Working memory load affects intelligence test performance by reducing the strength of relational item bindings and impairing the filtering of irrelevant information

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Author Note

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Abstract

There is a broad consensus that individual differences in working memory capacity (WMC) are strongly related to individual differences in intelligence. However, correlational studies do not allow conclusions about the causal nature of the relationship between WMC and fluid intelligence. While research on the cognitive basis of intelligence typically assumes that simpler lower-level cognitive processes contribute to individual differences in higher-order reasoning processes, a reversed causality or a third variable giving rise to two intrinsically uncorrelated variables may exist. In two studies ($n_1 = 65$, $n_2 = 113$), we investigated the causal nature of the relationship between WMC and intelligence by assessing the experimental effect of working memory load on intelligence test performance. Moreover, we tested if the effect of working memory load on intelligence test performance increased under time constraints, as previous studies have shown that the association between the two constructs increases if intelligence tests are administered with a strict time limit. We show that working memory load impaired intelligence test performance, but that this experimental effect was not affected by time constraints, which suggests that the experimental manipulations of working memory capacity and processing time did not affect the same underlying cognitive process. Using a computational modeling approach, we demonstrated that external memory load affected both the building and maintenance of relational item bindings and the filtering of irrelevant information in working memory. Our results confirm that WMC causally contributes to higher-order reasoning processes. Moreover, they support the hypothesis that working memory capacity in general and the abilities to maintain arbitrary bindings and to disengage from irrelevant information in particular are intrinsically related to intelligence.

Keywords: intelligence; working memory capacity; cognitive processes; computational modeling

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1. Introduction

There is no doubt that individual differences in working memory capacity (WMC) are strongly related to individual differences in fluid intelligence. Ever since the seminal paper by Kyllonen and Christal (1990), in which they reported near-unity latent correlations between working memory capacity and reasoning ranging from .80 to .90, intelligence researchers have been intrigued by the possibility that individual differences in working memory processes might give rise to individual differences in fluid intelligence. Subsequent studies have corroborated the tight link between the two constructs (Ackerman et al., 2002; Buehner et al., 2005; Colom et al., 2005, 2008; Engle et al., 1999; Frischkorn et al., 2019; Gignac, 2014; Oberauer et al., 2008; Süß et al., 2002; Unsworth, 2010; Unsworth et al., 2014; Unsworth & Engle, 2006), with two meta-analyses estimating the latent-variable correlation between $r = .71$ (Kane et al., 2005) and $r = .85$ (Oberauer et al., 2005). Recently, Oberauer et al. (2018) listed the strong correlation between working memory capacity and intelligence as a high-priority benchmark finding that theories and models of working memory need to account for.

1.1 Theories of the relationship between working memory capacity and intelligence

The strong relationship between working memory capacity and fluid intelligence presumably suggests that a greater ability to simultaneously process and store information facilitates reasoning performance. However, there is currently no consensus on the precise mechanisms that explain how the ability to simultaneously process and store information contributes to greater intelligence. Cognitive process parameters that have been suggested to contribute to the association between working memory capacity and fluid intelligence include the efficiency of attentional control processes (Engle, 2018; Shipstead et al., 2016), short-term

storage capacity (Colom et al., 2006, 2008), the strength of elementary memory bindings (Chuderski, 2019; Oberauer et al., 2008), and processing speed (Jensen, 2006; Salthouse, 1996; Schubert et al., 2017).

A widespread approach to explain the relationship between working memory capacity and fluid intelligence assumes that both processes rely on the ability to control attention in order to ignore external or internal distractors (Engle, 2002, 2018; Kane et al., 2007). Recent revisions of the executive-attention account of working memory have distinguished between the maintenance of information, which is thought to play a major role in working memory tasks, and the disengagement from irrelevant information, which is thought to play a major role in fluid intelligence tests, where multiple hypotheses need to be generated and subsequently disregarded if they turn out to be incorrect (Engle, 2018; Shipstead et al., 2016). Associations between working memory capacity and fluid intelligence are thus thought to reflect the shared attentional control demands of maintaining and disengaging from information. Despite the intuitive appeal of a theory that attributes the correlation between working memory capacity and fluid intelligence to attentional control abilities, several alternative theoretical accounts have been proposed.

For example, individual differences in short-term storage capacity may contribute to the relationship between working memory capacity and fluid intelligence, as memory tasks without additional processing demands have also been shown to be strongly related to intelligence (Colom et al., 2006, 2008). It has been suggested that short-term storage capacity reflects a common capacity limit or a common resource that limits reasoning ability (Colom et al., 2008). Colom et al. (2008) tentatively suggested that this common resource might be related to structural and functional properties of frontal and parietal brain areas that are engaged when accessing and updating information stored in short-term memory. Alternatively, individual differences in short-term storage capacity may also reflect the ability to build and maintain memory bindings

(Oberauer et al., 2008). The ability to build and maintain arbitrary bindings in working memory may contribute to individual differences in fluid intelligence, because many fluid intelligence tests and in particular tests of reasoning ability require the building, maintenance, and manipulation of relational representations (Oberauer et al., 2007). Matrix reasoning tests may serve as an example: To identify the correct solution, test takers need to construct and update mental representations of the relations between different elements of each test item. In addition, they also have to build a mental model of the rules represented in each item by combining these mental representations and then have to hold this model in working memory while testing if it applies to all matrix elements. Hence, individuals better at building and maintaining arbitrary bindings in working memory should be better at building and testing mental representations and should therefore be more likely to identify the correct solution in tests of reasoning ability. In line with this reasoning, previous research has shown that tasks measuring the ability to build and maintain arbitrary bindings are as strongly related to intelligence as tasks including additional processing demands (Oberauer et al., 2008; Wilhelm et al., 2013).

Finally, several theoretical accounts attribute a central role to processing speed, which has been shown to be substantially related to both working memory capacity and fluid intelligence (Frischkorn et al., 2019; Nettelbeck & Burns, 2010; Schubert et al., 2017). Some of these accounts presume that a greater speed of information-processing increases the amount of information that can be processed in working memory before it decays (Jensen, 2006; Salthouse, 1996). Other accounts propose that a greater speed of information-processing increases the availability of information in working memory due to a more efficient transfer from frontal attention and working memory processes to temporal-parietal processes of memory storage (Schubert et al., 2017; Schubert & Frischkorn, 2020). What is particularly intriguing and underlines the role of processing speed in explaining the association between working memory

capacity and fluid intelligence is that the correlation between the latter two constructs has been shown to be moderated by speed constraints in intelligence tests (Chuderski, 2013). Chuderski (2013) found that the relationship between working memory capacity and fluid intelligence became near-isomorphic when intelligence tests were conducted under strict time constraints. This suggests that individuals with lower working memory capacity were, due to high time pressure, no longer able to compensate their capacity limits by employing other time-consuming cognitive processes such as careful perceptual analysis, learning, or abstraction (Carpenter et al., 1990; Chuderski, 2013; Garlick & Sejnowski, 2006). A subsequent study, however, found that a more gradual linear increase in time constraints of intelligence tests showed no corresponding effect on correlations (Colom et al., 2015). All in all, these two studies suggest that the introduction of any time constraints in intelligence testing seems to increase the relationship between working memory capacity and intelligence (probably due to the loss of feasible compensation strategies under time pressure), but that increasing time constraints does not further increase this correlation.

1.2 The causal nature of the relationship between working memory capacity and fluid intelligence

Taken together, there are several complementary theories that try to account for the relationship between working memory capacity and fluid intelligence. However, all studies reviewed so far are correlational and do therefore not allow firm conclusions about the causal nature of the relationship between working memory capacity and fluid intelligence. While research on the cognitive basis of fluid intelligence typically assumes that simpler lower-level cognitive processes contribute to individual differences in higher-order reasoning processes (Schweizer, 2005), a reversed causality may exist. Further complexity arises from the possibility of a third variable that may give rise to the correlation between working memory capacity and

fluid intelligence, as proposed by the executive-attention account of working memory (Engle, 2002, 2018; Shipstead et al., 2016). The aim of the present study was therefore to investigate the causal nature of the relationship between working memory capacity and fluid intelligence by assessing the experimental effect of working memory load on intelligence test performance.

First evidence for a causal relationship between working memory capacity and fluid intelligence stems from studies that investigated the effect of working memory manipulations on reasoning performance. To assess the effects of working memory load on reasoning ability, Baddeley and colleagues proposed several procedures to specifically increase the load of certain components of their multi-component model of working memory (Baddeley, 1986; Baddeley et al., 1998; Baddeley & Hitch, 1974; Logie et al., 1990). In particular, random number generation was designed to engage the central executive of their multi-component model. Asking participants to generate random numbers during the completion of reasoning tasks has been repeatedly shown to impair performance in syllogistic, propositional, and spatial reasoning tasks, while secondary tasks that suppressed verbal or spatial rehearsal showed only small if any effects on reasoning performance (Gilhooly et al., 1993; Klauer et al., 1997). In the only published study on the effects of working memory load on intelligence test performance, Rao and Baddeley (2013) demonstrated that simultaneous backward counting affected solution times, but not solution rates in matrix reasoning performance, while articulatory suppression had no effect on either performance measure.

1.3 The present study

Taken together, the reviewed studies provide some evidence for a causal relationship between working memory capacity and fluid intelligence. However, three issues remain: First, Rao and Baddeley (2013) found only negligible effects of dual-task demands on intelligence test solution rates. If working memory capacity limits intelligence test performance, it needs to be

shown that working memory load not only affects solution times, but also the number of correctly solved items. The relatively low attentional demand of backward counting may account for the fact that participants were still able to solve matrices comparatively well under dual-task demands. Unfortunately, Rao and Baddeley (2013) did not test whether backward counting affected working memory test performance to a larger degree than it affected intelligence test performance. Hence, it may be that a secondary task with greater attentional demands such as random number generation affects not only solution times, but also solution rates. In a preliminary unpublished study, we found that simultaneous random number generation significantly impaired solution rates in comparison to a number of control conditions including the suppression of articulatory and visual-spatial rehearsal (Hagemann et al., 2016). In the present study, we therefore assessed how intelligence test performance was impaired by random number generation in comparison to an articulatory suppression task, the latter of which had no effect on intelligence test performance in comparison to a passive control condition in the preliminary study (Hagemann et al., 2016).

Second, it is currently unknown if the effects of working memory load on intelligence test performance increase under the same conditions under which the correlation between working memory capacity and intelligence increases. As discussed above, one moderating factor that has been identified to affect the relationship between working memory capacity and fluid intelligence is the time given to complete intelligence test items (Chuderski, 2013). We therefore introduced moderate and severe time constraints for some intelligence test items to evaluate if the deteriorating effect of random number generation increased under time constraints in comparison to items without any time constraints. Improving upon previous research on the effect of time constraints on intelligence test performance, we introduced item-wise time constraints to ensure

that reduce transfer effects of speed-accuracy tradeoffs between different items (Estrada et al., 2017).

Third, it needs to be shown that natural variation in working memory capacity and fluid intelligence moderates the effect of random number generation on intelligence test performance. Here, different theoretical frameworks make different predictions about the direction of such a moderating effect (see Figure 1 for an illustration of the different theoretical predictions). A recently proposed process theory of intelligence, which has been termed process overlap theory (Kovacs & Conway, 2016, 2019), suggests that certain domain-general cognitive processes act as bottlenecks, constraining performance in a variety of cognitive ability tests. According to process overlap theory, the correlation between different cognitive ability tests can be explained by a limited number of elementary executive processes affecting performance in any kind of ability test. Working memory would constitute such an elementary executive process involved in the vast majority of cognitive tasks. In addition, other domain-specific processes (e.g., verbal abilities) would also contribute to performance in a given task (e.g., a verbal reasoning task). Hence, an individual with a low working memory capacity would tend to show rather poor performance in any cognitive task because their performance would be constrained by their working memory capacity. In comparison, an individual with a high working memory capacity would perform well in some tasks (e.g., verbal tasks), but poorly in others (e.g., spatial tasks) because their performance would not be determined by a domain-general constraint, but rather by their domain-specific abilities. Thus, process overlap theory proposes that the performance of individuals with a low working memory capacity should already be determined by their working memory capacity, whereas the performance of individuals with a high working memory capacity should instead be largely determined by domain-specific processes. In consequence, the theory would predict that experimentally inducing working memory load through random number

generation should generate a domain-general performance constraint especially for those participants with a high working memory capacity, but less so among those participants with a low working memory capacity whose performance is already constrained by their low working memory capacity. Therefore, less intelligent individuals should be *less* affected by random number generation than more intelligent individuals, because their domain-general capacity limit should already be constraining their intelligence test performance. In comparison, intelligence test performance of more intelligent individuals as well as individuals with greater working memory capacity should be *strongly* impaired by random number generation, because experimentally reducing their working memory capacity might cause a domain-general performance constraint (see the upper left part of Figure 1 for a visualization of these predictions).

As an alternative, other theories proposing that working memory capacity is related to intelligence because working memory capacity acts as a limited resource, with more intelligent individuals having more resources available than less intelligent ones, would make different predictions. Resource-based theories would predict that intelligence test performance of more intelligent individuals as well as individuals with greater working memory capacity should be *only slightly* impaired by working memory load, because they have spare resources available and should therefore be able to tolerate additional load at least to some degree. In consequence, resource-based theories would predict that less intelligent individuals should be more *strongly* affected by working memory load than more intelligent individuals, because they are already operating at their capacity limit and further limiting their capacity would cause their performance to suffer (see the lower left part of Figure 1 for a visualization of these predictions).

Figure 1*Illustration of theoretical predictions*

To test these competing predictions, we measured participants' intelligence and working memory capacity as potential moderators of the experimental effect of working memory load. In addition, we also investigated how individual differences in intelligence and working memory capacity moderated the effect of time constraints on intelligence test performance. Again, we derived the prediction from process overlap theory that individuals with higher intelligence and greater working memory capacity should be more affected by the introduction of time constraints, because imposing time constraints might introduce a bottleneck in information-processing for them that is likely already present in individuals with lower cognitive abilities (see

the upper right part of Figure 1 for a visualization of these predictions). However, we could not rule out a reverse direction of this interaction, i.e., that individuals with higher intelligence and greater working memory capacity might be less affected by the introduction of time constraints because their higher processing speed might still allow them to finish reasoning in a shorter time (see the lower right part of Figure 1). Finally, we compared the trajectories of interactions between the two covariates and the two experimental effects. If processing speed is a functional mechanism underlying the relationship between intelligence and working memory capacity, then individual differences in these two constructs should similarly moderate the effects of time constraints on performance in the dual task.

2. Study 1

2.1 Methods

2.1.1 Participants

We recruited $N = 72$ participants from the participant pool of the Heidelberg psychology department. According to *G*Power* (Faul et al., 2007, 2009), this sample size gives us 99 % power to detect a between-subjects effect of $\omega^2 = .19$, which corresponds to the experimental effect of random number generation in comparison to articulatory suppression on solution rates in the APM found in a preliminary study (Hagemann et al., 2016).¹

Of these 72 participants, one participant had to be excluded because they had participated twice in the study, two participants were excluded because they had not understood or adhered to task instructions and four more participants were excluded because they had performed below chance performance in the APM. The remaining sample size of $N = 65$ participants still gave us 96 % power to detect a between-subjects effect of $\omega^2 = .19$. The final sample consisted of 21

¹ The data of the pilot study by Hagemann et al. (2016) is available in the Open Science Framework at <https://osf.io/hdcvj/> (Hagemann et al., 2022, November 8).

males and 44 females between 19 and 61 years ($M = 25.87$, $SD = 9.45$). All participants had at least a high-school diploma (German Abitur) and most participants were currently enrolled as students. However, of these only six were enrolled in highly competitive majors, whereas the rest studied majors without any or with less competitive entrance limitations. All participants signed an informed consent. The study was conducted in accordance with the Declaration of Helsinki.

2.1.2 Materials

2.1.2.1 Dependent variables.

2.1.2.1.1 Intelligence. Participants had to solve a computerized modified version of Raven's Advanced Progressive Matrices (APM; Raven et al., 1994) while performing their respective secondary tasks (see below). The modified APM deviated from the published test in the way that items were shown one at a time and that participants could not go back to previous items to correct their response. This deviation was necessitated because of the experimental manipulation of time constraint (for details see below). In addition, participants responded by clicking on the selected response alternative instead of marking it with a pen.

After reading standard instructions and studying two sample items from set I of the APM, participants were given instructions for their secondary task, which they practiced for one minute. Subsequently, they saw and worked on three blocks of Raven's matrices consisting of six easy and six more difficult items each while performing their secondary task. The three item sets contained only items from set II and were constructed to ensure similar item difficulties across the three item sets.

Each of the three blocks introduced a different time constraint (highly constrained vs. moderately constrained vs. unconstrained) and the order of time constraints was counterbalanced across participants. Time constraints were set to 50 % (highly constrained) and 75 % (moderately constrained) of the average solution time of APM items in a pilot sample. We specified one set of

time constraints for the 18 easiest items and another set of time constraints for the 18 most difficult items. Items were classified according to the test manual to account for differences in item difficulties. Participants had to solve each easy item in 13.5 (highly constrained) or 20.25 (moderately constrained) seconds, and each difficult item in 34 (highly constrained) or 51 (moderately constrained) seconds. Participants had to respond within the allotted time for each item; once time was up, the next item was shown, and their response was coded as incorrect.

At the beginning of each block, participants were informed about any time constraints and completed three practice items from set I with the newly introduced time constraint. They then worked on the 12 test items of each block before progressing to the next block. Whenever participants were working under time constraints, the screen frame turned red 10 seconds before time was over to inform them that they needed to make their decision for the current item. Participants could indicate that they were unable to solve an item by clicking a designated button and did not have to guess to progress with the experiment. The modified APM showed a moderate internal consistency of $\alpha = .72$ across the two repeated measures factors Time Constraint and Item Difficulty.

2.1.2.1.2 Working memory capacity. Participants completed the spatial short-term memory (SSTM) task developed by Lewandowsky et al. (2010) while performing their respective secondary tasks (see below). They had to remember the locations of sequentially presented dots in a 10 x 10 grid. Participants were instructed to remember only the overall pattern of dots (i.e., their spatial relations), not their absolute positions. Subsequently, they had to reproduce the previously seen pattern in any order by clicking the respective cells in an empty 10 x 10 grid. Set sizes ranged from two to six dots.

Due to a coding error, participants completed only 14, not 30 trials of the SSTM task. Hence, the factors set size and trial numbers were not fully crossed and participants saw different

subsets of trials due to randomized presentation orders. To account for this, we modified the scoring procedure suggested by Lewandowsky et al. (2010) by first calculating participants' average performance within each set size before averaging across set sizes. Nevertheless, there were five participants who only saw five of the six set sizes. The SSTM task showed a moderate internal consistency of $\alpha = .61$ across the five set sizes.

2.1.2.2 Covariates.

2.1.2.2.1 Intelligence. Participants' intelligence was assessed with a modified short version of the Intelligence Structure Test (IST; Liepmann, 2007). The test was modified in the way that we selected only three subscales from different content domains of the IST-2000-R with the highest loading on the general intelligence factor reported in the manual (arithmetical problems – numerical, similarities – verbal, and figure selection – spatial), shortened them by 50 percent, and had participants work on each of the three subscales without time limit to prevent any spurious correlations with experimentally induced time constraints in the APM. The test showed a low internal consistency of $\alpha = .51$ across the three subscales with test items aggregated within each of the subscales. The number of correct responses per subscale were summed and z -standardized (irrespective of experimental group assignment) and subsequently averaged across the three scales. On average, participants correctly solved 65.59 % ($SD = 12.00$ %) of arithmetical problems, 76.62 % ($SD = 20.69$ %) of similarity items, 71.02 % ($SD = 16.47$ %) of figure selection items. The two experimental groups to which participants were randomly allocated did not differ in their intelligence test performances, all $F_s \leq 0.20$, all $p_s \geq .656$, all $\omega^2_s = .00$.

2.1.2.2.2 Working memory capacity. Participants' working memory capacity was assessed with the memory updating (MU) task developed by Lewandowsky et al. (2010). Participants had to remember sets of three to five digits that were then followed by two to six cues for arithmetic operations. Subsequently, participants had to recall the updated digits in the previously seen

order. They completed a total of 15 trials. The MU task showed a high internal consistency of $\alpha = .82$ across the three set sizes. Performance was scored as recommended by Lewandowsky et al. (2010). On average, participants correctly recalled 63.98 % ($SD = 17.58$ %) of memory items. The two experimental groups to which participants were randomly allocated did not differ in their working memory capacity, $F(1,63) = 0.32$, $p = .573$, $\omega^2 = .00$.

2.1.3 Design

We used a $2 \times 3 \times 2$ design with the between-subjects factor Secondary Task (random number generation vs. articulatory suppression) and the within-subjects factors Time Constraint (highly constrained vs. moderately constrained vs. unconstrained) and Item Difficulty (easier vs. more difficult). The primary dependent variable was the number of correctly solved intelligence test items. In addition, we assessed the effect of the Secondary Task factor on performance in the SSTM task as a manipulation check for the experimental load manipulation.

2.1.4 Procedure

After giving their informed consent, all participants completed the modified short version of the IST-2000-R and the MU task. Participants were then randomly allocated to one of two experimental conditions and were either instructed to generate a sequence of random numbers using the digits 0-9 or to count from 1 to 4 during the following two experimental tasks. Participants in both conditions were asked to articulate these numbers immediately to the beat of a metronome at a rate of 60 bpm. After a brief practice period without primary task demands, participants then completed the modified version of the APM and the SSTM task while performing their respective secondary tasks. Participants read primary task instructions and completed practice trials without secondary task demands and were then instructed to resume their secondary task before starting to work on the experimental trials. Experimenters ensured task adherence and instructed participants to adhere to the secondary task instruction if they

noticed that they did not utter a number on each metronome beat. At the end of the session, participants completed a brief demographic questionnaire and were paid 8 € as compensation.

2.1.5 Data analysis

We first conducted a manipulation check by calculating a between-subjects ANOVA with the independent variable Secondary Task (random number generation vs. articulatory suppression) and the dependent variable mean accuracy in the spatial short-term memory task using the R package *afex* (Version 1.0-1; Singmann et al., 2020).

Subsequently, we analyzed the experimental effects on APM performance with hierarchical logistic mixed-effects regression models using the R package *lme4* (Version 1.1-29; Bates et al., 2015). Logistic mixed-effects models are often better suited than traditional analyses of variance approaches for analyzing dichotomous performance data (correct vs. incorrect), because they make less restrictive assumptions and reduce the likelihood of obtaining spurious results due to confidence intervals falling outside interpretable values between 0 and 1 (Bayne et al., 2008; Jaeger, 2008; Singmann & Kellen, 2019). We analyzed APM performance on the item-level by scoring correctly solved items with 1 and incorrectly solved items with 0. In these models, we included the experimental between-subjects factor Secondary Task (random number generation vs. articulatory suppression) and the within-subjects factors Time Constraint (highly constrained vs. moderately constrained vs. unconstrained) and Difficulty (easier vs. more difficult) as effect-coded fixed effects. In addition, we included performance in the IST-2000-R and the MU task as z-standardized fixed-level covariates to assess how individual differences in working memory capacity and intelligence moderated the experimental effects. Covariates were standardized irrespective of experimental group. Finally, we included random intercepts for participants and items to account for the nested data structure. We specified two effect-coded contrasts for the experimental factor Time Constraint: One that compared the presence of any time constraints to

the absence of time constraints (highly constrained weighted with -0.5, moderately constrained weighted with -0.5, and unconstrained weighted with 1), and a second one that compared the effects of high time constraints to moderate time constraints (highly constrained weighted with -1, moderately constrained weighted with 1, and unconstrained weighted with 0).

2.1.6 Transparency and Openness

The data supporting the findings of the study are available in the Open Science Framework repository at <https://osf.io/kjbf3> (Schubert et al., 2022, November 8). The study was preregistered prior to conducting the research on February 24th, 2020, at <https://osf.io/nygcp>. We deviated from the preregistered analysis plan because hierarchical logistic mixed-effects regression models are more appropriate for the analysis of dichotomous performance data than traditional analyses of variance (Jaeger, 2008). Moreover, we do not report how the two experimental manipulations affected solution times because these results are of little value given that solution times were predetermined by time constraints. For greater transparency, we report the results of the preregistered analyses in the supplementary material. All in all, those results were largely comparable unless otherwise noted in the main text.

2.2 Results

2.2.1 Manipulation check

Participants generating random numbers as a secondary task performed worse in the spatial short-term memory task than participants counting from 1 to 4, $F(1, 63) = 6.19, p = .015$, $\omega_p^2 = .07$. Random number generation successfully manipulated participants' working memory capacity (see Table 1 for descriptive statistics).

Table 1*Mean accuracies (SDs in parentheses) in the SSTM task and the APM*

	SSTM task		
random number generation		0.81 (0.08)	
articulatory suppression		0.85 (0.05)	
	APM: easier items		
	highly constrained	moderately constrained	unconstrained
random number generation	0.28 (0.45)	0.46 (0.50)	0.72 (0.45)
articulatory suppression	0.44 (0.50)	0.52 (0.50)	0.82 (0.39)
	APM: more difficult items		
	highly constrained	moderately constrained	unconstrained
random number generation	0.17 (0.37)	0.21 (0.41)	0.32 (0.47)
articulatory suppression	0.16 (0.37)	0.19 (0.39)	0.44 (0.50)

Note. SSTM = spatial short-term memory; APM = advanced progressive matrices.

2.2.2 Effects of working memory load and time constraints on intelligence test performance

We analyzed the experimental effects on APM performance with hierarchical logistic mixed-effects regression models (see Table 1 for descriptive statistics and Table 2 for model results).

Both experimental manipulations impaired intelligence test performance significantly (see Figure 2 for a figure of estimated marginal means and Figure S1 for a jittered boxplot of participants' raw performance data). Participants solved fewer APM items when generating random numbers than when counting from 1 to 4, $OR = 1.26$, $p = .007$. In addition, participants also solved fewer items when working under time constraints. Intelligence test performance did not only suffer from the very introduction of time constraints, $OR = 2.76$, $p < .001$, but high time constraints reduced performance even above and beyond moderate time constraints, $OR = 1.28$, $p < .001$. We also found a significant interaction between the Secondary Task and Time Constraint factors that indicated that the effect of working memory load on APM performance was larger when there were no time constraints than when there were time constraints (contrast C1), $OR =$

1.31, $p = .003$.² The effect of Secondary Task on APM performance did not differ between moderate and high time constraints, $OR = 1.01$, $p = .894$.

Figure 2

Experimental effects of secondary task and time constraint on solution rates

Note. Error bars show 95% confidence intervals.

In addition to a trivial main effect of Difficulty on solution rates, $OR = 2.31$, $p < .001$, we observed interactions between the Difficulty and Time Constraint factors (see Figure 2).³ The significant interaction between Difficulty and the first Time Constraint contrast (C1) reflected that the introduction of time constraints reduced solution rates more for the easier items than for more difficult ones, $OR = 1.30$, $p = .001$. Similarly, the significant interaction between Difficulty and the second Time Constraint contrast (C2) demonstrated that high time constraints impaired performance above and beyond moderate time constraints in easier items but not more difficult ones, $OR = 1.14$, $p = .044$. Taken together, these interactions show that the experimental effects were attenuated in more difficult items, probably due to floor effects.⁴

² This effect was not significant in the preregistered analyses (see Supplementary Material and the discussion below).

³ We also observed a significant interaction between the Difficulty and Secondary Task factors in the preregistered analyses (see Supplementary Material).

⁴ To address possible statistical issues due to those floor effects, we repeated our analysis after excluding ten more participants (i.e., 16 %) who had performed worst in the APM in the within-subjects condition without any time constraints, assuming those participants may not have taken the study seriously. Applying this criterion, we excluded eight participants from the random number generation group and two participants from the articulatory suppression

Table 2*Results of the hierarchical logistic mixed-effects regression models*

Fixed effects				
	<i>OR</i>	<i>SE</i>	<i>CI</i>	<i>p</i>
Intercept	0.57	0.09	0.42 – 0.77	<.001
Experimental effects				
Secondary Task	1.26	0.11	1.07 – 1.49	.007
Time Constraint (C1)	2.76	0.21	2.37 – 3.21	<.001
Time Constraint (C2)	1.28	0.08	1.13 – 1.46	<.001
Difficulty	2.31	0.33	1.75 – 3.05	<.001
Secondary Task x Time Constraint (C1)	1.31	0.12	1.10 – 1.56	.003
Secondary Task x Time Constraint (C2)	1.01	0.07	0.88 – 1.17	.894
Secondary Task x Difficulty	1.10	0.06	0.99 – 1.22	.066
Time Constraint (C1) x Difficulty	1.30	0.10	1.12 – 1.51	.001
Time Constraint (C2) x Difficulty	1.14	0.07	1.00 – 1.29	.044
Secondary Task x Time Constraint (C1) x Difficulty	0.88	0.08	0.74 – 1.05	.159
Secondary Task x Time Constraint (C2) x Difficulty	0.97	0.07	0.84 – 1.11	.629
Covariates				
Intelligence	1.36	0.13	1.13 – 1.63	.001
WMC	1.39	0.13	1.16 – 1.66	<.001
Interactions betw. experimental effects and covariates				
Secondary Task x intelligence	1.06	0.10	0.88 – 1.27	.559
Time Constraint (C1) x intelligence	1.20	0.10	1.02 – 1.40	.025
Time Constraint (C2) x intelligence	0.93	0.07	0.81 – 1.07	.329
Secondary Task x WMC	0.95	0.09	0.79 – 1.14	.574
Time Constraint (C1) x WMC	0.98	0.08	0.84 – 1.15	.832
Time Constraint (C2) x WMC	1.18	0.08	1.03 – 1.35	.020
Secondary Task x Time Constraint (C1) x intelligence	1.03	0.08	0.88 – 1.21	.721
Secondary Task x Time Constraint (C2) x intelligence	1.08	0.08	0.88 – 1.21	.256
Secondary Task x Time Constraint (C1) x WMC	0.83	0.07	0.71 – 0.97	.018
Secondary Task x Time Constraint (C2) x WMC	1.00	0.07	0.88 – 1.15	.948
Random Effects				
σ^2	3.29			
τ_{00} participant	0.29			

group. Results of this analysis were largely identical to the results presented in Table 2 with three notable exceptions. The main effect of Secondary Task was no longer significant, $OR = 1.14$, $p = .163$, likely due to the lower statistical power and the unequal ratio of participants in the two between-subjects groups. Moreover, the interaction between Difficulty and the second Time Constraint contrast (C2) was no longer significant, $OR = 0.88$, $p = .051$, which suggests that the exclusion of participants with relatively low performance (possibly due to lack of motivation or cognitive overload) helped to reduce floor effects. Finally, the interaction between the first Time Constraint contrast (C1) and participants' intelligence was no longer significant, $OR = 1.13$, $p = .220$, which may indicate that this effect could be attributed to floor effects.

τ_{00} item	0.61
Marginal R^2 / Conditional R^2	0.29 / 0.45

Note. C1 = first contrast of the Time Constraint factor, coded to compare effects of the presence of any time constraints to the absence of time constraints; C2 = second contrast of the Time Constraint factor, coded to compare the effects of high time constraints to moderate time constraints; WMC = working memory capacity. Significant effects are highlighted in bold.

2.2.2.1 Moderation of experimental effects by covariates. The two covariates intelligence and working memory capacity were positively correlated, $r = .37$, $p = .003$. The effect of random number generation on solution rates was not moderated by participants' intelligence, $OR = 1.06$, $p = .559$, or working memory capacity, $OR = 0.95$, $p = .574$. However, the effect of time constraints on solution rates interacted with participants' intelligence and their working memory capacity (see Figure 3).

Figure 3

Moderation of the experimental effect of time constraints on solution rates by covariates

Note. Displayed effects are based on estimated marginal means.

More intelligent participants were more affected in their performance by the introduction of time constraints (contrast C1) than less intelligent participants (see the left part of Figure 3), $OR = 1.20$, $p = .025$. Beyond that, the effect of high in comparison to moderate time constraints on APM solution rates (contrast C2) did not vary depending on participants' intelligence, $OR =$

0.93, $p = .329$. We observed a complementary pattern of result for the interaction between time constraints and working memory capacity, as the effect of introducing time constraints on APM solution rates (contrast C1) did not vary depending on participants' working memory capacity, $OR = 0.98$, $p = .832$. Participants with higher working memory capacity were, however, more affected by high in comparison to moderate time constraints (contrast C2) than those with lower working memory capacity (see the right part of Figure 3), $OR = 1.18$, $p = .020$. Most likely, participants with lower working memory capacity could not show further decrements in performance under high time constraints because they had already reached their capacity limit under moderate time constraints.

Figure 4

Moderation of the experimental effects of secondary task and time constraints on solution rates by working memory capacity

Note. WMC = working memory capacity. Displayed effects are based on estimated marginal means (note that the spacing of intelligence and working memory test scores was limited by the number of items in each of the two tests).

In addition, we also observed a three-way interaction between participants' working memory capacity and the two experimental effects (see Figure 4). Random number generation impaired participants' performance more strongly for those participants with lower working

memory capacity than for those with higher working memory capacity when participants were facing no time constraints than when they were facing any time constraints (see Figure 4), $OR = 0.83, p = .018$. This three-way interaction was only significant for the first contrast of the Time Constraint factor (contrast C1), but not for the second one (contrast C2), indicating that the interaction between working memory capacity and secondary task demands did not differ between moderate and high time constraints. This pattern of results was further confirmed in follow-up analyses, in which we assessed the interaction between participants' working memory capacity and secondary task separately for the three levels of the Time Constraint factor. We only found a significant two-way interaction when no time constraints were present, $p = .014$, but not under moderate, $p = .704$, or high time constraints, $p = .762$.

As an exploratory (not-preregistered) analysis, we also tested if item difficulties moderated the effect of participants' intelligence and/or working memory capacity on APM solution rates, as such an interaction might be interpreted as additional evidence for process overlap theory.⁵ Because more difficult items have greater executive demands than easier items, they should be more likely to create a bottleneck with regard to those executive demands than easier items, which would be reflected in an interaction between item difficulties and covariates. However, the effect of Difficulty on solution rates was neither moderated by participants' intelligence, $OR = 1.12, p = .065$, nor their working memory capacity, $OR = 0.98, p = .778$, and adding an interaction between Difficulty and the two covariates did not improve model fit significantly in comparison to the model without those interaction terms, $\Delta\chi^2(2) = 3.52, p = .172$.

⁵ We would like to thank an anonymous reviewer for this suggestion.

2.3 Discussion

The aim of Study 1 was to investigate the causal nature of the relationship between working memory capacity and fluid intelligence by assessing the experimental effect of working memory load on intelligence test performance. We demonstrated that simultaneous random number generation had a small effect ($OR = 1.26$) on intelligence test performance in comparison to simultaneous articulatory suppression. This finding is consistent with process theories of fluid intelligence proposing that working memory is closely related to intelligence (Ackerman et al., 2002; Buehner et al., 2005; Colom et al., 2005, 2008; Engle et al., 1999; Frischkorn et al., 2019; Gignac, 2014; Kane et al., 2005; Oberauer et al., 2005, 2008, 2018; Süß et al., 2002; Unsworth, 2010; Unsworth et al., 2014; Unsworth & Engle, 2006). Moreover, our study is one of the first to demonstrate that an experimental manipulation of working memory capacity has a causal effect on intelligence test performance. We experimentally reduced the available capacity of working memory by loading working memory with random number generation. Thus, our experimental approach emulated naturally occurring variation in working memory capacity while controlling for nuisance variables by randomizing and controlling for individual differences in intelligence and working memory capacity. Our results confirmed that working memory capacity causally contributes to higher-order reasoning processes.

What makes interpreting the mechanisms underlying this experimental effect challenging is that random number generation is a complex process that likely has multifaceted effects on the cognitive system. The experimental procedure of random number generation was originally used to specifically load the central executive component of the multi-component model of working memory (Baddeley et al., 1998; Baddeley & Hitch, 1974) and there is a broad consensus that random number generation requires central executive resources (Peters et al., 2007). However, there is also evidence that it relies on a number of elementary control processes such as attention

allocation (Joppich et al., 2004), the inhibition of habitual responses (Jahanshahi et al., 1998; Joppich et al., 2004; Miyake et al., 2000), maintaining and updating information in working memory (Cooper, 2016; Miyake et al., 2000), output monitoring (Cooper, 2016; Joppich et al., 2004), schema selection (Cooper, 2016), and set shifting (Cooper, 2016; Miyake et al., 2000). From a process-based point of view, it is therefore unclear which of these elementary processes contributed independently or jointly to the effect of random number generation on intelligence test performance. In particular, the heterogeneous set of elementary processes involved in random number generation raises the question if the effect of random number generation on intelligence test performance can be attributed to increased working memory or cognitive control demands. We addressed this open question in Study 2 by using a computational modeling approach that allowed us to formally quantify the effects of random number generation on binding- and control-related processes in working memory to distinguish between the two interpretations. We fit the memory measurement model (M^3 ; Oberauer & Lewandowsky, 2019) to data from a novel complex spatial span task designed to allow the estimation of M^3 parameters. The M^3 is a computational measurement model of working memory that assumes that distinct processes in working memory contribute to correct responses and different types of error responses in a working memory task. The efficiency of these processes is captured in three parameters: The activation parameter a , reflecting the memory of individual elements, the binding parameter c , providing information about the memory for relations of memory contents, and finally the filter parameter f , reflecting control-related processes. In the present study, we fixed the activation parameter a when fitting the M^3 to our data to overcome issues with model convergence (see below). Hence, we did not test the effects of random number generation on general item activation reflected in parameter a .

Transforming the activation of the different item categories into their respective recall probabilities then allows estimating the contributions of different memory processes to task performance. Thus, the model permits to evaluate which model parameters are specifically affected by the secondary tasks and hence to make inferences about the affected elementary processes in working memory. To test if random number generation had a larger effect on memory- or control-related processes, we compared the experimental effect on the binding parameter c of the model (reflecting memory-related processes) to the experimental effect on the filter parameter f of the model (reflecting control-related processes) in Study 2. Moreover, we assessed which of the two parameters mediated the effect of random number generation on intelligence test performance.

Another goal of Study 1 was to explore if the effect of working memory load on intelligence test performance changes under the same conditions under which the correlation between working memory capacity and intelligence changes. Because the introduction of time constraints has been shown to increase the association between working memory capacity and intelligence (Chuderski, 2013), we investigated if the effect of random number generation increased under time constraints. To our surprise, we found tentative evidence for the opposite, i.e., that the effect of working memory load on intelligence test performance decreased under time constraints. However, this interaction between external load and time constraints only emerged in the hierarchical logistic mixed-effects regression models but not the preregistered analyses, where we instead found no evidence for this interaction. Overall, this inconsistent effect was small ($OR = 1.31$) and may simply be a fluke in the data due to substantial floor effects in performance caused by our choice of time constraints. We therefore tried to replicate this unexpected interaction in Study 2.

The third goal of Study 1 was to explore how individual differences in intelligence and working memory capacity moderated the effects of working memory load and time constraints on intelligence test performance. Contrary to our expectations, we found that neither intelligence nor working memory capacity moderated the effect of random number generation on intelligence test performance. Because our sample consisted of only 65 participants, we may have had insufficient power to detect an interaction between two between-subjects effects.

Consistent with our expectations, we found that the effect of time constraints on intelligence test performance was moderated by individual differences in intelligence and working memory capacity. Our results were consistent with predictions from process overlap theory, as the introduction of time constraints affected participants with higher cognitive abilities more than participants with lower cognitive abilities. Of note, intelligence and working memory capacity showed quite distinct patterns in the way they moderated the experimental effect of time constraints on intelligence test performance across different levels of the time constraint factor. If processing speed exerted its influence on intelligence by limiting the amount of information that can be processed in working memory before it decays (Jensen, 2006; Salthouse, 1996), we should have seen a parallel pattern across the different levels of the time constraint factor. However, due to the moderate sample size and substantial floor effects in intelligence test performance, these diverging patterns of interactions should be interpreted as preliminary effects. In addition, we found no evidence that participants' intelligence or working memory capacity moderated the effect of item difficulties on intelligence test performance, which would be predicted by process overlap theory as more difficult items should have greater executive demands than easier items.

Taken together, Study 1 successfully demonstrated that experimentally induced working memory load impaired intelligence test performance, confirming that working memory capacity causally contributes to reasoning abilities. However, the study had several limitations that restrict

the interpretability of these findings. First, it is unclear if the effect of random number generation on intelligence test performance can be attributed to increased working memory or cognitive control demands. Second, the sample size was too small to reliably assess how individual differences in intelligence and working memory capacity moderated the results. The sample size may also have been too small to be conclusive with regard to the interaction between experimental effects. Third, we found some evidence that the experimental effects were attenuated under high time constraints due to floor effects. Fourth, the modified short version of the intelligence test we used as a covariate showed a low internal consistency, which may have led to an underestimation of the moderating effect of intelligence on task performance.

We therefore addressed these issues in Study 2 and collected a larger sample of 120 participants to increase the statistical power and robustness of findings. We also improved the experimental design by setting time constraints separately for each APM item based on previously collected item-wise solution times (Goldhammer et al., 2015) to prevent floor effects. Moreover, we used a non-speeded version of the Hagen Matrices Test (HMT; Heydasch, 2014) to measure participants' intelligence as a covariate with higher reliability. Finally, we used the Memory Measurement Model (Oberauer & Lewandowsky, 2019) to discern which processes in working memory were affected by random number generation.

3. Study 2

3.1 Methods

3.1.1 Participants

We recruited $N = 121$ participants from the participant pool of the Heidelberg psychology department and by advertising the study with flyers and posters. Sample size was planned with the R package *Superpower* (Lakens & Caldwell, 2019), which conducts Monte Carlo simulations of factorial experimental designs. We used the effect estimates obtained in Study 1 to get an

estimate for an adequately powered sample size for a $2 \times 3 \times 2$ ANOVA with the between-subject factor Secondary Task (random number generation vs. articulatory suppression) and the within-subject factors Time Constraint (highly constrained vs. moderately constrained vs. unconstrained) and Difficulty (easier vs. more difficult). We aimed to recruit a sample size of 120 participants, which gave us 100 % power to detect a main effect of Secondary Task, 100 % power to detect a main effect of Time Constraint, and 88 % power to detect an interaction between Secondary Task and Time Constraint. Moreover, a sample size of 120 participants is in accordance with the guidelines for mixed models that suggest collecting at least 50 observations within each Level-2 factor level (Paccagnella, 2011). We recruited 121 instead of 120 participants because one participant did not complete the study. We did not include their data in any analyses.

Of these 120 participants, one participant was excluded because they had not understood or adhered to task instructions, one participant was excluded because they had recently completed the HMT, one participant was excluded because their data on the HMT was lost due to a technical problem, two participants were excluded because they had performed below chance performance in the APM, one participant was excluded because they had performed below chance performance in the HMT, one participant was excluded because they had performed below chance performance in the APM and the HMT, and two more participants were excluded because they had performed below chance performance in the complex span task. The final sample consisted of 111 participants and still gave us 100 % power to detect a main effect of Secondary Task, 100 % power to detect a main effect of Time Constraint, and 86 % power to detect an interaction between Secondary Task and Time Constraint. Demographic data from eight participants were lost due to technical reasons and can therefore not be reported here. The sample consisted of 30 males, 72 females, and one participant who identified as non-binary between 18 and 43 years ($M = 23.51$, $SD = 4.58$). 98 percent of participants who disclosed their educational

background had at least a high-school diploma (German Abitur) and most participants were currently enrolled as students. As in Study 1, we tried to recruit students from different majors to include a large number of students from majors without any or with less competitive entrance limitations. All participants signed an informed consent. The study was conducted in accordance with the Declaration of Helsinki.

3.1.2 Materials

3.1.2.1 Dependent variables.

3.1.2.1.1 Intelligence. The experimental design of the APM was identical to Study 1 except that time constraints were adjusted and set separately for each item to prevent floor effects. Time constraints were set to 65 % (highly constrained) and 85 % (moderately constrained) of the item-specific average solution time measured in a sample of 230 German high school and university students (Goldhammer et al., 2015). If participants had not responded within the allotted time window, their response was coded as incorrect, and their response time was set to the maximum of the allotted time window. Participants had to respond within the allotted time for each item; once time was up, the next item was shown. Items without time constraint were presented without time limit. The modified APM showed a high internal consistency of $\alpha = .82$ across the repeated measures factor Time Constraint.

3.1.2.1.2 Working memory capacity. Participants completed a complex spatial span (CSS) task while performing their secondary task. The task was designed to allow fitting parameters of the Memory Measurement Model (Oberauer & Lewandowsky, 2019, see below). In each trial, they had to remember four different 4x4 grids with different patterns. These patterns consisted of four squares colored in red and twelve uncolored squares. Analogous to a complex span task, each of these four grids was subsequently followed by another 4x4 grid with a pattern of black squares as a distractor item. For every distractor item, participants had to decide whether

the shown pattern was symmetrical either on the vertical or horizontal axis. After the presentation of all four memory items and their corresponding distractors, participants had to choose the correct sequence of shown memoranda out of 16 same-colored alternatives. The response set always consisted of the four correct memory items, the four distractor items, and eight not presented lures (items not presented in the current trial). The CSS task showed a high internal consistency of $\alpha = .96$.

3.1.2.2 Covariates.

3.1.2.2.1 Intelligence. Participants' intelligence was assessed with a modified version of the HMT (Heydasch, 2014). The HMT is a freely available fluid intelligence test consisting of 20 items. Each item shows a 3 x 3 matrix with the element omitted that consists of geometric figures following certain logical rules and symmetries. Participants had to identify the missing matrix element out of eight plausible alternatives. Usually, the test allots two minutes for solving each item, but we removed this time constraint to ensure that interactions of intelligence test performance with the experimental Time Constraint factor were not due to time constraints of the intelligence test. The modified HMT showed a high internal consistency of $\alpha = .81$. On average, participants solved 57.70 % ($SD = 20.71$ %) of intelligence test items. The two experimental groups to which participants were randomly allocated did not differ in their intelligence test performance, $F(1,109) = 0.22$, $p = .643$, $\omega^2 = .00$.

3.1.2.2.2 Working memory capacity. Participants' working memory capacity was assessed with the memory updating (MU) task developed by Lewandowsky et al. (2010). The MU task showed a high internal consistency of $\alpha = .92$ across the three set sizes. Performance was scored as recommended by Lewandowsky et al. (2010). On average, participants correctly recalled 61.34 % ($SD = 22.24$ %) of memory items. The two experimental groups to which participants

were randomly allocated did not differ in their working memory capacity, $F(1,109) = 0.02$, $p = .890$, $\omega^2 = .00$.

3.1.3 Design

We used a 2 x 3 x 2 design with the between-subjects factor Secondary Task (random number generation vs. articulatory suppression) and the within-subjects factors Time Constraint (highly constrained vs. moderately constrained vs. unconstrained) and Item Difficulty (easier vs. more difficult). The primary dependent variable was the number of correctly solved intelligence test items. In addition, we assessed the effect of the Secondary Task factor on working memory capacity in the CSS task as a manipulation check.

3.1.4 Procedure

After giving their informed consent, all participants completed the modified version of the HMT and the MU task. Participants were then randomly allocated to one of two experimental conditions and were either instructed to generate a sequence of random numbers using the digits 0-9 or to count from 1 to 4 during the following two experimental tasks. Participants in both conditions were asked to articulate these numbers immediately to the beat of a metronome at a rate of 60 bpm. After a brief practice period without primary task demands, participants then completed the modified version of the APM and the CSS task while performing their respective secondary tasks. They read task instructions and completed practice trials without secondary task demands and were instructed to resume their secondary task before starting to work on the experimental trials. Experimenters ensured task adherence and instructed participants to adhere to the secondary task instruction if they noticed that they did not utter a number on each metronome beat. At the end of the session, participants completed a brief demographic questionnaire and were paid 15€ as compensation.

3.1.5 Data analysis

We first conducted a manipulation check by calculating a between-subjects ANOVA with the independent variable Secondary Task (random number generation vs. articulatory suppression) and the dependent variable mean accuracy in the CSS task using the R package *afex* (Version 1.0-1; Singmann et al., 2020). Moreover, to further assess which specific working memory processes were affected most by the secondary task manipulation, we fitted the Memory Measurement Model (M³; Oberauer & Lewandowsky, 2019) to the data. The model consists of three parameters describing memory retrieval. The parameter a reflects the strength of memory for an individual item and the parameter c reflects the strength of relational memory (e.g., the strength of the binding between a memory item and its serial position). In addition, the filter parameter f captures the proportional reduction of list memory strength through partial filtering of the encoding of distractors (Oberauer & Lewandowsky, 2019). In the present study, we compared the estimated posterior means of the subject-level parameter distributions of the parameters c (context binding) and f (filtering of distractors) between the two experimental groups. Subsequently, we calculated a t -test for independent groups to assess the effects of the secondary task manipulation on the M³ model parameters.

All M³ models were fitted using *rstan* (Version 2.21.3; Stan Development Team, 2022). Each model was estimated with four Markov chains with 10,000 iterations each, with the first 5,000 samples dropped as warm-up. As the M³ models did not converge properly when all three parameters a , c , and f were freely estimated and we were mainly interested in the context binding and filter parameters, the general activation parameter a was fixed to its prior mean of 2. The normal priors of the hyper-parameters for c and f were set to moderately informative values following the recommendations of Oberauer and Lewandowsky (2019), $\mu_c \sim N(20, 10)$ and $\mu_f \sim N(0, 10)$. For fitting purposes, the maximum tree depth of the NUTS sampler was set to 15,

and the average acceptance rate for posterior draws was set to .90 to avoid divergences. M³ model parameters showed acceptable to good reliabilities, with Spearman Brown corrected odd-even correlations ranging from .91 (random number generation condition) to .97 (articulatory suppression condition) for the parameter *c* and from .70 (random number generation condition) to .81 (articulatory suppression condition) for the parameter *f*.

Subsequently, we analyzed the experimental effects on APM performance with hierarchical logistic mixed-effects regression models the same way as in Study 1 using the R package *lme4* (Version 1.1-29; Bates et al., 2015). We included the experimental between-subjects factor Secondary Task (random number generation vs. articulatory suppression) and the within-subjects factors Time Constraint (highly constrained vs. moderately constrained vs. unconstrained) and Difficulty (easier vs. more difficult) as effect-coded fixed effects. In addition, we included performance in the HMT and the MU task as *z*-standardized fixed-level covariates to assess how individual differences in working memory capacity and intelligence moderated the experimental effects. Covariates were again standardized irrespective of experimental group. Finally, we included a random intercept for participants and items to account for the nested data structure. Contrasts were coded as in Study 1.

To analyze whether the effect of working memory load on intelligence test performance could be explained by impairments in memory- or control-related processes in working memory, we estimated exploratory hierarchical logistic mixed-effects mediation models with a random intercept for participants with *Mplus* (Version 8.8; Muthén & Muthén, 2017). In these models, we tested if the M³ parameters *c* or *f* mediated the relationship between the experimental between-subjects factor Secondary Task (random number generation vs. articulatory suppression) and performance in the APM. These mediation models were not included in the preregistration.

3.1.6 Transparency and Openness

The data supporting the findings of the study are available in the Open Science Framework repository at <https://osf.io/kjbf3> (Schubert et al., 2022, November 8). The study was preregistered prior to conducting the research on March 26th, 2021, at <https://osf.io/hcyga>.

3.2 Results

3.2.1 Manipulation check

Participants generating random numbers as a secondary task performed worse in the CSS task ($M = 0.29$, $SD = 0.16$) than participants counting from 1 to 4 ($M = 0.44$, $SD = 0.22$), $F(1, 109) = 17.15$, $p = .001$, $\omega_p^2 = .13$. Random number generation successfully manipulated participants' working memory capacity. To assess which specific processes in working memory were affected by random number generation, we compared the posterior means of the M³ subject parameters. All models converged properly, showing no divergent transitions and $\hat{R}$ statistics ≤ 1.01 for all parameters in all Markov chains. Highest density intervals (HDIs) of the hyper-parameters for c and f showed no overlap between the two experimental groups (see Table 3), which suggests that random number generation affected both memory- and control-related processes. Participants generating random numbers had more difficulties binding items to serial positions in memory, $F(1, 103) = 13.98$, $p < .001$, $\omega_p^2 = .11$, and filtering irrelevant information, $F(1, 103) = 15.63$, $p < .001$, $\omega_p^2 = .12$, than participants counting from 1 to 4. This finding indicates that the external load manipulation affected both memory- and control-related processes in working memory.

Table 3*M³ parameter estimates*

	parameters			
	random number generation		articulatory suppression	
	μ [95 % <i>HDI</i>]	<i>M</i> (<i>SD</i>)	μ [95 % <i>HDI</i>]	<i>M</i> (<i>SD</i>)
<i>c</i>	2.82 [1.10;4.62]	2.80 (3.35)	7.30 [5.58;9.07]	7.30 (7.81)
<i>f</i>	0.21 [.17;.25]	0.22 (0.08)	0.13 [0.11;0.16]	0.16 (0.09)

Note. μ hyper parameter; *HDI* = highest density interval; *M* = mean of subject-level parameters; *SD* = standard deviation of subject-level parameters; *c* = context binding parameter; *f* = filter parameter (a higher filter parameter indicates a lower filter ability).

3.2.2 Effects of working memory load and time constraints on intelligence test performance

Solution rates were higher than in Study 1, suggesting that we successfully addressed the issue of floor effects due to time constraints (see Table 4 for descriptive statistics). Both experimental manipulations impaired intelligence test performance significantly and in the same way as in Study 1 (see Table 5 for model results, Figure 5 for a figure of estimated marginal means and Figure S2 for a jittered boxplot of participants' raw performance data). Contrary to the results from Study 1, we found no significant interaction between the Secondary Task and Time Constraint factors, as the effect of Secondary Task on APM performance did not differ between unconstrained and moderate time constraints, $OR = 1.01$, $p = .866$, nor between moderate and high time constraints, $OR = 1.05$, $p = .381$.

Table 4*Mean accuracies (SDs in parentheses) in the APM*

	easier items		
	highly constrained	moderately constrained	unconstrained
random number generation	0.35 (0.24)	0.51 (0.24)	0.68 (0.30)
articulatory suppression	0.64 (0.25)	0.71 (0.23)	0.87 (0.18)
	more difficult items		
	highly constrained	moderately constrained	unconstrained
random number generation	0.25 (0.24)	0.19 (0.18)	0.33 (0.22)
articulatory suppression	0.41 (0.26)	0.44 (0.29)	0.53 (0.28)

Note. APM = advanced progressive matrices.

Table 5*Results of the hierarchical logistic mixed-effects regression models*

Fixed effects				
	<i>OR</i>	<i>SE</i>	<i>CI</i>	<i>p</i>
Intercept	1.00	0.14	0.75 – 1.32	.989
Experimental effects				
Secondary Task	1.84	0.12	1.62 – 2.09	<.001
Time Constraint (C1)	1.97	0.12	1.76 – 2.21	<.001
Time Constraint (C2)	1.11	0.05	1.01 – 1.21	.028
Difficulty	0.47	0.06	0.36 – 0.61	<.001
Secondary Task x Time Constraint (C1)	1.02	0.07	0.89 – 1.16	.793
Secondary Task x Time Constraint (C2)	1.04	0.05	0.94 – 1.15	.425
Secondary Task x Difficulty	0.94	0.04	0.87 – 1.01	.112
Time Constraint (C1) x Difficulty	0.78	0.05	0.70 – 0.88	<.001
Time Constraint (C2) x Difficulty	0.84	0.04	0.77 – 0.92	<.001
Secondary Task x Time Constraint (C1) x Difficulty	0.89	0.06	0.78 – 1.02	.087
Secondary Task x Time Constraint (C2) x Difficulty	1.08	0.06	0.98 – 1.20	.124
Covariates				
intelligence	1.68	0.11	1.47 – 1.91	<.001
WMC	1.25	0.08	1.09 – 1.42	.001
Interactions betw. experimental effects and covariates				
Secondary Task x intelligence	1.19	0.08	1.05 – 1.36	.008
Time Constraint (C1) x intelligence	1.15	0.07	1.02 – 1.29	.023
Time Constraint (C2) x intelligence	1.02	0.05	0.93 – 1.12	.713
Secondary Task x WMC	1.11	0.07	0.97 – 1.26	.131
Time Constraint (C1) x WMC	1.06	0.06	0.94 – 1.18	.343
Time Constraint (C2) x WMC	0.96	0.05	0.88 – 1.06	.415
Secondary Task x Time Constraint (C1) x intelligence	1.11	0.07	0.99 – 1.25	.075
Secondary Task x Time Constraint (C2) x intelligence	0.98	0.05	0.89 – 1.08	.690
Secondary Task x Time Constraint (C1) x WMC	1.02	0.06	0.92 – 1.15	.677
Secondary Task x Time Constraint (C2) x WMC	1.05	0.05	0.96 – 1.15	.303
Random Effects				
σ^2	3.29			
τ_{00} participant	0.29			
τ_{00} item	0.60			
Marginal R^2 / Conditional R^2	0.30 / 0.45			

Note. C1 = first contrast of the Time Constraint factor, coded to compare effects of the presence of any time constraints to the absence of time constraints; C2 = second contrast of the Time Constraint factor, coded to compare the effects of high time constraints to moderate time constraints; WMC = working memory capacity. Significant effects are highlighted in bold.

We again observed interactions between the Difficulty and Time Constraint factors (see Figure 5). The significant interaction between Difficulty and the first Time Constraint contrast (C1) reflected that the introduction of time constraints reduced solution rates more for the easier items than for more difficult ones, $OR = 0.78, p < .001$. Similarly, the significant interaction between Difficulty and the second Time Constraint contrast (C2) demonstrated that high time constraints impaired performance above and beyond moderate time constraints in easier items but not more difficult ones, $OR = 0.84, p < .001$. All levels of the Time Constraint factor differed from each other, all $ps \leq .013$, except for the comparison between moderate and high constraints in more difficult items, $p = .308$. This interaction suggests that there may have still been floor effects in the most difficult conditions of our experimental design (albeit much smaller than in Study 1) despite our attempts to address this issue using item-specific time constraints.

Figure 5

Experimental effects of secondary task and time constraint on solution rates

Note. Error bars show 95% confidence intervals. Displayed effects are based on estimated marginal means.

3.2.3 Moderation of experimental effects by covariates

The two covariates intelligence and working memory capacity were positively correlated, $r = .23, p = .016$. The effect of random number generation on solution rates was moderated by participants' intelligence, $OR = 1.19, p = .008$, but not their working memory capacity,

$OR = 1.11, p = .131$. More intelligent participants were more strongly affected by random number generation in comparison to articulatory suppression than less intelligent ones (see Figure 6). We replicated the interaction between time constraints and participants' intelligence, but not the interaction between time constraints and participants' working memory capacity from Study 1. Consistent with the results from Study 1, more intelligent participants were more affected by the introduction of time constraints (contrast C1) than less intelligent participants (see the left part of Figure 7), $OR = 1.15, p = .023$. Just as in Study 1, the effect of high in comparison to moderate time constraints on APM solution rates (contrast C2) did again not vary depending on participants' intelligence, $OR = 1.02, p = .713$. Participants' working memory capacity did not moderate the effect of time constraints on solution rates (see Table 5 and the right part of Figure 7). We also did not replicate the spurious three-way interaction between participants' working memory capacity and the two experimental effects found in Study 1 that can therefore be most likely attributed to floor effects of the previous study.

Figure 6

Moderation of the experimental effect of time constraints on solution rates by covariates

Note. Displayed effects are based on estimated marginal means (note that the spacing of intelligence and working memory test scores was limited by the number of items in each of the two tests).

Figure 7*Moderation of the experimental effect of time constraints on solution rates by covariates*

Note. Displayed effects are based on estimated marginal means (note that the spacing of intelligence and working memory test scores was limited by the number of items in each of the two tests).

As an exploratory (not-preregistered) analysis, we again tested if item difficulties moderated the effect of participants' intelligence and/or working memory capacity on APM solution rates, as such an interaction might be interpreted as additional evidence for process overlap theory. Because more difficult items have greater executive demands than easier items, they should be more likely to create a bottleneck with regard to those executive demands than easier items, which would be reflected in an interaction between item difficulties and covariates. However, the effect of Difficulty on solution rates was neither moderated by participants' intelligence, $OR = 1.01$, $p = .126$, nor their working memory capacity, $OR = 1.00$, $p = .733$, and adding an interaction between Difficulty and the two covariates did not improve model fit significantly in comparison to the model without those interaction terms, $\Delta\chi^2(2) = 2.69$, $p = .261$.

3.2.4 Mediation analysis

To analyze whether the effect of external load on intelligence test performance could be explained by impairments in memory- or control-related processes in working memory, we estimated hierarchical logistic mixed-effects mediation models with a random intercept for

participants that assessed which parameter of the M³ model mediated the effect to external load on intelligence test performance. Note that model parameters could not be jointly entered into a single mediation model due to the artificially inflated correlation between them caused by the between-subjects factor *Secondary Task*. We found that both the binding-related parameter c of the M³ model, $\beta_{\text{indirect}} = -.15, p = .002$, as well as the control-related parameter f of the M³ model, $\beta_{\text{indirect}} = -.15, p = .001$, mediated part of the experimental effect of random number generation in comparison to articulatory suppression on intelligence test performance. The direct effect remained significant after introducing either mediator, $p < .001$, which suggests that the experimental effect of random number generation on intelligence test performance could not be fully accounted for by memory- and control-related processes in working memory.

Figure 8

Mediation of the experimental effect of Secondary Task on intelligence test performance

Note. *** $p < .01$. The experimental factor *Secondary Task* was entered as a dummy-coded variable.

3.3 Discussion

The aim of Study 2 was to replicate the findings from Study 1 in an improved study design with a larger sample size. We replicated the finding that simultaneous random number generation impaired intelligence test performance in comparison to articulatory suppression. Although the effect size was only small ($OR = 1.84$), the consistency of this finding demonstrates that the

cognitive processes affected by random number generation, i.e., working memory and cognitive control, causally contribute to intelligence test performance. To decide whether random number generation had a larger effect on memory- or control-related processes, we used the Memory Measurement Model (Oberauer & Lewandowsky, 2019) as a computational model of working memory and compared the experimental effect on the binding parameter c of the model (reflecting memory-related processes) to the experimental effect on the filter parameter f of the model (reflecting control-related processes). We found evidence for a medium effect on the parameter c , which reflects the strength of memory relations, and a medium effect on the parameter f , which reflects the degree to which distractors are successfully kept from being encoded into working memory. Unfortunately, we could not estimate the effect of random number generation in comparison to articulatory suppression on the parameter a , which reflects the strength of memory for individual elements, because this parameter had to be fixed for successful model convergence. This was unfortunate but only a minor limitation of the present study because the activation parameter a reflects the general item activation in memory, which is a process less likely to contribute to intelligence differences in comparison to binding and filter processes (Chuderski, 2019; Engle, 2018; Halford et al., 1998; Jastrzębski et al., 2020; Oberauer et al., 2008; Shipstead et al., 2016). Taken together, these computational modeling results show that random number generation had an effect on memory-related processes (reflected in the parameter c) as well as on control-related processes (reflected in the parameter f). Subsequent mediation analyses confirmed that the effect of random number generation on intelligence test performance can be attributed to difficulties in building and maintaining relational bindings as well as impaired cognitive control. In particular, our results suggest that random number generation affected the building and maintenance of relational bindings in working memory, which is a process that has been repeatedly suggested to play a central role in explaining

individual differences in fluid intelligence (Chuderski, 2019; Halford et al., 1998; Jastrzębski et al., 2020; Oberauer et al., 2008). Moreover, they also provide experimental evidence for the executive-attention account of working memory (Engle, 2002, 2018), which proposes that the relationship between working memory capacity and fluid intelligence is due to shared attentional control demands. Our results show that both processes are likely to contribute to the relationship between working memory capacity and fluid intelligence.

In Study 1, we found preliminary evidence for an interaction between working memory load and time constraints that did not replicate in Study 2. The interaction in Study 1 suggested that the effect of working memory load on intelligence test performance decreased under time constraints, which contradicts our predictions and is hard to reconcile with correlational findings of an increase of the association between working memory capacity and intelligence under time pressure (Chuderski, 2013). Moreover, this interaction only emerged in the hierarchical logistic mixed-effects regression models but not the preregistered analyses, where we instead found no evidence for this interaction. Hence, we think it likely that the results from Study 1 are likely a fluke in the data and conclude that the effect of working memory load on intelligence did not vary depending on time constraints. Taken together, these results suggest that the experimental manipulations of working memory capacity and processing time did not affect the same underlying cognitive process. Instead, they are consistent with the interpretation that the moderating effect of time constraints is likely driven by the loss of feasible compensation strategies and the unavailability of more time-consuming cognitive processes under time pressure. This interpretation would also explain why Colom et al. (2015) found that gradually increasing time constraints had no effect on the association between working memory capacity and intelligence, as their study included no condition without time constraint and these

compensation strategies may have already been rendered ineffective under moderate time constraints of 40 minutes.

One of the main goals of Study 2 was to allow a more reliable evaluation of how individual differences in intelligence and working memory capacity moderated the effects of working memory load and time constraints on intelligence test performance. Due to a much-increased sample size of 111 participants included in Study 2 in comparison to 65 participants in Study 1, we were able to assess the interaction between participants' cognitive abilities and the experimental effects more robustly. We found small but significant interactions between participants' intelligence and both experimental manipulations. Unlike intelligence, working memory capacity did not moderate the effects of working memory load and time constraints on intelligence test performance in Study 2. Due to the larger sample size and the improved experimental design of Study 2 in comparison to Study 1, it is likely that the interactions found in Study 1 were flukes in the data caused by floor effects due to the extremely high time pressure.

The interactions between participants' intelligence and both experimental manipulations were consistent with predictions from process overlap theory. In particular, the performance of more intelligent participants was more strongly affected by random number generation in comparison to articulatory suppression than the performance of less intelligent ones. Moreover, and consistent with Study 1, the introduction of time pressure impaired the performance of more intelligent participants more strongly than the performance of less intelligent ones. Together, this pattern of results supports the central claim of process overlap theory that domain-general cognitive processes act as bottlenecks, constraining performance in a variety of cognitive ability tests (Kovacs & Conway, 2016, 2019). In less intelligent participants, it is likely that a domain-general process such as the building and maintenance of relational bindings in memory already acts as a bottleneck, constraining performance in cognitive tests. In more intelligent participants,

however, working memory capacity may be abundant so that the building and maintenance of relational bindings in memory is not a critical process constraining performance in cognitive tests. By experimentally loading working memory and introducing time pressure, we introduced such bottlenecks in the information processing of participants with higher cognitive abilities, which subsequently impaired their performance more strongly than it did for participants with lower cognitive abilities whose performance was already to a larger degree limited by their lower working memory capacity and processing efficiency. Overall, these results provide experimental evidence for process overlap theory and suggest that working memory processes causally contribute to intelligence by acting as a bottleneck in information processing. Note, however, that we again found no evidence that participants' intelligence or working memory capacity moderated the effect of item difficulties on intelligence test performance, which would have been predicted by process overlap theory.

4. General Discussion

In two studies we consistently showed that experimentally manipulating working memory capacity has a causal effect on intelligence test performance. Our findings confirm the much-discussed hypothesis that individual differences in working memory capacity contribute to individual differences in fluid intelligence (Chuderski, 2013; Colom et al., 2006, 2008; Engle, 2018; Oberauer et al., 2008; Shipstead et al., 2016). The size of the experimental effect was only small (Cohen, 1988), which suggests that there are likely additional processes contributing to intelligence test performance such as executive attention (e.g., Engle, 2002), processing speed (e.g., Schubert et al., 2017), motivation (e.g., Duckworth et al., 2011) or previous experience with intelligence tests (e.g., Scharfen et al., 2018) that were not affected by memory load.

4.1 The causal nature of the relationship between working memory capacity and fluid intelligence

Critically, this main conclusion rests on the validity of the experimental manipulation. Because random number generation relies on a number of elementary control processes in addition to memory processes (Cooper, 2016; Jahanshahi et al., 1998; Joppich et al., 2004; Miyake et al., 2000), we have to ascertain that its effect on intelligence test performance is due to increased working memory demands but not due to increased cognitive control demands. Using a computational modeling approach, we found that random number generation affected memory- and control-related processes in working memory to a similar degree and that random number generation affected intelligence test performance through an impairment of both memory- and control-related processes.

On the one hand, random number generation affected the building and maintenance of temporary relational bindings in memory, which is a process that has been suggested to underlie the relationship between working memory capacity and fluid intelligence (Chuderski, 2019; Halford et al., 1998; Jastrzębski et al., 2020; Oberauer et al., 2008). Previous correlational studies have shown that the ability to form and maintain arbitrary bindings predicts fluid intelligence at least as well as the ability to hold items in memory while completing a concurrent processing task (Oberauer et al., 2008; Wilhelm et al., 2013). Moreover, a recent experimental study in which the complexity of reasoning tasks was systematically manipulated found that the ability to form very simple relational bindings was as strongly related to fluid intelligence as was performance in more complex transitive reasoning tasks (Chuderski, 2019). Our results experimentally support the notion that the ability to flexibly form and maintain arbitrary bindings is an important component of reasoning abilities.

On the other hand, random number generation affected the filtering of irrelevant information, which is a cognitive control process that has also been suggested to underlie the relationship between working memory capacity and fluid intelligence (Engle, 2002, 2018; Kane et al., 2007; Shipstead et al., 2016). The executive-attention account of working memory proposes that the large correlations between working memory capacity and fluid intelligence reflect the shared attentional control demands of maintaining and disengaging from information in working memory tasks and intelligence tests. This hypothesis is as of yet mainly supported by correlational studies reporting relations between working memory capacity, fluid intelligence, and attentional control (e.g., Friedman et al., 2006; Tsukahara et al., 2020; Wongupparaj et al., 2015), but has recently been challenged by psychometric work on the unfavorable measurement properties of typical measures of attentional control (Draheim et al., 2020; e.g., Frischkorn et al., 2019; Hedge et al., 2018; Löffler et al., 2022; Rey-Mermet et al., 2018; Rouder & Haaf, 2019; Schubert & Rey-Mermet, 2019). The present study adds to this debate by experimentally demonstrating that the ability to filter irrelevant information is another important component of reasoning abilities.

Despite the high face validity of random number generation affecting memory- and control-related processes in working memory, we cannot rule out that other processes were also affected by the experimental manipulations and that they exerted some additional influence on intelligence test performance. For example, some participants solve matrix reasoning items by using a constructive matching strategy, that is, they mentally construe a possible answer before inspecting the response alternatives. Other participants use a less effective response elimination strategy, that is, they first inspect and consecutively discard unlikely response alternatives (Arendasy & Sommer, 2013; Bethell-Fox et al., 1984; Mitchum & Kelley, 2010). Gonthier and Thomassin (2015) demonstrated that strategy use depended on participants' working memory

capacity, with participants with higher working memory in comparison to those with lower working memory more often using the more effective constructive matching strategy. In addition, intraindividual shifts in strategy use during the course of the test were also moderated by participants' working memory capacity (Gonthier & Roulin, 2020). Hence, it is conceivable that external memory load induced a shift towards the less effective response elimination strategy and thus reduced performance in the present study. Future studies should include questions about strategy use (e.g., Gonthier & Thomassin, 2015) or collect eye movement data (e.g., Bethell-Fox et al., 1984) to tease apart how working memory load affects strategy use. What is important to note, however, is that even *if* shifts in strategy use moderated the effect of working memory load on intelligence test performance, it would not imply that memory load does not exert a causal influence on intelligence. Rather, we would be one step closer to understanding *how* capacity limits in working memory affected intelligence test performance.

4.2 Individual differences in intelligence moderated the experimental effects

Individual differences in participants' intelligence moderated the effect of working memory load and time pressure on APM performance in such a way that more intelligent participants were more strongly affected by higher working memory load and time pressure than less intelligent ones. These results are consistent with process overlap theory, which proposes that certain domain-general processes act as bottlenecks in information processing (Kovacs & Conway, 2016, 2019). Experimentally inducing such bottlenecks therefore had a larger effect on the performance of more intelligent participants than of less intelligent ones, whose reasoning performance, according to process overlap theory, was already limited by their working memory capacity. Hence, using a combined experimental and individual-differences approach, we found that participants' intelligence moderated the experimental effects in a way that confirmed predictions from process overlap theory.

4.3 Limitations and outlook

The biggest limitation of the present studies is that we conducted both studies in student samples. To increase variability in cognitive abilities, we recruited participants from a broad range of different majors and included only a limited number of participants who were currently enrolled in highly competitive majors with strict entrance limitations. Nevertheless, there may still have been some restriction in the variation of cognitive abilities that may have resulted in an underestimation of the associations of the experimental effects with the cognitive ability covariates. To evaluate the representativeness of our sample, we compared the performance of participants in the articulatory suppression condition without any time constraints to data from a representative norm sample (Raven et al., 1994). For this purpose, we compared the average number of correctly solved items ($M = 7.15$ in study 1 and $M = 8.44$ in study 2) by means of extrapolation to the performance by participants in the representative norm sample reported in the test manual. Participants' performance in Study 1 was comparable to the performance by those participants in the representative norm sample who were in the age range from 23 to 27 years and who were placed in the 50th percentile of the ability distribution when solving 22 of the 36 items (Raven et al., 1994). Participants in Study 2 performed slightly better than participants in the 50th percentile of the norm sample. All in all, these results suggest that our samples were fairly representative of their age group in terms of their cognitive abilities. Nevertheless, it may be worthwhile to replicate our findings in a more heterogeneous sample with participants from different occupational and educational backgrounds.

Another limitation of the present study was that we had to manipulate working memory load between subjects to ensure that each cell of the experimental design contained a sufficient number of APM items to generate reliable measures of performance. Because between-subjects designs have several disadvantages, in particular with regard to their statistical power, future

studies should consider manipulating working memory load within subjects, either dropping the Time Constraint factor or using intelligence tests with a larger set of items.

5. Conclusions

To the best of our knowledge, this is one of the first studies to show that experimental manipulations of working memory capacity have a causal influence on intelligence test performance. The present study demonstrated that experimental manipulations of working memory capacity and processing time affect intelligence test performance. Using a computational modeling approach, we showed that our experimental manipulation affected the building and maintenance of relational item bindings and the filtering of irrelevant information in working memory. Our results are consistent with the idea that working memory capacity in general and the abilities to maintain arbitrary bindings in working memory and to disengage from irrelevant information are intrinsically related to fluid intelligence. The experimental effect of working memory load on intelligence test performance was not affected by time constraints during the test, which suggests that the experimental manipulations of working memory capacity and processing time did not affect the same underlying cognitive process. Individual differences in participants' intelligence moderated the effect of working memory load and time pressure on intelligence test performance in a way consistent with predictions from process overlap theory.

Taken together, our experimental approach emulated naturally occurring variation in working memory capacity while controlling for nuisance variables by randomizing and controlling for individual differences in intelligence and working memory capacity. Hence, our results experimentally confirmed that working memory capacity causally contributes to higher-order reasoning processes.

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