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An Investigation of the Slope Parameters of Reaction Times and P3 Latencies in the Sternberg Memory Scanning Task – A Fixed-Links Model Approach

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Abstract: The speed of retrieving information from short-term memory is thought to be captured in the slope of the linear function of reaction times (RTs) regressed on set size in the Sternberg memory scanning task (SMST). Individual differences in the slope parameter have been hypothesized to correlate with general intelligence (*g*). However, this correlation can usually not be found. This present study chose a fixed-links model (FLM) approach to re-evaluate the RT slope parameter on a latent level in a sample of 98 participants aged 18 to 61 years. The same was tried for P3 latencies to investigate whether or not both parameters measure the same cognitive processes in the SMST, and to assess the usability of both slopes to predict *g*. For RTs, a linear increase with set size was found. The RT slope correlated with *g* on a manifest level already. The FLM approach could significantly increase the relationship between the slope and *g*. For P3 latencies, no evidence for a linear increase was found. This indicates that RTs and P3 latencies do not measure the same cognitive processes in the SMST. The FLM proved suitable to investigate the association between the speed of short-term memory scanning and intelligence.

Keywords: Intelligence; Sternberg Memory Scanning Task; Reaction Times; P3 Latencies; Fixed-Links Model; Mental Speed

1. Introduction

The search for neuro-cognitive processes that are the basis of intelligence and that differ in individuals of higher and lower general intelligence (*g*) is ongoing in the field of differential psychology. In 2006, Jensen proposed the speed of information processing to be one possible underlying general process. In the present study, we focused on the speed of the retrieval of information from short-term memory as one possible specific cognitive process that contributes to interindividual differences in intelligence. The goal of the following analyses was to answer the question whether reaction times (RTs) and P3 latencies of the event-related potential (ERP) both measure retrieval from short-term memory by regressing RTs and P3 latencies on the varying set size conditions in the Sternberg memory scanning task (SMST; Sternberg 1966). The slopes of the resulting linear functions were then used to predict intelligence. This allows to see whether the speed of retrieving information from short-term memory differs between individuals of higher and lower general intelligence. To do this, the fixed-links model (FLM; introduced by Schweizer 2006) as a special form of structural equation modeling (SEM) was chosen because earlier research has often failed to correlate the slope parameter with intelligence on a manifest level (Jensen 1987, 1998).

In the SMST, participants see a set of numbers (called memory set or positive set) varying in set size. They are asked to remember the memory set displayed. After a short amount of time, the memory set disappears and, after another short delay, a probe stimulus is presented on the screen.

Participants then must decide as quickly as possible whether the test stimulus belongs to the positive set or not (and thus belongs to the so-called negative set). Many authors have shown that RTs in this task increase linearly with set size (e.g., Chiang and Atkinson 1976; Ergen et al. 2012; Jensen 1987; Pelosi, McHayward, and Blumhardt 1995; Sternberg 1969). Sternberg (1969) offered a psychological explanation for both the slope and the intercept of the linear function of RTs regressed on set size. He interpreted the intercept of the linear function as the time needed for all processes that happen regardless of the number of digits in the memory set. These processes include, for example, the encoding of the test stimulus as well as the preparation and execution of the motor response. The slope of the linear function, on the other hand, is thought to represent the additional time needed for the specific process that happens for each member of the positive set. More precisely, this specific process includes a comparison between each member of the memory set and the test stimulus and a switch from one member to the next. Therefore, the number of digits in the positive set determines the number of comparison operations executed. The specific process associated with the slope of the linear function is what Sternberg (1969) called serial memory scanning. In other words, the time needed for this specific process reflects the time one needs to withdraw information (the memory set) from short-term memory. At the same time, serial memory scanning can be interpreted as one specific process on a very low level of a hierarchical intelligence model (e.g., Carroll 1993; Spearman 1923) that, among others, gives rise to a single *g*-factor.

RTs in the SMST have repeatedly been shown to be negatively correlated with intelligence. In other words, more intelligent individuals show shorter RTs in the memory task. A meta-analysis by Sheppard and Vernon (2008) found a mean correlation of $r = -.25$ in the SMST and similar tasks. Similarly, McGarry-Roberts, Stelmack, and Campbell (1992) found a correlation of similar size, $r = -.21$, between RTs in the SMST and general intelligence measured with the Wechsler Adult Intelligence Scale-Revised (WAIS-R; Wechsler 1981). This negative correlation between RTs and intelligence is not exclusive for the SMST. Several reviews and meta-analyses have shown a consistent negative association between RTs in different simple and choice RT tasks and intelligence. Sheppard and Vernon (2008) found a negative relationship of $r = -.24$ across 172 studies in their review. A meta-analysis investigating the worst performance rule found a correlation of $r = -.28$ between mean RTs and cognitive abilities (Schubert 2019). Likewise, Doeblner and Scheffler (2016) found correlations in the Hick task ranging from $r = -.18$ to $r = -.28$ in their meta-analysis.

The two general findings that RTs increase in a linear fashion with increasing set size and that shorter RTs are associated with higher general intelligence, led researchers to use the slope parameter of the linear function to predict individual differences in intelligence. By this method, a lower slope should be associated with higher general intelligence and vice versa. However, this hypothesized correlation cannot be consistently confirmed in the literature (Jensen 1987, 1998). Even if a correlation is found, it is usually small and insignificant (e.g., Neubauer et al. 1997). In addition to the small size of this correlation, mean RTs themselves tend to correlate much higher with intelligence than the slope parameter does. Consequently, this led researchers to abolish the idea of using the slope to predict individual difference in intelligence. Jensen (1992) explained that the reason for a poor prediction of *g* using the slope lies in a statistically built-in negative correlation between the slope and the intercept of the linear function. It is this negative correlation that suppresses any correlation of the slope with other constructs like intelligence. The intercept therefore becomes a suppressor variable that impedes an association between the slope and intelligence. This negative correlation seems theoretically paradoxical as it would mean that individuals who are faster at comparing the probe stimulus with each member of the memory set tend to need more time for processes like motor planning and execution. However, the negative association can be explained statistically by the fact that the slope and the intercept share the same measurement errors. Because the shared measurement errors of the slope and the intercept tend to go in opposite directions, a negative correlation results (Jensen 1998). At the same time, a study by (Jensen 1987) reports a much lower reliability of the slope than of the intercept. Taken together, these two properties of slope measures (negative correlation of slope and intercept and low reliability of the slope) may account for the typically low associations between the speed of serial memory scanning and intelligence. In order to still use the slope

parameter, one has to control for the artificial correlation of intercept and slope, and decrease measurement errors (Jensen 1998).

1.1. Using a Fixed-Links Model Approach to Estimate the Speed of Serial Memory Scanning

Rammsayer, Pahud, and Troche (2017) showed that it is possible to tackle both problems (controlling for an artificial correlation between slope and intercept and decreasing measurement errors) using a model with latent variables. In their study, the authors used a FLM approach as first introduced by Schweizer (2006) to investigate the relationship between RTs and g in the Hick task. The Hick task (Hick 1952) is a classical choice RT task in which participants sit in front of an apparatus with up to 8 bulbs lightening up. They must push the button adjacent to the light bulb as quickly as possible. Typically, participants react fastest when there is only one possible light and slowest when all eight response alternatives are possible. The resulting RTs in this task can be described with a linear function of the BITs, the binary logarithm of the number of lights presented. This finding is commonly known as Hick's Law:

$$RT = a + b(\log_2 n) = a + b(\text{BITs}).$$

The FLM as a special kind of SEM allows the estimation of the variance of a construct on a latent level (in this case the slope of the linear function). Measurement errors can therefore be controlled. Moreover, it allows researchers to decide whether latent variables should stay orthogonal or whether they can correlate with each other. In contrast to conventional SEM, factor loadings in the FLM are not estimated freely but rather fixed with regards to a hypothesized trajectory of the function. Consequently, the FLM can model a latent slope factor that is not correlated with the intercept, and thus, it can implement Jensen's (1998) demands for future research that uses the slope to predict individual differences in intelligence.

Rammsayer, Pahud, and Troche (2017) used variance decomposition to model two latent variables that both represented RT. The first latent variable, denoted the non-experimental latent variable, corresponded to the intercept of the linear model with manifest variables while the other, denoted experimental latent variable, corresponded to the slope. It was assumed that the non-experimental latent variable was not affected by the experimental manipulation and therefore all factor loadings in the FLM were fixed to 1. The experimental latent variable, on the other hand, was thought to be dependent on the experimental manipulation. Therefore, the factor loadings in the FLM were fixed to the expected trajectory of the function. In the case of the Hick task (Hick 1952), the authors fixed the factor loadings to 1, 2, and 4, representing the amount of information in the 0, 1, and 2 BIT condition of the Hick task. Using this FLM approach, Rammsayer, Pahud, and Troche (2017) could show that the experimental latent variable correlated substantially with a correlation of $r = -.34$ with psychometric intelligence measured through three subscales of the Berlin Intelligence Structure test (BIS; Jäger, Süß, and Beauducel 1997).

The FLM approach has proven to be able to successfully relate the slope parameter (modelled as an experimental latent variable) with intelligence. Therefore, one aim of the present study was to re-evaluate the usability of the slope parameter of the SMST to predict individual differences in intelligence. A FLM approach that accounts for the measurement errors of RTs and controls for an artificial correlation between the intercept and the slope should allow predicting intelligence to an extent that is not possible using a model with manifest variables only. Therefore, we predicted that the correlation between the slope of RTs as a linear function of set size should be more strongly association with intelligence when estimated in the FLM framework than when estimated on the manifest level.

1.2. Assessing the Speed of Neural Information-Processing

Individual differences in the speed of information-processing cannot only be measured as mean reaction times, but also as latencies of the event-related potential (ERP). The typical ERP waveform results when a participant performs a task many times while an electroencephalogram (EEG) is

recorded. Since the EEG recordings display the brain's response to an elicited stimulus combined with other activity irrelevant to the task, the EEG is aggregated over many trials to extract only the relevant brain response to the stimulus. The ERP waveform is characterized by several peaks differing in their latency, amplitude, and peak valence. ERP components are usually named after their valence and peak latency or ordinal position, respectively. Here, the term P3 latency refers to the peak latency of the third positive voltage wave.

As with RTs, there exists a large body of research on the role of ERP latencies in different single and choice RT tasks and their associations with intelligence. In the SMST in particular, P3 latencies seem to be sensitive to the experimental manipulation of the set size as they increase with a larger memory set (e.g., Ergen et al. 2012; Houlihan 1998; Pelosi, McHayward, and Blumhardt 1995; Schubert et al. 2015). Furthermore, especially latencies of ERP components associated with stimulus evaluation, memory updating, and response selection that occur later in the stream of information-processing have been shown to be strongly associated with intelligence (Bazana and Stelmack 2002; Kapanci et al. 2019; McGarry-Roberts, Stelmack, and Campbell 1992; Saville et al. 2015; Schubert et al. 2015; Schubert, Hagemann, and Frischkorn 2017; Schubert et al. 2018; Schubert et al. 2019; Troche et al. 2015; Troche and Rammsayer 2009). In particular, some studies have reported negative correlations between intelligence and P3 latencies measured in the SMST (McGarry-Roberts, Stelmack, and Campbell 1992; Schubert et al. 2015; Schubert, Hagemann, and Frischkorn 2017). Taken together, the findings that P3 latencies increase with increasing set size, and that shorter P3 latencies are correlated with higher intelligence resemble the general findings regarding RTs in the SMST. Therefore, to the degree that P3 latencies can be described as a linear function of set size in a manner similar to RTs, one could assume that P3 latencies also measure serial memory scanning *sensu* Sternberg (1969). Hence, if the slopes of RTs and ERP latencies in the SMST both reflected the speed of serial memory scanning, they should be positively related.

However, the evidence for converging associations between behavioral and neural measures of processing speed is generally inconsistent. Schubert et al. (2015) reported correlations between RTs and ERP latencies measured in three different experimental tasks including the SMST that ranged from $r = .46$ to $r = .53$, but only considered latencies of the P100, N150, and P200 component in their analyses. In comparison, McGarry-Roberts, Stelmack, and Campbell (1992) could not find a significant correlation between RTs and P3 latencies in the SMST. Donchin and Coles (1988) pointed out that correlations between RTs and P3 latencies are generally higher if the reaction to the stimulus is correct. However, with small error percentages ranging from 0.10% to 2.78% across the different RT tasks, this should not account for a low correlation between RTs and P3 latencies in McGarry-Roberts, Stelmack, and Campbell (1992). Hence, the authors concluded that the two measures do probably not reflect the same cognitive process. P3 latencies are interpreted to be independent of all response production processes like motor planning and execution whereas RTs are not (see also McCarthy and Donchin 1981).

In conclusion, there is inconsistent evidence for a correlation between P3 latencies and RTs. Moreover, this correlation alone cannot prove that both measures reflect the serial memory scanning *sensu* Sternberg (1969), because intercept measures of both RTs and P3 latencies are affected by a larger number of cognitive processes than just memory scanning. Instead, the trajectories of the linear regressions of RTs and P3 latencies regressed on set size need to be compared since it is in particular the slope that captures the specific process of interest.

We expect the same problems outlined for slope measures of RTs (an artificial correlation between intercept and slope and a low reliability of the slope as summarized by Jensen (1992)) will also apply to P3 latency data. Therefore, a FLM approach should, again, be helpful to assess the true variance of the latent variable that represents the slope, and to fix the correlation of both latent variables representing the P3 latency to zero. If slopes derived from P3 latencies reflect parameters of the same cognitive process as slopes derived from RTs, they should be positively correlated with the speed of serial memory scanning as measured by RTs. Moreover, they should show comparable negative correlations with intelligence, as more intelligent individuals should show a higher speed of serial memory scanning both on a behavioral and on a neural level. In the present study, we therefore

use a FLM approach to reanalyze a previously published dataset (Schubert, Hagemann, and Frischkorn 2017) and to estimate slope measures of serial memory scanning on a behavioral and a neural level to analyze their convergence and their respective associations with intelligence.

2. Materials and Methods

2.1. Participants

In the previously published dataset (Schubert, Hagemann, and Frischkorn 2017), data from $N = 134$ participants was acquired at three different measurement occasions. Here, we only analyzed data from the first two measurement occasions that were separated by approximately four months. Of the $N = 122$ participants who attended both the first and second measurement occasions, a total of $N = 117$ participants (68 females, 49 males) completed both the SMST at the first and the intelligence test at the second measurement occasion. Data of five participants was discarded due to missing intelligence test or P3 latency data. 19 participants were identified as multivariate outliers and excluded from the sample (see subsection on data analysis for more information on multivariate outlier detection). $N = 98$ participants (57 females, 41 males) were included in the final dataset. The participants were between 18 and 61 years old ($M = 35.9$, $SD = 13.5$). They were recruited via local newspaper advertisements, announcements on social media platforms, and distribution of flyers in Heidelberg, Germany. Attention was paid to recruit participants with different educational and occupational backgrounds. All participants had normal or corrected to normal vision and no history of mental illness. All participants gave their informed consent form and received €100 and individual feedback about their results as compensation for their participation. The study was conducted in accordance with the Declaration of Helsinki and the protocol was approved by the Ethics Committee of the Faculty of Behavioral and Cultural Studies at Heidelberg University.

2.2. Materials

In the following section, we only report materials relevant to the present study. In the original study, participants completed two additional RT tasks, Raven's advanced progressive matrices (APM; J. C. Raven, Court, and Jean Raven 1994), and a personality questionnaire. For more information see Schubert, Hagemann, and Frischkorn (2017) and Kretzschmar et al. (2018).

2.2.1. Sternberg Memory Scanning Task

A computer-adapted SMST was used. Participants were shown memory sets consisting of digits between 0 and 9. Three experimental conditions varying in set size were realized (set size 1, 3, and 5). The conditions were presented in a counterbalanced order across participants. A probe stimulus was presented 2000 ms after the memory set. The subjects were instructed to indicate as quickly as possible whether the probe was part of the previously shown positive set or not. Each of the three conditions started with 10 practice trials in which the participants received immediate feedback regarding their performance. The practice trials were followed by 100 test trials without feedback. The stimulus material exemplary for the set size 3 condition is depicted in Figure 1.

Each trial started with the presentation of a white fixation cross in the middle of a black screen. The cross was shown for 1000–1500 ms. The digits of the memory set were presented in a sequential fashion. Each digit was displayed in white on a black screen for 1000 ms with a black screen shown for 400–600 ms between each member of the positive set. Then, after the last digit was presented, a white question mark was shown for 1800–2200 ms. The question mark was followed by the presentation of the probe stimulus. In 50% of all trials, the probe stimulus was part of the memory set. Participants responded pressing one of two keys with their index fingers to indicate whether

the probe stimulus was part of the memory set or not. Before the next trial started, the screen remained unchanged for 1000 ms followed by an inter-trial interval of 1000–1500 ms.

Figure 1. Stimulus Material for the Sternberg Memory Scanning Task exemplary for set size 3.

2.2.2. Berlin Intelligence Structure Test (BIS)

The BIS (Jäger, Süß, and Beauducel 1997) is based on the hierarchical model of intelligence proposed by Jäger (1982). A single *g* factor stands on the highest hierarchy level. On the second level, Jäger (1982) breaks down general intelligence into the four operation-related components Processing Speed (PS), Processing Capacity (PC), Memory (M), and Creativity (C) and the three content-related levels Figural (F), Numeral (N), and Verbal (V). Each operation-related component is measured on the three content-related levels. In total, the BIS comprises 45 tasks that are all a combination of one operation-related component and one content-related level.

Participants completed the BIS in groups of up to four subjects. Their scores for all seven components were calculated by aggregating the normalized *z*-scores of all tasks belonging to the respective component as suggested by the test manual. Means for all seven components were computed. The mean score of the Processing Speed component was $M = 98.49$ ($SD = 6.37$), that of the Processing Capacity component was $M = 102.75$ ($SD = 7.49$), that of the Memory component was $M = 99.81$ ($SD = 5.84$), that of the Creativity component was $M = 98.09$ ($SD = 5.97$), that of the Verbal component was $M = 103.08$ ($SD = 6.31$), that of the Numerical component was $M = 98.67$ ($SD = 6.38$), and that of the Figural component was $M = 98.45$ ($SD = 6.27$). These scores are likely an underestimation of participants' cognitive abilities, as the norm data sample consisted of senior high school students. We subsequently transformed these scores into *z*-scores for further analysis. For manifest correlations, *z*-scores from the four subscales PS, PC, M, and C were averaged to form an estimate for *g*. For fixed-links SEMs, we used the four subscales as indicators of a latent general intelligence factor.

2.3. Procedure

Participants completed the SMST among other RT tasks that are not reported here (see Schubert, Hagemann, and Frischkorn 2017). The BIS and the APM, as well as a personality questionnaire, and questions concerning demographic data were completed at the second measurement occasion. In total, the first measurement occasion took approximately 3 hours while the second occasion lasted for about 3.5 hours. The EEG was recorded during the first measurement occasion while the participants sat in a dimly lit and sound-attenuated cabin and completed the RT tasks.

2.4. EEG Recording

The EEG was recorded with 32 equidistant Ag–AgCl electrodes. The aFz electrode was used as the ground electrode. Electrodes were initially referenced to Cz and offline re-referenced to an average reference. To correct for ocular artefacts, the electrooculogram was recorded bipolarly with two electrodes positioned above and below the left eye and two electrodes positioned at the outer canthi of the eyes. All electrode impedances were kept below 5 k Ω . The EEG signal was recorded continuously with a sampling rate of 1000 Hz (band-pass 0.1–100 Hz), and filtered offline with a low-pass filter of 16 Hz.

2.5. Data Analysis

2.5.1. Reaction time data

All RTs shorter than 100 ms or longer than 3000 ms were discarded as outliers. Moreover, only RTs of trials in which participants answered correctly were used for further analyses. Logarithmized RTs exceeding ± 3 SDs of the intraindividual mean of each set size condition were also discarded.

2.5.2. Electrophysiological data

ERPs were time-locked to the probe stimulus. Epochs had a duration of 1200 ms which included a baseline with a duration of 200 ms before stimulus onset. Segments with amplitudes exceeding ± 70 μ V or with amplitude changes larger than 100 μ V per 100 ms were discarded as artefacts as well as any segments with activity below 0.5 μ V. The P3 peak latency was measured at the parietal electrode over the midline separately for each of the three experimental conditions.

2.5.3. Statistical Analysis

After univariate outlier detection a multivariate outlier detection was performed prior to all further analyses. The Mahalanobis distance was calculated for each participant in the data space of RTs, P3 latencies, and BIS subscales resulting in 19 multivariate outliers, which were subsequently discarded. In a next step, the Shapiro-Wilk and Mardia tests were used to assess the univariate normality in all manifest variables. The R package MVN (Korkmaz, Goksuluk, and Zararsiz 2019) was used for calculating the Mahalanobis distance and to test the uni- and multivariate normality. The Shapiro-Wilk and Mardia tests showed that neither P3 latencies nor the BIS subscales deviated significantly from normal distribution. However, RTs in all set size conditions did ($p = .006$ for set size 1, $p < .001$ for set size 3, $p = .033$ for set size 5). Nevertheless, deviations from normal distribution of RTs in all set sizes were regarded as unproblematic because they stayed below threshold values of skewness = 2 and kurtosis = 7, respectively (West, Finch, and Curran 1995).

We used two-factorial repeated measures ANOVAs with the within-subjects factor set size (set size 1 vs. set size 3 vs. set size 5) and the between-subjects factors intelligence (low intelligence vs. high intelligence) to investigate the effects on RTs and P3 latencies, respectively. The Greenhouse-Geisser sphericity correction was applied by default. We also estimated Pearson correlation

coefficients to quantify the associations between mean RTs and mean P3 latencies with the averaged BIS-subscales. We also regressed RTs on set size for each participant to calculate individual slopes and estimate their correlation with individual differences in g . These analyses were conducted using the statistics software JASP (JASP Team 2019).

Following the computations on a manifest level, we used a FLM approach to tackle the problem of low reliability of the slope parameter and to control for the artificial correlation between the intercept and the slope of the linear function. Increasing the reliability of the slope parameter should, in theory, be possible because modeling with latent variables can attain an error-free estimate of the variable of interest (in this case the slope parameter). It should be noted that the FLM was also used to confirm a linear increase of RTs and P3 latencies with increasing set size, as a good model fit for a model that implements the foreseen linear trajectory should be evidence for its linearity.

We used the R package lavaan (Rosseel 2012) to specify structural equation models. Two separate models for RTs and P3 latencies were considered. The full model (exemplary for RTs) is depicted in Figure 2. In both models, RTs and P3 latencies were decomposed into two latent variables identified by three set size-specific manifest variable (mean RTs or P3 latencies). The first, denoted non-experimental latent variable, was thought to represent the intercept of the model with manifest variables. We assumed that the non-experimental latent variable was not sensitive to the experimental manipulation of the set sizes and fixed all factor loadings to 1. The second latent variable, denoted experimental latent variable, was thought to represent the slope of the model with manifest variables. The slope, as opposed to the intercept, is thought to be sensitive to the experimental manipulation. Factor loadings were therefore fixed to 1, 3, and 5 to reflect the linear increase of RTs or P3 latencies with increasing set size. Covariances between the two latent variables were fixed to zero to prevent a negative correlation. Goodness-of-fit was evaluated based on the comparative fit index (CFI; Bentler 1990) and the root mean square error of approximation (RMSEA; Browne and Cudeck 1992). In general, CFI values $\geq .90$ and RMSEA values $\leq .08$, were considered to indicate an acceptable model fit to the data, while CFI values $\geq .95$ and RMSEA values $\leq .06$ were considered to indicate a good model fit as suggested by Bentler and Hu (2009).

In a next step, a latent g factor was added to the FLM. This latent variable was measured through the z -standardized scores in the four operation-related components PS, PC, M, and C of the

Figure 2. FLM exemplary for RTs with an experimental latent variable (LV) RT, a non-experimental latent variable RT, and a latent variable g . Factor loading of the experimental latent variable RT were fixed to 1, 3, and 5. Factor loadings of the non-experimental latent variable RT were fixed to 1. Factor loadings of the latent variable g were estimated freely. The correlation between the experimental and non-experimental latent variable RT was set to zero, while they were both allowed to correlate with g freely. All fixed links are grayed out.

BIS. Correlations between the experimental latent variable in the RT or P3 latency model and the latent variable g were expected to be bigger than in the model with manifest variables only.

To assess the significance of the difference between the manifest and the latent correlation between the slope and g , factor scores of the experimental latent variable were extracted and correlated with the manifest intelligence and slope variable. A z-test for comparing correlations from dependent samples was computed to test the difference between the correlation between the estimated values of the experimental latent variable and BUS-scores and the correlation between the manifest slope and BIS-scores against each other. For this purpose, the freeware for testing correlations by W. Lenhard and A. Lenhard (2014) was used.

For both manifest and latent modeling, a significance level of $\alpha = .05$ was adopted.

3. Results

3.1. Reaction Time and General Intelligence

The two-way repeated measures ANOVA (see Figure 3) revealed a significant within-subjects main effect of set size on RTs, $F(2, 192) = 349.61$, $p < .001$, $\omega^2 = 0.45$, $\epsilon = 0.74$. Post-hoc comparisons showed a significant increase of RTs for each stepwise increase in set size; $t(97) = -12.46$, $p_{\text{bonf}} < .001$ for the increase from set size 1 to set size 3, and $t(97) = -13.97$, $p_{\text{bonf}} < .001$ for the increase from set size 3 to set size 5. The ANOVA also yielded a significant main effect of intelligence on RTs, $F(1, 96) = 5.33$, $p = .023$, $\omega^2 = .04$. Additionally, the Pearson correlation coefficient that was used to determine the strength of the association between mean RTs and the averaged BIS-scales PS, PC, M, and C yielded a significant negative association showing that more intelligent individuals exhibited faster RTs, $r = -.33$, $p < .001$. Furthermore, the ANOVA displayed a significant interaction between set size and intelligence on RTs, $F(1, 2) = 6.04$, $p = .007$, $\omega^2 = .01$.

The slope of the linear regression for each participant was significantly and negatively correlated with the BIS-scores, $r = -.32$, $p = .001$, indicating that more intelligent individuals exhibited a lower slope. We observed a statistically built-in negative correlation of $r = -.60$, $p < .001$ between the slope and the intercept of the linear function. All intercorrelations between the slope, intercept, the averaged BIS-scores, and mean RTs are summarized in Table 1.

These findings show that RTs increased with increasing set size, that RTs were negatively correlated with the BIS-scales, and that RTs of less intelligent individuals displayed a steeper trajectory with increasing set size.

In a next step, we used a FLM approach to further validate the linear increase of RTs with increasing set size and to investigate whether fixed-links modeling increased the association between the slope and intelligence. As described earlier, RT was decomposed into two latent variables, one experimental latent variable representing the slope and one non-experimental latent variable representing the intercept. The model provided an acceptable fit to the data, $\chi^2(1) = 2.45$, $p = .118$, $CFI = .99$, $RMSEA = .12$, indicating that RTs increased in a linear fashion with increasing set size. Next, a latent variable g was added to the model. Factor loadings of the latent general intelligence factor were estimated freely and the experimental and non-experimental latent variables were

Figure 3. Repeated Measures ANOVA for RTs. Participants were split into two groups by median split of general intelligence. Error bars display the 95% confidence interval.

Table 1. The Slope Parameter and its Correlation with the Intercept, Averaged BIS-Scores, and mean RTs

	Slope	Intercept	Averaged BIS-Scores	Mean RT
Slope	1 (–)	–	–	–
Intercept	-.60*** ¹ (<.001)	1 (–)	–	–
Averaged BIS-Scales	-.32** (.001)	-.05 (.660)	1 (–)	–
Mean RT	.57*** (<.001)	.32** (.001)	-.33*** (<.001)	1 (–)

¹ Note. * $p < .05$, ** $p < .01$, *** $p < .001$, p -values are displayed in parentheses.

allowed to covary freely with g . The model provided a good fit to the data, $\chi^2(13, 98) = 18.07$, $p = .155$, $CFI = .99$, $RMSEA = .06$. We observed a negative correlation between the latent slope factor and the latent g factor, $r = -.39$, $p = .006$.

As predicted, the FLM was able to substantially increase the previously reported manifest correlation of $r = -.32$ to $r = -.39$. To formally test if fixed-links modeling led to an increase of the estimated correlation, we extracted individual factor scores of the experimental latent variable and correlated them with participants' intelligence on a manifest level, $r = -.41$, $p < .001$. Correlations between the factor scores of the experimental latent variable RT, the manifest slope and BIS-scores are displayed in Table 2. The z -test for comparing correlations from dependent samples revealed a significant difference between the correlation between the estimated latent slope scores and BIS-scores and the correlation between the manifest slope and BIS-scores, $z = 2.72$, $p = .003$. This shows that the FLM approach allows to find a significantly larger relationship between the slope and intelligence. Please note, however, that this test is statistically not perfectly accurate, because it ignores the uncertainty in the estimation of individual slope scores. Nevertheless, our results suggest that participants' intelligence was more strongly related to their speed of information-uptake when estimated with the FLM approach than when estimated with the regression slope.

Table 2. Correlation Matrix of the Factor Score of the Experimental Latent Variable RT, the Manifest Slope, and averaged BIS-Scores

	FLM Factor Score	Manifest Slope	Averaged BIS-Scores
FLM Factor Score	1 (–)	–	–
Manifest Slope	.94*** ¹ (<.001)	1 (–)	–
Averaged BIS-Scales	-.41*** (<.001)	-.32** (.001)	1 (–)

¹ Note. * $p < .05$, ** $p < .01$, *** $p < .001$, p -values are displayed in parentheses.

3.2. P3 Latencies and General Intelligence

The two-way repeated measures ANOVA (see Figure 4) revealed no significant within-subjects main effect of set size on P3 latencies, $F(2, 192) = 2.15$, $p = .123$, $\omega^2 = .01$, $\varepsilon = 0.94$. This indicates that there was no increase in P3 latencies neither from set size 1 to set size 3 nor from set size 3 to set size 5. Consequently, the results of the ANOVA were not in favor of the hypothesis that P3 latencies increased linearly with set size. Thus, there was no support for the idea that they measure the same cognitive processes as RTs do. Still, a significant between-subjects main effect of intelligence on P3 latencies was found, indicating that more intelligent participants exhibited faster P3 latencies, $F(1, 96) = 71.47$, $p < .001$, $\omega^2 = .43$. In line with this main effect, the Pearson correlation coefficient unveiled a high and negative association between mean P3 latencies across all set size conditions and the aggregated BIS-scales, $r = -.73$, $p < .001$. Moreover, a significant interaction effect between set size and intelligence could be observed, $F(1, 2) = 3.51$, $p = .035$, $\omega^2 = .01$. Grand-average waveforms of the P3 latencies are presented in Figure 5 separately for more and less intelligent individuals and for each set size condition. These results indicate that more intelligent individuals displayed faster P3 latencies in general and a different trajectory than less intelligent individuals. However, these findings did not support the idea that P3 latencies increase linearly with set size since there was no main effect of set size and consequently, it cannot be said that more intelligent individuals displayed a lower slope. That is why we did not calculate individual slope values to estimate the correlation between the linear increase in P3 latencies across conditions and intelligence.

It is possible that the relatively large error bars accounted for the inability to find a linear increase of P3 latencies with set size. Therefore, the FLM approach was used to determine whether the idea of a linear increase of P3 latencies with set size should be rejected or not. As a first step, we modelled two latent variables for P3 latency: the first denoted non-experimental latent variable P3 representing the intercept, and the second denoted experimental latent variable P3 representing the slope. This model provided a good fit to the data, $\chi^2(1, 98) = 0.79$, $p = .374$, $CFI = 1$, $RMSEA = 0.00$. However, it also exhibited an insignificant variance of the experimental latent variable P3, $p = .613$, indicating that there was no latent slope factor of varying P3 latencies across set size. Hence, the FLM approach confirmed that there was no linear increase in P3 latencies across experimental conditions. Subsequently, we refrained from adding general intelligence to the FLM as we could not observe any association between the experimental latent variable and g .

Figure 4. Repeated Measures ANOVA for P3 latencies. Participants were split into two groups by median split of general intelligence. Error bars display the 95% confidence interval.

Figure 5. Grand averages of P3 latencies as measured at the parietal electrode over midline, separately for more and less intelligent individuals and experimental conditions.

Post-hoc analyses of a subsample of $n = 45$ subjects between the ages of 18 and 30 years were carried out to rule out possible effects of age differences on ERP components (Polich 1997). The ANOVA (see Figure 6) did reveal a significant main effect of set size on P3 latencies for this subsample, $F(2, 84) = 3.90$, $p = .030$, $\omega^2 = .03$, $\varepsilon = 0.86$. However, the post-hoc comparisons showed that only the increase from set size 3 to set size 5 led to an increase in P3 latencies, $t(45) = -2.75$, $p_{\text{bonf}} = .022$, whereas there was no significant difference between set sizes 1 and 3, $t(45) = 0.95$, $p_{\text{bonf}} = .347$. In line with this, the attempt to confirm a significant experimental latent variable P3 using an FLM approach with factor loadings fixed to 1, 3, and 5 failed, $p = .717$, despite good overall model fit, $\chi^2(1) = 0.002$, $p = .965$, $RMSEA = 0.00$, $CFI = 1$. We then fixed the factor loadings of the experimental latent variable P3 to 1, 1, and 5, since the post-hoc comparisons only confirmed an increase of P3 latency with set size from set size 3 to set size 5. The model provided a good fit, $\chi^2(1) = 0.101$, $p = .751$, $RMSEA = 0$, $CFI = 1$, the variance of the experimental latent variable P3, however, did not reach the level of significance, $p = .869$.

The findings on a manifest level in the main sample as well as in the subsample showed that intelligence was associated with shorter P3 latencies at all set sizes. However, the findings could not support the hypothesis that P3 latencies measure the same cognitive processes as RTs because a linear increase with set size was found in neither the model with manifest variables nor the model with latent variables.

4. Discussion

The aim of the present study was to investigate the relationship between the two measures RT and P3 latency in the SMST and to see whether they both measure serial memory scanning sensu Sternberg (1969). Furthermore, the capability of the slope parameter to predict intelligence was re-evaluated using a manifest and a latent variable approach.

4.1. Serial Memory Scanning and Intelligence: Reaction Times

Concerning RTs, the repeated measures ANOVA as well as the FLM supported the hypothesis that RTs increase linearly with set size. This is in line with previous research on the SMST (e.g. Chiang and Atkinson 1976; Ergen et al. 2012; McGarry-Roberts, Stelmack, and Campbell 1992; Pelosi, McHayward, and Blumhardt 1995; Sternberg 1969). The results agree with Sternberg's (1969) original interpretation of a serial memory scanning where every member of the memory set has to be compared to the probe stimulus in a single comparison operation, which in turn leads to a linear increase of RTs with every stepwise increase in set size.

Moreover, the present data could show that RTs in the SMST are negatively correlated with the BIS-scores. Former research on the relationship between RTs and intelligence in different RT paradigms (and specifically in the SMST) very much aligns with the present findings (e.g. Doeblér and Scheffler 2016; McGarry-Roberts, Stelmack, and Campbell 1992; Neubauer et al. 1997; Rammsayer, Pahud, and Troche 2017; Schubert 2019; Sheppard and Vernon 2008).

A negative correlation alone does not tell us a lot about which cognitive process parameters differ between more and less intelligent individuals. By describing RTs as a linear function of set size and thus, decomposing RTs into an intercept (processes like planning and execution of motor response) and a slope (the specific process of comparing every member of the positive set to the

Figure 6. Repeated Measures ANOVA for RTs. Participants were split into two groups by median split of general intelligence. Error bars display the 95% confidence interval.

probe stimulus), it is possible to only relate the slope parameter to intelligence. In the scope of Sternberg's (1969) serial memory scanning theory, a negative correlation between the slope and intelligence would indicate that more intelligent individuals profit from faster comparison operations and a faster retrieval from short-term memory, respectively. However, in the literature, the presumed relationship between the slope and intelligence has been difficult to confirm (Jensen 1987, 1998). Nonetheless, we observed a significant correlation of $r = -.32$, $p = .001$ in the present study. This finding was surprising because we expected the correlation to be rather low or even insignificant. Only a FLM approach was thought to be able to circumvent the problem of low reliability and artificial high correlation between intercept and slope (see Jensen 1998). Therefore, it needs to be asked why we could find a significant negative correlation of medium size while earlier research often failed to do so. For example, Jensen (1987) found a correlation between the slope of RTs regressed on set size in the SMST and intelligence of $r = -.06$. The same study also investigated the slope of the Hick function and reported a positive correlation of $r = .19$. A possible explanation for these counterintuitive and contradicting results might be a restriction of range of the intelligence variable that was measured with the APM. Jensen (1987) did not report the distribution of the APM scores. However, the sample ($N = 48$) consisted solely of university undergraduates, and thus, it is possible that individuals scoring low on the APM were underrepresented in the sample. A restriction of range in the general intelligence variable would inevitably lead to an attenuated correlation between intelligence and slope. In contrast to the findings of Jensen (1987), Neubauer et al. (1997) did find a negative correlation of $r = -.17$ between the slope of the linear regression and intelligence. Additionally, psychometric intelligence (again measured with the APM) was normally distributed and the sample included participants from different educational and occupational backgrounds. As indicated by the reported mean test scores ($M = 23.72$, $SD = 4.68$), it is reasonable to presume that there was no significant range restriction in the intelligence variable in Neubauer et al. (1997). Still, the correlation of $r = -.17$ is substantially smaller than the present finding of $r = -.32$. Furthermore, the correlations between mean RTs and psychometric intelligence (ranging from $r = -.20$ to $r = -.25$ across the different set size conditions) were much smaller than in the current study ($r = -.34$). Possibly, different outlier detection procedures that were applied might account for the discrepancy between the correlations. Neubauer et al. (1997) applied a stricter detection criterium with all RTs > 1500 ms discarded that might have led to a restriction of the RT range and consequently to an attenuated variance of the slope. Moreover, participants completed only a fifth (20 per condition) of the number of trials that participants completed in the present study (100 per condition), which must have affected the reliability of the resulting mean RT measures.

Furthermore, there was support for the hypothesis that a FLM approach is indeed able to increase the association between the slope and intelligence. The larger correlation between the factor scores of the latent variable RT and intelligence in comparison to the correlation between the manifest slope and intelligence shows that the FLM is a suitable model for investigating the effects of specific processes like serial memory scanning on intelligence. The FLM has also proven to be a suitable model to investigate specific processes in the Hick task (Hick 1952) as demonstrated by Schweizer (2006) and Rammsayer, Pahud, and Troche (2017).

4.2. Serial Memory Scanning and Intelligence: P3 Latencies

As opposed to RTs, it was not possible to find support for the underlying assumption that the P3 latency, interpreted as stimulus evaluation time, reflects serial memory scanning in the sense of Sternberg (1969). Neither the model with manifest variables nor the FLM approach provided evidence for a linear increase of P3 latencies with set size that corresponds to the trajectory of RT data. The P3 latencies of all participants remained stable across all set sizes, the manipulation of the set size had no effect on P3 latencies. The inability to demonstrate a linear increase of P3 latencies with set size is inconsistent with Donchin and Coles's (1988) context updating theory stating that P3 latencies reflect the stimulus evaluation time. On the basis of this theory, it was expected that an increased memory load in larger set sizes would lead to a stepwise increase of the time needed to evaluate the probe stimulus and to decide whether or not it was part of the memory set.

This finding is also surprising as it contradicts previous studies that found an increase in P3 latencies with set size (e.g. Ergen et al. 2012; Houlihan 1998; Pelosi, McHayward, and Blumhardt 1995; Schubert et al. 2015). The findings from previous research, however, are also inconsistent to some extent as Pelosi, McHayward, and Blumhardt (1995) could only confirm a significant increase of P3 latencies from set size 1 to set size 3. Ergen et al. (2012), Houlihan (1998), and Schubert et al. (2015) reported an overall increase of P3 latencies with set size. Ergen et al. (2012), however, only realized two set size conditions: set size 3 and set size 5. As a consequence, no conclusions concerning the trajectory of P3 latencies in smaller set sizes can be drawn.

The ambiguity between the findings of the aforementioned studies could be due to the throughout small sample sizes used. For example, Ergen et al. (2012) only recruited 18 participants. Similarly, the sample size in Houlihan (1998) was $N = 61$. The sample sizes in Pelosi, McHayward, and Blumhardt (1995) and Schubert et al. (2015) were also relatively small with a total of 37 and 40 participants, respectively. In the present study, the sample size was substantially larger with a total of 98 cases. If the true effect of set size on P3 latencies were small (e.g., $f = .10$), a sample size of $N = 134$ participants would be needed to detect it with a Type I-error probability of $\alpha = .05$ and a power of $1 - \beta = .80$ (Erdfelder, Faul, and Buchner 1996), given the correlations of ERP latencies across conditions found in the present study ($\bar{r} = 0.59$). This indicates that the sample sizes in all aforementioned studies including the present one were too small to reliably describe the effect of set size on P3 latencies.

In addition, Polich (1997) highlighted the effects of normal ageing on EEG and ERP components. In particular, the P3 component of the ERP was shown to be sensitive to increasing age which is reflected in smaller P3 amplitudes and longer P3 latencies (Polich 1997). Most of the studies that found an overall increase of P3 latencies acquired data from participants that were considerably younger than in the present study ($M = 35.9$, $SD = 13.5$). For example, Ergen et al. (2012) recruited participants with a mean age of 26 years ($SD = 5.1$). Similarly, the mean age in Houlihan (1998) was 22.7 years (aged 18 to 37 years). However, our post-hoc analysis that examined a subsample of $n = 45$ subjects between the ages of 18 and 30 years was not able to replicate earlier findings of an overall increase of P3 latencies with set size. Only the increase from set size 3 to set size 5 reached the level of significance. Again, we attribute the inability to find results that truly support earlier research to the small sample size of our subsample. A power analysis estimated that the sample size must be at least $N = 140$ to discover a small effect of $f = .10$ in a repeated measures ANOVA given $\alpha = .05$, $1 - \beta = .80$, and an intercorrelation among the repeated measures of $\bar{r} = .59$ (Erdfelder et al., 1996). Given this, it is not possible to say with certainty that the age of participants accounts for the different findings. A sample with sufficient power would be needed to investigate this issue further. Taken together, our results indicate that neural processing as measured by P3 latencies may reflect a different cognitive process than serial memory scanning, as we found no evidence that P3 latencies increased linearly with set size. The conclusion that behavioral and electrophysiological performance measures cannot readily be mapped onto each other is in line with previous research, which demonstrated that an increase in set size in the SMST did not only affect a specific ERP component, but several of them simultaneously (Schubert et al. 2015).

Because there was no linear increase in P3 latencies across set sizes, we did not compute a slope parameter that would have reflected individual differences in this increase. Subsequently, we found no evidence that more intelligent individuals show a shallower increase in P3 latencies across set sizes.

4.3. Limitations

Several limitations must be taken into consideration. Most importantly, Kretzschmar and Gignac (2019) highlighted the importance of sample size in order to estimate a stable correlation in a latent variable framework. For a latent correlation of $r = .40$ and latent variables with a reliability ranging from $\omega = .80$ to $\omega = .90$ (in our present study $\omega = .87$ for the experimental latent variable RT and $\omega = .85$ for the latent variable g), a sample size between $N = 220$ and $N = 290$ would have been needed to estimate a latent correlation with a confidence interval of 80% (Kretzschmar

and Gignac 2019). The relatively small sample size in the present data ($N = 98$) results in the difficulty of precisely estimating the size of the relationship between the latent constructs, and thus, it is likely that the FLM approach did not yet exploit its maximum potential to this point. In the future, it should be tested again with a larger sample size.

Another limitation concerns the question of linearity. In the present data, only three set size conditions were realized, leading to a restriction of range of the predictor variable set size. This could be an explanation for the inability to demonstrate a linear increase with set size, especially for the P3 latency data. In this context, it is interesting to consider possible floor and ceiling effects of linearity. Of course, it is always possible to fit a line through two points (i.e. two set size conditions) as for example in Ergen et al. (2012). However, with only two set size conditions realized, it is merely possible to describe the trend of the trajectory of P3 latencies regressed on set size. More data points are needed in order to be able to predict the P3 latency at different set size conditions. The more data points, the better the prediction will be. The ambiguity between the findings of this study and the research of Houlihan (1998) (an overall increase of P3 latencies with set size was found) and Pelosi, McHayward, and Blumhardt (1995) (an increase of P3 latencies with set size was found but only the increase from set size 1 to set size 3 reached the level of significance) could be due to the limited number of set size conditions in all of these studies. A low sampling rate of set sizes (all of these studies recorded ERP latencies only in set sizes 1, 3, and 5) makes it difficult to properly describe the function relating ERP latencies to memory set sizes. It would be interesting to explore not only the effect of set sizes left out in the present study (i.e., set sizes 2 and 4), but also the effects of larger set sizes on P3 latencies. It should be kept in mind, however, that set sizes too large to be simultaneously held in short-term memory, may result in the recruitment of additional neurocognitive processes, resulting in disproportional increases in RTs and P3 latencies. Alternatively, extremely large set sizes may result in no further increase in RTs and P3 latencies, as participants may no longer be able to conduct a full search of their (overtaxed) short-term memory (Sternberg 1969).

5. Conclusions

We found support for earlier findings that RTs in the SMST increase linearly with set size, that RTs are negatively correlated with g , and that the slope of the linear function of RTs regressed on set size is correlated with g . This relationship could be increased substantially using a FLM approach. No support for the idea that P3 latencies increase linearly with set size was found. The different trajectories of RTs and P3 latencies suggest that they do not both measure the serial memory scanning in the sense of Sternberg (1969). The results suggest that the process captured by P3 latencies that takes place during the SMST is less affected by the experimental manipulation. Still, the speed of the specific process of comparing the probe stimulus with every member of the memory set (reflected in the slope of RTs regressed on set size) could be identified as one specific process that differs in efficiency between more and less intelligent individuals. Most importantly, we demonstrated that the FLM approach is undoubtedly suitable for predicting g by decomposing individual differences in specific experimental processes such as the retrieval of information from short-term memory. The FLM could overcome deficiencies of the slope on a manifest level (low reliability and negative correlation with the intercept) and is therefore more appropriate to investigate associations between experimental slope measures and intelligence than manifest approaches.

Supplementary Materials: All data and R scripts are available online on this paper's project page on the Open Science Framework at <https://osf.io/q4xc8/>.

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