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What Makes Working Memory Work? A Multifaceted Account of the Predictive Power of Working Memory Capacity

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Working memory capacity (WMC) has received a great deal of attention in cognitive psychology partly because WMC correlates broadly with other abilities (e.g., reading comprehension, second-language proficiency, fluid intelligence) and thus seems to be a critical aspect of cognitive ability. However, it is still rigorously debated *why* such correlations occur. Some theories posit a single ability (e.g., attention control, short-term memory capacity, controlled memory search) as the primary reason behind WMC's predictiveness, whereas others argue that WMC is predictive because it taps into multiple abilities. Here, we tested these single- and multifaceted accounts of WMC with a large-scale ($N = 974$) individual-differences investigation of WMC and three hypothesized mediators: attention control, primary memory, and secondary memory. We found evidence for a multifaceted account, such that no single ability could fully mediate the relation between WMC and higher order cognition (i.e., reading comprehension and fluid intelligence). Further, such an effect held regardless of whether WMC was measured via complex span or *n*-back.

Public Significance Statement
Individual differences in working memory capacity predict a host of important outcomes such as intelligence, academic performance, emotion regulation, and second-language acquisition. This study indicates that these relationships are likely multifaceted. Complex cognitive processes require the instantiation of task goals, the maintenance of goal-relevant information in short-term memory, and the controlled retrieval of information from long-term memory. We find that these three abilities can explain why working memory capacity is such a diverse predictor of critical outcomes.

Keywords: working memory, long-term memory, attention control, fluid intelligence, reading comprehension

Working memory (WM) is a core cognitive ability that allows people to manage goal-directed information flexibly and dynamically. Individual differences in working memory capacity (WMC) predict a host of important outcomes like fluid intelligence (Engle et al., 1999; Kyllonen & Christal, 1990), academic standardized test scores (Cowan et al., 2005; Engle et al., 1999; Mrazek et al., 2012), second-language acquisition (Linck et al., 2014; Martin et al., 2020), and reading comprehension (Daneman & Carpenter, 1980; Martin et al., 2020; McVay & Kane, 2012b; Peng et al., 2018; Robison & Unsworth, 2015; Unsworth & McMillan, 2013).

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Because of WMC's predictive power, considerable research has been dedicated to understanding the working memory system and WMC as an individual difference. At least three important sources of variation in WMC have been identified: (a) attention control (AC), (b) primary memory (PM), and (c) secondary memory (SM).

We conceptualize PM, SM, and attention control as three distinct yet conceptually overlapping *processes*. Thereby, we subsequently measure the relative effectiveness of each process within a person as an *ability* (or individual difference). The conceptual overlap among these processes warrants specifying and delineating them. By attention control, we mean the set of processes by which people select, maintain, and execute task goals, especially when those goals cannot be executed via automatic processes. By PM, we mean the process by which a relatively small amount of information is encoded into and then actively maintained in a short-term store. People have direct access to this store, and items can be retrieved from it quickly and effectively. However, this store has only a small capacity (typically three to four items; Cowan, 2001). The individual differences in PM are thus conceptualized as the number of distinct representations that a person can simultaneously hold active. As new information enters the senses, PM representations must be protected from interference lest they are lost permanently. As a protective strategy, goal-relevant representations can be transferred via additional processing into more stable, yet less easily retrievable representations held in a long-term store (*SM*). SM is a subset of long-term memory that contains goal-relevant information. Importantly, information must be effectively transferred into SM and be recalled from SM via controlled retrieval processes, both of which are fallible. Therefore, the individual differences in SM typically result from the (in)ability to either encode information into or retrieve goal-relevant information from this long-term memory store. Continually, people must act in a goal-directed manner to effectively employ PM and SM. That is, any deviation of attention from the task goal can result in (a) failing to encode information into PM, either due to short-term storage limitations or attention lapses, (b) failing to convert PM representations to SM representations, or (c) failing to retrieve correct information from SM.

In the context of a working memory measure (e.g., operation span), we would argue that PM, SM, and attention control are all required. Take, for example, a trial of the operation span task with a set size of five items. In a sequence of interleaved steps, a participant encodes a letter (PM), and then the goal shifts to solving a math operation (attention control), before shifting back again to encoding another letter (PM) and so forth. As the number of letters meets and then exceeds one's PM limitations, older letters must be converted to long-term memory representations for later access, so that new information can be given priority (SM). Then, during the recall phase, any letters that are currently active (PM) can be recalled, and any letters that are not active can be retrieved (SM). A person's score is the number of letters they recall in the correct serial position on that trial and then summed across several trials. As proponents of a multifaceted view of working memory, we would argue that what we call WMC is an individual difference that arises from at least three distinct processes. Thus, three individuals may receive the same low WMC score but for different reasons. One person may perform poorly due to an inability to manage task goals and task-relevant memoranda in the presence of internally or externally distracting information (attention control), whereas another may perform poorly due to an inability to maintain more than two items at any given moment (PM). And yet a third individual may perform poorly due to inability to encode and subsequently retrieve temporarily displaced items from SM once capacity limitations are exceeded. In turn, when we observe that WMC is correlated with some other aspects of psychological functioning (e.g., fluid intelligence, reading comprehension, second-language acquisition, multitasking), the overlap could be due to one of these three subprocesses. That is, WMC may predict one domain (e.g., reading comprehension) because both depend significantly on SM. Conversely, WMC may predict another domain (e.g., fluid intelligence) because optimal performance relies heavily on attention control. Of course, it could also be the case that both WMC and the correlate similarly require a combination of all three processes. Indeed, prior theories have posited that each of these three abilities is *the* primary determinant of WMC as an individual difference, whereas other theories have proposed that WMC's predictiveness is multiply determined. The present study will test and compare such theories using latent variable and structural equation modeling and examine the extent to which these theories generalize across WMC measurements and across outcome constructs.

Attention Control Account of Working Memory Capacity

The attention control (i.e., executive attention) account of WMC argues that attention is the primary driver of WMC's ability to predict higher order cognition (Engle, 2002, 2018). This account implicates a similar mechanism as the *central executive* component of the working memory system proposed by Baddeley (1992), the *supervisory control system* proposed by Norman and Shallice (1986), and what Posner and Petersen (1990) called the *anterior attention system*. Engle (2002) made the case for WMC being best conceptualized as *executive attention*, and Engle and Kane (2004) further encapsulated this viewpoint into a two-factor theory of attention control. Specifically, Engle and Kane (2004) argued that WMC captures two important aspects of attention control—goal maintenance and conflict resolution. Goal maintenance refers to the ability to keep task goals active in mind, especially when those task goals could be superseded by irrelevant internal and external distractions. Conflict resolution refers to the ability to resolve stimulus–stimulus and stimulus–response conflict in a goal-directed manner. Namely, when faced with interfering information, one needs to override automatic or habitual reactions to respond in accordance with task goals. This view hypothesizes that the degree to which any cognitive behavior requires these two factors, WMC will correlate with that behavior. For example, WMC correlates with reading comprehension specifically because reading comprehension and working memory measures similarly require executive attention (see McVay & Kane, 2012b).

A bevy of evidence supports attention-centered accounts of WMC. Perhaps most importantly, WMC correlates well with performance on attention tasks that do not require remembering any information other than a task goal and stimulus–response mappings, such as the antisaccade task (Kane et al., 2001; Unsworth et al., 2004), Stroop tasks (Kane & Engle, 2003), flanker tasks (Heitz & Engle, 2007; Kane et al., 2016), the Sustained Attention to Response Task (McVay & Kane, 2012a), and the psychomotor vigilance task (PVT; Unsworth & Robison, 2020). Further evidence for the role of executive attention in WMC comes from studies that show a negative correlation between WMC and the tendency to experience task-unrelated thoughts such as mind wandering, especially during tasks that require high levels of controlled processing (Kane, Brown, et al., 2007; Kane et al., 2016; Krimsky et al., 2017; McVay & Kane, 2012a; Mrazek et al., 2012; Robison & Brewer, 2020; Robison et al., 2017; Robison & Unsworth, 2015, 2018; Unsworth & McMillan, 2013, 2014a; Unsworth & Robison, 2016). These studies support the notion that attention control abilities are a primary source of covariation between WMC and higher order cognition.

Despite this evidence, attention control accounts of WMC are not without their criticisms. When examining the shared variance among short-term memory, WMC, and fluid intelligence, it has often been assumed that residual variance in WMC after controlling for short-term memory capacity represents executive attention abilities (Engle et al., 1999). Kane et al. (2005) noted this, saying that a latent-level analysis of attention control was necessary to confirm the predictions of an attention account of WMC. More recently, researchers have specified attention control-specific factors in latent variable models of WMC and other constructs like fluid intelligence. For example, Unsworth, Spillers, and Brewer (2009) measured an attention control latent factor with the antisaccade, psychomotor vigilance, and arrow flanker tasks. Performance on these tasks formed a coherent latent factor that was distinguishable from latent factors for WMC and fluid intelligence. Although the WMC and attention control latent factors correlated moderately (latent $r = 0.41$), they each accounted for unique variance in fluid intelligence beyond their shared variance. In other words, accounting for attention control did not fully explain the WMC–intelligence relation. Similar partial mediation was found by Unsworth and Spillers (2010), Unsworth et al. (2014), and Burgoyne et al. (2023). Frequently, latent variable models show that attention control and WMC tend to share about 30%–50% of their variance (Burgoyne et al., 2023; Draheim et al., 2021; Kane et al., 2016; Robison & Brewer, 2022; Robison et al., 2017; Robison & Unsworth, 2018; Tsukahara et al., 2020; Unsworth et al., 2014; Unsworth & McMillan, 2014a; Unsworth, Miller, & Robison, 2021; Unsworth, Robison, & Miller, 2021; Unsworth & Spillers, 2010). Although attention control abilities tend to partially mediate the relation between WMC and other abilities, attention control rarely fully mediates the relation (but see Draheim et al., 2021; Tsukahara et al., 2020). Because there is often a relation between measures of higher order cognition and WMC, even after accounting for attention control, there seems be more to WMC's predictive power than just attention.

Further complicating the attention account is the fact that attention control has proven difficult to measure as an individual difference. Many classic attention measures, such as the Stroop Color–Word Interference Test, the Eriksen flanker task, and the Simon task produce robust within-subject effects on reaction times (RTs). In each of these tasks, incongruent trials require resolving some stimulus–stimulus or stimulus–response conflict and thus produce longer RTs than congruent trials, which do not require resolving conflict. As a result, researchers have used these tasks to measure individual differences in attention control. However, these difference scores (incongruent RTs minus congruent RTs) have rather poor psychometric properties for individual differences analyses. Specifically, because congruent and incongruent RTs correlate so highly across individuals, their difference score tends to have a low reliability estimate; hence, tasks that produce robust within-person effects, like the Stroop task, do not always yield high within-person reliability estimates. In fact, the opposite can be true (Salthouse & Siedlecki, 2007). This issue, known as the *reliability paradox*, has thwarted some attempts to measure attention control as an individual difference (Draheim et al., 2019; Enkavi et al., 2019; Feldman & Freitas, 2016; Hedge et al., 2018; Rey-Mermet et al., 2019; Rouder et al., 2023; Rouder & Haaf, 2019; Whitehead et al., 2019, 2020). But even leaving aside RT difference scores, some studies have been unable to specify a coherent attention control factor with accuracy-based measures of attention (Rey-Mermet et al., 2019), leading those authors to conclude that attention/executive control is not a unitary cognitive construct and should be abandoned in theory. It is also worth noting that many studies do indeed form a coherent latent factor for attention control, even given these potential pitfalls (Unsworth, Miller, & Robison, 2021). Others have argued that the issue lies more with measurement approaches, which can be improved via accuracy-based measures (Draheim et al., 2021). For example, Burgoyne et al. (2023) developed a suite of attention control measures that manipulate both stimulus congruency and response congruency in arrow flanker, color–word Stroop, and Simon tasks, inspired by the Double Trouble task of the Cambridge Brain Sciences Neurocognitive Battery. Then, they used sums of accurate responses minus sums of inaccurate responses over a tight time window (90 s) as the dependent variable (DV). Doing so, they found that these "squared" tasks all had high intrasession reliability (>0.92), and a factor formed by these three tasks accounted for most of the WMC–fluid intelligence relation. Regardless, attention accounts of WMC have not been without criticism, leaving open the door for other theoretical explanations for WMC's predictive power.

Primary Memory Accounts of Working Memory Capacity

PM accounts argue that individual differences in WMC are driven by the sheer amount of information people can hold actively in mind. Cowan et al. (2005) referred to this individual difference as the *scope* of attention to differentiate it from the *control* of attention, discussed above. Here, we will refer to actively maintaining a set of representations as PM, using the language of James (1890). Evidence consistent with PM accounts comes from the fact that complex span WMC measures correlate well with short-term memory tasks like visual change detection, simple auditory and visual span tasks, and running span tasks. Further, simple span tasks, which do not layer a processing component on top of a memory component like complex span tasks, also tend to predict outcomes like scholastic aptitude and general cognitive abilities (Colom et al., 2005, 2006, 2008; Cowan et al., 2005). At the latent level, PM and WMC tend to share about 30%–60% of their variance (Colom et al., 2005, 2006, 2008; Martin et al., 2021; Robison & Brewer, 2020; Shipstead et al., 2012, 2014, 2015; Unsworth et al., 2014; Unsworth & Spillers, 2010).

Importantly, Colom et al. (2005) demonstrated that, after accounting for short-term memory abilities, the residual covariance between intelligence and WMC was small. However, it is worth noting that full mediation of the WMC–intelligence relation via simple span tasks does not necessarily indicate that the mediation is driven by PM alone. As Unsworth and Engle (2007a) showed, even simple span tasks can tap into both PM and SM. Therefore, the work by Colom et al. (2005, 2006, 2008) may be evidence for a multifaceted account, similar to that proposed by Unsworth and Engle (2007b). However, other studies have demonstrated only partial mediation of the WMC–intelligence relation after accounting for PM (Colom et al., 2006; Unsworth et al., 2014). Further still, some studies have shown that PM does *not* contribute to general cognitive abilities after controlling for its shared variance with WMC (Engle et al., 1999). Thus, although PM may be another reason WMC predicts higher order cognitive abilities, there is still considerable debate as to whether PM is *the* reason for WMC's predictive power.

Secondary Memory Accounts of Working Memory Capacity

A third set of theories argues that WMC's predictive power comes from the ability to commit information to long-term memory and subsequently perform targeted and controlled search for relevant long-term memory representations. In the present study, we will refer to this ability as SM, again borrowing the language of James (1890). Evidence consistent with a SM account comes from studies demonstrating that WMC measures correlate well with measures of long-term and episodic memory, such as free recall, cued recall, source recognition, and verbal fluency (Kane & Engle, 2000; Miller et al., 2019; Miller & Unsworth, 2018, 2021; Mogle et al., 2008; Rosen & Engle, 1997; Shelton et al., 2010; Unsworth, 2007, 2009a, 2009b; Unsworth & Brewer, 2009; Unsworth et al., 2010, 2011; Unsworth & Spillers, 2010).

Further, one study showed that the WMC–fluid intelligence relation could be completely accounted for by secondary abilities (Mogle et al., 2008). Specifically, Mogle et al. (2008) gave participants a set of working memory (complex span), PM (simple span), SM (recognition and cued recall), and processing speed tasks and formed latent factors for those constructs. Then, they allowed these three latent variables to predict performance on the Raven Advanced Progressive Matrices, a popular measure of fluid intelligence. After accounting for PM and SM, WMC did not account for significant, unique variance in Raven performance. Further, the direct path from SM to Raven was much larger than the direct path from PM to Raven, although both were significant in their model. Mogle et al. (2008) therefore concluded that SM abilities are the major driver of the WMC–intelligence relation. However, the result relied on a single measure of intelligence (Raven), whereas WMC, PM, SM, and processing speed were estimated at the latent level.

Following up on Mogle et al. (2008), Unsworth (2009a; Unsworth & Spillers, 2010) estimated latent factors for WMC, SM, and fluid intelligence. In a structural regression model, both WMC and SM made significant, unique contributions to fluid intelligence. Further, there was a significant correlation between the residual variance in WMC and fluid intelligence, even after partialling out variance common to the complex span and SM measures. Therefore, Unsworth et al. (2009a) did not replicate Mogle et al.'s full mediation of the WMC–fluid intelligence relation via SM abilities. Shelton et al. (2010) also did not replicate Mogle et al. Specifically, Shelton et al. found that processing speed, SM, and working memory all made significant contributions to fluid intelligence independently of their shared variance. Thus, collectively, SM may be *one* reason by which WMC predicts higher order cognitive abilities. But again, it is debatable whether it can be considered *the* reason.

Multifaceted Theories of Working Memory Capacity

In response to single-factor theories of WMC described above, several multifaceted theories of WMC have been proposed. These theories argue that there is not one single reason that WMC predicts higher order cognitive abilities but rather a combination of factors, all of which are captured by complex span measures of WMC. Unsworth and Engle (2007b) proposed a two-component model of individual differences in WMC: active maintenance in PM and controlled retrieval from SM. By active maintenance, Unsworth and Engle referred to the ability to actively maintain a limited number of goal-relevant item representations via continuous attention, which is similar to how we defined attention control above. In a sense, Unsworth and Engle (2007b) used the PM component to account for both attention control and PM abilities. By SM, Unsworth and Engle (2007b) referred to the ability to retrieve goal-relevant information from long-term memory, to self-generate retrieval cues, and to delimit the search set to only goal-relevant information. They reviewed evidence that individual differences in WMC correlate with performance on attentional tasks that make minimal memory demands, as described earlier, and long-term memory tasks that require people to encode and retrieve information. Thus, Unsworth and Engle made the case that *both* PM and SM are aspects of WMC that make it predictive of higher order cognition. Later, Unsworth (2014, 2016) collated these ideas into a formal multifaceted theory of WMC.

To test the multifaceted account of WMC, Unsworth et al. (2014) gave participants a battery of tasks specifically designed to capture latent constructs for WMC, PM, SM, and fluid intelligence. Ultimately, Unsworth et al. found that the relation between WMC and fluid intelligence could be mediated by attention control, PM, and SM. Critically, *full* mediation of the WMC–fluid intelligence link only occurred via the combination of all three facets—no combination of two of attention control, PM, and SM was sufficient to produce full mediation. Thus, they argue for a multifaceted account of WMC, one that acknowledges important and distinct roles of attention control, PM, and SM in accounting for why indeed WMC is such a strong predictor of higher order cognitive abilities.

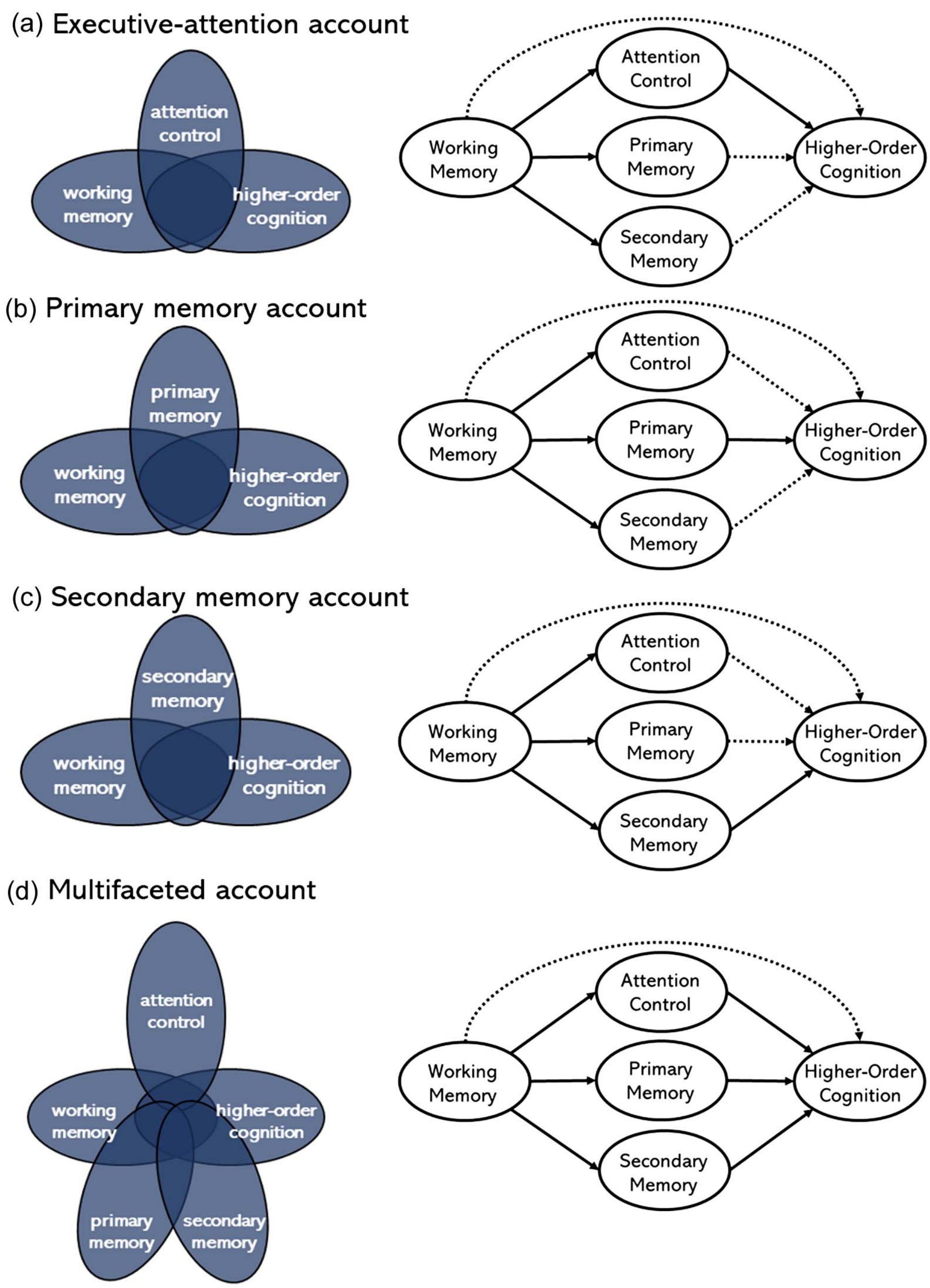
Shipstead et al. (2012) have also posited a two-component framework for WMC, with the two components being the scope and control of attention, using Cowan et al.'s (2006) language. Shipstead et al. (2012) formed latent factors representing these two abilities, using visual arrays change-detection tasks (Luck & Vogel, 1997) to measure the scope of attention and complex span tasks to measure the control of attention. The two factors were distinguishable and made unique contributions to fluid intelligence. More importantly, Shipstead et al. (2012) demonstrated that the shared variance between the scope and control of attention accounted for the largest source of variance in fluid intelligence, relative to variance unique to the scope and control of attention, respectively. Thus, whatever abilities drive performance on both visual arrays and complex span tasks, perhaps a confluence of PM and attention control, seems to be the most important predictor of higher order cognition. However, it is worth noting that Shipstead et al. (2012) did not specifically measure attention control. Rather, they assumed that the residual variance in complex span tasks, after accounting for visual array performance, was indicative of attention control. In a follow-up study, with tasks tapping into attention control, PM, and SM, Shipstead et al. (2014) found full mediation of the WMC–intelligence relation by the three factors, like Unsworth et al. (2014).

The Present Study

We had several aims for the present study. Our first aim was to test the multifaceted account of WMC against single-faceted theories. The predictions made by the four theories of interest are summarized in Figure 1. A strict executive attention account (Engle, 2002, 2018) argues that the covariance between WMC and higher order factors (i.e., fluid intelligence and reading comprehension) can be fully explained by attention control (Figure 1A). Statistically, this predicts that, in a structural model, WMC will have an indirect effect on the higher order factors via attention control, but not via primary or SM. Similarly, a strict PM account (Figure 1B; Colom et al., 2005, 2008) argues that the covariance between WMC and higher order cognition can be fully accounted for by PM. In the structural model, WMC should have an indirect effect on higher order cognitive ability factors via PM, but not via attention control or SM. A strict SM account (Figure 1C; Mogle et al., 2008) argues that the

Figure 1

The Blue Ovals (Left) Represent Variance in Each Construct, With the Overlapping Portions Representing Their Covariance



Note. The structural models (right) show the predicted result, with solid lines indicating significant paths and dashed lines indicating nonsignificant paths. See the online article for the color version of this figure.

covariance between WMC and higher order cognition can be fully accounted for by SM abilities. In the structural model, WMC should have an indirect effect on the higher order cognitive abilities via SM, but not via attention control and PM. Finally, a *multifaceted* account (Figure 1D; Shipstead et al., 2012, 2014, 2015; Unsworth, 2014, 2016; Unsworth et al., 2014) predicts that WMC will have indirect effects on higher order cognition via all three: attention control, PM, and SM. We hypothesized that we would observe evidence consistent with predictions made by the multifaceted account.

In sum, many prior studies have employed a multimeasure approach using factor analysis and structural equation modeling (Burgoyne et al., 2023; Draheim et al., 2021; Oberauer et al., 2003; Rey-Mermet et al., 2019; Shelton et al., 2010; Unsworth, Brewer, et al., 2009; Unsworth et al., 2014; Unsworth & Spillers, 2010; Wilhelm et al., 2013). But the second and third major aims of the present study will advance prior work in two important ways. First, we generalize the multifaceted account beyond an explanation of the WMC–fluid intelligence relation. Much of the research described above tested used fluid intelligence as the (only) candidate construct representing an important external correlate of WMC or of *higher order cognition*. However, as mentioned earlier, WMC predicts many other important psychological outcomes, such as reading comprehension, emotion regulation, second-language acquisition, and academic aptitude. Therefore, it is worth asking to what extent models of WMC are generalizable beyond a specific examination of fluid intelligence. Otherwise, a particular model might do well to explain the WMC–intelligence relation, but not do well to explain, for example, the WMC–multitasking relation. To our knowledge, this has not been explored using a multifaceted approach, especially at the latent level. To address this question, we used both fluid intelligence and reading comprehension as proxies for higher order cognition more generally. If the multifaceted account is generalizable, we should observe similar mediation when we use fluid intelligence and reading comprehension as the factor representing higher order cognition. Alternatively, attention control, PM, and SM could have different predictive values for fluid intelligence versus reading comprehension, and therefore different models might perform differently given the representative construct for “higher order cognition.” If this is true, the mediation pattern could vary when comparing models using fluid intelligence versus reading comprehension (for similar findings with different assessments of multitasking, see Redick et al., 2016).

The third aim of the present study was to generalize the multifaceted account beyond just complex span measures of WMC. Although the research described above leans heavily on complex span tasks to estimate a latent factor for WMC, it is worth questioning whether the multifaceted model’s predictions are specific to complex span. That is, if we use another paradigm to measure a latent WMC factor, will we find similar evidence for a multifaceted account? To answer this question, we also estimated WMC using a set of n-back tasks. As noted by Redick and Lindsey (2013), complex span and n-back measures both show evidence for a domain-general working memory system (Kane & Engle, 2000; Kane et al., 2004; Nystrom et al., 2000), both correlate significantly with measures of fluid intelligence (Jaeggi, Buschkuehl, et al., 2010; Jaeggi, Studer-Luethi, et al., 2010; Kane, Conway, et al., 2007), and both demonstrate age-related deficits (Bopp & Verhaeghen, 2005; Spencer & Raz, 1995). Yet, complex span and n-back measures correlate only weakly. In a meta-analysis, Redick and Lindsay estimated the zero-order correlation to be 0.20, suggesting that complex span and n-back tasks only share about 4% of their variance. Therefore, they cannot and should not be used interchangeably (but see Schmiedek et al., 2009; Wilhelm et al., 2013, for different results using latent variables). In practice, a person’s performance on such tasks is often labeled as their WMC. But, to our knowledge, no prior work has directly compared complex span with n-back measures of WMC at the construct level while also measuring attention control, PM, SM, fluid intelligence, and reading comprehension. Therefore, the present study attempts a more thorough and generalizable test of WMC theories beyond any that has been previously attempted in two important ways: (a) a more construct-general test of the relation between WMC and higher order cognition and (b) a more measurement-general approach to WMC. To address these aims, we used latent variable structural equation modeling to test the predictions made by the single- and multifaceted theories. To preview the results, we found consistent and generalizable evidence for a multifaceted account of individual differences in WMC.

Method

Participants and Procedure

A total of 974 participants completed the study across three sites: Arizona State University (n = 406), Purdue University (n = 381), and the University of Oregon (n = 187). A breakdown of demographic data for each site is listed in Table 1. Participants at all sites completed the study in exchange for partial course credit. All participants provided written informed consent. The experimental protocols were approved by the institutional review boards at each university. At Arizona State and Purdue, participants completed a 3-hr session that included all tasks. At Oregon, participants completed

Table 1
Demographic Data of the Initial Sample at the Three Data Collection Sites and Overall

Variable	Data collection site: Arizona State University	Purdue University	University of Oregon	Overall
Age (*SD*)	19.59 (2.98)	19.37 (1.51)	19.73 (1.96)	19.52 (2.27)
Age range	(18, 48)	(17, 31)	(18, 32)	(17, 48)
Female	51%	57%	42%	51%
Male	47%	41%	55%	46%
Nonbinary/other	1%	1%	1%	1%
Native English speakers	93%	85%	93%	90%

a 2-hr session that did not include the reading comprehension or *n*-back measures.

All tasks were completed in a single session, and all tasks were computerized with onscreen instructions. Between 1 and 6 participants were in a room, all starting the session at the same time. Brief individual instructions were given quietly while the experimenter started each task. At all sites, a demographic survey was administered on the computer before the first task (operation span). Participants were asked to report their age, gender, and whether they were proficient speakers of English. Tasks were completed in the same established order at all sites (Robison et al., 2023).

Tasks

Working Memory: Complex Span

Operation Span (Unsworth et al., 2005). In this task, a math problem appeared on the screen, and the participant clicked the mouse when they believed they had solved it. Then, a potential solution and the words "True" and "False" appeared prompting the participant to decide if the provided response was the solution to the math problem they just solved. Participants then saw a letter appear in the center of the screen for 1 s. After three to seven math problems and letters appear, participants saw a recall screen and clicked the letters in the order they appeared. There was a time limit imposed on the math problem section based on the time it took to practice just that part of the task. Before the experimental trials, participants practiced just the letter recall, then just the math problems, then both parts together. During the experimental trials, each of the list lengths 3, 4, 5, 6, and 7 appeared two times, resulting in a total possible recall score of 50.

Symmetry Span (Unsworth, Redick, et al., 2009). This task was very similar to the operation span task except that participants saw a 4 × 4 grid with one square colored in red instead of a letter and they were asked to make a "yes" or "no" judgment about whether a black and white image was symmetric about a vertical line (not provided) rather than solving math problems. This task used list lengths 2, 3, 4, and 5 twice each for a total possible score of 28.

Reading Span (Unsworth, Redick, et al., 2009). This task was also a shortened complex span task similar to operation span. Again, participants saw letters they would need to recall later, but between presentations of each letter, there were sentences that either made sense or had a critical word swapped out for a word that did not make sense in context. For example, the sentence "Jen wanted to pet the friendly dog" makes sense, whereas "Jen wanted to pet the friendly school" does not. This task used the same list lengths as operation span resulting in a total possible score of 50.

Working Memory: n-Back

***n*-Back Letters (Kane, Conway, et al., 2007).** In this task, letters appeared in the center of the screen one at a time for 2.5 s each. Participants were asked to make a left click if the letter they saw was the same as the letter presented *n* items back and a right click if it was not the same. There were two blocks of 48 trials, and eight of those trials should have elicited a right click. Before the real trials, participants completed 20 practice trials with three target trials (and performance feedback) where *n* was 1 and another practice where *n* was 3. In the real block, $n = 3$ was used for all trials. The stimulus list for each block was selected out of six possible lists by the program based on the subject number entered at the beginning of the task. Each list presented the targets and nontargets in different positions within the list. The same lists were used across the three *n*-back tasks but were selected such that participants never saw the same list twice, even with different stimuli. The dependent variable was sensitivity (*dL*): ln [hit rate × (1 − *false alarm rate*)]/[(1 − *hit rate*) × *false alarm rate*] (Kane, Conway, et al., 2007).

***n*-Back Spatial.** This task was similar to the *n*-back letters task with the exception that large blue squares appeared in one of eight locations around the perimeter of the screen rather than letters at the center. Participants were asked to determine whether the location rather than the stimulus was the same as the item *n*-trials back. The dependent variable was sensitivity (*dL*).

***n*-Back Digits.** This task was identical to the *n*-back letters task with the exception that digits 1–9 were used as stimuli instead of letters. The dependent variable was sensitivity (*dL*).

Primary Memory

Color Change Detection (Luck & Vogel, 1997). In this task four, six, or eight colored squares appear on the screen for 100 ms. A blank screen followed for 900 ms before a second set of colored squares appears. The second set of colored squares would either be identical to the first or have a single square changed in color. One square, the altered one if there was one, was circled in the second set, and the participant is asked to click the left mouse button if that square is the same color as the previous screen and press the right button if it is a different color than it was on the previous screen. There were two blocks of 24 trials each with 50% in each block involving a change and 50% involving no change. The square locations and colors were random with only the stipulation that a changing color not be the color it just was. The outcome variable for this task is a *k* score calculated using the formula suggested by Cowan et al. (2005).

Orientation Change Detection (Luck & Vogel, 1997). This task was similar in structure to the color change-detection task but showed participants two sets of red rectangles. One rectangle in the second set had a white dot on it, and participants were asked to report whether that rectangle had changed orientation. All other rectangles would not have changed. There were between four and eight rectangles on the screen for each trial, and there were 48 trials. Responses were recorded with the mouse using a left click for "same" and a right click for "different." Again, *k* scores were calculated to evaluate performance on this task.

Secondary Memory

Immediate Free Recall. This task showed participants five lists of 10 words each and asked them to type as many of those ten words as they could remember. The instructions suggest beginning with the most recent words as those would be easiest to remember. This instruction was given to create a possibility of measuring both PM and SM within this task. Each word was presented for 1 s, and the participants were given 45 s to recall as many of the ten words as possible. Before the trial lists, there was a typing practice and two practice lists that used letters instead of words. PM and SM scores were calculated using Tulving and Colotla's (1970) method.

Picture Source Recognition. This task showed clipart-style images one at a time in one of the four corners of the screen. Images were presented for 3 s with a 1-s blank screen between them. After all images were presented, participants were instructed on how to respond to the test images that would appear after the instructions. The instructions were to use the keypad at the right side of the keyboard and respond with 1, 3, 7, or 9 if the image shown at the center was one they had seen in the initial presentation of images using the four keys to indicate in which corner of the screen it had appeared. If the image presented was a new image that had not been seen before, participants were instructed to press the center key, 5, on the keypad. Each test image was presented for a maximum of 5 s while waiting for a response. There were 30 images in the initial set and 60 images in the test set with the added 30 being novel images. The outcome variable for this task was accuracy of responses to test items.

Cued Recall. This task presented three lists of 10 word pairs with each pair presented sequentially for 1 s each. After each word pair list, participants saw the first word in each pair (the cue) one at a time and were asked to type in the corresponding word (the target). Participants had 5 s to type in their response before the next cue word appeared. The dependent variable was the proportion of correctly recalled target words averaged across the three lists.

Attention Control

Psychomotor Vigilance (Dinges & Powell, 1985). This task presented a set of zeros in the center of the screen that began to count upward at a pace of one digit per millisecond. Participants were instructed to press the spacebar as soon as they saw the numbers begin to count. The interval between the onset of the zeros and the beginning of the counting up varied by 500 ms intervals between 1 and 10 s. The task lasted 10 min, which allowed for around 75 trials. For each participant, we rank ordered their reaction times (RTs) and sorted them into five quintiles, fastest to slowest. The dependent variable was the average of a participant's slowest quintile of trials.

Arrow Flanker (Eriksen & Eriksen, 1974; Stoffels & van der Molen, 1988). This task showed participants a row of five arrows in the center of the screen oriented toward the left or right of the screen. Participants were asked to use the *Z* and /? keys, which had arrow stickers on them, to indicate in which direction the center arrow was facing. On congruent trials, the distractor arrows were facing the same direction as the center arrow. On incongruent trials, the distractor arrows were facing the opposite direction of the center arrow. Two practices proceeded real trials, with the first practice only showing a target arrow and the second adding in the distractor arrows. There were 80 real trials, equally split between congruent and incongruent trials and left- and right-facing targets. During real trials, a fixation cross appeared at the center of the screen for a variable duration between 400 and 1,600 ms before being replaced by the arrows. Arrows were onscreen for a maximum of 1,700 ms waiting for a response. The dependent variable was the average of a participant's RTs to correct congruent trials subtracted from the average of their RTs to correct incongruent trials.

Antisaccade (Kane et al., 2001). In this task, participants first saw three light blue asterisks at the center of the screen for a variable delay of either 200, 600, or 1,000 ms. Then, they saw an equal sign at either the left or right of the screen. This cue would flash twice for 100 ms each and indicate that the stimulus would appear at the opposite side of the screen. The stimulus was one of three letters, B, P, and R, which would appear for 250 ms. After the stimulus, the mask would appear in the form of an H for 50 ms and then an 8, which remained on screen until a response was made or until 10 s had elapsed with no response. Participants responded using the left, down, and right arrow keys, which had stickers "B," "P," and "R" on them, respectively. Before the real trials, participants practiced with a slower presentation at the center of the screen, then a full-speed version at the center of the screen, and then a pro-saccade version where the cue indicated the side the stimulus would appear rather than cuing the opposite side. Finally, participants practiced the real version with the cue appearing on the opposite side of the screen from where the stimulus was about to appear. Each of these practices had nine trials. There were 36 real trials balanced equally between each letter stimulus at each fixation delay on each side of the screen. The dependent variable was the proportion of correctly identified target letters (thus, this was the only attention control manifest variable where a higher score meant better performance).

Fluid Intelligence

Raven's Advanced Progressive Matrices (Engle & Kane, 2004; Raven & Court, 1962). This task was a computerized version of the odd-numbered problems from Raven's Advanced Progressive Matrices. Participants were instructed through three practice problems before beginning the test. There were 18 items, and participants were given 10 min to complete as many items as they could. Each item shows a 3 × 3 grid with eight of the squares filled with shapes that create a pattern. The right-most bottom square is blank, and participants were asked to respond which available option listed below the grid completed the pattern when placed into the empty square. Items generally increased in difficulty as the test progressed. The dependent variable was the total number of items correctly reported.

Number Series (Thurstone, 1938). In this task, patterns of numbers were provided on screen, and participants evaluate the possible responses listed below the numbers and select the answer that would come next if the pattern were continued. Patterns had several numbers and there were five response options. There were five examples before the real trials. Then, there were 15 patterns to complete in the allotted 4.5 min. The dependent variable was the total number of items correctly reported.

Letter Sets (Ekstrom & Harman, 1976). For this task, five sets of four letters were shown simultaneously on the screen. Participants were asked to determine which set did not follow the same pattern or rule as the other sets. After two example problems, participants had a maximum of 5 min to complete 20 items. The dependent variable was the total number of items correctly reported.

Strategy Report. This survey asked participants about the Raven's, number series, and letter sets tasks. Specifically, the questions ask participants to rate on a 9-point scale how accurately they felt a provided strategy described their performance on each task. There were four questions per task and no time limits. These data were collected as part of a separate study and are not analyzed here (Wingert, 2018).

Reading Comprehension

Inference Verification Test (Griffin et al., 2008). This task had two sets of readings and questions. First, participants were given a series of paragraphs about bacteria and asked to read at their own pace moving from one paragraph to the next using the spacebar. Participants were told to read thoroughly as they were not allowed to go back after advancing to the next paragraph. After completing the reading, participants were given a series of true/false questions about the reading, which were presented onscreen one at a time. Then, the process was repeated with a reading and questions regarding volcanoes. There were 10 paragraphs in the bacteria reading and 12 paragraphs in the volcano reading. There were 16 questions for each topic and no time limits. The dependent variable was the proportion of correct responses.

Air Force Officer Qualifying Test. For this task, each question had a short paragraph ending with an unfinished sentence or a blank and five possible answers that would fill in or complete the sentence. There were two examples before participants began the timed section. Participants had 9 min to answer as many of 14 questions as they could. The dependent variable was the total number of correct responses.

Data Analysis

All analyses were conducted in R using the *psych* (Revelle, 2018), *tidyverse* (Wickham et al., 2019), *lavaan* (Rosseel, 2012), and *foreign* (R Core Team, 2022) packages. Data were screened with the following criteria: (a) Data were only included for participants between the ages of 18 and 35; (b) for the complex span tasks, participants were excluded if they committed either speed or accuracy errors on the processing portion of the task on more than half of trials (see Richmond et al., 2022, for justification of this criteria); (c) for the visual arrays tasks, data were excluded for participants who only ever pressed one key; (d) for the immediate free recall task, data were excluded for participants who had two or more lists with zero correct responses or no responses at all; (e) for picture source recognition, data were excluded for participants who never indicated an image was "new" or who gave more than 33% of their responses in less than 1 s; (f) for the cued recall task, data were excluded for participants who gave zero correct responses on two or more lists; (g) for the PVT, data were excluded for participants who hit the space bar before stimulus onset on 30 or more trials; (h) for the arrow flanker task, data were excluded for participants who did not respond on 33% or more trials or who had less than 50% accuracy on either trial type; (i) for the Raven, number series, or letter sets tasks, data were excluded for participants who always gave the same response or who took less than 30 s on the task; (j) for the inference verification test, data were excluded from participants who spent less than 1 s reading more than 33% of the paragraphs or who responded to the questions in less than 0.5 s on more than 33% of trials; (k) for the Air Force Officer Qualifying Test, data were excluded for participants who spent less than 2 s reading more than 33% of paragraphs; and (l) for the *n*-back tasks, participants were excluded if they did not make a response on more than 33% of trials or if they used the same key press on every trial. Table 2 lists the achieved sample sizes after exclusions.

Reliability

For most tasks, reliability was computed by randomly splitting the task's trials into two equal halves, computing that task's dependent measure on each half, correlating the two halves, and applying the Spearman–Brown split-half correction. That process was performed 500 times, and the mean estimate is reported in Table 1. For the

Table 2
Descriptive Statistics for Cognitive Measures

Measure	*N*	*M*	*SD*	Min.	Max.	Skew	Kurtosis	Reliability
Operation span	950	38.69	7.65	14.00	50.00	−0.72	0.15	0.68
Symmetry span	948	19.53	5.23	4.00	28.00	−0.55	−0.12	0.62
Reading span	943	36.36	8.86	9.00	50.00	−0.66	−0.17	0.76
Antisaccade	957	0.63	0.18	0.20	0.98	−0.31	−0.80	0.84
Flanker	894	70.19	41.30	−76.85	223.06	0.53	1.04	0.38
PVT	941	531.30	165.54	304.00	1,459.00	2.33	7.26	0.87
Color *k*	931	3.94	1.03	0.42	6.00	−0.58	0.05	0.69
Orientation *k*	950	2.88	1.23	−0.92	5.75	−0.23	−0.24	0.62
IFR PM	953	8.38	4.79	0.00	22.00	0.01	−0.76	0.78
IFR SM	949	19.74	6.42	2.00	39.00	0.36	0.04	0.74
PicSource	922	0.82	0.12	0.42	0.98	−1.08	0.92	0.90
Cued recall	942	13.47	7.25	0.00	30.00	0.40	−0.79	0.80
Raven	940	8.52	3.54	0.00	17.00	−0.17	−0.51	0.79
Number series	932	8.77	2.74	1.00	15.00	−0.17	−0.23	0.73
Letter sets	927	10.13	3.37	2.00	19.00	0.12	−0.29	0.79
IVT-B	761	0.66	0.16	0.19	1.00	−0.03	−0.55	0.66
IVT-V	705	0.75	0.14	0.38	1.00	−0.27	−0.55	0.53
AFOQT	751	7.53	3.26	0.00	14.00	0.05	−0.98	0.79
Letter *n*-back	749	0.83	0.70	−1.32	2.92	0.32	0.08	0.70
Digit *n*-back	756	1.32	0.96	−1.06	3.97	0.46	−0.13	0.81
Spatial *n*-back	754	1.29	0.99	−1.30	3.97	0.20	−0.65	0.82

Note. Min. = minimum; Max. = maximum; PVT = psychomotor vigilance task; *k* = capacity estimate; IFR = immediate free recall; PM = primary memory estimate; SM = secondary memory estimate; PicSource = picture source recognition; IVT = inference verification test; B = bacteria; V = volcanoes; AFOQT = Air Force Officer Qualifying Test.

complex span tasks, reliability was computed using Cronbach's α on accuracy by set size. For the immediate free recall and cued recall tasks, reliability was estimated using Cronbach's α on accuracy by list.

Transparency and Openness

The data and R analysis scripts are publicly available on the Open Science Framework and can be accessed at https://osf.io/g5964/. This study was not preregistered.

Results

Descriptive statistics for each measure are listed in Table 2, and zero-order correlations among the measures are listed in Table 3. Most of the measures showed acceptable levels of reliability except for the flanker effect. As noted earlier, difference scores such as these tend to have low reliability because congruent and incongruent trials correlate so highly (r = 0.85 in these data). Regardless, we have retained this measure for the analyses, but note its relatively low loading on an attention control latent factor.

Confirmatory Factor Analysis

To estimate a measurement model, we specified a series of latent variable models using confirmatory factor analysis. To assess model fit, we used a combination of χ^2, comparative fit index (CFI), Tucker–Lewis index (TLI), root-mean-squared error of approximation (RMSEA), and standardized root mean residual (SRMR). We considered CFIs and TLIs >0.90 and RMSEA and SRMRs of <0.08 as acceptable. We compared nested models using χ^2 tests. For all models, we used a full-information maximum likelihood estimator to account for missing data, which allows all available data to inform the observed variance–covariance matrix rather than performing listwise deletion of participants with missing values.

In Model 1, we allowed digit n-back, letter n-back, and spatial n-back to load onto an N-back factor; operation span, symmetry span, and reading span to load onto a complex span factor; antisaccade, flanker, and PVT to load onto an attention control factor; orientation change detection k estimates, color change detection k estimates, and PM estimates from the immediate free recall task to load onto a PM factor; SM estimates from the immediate free recall task, picture source recognition, and cued recall to load onto an SM factor; the inference verification task (bacteria), inference verification task (volcanoes), and Air Force Officer Qualifying Test tests to load onto a reading comprehension factor; and Raven, number series, and letter sets to load onto a fluid intelligence factor. This model did not fit the data well, $\chi^2(168)$ = 778.61, CFI = 0.89, TLI = 0.86, RMSEA = 0.061, 90% CI [0.057, 0.067], SRMR = 0.05. Modification indices revealed a large residual correlation between the primary and secondary estimates from the free recall task, which is not entirely unexpected given that these measures came from the same task yet were specified to load onto different factors. Freeing this correlation significantly improved model fit, $\Delta\chi^2(1)$ = 293.4, $p < .001$, and this model fit the data well overall, $\chi^2(167)$ = 485.21, CFI = 0.94, TLI = 0.93, RMSEA = 0.05, 90% CI [0.04, 0.05], SRMR = 0.05. Therefore, we selected this as our measurement model. It is depicted visually in Figure 2.

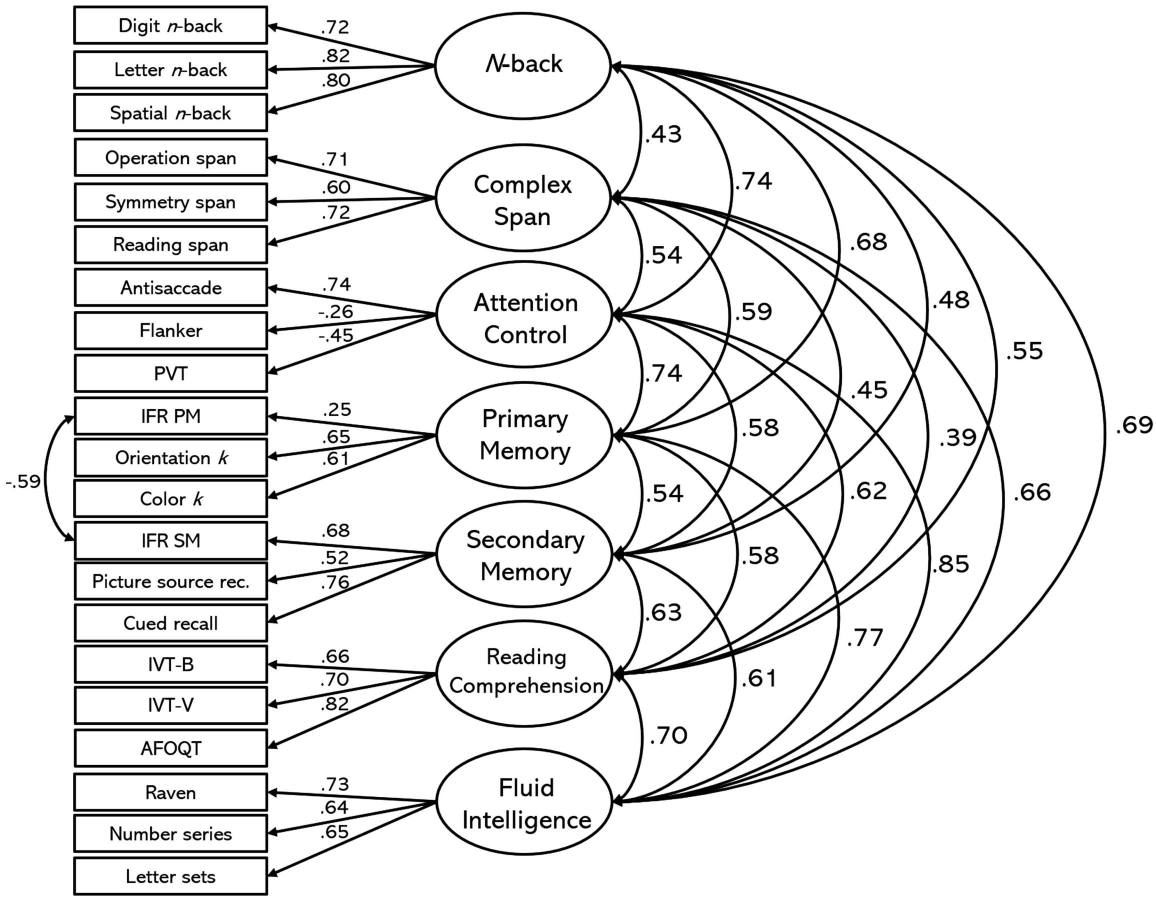
The model validated the hypothesized structure of cognitive abilities. Specifically, all factors were significantly and positively correlated. People with high WMC, measured by both complex span and n-back tasks, performed better on measures of attention control, PM, SM, reading comprehension, and fluid intelligence. Further, the latent factors representing WMC formed by complex and n-back tasks were correlated (latent r = 0.43). However, the factors were also clearly not isomorphic. Forcing the complex span and n-back

Table 3
Zero-Order Correlations Among Cognitive Measures

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1. Operation span	—																				
2. Symmetry span	**.42**	—																			
3. Reading span	**.54**	**.37**	—																		
4. Antisaccade	**.22**	**.31**	**.29**	—																	
5. Flanker	−.06	**−.11**	−.03	**−.15**	—																
6. PVT	**−.13**	**−.14**	**−.12**	**−.29**	**.18**	—															
7. Color k	**.18**	**.28**	**.26**	**.32**	**−.10**	**−.23**	—														
8. Orientation k	**.23**	**.31**	**.26**	**.34**	**−.10**	**−.20**	**.43**	—													
9. IFR PM	.06	**.11**	**.10**	**.15**	**−.09**	**−.11**	**.13**	**.13**	—												
10. IFR SM	**.20**	**.17**	**.30**	**.27**	−.05	**−.11**	**.20**	**.20**	**−.27**	—											
11. PicSource	**.14**	**.22**	**.19**	**.30**	−.07	**−.20**	**.30**	**.31**	**.22**	**.23**	—										
12. Cued recall	**.12**	**.14**	**.22**	**.26**	**−.10**	**−.18**	**.20**	**.22**	**.20**	**.49**	**.39**	—									
13. Raven	**.26**	**.33**	**.25**	**.45**	**−.18**	**−.23**	**.32**	**.41**	**.21**	**.27**	**.33**	**.31**	—								
14. Number series	**.32**	**.30**	**.30**	**.38**	**−.12**	**−.17**	**.25**	**.33**	.06	**.25**	**.19**	**.19**	**.45**	—							
15. Letter sets	**.30**	**.29**	**.29**	**.39**	**−.11**	**−.18**	**.23**	**.29**	**.16**	**.29**	**.27**	**.27**	**.43**	**.45**	—						
16. IVT-B	**.16**	**.12**	**.23**	**.26**	−.08	**−.22**	**.17**	**.21**	**.20**	**.25**	**.24**	**.28**	**.32**	**.23**	**.23**	—					
17. IVT-V	**.16**	**.15**	**.19**	**.30**	**−.14**	**−.12**	**.20**	**.28**	**.13**	**.25**	**.22**	**.27**	**.38**	**.23**	**.22**	**.47**	—				
18. AFOQT	**.18**	**.14**	**.30**	**.36**	**−.15**	**−.17**	**.24**	**.32**	**.24**	**.32**	**.28**	**.35**	**.47**	**.31**	**.35**	**.52**	**.54**	—			
19. Letter n-back	**.16**	**.17**	**.22**	**.34**	−.07	**−.22**	**.29**	**.28**	**.17**	**.26**	**.24**	**.21**	**.29**	**.29**	**.30**	**.25**	**.26**	**.30**	—		
20. Digit n-back	**.22**	**.25**	**.26**	**.43**	**−.11**	**−.23**	**.31**	**.36**	**.21**	**.23**	**.28**	**.23**	**.37**	**.30**	**.38**	**.27**	**.27**	**.35**	**.62**	—	
21. Spatial n-back	**.22**	**.33**	**.25**	**.46**	**−.16**	**−.23**	**.35**	**.39**	**.17**	**.24**	**.31**	**.23**	**.42**	**.40**	**.37**	**.26**	**.32**	**.37**	**.55**	**.65**	—

Note. PVT = psychomotor vigilance task; k = capacity estimate; IFR = immediate free recall; PM = primary memory estimate; SM = secondary memory estimate; PicSource = picture source recognition; IVT = inference verification test; B = bacteria; V = volcanoes; AFOQT = Air Force Officer Qualifying Test. Bolded correlations are significant at $p < .01$.

Figure 2
Confirmatory Factor Analysis (Measurement Model)



Note. PVT = psychomotor vigilance task; IFR = immediate free recall; PM = primary memory estimate; SM = secondary memory estimate; picture source rec. = picture source recognition; IVT-B = inference verification task—bacteria; IVT-V = inference verification task—volcanoes; AFOQT = Air Force Officer Qualifying Test. All factor loadings and interfactor correlations were significant at $p < .05$.

measures to load onto a common factor significantly worsened the model fit, $\Delta\chi^2(1) = 401.46$, $p < .001$, and led to a poorly fitting model overall, $\chi^2(173) = 886.67$, CFI = 0.87, TLI = 0.84, RMSEA = 0.065, 90% CI [0.061, 0.070], SRMR = 0.06. Thus, there is reason to believe that WMC estimates from complex span and *n*-back tasks measure some overlapping but mostly distinct sources of interindividual variation.

Note, given the large sample size, a strength of the present study is that it allows for precise parameter estimates with narrow confidence intervals. Some parameter estimates were low, albeit significant. For example, flanker score's loading on the attention control factor was −0.26 (95% CI [−0.34, −0.19]). The PM estimate from immediate free recall also loaded weakly onto the PM factor but was still significant at 0.25 [0.18, 0.32]. We can conclude that although these measures were relatively weaker indicators of their respective constructs, those constructs accounted for a small yet significant amount of variance in the individual measures. Another notable finding is the negative residual correlation between PM and SM estimates from immediate free recall. We believe this arose because participants tended to adopt either a primacy or a recency recall initiation strategy (i.e., beginning recall with the first items in a list or the last items in a list). To be clear, participants were instructed to adopt a recency strategy by beginning recall with the end-of-list items, as participants tend to adopt different recall initiation strategies, and these strategies impact PM and SM estimates (Gibson et al., 2014; Unsworth et al., 2010). However, not all participants heeded these instructions. When participants adopted a primacy strategy, they tended to have high SM estimates and low PM estimates; and when participants adopted a recency strategy, they tended to have high PM estimates and low SM estimates, hence the negative correlation. Regardless, the measurement model confirmed our hypothesized structure with tasks selected to measure respective constructs loading together onto latent variables, and those latent variables correlated in a manner consistent with prior work (Engle et al., 1999; Shipstead et al., 2014; Unsworth et al., 2014).

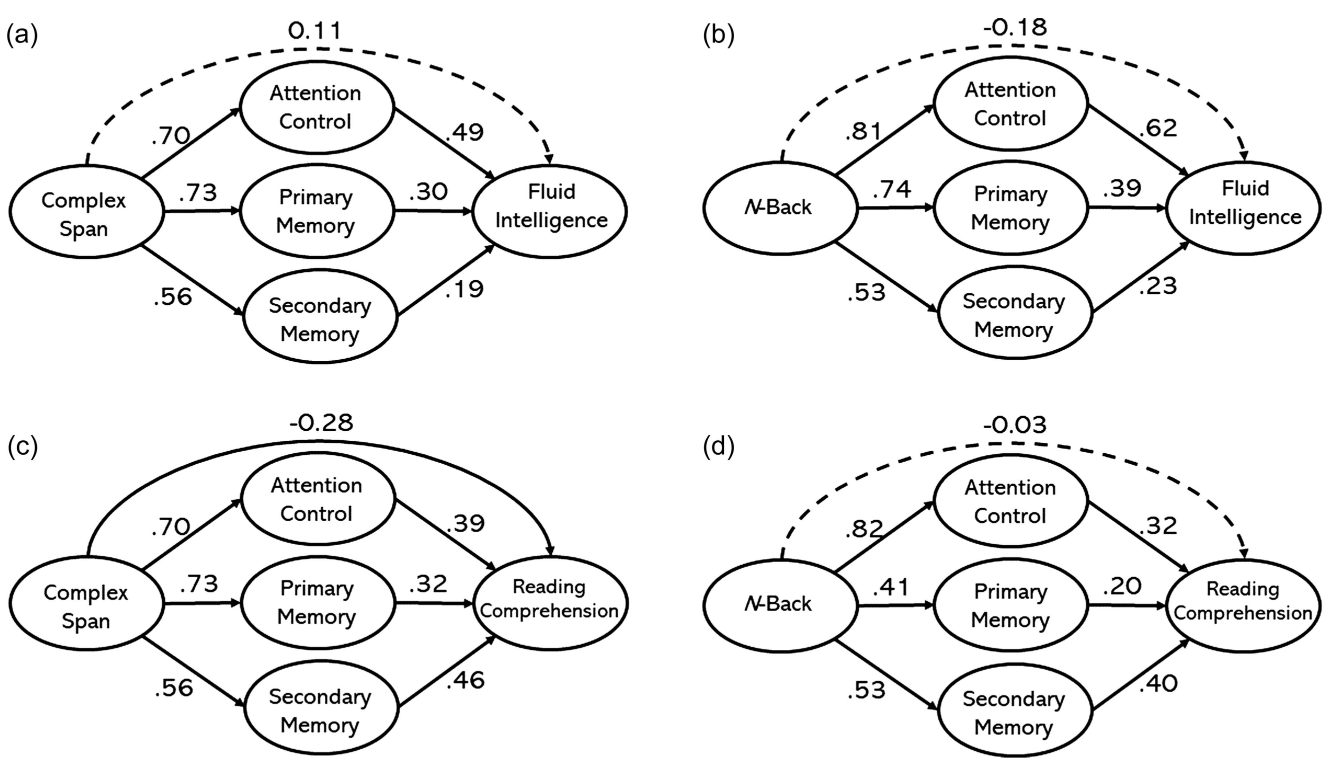
To test predictions made by executive attention, PM, SM, and multifaceted accounts of WMC, we next specified a series of structural regression models estimating mediating pathways between WMC and higher order cognition. First, we examined mediations between WMC and fluid intelligence. In separate models, we examined whether attention control, PM, and SM mediate the WMC–fluid intelligence relation. Namely, the first set of models tests the executive attention (Figure 3a), PM (Figure 3b), SM (Figure 3c), and multifaceted (Figure 3d) theories of WMC with fluid intelligence as the indicator of higher order cognitive ability. Then, we examined mediations between WMC and reading comprehension using the same approach. As an additional layer to the analysis, we examined whether support for each account differs based on precisely how WMC was measured (complex span vs. *n*-back tasks).

The first structural model examined the relation between complex span and fluid intelligence. When tested individually, none of attention control, PM, or SM fully mediated the relation between WMC and fluid intelligence. That is, there was a significant residual relation between WMC and fluid intelligence when accounting for attention control (residual relation = 0.31 [0.19, 0.42]), PM (residual relation = 0.70 [0.52, 0.89]), or SM (residual relation = 0.78 [0.68, 0.88]) as single mediators. However, when including all three as mediators (Figure 3a), the combination of attention control, PM, and SM fully mediated the relation between WMC and fluid intelligence, as the direct path from the complex span to fluid intelligence factors was no longer significant (residual relation = 0.11 [−0.09, 0.31]). Complex span had significant indirect effects through all three: attention control (0.34 [0.21, 0.47]), PM (0.22 [0.11, 0.33]), and SM (0.10, [0.05, 0.16]). Thus, attention control, PM, and SM each partially explained the relation between WMC and fluid intelligence. But on their own, none fully explained it. We also compared the magnitude of the three indirect effects by estimating the magnitude and significance of their difference. The indirect effect of complex span on fluid intelligence via attention control was significantly larger than the indirect effect via SM (difference = 0.24 [0.10, 0.37]). But the difference between the indirect effect via attention control and the indirect effect via PM was not significant (difference = 0.12 [−0.05, 0.29]) and neither was the difference between the indirect effect via PM and via SM (difference = 0.12 [−0.01, 0.24]). Overall, this model provided evidence for the *multifaceted account* of WMC. Regarding the facets individually, we could only conclude that attention control accounts for more of the relation between complex span and fluid intelligence than does SM, as no other comparisons between factors were significant.

The next structural models examined the relation between *n*-back and fluid intelligence. No single factor fully mediated the relation. Specifically, there was a significant residual relation between the *n*-back and fluid intelligence factors when attention control (residual relation = 0.27 [0.02, 0.51]), PM (residual relation = 0.47 [0.32, 0.62]), and SM (residual relation = 0.60 [0.53, 0.68]) were entered as single mediators. But the combination of attention control, PM, and SM fully mediated the relation between WMC and fluid intelligence, as the direct path from the *n*-back to fluid intelligence factors was no longer significant (residual relation = −0.18 [−0.46, 0.11]) when all three were included as mediators (Figure 3b). The *n*-back factor exerted significant indirect effects through all three:

Figure 3

Mediation Models Testing Multifaceted Model of Working Memory With n-Back



Note. Models mediating the relation between working memory capacity and fluid intelligence (Panels a and b) and between working memory capacity and reading comprehension (Panels c and d) with attention control, primary memory, and secondary memory. Solid lines indicate significant paths at $p < .05$. Dashed lines indicate nonsignificant paths.

attention control (0.50 [0.26, 0.74]), PM (0.29 [0.17, 0.42]), and SM (0.12, [0.07, 0.17]). Again, attention control, PM, and SM each partially explained the relation between WMC and fluid intelligence, but on their own, none fully explained it. Therefore, this model also provided evidence for the multifaceted account of WMC. Comparing the magnitude of the indirect effects revealed a significant difference between the indirect effect via attention control and the indirect effect via SM (difference = 0.38 [0.13, 0.62]) and a significant difference between the indirect effects via PM and SM (difference = 0.17 [0.03, 0.31]). The difference between the indirect effects via attention control and PM was not significant (difference = 0.21 [−0.06, 0.48]). Therefore, we can conclude that the role of SM is significantly smaller than roles of attention control and PM in explaining the relation between *n*-back performance and fluid intelligence.

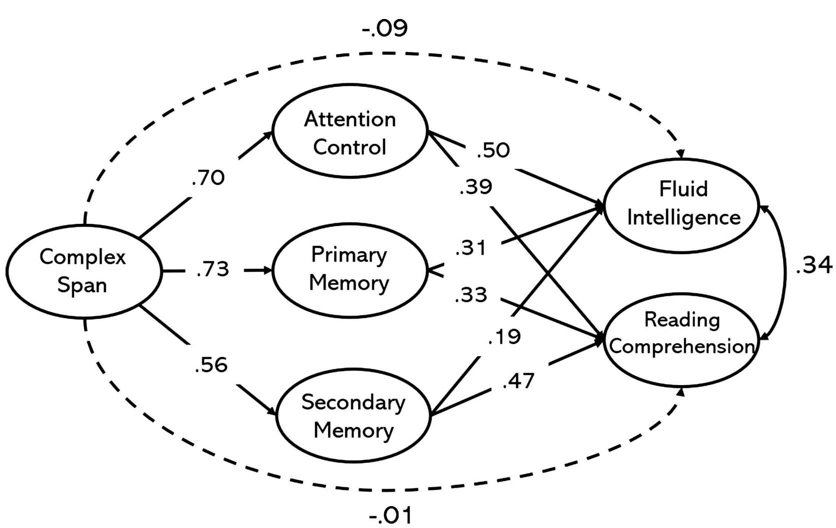
The next set of structural models examined the relation between complex span and reading comprehension. Like the two models described above, no single factor fully mediated the relation. Specifically, there was a significant residual relation between the complex span and reading comprehension factors when attention control (residual relation = 0.25 [0.06, 0.44]), PM (residual relation = 0.28 [0.08, 0.48]), and SM (residual relation = 0.25 [0.14, 0.35]) were entered as single mediators. However, as demonstrated in Figure 3c, the combination of attention control, PM, and SM fully mediated the relation between WMC and reading comprehension. That is, when accounting for all three mediators, the direct path from the complex span to reading comprehension factor was significant, but negative (residual relation = −0.28 [−0.52, 0.04]). In comparing the magnitude of the indirect effects, none of the comparisons were significant (attention control−PM difference = 0.04 [−0.16, 0.25]; attention control−SM difference = −0.03 [−0.18, 0.13]; PM−SM difference = 0.02 [−0.15, 0.18]).

Next, we estimated mediation of the relation between *n*-back and reading comprehension. Here, attention control fully mediated the relation between WMC and reading comprehension on its own, as the residual relation between WMC and reading comprehension was no longer significant (residual relation = 0.26 [−0.004, 0.51]). But when entered alone, neither PM (residual relation = 0.38 [0.20, 0.55]) nor SM (residual relation = 0.37 [0.28, 0.47]) fully mediated the relation. Figure 3d shows that, when attention control, PM, and SM were entered as mediators simultaneously, the *n*-back factor had significant indirect effects through all three: attention control (B = 0.28 [0.13, 0.42]), PM (B = 0.23 [0.09, 0.37]), and SM (B = 0.26, [0.19, 0.33]). In the structural model, attention control, PM, and SM each partially explained the relation between complex span and reading comprehension. None of the comparisons of indirect effects yielded significant differences (attention control−PM difference = 0.11 [−0.25, 0.37], attention control−SM difference = 0.05 [−0.18, 0.28], PM−SM difference = 0.05 [−0.18, 0.28]). Therefore, attention control, PM, and SM accounted for roughly equal portions of variance in the relation between complex span performance and reading comprehension. Therefore, these models provided support for both an attention control account and for the multifaceted account of WMC.

Our next set of structural models examined (a) whether the relations between WMC and fluid intelligence and (b) between WMC and reading comprehension were differentially mediated by attention control, PM, and SM. To assess this, we specified two models. First, we specified a model in which the relations between WMC and fluid intelligence and between WMC and reading comprehension were simultaneously mediated by attention control, PM, and SM (Figure 4). All parameters were freely estimated in this model. Then, we performed a series of contrasts on the indirect effects to examine whether each facet differentially mediated the

Figure 4

Simultaneous Mediation of the Relations Between Working Memory Capacity, as Measured by Complex Span, and Higher Order Cognition



Note. The relations were mediated by attention control, primary memory, and secondary memory. Solid lines indicate significant paths at $p < .05$. Dashed lines indicate nonsignificant paths.

associations between complex span and fluid intelligence and between complex span and reading comprehension.

The first contrast compared the mediating role of attention control in the relation between complex span and fluid intelligence and in the relation between complex span and reading comprehension. Results indicated that the indirect effect via attention control did not significantly differ across the two domains (difference = 0.07 [−0.05, 0.20]). Therefore, attention control mediated the relation between complex span and fluid intelligence and between complex span and reading comprehension to roughly the same extent. The next contrast compared the mediating role of PM in the complex span–fluid intelligence and complex span–reading comprehension relations. This contrast also yielded a nonsignificant difference across domains (difference = −0.01 [−0.16, 0.13]). PM about equally mediated the complex span–fluid intelligence and complex span–reading comprehension relations. The third contrast compared the mediating role of SM. This contrast was significant (difference = −0.16 [−0.23, −0.08]). SM accounted for more of the relation between complex span and reading comprehension than it did the relation between complex span and fluid intelligence.

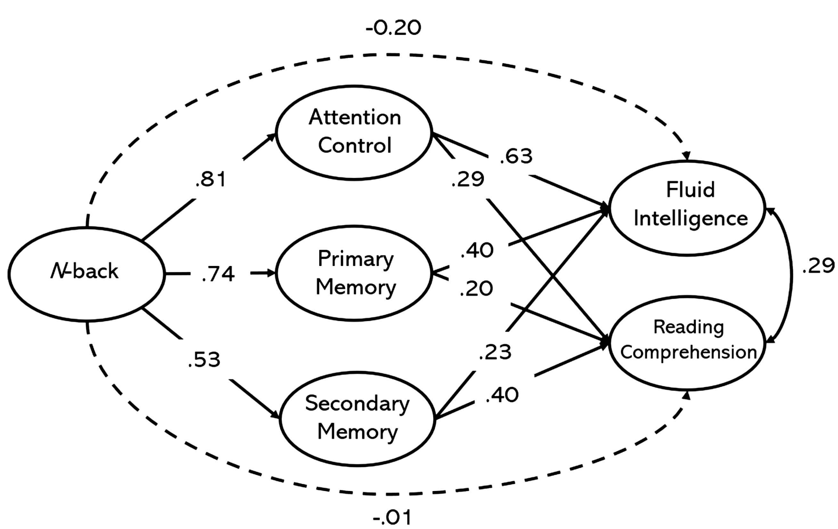
Next, we repeated this analysis using an *n*-back factor as the construct representing WMC (Figure 5). The first contrast compared the mediating role of attention control in the *n*-back–fluid intelligence and *n*-back–reading comprehension relations. The comparison yielded a significant difference (0.27 [0.05, 0.50]). Thus, we can conclude that attention control explains more of the relation between *n*-back performance and fluid intelligence than it does the relation between *n*-back and reading comprehension. The next contrast compared the mediating role of PM in the *n*-back–fluid intelligence and complex span–reading comprehension relations. This contrast also yielded a significant difference (0.15 [0.01, 0.30]). PM accounted for more of the relation between *n*-back and fluid intelligence than it did the relation between *n*-back and reading comprehension. The third contrast compared the mediating role of SM. Again, there was a significant difference, yet in the opposite direction. SM accounted for more of the relation between *n*-back and reading comprehension than it did for the relation between *n*-back and fluid intelligence.

Alternative Approaches

A complementary approach to examining differential patterns of shared and unique variance is to examine which factors among attention control, PM, and SM account for variance in WMC, as measured by complex span and *n*-back, respectively, and in fluid intelligence and reading comprehension. To examine this, we estimated a series of regression models that allowed us to partition variance in each of the four constructs to attention control, PM, and SM uniquely and to their shared influences. The results of these analyses are shown in Figure 6. To summarize, the shared variance among attention control, PM, and SM accounted for the largest portions of variance in each of the four constructs. That is, whatever factors drive individual differences in these three abilities seem to drive a large portion of the variance in WMC, fluid intelligence, and reading comprehension, too. However, there were also significant portions of variance in each construct uniquely driven by the individual components. For example, a substantial portion (9%) of variance in complex span was uniquely attributable to PM with only very little variance uniquely attributable to attention control and SM. But for fluid intelligence, about twice as much variance (13%) was uniquely attributable to attention control than to PM (6%). Together, these findings show that there is a considerable degree of overlap in the process, or set of processes, that drive individual differences in these important aspects of cognitive functioning. However, there are also situations in which the relative portions of variance due to each component substantially differ.

Figure 5

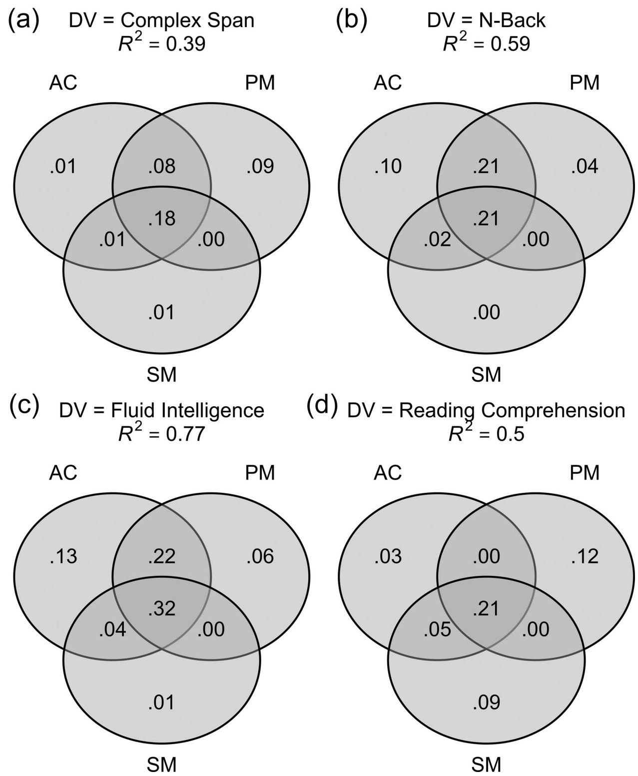
Simultaneous Mediation of the Relations Between Working Memory Capacity, as Measured by n-Back Tasks, and Fluid Intelligence and Between Working Memory Capacity, as Measured by n-Back Tasks, and Reading Comprehension



Note. The relations were mediated by attention control, primary memory, and secondary memory. Solid lines indicate significant paths at $p < .05$. Dashed lines indicate nonsignificant paths.

Figure 6

Variance Portioning Analysis of (a) Complex Span, (b) n-Back, (c) Fluid Intelligence, and (d) Reading Comprehension



Note. PM = primary memory; SM = secondary memory; AC = attention control; DV = dependent variable.

Finally, an additional way to assess the degree to which individual differences in the three components of the multifaceted framework—attention control, PM, and SM—can be attributed to a common underlying process, or set of processes, is to specify a higher order factor representing their shared variance. This model is depicted in Figure 7. This model fits the data similarly to the initial measurement model, $\chi^2(175) = 518.40$, CFI = 0.94, TLI = 0.93, RMSEA = 0.045, 90% CI [0.04, 0.05], SRMR = 0.05.[1] The very large latent correlation between fluid intelligence and the common factor (r = .94) thus suggests that whatever set of processes drives individual differences in fluid intelligence is largely the same as whatever *shared* process, or set of processes, drives individual differences in PM, SM, and attention control. It is worth noting, however, that this model does not allow for a simultaneous assessment of the unique variances in attention control, PM, and SM.

Discussion

Here we compared single- and multifaceted theories for the predictive role of WMC in higher order cognition. Prior theorizing has implicated attention control, PM, and SM as *the* important reason why WMC tends to correlate with higher order cognitive abilities like second-language proficiency, fluid intelligence, and reading comprehension. However other theories propose that multiple facets must be implicated to fully explain those relations. We tested these theories by measuring WMC, attention control, PM, SM, fluid intelligence, and reading comprehension from a large sample of young adults. Then, using confirmatory factor analysis and structural equation modeling, we tested predictions made by each account. Overall, the data largely supported a multifaceted explanation of the relation between WMC and higher order cognition. That is, in all but one case, we only observed full mediation of the WMC–fluid intelligence and WMC–reading comprehension relations when PM, SM, *and* attention control were specified as mediators. And in call cases, WMC had significant indirect effects via each of the three hypothesized mediators, regardless of whether WMC was measured via complex span or n-back tasks and regardless of whether we used fluid intelligence or reading comprehension as the indicator of higher order cognition.

Working Memory Capacity and Fluid Intelligence

Perhaps the most heavily researched relation regarding working memory and higher order cognitive abilities is that with fluid intelligence. As is typical, we found a strong latent correlation between WMC and fluid intelligence, but the constructs were clearly not isomorphic (Ackerman et al., 2005; Engle, 2018; Kane et al., 2005). Further, the correlation was remarkably similar for a factor formed by complex span measures (r = 0.66) and n-back measures (r = 0.69). But we also found that both WMC and fluid intelligence were strongly correlated with the putative subcomponents of working memory. In a structural equation model, we allowed PM, SM, and attention control to act as mediators of the relation between working memory and fluid intelligence, first with WMC measured with complex span tasks and then with WMC measured via n-back tasks. Importantly, WMC had significant indirect effects on fluid intelligence via attention control, PM, and SM, regardless of how WMC was measured.

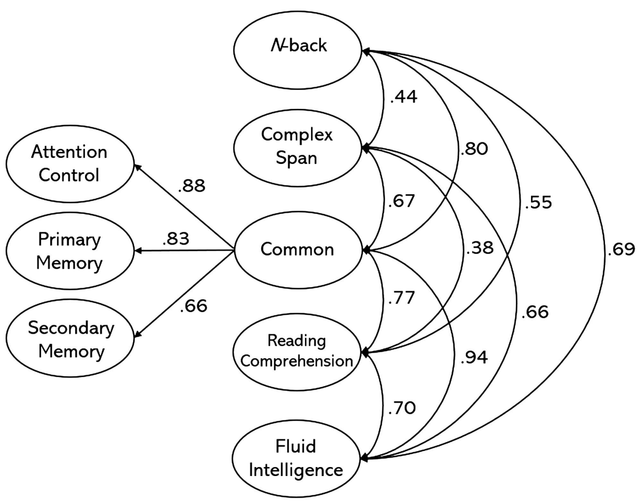
Overall, complex span and fluid intelligence shared about 44% of their variance. To estimate the *relative* roles of attention control, PM, and SM, we estimated the magnitude of the difference in the indirect effects. The indirect effect of complex span on fluid intelligence via attention control was significantly stronger than the indirect effect via SM, and the other two differences were not significant. So, we can conclude that attention control plays more of a role in the complex span–fluid intelligence relation than SM.

To extend the findings beyond just complex span, we also estimated a factor for WMC with n-back tasks. Like the model with the complex span factor, full mediation of the working memory–fluid intelligence relation was only achieved when accounting for all three: attention control, PM, and SM. Specifically, n-back had significant indirect effects on fluid intelligence via each of attention control, PM, and SM. In relative terms, attention control and PM accounted for more of the relation between n-back and fluid intelligence than SM. Even though the n-back and complex span factors correlated moderately (r = 0.43), the results of the mediation analyses were quite similar. The multifaceted account was supported by the mediation analyses involving fluid intelligence, regardless of how WMC was measured.

[1] A direct comparison of this model to the measurement model shown in Figure 2 indicated a significant comparison using a χ^2 test, $\Delta\chi^2(8) = 1.03$, $p < .001$, meaning this model provides a better fit to the data. Additionally, a BIC comparison indicated a lower BIC (48,255) for the model in Figure 8 compared with the model in Figure 2 (BIC = 48,276).

Figure 7

Confirmatory Factor Model With an Additional Hierarchical Factor Representing the Shared Variance Among Attention Control, Primary Memory, and Secondary Memory



Note. All paths were significant at $p < .05$.

Working Memory Capacity and Reading Comprehension

In addition to fluid intelligence, reading comprehension is an oft-cited correlate of WMC that has received considerable attention (Daneman & Carpenter, 1980; McVay & Kane, 2012b; Peng et al., 2018; Robison & Unsworth, 2015; Unsworth & McMillan, 2013). Therefore, we also investigated the mediating roles of PM, SM, and attention control in the relation between WMC and reading comprehension. Replicating prior work, there were moderate latent correlations among the complex span, *n*-back, and reading comprehension factors. Reading comprehension also correlated with PM, SM, and attention control. First, using the complex span factor as the representative WMC latent variable, no single factor fully mediated the relation, although all three partially mediated it. When all three, attention control, PM, and SM, were included as mediators, the complex span–reading comprehension relation was fully mediated. Further, the comparisons on the indirect effects were all nonsignificant, suggesting that each facet accounted for roughly equal amounts of the relation between complex span and reading comprehension. With *n*-back as the factor for WMC, attention control fully mediated the relation, as evidenced by a nonsignificant direct path from WMC to reading comprehension. PM and SM, on their own, only partially mediated the relation. But, when all three were entered as mediators simultaneously, there were significant indirect effects of WMC on reading comprehension via all three: attention control, PM, and SM.

Differential Mediation of Fluid Intelligence and Reading Comprehension

Our final set of analyses examined whether attention control, PM, and SM played a differentially large role in mediating the relation between WMC and fluid intelligence and between WMC and reading comprehension. With complex span as the representative WMC factor, attention control and PM about equally mediated the WMC–fluid intelligence and WMC–reading comprehension relations. However, SM accounted for more of the WMC–reading comprehension relation than it did for the WMC–fluid intelligence relation. With *n*-back as the representative WMC factor, attention control accounted for more of the WMC–fluid intelligence relation than the WMC–reading comprehension relation, as did PM. But SM again accounted for more of the WMC–reading comprehension relation than the WMC–fluid intelligence relation.

Overall, these data indicate that there are some differences in the precise ways in which the relations between WMC and higher order cognition can be mediated. SM seems to be more important in explaining the relation between WMC and reading, whereas attention control and PM seem to be more important in explaining the relation between WMC and fluid intelligence. The former finding was observed when WMC was measured with either complex span or *n*-back tasks. However, the latter finding was only the case when *n*-back tasks were used to measure WMC. It should also be noted that we used a single set of three tasks (Raven, number series, and letter sets) to measure fluid intelligence. These three tests were intentionally selected to include spatial, numeric, and letter stimuli while also having very high *g* loadings (Snow et al., 1984; Tucker-Drob & Salthouse, 2009). However, it could be the case that different assessments of fluid intelligence, for example, untimed tests, place greater emphasis on memory abilities than on attention control. It could also be the case that SM is more predictive of other aspects of intelligence (e.g., crystallized knowledge) than it is of fluid abilities.

Adjudicating Between Single- and Multifaceted Accounts

Evidence for a single-faceted account of WMC could be observed in two ways: (a) full mediation of the relation between WMC and higher order cognitive ability (either fluid intelligence or reading comprehension) when *only* that factor was entered as a mediator or (b) selective mediation by that factor when *all three* putative mediators were entered. None of the mediation models yielded evidence for either a PM or an SM account of WMC. However, one model did yield evidence for the attention control account—attention control fully mediated the *n*-back–reading comprehension relation. All four structural models, though, provided evidence consistent with a *multifaceted* account. In all mediations, the three theoretical subfacets of WMC—attention control, PM, and SM—each mediated part of the relation. Therefore, we argue that the multifaceted account is the most accurate way to explain why WMC predicts higher order cognitive abilities. The tasks we use to measure WMC—complex span and *n*-back—require not a single ability but rather a combination of abilities. In both tasks, people must manage goals in the presence of interference, either internal or external (attention control); actively maintain multiple goal-relevant representations (PM); and retrieve goal-relevant information from an activated portion of long-term memory, when necessary (SM).

Our argument is that single-faceted theories of WMC are incomplete and overly simplified. In all cases, PM and SM did not fully explain the relation between WMC and higher order abilities. However, in all cases they did partially explain the relation. Of any single-faceted account, the attention control account had the most support, as it did fully mediate the relation between *n*-back and reading comprehension. Further, attention control often accounted for the largest proportion of shared variance between WMC and the higher order abilities. However, in all models, PM and SM still mediated part of the relation, even after accounting for attention control. Therefore, it is still our contention that attention control alone does not fully explain the predictive power of WMC.

Our conclusion might lead one to argue that WMC, as it is currently measured, is not a coherent construct but rather a constellation of constructs (Cowan, 2017). If WMC's predictive power comes from three separable abilities, does this not make it a cognitive catch-all—a mere placeholder term for a *set* of cognitive abilities rather than a single cognitive construct? This is a valid question worth some consideration. Our answer would be that virtually any cognitive ability can be deconstructed into subcomponents. For example, attention control might be further broken down into inhibition, conflict resolution, preparatory control, and sustained attention/vigilance; PM might be broken down into separate storage capacities for verbal and visuospatial information; SM might be broken down into encoding and retrieval (e.g., search set delimitation, source monitoring) operations. Further, prior studies have attempted to identify subcomponents of working memory with some success (Oberauer et al., 2003). Of course, any such argument toward decomposition of an ability should be tested using a similar multivariate approach taken here. Via this approach, we believe we have provided more specificity to the consensus viewpoint that WMC is an important cognitive individual difference. That is, we argue that WMC correlates with so many outcomes precisely because having high WMC requires one to control their attention, actively maintain information over the short term, and retrieve relevant information from long-term memory, when necessary. Higher order cognitive abilities, like reading comprehension, fluid intelligence, and second-language learning, also require these abilities, giving rise to the robust and consistent correlations between WMC and higher order abilities.

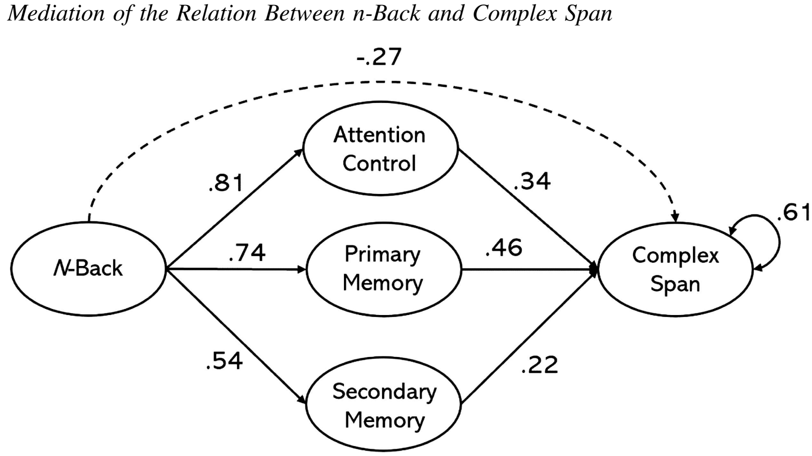
The utility of this level of abstraction of WMC from a more comprehensive ability into its subcomponents also depends on a researcher's goals. In the cognitive realm, the abstraction is important for detailed and precise theories. However, in some clinical or educational settings, demonstrating a reliable symptom-related or developmental difference in WMC may be sufficient to advance the researcher's goals. From a practical perspective, the fact that WMC captures a broad range of specific cognitive subcomponents can be helpful. WMC tasks can be delivered quickly and efficiently (i.e., a single task can be delivered in 10–15 min). In contrast, a large battery encompassing PM, SM, and attention control would take considerably longer. Therefore, researchers must decide on a contextual basis the level of measurement specificity they desire weighed against the pragmatics of administration.

Complex Span Versus *n*-Back

Historically, complex span and *n*-back measures have been two of the most common measures of WMC. Yet, complex span and *n*-back tasks sometimes correlate only weakly (Jaeggi, Buschkuehl, et al., 2010; Jaeggi, Studer-Luethi, et al., 2010; Kane, Conway, et al., 2007; Oberauer, 2005; Redick & Lindsey, 2013). Although some prior latent variable analyses have demonstrated very high ($r \sim 0.90$) correlations between a factor formed by complex span tasks and a factor formed by updating tasks (e.g., *n*-back; Schmiedek et al., 2009; Wilhelm et al., 2013), we observed a modest latent correlation ($r =$ 0.43). This estimate is higher than previous meta-analytic estimates of the zero-order correlation (Redick & Lindsey, 2013), but the complex span and *n*-back tasks clearly measured different cognitive abilities, as evidenced by their loading onto different factors in a confirmatory factor analysis and only modest latent correlation. So, what are the unifying features of these tasks, and what makes them different? We can answer this question with the existing data.

As a final, exploratory model, we examined the relation between complex span and *n*-back factors with mediation by attention control, PM, and SM (see Figure 8). On its own, attention control partially mediated the relation between complex span and *n*-back. There was both a significant indirect effect of complex span on *n*-back via attention control (indirect effect = 0.28 [0.08, 0.48]) and a significant residual relation between the complex span and *n*-back factors (residual relation = 0.23 [0.01, 0.45]). On its own, PM fully mediated the relation between the *n*-back and complex span factors (indirect effect = 0.36 [0.21, 0.51], residual relation = 0.14 [−0.04, 0.32]). And, on its own, SM partially mediated the relation (indirect effect = 0.13 [0.08, 0.19], residual relation = 0.38 [0.28, 0.47]). Finally, when entered as simultaneous mediators, all three indirect effects were significant, and the relation between complex span and

Figure 8
Mediation of the Relation Between n-Back and Complex Span



n-back was fully mediated. Comparing the magnitude of mediation, attention control and PM did not have significantly different indirect effects (difference = −0.06 [−0.30, 0.19]) nor did attention control and SM (difference = 0.16 [−0.05, 0.37]). Whereas the indirect effect through PM was larger than that through SM (difference = 0.22 [0.05, 0.38]). Thus, PM mediated *more* of the relation than did SM. Overall, complex span and *n*-back seem to require PM to a similar extent, whereas SM accounts for less of the relation between *n*-back and complex span. However, it is also clear that these tasks require many nonoverlapping abilities, as they share only about 19% of their variance.

Shared Versus Unique Variance

Although the primary test of the hypotheses was conducted by assessing the *unique* contributions of PM, SM, and attention control to variance in WMC, fluid intelligence, and reading comprehension, after controlling for the other factors, it is worth noting that the three facets were all intercorrelated. It is not our contention that any single measure used in our design is process pure. Nor is it our contention that attention control, PM, and SM are unrelated. Most measures of cognitive performance/ability will, at least to some extent, rely upon a shared set of processes to be completed successfully. For example, it has been demonstrated that one source of variance in change-detection tasks, which we used to measure PM, is the ability to encode and store some information in the presence of irrelevant or otherwise supracapacity amounts of information (Fukuda et al., 2015; Robison et al., 2018; Robison & Unsworth, 2017; Unsworth & Robison, 2016; Vogel et al., 2005). Further, when change-detection tasks force participants to select a particular subset of items, the tasks correlate more strongly with measures of attention control (Draheim et al., 2021; Martin et al., 2021). Finally, the tendency to mind wander during tasks also negatively correlates with performance (Krimsky et al., 2017; Mrazek et al., 2012; Unsworth & Robison, 2016). But this is also true of other measures. For example, previous work has shown that attentional dynamics in long-term memory paradigms, like free recall, are a source of individual variation in those measures (Miller et al., 2019; Miller & Unsworth, 2020, 2021; Robison et al., 2022). Further, the consistency of attention has also been shown to correlate with performance on measures of fluid intelligence (Unsworth & McMillan, 2014b). But we believe that some collections of tasks require processes that are involved to a substantially weaker extent in others. For example, the tasks used to measure attention control here are specifically designed to lack a memory component. That is, the execution of those tasks requires remembering only the task goal. In contrast, our SM measures demand the use of a controlled search process that is not required in tasks like antisaccade, flanker, and PVT.

With those acknowledgments, we ran follow-up analyses to assess the degree to which the three proposed subcomponents accounted for shared and unique components in WMC, fluid intelligence, and reading comprehension (see Figure 6). These analyses indicated that the largest proportions of variance in each of a complex span factor, *n*-back factor, fluid intelligence factor, and reading comprehension factor can be ascribed to a confluence of PM, SM, and attention control. However, even after accounting for these shared sources of variance—including that shared by just two of the components—there was often variance uniquely attributable to some components. For example, 13% of the variance in fluid intelligence was uniquely attributable to attention control; 9% of the variance in complex span was attributable to PM; 12% and 9% of the variance in reading comprehension were uniquely attributable to PM and SM, respectively. Therefore, there are both shared reasons for why these components account for variance in working memory, fluid intelligence, and reading comprehension, but unique reasons, as well.

A second way to examine this question is to assess the extent which variance in attention control, PM, and SM was driven by a common process, or set of processes. To do so, we specified an additional measurement model, similar to that shown in Figure 2, but introducing an additional hierarchical factor onto which the PM, SM, and attention control loaded (see Figure 7). However, this model does not orthogonalize the factors such that we can simultaneously assess correlations between the *shared* variance among PM, SM, and attention and the *unique* variance in those abilities after extracting their communality. We attempted to conduct an analysis that would separate shared and common variance (i.e., a bifactor model), but this unfortunately this model did not converge upon a solution, and therefore we could not interpret it.

To reiterate, the multifaceted theory of WMC does not operate under the assumption that PM, SM, and attention control are orthogonal. That is, it specifically recognizes that there may be some processes that give rise to individual differences in multiple abilities. But what both the mediation and variance partitioning analyses show is that individual differences in higher order cognition are determined by both those shared processes and by some processes that are uniquely manifest in measures of attention control, PM, and SM, respectively. These results were all largely consistent with the variance partitioning performed by Unsworth et al. (2014), who used some overlapping and some different measures of the constructs yet found similar distributions of variance in fluid intelligence attributable to attention control, PM, and SM. Whereas they accounted for 78% of variance in fluid intelligence, we accounted for 77% here.

One notable difference was that Unsworth et al. (2014) found a relatively larger proportion of variance in fluid intelligence due uniquely to SM (17%), whereas here it was only 1%.

Other Abilities

Although the present study measured many abilities from a large sample, there are several relevant abilities that were not measured here and may need to be included in future work. Specifically, we did not include measures of processing speed, which have been argued as a critical source of individual differences in both WMC and fluid intelligence. We also did not include specific measures that would likely correlate with weaker WMC correlations than fluid intelligence and reading comprehension, such as vocabulary or crystallized intelligence. This would have allowed for a more stringent test of the theories, showing instances in which attention control, PM, and SM, or their combination do *not* mediate WMC relations.

Further, there is a separate theory—the *binding hypothesis*—that individual differences in WMC are driven by the ability to quickly and efficiently build, use, and update bindings between representations and context (e.g., a color to a location, a response map to a stimulus; Bartsch & Oberauer, 2023; Oberauer, 2005, 2019). Further, higher order cognition may also rely upon this binding process, which could likewise explain the covariance between WMC and abilities like fluid intelligence. We did not design the present study to test predictions made by the binding hypothesis. But many of the tasks we use likely require binding to a certain extent (e.g., binding a color to a spatial location in change detection, binding a letter to a serial position in operation span). Finally, several studies have shown that associative learning—the ability to learn, understand, and apply relations among pieces of information—can explain all the working memory and SM-related variance in fluid intelligence (Kaufman et al., 2009; Tamez et al., 2008, 2012; Williams & Pearlberg, 2006). Therefore, future work may be able to compare the binding and multifaceted accounts of WMC.

Limitations

We would be remiss to not mention several limitations of the present approach. First and foremost, our cross-sectional correlational data set cannot arrive at firm conclusions regarding causal pathways. Although it is our contention that WMC plays a causal role in higher order cognition, and does so via several mediating processes, the data here can only be consistent with such a hypothesis, not confirm it. More than anything, our approach attempts to account for patterns of covariance. The theories we test make specific predictions about how patterns of covariance across constructs should be statistically recovered. Our models test those predictions and, in doing so, find evidence for a multifaceted account. Second, as mentioned in the Results section, the arrow flanker task had poor psychometrics. Its split-half reliability was only 0.38, which placed an upper bound on the extent to which it could have correlated with other measures. Further, it had a low loading on the attention control factor. At the time these data were collected, this was a known but unsolved issue with inhibition-style tasks like flanker, Stroop, and Simon, which use an RT difference core as a dependent variable. In the years since these data were collected, there has been considerable discussion about how to measure attention control at the construct level, new and improved psychometrics for attention tasks, and a drift away from the use of reaction time difference scores (Draheim et al., 2019, 2021; Enkavi et al., 2019; Feldman & Freitas, 2016; Hedge et al., 2018; Rey-Mermet et al., 2019; Rouder et al., 2023; Rouder & Haaf, 2019; Salthouse & Siedlecki, 2007; Unsworth, Miller, & Robison, 2021; Whitehead et al., 2019, 2020).

In a follow-up work, Draheim et al. (2021) have developed a set of attention control measures that show adequate psychometrics. And, when used in a factor-analytic model, it can fully account for the relation between WMC and fluid intelligence. However, we have one contention with these findings. Specifically, Draheim et al. (2021) found full mediation of the WMC–fluid intelligence relation via attention control when orientation change detection was one of the tasks loading onto the attention control factor. However, most researchers consider change detection to measure processes involving PM and not strictly attention control (Cowan et al., 2005; Unsworth et al., 2014).[2] In a recent study, Burgoyne et al. (2023) developed a new set of attention control tasks that showed high reliability estimates, and the factor formed by those measures accounted for most, but not all, of the WMC–fluid intelligence relation, which is consistent with our multifaceted argument here. Regardless, in future work, we will need to replicate these findings with more psychometrically stable and validated measures of attention control.

Another weakness was the fact that one of our putative measures of PM, end-list output in a free recall task, had a high negative correlation with one of our measures of SM, early-list output in the free recall task. Although we instructed participants to begin their recall of end-list items to empty those items from PM, not all participants heeded this instruction. Therefore, the mixtures in recall initiation strategies may have thwarted our attempts to measure PM and SM in the same task. In hindsight, it may have been problematic to do so regardless. Therefore, in future work, we will need to measure PM and SM with discrete tasks.

Constraints on Generality

As an individual differences investigation including mostly young adults, all of whom were undergraduate students at research universities, there are certainly some constraints on the populations and contexts into which our results will generalize. For example, our findings do not have bearings on how WMC develops in early childhood and through adolescence nor how it changes over the adult lifespan. Although the present results are still informative, the structural relations among cognitive abilities may be different in different age strata. Moreover, as previously mentioned, we investigated a broad but still limited cognitive battery that did not measure other aspects of intelligence besides fluid ability nor did it measure processing speed, binding, or associative learning abilities. Finally, as previously described, correlational data can be used to offer support for a hypothesized causal pathway, but they cannot be used to definitively assert evidence for such pathways.

Conclusion

We found consistent evidence for a multifaceted account of the predictive power of WMC. As measured by complex span and *n*-back tasks, WMC requires the management of task goals, the active maintenance of goal-relevant representations, and the controlled retrieval of long-term memory representations. In turn, these three facets each explain part of the reason why WMC correlates with higher order cognitive abilities, in this case measured as fluid intelligence and reading comprehension. In combination, the three facets fully explain the relations.

[2] In a mediation model in which attention control and PM (but not SM) are set as mediators of the complex span–fluid intelligence relation, we still do not find full mediation (residual relation = 0.24 [0.04, 0.44]).

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