Within-person structures of daily cognitive performance cannot be inferred from between-person structures of cognitive abilities

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Over a century of research on between-person differences has resulted in the consensus that human cognitive abilities are hierarchically organized, with a general factor, termed general intelligence or "*g*," uppermost. Surprisingly, it is unknown whether this body of evidence is informative about how cognition is structured within individuals. Using data from 101 young adults performing nine cognitive tasks on 100 occasions distributed over six months, we find that the structures of individuals' cognitive abilities vary among each other, and deviate greatly from the modal between-person structure. Working memory contributes the largest share of common variance to both between- and within-person structures, but the *g* factor is much less prominent within than between persons. We conclude that between-person structures of cognitive abilities cannot serve as a surrogate for within-person structures. To reveal the development and organization of human intelligence, individuals need to be studied over time.

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Abstract

Over a century of research on between-person differences has resulted in the consensus that human cognitive abilities are hierarchically organized, with a general factor, termed general intelligence or "*g*," uppermost. Surprisingly, it is unknown whether this body of evidence is informative about how cognition is structured within individuals. Using data from 101 young adults performing nine cognitive tasks on 100 occasions distributed over six months, we find that the structures of individuals' cognitive abilities vary among each other, and deviate greatly from the modal between-person structure. Working memory contributes the largest share of common variance to both between- and within-person structures, but the *g* factor is much less prominent within than between persons. We conclude that between-person structures of cognitive abilities cannot serve as a surrogate for within-person structures. To reveal the development and organization of human intelligence, individuals need to be studied over time.

Introduction

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The quantitative measurement of intelligence is one of the greatest accomplishments in the behavioral sciences (Nisbett et al., 2012). A century or more of research has resulted in a consensual view that human cognitive abilities are hierarchically organized (Carroll, 1993). At the bottom of the hierarchy, numerous specific abilities, such as numerical reasoning or verbal fluency, can be identified. Differences between individuals in specific abilities form broader abilities like reasoning or episodic memory, which again show substantial positive correlations with one another. This pattern has led researchers to postulate the concept of a general cognitive ability, or "*g*," at the top of the hierarchy (Jensen, 1998; Spearman, 1927). Often equated with the term "intelligence," the *g* factor is a dominant predictor of between-person differences in real-life outcomes such as educational success, vocational achievement, health, and mortality (Batty, Deary, & Gottfredson, 2007; Deary et al., 2007; Gottfredson & Deary, 2004; Schmidt & Hunter, 1998; Strenze, 2007).

Virtually all of the evidence on the hierarchical structure of human intelligence is based on associations among between-person differences in performance on batteries of cognitive tasks. A large body of research shows that both genetic and epigenetic differences (e.g., reflecting birth weight, nutrition, formal schooling, etc.) contribute to the hierarchical organization of these between-person differences (Deary, 2001). However, it is likely that many factors contributing to differences *between* individuals vary less, or differently, *within* individuals. One example are allelic variations of the genome, which are present between but not within individuals. Conversely, the factors that contribute to variations within persons over time may contribute little to average between-person differences. The effects of weather conditions on cognitive performance may be an example—at least for people living in the same place. Besides these pronounced examples, there is a host of factors that may influence both, differences between persons as well as variation within persons over time. For example, people differ from each other in their average level of motivation and they vary in their momentary levels of motivation over time (Brose et al., 2010). These different factors may potentially influence all tasks (contributing to the *g* factor), only tasks of one or more of the broader or narrower abilities (contributing to the variance of the corresponding ability factors), or only single tasks (contributing to the variance of just the corresponding task), and they might do so to different degrees at the different levels of analysis. Furthermore, the different factors that are operating might be correlated to different degrees across persons and/or across time. It can therefore be expected that corresponding correlation structures at the between-person and the within-person level could only be found after accounting for all the factors that differentially affect the different levels (Voelkle et al., 2014).

Without taking into account these factors, many of which are probably unknown or unobservable, there is no strong theoretical reason to expect a close correspondence between within-person and between-person structures of cognitive abilities (Molenaar, Huizenga, & Nesselroade, 2003). As an illustration, imagine that episodic memory and working memory correlate $r = .70$ when assessed in 100 different individuals at a single occasion. Further consider that each of these 100 individuals is assessed on 100 different days on the same two sets of

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measures, and correlations are computed for each individual separately across the 100 days. How much do within-person correlations of these 100 individuals differ from each other? Will an observed between-person correlation of r = .70 fall within or outside the distributional range of the 100 within-person correlations? These questions await empirical testing. Nevertheless, in psychology and cognitive neuroscience, the structure of between-person variation is often treated as a proxy or surrogate for the organization of intelligent behavior at the individual level. Such research practice has become subject to challenge on theoretical grounds, necessitating a need for a formal comparison of between-person and within-person structures of psychological constructs directly (Borsboom, Mellenbergh, & van Heerden, 2003; Kievit et al., 2013; Lautrey, 2003; Molenaar, 2004). However, no comprehensive investigation of the correspondence between within- and between-person structures of cognitive abilities has been reported thus far.

To address this question, we conducted the COGITO study, in which 101 adults aged 20 to 31 years worked on a battery of twelve cognitive tasks on over 100 daily occasions. In an earlier report, we demonstrated the presence of reliable day-to-day fluctuations in cognitive performance within individuals (Schmiedek, Lövdén, & Lindenberger, 2013; for similar results, see Rabbitt, Osman, Moore, & Stollery, 2001). Here we determine the degree of similarity between within-person and between-person structures of cognitive abilities using the Kullback-Leibler (KL) divergence (Kullback & Leibler, 1951). Specifically, we investigate whether correlation structures based on between-person differences are similar to within-person structures based on repeated daily assessments. The KL divergence is an appropriate metric for this question because it provides a symmetrical measure of how much information (measured in nats = 1.44 bits) is lost when one statistical distribution (i.e., a between-person correlation matrix) is used to describe another distribution (i.e., a within-person correlation matrix; see below for further information).

Materials & Methods

Participants and Procedure

During the daily assessment phase of the COGITO Study, 101 younger adults (51.5% women, age: 20–31 years, M = 25.6, SD = 2.7) completed an average of 101 practice sessions. The sample was quite representative regarding general cognitive functioning, as indicated by comparisons of Digit-Symbol performance with data from a meta-analysis (Schmiedek, Lövdén, & Lindenberger, 2010). The attrition rate for those participants who had entered the longitudinal practice phase was low (for details on dropout rates and reasons for dropout in the different study phases, see Schmiedek et al., 2010).

Participants practiced individually in lab rooms containing up to six computer testing places. They could come to the lab and do testing sessions on up to six days per week (Mondays to Saturdays). On average, it took participants 197 days to complete the 100 sessions. Before and after this longitudinal phase, participants completed pre- and posttests in ten sessions that consisted of 2–2.5 h of comprehensive cognitive test batteries and self-report questionnaires. Participants were paid between 1450 and 1950 Euros, depending on the number and temporal density of completed sessions. The ethical review board of the Max Planck Institute for Human Development, Berlin, approved the study. All research was performed in accordance with relevant guidelines. Informed written consent was obtained from all participants.

Tasks

In each practice session, participants practiced twelve different tasks drawn from a facet structure cross-classifying cognitive abilities (perceptual speed, episodic memory, and working memory) and content material (verbal, numerical, figural-spatial) with two to eight blocks of trials each (for information on all practiced tasks, see Schmiedek, Lövdén, & Lindenberger, 2010). Three of a total of six tasks of perceptual speed were choice reaction tasks that were included to measure basic aspects of information processing. They were not considered in the current analyses. Here, we used three comparison tasks of perceptual speed that are more typical for cognitive test batteries applied in research on the structure of intelligence (see below for information on tasks applied here).

For the episodic and working memory tasks, presentation time (PT) was adjusted individually based on pretest performance. For each task and each individual, mean accuracies for the different PT conditions at pretest were fitted with exponential time-accuracy functions (including freely estimated parameters for onset, rate, and asymptote as well as a lower asymptote parameter fixed to different values for each task, e.g., 0.10 for memory updating). The fitted values from these functions were used to choose PTs that are clearly above random guessing but below some upper level. The upper level was defined by the midpoint between the lower asymptote level and perfect accuracy [e.g., (0.10 + 1.0)/2 = 0.55 for Memory Updating; see below], while the minimum level was defined by the midpoint between the lower asymptote level and the upper level [e.g., (0.10 + 0.55)/2 = 0.325 for Memory Updating]. The PT was then chosen such that the predicted performance level based on the time-accuracy function was above the minimum level and below the upper level. If performance was above the upper level for the second-fastest PT, the fastest PT was chosen even if predicted accuracy was below the minimum level for the fastest PT. The lower asymptote level was set to 0.10 for Memory Updating, to 0.50 for the 3-Back, and to 0.00 for the episodic memory tasks. For the Alpha Span task, we deviated from the described procedure and chose 0.00 as the lower asymptote, 0.40 as the minimum level, and 0.60 as the upper level on the basis of empirically observed time-accuracy functions.

Perceptual speed: Comparison tasks. In the numerical, verbal, and figural versions of the comparison task, either two strings of five numbers or digits each, or two colored three-dimensional objects consisting of several connected parts (“fribbles”) appeared on the left and right of the screen. Participants had to decide as quickly as possible whether both stimuli were exactly the same or different. If different, the strings differed only by one number or letter and the objects differed only by one part. Number strings were randomly assembled using digits 1 to 9. Letters were lower case and randomly assembled from all consonants in the alphabet, thus ensuring that they could not actually form real words. In each session, two blocks of 40 items were included with equal numbers of same and different stimuli. Images of fribbles used in this task are courtesy of Michael J. Tarr, Brown University, http://www.tarrlab.org/.

All three comparison tasks were scored by dividing the number of correct responses by the total response time (in seconds) and multiplying this quotient by 60 (i.e., creating a score of correct responses per minute). To reduce the influence of outliers, scores above 100 were set to missing (0.5% of the observed data).

Episodic memory tasks.

- ***Verbal episodic memory: Word Lists.*** Lists of 36 nouns were presented sequentially with PTs of 1000, 2000, or 4000 ms, and an interstimulus interval (ISI) of 1000 ms. Word lists were assembled so as to balance word frequency, word length, emotional valence, and imageability across lists. After presentation, words had to be recalled in the correct order by entering the first three letters of each word using the keyboard. Two blocks were included in each daily session. The performance measure was based on the percentage of correctly recalled words multiplied by a score ranging from 0 to 1, which represented the correctness of the order (based on a linearly rescaled tau rank correlation). The resulting scores were logit-transformed before entering the analyses.
- ***Numerical episodic memory: Number-Noun Pairs.*** Lists of 12 two-digit numbers and nouns in plural case pairs were presented sequentially with PTs of 1000, 2000, or 4000 ms; and an ISI of 1000 ms. After presentation, all numbers had to be entered based on random noun prompts. Two blocks were included in each daily session. The performance measure used in the analyses was the logit-transformed percentage of number of correctly recalled numbers.
- ***Figural-spatial episodic memory: Object Position Memory.*** Sequences of 12 coloured photographs of real-world objects were displayed at different locations in a six-by-six grid with PTs of 1000, 2000, or 4000 ms, and an ISI of 1000 ms. After presentation, objects appeared at the bottom of the screen and had to be moved to the correct locations in the correct order by clicking on objects and locations with the computer mouse. Two blocks were included in each daily session. The performance measure was the percentage of items placed in the correct locations multiplied by a score ranging from 0 to 1, which represented the correctness of the order (based on a linearly rescaled tau rank correlation). The resulting scores were logit-transformed before entering the analyses.

Working memory tasks.

- ***Verbal working memory: Alpha Span.*** Ten upper-case consonants were presented sequentially together with a number located below the letter. For each letter, participants had to decide as quickly as possible whether the number corresponded to the alphabetic position of the current letter within the set of letters presented up to this step. Five of the ten items were targets. If position numbers were incorrect (non-targets), they differed from the correct position by +/- one. PTs were 750, 1500, or 3000 ms, and the ISI was 500 ms. Eight blocks were included in each daily session. The performance measure used in the analyses was based on the percentages of correct responses. Scores were averaged across odd and even blocks and logit-transformed.

- ***Numerical working memory: Memory Updating.*** Participants had to memorize and update four one-digit numbers. In each of four horizontally placed cells, one of four single digits (from 0 to 9) was presented simultaneously for 4000 ms. After an ISI of 500 ms, a sequence of eight "updating" operations were presented in a second row of four cells below the first one. The updating operations were subtractions and additions from -8 to +8. The updating operations had to be applied to the digits memorized from the corresponding cells above and the new results then also had to be memorized. Each updating operation was applied to a cell different from the preceding one, so that no two updating operations had to be applied to one cell in sequence. PTs were 500, 1250, or 2750 ms, and the ISI was 250 ms. The final result for each of the four cells had to be entered at the end of each trial. Eight blocks were included in each daily session. The performance measure used in the analyses was based on the percentages of correct responses. Scores were averaged across odd and even blocks and logit-transformed.
- ***Spatial working memory: 3-Back.*** A sequence of 39 black dots appeared at varying locations in a four-by-four grid. For each dot, participants had to determine whether it was in the same position as the dot three steps earlier in the sequence or not. Dots appeared at random locations with the constraints that (a) 12 items were targets, (b) dots did not appear in the same location at consecutive steps, (c) exactly three items each were 2-, 4-, 5-, or 6-back lures, that is, items that appeared in the same position as they had 2, 4, 5, or 6 steps earlier. The presentation rate for the dots was individually adjusted by varying ISIs (500, 1500, or 2500 ms). PT was fixed at 500 ms. Four blocks were included in each daily session. The performance measure used in the analyses was based on the percentages of correct responses on trials 4-39. Scores were averaged across odd and even blocks and logit-transformed.

Validity of the tasks. To evaluate the validity of our tasks for the assessment of cognitive abilities, we made use of an established paper-and-pencil intelligence test battery, the Berlin Intelligence Structure (BIS) Test (Jäger, Süß, & Beauducel, 1997), which included the cognitive ability factors of perceptual speed, episodic memory, and reasoning (used here as the criterion ability for working memory).

For the perceptual speed tasks, the latent correlation with BIS factor at pretest was .58, while the correlations with reasoning and episodic memory in the BIS were .25. At posttest, the correlation with perceptual speed in the BIS significantly decreased to .28, whereas the correlations to reasoning and episodic memory did not differ significantly (Table 1). For the working memory tasks, the latent correlations with reasoning ranged from .82 to .96 at pretest (for the different presentation times), and decreased to .50–.68 at posttest, with differences being significant for the two slower presentation time conditions. The correlations with perceptual speed and episodic memory in the BIS did not differ significantly between pretest and posttest (Table 2). For our EM tasks at pretest, the latent correlations with the BIS episodic memory factor ranged from .76 to .82 and were lower for reasoning (.51–.54) and for perceptual speed (.51–.52). At posttest, none of the correlations differed significantly from the correlations at pretest (Table 3). In sum, in line with early suggestions (Hofland, Willis, & Baltes, 1981; Labouvie et al., 1973), there were some indications that perceptual speed and working memory lost some of their criterion validity, when taking paper-and-pencil based assessments as reference. Because of this, we included the posttest scores into the comparisons of between-person and within-person structures.

Data Analysis

De-trending. All analyses were carried out with raw data and de-trended data. The de-trended data were computed by first smoothing every within-person time series using a Gaussian filter with a standard deviation of three sessions. Afterwards, the smoothed time series was subtracted from the raw time series to obtain the de-trended time series. The algorithm used is part of the Onyx SEM software system backend (von Oertzen, Brandmaier, & Tsang, 2015).

Kullback-Leibler divergences. Distances between correlation structures were computed as the symmetrical KL divergence (Kullback & Leibler, 1951). The KL divergence of two distributions A and B is the number of information units lost when describing a random variable by A if it really follows B. The symmetrical KL divergence is the sum of the distance from A to B and the distance from B to A. For normal distributions with covariance matrices Σ_1 and Σ_2 of K variables, the symmetrical KL is given by

$$symKL\ (\Sigma_1,\ \Sigma_2) = 2K + Tr(\Sigma_1\Sigma_2^{-1}+\Sigma_2\Sigma_1^{-1})$$

Statistical testing with KL divergences. To establish that the differences of the within-person correlation matrices from each other and from the between-person centroid are significant, a null distribution was sampled, and the actual divergences were compared to this distribution. We simulated the same data structure as that of the actual data, namely, 101 data lines with nine tasks, under the null hypothesis that the underlying correlation matrix is the same for all participants, that is, either the within-person centroid or the between-person centroid. The average symmetrical KL divergence in the simulated data was computed for each of 10,000 trials, either the KL divergence of all within-person pairs or the distance from each within-person pair to the between-person centroid, respectively. The actual average symmetrical KL divergence was then compared to this distribution. If, for example, the actual average symmetrical KL divergence is within the highest 5% of the simulated trials, this indicates a significant rejection of the null hypothesis with $\alpha = 5\%$.

Multidimensional scaling (MDS). To illustrate the distance between within-person and between-person correlation matrices, KL divergences were embedded in a lower-dimensional space that preserves the maximal precision of the pairwise differences using MDS (Torgerson, 1958). MDS finds a vector of coordinates for every correlation matrix such that the Euclidean distances between pairs of vectors are closest to the KL distances of the correlation matrices. A property of MDS is that a solution for fewer dimensions is a projection from the solutions for more dimensions, that is, the coordinates of the first dimensions are always the same for any number of dimensions in the MDS. A plot of the first two coordinates is read as an illustration of the distances of the covariance matrices. The MDS was computed using an algorithm that is part of the Onyx SEM software system backend (von Oertzen et al., 2015).

Hierarchical factor models of centroid correlation matrices. Centroid correlation matrices based on the between-person and the raw or de-trended within-person data were calculated as the component-wise average of all correlation matrices. These correlation matrices were then submitted to confirmatory factor models (using SAS PROC CALIS) imposing a hierarchical structure, with tasks loading on three ability factors (i.e., perceptual speed, working memory, and episodic memory) that loaded on a general factor (thereby forming a saturated second-order factor sub-model). For the between-person correlation matrix, this resulted in very good model fit ($\chi^2[24] = 20.77$, $p = .998$; Root Mean Squared Error of Approximation (RMSEA) = .00; CFI) = 1.00; Standardized Root Mean Squared Residual (SRMR) = .06). Standardized factor loadings ranged from .60 to 1.00 for the perceptual speed tasks', from .52 to .84 for the episodic memory tasks', and from .46 to .50 for the working memory tasks' loading on the respective ability factors. The ability factors' loadings on the general factor were .27 for perceptual speed, .54 for episodic memory, and 1.00 for working memory.

For the centroid within-person correlation matrix of raw data, model fit was also very good ($\chi^2[24] = 9.03$, $p = 1.00$; RMSEA = .00; CFI = 1.00; SRMR = .04). However, as the number of independent observations for the average within-person correlation matrix is unknown due to possible autocorrelations of the repeated assessments, the fit indices based on χ^2 (RMSEA and CFI) for this, and the analysis of de-trended data below, need to be interpreted with caution. Standardized factor loadings ranged from .71 to .78 for the perceptual speed tasks, from .46 to .53 for the episodic memory tasks, and from .54 to .65 for the working memory tasks loading on the respective ability factors. The ability factors' loadings on the general factor were .55 for perceptual speed, .71 for episodic memory, and 1.00 for working memory.

For the centroid within-person correlation matrix of raw data, model fit was again very good ($\chi^2[24] = .90$, $p = 1.00$; RMSEA = .00; CFI = 1.00; SRMR = .02). Standardized factor loadings ranged from .44 to .63 for the perceptual speed tasks', from .31 to .46 for the episodic memory tasks', and from .16 to .44 for the working memory tasks' loading on the respective ability factors. The ability factors' loadings on the general factor were -.06 for perceptual speed, .82 for episodic memory, and 1.00 for working memory. In other words, while there were only very small amounts of shared variance among the working memory tasks, the common variance was strongly shared with the episodic memory tasks once variance due to longer-term trends was taken out.

Results

For the present analyses, we used nine cognitive tasks that are (a) suitable for intensively repeated assessments and (b) representative of broad ability factors in established hierarchical models of intelligence. Specifically, the tasks represent perceptual speed with comparison tasks, episodic memory with different recall tasks, and different working memory paradigms. The latter were chosen because of the close relation of working memory to the important factor of fluid intelligence/reasoning in our study (Schmiedek, Lövdén, & Lindenberger, 2014) and in the literature (Conway, Kane, & Engle, 2003; Duncan, 2013; Kyllonen & Christal, 1990; Wilhelm, Hildebrandt, & Oberauer, 2013), and the fact that they are much better suited for repeated assessment across 100 occasions than typical reasoning tasks. Latent factor correlations with ability factors from an established paper-and-pencil test of intelligence showed that the ability factors of the practiced tasks show patterns of good convergent and discriminant validity at pretest, which do shift to some degree at posttest (see Method: Validity of the tasks, for details). Presentation times of episodic memory and working memory tasks were individually adjusted based on pretest performance to avoid floor or ceiling effects, and then kept constant throughout the daily testing occasions. At pretest and posttest, participants worked on all tasks under all possible presentation time conditions, providing reliable measurements of between-person correlation structures that correspond to each of the presentation time constellations of the within-person covariance structures. That is, for each individual pattern of presentation time conditions of the 101 participants, the corresponding presentation time conditions from the pretest (or posttest) data could be picked to compute a between-person correlation matrix that matches the presentation times of this participant's within-person data. As the correlations with the abilities of the paper-and-pencil intelligence test did change from pretest to posttest, we included both, the between-person structures from pretest and from posttest, into the analysis to be able to evaluate the between/within differences in relation to the changes of the between-person structures.

For all unique comparisons of the resulting 202 between-person (101 from pretest and 101 from posttest) and 202 within-person correlation matrices (101 based on raw data and 101 based on de-trended data), a total of 163,216 KL divergences were calculated. These distance measures were then submitted to MDS to represent the relative distance of the within-person matrices to the between-person matrices, and of the within-person matrices (or between-person matrices) to each other in a low-dimensional space (Fig. 1).

We found that within-person structures based on raw data differed reliably from the corresponding between-person structures from pretest (average KL divergence = 5.90; $p < .001$; for information on how p values were determined, see Data analysis: Statistical testing with KL divergences), and among each other (average KL divergence = 6.84; $p < .001$; $SD_{Dimension\ 1}$ = 3.66; $SD_{Dimension\ 2}$ = 1.81). When within-person data were first de-trended to account for longer-term trends such as practice-related improvements (for details, see Data analysis: De-trending), within- and between-person structures from pretest did show no overlap at all (Fig. 1; difference between within- and between-person structures from pretest: average KL divergence = 5.67; $p < .001$; differences among within-person structures for de-trended data: average KL divergence = 3.01; $p < .001$; $SD_{Dimension\ 1}$ = 2.57; $SD_{Dimension\ 2}$ = 2.14). For raw data, MDS Dimension 1 (horizontal) correlated strongly with the magnitude of the first eigenvalue of the within-person correlation structures (r = -.78; $p < .001$). For de-trended data, MDS Dimension 1 even fully separated all within- from all between-person structures and was again strongly correlated with the first eigenvalue of the within-person structures (r = -.59; $p < .001$). Together, this indicates that the size of the differences between within- and between-person structures was associated with the degree to which longer-term changes (that are likely to reflect practice-related improvements) or short-term fluctuations are general across tasks, and thereby mimic the positive manifold of between-person differences. In other words, individuals with a greater hint of *g* in the structure of their daily fluctuations were more similar to the between-person structure than individuals with no such hint. The average loadings of the tasks on the normalized first eigenvector (with a theoretical maximum of three for nine exactly equal loadings, whereby lower values indicated less equal loadings or even some negative loadings) were 2.93 (SE = 0.0044) for the between-person, 2.08 (SE = 0.13) for the raw within-person, and 1.06 (SE = 0.14) for the de-trended within-person structures, indicating that the *g* factor was less dominant for the within-person structures, particularly when practice-related trends were taken out. When comparing the within-person structures with the between-person structures at posttest, which were significantly different from the between-person structures at pretest (average KL divergence = 4.15; $p < .001$), the resulting average divergences were even larger (average KL divergence = 9.77; $p < .001$, for within-person structures based on raw data; average KL divergence = 14.08; $p < .001$, for within-person structures based on de-trended data). It therefore seems not likely that the differences of the within-person structures from the between-person structures at pretest can be explained by practice-induced changes of the psychometric properties of the tasks (see Method: Validity of the Tasks) that lead to the apparent shift of the between-person structures from pretest to posttest—at least for the majority of participants whose within-person structures did not lie in the area between the between-person structures from pretest and posttest (Fig. 1).

When KL divergences were calculated separately for each ability factor, the within- and corresponding between-person correlation patterns still differed reliably from each other, with the distance being smallest for the working memory factor, both for raw and for de-trended data (Fig. 2). Importantly, these separate distances correlate only weakly with each other across persons (correlations for raw/de-trended data: -.02/.03 for perceptual speed and working memory, .44/.19 for perceptual speed and episodic memory, and .31/-.13 for working memory and episodic memory; with correlations of .19 or higher being significant at $\alpha < .05$). This indicates that for different individuals, the overall deviation of within-person, and corresponding between-person structures can be attributed to different patterns of deviations at the level of separate abilities. Put simply, some individuals showed greater deviations for tests of perceptual speed, others for tests of working memory, and still others for tests of episodic memory factors.

The observed divergences of within-person structures from each other and from between-person structures have important implications for the predictability of behavior. At the between-person level, knowing how a person performs on a particular cognitive task allows prediction, to some extent, of her/his individual performance (relative to other persons') on other cognitive tasks. It remains an open question, however, to what degree knowledge of a person's performance level on a particular task and a particular day also allows prediction of that person's performance (relative to her or his average) on other tasks on the same day. To answer this question, we conducted a series of regression analyses that aimed at predicting performance of each person on each task and each day with performance of the same person at the same day on the remaining eight tasks. The regression coefficients for these other tasks were based on: either (a) the individual within-person correlation matrix of this person, (b) the average within-person correlation matrix, or (c) the between-person correlation matrix from pretest. We ran all of these models once for the raw, and once for the de-trended data. We also conducted a set of prediction models in which we did the reverse, that is, we tried to predict between-person differences at pretest on single tasks using scores on the other eight tasks and regression equations based on information either from the corresponding between-person correlation matrix or from the individual or average within-person matrices. In total, about 90,000 prediction models (101 persons * 101 days * 9 tasks) were run and results averaged for each of the bars in Fig. 3, Panels A and B, and 909 prediction models (101 persons * 9 tasks) were run and results averaged for each of the bars in Fig. 3, Panel C.

Summary results from this large number of predictions (see Fig. 3) follow a consistent pattern. Predictions are best when between-person information is used to predict between-person differences and when individual within-person information is used to predict individual within-person variability. It is worst when within-person information is used to predict between-person differences and when between-person information is used to predict individual within-person variability; prediction with the average within-person structure fell in-between. It was striking to find that for almost all of the tasks, trying to predict de-trended within-person variability using between-person models did not work any better (or was even worse) than simply taking the within-person means.

We next took a closer look at the divergence of the *average* between- and within-person structures. The distribution of the correlation matrices in the MDS solution showed indications of normality in quantile-quantile plots (see Fig. 1 in Supplemental materials). Therefore, the centroid correlation matrix of the within-person cluster and the centroid correlation matrix of the between-person cluster were considered as viable average representations of within-person and between-person structures, respectively. Confirmatory modelling of a hierarchical factor structure was used to compare the two average correlation matrices. The model specified first-order ability factors for episodic memory, working memory, and perceptual speed, and a second-order general ability factor.

Average between-person data and average within-person raw data showed similar factor loadings for perceptual speed and working memory; for episodic memory, within-person raw data showed lower loadings than between-person data (Fig. 4A). When de-trending the data, within-person factor loadings were further reduced, particularly for the working memory tasks, indicating that shared within-person variance among tasks was to some degree due to longer-term trends (e.g., practice-related improvements). Comparing the loadings of ability factors on the general factor (Fig. 4B) revealed that the general factor was identical to the working memory factor both between and within individuals, whereas the loading of perceptual speed on the general factor was much less strong for the raw, and absent for the de-trended within-person data.

Discussion

Our results demonstrate that well-established between-person findings provide little information about correlations among day-to-day fluctuations in cognitive performance within healthy younger adults. Knowing that a given person shows high or low levels of performance on a particular task or ability relative to herself/himself on a particular day does not allow us to predict this person's performance on different tasks or abilities on the same day, unless his/her within-person structure has been assessed. Individuals showed idiosyncratic correlational patterns, resulting in weak average loadings of tasks on ability factors for de-trended data, and in ability-specific deviations of within-person structures from between-person structures. The *g* factor was less prominent within than between persons, and within-person structures with larger first eigenvalues were more similar to between-person structures than within-person structures with smaller first eigenvalues. Measures of working memory contributed a large share of the common variance in both between- and within-person structures, confirming the central role of working memory for human intelligence (Conway et al., 2003; Duncan, 2013; Kyllonen & Christal, 1990; Wilhelm et al., 2013).

Conclusions

The present findings do not militate against the practical utility of hierarchical between-person structures for prediction and personnel selection. However, the data show that between-person differences cannot be taken as a surrogate for within-person structures. Instead, if the aim is to describe, explain, and modify cognitive structures at the individual level, we need to measure and follow individuals over time. To understand the cognitive, motivational, and experiential mechanisms generating heterogeneity among within-person structures, researchers need to measure individual people intensively in time (Voelkle, 2015). Our findings indicate that the hierarchical model of intelligence is not necessarily the best template for capturing the organization of intelligence within individuals. Dynamic network models with reciprocal causal effects between different cognitive mechanisms may be more appropriate (van der Maas et al., 2006). In line with calls for person-oriented medicine (Schork, 2015) and person-oriented neuroscience (Finn et al., 2015; Mechelli, Penny, Price, Gitelman, & Friston, 2002), there is an urgent need for the person-oriented study of behavior (Molenaar & Campbell, 2009; Nesselroade & Schmidt McCollam, 2000). To make fundamental progress in understanding the development and organization of intelligence, we need to exploit the insight gained from following individuals over time and measure them sufficiently often to reveal the structural dynamics of their behavioral repertoire.

We would like to note that the scientific rationale of developmental research is not restricted to describing differences between the structure of within-person variability and the structure of between-person differences for particular age periods such as young adulthood, as was done in this article. Rather, its goal is to identify mechanisms that are contributing to (i) short-term variability and (ii) long-term change within individuals, or to (iii) differences between individuals, or to two or more of these components of variation (Nesselroade, 1991; Voelkle et al., in press). The relative importance of different mechanisms to these three components of variation may depend upon the age range studied and on other sampling characteristics. Therefore, the present results should not be generalized to other age periods. Rather, the present analyses and findings are a first, and admittedly descriptive, step towards the more general goal of delineating the driving forces of individual differences in development (Baltes, Reese, & Nesselroade, 1988).

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Table 1(on next page)

Table 1

Correlations of the perceptual speed factor to ability factors of the Berlin Intelligence Structure Test.

Table 1:

Correlations of the perceptual speed factor to ability factors of the Berlin Intelligence Structure Test.

BIS-PS	
Pretest	**.578**
Posttest	**.278**
χ^2 Test of Difference	11.275
BIS-Reasoning	
Pretest	.245
Posttest	.146
χ^2 Test of Difference	0.756
BIS-EM	
Pretest	.252
Posttest	.159
χ^2 Test of Difference	0.944

Note. Differences between pretest and posttest correlations were tested with likelihood-ratio tests, comparing the model in which the correlation were freely estimated with a model in which it was constrained to be equal. The resulting χ^2 tests all have df = 1 and a critical value (with α = .05) of 3.841; significant differences (pretest vs. posttest) are shown in bold face; BIS: Berlin Intelligence Structure Test; PS: Perceptual Speed; EM: Episodic Memory.

Table 2(on next page)

Table 3

Correlations of the episodic memory factor to ability factors of the Berlin Intelligence Structure Test.

Table 2:

Correlations of the working memory factor to ability factors of the Berlin Intelligence Structure Test.

	Presentation Time Condition		
	1	2	3
BIS-PS			
Pretest	.703	.639	.609
Posttest	.500	.433	.394
χ^2 Test of Difference	1.569	3.188	3.175
BIS-Reasoning			
Pretest	.819	**.957**	**.868**
Posttest	.679	**.505**	**.500**
χ^2 Test of Difference	0.938	20.699	13.691
BIS-EM			
Pretest	.505	.680	.615
Posttest	.683	.515	.624
χ^2 Test of Difference	1.186	2.337	0.007

Note. Differences between pretest and posttest correlations were tested with likelihood-ratio tests, comparing the a model in which the correlation were freely estimated with a model in which it was constrained to be equal. The resulting χ^2 tests all have df = 1 and a critical value (with $\alpha = .05$) of 3.841; significant differences (pretest vs. posttest) are shown in bold face; BIS: Berlin Intelligence Structure Test; PS: Perceptual Speed; EM: Episodic Memory.

Table 3 (on next page)

Table 2

Correlations of the working memory factor to ability factors of the Berlin Intelligence Structure Test.

Table 3:

Correlations of the episodic memory factor to ability factors of the Berlin Intelligence Structure Test.

	Presentation Time Condition		
	1	2	3
BIS-PS			
Pretest	.517	.507	.516
Posttest	.405	.407	.426
χ^2 Test of Difference	2.205	2.162	1.983
BIS-Reasoning			
Pretest	.509	.506	.543
Posttest	.489	.416	.443
χ^2 Test of Difference	0.066	1.693	2.392
BIS-EM			
Pretest	.822	.759	.790
Posttest	.698	.677	.708
χ^2 Test of Difference	3.449	1.785	1.859

Note. Differences between pretest and posttest correlations were tested with likelihood-ratio tests, comparing the a model in which the correlation were freely estimated with a model in which it was constrained to be equal. The resulting χ^2 tests all have df = 1 and a critical value (with α = .05) of 3.841; significant differences (pretest vs. posttest) are shown in bold face; BIS: Berlin Intelligence Structure Test; PS: Perceptual Speed; EM: Episodic Memory.

Figure 1(on next page)

Figure 1

Comparisons of between-person and within-person structures of cognitive abilities. Locations of within-person (raw data: red dots; de-trended data with longer-term trends taken out: green dots) and between-person structures (at pretest: blue dots; at posttest: yellow dots) on the first two dimensions of a multidimensional scaling solution for the Kullback-Leibler (KL) divergences between all within- and between-person structures. Between-person structures are based on performance of the same sample on the same tasks under different presentation time conditions, and are relatively similar to each other. Within-person structures evidently differ more from each other and clearly overlap little (for raw data) or nor not at all (for de-trended data) with the between-person structures.

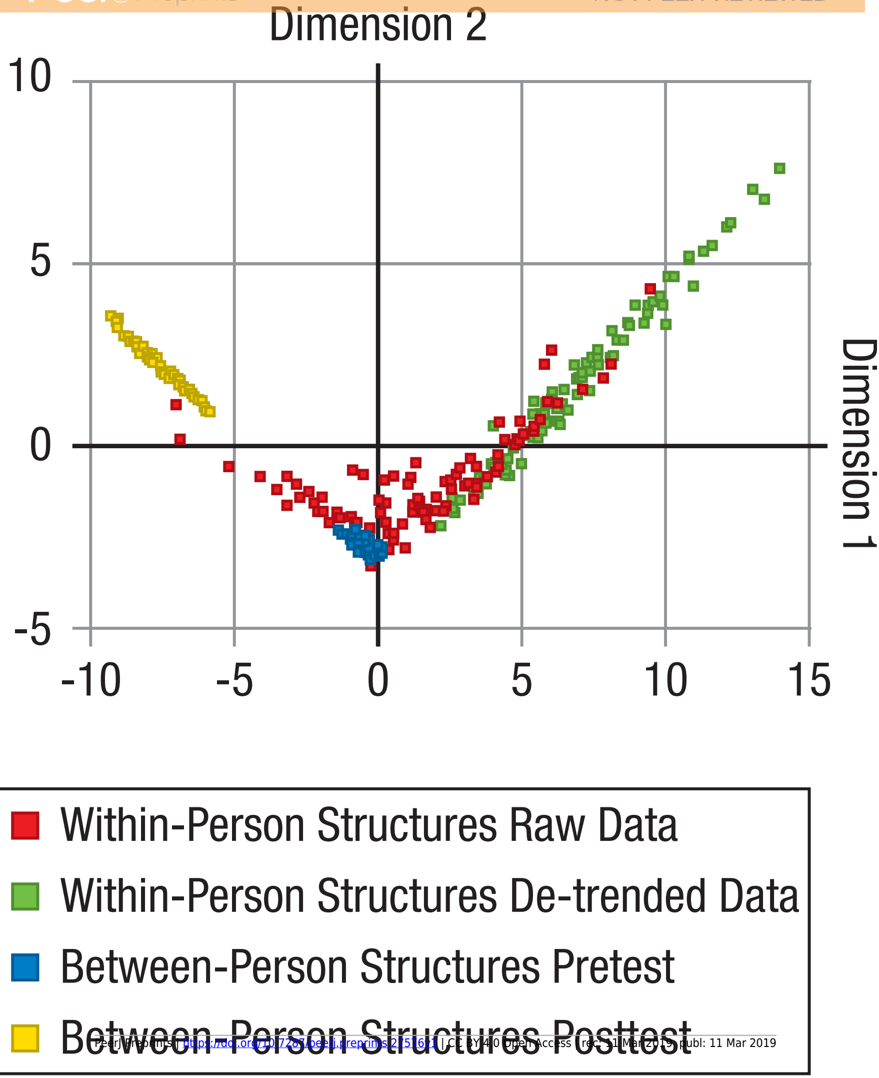
Dimension 2
Dimension 1
10
5
0
-5
-10
-5
0
5
10
15
Within-Person Structures Raw Data
Within-Person Structures De-trended Data
Between-Person Structures Pretest
Between-Person Structures Posttest

Figure 2(on next page)

Figure 2

KL divergences between within- and between-person structures for different abilities on the basis of (A) raw, and (B) de-trended within-person data. Calculating KL divergences separately for the different ability factors shows that within- and between-person structures differ reliably from each other for each ability. These differences are more pronounced for episodic memory and perceptual speed than for working memory. Error bars indicate the standard deviations from simulated distributions under the null hypothesis of no difference between within- and between person structures. All = all nine tasks; WM = working memory; PS = perceptual speed; EM = episodic memory.

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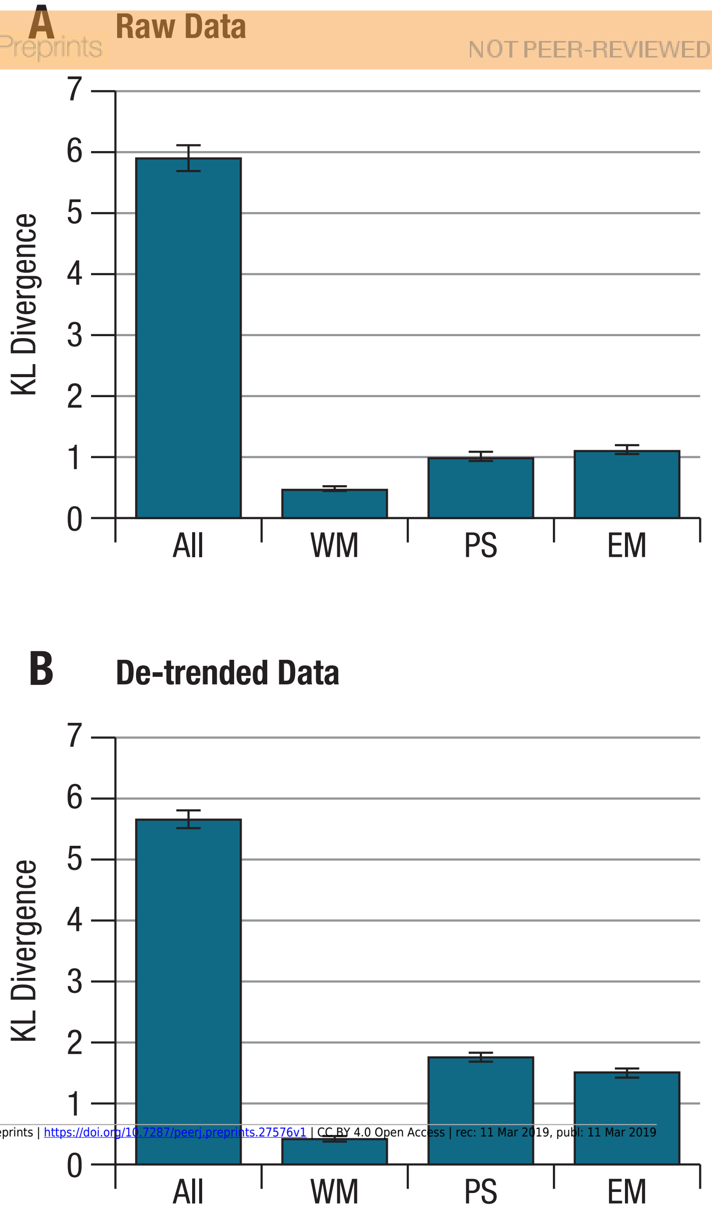

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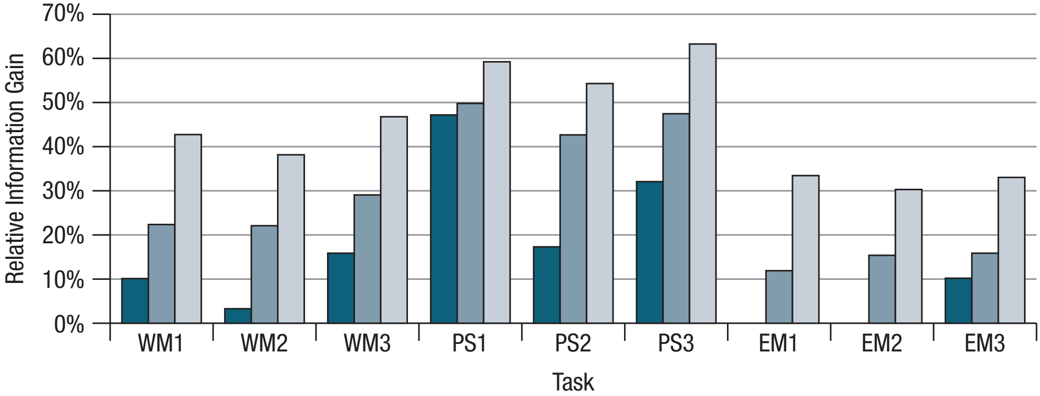
Figure 3(on next page)

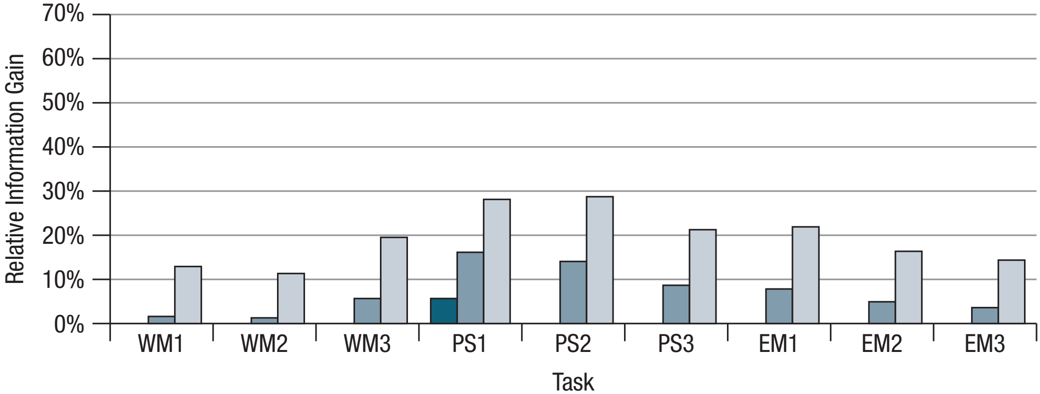
Figure 3

Differential predictive validity of within- and between-person structures. Performance on each of the nine tasks was predicted by performance on the remaining eight tasks. Regression coefficients were based on between-person correlations (dark bars), average within-person correlations (middle blue bars), or individual within-person correlations (light bars). The bars show relative positive information gain compared to predicting performance with the corresponding means. Positive values can be interpreted as coefficients of determination (multiple R^2), while zero values refer to predictions equal or worse than prediction with the mean. (A-B) Performance of each person on each single task on each daily session (WM1–3 = working memory tasks; PS1–3 = perceptual speed tasks; EM1–3 = episodic memory tasks) was predicted by this person's performance on the other eight tasks on the respective same day. Results are shown for raw (A) and de-trended (B) within-person data. (C) Performance of each person on each task at pretest was predicted by this person's performance on the remaining eight tasks on that occasion. Predictions are best when between-person information is used to predict between-person differences (C), and when individual within-person information is used to predict individual within-person variability (A).

A **Predicting Raw Within-Person Data**



B **Predicting De-trended Within-Person Data**



C **Predicting Between-Person Data**

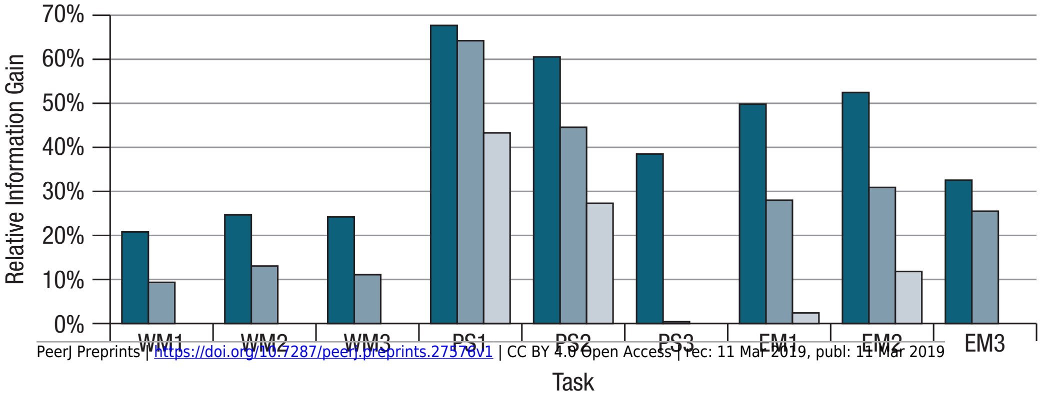
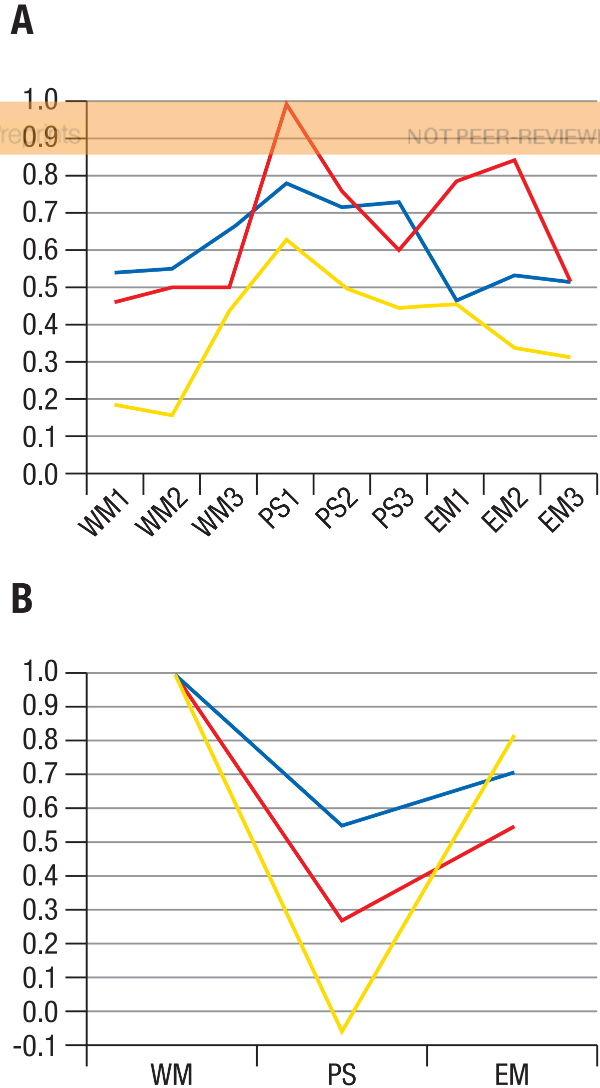
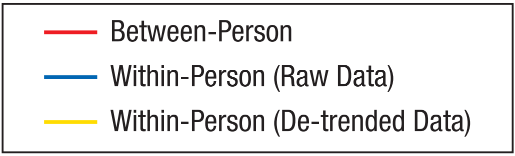


Figure 4(on next page)

Figure 4

Factor loadings of hierarchical models. Factor loadings of working memory (WM), perceptual speed (PS), and episodic memory (EM) tasks on corresponding ability factors (A) and of ability factors on the general factor g (B), based on a hierarchical model applied to the centroids (average correlation matrices) of the individual structures shown in Fig. 1. At both the between-person and within-person level, the g factor was identical to WM, but the PS factor related to the g factor only when between-person or raw data within-person variance was analyzed (B).


A
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
WM1
WM2
WM3
PS1
PS2
PS3
EM1
EM2
EM3
B
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
-0.1
WM
PS
EM


Between-Person
Within-Person (Raw Data)
Within-Person (De-trended Data)