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On the relationship between spatial suppression, speed of information processing, and psychometric intelligence

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ABSTRACT

Spatial suppression refers to the increasingly difficult identification of motion direction with increasing size of the moving stimulus. Previous research indicated a close association between stronger spatial suppression and higher psychometric intelligence. Since the measurement of spatial suppression is based on the time needed to correctly identify the motion direction of small vs. large stimuli, the present study aimed to elucidate the unique and shared effects of mental speed, as assessed by reaction times from the Hick task, and spatial suppression on psychometric intelligence. In 177 young adults, neither manifest nor latent variables representing spatial suppression were related to psychometric intelligence. Irrespective of stimulus size, however, individuals with higher intelligence detected motion direction faster than individuals with lower intelligence. While we cannot fully rule out stimulus and apparatus differences as being behind this discrepancy with prior work, our results indicate that the link between spatial suppression and intelligence is at best confined to a specific range of stimulus parameters. The relation between intelligence and speed of motion direction detection (independent from stimulus size) overlapped with the relation between psychometric intelligence and reaction times in the Hick task. This latter result is consistent with the assumption that there is a general (task-independent) speed of information processing, which is robustly related to psychometric intelligence.

1. Introduction

Over the last four decades, a large body of empirical evidence has suggested a consistent relationship between processing speed derived from different elementary cognitive tasks (ECTs) and psychometrically determined general intelligence also referred to as psychometric *g* (for reviews see Deary, 2000; Jensen, 2006; Sheppard & Vernon, 2008). The rationale of ECTs is that, because these tasks are so easy, they leave no room for intelligent strategic variations, so that differences in performance can only be attributed to differences in the speed with which simple stimuli are processed and simple decisions are made (e.g., Anderson, 2001; Jensen, 1998, 2006). Overall, the correlations between psychometric *g* and measures of speed of information processing vary between $r = 0.20$ and $r = 0.40$ (Sheppard & Vernon, 2008). Shorter reaction times (RTs) in higher psychometric intelligence are assumed to reflect faster and more efficient information transmission in the central nervous system (e.g., Jensen, 2006; Stelmack & Houlihan, 1995). Furthermore, it is assumed that the probability of interfering incidents is reduced if a sequence of mental operations is processed faster so that errors in this sequence are less likely and information processing is not only faster but also more efficient (Salthouse, 1996).

Neuroscientific research and numerous experimental studies also point to a fundamental role of suppressive or inhibitory processes in cognitive functioning and general intelligence (e.g., Burgess, Gray, Conway, & Braver, 2011; Carandini & Heeger, 2012; Dempster, 1991; Gray, Chabris, & Braver, 2003; Zanto & Gazzaley, 2009). Proceeding from these findings and against the background of the mental speed approach, Melnick, Harrison, Park, Bennetto, and Tadin (2013) hypothesized that individual variability in a low-level information-processing task that reflects both processing speed and perceptual suppression should strongly correlate with psychometric intelligence.

To test their hypothesis, Melnick et al. (2013) used a spatial suppression task in context of visual motion perception. With this task, first introduced by Tadin, Lappin, Gilroy, and Blake (2003), participants were required to identify the motion direction of briefly presented visual grating stimuli. As dependent variable, the shortest presentation time required for correct identification of motion direction was determined. This threshold estimate provided a measure of perceptual processing speed. The critical experimental manipulation, however, was stimulus size. For high contrast stimuli, as stimulus size increases,

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correct identification of motion direction becomes much more difficult (Tadin et al., 2003). This effect, referred to as spatial suppression, is considered to be a perceptual correlate of antagonistic center-surround neurons in the middle temporal visual area (Liu, Haefner, & Pack, 2016; Tadin, 2015; Tadin, Silvanto, Pascual-Leone, & Battelli, 2011). Center-surround antagonism is a property of center-surround neurons which reduce their firing rate (i.e., the neuron gets suppressed) when the stimulus size is large enough so that it fills both the center and surround regions of a neuron's receptive field.

As a measure of the magnitude of spatial suppression, Tadin et al. (2006) introduced the Suppression Index (SI). SI is computed by subtracting the mean threshold for motion detection for the small from the respective threshold for the large stimulus. In two studies, Melnick et al. (2013) found SI to be highly correlated with a four-item short form of the WAIS-III (Axelrod, 2002) as well as with the WAIS-IV (Psychological Corporation, 2008) full-scale score; the respective correlation coefficients were $r = 0.65$ ($p < 0.05$) and $r = 0.71$ ($p < 0.001$), respectively. These strong positive correlations between magnitude of the spatial suppression effect and intelligence reflected a combination of two effects. First, a positive correlation between speed of processing of small stimuli and IQ scores. Second, the effect that high-intelligent individuals, while exhibiting low duration thresholds for small stimuli, also showed disproportionally large increases in thresholds with increasing stimulus sizes. This, taken together, resulted in increasing SI with increasing IQ scores. Because such large motion patterns are less likely to be perceptually relevant, a pronounced spatial suppression effect should be indicative of a more efficient perceptual suppression system in high-intelligent individuals (Melnick et al., 2013).

In addition, Melnick et al. (2013) pointed out that rapid processing of information is of only limited utility unless it is restricted to the most relevant information. Hence, perceptual suppression is supposed to play a critical role in all kinds of low-level information processing, where it enables the perceptual systems to efficiently process an enormous amount of incoming sensory information. If this highly intriguing assumption holds, perceptual suppression, as indicated by the magnitude of spatial suppression, should account for variance in psychometric intelligence over and above traditional mental speed measures such as reaction times (RTs) obtained with the Hick RT paradigm (Hick, 1952; see also Jensen, 2006). With this paradigm, the number of response alternatives is increased systematically across several task conditions. In the easiest condition (i.e., simple RT) there are no response alternatives and, thus, no decision is required. In the more complex choice RT conditions, the number of response alternatives is systematically increased so that an increasing number of binary decisions are required for a proper response. Within the mental speed approach to intelligence, numerous studies confirmed a consistent, albeit quite moderate, negative relationship between Hick RT and psychometric intelligence that becomes stronger with increasing task complexity (for reviews see Jensen, 1998, 2006; Sheppard & Vernon, 2008). Based on these considerations, the primary goal of the present study was to systematically investigate the unique and common portions of variance in psychometric intelligence predicted by spatial suppression, as an indicator of a more efficient perceptual suppression system, and Hick RT as the most common, traditional mental speed measure.

The time required to perform a cognitive task can usually be considered an outcome of a number of different processes (cf. Jensen, 1982, 1987; Miller & Ulrich, 2013; Unsworth & Engle, 2007). For example, tasks capturing cognitive functions do not only measure variance due to the intended experimental manipulation (e.g., systematically increasing the number of binary decisions in the Hick task) but also variance caused by other processes unrelated to the experimental manipulation (e.g., encoding of the imperative stimulus which is considered to remain constant across all conditions of the Hick RT task). Furthermore, if we assume, for example, that a person's state of alertness and/or motivation also influences task performance, then it is not evident whether an observed correlation between performance on a specific task and a (potentially) related construct (e.g., intelligence) was produced by the experimentally induced variance or by another, unintended, source of variance (cf. Rammsayer, Pahud, & Troche, 2017). Also Melnick et al. (2013) considered the possibility that non-experimental differences may be responsible for their findings. This crucial issue has been referred to as the impurity problem (Schweizer, 2007).

A methodological tool to tackle the impurity problem represents the fixed-links modeling approach first introduced by Schweizer (2006a, 2006b). This statistical method is a variant of confirmatory factor analysis (CFA) and allows for the decomposition of variance of manifest variables into multiple parts. While in conventional CFA, links between manifest and latent variables are estimated (although some are fixed for reasons of scaling), in the fixed-links modeling approach the matrix of factor loadings is not estimated. Instead, loadings are fixed and justified by theoretical considerations. Due to the fixation of factor loadings it has to be ensured that the variance captured by the latent variable reflects a meaningful process. If the variance of the latent variable is statistically significant and the model-fit is acceptable, it can be concluded that the processes represented by the latent variable are relevant for task performance and the model represents the empirical data appropriately (Schweizer, 2008).

In the present study, we aimed at replicating Melnick et al.'s (2013) findings on the relationship between spatial suppression and psychometric intelligence. Another goal was to extend the existing data by elucidating the unique and shared effects of mental speed, as indicated by Hick RTs, and spatial suppression on psychometric intelligence by combining traditional structural equation modeling and the quite novel fixed-links modeling approach.

2. Method

2.1. Participants

Because sufficient variance of psychometric intelligence is prerequisite to observe correlations with the experimental measures to be obtained, a convenience sample consisting of university students as well as participants with lower education was recruited. Furthermore, as aging might influence both psychometric intelligence and performance on the experimental tasks used in this study (cf. Rammsayer & Troche, 2010; Tadin & Blake, 2005), only participants ranging in age between 18 and 30 years were included in the present study. The participants were 61 male and 116 female volunteers from a convenience sample ranging in age from 18 to 30 years (mean and standard deviation of age: 21.1 ± 2.7 years). All participants had normal or corrected-to-normal vision and gave their written informed consent. The study was approved by the ethics committee of the Faculty of Human Sciences, University of Bern, Switzerland.

2.2. Measures of psychometric intelligence

For measurement of psychometric intelligence, a short version of the Berlin Intelligence Structure (BIS) test (Jäger, Süss, & Beauducel, 1997) was used. This short version consisted of 18 subtests to measure Processing Capacity, Processing Speed, and Memory as three major facets of psychometric intelligence. Each facet was assessed by two figural, two numerical, and two verbal subtests. In contrast to the original short version of the BIS test, the three creativity subtests were omitted in the present study. Instead three additional subtests assessing Processing Speed and three additional subtests assessing Memory were included. Thus, measures of Processing Capacity, Processing Speed, and Memory were based on the same number of subtests so that the *g* factor extracted from this test battery was not biased in favor of Processing Capacity. For modeling a *g* factor of intelligence, the raw scores of each subtest were *z*-standardized. Then, in a next step, the *g* factor of intelligence was derived from the aggregated mean *z*-scores of the three facets of intelligence (cf. Stauffer, Troche, Schweizer, & Rammsayer, 2014). In an unpublished pilot study on our selection of subtests (N = 122; test-retest interval of one month), we obtained test-retest reliability coefficients of r_{tt} = 0.79, r_{tt} = 0.85, and r_{tt} = 0.86 for the facets Processing Capacity, Processing Speed, and Memory, respectively (Wicki, 2014).

2.3. Spatial suppression task

We used a modified version of the spatial suppression task introduced by Melnick et al. (2013). As a practical aim, we conducted this experiment on a typical gaming LCD monitor (Asus VG248QE, 144 Hz, 1920 × 1080 resolution). Unlike equipment used by Melnick et al. (i.e., a custom-designed DLP projector), these types of displays are inexpensive, easy to find and are increasingly being used in psychophysical experiments (Wang & Nikolić, 2011). In our pilot work, however, we found fairly attenuated spatial suppression when using stimulus parameters matched to those used by Melnick et al. (2013). This might reflect effects of less pronounced frame onset transients in LCD monitors—types of transients that have been linked to spatial suppression (Churan, Richard, & Pack, 2009). To bring spatial suppression strength close to values reported by Melnick et al. (2013), we increased stimulus contrast from 42% to 95%. Other stimulus parameters were similar to those used by Melnick et al. (2013). Stimuli consisted of briefly presented visual grating-like textures (spatial frequency was 1 cycle/°, see Fig. 1), moving either leftward or rightward, on a linearized display (178 cd/m^2 background, 2 cd/m^2 ambient illumination). Moving speed of the gratings was held constant at 4.8°/s. Stimulus size was determined by stationary raised cosine spatial envelopes through which moving gratings were shown, with stimulus size defined as the visible stimulus diameter (with visibility defined as local contrast higher than 1%, following convention used by Melnick et al., 2013). Four different stimulus sizes were used subtending a visual angle of 1.8°, 3.6°, 5.4°, and 7.2°, respectively. Stimulus duration was defined as the full-width at half-height of the trapezoidal temporal envelope (Tadin et al., 2011).

Viewing distance was held constant by a chin rest at 61 cm. Participants' responses were registered by means of two designated response keys of a computer keyboard.

After a practice session of 180 trials, a total of three blocks were administered, with each block consisting of 44 trials of each stimulus size resulting in 528 trials. The four stimulus sizes were randomly interleaved within each block. On each trial, a moving stimulus was presented in the center of the participant's visual field. After the presentation of the stimulus, the participant had to indicate the perceived motion direction of the drifting grating (either leftward or rightward). Each correct response was followed by an auditory feedback. For each stimulus size, six estimates of the 82%-detection threshold for motion perception were obtained using a Bayesian adaptive QUEST procedure (Watson & Pelli, 1983). Because the QUEST procedure was designed to work in the log space, the estimated thresholds for motion perception represented the $\log_{10}$ of the presentation time required by a given participant to produce 82% correct responses. Thus, better performance on motion perception was indicated by smaller threshold values. As recommended by Melnick et al. (2013), the highest and the lowest threshold estimates for each stimulus size were excluded. For each participant, the remaining four threshold estimates were averaged separately for each stimulus size. Hereafter, the resulting thresholds are referred to as 1.8°-, 3.6°-, 5.4°-, and 7.2° threshold.

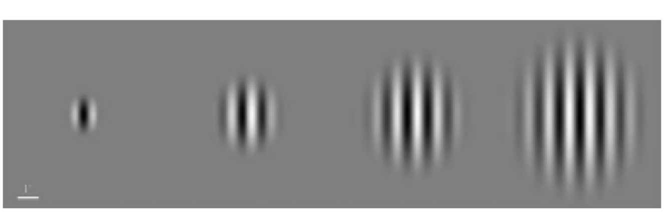

Fig. 1. The four stimulus sizes (1.8°, 3.6°, 5.4°, 7.2°) of the spatial suppression task. Only one stimulus was presented on each trial. The scale bar indicates 1° of visual angle.

As a measure of the magnitude of spatial suppression, the suppression index SI was computed by subtracting the mean threshold value for the small from the mean threshold value for the large stimulus size (Tadin et al., 2006). In a preceding pilot study (N = 12), test-retest reliability of the SI was r_{tt} = 0.84 for a one-week test-retest interval. Following a suggestion by Melnick et al. (2013), we also employed the suppression slope as an alternative measure of spatial suppression and derived from individual regression curves (see below). The advantage of the slope measure is that it depends neither on a particular stimulus size nor on the overall individual level of performance.

2.4. Hick reaction time task

A modified version of the Hick reaction time (RT) task introduced by Rammsayer and Brandler (2007) was applied. Stimuli were rectangles (subtending 1.5° of visual angle vertically and 1.8° horizontally) and a '+' sign (0.5° of visual angle vertically and horizontally) presented on a monitor screen. For registration of the participant's responses, an external response panel was used. Responses were registered with an accuracy of ± 1 ms. The task consisted of four conditions and each condition comprised 32 trials. In the 0-bit condition (simple RT condition), one rectangle was presented in the center of the screen. After a variable foreperiod, the imperative stimulus ('+') was presented in the center of the rectangle. The rectangle and the imperative stimulus remained on the screen until the participant pressed a designated response key. In the 1-bit condition two rectangles were presented next to each other. Presentation of the imperative stimulus was randomized and balanced. Thus, the imperative stimulus appeared in each of the two rectangles in 50% of the trials. Participants had to decide whether the imperative stimulus was presented in the right or the left rectangle by pressing one of two designated keys. Similarly, in the 2- and 2.58-bit conditions, four and six rectangles, respectively, were displayed. The four conditions were presented in increasing order from the 0- to the 2.58-bit condition to all participants. All responses with latencies shorter than 100 ms and longer than 2500 ms and deviating more than three standard deviations from individual mean RT were discarded from statistical analysis. For each of the four task conditions, mean RTs from correctly responded trials were computed separately as dependent variables.

2.5. Time course of the study

In a first session, psychometric measures of intelligence were obtained. Experimental testing took place in a subsequent testing session one week later. The order of the experimental tasks was balanced across participants. While the psychometric session took approximately 90 min, the experimental session lasted for approximately 120 min.

3. Results

The descriptive statistics of the thresholds in the four conditions of the spatial suppression task and reaction times in the four conditions of the Hick task are presented in Table 1. The thresholds increased from the 1.8°- to the 7.2°-condition of the spatial suppression task. While this increase was lower than the 125% increase reported by Melnick et al. (2013), we still observed a 60% change in thresholds as stimulus size increased from 1.8°to 7.2° — a result that is a defining characteristic of spatial suppression. A one-way analysis of variance (ANOVA) with the logarithmic thresholds as four levels of a repeated-measures factor was conducted to test the differences between the thresholds for statistical significance. Due to a violation of sphericity, the Greenhouse-Geisser correction was used with ε = 0.554. The main effect was statistically significant, $F(1.66, 292.39) = 275.26$, $p < 0.001$, $\eta_p^2 = 0.61$. As

Table 1
Descriptive statistics for the four conditions of the spatial suppression task (threshold values in ms) and the Hick RT task (ms) as well as Spearman-Brown corrected split-half reliability coefficients r_{tt}.

Task	*M*	*SD*	Min	Max	Skewness	Kurtosis	r_{tt}
Spatial suppression							
1.8°	82	28	31	216	− 0.25	0.19	0.96
3.6°	89	31	37	282	0.02	0.80	0.96
5.4°	109	40	45	422	0.73	1.78	0.96
7.2°	136	60	61	705	1.14	1.86	0.96
Hick RT							
0 bit	240	29	188	394	1.58	4.99	0.90
1 bit	296	32	234	416	0.94	1.33	0.93
2 bit	377	54	280	590	0.88	1.01	0.94
2.58 bit	438	67	315	650	0.82	0.41	0.93

indicated by pairwise comparisons, all four thresholds were significantly different from each other, all *p*s < 0.001.

Analogously, the increase of RT from the 0-bit to the 2.58-bit condition, reported in Table 1, was analyzed by a further ANOVA. The four conditions of the Hick task were four levels of a repeated-measures factor. Again, a Greenhouse-Geisser correction was used with $\varepsilon = 0.569$. This analysis revealed a significant main effect, $F(1.71, 300.23) = 1434.32$, $p < 0.001$, $\eta_p^2 = 0.89$. Pairwise comparisons corroborated that all mean RTs significantly differed from each other, all *p*s < 0.001. Thus, the experimental manipulations in the present study have been successful: The Hick task showed the pattern of increasing RT with increasing numbers of response alternatives – known as Hick's law (Hick, 1952) – and the spatial suppression task revealed increasing thresholds with increasing stimulus size referring to a spatial suppression effect (Tadin et al., 2003).

Pearson correlations between the *g* factor derived from Processing Capacity, Processing Speed, and Memory as three facets of psychometric intelligence and thresholds in the four conditions of the spatial suppression task are reported in Table 2. All four thresholds correlated negatively with the *g* factor. The same was true for RT in the four conditions of the Hick task.

In order to investigate the relationship between the *g* factor and spatial suppression, defined as the difference between the smallest and the largest stimulus pattern, the logarithmic 1.8° threshold was subtracted from the logarithmic 7.2° threshold (cf. Melnick et al., 2013). This spatial suppression index becomes positive and large when an individual shows a pronounced impairment to detect motion direction in the 7.2° condition compared to the 1.8° condition. In the case of no difference in the thresholds for detection of motion direction between the 7.2° and the 1.8° condition the spatial suppression index equals zero. The spatial suppression index becomes negative, when an individual needs less time to detect the motion direction in the 7.2° than in the 1.8° condition. Individual spatial suppression indices ranged from − 0.19 to 0.89 with a mean value (± SD) of 0.22 ± 0.16. The correlation between the spatial suppression index and the *g* factor did not reach statistical significance, $r = -0.01$, $p = 0.84$.

As proposed by Melnick et al. (2013), an alternative measure to quantify individual levels of spatial suppression can be obtained by regression analysis. With this approach, for each participant a regression curve was calculated based on the following equation: $y = a \cdot e^{bx}$. In this equation, x represented the four task conditions, b the slope of the threshold across the four stimulus sizes, and a the intercept with the y axis. It should be noted that, consistent with Melnick et al. (2013), this analysis was based on the re-inverted thresholds rather than on its $\log_{10}$. Mean values for a and b were 70 (± 28) ms and 0.103 (± 0.081) ms, respectively. Correlational analyses revealed a negative correlation between the *g* factor and the intercept a, $r = -0.18$, $p < 0.05$, but no functional relationship between the *g* factor and the slope b of the exponential function, $r = -0.01$, $p = 0.90$. Thus, at the manifest level, motion detection thresholds, but not spatial suppression, were significantly correlated to general intelligence. This conclusion was corroborated by further analyses of subsamples. When the sample was divided randomly into three subsamples of 59 participants each, into two subsamples of men and women, or into two subsamples of 91 older and 86 younger participants, measures of spatial suppression (i.e., the spatial suppression index and the slope measure) were not related to psychometric intelligence.

To investigate the relationship between spatial suppression and the *g* factor of psychometric intelligence at the level of latent variables, it was necessary to establish a latent trait model that described the data appropriately. A fixed-links modeling approach was used so that variance, which does not change from condition to condition, was represented by a first latent variable (hereafter referred to as *constant latent variable*). Accordingly, the factor loadings of the thresholds on this latent variable were fixed to the same value ("1"). In addition, variance increasing from the 1.8° to the 7.2° condition was described by a second latent variable referred to as *increasing latent variable* and considered a latent representation of individual differences in spatial suppression. The factor loadings of this latent variable were fixed in a monotonically increasing way across the task conditions. A linear function ($y = x$; $x \in \{0, 1, 2, 3\}$) for the fixation of factor loadings was chosen and the correlation between the two latent variables was set to zero. Due to deviations from the normal distribution (for skewness and kurtosis see Table 1), the χ^2 test statistic was Satorra-Bentler (SB)

Table 2
Pearson correlations between detection thresholds in the four conditions of the Spatial suppression task, reaction times (RT) in the four conditions of the Hick task and the *g* factor derived from Processing Capacity, Processing Speed, and Memory as three facets of psychometric intelligence.

Task		*g* factor	Spatial suppression task					Hick RT task		
			1	2	3	4	5	6	7	8
Spatial suppression										
1	1.8°	− 0.18*								
2	3.6°	− 0.19*	0.85***							
3	5.4°	− 0.19*	0.73***	0.87***						
4	7.2°	− 0.16*	0.54***	0.72***	0.87***					
5	SI	− 0.01	− 0.28***	0.05	0.34***	0.66***				
Hick task										
6	0 bit	− 0.20**	0.17*	0.24**	0.25***	0.14	0.01			
7	1 bit	− 0.28***	0.09	0.11	0.13	0.07	0.00	0.76***		
8	2 bit	− 0.28***	0.12	0.08	0.08	0.04	− 0.06	0.58***	0.72***	
9	2.58 bit	− 0.27***	0.14	0.09	0.12	0.07	− 0.04	0.52***	0.66***	0.83***

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

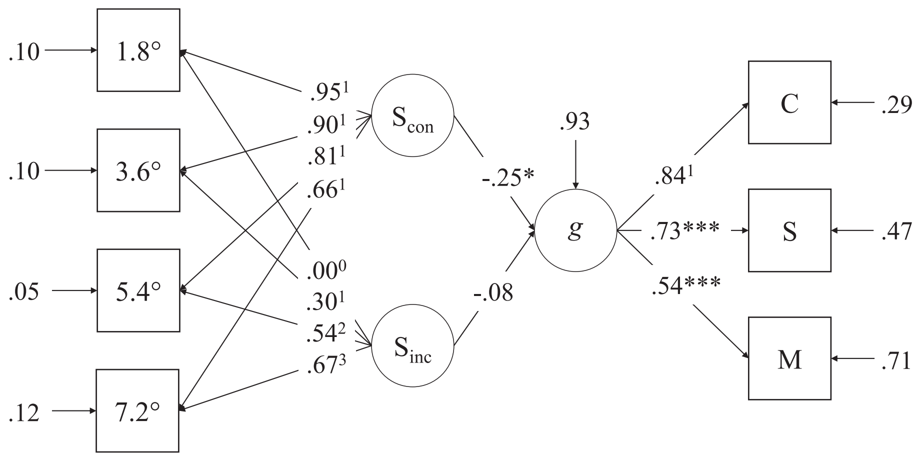

Fig. 2. Structural equation model on the relation between the *g* factor of intelligence and two latent variables derived from the spatial suppression task to represent individual differences in spatial suppression (S_{inc}) and in motion detection thresholds irrespective of stimulus size (S_{con}). Reported are standardized factor loadings and regression coefficients. Unstandardized factor loadings are given in superscript.

corrected. This model led to a good model fit, $SB\chi^2(4) = 6.09$, $p = 0.19$, CFI = 0.995, RMSEA = 0.054, SRMR = 0.123. Variances of both the constant latent variable, $\varphi = 0.018$, $z = 8.45$, $p < 0.001$, and the increasing latent variable, $\varphi = 0.002$, $z = 5.53$, $p < 0.001$, were statistically significant indicating that both latent variables represented psychologically meaningful processes. McDonald's omega coefficients (cf., Brunner & Süß, 2005) were $\omega = 0.88$ and $\omega = 0.97$ for the increasing and the constant latent variable, respectively.

After having established this confirmatory factor model, the two latent variables were regressed on the *g* factor extracted from the three facets of psychometric intelligence. The resulting structural equation model is presented in Fig. 2. The model fit was good, $SB\chi^2(14) = 19.06$, $p = 0.16$, CFI = 0.993, RMSEA = 0.045, SRMR = 0.094. The regression between the constant latent variable and the *g* factor yielded statistical significance, $\beta = -0.25$, $p = 0.01$, whereas the increasing latent variable, representing spatial suppression, was not systematically associated with the *g* factor, $\beta = -0.08$, $p = 0.44$. Thus, neither at the manifest nor at the latent level, a functional relationship between spatial suppression and psychometric intelligence could be confirmed.

Independent of stimulus size, the motion detection thresholds were associated with *g* as can be taken from Table 2. This effect was also reflected by the functional relationship between the constant latent variable and the *g* factor. The motion detection thresholds represent the time participants need to correctly perceive the motion direction of a given stimulus pattern. Thus, participants with lower thresholds needed less time to correctly perceive the motion direction than participants with higher thresholds. From this point of view, the relationship between the constant latent variable and the *g* factor might represent the well-established relationship between speed of information processing and psychometric intelligence. To investigate this conclusion, we added speed of information processing as measured by RTs from the Hick task to the structural equation model.

For this purpose, a measurement model of RT in the four conditions of the Hick task was required. Again, we probed a fixed-links model with two latent variables. The factor loadings of one latent variable were fixed to 1 to represent aspects of information processing not varying with the increasing task complexity (*constant latent variable*). An increasing course of factor loadings reflecting the increasing number of response alternatives of the four Hick RT task conditions ($y = x$; $x \in \{0, 1, 2, 2.58\}$) was used for the second latent variable to describe complexity-related aspects of speed of information processing. This model did not describe the data adequately, $SB\chi^2(4) = 32.20$, $p < 0.001$, CFI = 0.908, RMSEA = 0.200, SRMR = 0.136. Therefore, we adapted the increasing course of factor loadings. The premise of the adaptation was to maintain a monotonically increasing course of factor loadings. As can be derived from the standard deviations reported in Table 1, variance in the 0-bit and the 1-bit condition were quite similar but, at the same time, differed clearly from the 2-bit and the 2.58-bit conditions. Therefore, we attenuated the factor loading on the 1-bit condition from 1 to 0.5 to better represent the differences in variance between the 1-bit condition, on the one hand, and the 2-bit and 2.58-bit conditions, on the other one. The resulting course of factor loadings still monotonically increased with increasing number of response alternatives in the Hick task ($y = x$; $x \in \{0, 0.5, 2, 2.58\}$) so that this latent variable could still be referred to as *increasing latent variable*. The model described the data well, $SB\chi^2(4) = 5.61$, $p = 0.23$, CFI = 0.995, RMSEA = 0.048, SRMR = 0.092. Variances of both the constant latent variable, $\varphi = 671$, $z = 5.91$, $p < 0.001$, and the increasing latent variable, $\varphi = 361$, $z = 7.00$, $p < 0.001$, were statistically significant. Omega was $\omega = 0.85$ for the increasing latent variable and $\omega = 0.87$ for the constant latent variable.

To investigate the common influence of speed of information processing in the spatial suppression and the Hick RT tasks on the *g* factor, the measurement models were combined and the four latent variables derived from the two tasks were regressed on the *g* factor. Correlations between the four latent variables from the two tasks were set to zero. The resulting structural equation model is depicted in Fig. 3 and yielded a good model fit, $SB\chi^2(44) = 59.60$, $p = 0.06$, CFI = 0.987, RMSEA = 0.045, SRMR = 0.098. Significant and negative associations were observed between the *g* factor and both latent variables from the Hick RT task as well as the constant latent variable from the spatial suppression task. Setting the correlations between the latent variables from the spatial suppression task and the Hick RT task free for estimation did not improve the model fit with one exception. When the two constant latent variables from the spatial suppression task and from the Hick RT task were allowed to correlate with each other, this correlation was statistically significant, $r = 0.20$, $p = 0.01$, and improved the model fit, $SB\chi^2(43) = 54.34$, $p = 0.12$, CFI = 0.990, RMSEA = 0.039, SRMR = 0.077. The test for Satorra-Bentler corrected chi-square differences (Satorra & Bentler, 2010) indicated that this improvement was statistically significant, $\Delta\chi^2(1) = 5.92$, $p = 0.01$. Most importantly, however, the regression coefficient between the constant latent variable from the Hick RT task and the *g* factor was no longer statistically significant, $\beta = -0.174$, $p = 0.054$. Thus, the significant associations between the *g* factor and the constant latent variables from the spatial suppression and the Hick tasks appeared to rely on common variance of these two constant latent variables.

4. Discussion

The main aim of the present study was to replicate Melnick et al.'s, 2013 finding of a functional relationship between spatial suppression and psychometric intelligence and to embed this relationship into the

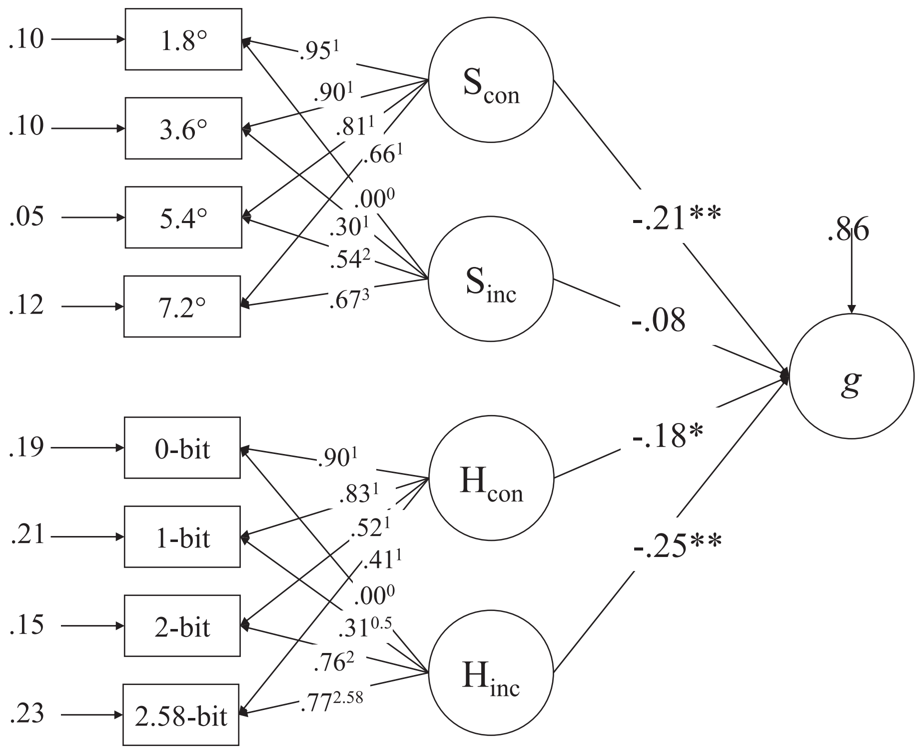

Fig. 3. Structural equation model on the relation between the *g* factor and latent variables derived from the spatial suppression task (S) and the Hick RT task (H) representing individual differences in the response to the experimental manipulation (S_{inc} and H_{inc}) and individual differences in task performance irrespective of experimental manipulation (S_{con} and H_{con}).
Reported are standardized factor loadings and regression coefficients. Unstandardized factor loadings are given in superscript.

mental-speed approach to psychometric intelligence. The significant increase of the motion detection thresholds with increasing stimulus size indicated that the experimental manipulation was successful to evoke the phenomenon referred to as spatial suppression (Tadin et al., 2003). In all four conditions of the spatial suppression task, lower thresholds were consistently associated with higher psychometric intelligence. In contrast to our expectations, however, measures of spatial suppression strength were not related to psychometric intelligence. In addition, variance of individual differences in spatial suppression was described successfully as a latent variable within a fixed-links model. But even with this latent-variable approach, a relationship between spatial suppression and psychometric intelligence could not be established.

This absence of an association between spatial suppression and psychometric intelligence was a most unexpected finding. While Melnick et al. (2013) reported a highly significant positive relationship between spatial suppression and psychometric intelligence in two different samples, the present results did not confirm such an association. At the level of manifest variables, neither the conventional suppression index defined as a difference score (Betts, Taylor, Sekuler, & Bennett, 2005; Tadin et al., 2006; Tadin et al., 2011) nor the measure based on the slope of individual regression curves (Melnick et al., 2013) was related to psychometric intelligence.

The fixed-links modeling of the motion detection thresholds revealed that two systematic sources for individual differences could be dissociated and described by two latent variables. The first source of variance did not change with stimulus size and, hence, described the speed with which the direction of a motion can be detected, irrespective of stimulus size. The second source of variance increased with increasing stimulus size. Thus, this latent variable represented individual differences in spatial suppression, i.e., the worsening of thresholds with increasing stimulus size. In contrast to the conventional spatial suppression index, the latent variable representing spatial suppression is less vulnerable to low reliability since no difference score is built and unsystematic errors of measurement cannot contribute to latent variance. The identification of this latent variable indicated a substantial portion of systematic individual differences in spatial suppression, which represents a necessary prerequisite for proving a functional relationship between spatial suppression and psychometric intelligence. Although this important requirement was met, an association between spatial suppression and psychometric intelligence could not be established at the level of latent variables. This finding indicated that the way of operationalizing spatial suppression can be ruled out as a possible reason for the lacking association. Against this background, it seems noteworthy that research on the relation between executive functions and psychometric intelligence revealed a mixed pattern of results regarding the role of inhibitory processes for the explanation of individual differences in psychometric intelligence (cf. Colom, Chuderski, & Santarnecchi, 2016). Moreover, recent work has shown that individual differences in inhibitory function do not predict individual differences in spatial suppression (Schallmo et al., 2017).

The frequent failure in psychological science to replicate past significant study results has been addressed by the current debate referred to as replication crisis (e.g., Diener & Biswas-Diener, 2017; Maxwell, Lau & Howard, 2015; Open Science Collaboration, 2015). In the context of this methodological discussion, the so-called failure to replicate an initial result may not be a failure at all, but rather a consequence of statistical, procedural, or sample-related differences between the original and the replication study. With regard to the present study, a possible explanation for the diverging results could be sampling errors that may have led to a false positive outcome in the case of Melnick et al.'s (2013) study or to a false negative outcome in the case of the present study. However, given the relatively large sample size of 177 participants, a false negative outcome due to sampling error or lacking statistical power appears to be rather unlikely in the present study. Even if we proceeded from a "true" correlation of $r = 0.45$ between spatial suppression and psychometric intelligence (which would be reasonably lower than $r = 0.64$ to $r = 0.71$ as suggested by Melnick et al.'s empirical results), a sample size of 177 participants would have been large enough to detect this effect with a statistical power > 0.999.

Most of the relevant studies confirming the positive association between psychometric intelligence and speed of information processing have been conducted in Western countries including the U.S., Canada, and Western European countries (cf., Jensen, 2006; Sheppard & Vernon, 2008). Moreover, this speed-intelligence relationship was also shown to hold when comparing Western and non-Western countries (e.g., Neubauer & Benischke, 2002). Therefore, it is highly unlikely that cultural or language differences between the U.S. samples tested by Melnick et al. (2013) and the Swiss sample of the present study may account for the divergent results.

Also age was not related to spatial suppression and psychometric intelligence in the present sample and a correlation between spatial suppression and psychometric intelligence could be found neither in older nor in younger participants. While Melnick et al. (2013) used a short-form of the Wechsler Adult Intelligence Scale (WAIS-III; Axelrod, 2002) and the full-length WAIS-IV (Psychological Corporation, 2008) in their Studies 1 and 2, respectively, the present study employed a modified short-form of the BIS test. Different measures of general psychometric intelligence, however, were shown to be highly correlated with each other (Johnson, te Nijenhuis, & Bouchard, 2008). Melnick et al.'s (2013) participants were notably older (33.1 vs. 22.1 years average). However, the Melnick et al. (2013) result stands even if only participants 25 years and younger are included ($N = 24$, $r = 0.62$) as indicated by a re-analysis.

Arguably, the most notable differences between the present study and Melnick et al. (2013) are in the display apparatus and stimulus contrast. Melnick et al. (2013) used a CRT display in Study 1 (a display type that is now hard to find) and a custom-built DLP projector in Study 2. Here we opted to use a LCD display — a more accessible display option. Generalizing Melnick et al. (2013) to LCD displays would be of practical value as it would make this paradigm easier to implement. However, our initial pilot testing revealed considerably weaker spatial suppression when tested on a LCD display. This is likely because frame onset transient are attenuated on LCD displays — types of transients that have been linked with increasing spatial suppression strength (Churan et al., 2009). To increase spatial suppression strength, we took advantage of the fact that spatial suppression strength increases with increasing contrast (Tadin et al., 2003) and used a stimulus contrast that was approximately twice as high as the contrast used in Melnick et al. (2013). As expected, this resulted in increased suppression strength. While still weaker than that reported by Melnick et al. (2013), the data showed clear increases in thresholds with increasing stimulus size — a defining feature of spatial suppression (Tadin, 2015). We cannot say if either this change in contrast or the difference in the display apparatus underlines the observed discrepancy between the present study and Melnick et al. (2013). However, it does appear that the link between spatial suppression and intelligence reported by Melnick et al. (2013) is, at best, confined to a specific range of stimulus parameters and/or certain types of displays. Future work will be needed to determine if that is indeed the case. At present, the most plausible explanation for the difference between the present results and those reported by Melnick et al. (2013) is the rather small sample sizes of 12 and 53 participants in the two studies by Melnick et al. (2013). Given that the stability of correlation coefficients is quite low for small sample sizes (Bonett & Wright, 2000), this might have led to false positive results.

Although the expected relationship between spatial suppression and psychometric intelligence could not be confirmed, a consistent pattern of negative correlations was found between the motion detection thresholds in all four conditions of the spatial suppression task and psychometric intelligence. These negative correlations indicate higher psychometric intelligence to come along with better detection of motion direction, irrespective of size of the stimulus pattern. The fact that this correlational relationship did not vary as a function of stimulus size mirrored the relationship between psychometric intelligence and the constant latent variable derived from the four conditions of the spatial suppression task by means of fixed-links modeling. It is important to note though, that this pattern of correlations between thresholds and psychometric intelligence cannot be taken as evidence for a relationship between spatial suppression and intelligence. Rather, such a pattern indicates that – irrespective of stimulus size – participants with higher psychometric intelligence were faster to correctly detect motion direction than participants with lower psychometric intelligence. From this point of view, our results add to the large number of studies on the relationship between speed of information processing and psychometric intelligence.

One of the most frequently used tasks to assess speed of information processing is the Hick RT task. Using fixed-links modeling of RT in the four conditions of the Hick task, variance in RT could be explained by two latent variables. One latent variable represented variance, which increased from the 0-bit to the 2.58-bit condition. Thus, this *increasing* latent variable described individual differences in the time needed for the increasing number of binary decisions. Although mean RT increased linearly from the 0-bit to the 2.58-bit condition as predicted by Hick's law, a better data description was obtained when a monotonically increasing trajectory of factor loadings, deviating from linearity, was used. It should be noted, however, that the results regarding the interplay among the latent variables derived from the Hick RT task, the spatial suppression task, and psychometric intelligence did not depend on whether a strictly linear trajectory or a better fitting simply monotonic trajectory of factor loadings was chosen.

The other latent variable described variance not varying as a function of task condition. For this reason, this latter latent variable has been referred to as *constant* latent variable (cf. Schweizer, 2008; Stauffer et al., 2014). Being unrelated to the experimental manipulation of response alternatives in the Hick task, the constant latent variable has been assumed to reflect an amalgam of various speed-related processes, which cause individual differences in RT independently of the experimental manipulation (Rammsayer et al., 2017). These processes may comprise basic processing speed (e.g., Heitz, Unsworth, & Engle, 2005), speed of sensorimotor processes (e.g., Jensen, 2006; Schweizer, 2007; Stauffer, Indermühle, Troche, & Rammsayer, 2012), as well as individual differences in participants' mental or physical state such as their alertness or fatigue (cf. Thomas, Rammsayer, Schweizer, & Troche, 2015).

Of particular interest for the present study was the finding that both speed of decision-making and speed of the subsidiary processes underlying the constant latent variable of the Hick task were significantly correlated with psychometric intelligence. When combining the measurement models for the Hick task and for the spatial suppression task to predict psychometric intelligence, both latent variables derived from RT in the Hick task and the constant latent variable extracted from thresholds in the spatial suppression task explained significant portions of variance in psychometric intelligence. Most interestingly, when the constant latent variables from the two experimental tasks were allowed to correlate with each other, the significant association between the constant latent variable from the Hick task and psychometric intelligence disappeared. This finding indicates that the correlation between the constant latent variable from the Hick task and psychometric intelligence is reasonably accounted for by the same mechanism(s) underlying the correlation between the constant latent variable from the spatial suppression task and psychometric intelligence. Because speed-related motor processes were not involved in the spatial suppression task, a tentative explanation for this finding points to speed of stimulus encoding as a common information-processing component underlying the observed relationship (cf. Stauffer et al., 2014).

Whatever the underlying processes may be, it is obvious that they are independent of the specific task, but shared by both the spatial suppression task and the Hick task. Furthermore, the processes reflected by the increasing latent variables extracted from both experimental tasks proved to be independent from each other. While the increasing latent variable derived from the Hick task was significantly associated with psychometric intelligence, the increasing latent variable from the spatial suppression task was unrelated to measures of speed of information processing derived from the Hick task as well as to psychometric intelligence.

To sum up, significant correlations between psychometric intelligence and (1) the motion detection threshold in each of the four conditions of the spatial suppression task, (2) the intercept of the individual regression curves, and (3) the constant latent variable of the fixed-links model indicated a functional relationship between psychometric intelligence and motion detection regardless of the size of the stimulus. When combining the fixed-links model of the spatial suppression task and the fixed-links model of the Hick task to predict psychometric intelligence, the constant latent variables from both tasks explained a common portion of variance of psychometric intelligence. This pattern of results clearly argues for a functional relationship based on general speed of information processing as put forward by the mental speed approach to intelligence. No evidence, however, could be provided for an association between spatial suppression and mental ability.

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