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The domain specificity of working memory is a matter of ability

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ABSTRACT

The relative importance of domain-general and domain-specific sources of variance in working memory capacity (WMC) is a matter of debate. In intelligence research, the question of domain-generality is informed by differentiation: the phenomenon that the size of across-domain correlations is inversely related to ability: the lower the ability, the more domain-general the variance. Since WMC and intelligence are related constructs, differentiation might exist in WMC, too. Differentiation in WMC is also predicted by process overlap theory, a recent model of intelligence. We used moderated factor analysis to test for differentiation. The results demonstrate the existence of differentiation in WMC: as capacity increases, variance in WMC becomes more domain-specific. Fluid reasoning (Gf) also contributes to differentiation in WMC: when Gf is lower, WMC variance is more domain-general. There was no significant moderation by crystallized (Gc) and spatial (Gv) ability and Gf only moderated differentiation in WMC but not in short-term memory.

Introduction

Working memory is a psychological construct used to characterize and help further investigate how humans maintain access to goal-relevant information in the face of concurrent processing and/or distraction (Baddeley, 1992). According to its first conception working memory is characterized as a multi-component system which includes domain-specific verbal and spatial “slave” storage systems, as well as a domain-general central executive responsible for attention control (Baddeley & Hitch, 1974).

Even though the model of working memory was initially developed to account for intra-individual phenomena, interest soon arose in measuring individual differences in the capacity of this system. One of the first measures of the capacity of working memory was the reading span task (Daneman & Carpenter, 1980), which requires subjects to read sentences aloud and remember the last word of each sentence for later recall. Another early example is the counting span task (Case, Kurland, & Goldberg, 1982) in which subjects are instructed to count a particular class of items and, after counting aloud, remember and later recall the totals. There are also spatial working memory tasks, such as letter rotation task (Shah & Miyake, 1996) and symmetry span (Kane et al., 2004).

Several of these “complex span tasks” have now been developed to measure working memory capacity (for a review, see Conway et al., 2005). These tasks are thought to be valid measures of working memory capacity because they require access to information in the face of concurrent processing. In contrast, simple memory span tasks (e.g., digit span, word span, letter span), which do not include an interleaved processing task between the presentations of to-be remembered items, are thought to be less ecologically valid measures of working memory capacity (Baddeley & Hitch, 1974; Daneman & Carpenter, 1980; Dempster, 1981).

Besides such progress in measurement, substantial theoretical developments have been made and alternative models have been created since the publication of the original Baddeley and Hitch model (e.g. Cowan, 1999; Oberauer, Süß, Wilhelm, & Wittman, 2003). Virtually all current models of working memory include domain-specific and domain-general processes and in the working memory literature there is considerable debate about their relative importance. In particular, the domain-generality of *variation* in working memory capacity remains a controversial issue.

One of the most important findings from studies investigating complex and simple span tasks is that variation in complex span is more domain-general than in simple span; across domain correlations are larger in complex than in simple span tasks (Turner & Engle, 1989). This implies that working memory capacity is determined to a larger extent by domain-general processes, relative to domain-specific processes, than short-term memory capacity. Yet the domain-generality of

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WMC is controversial: although there are larger cross-domain correlations in complex span, other evidence appears supportive of a domain-specific view of individual differences. For instance, Shah and Miyake (1996) found that verbal and spatial working memory predicts verbal and spatial ability better, respectively, arguing for a domain-specific view of individual differences.

Since working memory tasks require parallel storage and processing, observed correlations with other variables may reflect variation in either the storage or the processing components of working memory tasks, or both. Latent variable studies of individual differences in working memory capacity are useful because they are able to decompose storage components (variance common to short-term memory tasks and working memory tasks) from processing components (variance unique to working memory tasks). Kane and colleagues (Kane et al., 2004) applied exactly this method in a latent variable analysis; they decomposed the storage components of complex span tasks and found that while storage processes indeed appear to be more domain-specific, the processes that complex span tasks tap beyond the pure storage and retrieval of information appear to be largely domain-general.

Latent variable studies of working memory have provided additional important results. First, they identified a general factor of working memory, which is generally referred to as “working memory capacity” or WMC (Conway, Cowan, Bunting, Therriault, & Minkoff, 2002; Conway, Kane, & Engle, 2003; Engle, Tuholski, Laughlin, & Conway, 1999). This is the result of all-positive correlations between different working memory tasks. This finding is similar to one of the main findings in the study of intelligence, called the positive manifold: cognitive ability tests with diverse content, ranging from reading comprehension to number series to mental rotation, all correlate positively. This finding is the basis of the general factor of intelligence, *g*, which explains 40–50% of the variance in cognitive ability tests. The general factor of WMC is similar to the general factor of intelligence since it accounts for the positive correlations between working memory tasks with different content.

There is evidence that the general factor of WMC reflects individual differences in the executive component of working memory, particularly executive attention and cognitive control (Engle & Kane, 2004; Engle et al., 1999; Kane & Engle, 2002; Kane, Bleckley, Conway, & Engle, 2001). Also, latent variable studies employing both intelligence tests and working memory tasks revealed that WMC is strongly related to intelligence. Two studies, conducted by different groups of researchers, estimate the median correlation between WMC and non-verbal fluid reasoning (Gf) to be somewhere between $r = .72$ (Kane, Hambrick, & Conway, 2005) and $r = .85$ (Oberauer, Schulze, Wilhelm, & Süss, 2005). Thus, according to these analyses, WMC accounts for between half and two-thirds of the variance in Gf. This is substantially higher than the proportion of variance in *g*, the general factor of intelligence, that is explained by WMC (Ackerman, Beier, & Boyle, 2005).

That is, WMC is more strongly related to the fluid factor of intelligence than to other factors. This is, once again, demonstrably caused by the processing, not the storage component of working memory tasks; when latent variable studies decompose what complex span tasks require beyond storage and retrieval they find that such processing components correlate to a much smaller extent with tests of crystallized intelligence (Gc) or processing speed (Gs) than with fluid reasoning (Gf) (Conway & Kovacs, 2013).

Finally, when one compares complex and simple span in terms of how well they predict fluid intellience (Gf), complex span tasks turn out to be stronger predictors (Conway et al., 2002; Engle et al., 1999; Kane et al., 2004, but see Colom, Shih, Flores-Mendoza, & Quiroga, 2006; Unsworth & Engle, 2007). Taken together, these studies demonstrate that: (1) it is the processing component of working memory tasks, mostly reflecting executive processes, that drives the WMC-intelligence relationship, and (2) it is the fluid component of intelligence that correlates most strongly with WMC.

The factorial analysis of intelligence test results is also able to identify a general factor (g), as well as specific factors, and in the intelligence literature there has also been a long-standing debate about domain-generality vs. specificity, and in particular whether *g* can be identified as a general mental ability permeating all human cognition (Conway & Kovacs, 2013). This debate has been influenced by research on *ability differentiation*: the phenomenon that across-domain correlations are higher in low ability groups (Blum & Holling, in press; Juan-Espinosa, Cuevas, Escorial, & García, 2006; Kane, Oakland, & Brand, 2006). Importantly, differentiation is not simply the result of the restriction of range: in *high ability* groups the correlation between different tests is lower than in *low ability* groups with equally restricted range (Blum & Holling, 2017). Differentiation, then, means that unidimensionality of variance is more applicable in low ability groups than in high ability groups. Thus the question of domain-specificity in intelligence is not independent of the level of intelligence of the sample in question.

A recent theoretical account of human intelligence, process overlap theory (Kovacs & Conway, 2016a, 2016b), provides an explanation of the positive manifold in intelligence. The theory postulates an overlap of cognitive processes activated by various mental ability tests and working memory tasks. In particular, it is hypothesized that any item or task requires a number of domain-specific as well as domain-general cognitive processes. Domain-general processes responsible for executive attention and cognitive control are central to performance on mental tests as well as working memory tasks since they are activated by a large number of items, alongside with domain-specific processes tapped by specific types of items/tests only.

Process overlap theory draws heavily on the concept of working memory capacity in explaining the positive manifold in intelligence. In fact, it provides an explanation of both positive manifolds, the one in intelligence and the one in working memory. The positive correlations between diverse working memory tasks on the one hand and diverse ability tests on the other are both caused by domain-specific processes overlapping with a set of domain-general executive processes that are tapped by a large number of ability tests and working memory tasks. Since the general factors are statistical accounts of the positive manifolds, process overlap theory provides an explanation of the general factor of WMC as well as *g*. Moreover, since it proposes that the same pool of domain-general executive processes is tapped by different working memory tasks as different psychometric tests of cognitive ability (especially the ones that measure fluid reasoning), the theory also explains why the general factors of working memory and (fluid) intelligence correlate so strongly.

The theory actually focuses on limitations in its account of the positive manifold. That is, the central processes that are tapped by a large numbers of tasks limit performance in a general way and make errors more likely regardless of the domain-specific processes that are also tapped by the same tasks. This way executive processes function as a bottleneck and can potentially mask individual differences in more specific abilities. This is, according to the theory, the explanation of ability differentiation: it occurs because the lower the ability on central executive processes the lower the probability of correctly solving cognitive tasks, regardless of the level of ability on domain-specific processes.

Differentiation means that the lower the ability of a population, the higher the average correlations between tests; therefore differentiation can also be described as the general factor, *g*, accounting for more variance at lower levels of ability, whereas in high ability samples more variance is accounted for by domain-specific ability factors.

According to process overlap theory, the same “executive bottleneck effect” that is described above operates in working memory, too. Therefore, it a clear prediction of the theory that differentiation has to manifest itself in WMC as well. This is because the worse the performance of executive processes the more it is likely that executive processes will be the source of error, hence the larger section of the total variance they will account for, relative to specific processes. This prediction is practically agnostic with regard to most actual models of working memory as long as they propose both domain-specific and domain-general sources of variance.

The current study focuses on three specific predictions regarding differentiation in WMC that follow from process overlap theory:

(1) Ability differentiation occurs in tasks measuring WMC.
(2) Since executive functions are strongly related to fluid reasoning (Gf), to a much larger extent than to verbal and spatial ability, Gc and Gv, respectively (Conway & Kovacs, 2013; Conway, Macnamara, Getz, & Engel de Abreu, 2011; Unsworth & Engle, 2006), differentiation in WMC is moderated by Gf, but not, or to a much smaller extent by Gc or Gv.
(3) Since executive processes are tapped by complex span tasks to a much larger extent than by simple span tasks (Engle & Kane, 2004; Unsworth & Engle, 2007), differentiation occurs in working memory, but not to or to a much smaller extent in short term memory.

In the current study we investigated these three predictions. Specifically, in Study 1 we tested prediction 1 using the non-linear differentiation methodology by Tucker-Drob (2009) and Molenaar, Dolan, and Verhelst (2010). Next, in Study 2, we tested predictions 2 and 3 using the moderation methodology of Bauer and Hussong (2009).

Study 1: Differentiation in working memory capacity (WMC)

Method

In the first study we analyzed data from a large-scale study (N = 5316) of three complex span tasks: Operation Span, Reading Span, and Symmetry Span (Redick et al., 2012).[1] As discussed above, complex span tasks operationalize the central aspect of the concept of working memory: parallel storage and processing. In contrast to simple span tasks, such as digit span or word span, which only require storage and retrieval, in complex span there is additional processing, which distracts from the stimuli to remember. For instance in this version of the Operation span task, which is a complex version of letter span, the presentation of letters is interrupted by easy equations, and subjects have to decide whether each equation is correct. Importantly, the three tasks in this study tap different cognitive domains and, as such, their intercorrelations represent across-domain variance.

In intelligence, if ability differentiation occurs then observed intelligence subtasks are more strongly correlated for participants lower on the underlying latent dimension (which represents *g* in this case) as compared to participants higher on the underlying latent dimension. Various methods have been proposed to test this prediction. Researchers have relied on the creation of two or more subgroups that differ on ability. These groups are subsequently compared in terms of their inter-test correlations or factor structure. Commonly these groups have been created by a median split on an observed test score (Deary et al., 1996; Detterman & Daniel, 1989; Jensen, 2003) or on factor scores (Carlstedt, 2001; Reynolds & Keith, 2007) or by using existing groups that are assumed to differ on the underlying dimension (te Nijenhuis & Hartmann, 2006). As discussed by Tucker-Drob (2009) and Molenaar, Dolan, Wicherts, and van der Maas (2010) these methods are suboptimal to test for differentiation as (1) splitting observed scores may distort the factor structure in the subsamples; (2) the cut-off and the number of subgroups that are formed are arbitrary decisions that may affect the power to detect a differentiation effect; and (3) the comparison of existing groups may be confounded by other differences between the groups.

[1] Please cf. the original reference for details of the sample and the tasks.

Tucker-Drob (2009) and Molenaar, Dolan, and Verhelst (2010) derived an explicit statistical test on differentiation that does not require subgroups. We will use this approach here. The main rational behind the approach is that if subtask correlations are decreasing for increasing levels of a given latent dimension (i.e., general intelligence in the case of ability differentiation, and working memory in the present study), this will be evident in the factor loadings of the subtasks on the latent dimension. That is, the factor loadings will also decrease for increasing levels of the latent dimension. In Fig. 1 this is illustrated. In the figure, the linear factor loadings from a conventional factor analysis (solid grey lines) are decreased across the latent dimension for 3 increasing example levels (levels A, B, and C). That is, at level A, the conventional factor loading is relatively large (i.e. a steep line), for level B, the factor loading is smaller, and for level C the factor loading is relatively small.

As can be seen, the resulting factor loading (solid black line) is non-linear. That is, differentiation of working memory (i.e., the question whether the inter-working memory task correlations are decreasing for increasing levels of the latent working memory dimension) can be investigated by testing whether the factor loadings of the working memory tasks are non-linear. Specifically, in applying the method above to our data, we obtain a non-linearity parameter. If this parameter is larger than 0, the working memory task correlations are *increasing* across the latent working memory dimension, and if the non-linearity parameter is smaller than 0, the working memory task correlations are *decreasing* across the latent working memory dimension. Thus, in the full model, we investigated differentiation by testing whether the non-linearity parameter is smaller than 0 for all tasks. Technical details of this method are described in Appendix A.

Results

We first fitted the baseline model to the data (Fig. 2). We identified the model by fixing the variance of the working memory factor to equal one. Note that the baseline model is saturated as it only has three indicators, therefore the model fit is perfect. Next we estimated the non-linearity parameters, which are informative about the extent to which the latent score, i.e. WMC, moderates the factor loadings of the manifest variables, i.e. the complex span tasks.[2] Negative values indicate differentiation in the predicted direction, i.e. smaller correlations for higher levels of working memory.

Table 1 contains the parameter estimates of the non-linearity parameters.[3] It can be seen that all estimates are negative and significant (at least $p < .05$), as predicted. The non-linearity parameters in Table 1 tune the curvature of the factor loadings across the latent WMC score. See Fig. 3 for a graphical representation of the implied factor loadings. As can be seen from the figure, Symmetry span has the largest curvature, followed by Operation span. Reading span has the smallest curvature. These graphical results are in line with the parameter estimates in Table 1, where Symmetry span has the largest absolute parameter estimate, followed by Operation span, and Reading span respectively.

As all non-linearity parameters differ from 0, question arises whether the effects differ across subtests. To this end, we fitted an extra series of models in which we sequentially equated two non-linearity parameters to see how model fit was affect in terms of the AIC, BIC, and sample size adjusted BIC fit indices. See Table 2. As can be seen from the table, the model with all effects estimated freely fits best (i.e., this model has the lowest AIC, BIC, and sample size adjusted BIC) indicating that all effects differ significantly from one another. Note that for the

[2] As is described in Appendix A, besides non-linear factor loadings, the model includes heteroscedastic residuals to account for subtest specific effects related to scaling.

[3] As Mx does not output standard errors by default, the standard errors were based on 100 bootstrap samples.

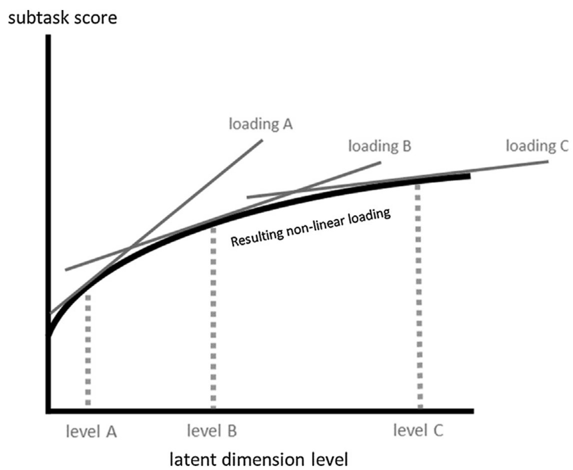

Fig. 1. Example of decreasing subtask factor loadings (solid grey lines) for 3 increasing levels on the latent dimension (dashed grey lines: levels A, B, and C). The resulting factor loading (solid black line) is non-linear.

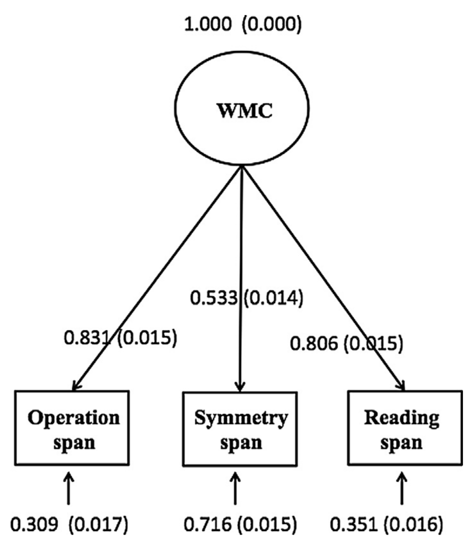

Fig. 2. The baseline model for study 1, consisting of a single factor of WMC reflected by three complex span tasks.

Table 1
Parameter estimates, Standard Errors (SE), and Z-values for the non-linearity parameters.

Task (i)	Estimate	SE	Z	p
Operation span	−0.068	0.009	−7.566	< .001
Symmetry span	−0.149	0.018	−8.278	< .001
Reading span	−0.017	0.007	−2.433	0.016

models with two non-linearity parameters fixed to be equal, the fit indices correlate negatively with the effect sizes in Table 1 (and Fig. 3). That is, the larger the differences between the two non-linearity parameters (i.e., the larger the difference in curvature), the larger the AIC, BIC, and sample size adjusted BIC indicating that the non-linearity parameters are not equal.

Overall, these results clearly demonstrate the existence of differentiation in WMC: the higher it is, the less variance explained in all of the tasks. The effect is relatively stronger in Operation span and relatively weaker in Reading span.

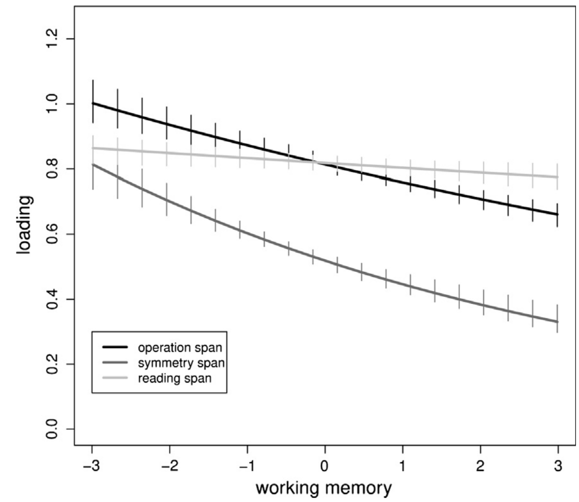

Fig. 3. Graphical representation of how the factor loadings vary as a function of the underlying working memory dimension for the three tasks in Study 1. Vertical lines represent (bootstrapped) 95% confidence intervals.

Table 2
Fit indices for 4 different models testing the equality of the non-linearity parameters across working memory tasks.

Model	AIC	BIC	sBIC
All unequal	**8634**	**−48031**	**−22745**
OS and SS equal	8643	−48030	−22742
OS and RS equal	8644	−48030	−22742
SS and RS equal	8665	−48019	−22731
All equal	8667	−48021	−22732

Note. OS: Operation span; SS: Symmetry span; RS: Reading span. sBIC: sample size adjusted BIC. In addition, yhe best values of the fit indices are in bold face.

Study 2: Differentiation of WMC and STM as the function of fluid, crystallized, and visuospatial intelligence

Method

In the second study we analyzed data from a study on the domain-specificity of WMC (N = 249), applying a large number of working memory and short-term memory tasks as well as cognitive ability tests (Kane et al., 2004). There were short-term memory, working memory, and reasoning tasks that belonged either to the spatial or verbal domain, and, additionally, three tests of fluid intelligence were administered. Table 3 lists the memory tasks and the psychometric tests that were used in the study.[4]

In this second study, we investigated differentiation in working memory and short-term memory across fluid (Gf), crystallized (Gc), and visuospatial intelligence (Gv). Similarly as in Study 1, a possible procedure would be to perform a median split on a Gf measure and test whether the correlations among a set of working memory tasks are smaller for participants high on Gf as compared to participants low on Gf. This could be subsequently done for a Gc and Gv measure. Such an approach suffers from similar shortcomings as the ones discussed for Study 1 (Molenaar, Dolan, Wicherts, et al. (2010); Tucker-Drob, 2009). We therefore adopted a more statistically explicit model: the method of moderated factor analysis (Bauer & Hussong, 2009).

That is, to investigate whether the latent working memory and the latent short-term memory dimensions are differentiated across Gf, Gc, and Gv, we test whether the factor loadings differ across Gf, Gc and Gv. The rational of moderated factor analysis is illustrated in Fig. 4 for a

[4] Please cf. the original reference for details of the sample, tasks, and tests.

Table 3
Spatial and verbal short-term and working memory tasks, and spatial, verbal, and fluid reasoning tests used in study 2. Rows indicate domains, columns indicate the type of task or test.

	Short-term memory	Working memory	Reasoning
Verbal	1. Word span 2. Letter span 3. Digit span	1. Reading span 2. Operation span 3. Counting span	1. ETS Inference Test 2. AFOQT Analogies Test 3. AFOQT Reading Comprehension 4. Remote Associates Test 5. ETS Nonsense Syllogisms Test
Spatial	1. Ball span 2. Arrow span 3. Matrix span	1. Symmetry span 2. Navigation span 3. Rotation span	1. DAT Space Relations Test 2. AFOQT Rotated Blocks Test 3. ETS Surface Development Test 4. ETS Form Board Test 5. ETS Paper Folding Test
Fluid			1. Raven's Progressive Matrices 2. WASI Matrix Reasoning 3. Beta III Matrix Reasoning

moderated factor model above to data, one obtains a moderation parameter for each subtask. If this parameter is 0, the corresponding subtask is unmoderated. If the moderation parameter is larger than 0, the task correlations (and factor loading) are *increasing* across the moderator dimension for that task, and if the moderation parameter is smaller than 0, the task correlations are *decreasing* across the moderator variable: this latter case would indicate differentiation.

In this study our point of departure will be a second-order factor model as there are three verbal and three spatial tasks both for short-term memory and working memory (see Table 3). There is a number of different models applied in the study of individual differences in memory capacity, including hierarchical as well as bi-factor models (Conway & Kovacs, 2013). In this study we decided to use the hierarchical model for methodological, not substantive considerations, since there is no appropriate method applicable for bi-factor models.

We thus have two first-order factors (each measured by 3 tasks) and one second-order factor both for short-term memory (see Figs. 5 and 6 for the baseline models). To identify the model, we equated the two second-order factor loadings, fixed the variance of the second–order factors to unity, and the mean of the first-order factors to zero in both the short-term memory and working memory model. Note that, as we

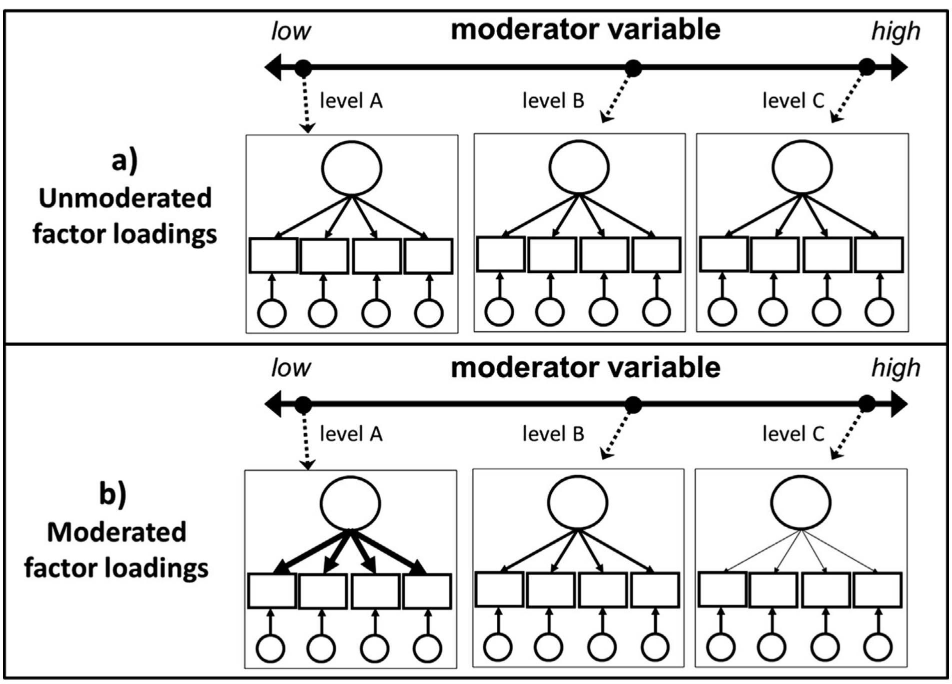

Fig. 4. The one-factor model depicted at 3 increasing example levels on a moderator variable (levels A, B, C) in the case of unmoderated factor loadings (a) and moderated factor loadings (b).

one factor model and a single moderator variable[5]. In the figure, the factor model from a conventional factor analysis is depicted for 3 increasing example levels on a moderator variable (levels A, B, and C). In general, this moderator variable can be any observed variable (e.g., age or SES).

In Fig. 4a, the factor loadings are *unmoderated*, that is, the factor loadings do not differ across the moderator. In Fig. 4b, the factor loadings are *moderated*, that is, they are differing across the moderator variable. Specifically, at level A, the factor loading is relatively large (represented by ticker arrows), for level B, the factor loading is smaller, and for level C the factor loading is relatively small. Thus, the factor loadings are decreasing across the moderator variable. In applying the

equated the two first-order factor loadings, we only have one second-order factor loading to be estimated.[6]

Subsequently, we investigated differentiation of working memory and short term memory by fluid (Gf) crystallized (Gc), and visuospatial ability (Gv) by testing for moderation of the second-order factor loading by Gf, Gc, and Gv. The ability scores were calculated as composite scores of the corresponding ability tests. We tested for the moderating effects of all moderators (Gf, Gc, and Gv) simultaenously to account for correlations between the moderators. In addition, we considered working memory and short-term memory separately. We expected that differentiation occurs for Gf but not or to a lesser extent for Gc and Gv. For short-term memory, we hypothesized that either there would be no

[5] In the actual analysis we use multiple moderators and a second-order factor model as will be explained later.

[6] While the unstandardized loadings are thus equal, the standardized loadings may still be different.

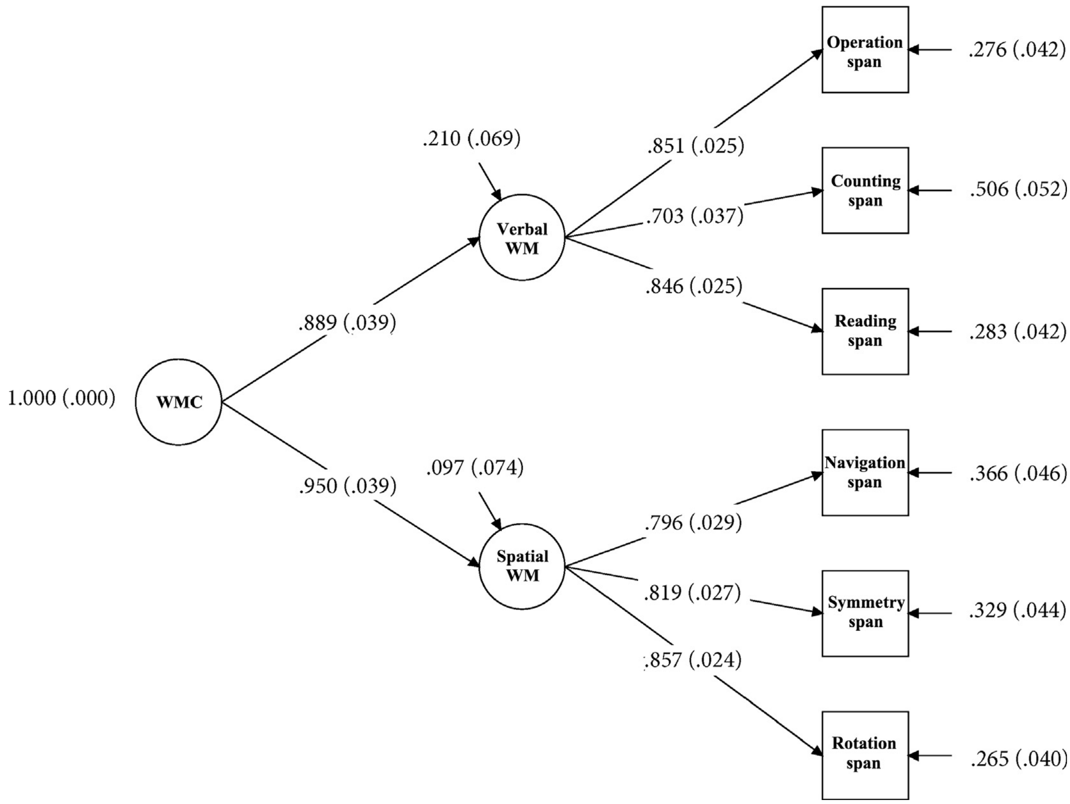

Fig. 5. Higher-order baseline model for working memory in study 2.

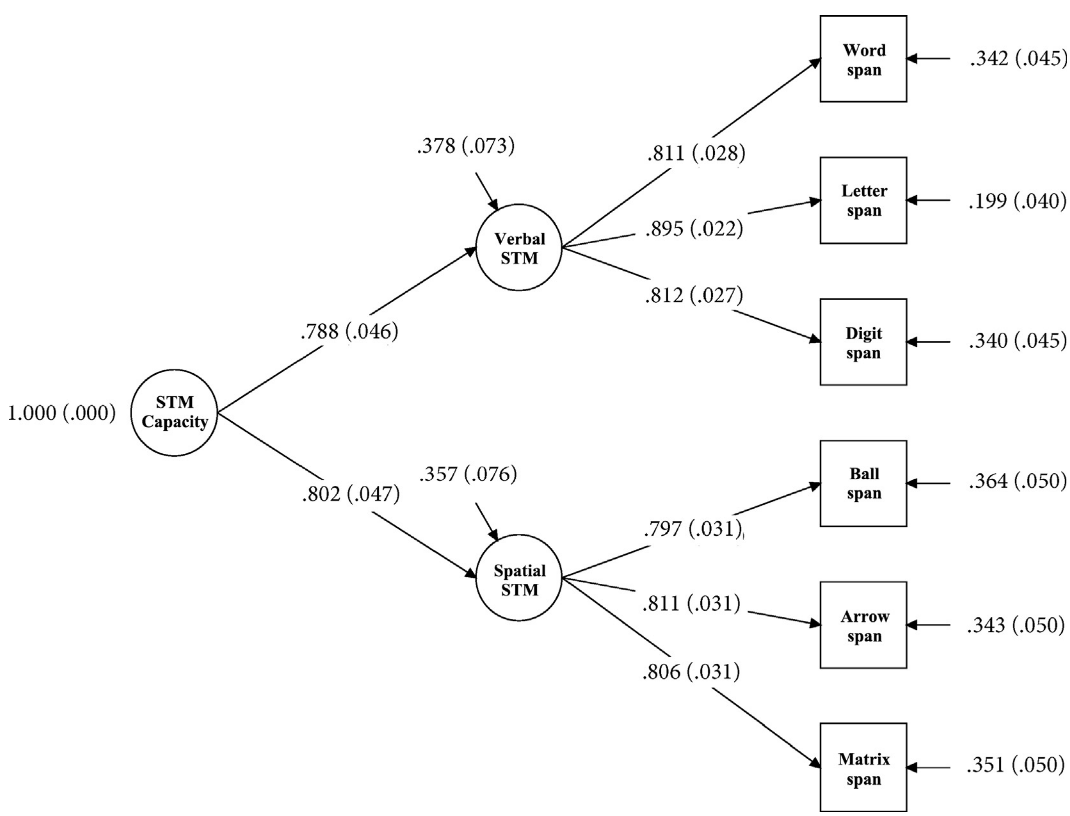

Fig. 6. Higher-order baseline model for short-term memory in study 2.

differentiation for either of the external moderators, or the effects would be substantially smaller.

Results

We first fitted the baseline models without moderation to see whether they fit well to the data.[7] It appeared that the fit was acceptable for both the working memory tasks (RMSEA: 0.067, CFI: 0.990, TLI: 0.981) and the short-term memory tasks (RMSEA = 0.029, CFI = 0.998, TLI = 0.996). We proceeded by fitting the moderation model to the working memory tasks and the short-term memory tasks separately.

Tables 4 and 5 contain the parameter estimates of the moderation parameters for both working memory and short-term memory, respectively.[8]

For WMC, as hypothesized, the moderation of the second-order loading for Gf is significant at $p < .05$ and less than zero, while for Gc, and Gv the moderation parameters are non-significant. In the case of short-term memory, all moderation parameters of the second-order loadings are non-significant for Gf, for Gc, and for Gv. See Fig. 7 for a graphical representation of how the second-order factor loadings differ across Gf for WMC and STM.

Table 4
WMC: Parameter estimates and Standard Errors (SE) for the moderation parameters (bold is significant at $p < 0.05$).

Moderator	Estimate	SE	Z	p
Gf	**−0.198**	**0.089**	**−2.225**	**.026**
Gc	0.034	0.085	0.400	.690
Gv	0.102	0.088	1.159	.246

Table 5
Short Term Memory: Parameter estimates and Standard Errors (SE) for the moderation parameters.

Moderator	Estimate	SE	Z	p
Gf	0.065	0.135	0.481	.630
Gc	−0.133	0.120	−1.108	.268
Gv	−0.033	0.136	−0.243	.808

Discussion

The results demonstrate the existence of ability differentiation in WMC. Results obtained in the first study provide evidence for internal moderation: loadings of three complex span measures on a domain-general WMC factor are inversely related to general WMC capacity itself. The higher the level of WMC, the more domain-specific the variance in complex span tasks.

The second study demonstrates external moderation by fluid reasoning (Gf). That is, loadings on the domain-general WMC factor are inversely related to fluid reasoning: as Gf increases, correlations between WMC tasks decrease. Importantly, this phenomenon does not occur in short-term memory as measured by simple span tasks. Also, the external moderation of crystallized (Gc) and spatial (Gv) intelligence was not significant for WMC either.

These results are in agreement with the predictions of process overlap theory, according to which the capacity of one's working memory is jointly determined by the capacity of (1) the domain-general executive system, and (2) the capacity of the corresponding domain-specific system. The core idea of process overlap theory is that when the capacity limitations of the domain-general executive system are severe, overall capacity will be limited to a large extent, regardless of the capacity limit of the slave systems. Therefore executive processes function as a bottleneck for overall performance; when the level of executive processes is low then these processes are likely to be the source of errors in overall performance, regardless of the limits of domain-specific storage. But if the executive system does not impose substantial limitations, the capacity limits of the independent, domain-specific slave systems have a larger role in determining overall capacity limits. Therefore, differentiation occurs: the size of across-domain correlations will be related to overall capacity.

Moreover, according to the results of the studies presented in this paper, differentiation is limited to WMC as opposed to short-term memory span. This is also explained by process overlap theory. Since complex span requires additional processing as well as the coordination of storage and processing, the executive involvement is substantially larger. Therefore, capacity limits will be determined to a larger extent by executive processes than in short-term memory tests, where performance mostly reflects domain-specific storage. This, according to process overlap theory, casues differentiation to manifest itself more strongly in WMC, where executive processes are relatively more important than short-term storage, than is short-term memory tasks, where performance is determined by pure storage and retrieval.

Finally, we found that fluid reasoning (Gf), but not visuospatial ability (Gv) or or perceptual speed (Gs) moderate the factor loadings. Once again, this is explained by, and was predicted by, the theoretical propositions of process overlap theory. Since, as discussed in the Introduction, executive processes are much more involved in fluid reasoning than in other components of intelligence, the moderating effect should be stronger by Gf than by any other factor.

From a more general perspective the finding that differentiation exists means, at least from an individual differences perspective, that research on the structure of working memory should be informed by overall capacity levels. At different levels of capacity different components might have a more dominant role in determining capacity itself.

In the following points we summarize the general implications our findings have for models and theories of working memory capacity:

(1) Our results imply that WMC is not a unitary ability; rather, it is a combination of domain-general and domain-specific abilities. Our results are more compatible with the multi-component model (Baddeley & Hitch, 1974; Baddeley, 1992) than models that propose that WMC is determined almost exclusively by executive attention and assume that attention as a unitary resource fuels both storage and processing, such as Engle's controlled attention theory (Engle, 2002; Engle, 2018) or Cowan's embedded process model (Cowan et al., 2005; Cowan, 1999). The existence of differentiation demonstrates that WMC is determined by different sources and the relative weight of each source in determining overall WMC is different at different capacity levels.

(2) There is no universal value of the domain-generality of WMC unless the sample studied actually covers the entire range of capacity in the population. That is, studying samples differing in ability will provide different answers to the question whether verbal WMC is equivalent to spatial WMC (see e.g. Kane et al., 2004). This might mean that WMC researchers seeking an ultimate answer to the domain-specificity of variation in WMC might have to turn to representative samples, which is challenging and, even so, it will have to be noted that different correlation structures hold for different levels of ability.

[7] In Study 1 we did not test this explicitly as we only had three tasks. The traditional factor model is thus saturated in that case and the fit will always be perfect. As in Study 2 we have six tasks, question arises whether the one-factor model fits the data to begin with.

[8] These are the analytical standard errors as outputted by Mplus. In addition, as can be seen in Appendix B, besides the moderation of the second-order factor loadings, the model includes moderation of the residuals to account for subtest specific effects.

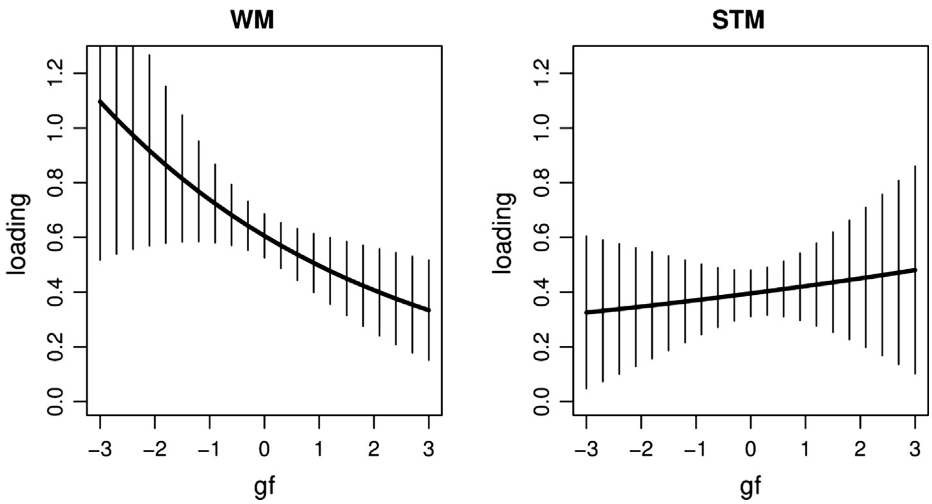

Fig. 7. Graphical representation of how the second-order factor loadings vary as a function of the underlying second-order factor which represents WMC and STM. Note that this graph only involves the moderation parameter of Gf as only this parameter was significant for WMC (but not for STM). Vertical lines represent (bootstrapped) 95% confidence intervals.

(3) Differentiation in WMC is in accordance with the assumption proposed by process overlap theory that different, domain-specific WMC tasks (e.g. spatial, verbal) tap a number of processes in an overlapping fashion and domain-general executive processes have a larger role in determining overall capacity in (1) WMC tasks as compared to STM tasks, (2) in individuals with lower capacity.

(4) The fact that we have found ability differentiation in complex span but not simple span is inconsistent with views that equate short-term memory with working memory as the same construct (e.g. Colom et al., 2006). Instead, it supports the theoretical distinction between simple and complex span tasks (Conway & Kovacs, 2013; Engle et al., 1999).

Conclusions

This is the first set of studies to demonstrate the existence of differentiation in WMC. These results inform the debate about the domain-generality of WMC, which appears to be influenced by capacity itself: in higher ability samples it is more likely for correlational and latent variable studies to find domain-specific variance and thus identify separate domain-specific components. In contrast, in lower ability samples a larger portion of the variance will be across-domains.

If the relative contribution of psychological sub-processes to overall WMC is not universal and such limits indeed reflect different mechanisms in different people then identifying the within-individual processes responsible for WMC might be more challenging than previously thought. In fact, it is quite possible that a substantial bulk of the controversy regarding the domain-specificity of WMC is the consequence of sample selection. Researchers should be cautious not only when dealing with samples with restricted range in general, but also with samples consisting solely of college students in particular.

Declaration of Competing Interest

The authors have no competing interests to declare.

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Appendix A. Testing for non-linearity of the working memory factor loadings in study 1

In the traditional factor model, the observed task scores of participant p on task i (y_{pi}) are regressed on the underlying working memory dimension (η_p) resulting in an intercept (ν_i), a factor loading (λ_i) and a residual (ε_{pi}), that is,

$$y_{pi} = \nu_i + \lambda_i \eta_p + \varepsilon_{pi} \tag{A.1}$$

where COR(ε_{pi}, η_p) = 0 and VAR(ε_{pi}) is denoted by $\sigma_{\varepsilon i}{}^2$. In addition, VAR($\eta_p$) = 1 for identification purposes. It follows from (1) that the correlation between tasks i and task j depend on λ_i and $\sigma_{\varepsilon i}{}^2$: As differentiation predicts lower correlations between y_{pi} for higher levels of η, (Tucker-Drob, 2009) and Molenaar, Dolan, and Verhelst (2010) proposed to test for differentiation by investigating whether λ_i varies systematically over the levels of η_p. This can be done by making λ_i to depend on η, that is

$$\lambda_i(\eta_p) = \exp(\lambda_{0i} + \lambda_{1i}\eta_p) \tag{A.2}$$

Here, parameter λ_{0i} is the baseline factor loading, that is, it accounts for the size of the factor loading at $\eta_p = 0$. In addition, λ_{1i} is the non-linearity parameter, that is, it accounts for the amount by which the factor loadings increase or decrease across η.[9] Note that as advocated by Molenaar, Dolan, and Verhelst (2010), we use an exponential function as we expected all factor loadings to be positive. If λ_{1i} is smaller than 0, factor loadings are decreasing for increasing levels of η. Thus, an explicit test on differentiation is the test whether λ_{1i} is significantly smaller than 0.

As discussed by Tucker-Drob (2009), tests on differentiation (i.e., tests on the hypothesis that λ_{1i} is smaller than 0) may be affected by the measurement properties of the task scores y_{pi}. That is, the task scores in y_{pi} are commonly sum scores of individual items. If a task consists of a

[9] More specifically, λ_{0i} equals to log(λ_i) for $\eta_p = 0$, and λ_{1i} models the linear increase or decrease of log(λ_i) across η_p.

disproportional number of easy items, an artificial differentiation effect may arise in the data. That is, there may be more information about individual differences at the lower range of η (due to the more easy items) and less information at the upper range of η (due to less difficult items). This difference in the amount of information makes the factor loadings to appear smaller for the respondents high on η. Molenaar, Dolan, and Verhelst (2010) proposed a method to account for these biasing effects (see Tucker-Drob, 2009 for an alternative approach). That is, by allowing the residual variances ($\sigma_{\varepsilon i}^2$) to differ systematically across η (heteroscedasticity) in a similar way as the factor loadings, the systematic biasing effects of the measurement scale can be absorbed. Thus, they proposed

$$\sigma_{\varepsilon i}^2(\eta_p) = \exp(\beta_{0i} + \beta_{1i}\eta_p) \tag{A.3}$$

In this equation, β_{01} is a baseline parameter, that is, it accounts for the value of $\sigma_{\varepsilon i}^2$ for $\eta = 0$. In addition, β_{1i} is the so-called heteroscedasticity parameter, that is, it accounts for the amount by which $\sigma_{\varepsilon i}^2$ increases or decreases across η.[10] Note that an exponential function [exp(.)] is used to prevent negative variances. While investigating differentiation by testing for moderation in the factor loadings, we accounted for heteroscedastic residuals to absorb possible measurement effects. Models were fitted in the Mx software package (Neale, Boker, Xie, & Maes, 2002) using the scripts by Molenaar, Dolan, and Verhelst (2010).

Appendix B. Moderated factor analysis in study 2

In this study we used hierarchical models for both STM and WMC. Therefore, the first-order level we get the following factor models:

$$y_{pi} = \nu_i + \lambda_i\eta_{1p} + \varepsilon_{pi}, \quad \text{for task } 1-3 \tag{B.1}$$

$$y_{pi} = \nu_i + \lambda_i\eta_{2p} + \varepsilon_{pi}, \quad \text{for task } 4-6 \tag{B.2}$$

and at the second-order level we have:

$$\eta_{1p} = \gamma\zeta_p + \omega_{p1} \tag{B.3}$$

$$\eta_{2p} = \gamma\zeta_p + \omega_{p2} \tag{B.4}$$

where γ is the second-order loading (which is equal for the two first-order factors), ζ_p is the second-order factor (which represents WMC or STM) and ω_{pi} is the first-order residual variance. Note that there is no intercept in the second-order model as we fixed this to zero. We are now interested in testing whether the second-order factor loadings differ across Gf, Gc and Gv, we make γ a function of these variables, that is

$$\gamma(\zeta_p) = \exp(\gamma_0 + \gamma_1 Gf_p + \gamma_2 Gc_p + \gamma_3 Gv_p) \tag{B.5}$$

Parameter γ_0 is the baseline parameter modeling the size of γ for $Gf_p = Gc_p = Gv_p = 0$. Parameters γ_1, γ_2, and γ_3 model respectively the increase/decrease of γ across Gf, Gc, and Gv.[11] We refer to these parameters as moderation parameters. The Gf, Gc, and Gv variables are observed measures of these dimensions. Since we hypothesized that differentiation occurs for Gf but not or to a lesser extent for Gc and Gv, we expected γ_1 to be significantly smaller than 0, and γ_2 and γ_3 to be either not significantly different from 0 or at least substantially less different from 0 than γ_1 for the working memory data. For the short term memory data, we expect either none of them to be significant or at least substantially less different from 0 than γ_1 in the working memory model.

As we test for moderation between WMC (ζ_p) on the one side and Gf, Gc, and Gv on the other side, we need to include the main effects of Gf, Gc, and Gv in the first-order model (see Nelder, 1994). We do this by allowing for moderation of the intercept parameters (ν_i) in Equation (1), that is, at the first-order level (see Molenaar, Dolan, Wicherts, et al., 2010), that is,

$$\nu_i(\eta_p) = \nu_{0i} + \nu_{1i}Gf_p + \nu_{1i}Gc_p + \nu_{1i}Gv_p \tag{B.6}$$

where ν_{0i} is the general intercept parameter and ν_{1i}, ν_{2i}, and ν_{3i} are the main effects of Gf, Gc, and Gv respectively. Note that we are not interested in these effects, but we need to partial them out of the task scores (y_{pi}) to enable a test on moderation (Molenaar, Dolan, Wicherts, et al., 2010).

To finalize the model, we add moderation of the residual variances, for similar reasons as in Study 1. That is, we want to account for possible differences in the measurement properties of the tasks (y_{pi}) across the Gf, Gc, and Gv measures because such differences may bias our tests on differentiation as discussed above. Thus, we add

$$\sigma_{\varepsilon i}^2(\eta_p) = \exp(\beta_{0i} + \beta_{1i}Gf_p + \beta_{1i}Gc_p + \beta_{1i}Gv_p) \tag{B.7}$$

where β_{0i} is the baseline parameter, and β_{1i}, β_{2i}, and β_{3i} are moderation parameters. Models are fit in Mplus (Muthén & Muthén, 2007). The scripts are available upon request.

Appendix C. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jml.2019.104048.

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[10] More specifically, β_{0i} equals $\log(\sigma_{\varepsilon i}^2)$ for $\eta_p = 0$, and β_{1i} models the linear increase or decrease of $\log(\sigma_{\varepsilon i}^2)$ across η_p.

[11] More specifically, γ_0 equals to $\log(\gamma)$ for $Gf_p = Gc_p = Gv_p = 0$, and γ_1, γ_2, and γ_3 model the linear increase or decrease of $\log(\lambda_i)$ across Gf_p, Gc_p, and Gv_p respectively.

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