2003) showed that as the length of the relevant lists get longer, response times also increase. This finding shows that the DA region is limited in capacity and becomes less effective as list lengths increase. Furthermore, Oberauer's model contends that the focus of attention is limited to processing one item at a time. Evidence for this idea comes from dual-task studies. In these studies participants are instructed to attend to more than one stimulus at a time and make a response to these stimuli (e.g., remembering letters while making judgments about the veracity of sentences that are presented). Findings typically show that even when performing simple cognitive operations, participants' responses slow significantly when making a selection if they are asked to attend to more than one stimulus. This concept is referred to as a response-selection bottleneck (Oberauer & Gothe, 2006). In sum, these findings support Oberauer's model of working memory by showing that working memory operates via distinct layers with separate functions.

Figure 5

Oberauer (2002) working memory task involving memory updating and recall.



Taken together, Oberauer’s findings support his model and provide a more accurate theoretical account of working memory than does the model of Baddeley. Importantly, Oberauer’s model converges with psychometric models of working memory (Engle & Kane, 2004; Unsworth et al., 2006). This overlap allows for the development of more well-rounded models that are supported by findings from multiple fields.

The next section builds from the evidence reviewed above by discussing work done on Oberauer’s model connecting it to current psychometric models of working memory. Doing so sheds light on the idea that a more inclusive psychometric model of working memory is needed in the field.

Psychometric Models of Working Memory

In this section, a review of the most influential psychometric models of WM will be provided. In comparison to the cognitive models above, psychometric models focus on examining the underlying measurement structure of cognitive abilities as opposed to understanding mechanisms that underlie cognitive performance. In this case, the psychometric models reviewed below will all speak to the measurement structure of WM.

The work reviewed in the previous section clarified how Oberauer's model of working memory provides a more precise and detailed account of working memory than other models previously discussed (e.g., Baddeley's model). This allows the Oberauer model to better inform psychometric models of working memory that can be more inclusive. A more inclusive psychometric model of this sort is currently lacking in the field. To preview, the most influential and widely cited psychometric models of working memory are all latent variable models (factor models) but there is no consensus on the number of factors. The most parsimonious of these models consists of just one factor that is thought to be attention (executive attention theory, Engle, 2002). An alternative, more complex model, specifies three factors that are thought to reflect attention, verbal storage, and spatial storage (Kane et al., 2004 model). Unsworth's inclusive model of working memory is an alternative model that specifies three factors, thought to reflect attention, primary memory capacity, and retrieval from secondary memory. Here we propose that all of these models fall short, and that working memory capacity is best explained by a four-factor psychometric model that reflects attention, verbal storage, spatial storage, and retrieval from secondary memory. Moreover, this inclusive model should be expressed as a network model, rather than a latent variable model, for numerous reasons to be discussed. An overview of current psychometric models is discussed next.

Executive attention view of working memory

An influential psychometric model of working memory is the executive attention model (Engle & Kane, 2004). According to this model, variation in working memory capacity and its relationship with other abilities (e.g., reading comprehension, reasoning) is primarily driven by individual differences in cognitive control, also known as executive attention. This is the ability to regulate behavior to achieve a particular goal (Braver, 2012). Moreover, according to this model, cognitive control is a unitary ability that influences performance in a range of tasks in a domain-general manner. Numerous studies have shown that individual differences in working memory capacity are predictive of real-world outcomes. Starting with the work of Daneman and Carpenter (1980), performance on the reading span task was shown to predict reading comprehension. The reason for this is that the reading span task imposes a processing component that places greater demands on the executive attention component of working memory. Later research followed in which memory span tasks were utilized to test a host of questions, with the goal of understanding individual differences in working memory capacity and its predictive validity. The original reading span task developed by Daneman and Carpenter reflected the theoretical conceptualization of working memory posed by Baddeley and Hitch (1974). Specifically, the reading span task included a dual-task design that incorporated both storage and processing. Kane et al. (2007) added that the dual task requirements allow for an accurate measure of the executive component of working memory. The executive component of working memory is not only responsible for the ability to "control" attention for the successful completion complex tasks, but also for the ability to inhibit distracting information in the face of concurrent processing. Because of this, working memory tasks like span tasks are good predictors of higher-order complex activities like writing (Swanson & Beringer, 1996) and mathematics performance (Ramirez et al., 2013).

Another important contribution of the executive attention theory of working memory is the empirical evidence it generated on individual differences in working memory capacity and how these individual differences impact real-world outcomes and are related to other cognitive abilities. For example, Kane et al. (2001) had high and low working memory span individuals perform pro-saccade and anti-saccade tasks. In the pro-saccade task, participants were instructed to look in the direction of a visual signal that indicated where an upcoming stimulus (a letter) would appear on a screen. Once the stimulus appeared, the participant was to identify the target letter as quickly and accurately as possible. In the anti-saccade task, participants were presented with a visual signal and were instructed to look in the opposite direction of the signal and then identify the target letter. On the pro-saccade task, accuracy and response time were equivalent for high and low working memory span individuals. However, performance differed in the anti-saccade condition; high working memory span individuals had faster response times and lower error rates than did low working memory span individuals. As discussed by Kane et al. (2001), the discrepancy in performance in the anti-saccade task can be attributed to the ability of high span individuals to maintain a goal, resist task interference (i.e., a salient visual stimulus), and consequently look to where the target letter is to be presented (i.e., the opposite location of visual signal). These factors all contribute to one's capacity to control attention in high interference situations, in other words, cognitive control ability. In turn, high working memory span individuals effectively resist distracting information and maintain task goals due to higher levels of cognitive control compared to low working memory span individuals.

Other studies have reported similar findings. Kane and Engle (2003) examined the relationship between working memory capacity and cognitive control in the Stroop paradigm. Participants were differentiated in terms of their working memory capacity (high spans vs. low spans) and then engaged in several variations of the Stroop task. Overall, high span individuals were faster and more accurate than low span individuals on the Stroop task. On incongruent trials (i.e., word RED in green ink), high span individuals verbalized the color of words faster and more accurately than low span individuals, reflecting individual differences in working memory that are driven by differential levels of cognitive control. Compared to low span individuals, high span individuals were more successful at maintaining access to the task goal and inhibiting the habitual reading response. Importantly, Kane and Engle (2003) reported that when 100% of trials in the Stroop task are incongruent (i.e., for all of the trials the color of the word did not match the word), accuracy and response time did not differ between low and high span individuals. This finding suggests that when goal maintenance is facilitated by the task (each trial serves as a reminder of the task goal), the differences between high and low span individuals are not observed in response times or accuracy. These findings indicate that apart from inhibition, goal maintenance is also an important factor influencing performance on measures of cognitive control, and in turn, working memory.

Taken together, these studies suggest that working memory and cognitive control are strongly related, especially in tasks involving high interference (Shipstead, Harrison, & Engle, 2015; Shipstead et al., 2014). That is, success in complex tasks is a function of high levels of cognitive control and working memory capacity (Conway et al., 1999; Kane et al., 2001; Kane & Engle, 2003). These studies support the executive attention theory of working memory, according to which cognitive control is a unitary ability that influences performance in a domain-general manner across a variety of tasks.

Kane et al. (2004): A Three-factor model of WM

Another widely cited psychometric model of working memory capacity is an extension of the executive attention view, but it rejects the notion of a single factor and suggests instead that working memory capacity is a non-unitary ability that can be decomposed based on content (i.e., spatial & verbal). Kane et al. (2004) proposed a three-factor model of working memory capacity that contains executive attention, verbal storage, and spatial storage. In an influential study, Kane et al. (2004) conducted a series of confirmatory factor analyses to determine whether the shared variance between verbal and visuospatial simple and complex span tasks can be explained by a single domain-general ability factor or if multiple factors are necessary. In addition, Kane et al. examined the predictive validity of simple and complex span tasks. Specifically, the different span tasks were used to predict general fluid intelligence. There were several important findings. First, the verbal and spatial complex span tasks were more strongly correlated with each other than were the verbal and spatial simple span tasks; the complex span tasks shared between 70% to 85% of their variance whereas the short-term spatial and verbal simple span tasks only shared about 40% of their variance. These findings suggests that complex span tasks largely reflect a unitary domain-general ability. It also suggests that simple span tasks are more domain-specific than are complex span tasks. Second, the complex span tasks were more predictive of general fluid intelligence than were the simple span tasks (Kane et al., 2004). Again, this suggests that complex span tasks are more domain-general and simple span tasks are more domain-specific. These are important findings because they show that the shared variance (~40%) between complex span tasks and fluid intelligence occurs largely due to a domain-general executive mechanism (i.e., executive attention).

These results have been largely supported by other studies (Colom, Abad, Rebollo, & Shih, 2005; Conway et al., 2002; Cowan et al., 2005; Kane, Hambrick, Conway, 2005; Engle, Kane, & Tuholski, 1999; Engle, Tuholski, Laughlin, & Conway, 1999). In addition, the findings reported by Kane et al. (2004) provide support for the idea that working memory capacity is non-unitary and reflects both verbal and spatial abilities. As is, this model is largely compatible with Baddeley's multicomponent model of working memory. The central executive, visuospatial sketchpad, and phonological loop in Baddeley's model would map onto the domain-general executive attention component and the visual and spatial storages in the Kane et al model respectively.

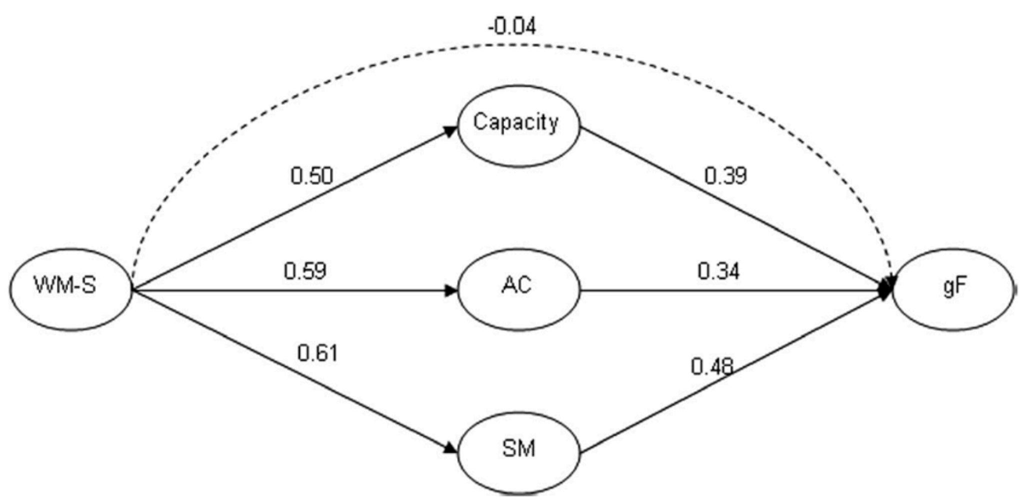
Though the work above identifies cognitive control as being an important individual difference measure of working memory, and Kane et al.'s work shows that working memory can be further specified by both verbal and visuospatial domains, this theory is limited in that attention seems to be the only central component of working memory. Moreover, attention is described as a unitary ability. Both of these theoretical tenets produce an overly simplistic model of working memory that does not converge with other lines of work that suggest a more inclusive model of working memory.

Unsworth's model of working memory

Other studies have sought to identify the components of working memory that explain the relationship between working memory capacity and other cognitive abilities, such as fluid intelligence. This is important because work of this kind helps identify the components of working memory that are most important to include in psychometric models of working memory capacity. In light of this, Unsworth has proposed a three-factor model of working memory capacity that includes primary memory capacity, attention control, and secondary memory retrieval. Studies have utilized structural equation modeling (SEM) to understand the psychometric structure of cognitive abilities. For example, Unsworth et al. (2014) examined the relationship between working memory capacity and fluid intelligence, specifically testing a mediation model in which working memory capacity and fluid intelligence are mediated by primary memory capacity, attention control, and secondary memory retrieval. The results indicated that the relationship between working memory capacity and fluid intelligence can be completely explained by primary memory capacity, attention control, and secondary memory retrieval. See Figure 6 below for a depiction of the results.

Figure 6

Unsworth's model of working memory showing capacity, attention, and secondary memory fully mediating the relation between working memory and fluid intelligence.



Note. WM-S= working memory storage, AC= attention control, SM= secondary memory retrieval, Gf= general fluid intelligence.

In another study, Unsworth et al. (2009) examined the storage and processing components of complex span tasks and their relationship to general fluid intelligence (Gf). They conducted mediated SEM analyses to test whether the relationship between recall on the span tasks and Gf could be fully mediated by processing speed. Their results showed that partial mediation models fit the data the best, indicating that storage and processing speed do not fully explain higher-order cognition (i.e., Gf). See Figures 7 and 8 below.

Figure 7

Mediated SEM model of recall, Gf, and processing time.

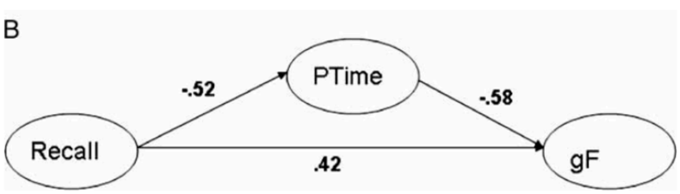
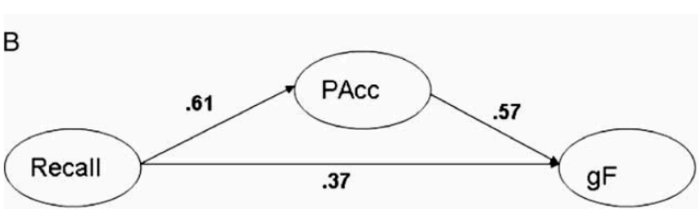


Figure 8

Mediated SEM model of recall, Gf, and processing accuracy



Based on these findings, Unsworth et al (2009) concluded that these psychometric models of working memory do not fully explain the “complexity” of complex span tasks and why they predict measures of complex cognition, like Gf. Though storage and processing add to the predictive validity of complex span tasks, it is likely that a larger set of abilities influences working memory capacity and its predictive validity. Again, this suggests that a more comprehensive psychometric model of working memory capacity is needed.

Nonetheless, findings like these provide important insight regarding components of the relationship between working memory and Gf. In sum, this view of working memory provides a mechanistic and inclusive view of working memory that is also coupled with an understanding of individual differences in working memory and how these differences impact other cognitive abilities and measures of real-world performance. Importantly, the role of secondary memory retrieval is emphasized as an important component of psychometric models of working memory. Because of this, Unsworth's model of working memory provides a blueprint for building a more inclusive psychometric model of working memory that includes secondary memory retrieval as an important component.

Understanding working memory psychometrically: A POT-based perspective

In addition to Unsworth's work, this paper has also been largely motivated by Process Overlap Theory (POT). POT complements the inclusive view of working memory proposed by Unsworth's model and support the goal of this paper. Kovacs and Conway (2016) proposed a novel model of intelligence, Process Overlap Theory. According to POT, the positive manifold of intelligence emerges from overlapping processes that are shared when engaging in complex tasks. Informed by evidence from cognitive, psychometric, and neuroscience data, POT supports the idea that "g", the general factor of intelligence, is not a psychological attribute, but rather, is a statistical index that is useful for prediction. Although POT is a theory of intelligence, the foundation of the theory comes from working memory research. A vast amount of research in the field of working memory has shown that multiple processes are involved in working memory performance (Kane & Engle, 2004; Unsworth et al., 2006; Miyake, 2000). For example, as discussed earlier, Unsworth's studies on working memory report that multiple mechanisms produce variation in working memory capacity. These mechanisms are retrieval from secondary memory, attention control, and capacity of primary memory. In the POT model of Kovacs and Conway (2016), maintenance, manipulation, and retrieval are also discussed as mechanisms that jointly impact working memory performance. Moreover, Oberauer's research on working memory shows that relational integration and coordination of information are also mechanisms that impact working memory capacity. The decades of research in the area of working memory converge on the idea that multiple processes overlap to produce individual differences in working memory capacity. Depending on tasks demands, different components of working memory are recruited for the service of complex cognition. Based on the POT theoretical framework, I propose that a novel psychometric modeling approach, network analysis, is more compatible with POT and is ultimately a more accurate approach to understanding the psychometric structure of working memory. Network modeling will now be discussed in more detail as an alternative psychometric approach to understanding cognitive abilities, specifically, working memory capacity.

An Alternative to Modeling Cognitive Abilities: Network Analysis

Historically, including the work discussed above, cognitive abilities research has predominantly used latent variable modeling to explore the structure of the cognitive abilities (e.g., working memory, fluid reasoning). Latent variable models are used to examine the covariation between observed (i.e., manifest) variables using multiple unobserved latent variables. Depending on the research goal, latent variable modeling can be data-driven via exploratory factor analysis or theory-driven via confirmatory factor analysis. Both are used to study the structure of cognitive abilities. However, recently, several lines of work have noted disadvantages of latent variable modeling.

First, latent variable models allow for subjective interpretations of the latent factors, that is, the researchers define the latent factors (Bollen, 2002; Borsboom et al., 2003). This feature is problematic given that tasks are not process-pure and are likely not measuring only what the researcher believes is being measured. The second disadvantage of latent variable modeling is the principle of local independence presupposed by latent variable models. The principle of local independence states that observations explained by a latent factor are independent from observations explained by other latent factors. For example, in a latent variable model, three spatial tasks that are fully explained by a spatial ability latent factor would not be related to other observed variables in the model. Under the lens of POT, this is problematic given that cognitive abilities frequently overlap during task performance, and thus, forcing local independence, is not an accurate method for testing the structure of cognitive abilities. Due to these limitations, research has shown that the use of network analysis as a statistical tool for overcoming such limitations held by latent variable models.

As discussed above, latent variable models possess two important limitations: subjectivity of the latent factors and the principle of local independence. Network modeling has been proposed to overcome these limitations. Kan et al (2019) discusses that network models do not suffer from any of the limitations held by latent variable models. First, network modeling does not require researchers to specify any latent factors. Instead, network modeling uses only the partial correlations to create a network of the tasks (manifest variables) in a study. By doing this, network modeling eliminates the subjectivity in psychometric models of cognitive abilities. Additionally, network modeling is not constrained by the principle of local independence. In a network model, the tasks are allowed to freely form connections with virtually any other task in the study. Tasks that share similar processes will cluster more closely than tasks in the model that may not share many processes. This approach is compatible with POT that states that cognitive abilities frequently overlap during cognitive activities and thus, network modeling is consistent with this idea that cognitive tasks are not process pure. In sum, network modeling overcomes the shortcomings possessed by traditional latent variable modeling.

Given the advantages of network modeling discussed above, network models can help advance psychometric theories of cognitive abilities. Both by overcoming subjectivity and not imposing the principle of local independence, network modeling is best suited for theories like POT that support the idea that cognitive abilities overlap during cognitive activities. According to POT, intelligent behavior is the cause of the overlap between cognitive abilities. Network modeling fits well with this tenet because by design, the nodes and edges in a network model illustrate this concept. Another important feature of network modeling is the ability to derive cluster scores. These scores represent a composite score of node strength in a cluster of nodes (tasks). They are the "factor scores" of network modeling. Cluster scores can be used to predict outcomes like academic achievement and job performance. The ability to predict academic outcomes and other higher-order cognitive abilities like fluid reasoning is preserved in network modeling and can ultimately speak to the predictive validity of the tasks in a network model just as would be the case in a latent variable model. For these reasons, network modeling shows to be beneficial for understanding working memory psychometrically and aligns well with POT as mentioned earlier. Taken together, all of the above provide strong arguments for the use of network modeling over latent variable modeling, especially in situations when the tasks of choice are theoretically driven (e.g., complex span tasks).

Though network modeling holds important advantages over latent variable modeling, some limitations are worth highlighting. First, network models are successful only if the covariance between variables is large (Kan et al., 2019). Second, if the data possess high measurement error, then the network structure can be misrepresented and be misleading (Kan et al., 2019). Finally, given the relative novelty of the network modeling technique in the field of cognitive abilities, there is no standard practice for implementing this technique on cognitive-behavioral data. Despite these shortcomings, network modeling shows important strengths in regard to uncovering the psychometric nature of working memory.

Proposed Research

The ultimate goal of the studies presented here is to propose and test a new psychometric model of working memory capacity. The proposed model includes multiple components of working memory and will be examined using psychometric network analysis rather than the more traditional latent variable modeling approach. The model is compatible with recent research on working memory (e.g., by Oberauer and Unsworth), and it is more consistent with contemporary models of intelligence, such as POT. More specifically, a network model is proposed here that includes four components: attention, verbal storage, spatial storage, and retrieval from episodic memory (see figure 9 below); all these components are theoretically informed by Oberauer's cognitive model of working memory and the psychometric models (i.e., Engle, Kane et al. & Unsworth) discussed earlier. For comparison, I will also test a latent variable model of working memory capacity that consists of the same four components and a higher-order factor (see Figure 10 below). Examining both psychometric models contributes to a greater understanding of which model explains the psychometric nature of working memory better. Doing so can bridge multiple forms of evidence together to propose a psychometric model of working memory that can inform both theory and guide the measurement of working memory. This can ultimately be useful for practical contexts such as educational and clinical settings where measuring working memory effectively is important.

The studies proposed here will be conducted using the data from Wilhelm et al. (2013). This dataset lends itself well to the current studies because there is performance data for measures of attention, working memory, episodic memory retrieval, and fluid intelligence; all of which are constructs of interest for the current studies. Furthermore, the data from Wilhelm et al. (2013) was used for a similar purpose as is proposed here, which is to study the psychometric structure of components of working memory and fluid intelligence. Thus, the number of tasks and type of tasks present in Wilhelm et al. are ideal for the current studies. However, a limitation of the Wilhelm dataset is worth noting as it pertains to the purpose of the current studies. Wilhelm et al. did not include direct measures of verbal and spatial storage, constructs of interest in the current studies. To overcome this shortcoming, the initial trials from the complex span tasks will be used to obtain measures of both verbal and spatial storage. This is discussed in further detail below.

The goal of Study 1 is to determine whether a network model of WM fits the data as well as a latent variable model. Study 1examines the psychometric structure of working memory capacity using data from Wilhelm et al. (2013). A psychometric network model will be compared to a latent variable model. To do so, undirected psychometric network analysis will be utilized which will emphasize mutual associations among cognitive measures. The constructs to be examined in this study are attention, verbal and spatial storage, and retrieval from secondary memory. See Table 3 below for a brief description of the tasks that represent each proposed construct. A latent network approach will also be applied to these data. This approach combines the advantages of both the network models and latent variable model approaches. The latent network model is a viable solution for accounting for measurement error and retaining the properties of latent variable models.

The goal of Study 2 is to examine the predictive validity of WM as conceptualized via a network model and compare it to the predictive validity of WM in a latent variable model. The predictive validity of the network components of WM will be tested by modeling the relationship between working memory capacity and Gf. This will be done using cluster scores. Cluster scores in a network model serve the same purpose as factor scores in a latent variable model. A latent variable model will also be derived with 2 higher-order factors, WM and Gf, and the relationship between the two will be assessed. This association in the latent variable model will be compared to the cluster scores in the network model. Doing so will ultimately help determine whether a network model of WM shows comparable predictive validity of Gf as compared to traditional latent variable models.

Study 1: A Network Modeling Approach to Investigating the Psychometric Structure of Working Memory

In this study, psychometric network modeling was applied on the Wilhelm et al. (2013) data. Specifically, a network model that accounts for attention, verbal and spatial storages, and retrieval from episodic memory was produced. Importantly, no higher-order factors are specified in network modeling and that will be the case in this study as well. This approach offers an alternative perspective to study the correlational structure of cognitive abilities. Particularly, this is an alternative approach that maps well onto recent work showing that the interrelationships between cognitive variables occurs in an overlapping manner during complex cognition, such that tasks involving similar demands will recruit similar cognitive processes (Kovacs & Conway, 2016), and that psychometric modeling is an ideal manner for maintaining congruency with such theoretical perspectives (Van Der Mass et al., 2017). Traditionally, in most studies including Wilhelm et al. (2013), confirmatory theory-driven techniques are used. These techniques use latent factor models to estimate the relationships between observed and unobserved variables that are driven by specific theories. These theories typically rely on conceptual and statistical assumptions. However, a shortcoming of confirmatory latent factor models is that they may be too restricted for uncovering information that is not consistent with theories. Thus, in this study we assess whether the exploratory nature of network modeling can provide a less-constrained approach to studying WM and help to clarify the nature of the components that underlie WM. This technique mirrors a factor analysis approach by focusing on the patterns of pairwise conditional dependencies (edges) among observed variables (nodes) rather than dimensional reduction of multivariate data. This model was subsequently compared to a traditional latent variable model containing the latent factors of attention, verbal and spatial storage, and retrieval from episodic memory. The latent variable model of WM was specified by a higher-order WM factor. The goal was to assess if a network model of WM fits the data as a well as a latent variable model of WM, in which the former does not specify a higher-order WM factor and the latter does specify a higher-order WM factor.

To provide more background on the current studies it is important to discuss Wilhelm et al. (2013) in more detail to gain an understanding of the nature of the measures that will be included in the current dissertation and how the models that will be derived in the current project compare with the latent variable models proposed by Wilhelm et al. (2013). In their study, Wilhelm et al investigated the relationship between different components of WM and Gf. Using structural equation modeling, measures of updating, binding, retrieval from secondary memory, WM, inhibition, and GF were tested to determine their correlational structure. In addition, the ability of the working memory components was also tested in terms of the predictive validity of Gf. Several models were tested and Model 2 was found to be the best fitting model that described the relationship between WM and gF. See Model 2 below.

Figure 9.

Model 2 from Wilhelm et al representing a confirmatory factor model of WM and reasoning

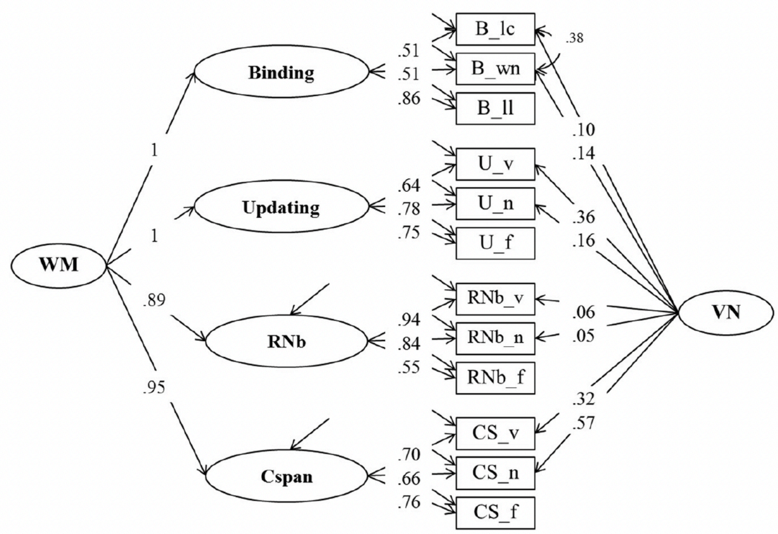


FIGURE 4 | Confirmatory factor analysis of Binding, Updating, Recall 1-back (RNb) and Complex Span (Cspan) Tasks (Model 2). The common variance of the task factors is accounted for by the higher-order Working Memory (WM) factor. The loadings of the Binding and Updating factors on WM were set to 1, the disturbance term of these factors was constrained to zero. _v, verbal indicators; _n, numerical indicators; _f, figural indicators; _lc, letter-color; _wn, word-number; _ll, location-letter; CS, Cspan indicators; VN, Verbal-numerical content factor.

As can be seen above, Wilhelm et al. found first, that the common variance of the tasks measuring binding, updating, retrieval from secondary memory, and attention was accounted for by the higher order working memory factor. This finding suggests that these components of working memory are important aspects to measure working memory. Second, the authors reported the relation between WM and GF to be .83. Thus, 69% of the variance in Gf is explained by WM, which is higher compared to previous work where effect sizes ranged from 30% to 50%. Taken together, the findings reported by Wilhelm et al. suggested that (a) WM can be effectively modeled with tasks that account for binding, updating, retrieval from secondary memory, and attention and (b) WM continues to be a strong predictor of Gf. Here in Study 1 of this dissertation, we attempted to produce findings similar to the former finding reported by Wilhelm et al, but instead, only included the constructs of interest, attention, verbal storage, spatial storage, and retrieval from secondary memory. The second finding obtained by Wilhelm et al will be relevant later in Study 2.

Study 1 Method

The current study is in part, a re-analysis of data by Wilhelm et al. (2013), where measures of attention, verbal and spatial storage, and retrieval from secondary memory will be used to produce a latent variable model of WM (as done by Wilhelm et al), but also, produce a network model of WM containing these measures. In their original study, they collected data from 276 participants across 17 measures. Specifically, there were 3 binding tasks, 3 updating tasks, 3 retrieval tasks, 3 reasoning tasks, 3 complex span tasks designed to measure working memory, and 2 attention tasks. For the purposes of the current study only the tasks measuring the constructs of interest will be included (attention, retrieval, verbal/spatial storage, & reasoning). See Table 3 below for a description of the tasks that will be used in these studies.

All psychometric network analyses in both Study 1 and Study 2 are conducted with the “psychonetrics” package (v 0.9; Epskamp, 2021) in R. All network models are estimated by modeling the variance-covariance matrix of the data as Gaussian graphical model (Epskamp et al., 2017). A model optimization process is conducted on both types of network models, in which the models are pruned by a step-down search process with significance level of .01 in a recursive manner, such that edges that are not significant at $\alpha = .01$ are automatically and recursively removed. The pruned models are then optimized by a step-up search process with significance level of .01, such that the edges that are removed in the previous steps are added back, based on modification indices, until BIC no longer increase.

To evaluate the models, model fit indices were examined. Model fit was deemed appropriate when: (a) the ratio of model chi-square ($\chi 2$) to degrees of freedom is less than or equal to 3.00, (b) comparative fit indices (e.g., Comparative Fit Index (CFI) and Tucker–Lewis Index (TLI)) are greater than or equal to 0.95, and (c) Root Mean Square Error of Approximation (RMSEA)1 values are less than or equal to 0.06. Additionally, Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) values can be used to compare models: smaller values indicate better fit. All of these thresholds are following the recommendations of Schreiber et al. (2006). Furthermore, fit indices were extracted using functions within the lavaan, openMx, and qgraph packages that compare original covariance matrices to the implied covariance matrices generated by each latent variable and psychometric network model. The hypothesis is that the network model of working memory and the latent variable model of working memory will fit the data equally well. If both models show similar fit statistics, then the network model will be the preferred model given its theoretical compatibility with theories like POT discussed above.

Table 3
Tasks of Cognitive Abilities from Wilhelm et al. (2013) that will be used in Study 1 and Study 2

Latent Construct	**Cognitive Task**
Attention	*Simon task*: Responses were made to diamond and square shapes that were presented either in the top half or bottom half of the screen *Flanker task*: Responses were made to arrows pointing left or right. Five arrows were shown at-a-time and responses were made based on the orientation of the middle arrow

Verbal Storage	*Initial trials of the Reading span task*: Participants remembered letters while judging whether sentences were sensical or not. Only the first trials of this tasks will be used as an index of verbal storage. List lengths varied from 2-5. Accuracy for list lengths 3 and 4 will be analyzed. *Initial trials of the Operation Span task*: Participants remembered letters while determining whether presented math problems were correct or not. Only the first trials of this tasks will be used as an index of verbal storage. List lengths varied from 2-5. Accuracy for list lengths 2 and 3 will be analyzed. Trials for set sizes 2 and 3 were extracted and aggregated, means were then calculated.
Spatial Storage	*Initial trials of the Rotation Span task*: Participants remembered the spatial orientation of arrows while judging whether letters were mirror-reversed or not *Recall 1-Back Spatial/Figural*: Participants are shown a 3x3 grid of squares and are asked to recall and click on the last square that lit-up on the grid. List lengths varied from 2-5. Accuracy for list lengths 2, 3, and 4 will be analyzed. Trials for set sizes 2 and 3 were extracted and aggregated, means were then calculated.
Secondary memory retrieval	*Word-word*: Participants recalled 20 pairs of words in sequential order across 2 blocks *Word-number*: Participants recalled 20 pairs of word-digit pairs sequentially across 2 blocks *Letter-position*: Participants recalled letters that were paired to spatial positions on a 4x4 matrix across 2 blocks
Reasoning (Gf) **Used in Study 2 only*	*Berlin Test of Fluid and Crystallized Intelligence*: Participants completed 3 subtests from this test battery requiring make inferences from a set of premises (verbal), solve arithmetic reasoning problems (numerical), and had to infer irregularities from geometric shapes (figural)

Note. A table providing a description of the tasks that will be used in Study 1 and Study 2.

Results

Data for 216 participants (56% female, 44% male) is reported here. This sample was of a mean age of 27.41(SD= 4.83) years. See Table 5 for descriptive statistics of the cognitive ability tasks used in Study 1 and Study 2. Correlations among the tasks ranged from small to large with tasks measuring the same construct showing higher correlations overall (see Table 6).

Table 5

Descriptive Statistics for Cognitive Ability Tasks from Wilhelm et al. (2013)

Task	Mean	SD	Skew	Kurtosis
Reading Span Storage	0.85	0.18	-2.04	4.92
Operation Span Storage	0.95	0.11	-4.29	23.00
Rotation Span Storage	0.84	0.16	-1.68	3.69
1-back Spatial	0.44	0.17	-0.23	.10
SM- Verbal	0.44	0.26	0.05	-1.06
SM- Figural	0.26	0.16	0.72	0.17
SM- Numerical	0.26	0.16	0.50	0.13
Simon	-0.05	0.10	-6.09	42.57
Flanker	-0.06	0.14	1.05	-4.97

Note. SM= Secondary memory. Descriptive statistics were calculated for accuracy across all tasks.

Variable	1	2	3	4	5	6	7	8
1. Reading- Span Storage								
2. Operation Span- Storage	.50**							
3. Rotation Span- Storage	.45**	.37**						
4. 1-back Storage	.18**	.27**	.36**					
5. SM Verbal	.31**	.31**	.29**	.22**				
6. SM Figural	.18**	.16*	.25**	.19**	.31**			
7. SM Numerical	.29**	.31**	.30**	.20**	.71**	.41**		
8. Simon	.28**	.34**	.41**	.25**	.17*	.12	.21**	
9. Flanker	.14*	.13	.17*	.07	.19**	.09	.19**	.32**

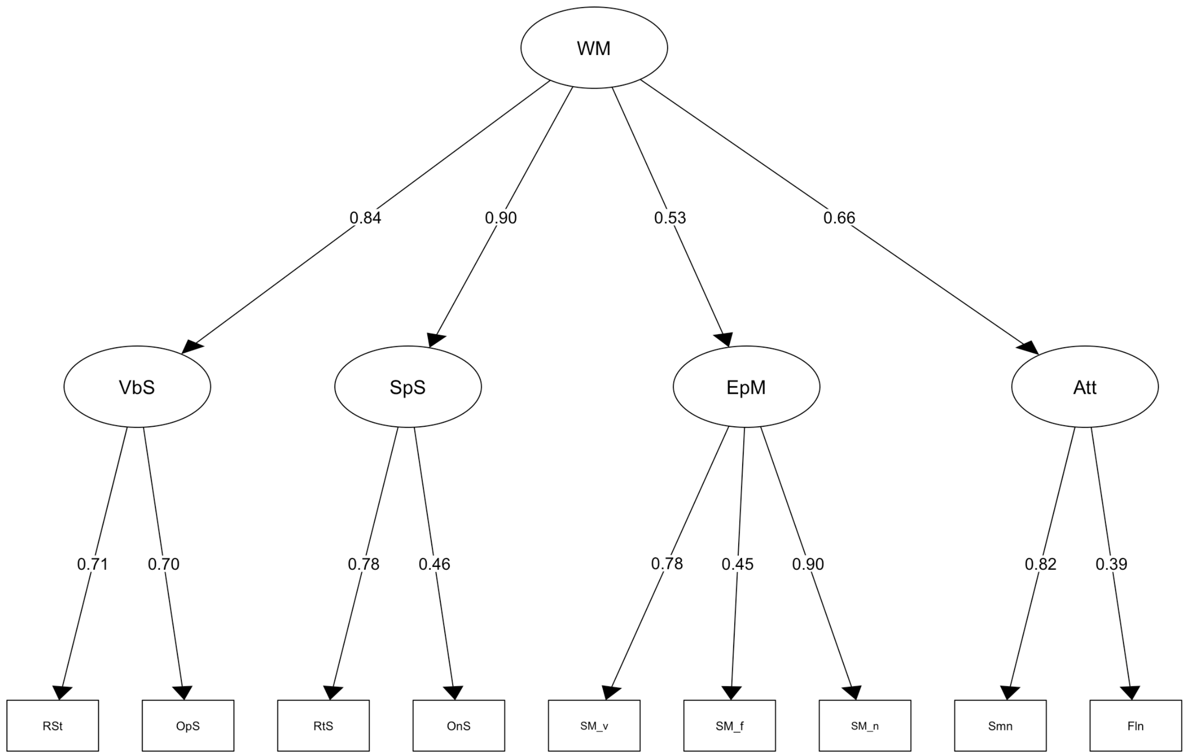
Note. SM= Secondary Memory. *= $p<.05$, **= $p<.01$.

Here in Study 1, a confirmatory factor analysis was conducted on the Wilhelm et al. (2013) data set using only tasks measuring attention, verbal storage, spatial storage, and secondary memory. As mentioned earlier, verbal and spatial storage were calculated by averaging performance on the initial trials (set sizes 2-3) of the operation, reading, and rotation span tasks. The CFA model we report here is a correlated four-factor higher order model of WM which can be referred to as Model 1. Overall, Model 1 shows good fit as indicated by the model fit indices, $\chi^2(23)= 23.44$, $p= 0.43$, CFI= 0.99, TLI= 0.99, SRMR= .03, RMSEA= .009, AIC= -2140.82, BIC= -2066.56. CFI for the present model is above the acceptable threshold of 0.95 as is also the case for TFI. Likewise, the SRMR value for Model 1 falls under the threshold of .05. In addition, the RMSEA value for Model 1 falls under the threshold of .06. Taken together, Model 1 shows good model fit.

Furthermore, as seen in Figure 9 below, the latent factors show standardized coefficients of 0.84 for verbal storage, 0.90 for spatial storage, 0.53 for episodic memory (secondary memory), and 0.66 for attention. The standardized coefficients range from moderate to large. Taken together, Model 1 shows good fit and the latent factors proposed to measure working memory show moderate to strong relations with a higher-order WM factor.

Figure 9

A four-factor higher-order model of working memory predicting verbal storage, spatial storage, episodic memory (secondary memory), and attention



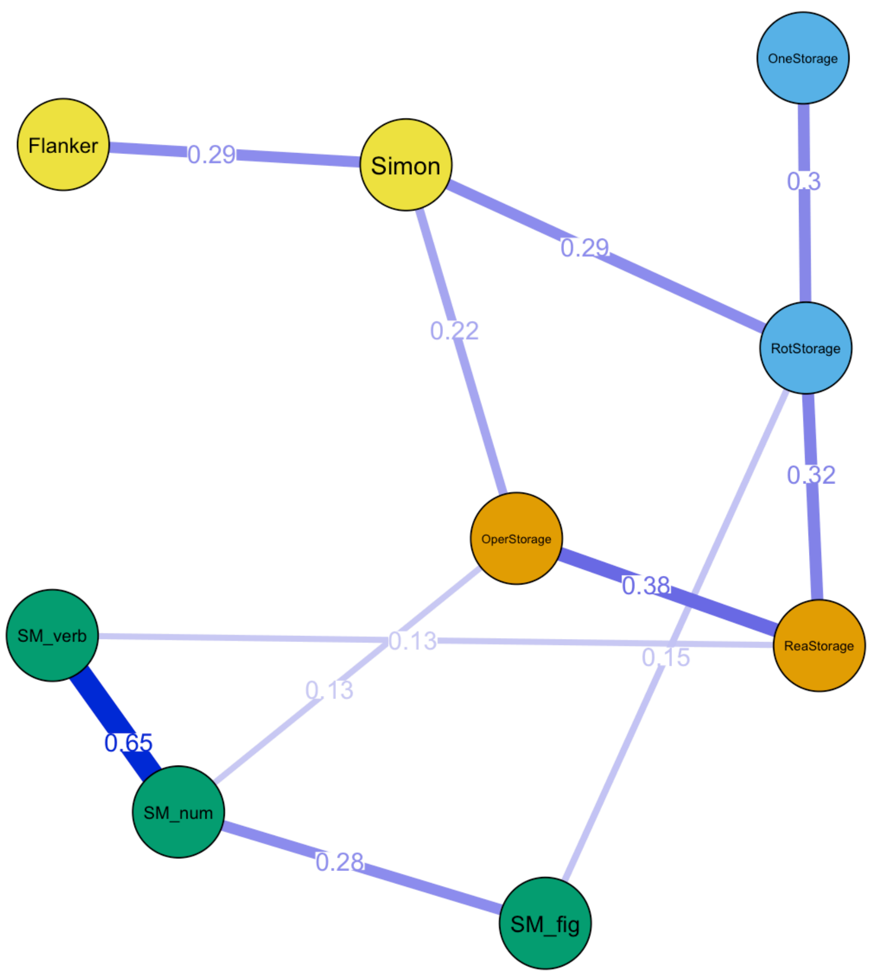
Note. Vbs= verbal storage, SpS= spatial storage, EpM= episodic memory, Att= attention, WM= higher-order working memory factor.

Network model of working memory

Using the same tasks from Model 1 above, a network model was produced. The tasks representing verbal storage, spatial storage, attention, and episodic memory (secondary memory) were included. Each node in a network model represents a task, while the coloring of each node represents a latent factor. Second, the connections between each node are termed edges, where blue edges between each node represent positive associations while red edges reflect negative associations. The thickness of the edges reflect the strength of the associations between the nodes (tasks) where thinner edges indicate weaker associations while thicker edges indicate stronger associations. Network models calculate partial correlations between each task and plots these relations. Given the literature reviewed above, we specified a network model with nodes representing four latent factors (i.e., verbal storage, spatial storage, episodic memory, and attention). See Figure 10 below.

Figure 10

A network model of WM representing verbal storage, spatial storage, episodic memory (secondary memory), and attention



Note. Sm_verb= secondary memory verbal, SM_num= secondary memory numerical, SM_fig= secondary memory figural, OperStorage= operations span storage, ReaStorage= reading span storage, RotStorage= rotation span storage, OneStorage= 1-back spatial storage. Yellow nodes= attention, green nodes= episodic memory (secondary memory), orange nodes= verbal storage, blue nodes= spatial storage.

The network model above, referred to as Model 2, showed good fit according to model fit indices, $\chi^2(25)= 24.65$, p= 0.48, CFI= 1.00, TLI= 1.00, RMSEA= 0.01, AIC= -2125.61, BIC= -2027.72. CFI for the present model is above the acceptable threshold of 0.95 as is also the case for TFI. In addition, the RMSEA value for Model 2 falls under the threshold of .06. Taken together, Model 2 shows good model fit.

The network model of WM shows that that tasks representing the same construct generally are more strongly connected with one another than with tasks representing other constructs. This is especially the case for verbal and numerical secondary memory and for the operation storage and reading storage (verbal storage). Similarly, but to a lesser extent, the spatial storage measures (rotation span storage & 1-back spatial storage tasks) also showed stronger edges between one another. However, the attention tasks, Simon and Flanker, did not show strong edges with each other. This will be discussed later.

Discussion

In Study 1 the goal was to produce a traditional CFA model of WM (Model 1) and using a more novel technique, produce a psychometric network model of WM (Model 2). Each model represented four components of WM: attention, verbal storage, spatial storage, and episodic memory (secondary memory). These four components were selected utilizing a theory-driven approach and are motivated by the following theories: Oberauer's model of WM (Oberauer, 2009), Unsworth's inclusive model of WM (Unsworth et al., 2014), the Executive Attention view of WM (Engle, 2002), and Baddeley's model of WM (Baddeley & Hitch, 1974). All of these propose one or more of the components of WM examined in this study. Here, in Experiment 1, we find that the four-factor higher-order CFA model of WM (Model 1) shows good fit. That is, the four components of WM along with a specified higher-order factor of WM, indicate a good measurement model of WM. Importantly, the network model of WM also showed good fit. This pattern of results supports the hypothesis for this study. Given that both the CFA model of WM and the network model of WM show good fit, the model of choice is the network model because it aligns well with theoretical perspectives like POT (Kovacs & Conway, 2016). Some notable findings to highlight from the network model are the clusters formed by the tasks. Generally, the episodic memory tasks formed relatively stronger edges with one another than with other nodes. This is also true of the verbal storage tasks. It is important to also highlight that the verbal secondary memory node is associated with Reading Span storage (a measure of verbal storage), and figural secondary memory is related to Rotation Span storage (a measure of spatial storage). This shows evidence for the idea that WM is in part driven by domain-specific components. This corroborates previous research showing that variability in WM is in part explained by domain-specific processes as well (Kane et al., 2004). In addition, another important finding is that the Simon task shows edges with both measures of verbal and spatial storage. This indicates that the relation between measures of attention and measures of storage is domain general. This corroborates a bulk of research supporting attention as a domain-general component of WM (Baddeley & Hitch 1974, Engle et al., 1999).

To further extend the findings from Study 1, in the next study, the predictive validity of WM was tested in two ways, first, using a traditional CFA approach, and later using a network model. Specifically, the predictive validity of Gf was tested. Fluid intelligence has traditionally been related to WM and thus, examining this relationship here can serve as a psychometric “check”. The goal of Study 2 is to test whether the components of WM in a network model predict Gf similarly as they would in a traditional CFA model. Testing this question can lead to further insight about the ability for network models to preserve predictive validity of other higher-order constructs. This is important given that establishing predictive validity in CFA models of WM is a common goal of psychometric studies of cognitive abilities.

Study 2: Predicting Gf via a Psychometric Network Model of WM

Historically, a great deal of research has been devoted to understanding the relationship between WM and Gf. Thus, to examine this relationship from a psychometric perspective in this study is important as this will address one of the aims of this dissertation, namely, to understand which components of working memory are crucial for measuring and in turn, predicting Gf. As discussed earlier, Wilhelm et al. (2013) tested the relationship between the various components of WM and Gf. They found WM and Gf to be highly related constructs. Here, we will utilize the tasks included in Wilhelm et al to also produce a latent variable model of WM and Gf. Specifically, we will specify a correlated 2-factor higher-order latent variable model of WM and Gf. In contrast to Wilhelm et al, we will also use network analysis to test the predictive validity of the different components of WM when predicting Gf. Specifically, Study 2 will test the extent to which attention, verbal and spatial storage, and retrieval from secondary memory predict Gf, and it is predicted that each of these constructs will account for unique variance in Gf. Importantly, we predict that the predictive power of WM in the network model will be equivalent to the predictive power of WM in the latent variable model regarding Gf. Showing this pattern of findings will strengthen the claim that not only does the network model of WM fit the data just as well as a latent variable model of WM (Study 1), but also that we preserve the ability to predict higher-order constructs like Gf using network modeling. This will lead to a greater understanding of how network modeling can inform our knowledge of how components of WM are structurally related to Gf.

Study 2 Method

Study 1 used both latent variable modeling and psychometric network modeling to examine the structure of WM. Here we extend Study 1 and include measures of Gf to examine the extent to which the different components of WM predict Gf. We utilized the tasks in Table 2 to carry out the goal of this study. First, we produced a latent variable model of WM and Gf. We used factor scores to determine the extent to which WM and Gf are related in the latent variable model. Next, we produced an undirected network model of the measures of the components of WM and the measures of Gf. Next, we used cluster scores to determine the strength of the network associations between nodes of WM and the Gf node. The cluster scores are comparable to the factor scores in the latent variable model. As such, we were able to compare the predictive validity of WM in predicting Gf in the network model and in the latent variable model. As stated above, the network modeling procedures used in Study 1 were also used here.

In addition, the model fit indices described above in Study 1 (Schreiber et al., 2006) were also used here to determine the fit of both the network and latent variable model of WM and Gf. In Study 2, it is predicted that the cluster scores of the components of WM will predict unique variance in Gf. Moreover, it is predicted that about 50% of the variance in Gf will be explained by the network model of WM. In addition, it is predicted that in the latent variable model, the WM factor will explain about 50% of the variance in the Gf factor. If these findings hold, this will be evidence that a network model of the components of WM preserves the predictive validity typically obtained in latent variable models of WM and Gf. As in Study 1, the network model will be the preferred model given its theoretical compatibility with models like POT that motivate the studies here.

Results

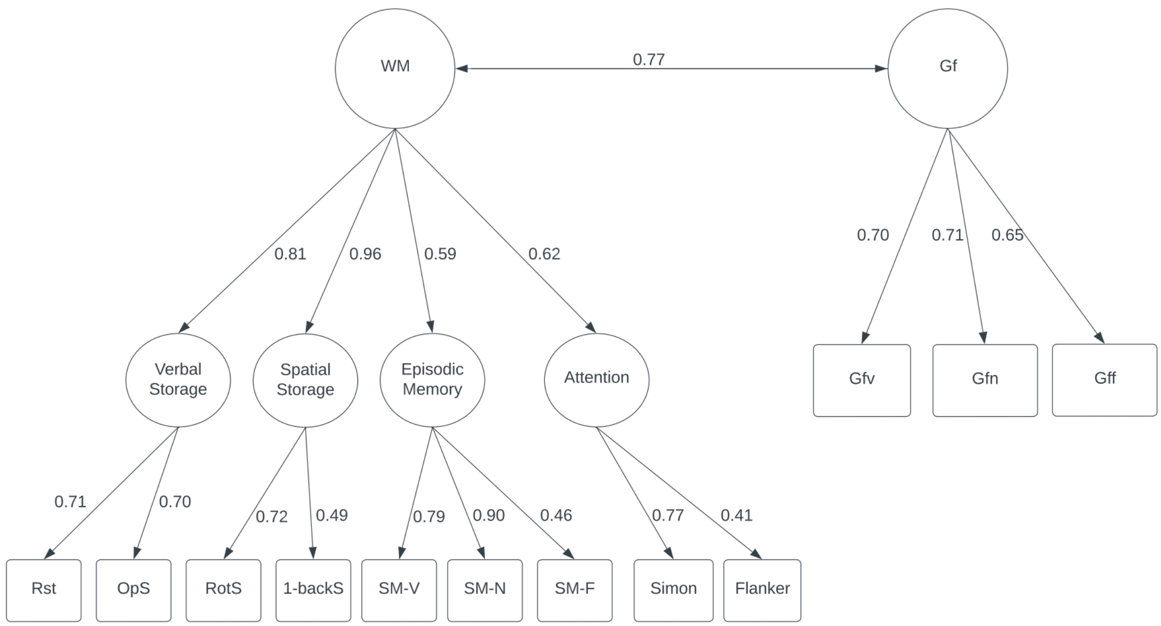
Participant data here in Study 2 is the same as that of Study 1. In addition to the measures used in Study 1, here in Study 2 we also included a composite measure of Gf. See Table 2 for a description of the measures.

First, a confirmatory factor analysis was conducted on measures of attention, verbal storage, spatial storage, episodic memory (secondary memory), and Gf. This model can be referred to as Model 3. Overall, Model 3 showed good fit statistics according to criteria proposed by previous sources (Schreiber et al., 2006; Kline, 2015). Specifically, Model 3 shows: $\chi^2(49)$= 84.40, $p< 0.01$, CFI= 0.95, TLI= 0.93, SRMR= 0.06, RMSEA= 0.05, AIC= -2841.14, BIC= -2743.25. CFI for the present model is above the acceptable threshold of 0.95 as is also the case for TFI. Likewise, the SRMR value for Model 3 falls within proximity of the .05 threshold. In addition, the RMSEA value for Model 1 falls under the threshold of .06. Taken together, Model 3 shows good model fit.

Furthermore, as seen in Figure 11 below, the latent factors show standardized coefficients of 0.81 for verbal storage, 0.96 for spatial storage, 0.59 for episodic memory (secondary memory), and 0.62 for attention. The standardized coefficient path between WM and Gf was 0.77, 95% CI [0.71, 0.82]. The standardized coefficients range from moderate to large. Taken together, Model 3 shows good fit and the latent factors proposed to measure working memory show moderate to strong relations with a higher-order WM factor. Further, the higher-order WM factor also shows a strong relation with the latent Gf factor. In terms of effect size, 64.8% of the variance in the verbal storage factor was shared with the higher-order WM factor, 92% explained in the spatial storage factor, and 34.8% explained in the episodic memory latent factor. Notably, 59% of the variance in the GF factor was shared with the higher-order WM factor. In sum, the effect sizes in this model were all large.

Figure 11

A CFA model depicting the structural relation between a higher-order WM factor and Gf



Note. Rst= reading span storage, OpS= operation span storage, RotS= rotation span storage, 1-backS= one-back storage, SM-V= secondary memory verbal, SM-N= secondary memory numerical, SM-F= secondary memory figural, WM= higher-order working memory factor, GF= fluid reasoning.

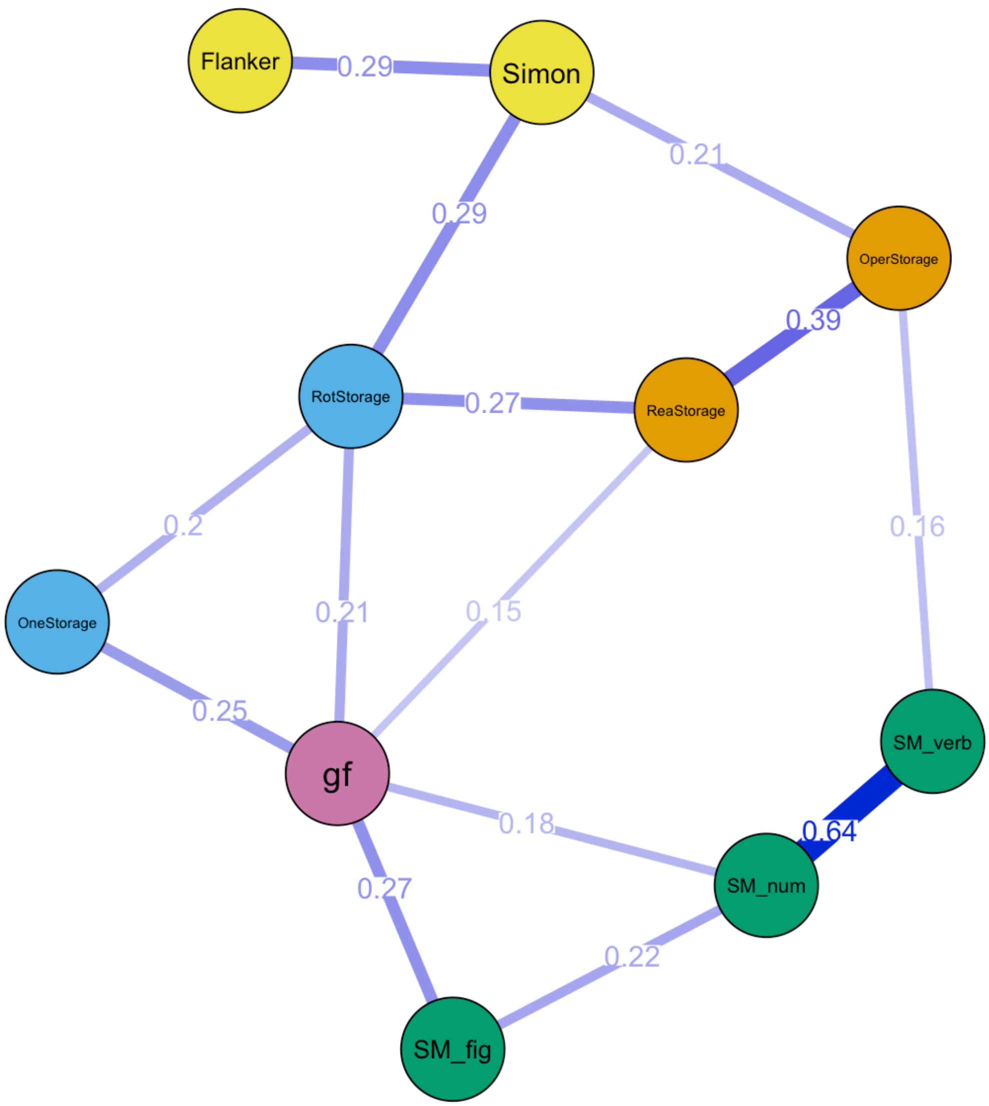
Network model analyses

Using the same tasks from Model 3 above, a network model was produced. The tasks representing verbal storage, spatial storage, attention, episodic memory (secondary memory) and

Gf were included. This model can be referred to as Model 4. The same specifications as those used for Model 2 earlier in Study 1 were used to calculate this model with the main difference being that in this Model 4 we proposed a fifth node representing Gf. See Figure 12 below.

Figure 12

Network model of WM components and Gf



Note. Sm_verb= secondary memory verbal, SM_num= secondary memory numerical, SM_fig= secondary memory figural, OperStorage= operations span storage, ReaStorage= reading span storage, RotStorage= rotation span storage, OneStorage= 1-back spatial storage, gf= fluid intelligence. Yellow nodes= attention, green nodes= episodic memory (secondary memory), orange nodes= verbal storage, blue nodes= spatial storage, pink node= Gf.

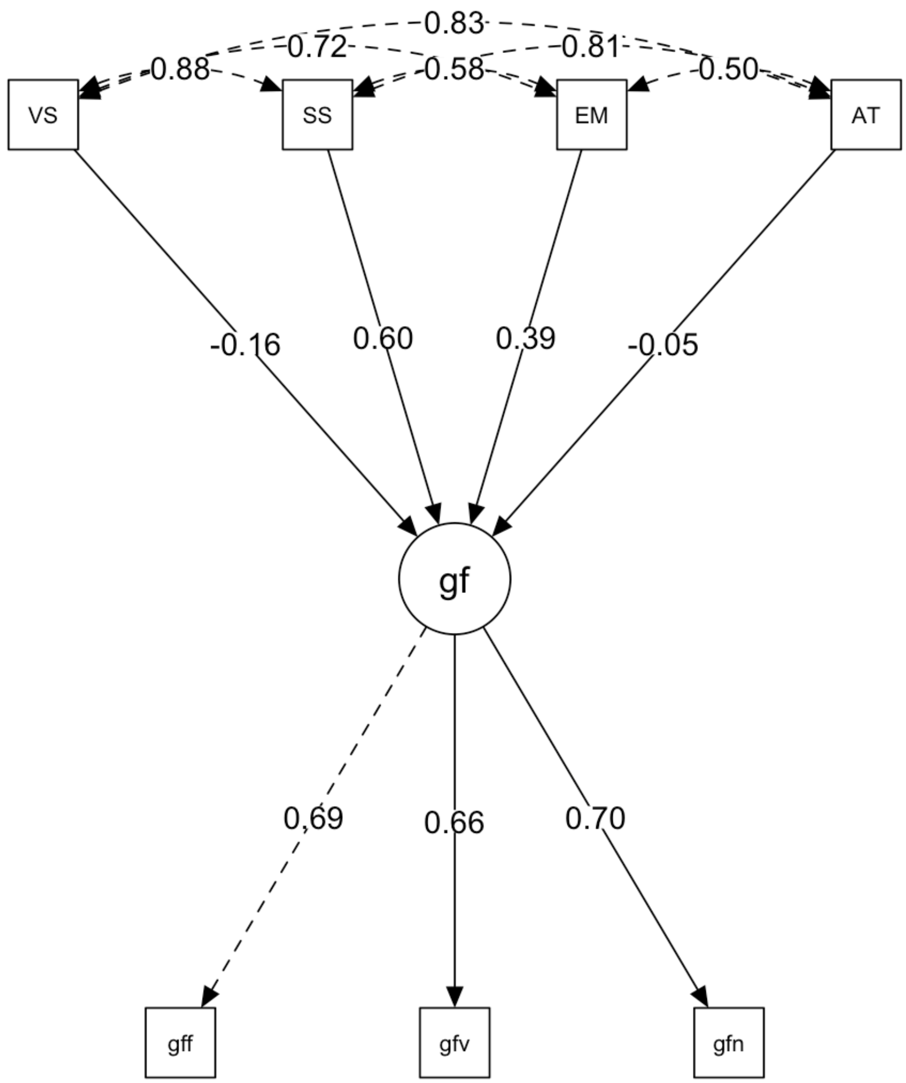
Model 4 showed good fit statistics according to criteria proposed by previous sources (Schreiber et al., 2006; Kline, 2015). Specifically, Model 4 shows: $\chi^2(31)= 27.21$, $p< 0.01$, CFI= 1.00 , TLI= 1.00, RMSEA= 0.01, AIC= -2490.14, BIC= -2375.38. CFI for the present model is above the acceptable threshold of 0.95 as is also the case for TFI. Likewise, the RMSEA value for Model 1 falls under the threshold of .06. Taken together, Model 4 shows good model fit.

In terms of the WM components (attention, verbal/spatial storage, and episodic memory), and similarly to Model 2 in Study 1, the network model of WM shows that that tasks representing the same construct generally are more strongly connected with one another than with tasks representing other constructs. This is especially the case for verbal and numerical secondary memory and for the operation storage and reading storage (verbal storage). Similarly, but to a lesser extent, the spatial storage measures (rotation span storage & 1-back spatial storage tasks) also showed stronger edges between one another. However, the attention tasks, Simon and Flanker, did not show strong edges with each other. Importantly, the Gf node is associated with most nodes in the network. The Gf node showed the strongest edge weights with the figural measure of secondary memory and then with the 1-back spatial storage measure.

In addition to producing a network model of WM, cluster scores were calculated to determine the extent to which the four components of WM (attention, verbal/spatial storage, & episodic memory) are predictive of Gf. In this analysis, Gf was calculated as a composite from three Gf tasks: Gf verbal, Gf numerical, and Gf figural. As outlined earlier, cluster scores are comparable to factor scores in traditional CFA analyses. This model can be referred to as Model 5. See Figure 13 below.

Figure 13

A regression model depicting cluster scores for each WM component predicting Gf



Note. VS= verbal storage, SS= spatial storage, EM= episodic memory, AT= attention, gf= fluid intelligence, gff= gf figural, gfv= gf verbal, gfn= gf numerical.

Per Model 5 above, not all components of WM were predictive of Gf. Spatial storage was predictive of Gf at 0.60 and episodic memory was predictive of Gf at 0.39. However, verbal storage was not predictive of Gf as was also the case with attention. Cumulatively, 51% of the variance in Gf was explained by the components of WM. An effect size of 51% is associated with an estimated association of 0.71 [0.64, 0.77]. Thus, in a follow-up analysis we tested for a difference of associations and found that the association between WM and Gf (0.77) in model 11 (CFA model) is not significantly different from the association between the components of WM and Gf (0.71) in model 13 (network model), $p = 0.17$. A discussion of these findings will now be provided.

Discussion

In Study 2 the goal was to determine the extent to which WM was predictive of Gf in both a traditional CFA model and a network model. First, the findings showed that both a CFA model and network model of WM and Gf fit the data well. Second, the findings show that the CFA model of WM predicted Gf at 0.77 with 59% of the variance being explained in Gf. Using cluster scores, the network model of WM explained 51% of the variance in Gf. Both findings are in-line with previous research showing that WM and Gf are correlated at about 0.72, where about 50% of the variance is shared between both constructs (Kane et al., 2005). Contrary to our hypothesis, the findings show that the network model of WM does not explain as much variance in Gf as does the CFA model of WM and Gf. A reason for this result is due to the lack of predictive validity shown by both the verbal storage and attention components. Between both cluster scores, only about 4% of the variance is explained in Gf. This does not corroborate previous findings showing that attention is a significant predictor of Gf (Engle, 2002). Nonetheless, though the network model of WM did not explain as much variance in Gf as the

WM factor in the CFA model (Model 3), the WM components in the network model still explained about 50% of the variance in Gf, which is what is typically reported in this field of work (Kane et al., 2005; Unsworth et al., 2014; Engle et al., 1999; Kane et al., 2004). Furthermore, a follow-up test of difference in correlations showed that the differences in variance explained between the CFA model (59%) and the network model (51%) are not significantly different. Thus, showing that network models of WM retain predictive validity, especially regarding Gf. Importantly, it is worth acknowledging that the CFA model in this study could be overestimating the relationship between WM and Gf, while the network model could be estimating this relationship more accurately; this will be discussed in the next section. A larger discussion of the findings from Study 1 and Study 2 will now be provided.

General Discussion

Across Study 1 and Study 2 the goal of this set of studies was to (1) examine the psychometric structure of WM via network modeling and (2) determine the extent to which network models of WM are predictive of Gf in comparison to traditional CFA models of WM. The results show support for the hypothesis proposed for Study 1, but the results do not fully support the hypothesis for Study 2.

In regard to Study 1, it was hypothesized that a network model of WM would fit equally well to a traditional CFA model of WM. In both models, the components of WM were attention, verbal storage, spatial storage, and episodic memory (secondary memory). The results indicated that the network model (Model 2) fit the data well just as the CFA model of WM memory (Model 1). This finding is important for several reasons. First, these findings corroborate previous work proposing important components that produce variation in WM. Namely, attention, verbal/spatial storage, and episodic memory. Starting with attention, a long line of work has argued that individual differences in WM are primarily driven by individual differences in attention (also known as cognitive control, attention control, controlled attention) (Conway et al., 2001; Kane et al., 2001). Numerous studies have shown that attention serves as the bottleneck of WM capacity. For example, Conway et al., (2001) showed that in dichotic listening tasks, high WM span participants were less likely to hear their name from the unattended listening channel compared to low WM span participants (20% vs 65%, respectively). This finding supports the idea that having a higher ability to resist distracting information is a defining feature of being a high WM span individual. More akin to the current study, other work, using latent variable modeling, has shown that a latent WM factor is more predictive of higher-order cognition (e.g., intelligence) than STM. Presumably, this is due to the domain-general shared variance between WM and intelligence (Engle et al., 1999). In the network model of WM produced here (Model 2), there is evidence for this domain-generality of attention in the WM network. The Simon task, a typical measure of attention, was related to both verbal and spatial storage. This corroborates previous research showing that attention is a domain-general ability.

Further, the network model of WM showed strong relations among most measures of domain-specific storage. The verbal storage tasks were related to one another non-storage abilities in the network. This pattern of findings was also true for the spatial storage tasks. The secondary memory tasks also showed associations with the storage tasks according to content. For instance, the secondary memory verbal task shared an edge with the reading span storage measure (both are verbal tasks) and the secondary memory figural task shared an edge with the rotation span storage measure. This is evidence for the convergent validity of the domain-specific measures. One potential caveat that is worth discussing is that the measures of verbal and spatial storage are derivatives of larger tasks. In other words, the storage measures calculated here are part of larger tasks. A consequence of this is that the associations between the verbal storage and spatial storage tasks are similar in this study. Past research shows that tasks measuring the same content domain should be more strongly correlated with one another than with tasks measuring a different content domain. However, that isn't necessarily the case here. For example, the reading span storage task and rotation span storage task share and edge weight of 0.32, while the edge weight shared between the rotation span storage task and 1-back spatial storage task is of 0.30. This finding can be attributed to the fact that the reading span storage measure and the rotation span storage measure represent the smaller list lengths of the larger more traditional reading and rotation complex span tasks, respectively. In these smaller list lengths, participants are still engaging in resolving the processing (distractor) task, which requires the ability to resist distraction and resolve interference. So, the potential reason why the associations between the verbal and storage tasks are more similar than expected is because these indices are not purely reflective of storage, but rather storage and attentional abilities. Despite this, the overall findings of Study 1 have important implications.

The findings of Study 1 show that a network model of WM fits the data just as well as a CFA model of WM. This supports our hypothesis. With that, the network model is the preferred model given its compatibility with theories like POT. Unlike traditional CFA models that are restricted by assumptions like the principle of local independence, the statistical assumptions that govern network modeling and their theoretical implications fit well with theories like POT, which suggests that cognitive abilities are best thought of as collaborating in an overlapping manner during complex tasks. Network models establish this kind of perspective, while CFA models do not. Not only are the findings from Study 1 consistent with POT, but they are also consistent with other WM theories. Mainly, Oberauer's (Oberauer, 2009) and Unsworth's

(Unsworth, 2014), theories of WM. Oberauer's theory of WM assumes a structure of working memory that relies on the ability to resolve retrieval competition from stimuli in WM and from representational interference. To resolve both, WM relies on the capacity of the FOA and the ability to update the contents in the FOA. Oberauer also produces a more accurate description of the FOA. Oberauer identifies numerous mechanisms that influence WM performance. Doing so aligns with the current findings where it is shown that accounting for multiple components of WM is psychometrically fitting and theoretically accurate. Furthermore, both Oberauer and Unsworth emphasize the importance of secondary memory retrieval. Accounting for secondary memory retrieval allows for a more comprehensive view of WM, which is also consistent with the findings of Study 1. Model 2 of Study 1 presents an inclusive network of components of WM that as a network structure, fit the data well statistically, and is theoretically compatible with the numerous theories outlined above. For this reason, the findings from Study 1 unify psychometric (Unsworth) and cognitive models (Oberauer) of WM. This outcome has been largely absent in previous work in the field of WM.

The goal of Study 2 was to test the predictive validity of WM as it pertains to Gf. This was done by comparing the degree to which WM explained variance in Gf in a traditional CFA model, and the degree to which the components of WM explained variance in Gf in a network model. Contrary to our hypotheses, the results showed that the latent WM factor in the CFA model predicted more variance in GF (59%) than the components of WM in the network model (51%) (though this difference was not statistically significant). We suspect that this can be for a couple of reasons. First, attention was not measured well in this study. The attention tasks were the Simon task and the Flanker task. These tasks correlated at $r = 0.32$, which is lower than expected. Second, these tasks showed very weak cluster scores in Model 5. Attention showed a coefficient of -0.05. This is abnormally low given previous research showing that attention is a significant factor that drives the relation between WM and Gf. Next, verbal storage also showed a low coefficient of -0.16. In this case it is suspected that there is a suppression effect on behalf of the spatial storage component. The path between spatial storage and verbal storage shows a coefficient of 0.88, which is alarmingly high. Thus, this leads to the inability for verbal storage to explain any meaningful variance in Gf. It is also plausible that the CFA model is overestimating the variance in Gf that is predicted by WM and that the network model approximates the true relation between WM components and Gf given its statistical advantages. More research is needed to confirm this explanation.

Expanding the idea of estimation above, a reason why CFA models could be overestimating the relationship WM and Gf could be due to the underlying differences in computation between CFA models and network models. CFA models rely on estimating the extent to which variance in observed variables is captured by a common cause or latent factor. The influence of other variables in the model are not accounted for. In network models, partial correlations among variables are calculated without assuming common causes or latent variables. In a network model, the association between two variables is not influenced by any other variable in the model; those influences have already been accounted for. However, this is not necessarily the case in CFA models. Thus, the differences in these computational approaches can lead to the idea that CFA models are overestimating the relationship between WM and Gf, while network models could be quantifying this relationship more accurately. Further research is necessary on this end.

Nonetheless, though the components of WM in the network model (Model 4) did not predict as much variance in Gf as the WM factor in the CFA model (Model 3), explaining 51%

of the variance is consistent with previous findings testing the relationship between WM and Gf. Typically, WM explains about 50% of the variance in Gf (Kane et al., 2005; Conway et al., 2002; Engle et al., 1999). Under this standard, the network model corroborates previous literature and establishes predictive validity of Gf. This is an important finding that showcases the ability for network models to retain predictive power, especially within this vein of research.

There are a few limitations that are worth discussing. First, the sample of measures used to assess attention was not ideal. Psychometrically, the attention measures did not show good psychometric properties, these include skewed distributions and weak correlations with every other cognitive task in this set of studies. Poor measurement of attention could have contributed to the findings of Study 2, where network component of attention did not explain any unique variance in Gf. Second, the indices of verbal and spatial storage are not ideal. As mentioned earlier, these are smaller portions of larger complex span tasks. Having true measures of storage, such as simple span tasks would be more appropriate. Future studies should attempt to administer the full range of WM tasks to attempt to investigate the veracity of this four-component model of WM. In addition, future studies should attempt to investigate how this network structure varies across different populations and changes developmentally as well. Addressing these inquiries can advance the field of WM meaningfully both at the theoretical level and at the applied level. Despite the limitations discussed earlier, the current study effectively tests the questions posed here and sheds light on understanding the psychometric nature of WM. Implications of the findings of these studies will now be discussed.

Overall, Study 1 provides important theoretical implications. First, Study 1 shows that a network model of four components of working memory (attention, verbal storage, spatial storage, and secondary memory) shows good model fit and is a psychometrically accurate manner of representing WM as compared to a CFA model of WM. Previous research has proposed models of working memory that includes at most three out of the four components proposed here. We extend these previous findings and show that a more inclusive approach to studying WM, accounting for four factors, not only shows to be psychometrically sound, but also is more compatible with strong cognitive models of WM, and also with emerging theories of cognition like POT. CFA models are not able to achieve this goal due to their statistical assumptions as discussed earlier. In sum, the current studies offer a novel psychometric perspective to conceptualize WM, both statistically and theoretically.

Not only do the current findings provide theoretical implications, but also practical implications. Specifically, the current studies identify four components of WM that should be measured in both educational and clinical settings. For instance, WM has primarily been measured through tasks that involve high interference and the ability to engage in dual-task demands. However, we show here that other components of WM should be accounted for in measurement (i.e., secondary memory retrieval, verbal storage, spatial storage) to ensure that WM is being assessed completely. Doing so allows for more accurate diagnoses of learning disabilities that might be caused by deficits in WM, for example. In addition, educational and clinical interventions can also be informed by the current findings such that any paradigm designed to remediate WM can be constructed in such a way that targets the four components of WM proposed here. Achieving this can essentially produce a greater impact on improving WM capacity.

Ultimately, the current studies provide novel insight regarding the psychometric structure of WM using the novel technique of network modeling. It is shown that a four-component model of working memory is an accurate and comprehensive approach to conceptualizing WM. This was done by unifying evidence from cognitive models and psychometric models of WM, which is an important endeavor that is largely lacking in the field. Convincing evidence is offered here that WM exists as a multicomponent construct that is best represented as a network of interacting abilities.

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