On the relationship between executive functions of working memory and components derived from fluid...
On the relationship between executive functions of working memory and components derived from fluid intelligence measures

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\textbf{ARTICLE INFO}

Keywords: Executive functions, Updating, Shifting, Inhibition, Intelligence

\textbf{ABSTRACT}

The aim of the current study is to provide new insights into the relationship between executive functions and intelligence measures in considering the item-position effect observed in intelligence items. Raven's Advanced Progressive Matrices (APM) and Horn's LPS reasoning test were used to assess fluid intelligence which served as criterion in investigating the relationship between intelligence and executive functions. A battery of six experimental tasks measured the updating, shifting, and inhibition processes of executive functions. Data were collected from 205 university students. Fluid intelligence showed substantial correlations with the updating and inhibition processes and no correlation with the shifting process without considering the item-position effect. Next, the fixed-link model was applied to APM and LPS data separately to decompose them into an ability component and an item-position component. The results of relating the components to executive functions showed that the updating and shifting processes mainly contributed to the item-position component whereas the inhibition process was mainly associated with the ability component of each fluid intelligence test. These findings suggest that improvements in the efficiency of updating and shifting processes are likely to occur during the course of completing intelligence measures and inhibition is important for intelligence in general.

1. Introduction

The relationship between working memory and intelligence has been in the focus of scientific research for quite a long time. Already in the 1990s it has been obvious that there is a substantial relationship between them (Carpenter, Just, & Shell, 1990; Kyllonen & Christal, 1990). Over the years further evidence has accumulated and provided the basis for a comprehensive meta-analysis that indicates a moderately strong relationship between working memory and intelligence (Ackerman, Beier, & Boyle, 2005; Oberauer, Schulze, Wilhelm, & Süß, 2005). There is even research work suggesting almost equivalence between the two constructs (Colom, Rebollo, Palacios, Juan-Espinosa, & Kyllonen, 2004).

Since the beginning of research on the relationship between working memory and intelligence, the concept of working memory has undergone a considerable change. In the beginning it was Baddeley's (1986) concept of working memory that was mainly reflected in the research on this relationship. This concept suggests a substructure consisting of the central executive, the visual sketchpad and the phonological loop. In research, special emphasis has been given to the central executive serving a number of different functions in human information processing. Subsequently the focus of research has shifted from the central executive to executive control (Logan & Gordon, 2001). Executive control is expected to focus the cognitive processing on the task that needs to be accomplished. Additionally executive control is assumed to ensure that task goals are actively maintained and to prevent deviations from the processing plan due to other distracting stimuli (Engle & Kane, 2004). Furthermore, the concept of executive control is in line with the concept of executive attention that refers to the control and supervision of subordinate processes of stimuli selection. This type of attention has been found to be a second-order type of attention that underlies a host of first-order attention types (Schweizer, 2010).

1.1. The conceptual elaborations regarding executive control

More recently the focus of research has concentrated on functions of executive control: the executive functions (EFs) mainly referred mainly to as updating, shifting, and inhibition (Miyake & Friedman, 2012). These EFs have been described as general-purpose control mechanisms

\url{http://dx.doi.org/10.1016/j.actpsy.2017.09.002}

Received 1 October 2016; Received in revised form 18 August 2017; Accepted 8 September 2017

0001-6918/ © 2017 Published by Elsevier B.V.
that are assumed to regulate the dynamics of human cognition and action. They are even regarded as core components of the self-control and self-regulation ability and, therefore, are assumed to significantly influence everyday life (Moffitt et al., 2011).

It has been argued that completing tasks that are demanding to executive control are frequently characterized by one or several intermediary states which need to be arrived at before reaching the final state. According to Morris and Jones (1990), this type of mental processing includes the monitoring of task-relevant information at hand and the manipulation of the contents of working memory. An important function is that older information no longer necessary is replaced with newer information. This kind of processing characterized by the succession of various intermediary states highlights updating as a major function of executive control (Bledowski, Rahm, & Rowe, 2009). There is already some evidence of a substantial relationship between updating and intelligence (Friedman et al., 2006). There is also evidence obtained by means of various versions of the star counting test that asks participants to continuously update the number of stars maintained in working memory (e.g., De Jong & Das-Smaal, 1995; Ren, Altmeyer, Reiss, & Schweizer, 2013). Furthermore, performance in completing the exchange test as a working memory measure that requires participants to update the mental positions of neighboring figures of an array has also been shown to correlate with measures of fluid intelligence (e.g., Schweizer, 2007).

The other important function of executive control referred to as shifting extends to the executive operations that perform the shifts between the demands of multiple tasks or mental sets (Miyake et al., 2000). The ability to conduct this kind of shifting operation is considered as one of the essential characteristics of mental information processing according to models of attention control like the supervisory attention system by Norman and Shallice (1986). In studies of this research area shifting is investigated by means of the so-called set switching paradigm (Allport, Styles, & Hsieh, 1994). Such switching tasks have also been used in studies on the relationship between cognitive performance and intelligence. Some of these studies report a substantial correlation between shifting and intelligence (e.g., Salthouse, Fristoe, McGuthry, & Hambrick, 1998). The findings by other studies do not support such a relationship (Friedman et al., 2006; Rockstroh & Schweizer, 2001).

Finally, there is inhibition considered as the third major function of executive control. The concept of inhibition has a long history in various areas of psychology and has frequently been considered as closely related to interference control (Friedman & Miyake, 2004). Inhibition is thought to suppress external and internal stimuli or impulses that potentially distract the focus of cognitive processing away from the task goal (Nigg, 2000). It is crucial for overriding dominant or prepotent responses (Friedman & Miyake, 2004). Inhibition is considered as essential “for normal thinking processes and, ultimately, for successful living” (Garavan, Ross, & Stein, 1999, p. 8301). The results regarding the relationship between inhibition and intelligence are mixed. The analysis of the results of several studies regarding the relationship between inhibition and intelligence led Dempster (1991) to conclude that there must be an association of intelligence with inhibition. Salthouse, Atkinson, and Berish (2003) also provide evidence in favor of the relationship. However, a more recent study indicates that there is no such relationship (Friedman et al., 2006).

1.2. The complication regarding fluid intelligence measures

The concept of fluid intelligence was proposed by Horn and Cattell (1966) and has found its way into almost all major models of intelligence, as for example, Carroll’s (1993) three stratum model of cognitive ability and the Cattell–Horn–Carroll theory of cognitive abilities (McGrew, 2005). Furthermore, research reveals that there is an especially close relationship between fluid intelligence and general intelligence (Kvist & Gustafsson, 2008). Because of this property fluid intelligence often serves as an indicator of general intelligence in investigating the relationship between intelligence and other constructs.

Although measures of fluid intelligence are considered as homogeneous, research on the item-position effect has revealed in-homogeneity, and the observed inhomogeneity may call the validity of a host of findings regarding fluid intelligence into question. The item-position effect refers to the dependency of the response to a specific item in a sequence of homogeneous items on the position of this item within the sequence. The research regarding the item-position effect started in the 1950s (Campbell & Mohr, 1950; Mollenkopf, 1950). Initially it was experimental research. A major result of this research was that items assigned to the latter part of a series of items show a larger item reliability than items assigned to the former part (Hartig, Hölzel, & Moosbrugger, 2007; Knowles, 1988; Knowles & Byers, 1996). The item-position effect was also observed in ability items by means of item response theory techniques (e.g., Debeer & Janssen, 2013; Embretson, 1991; Verguts and De Boeck, 2000) and by means of factor-analytic methods (e.g., Hartig et al., 2007; Schweizer, 2012).

In the factor-analytic framework, confirmatory factor analysis (CFA) is conducted since it allows the decomposition of the variance into two subcomponents (Schweizer, 2012). Factor loadings are constrained in such a way that they account for a systematic increase of the latent variance. The expectation of an increase of systematic variance has grown out of Knowles’ (1988) and others’ observations of an increase in reliability that means an increase in the relative amount of systematic variance from the first to last items. That is, if the data are collected by means of a fluid intelligence measure, the method yields two components: the ability component and the item-position component (Ren, Wang, Altmeyer, & Schweizer, 2014; Schweizer, 2012). The ability component represents the basic part of the measure that can be considered as purified fluid intelligence. This component has been shown to correlate almost perfectly with general intelligence (Schweizer, Troche, & Rammayer, 2011). Separating the item-position component from data of an intelligence test may result in higher correlations of external constructs with the ability component than with the raw score of the intelligence test (e.g., Ren et al., 2014).

The two components achieved by decomposing data on Raven’s Advanced Progressive Matrices (APM) have been related to measures of learning by Ren et al. (2014) since there is the hypothesis that the item-position effect is due to learning (Embretson, 1991; Verguts & De Boeck, 2000). According to the results of this study the item-position component is closely related to complex learning, that is, for example, characteristic of learning mathematics (Ren et al., 2014). In contrast, simple learning referred to as associative learning proved to show a moderate relationship with the ability component.

Since the ability and item-position components of an intelligence measure show different properties, as for example different relationships with learning, it can be expected that they relate to measures of EFs in different ways. There is already one study demonstrating that the position component, but not the ability component of APM, is related to executive attention (Ren, Goldhammer, Moosbrugger, & Schweizer, 2012). However, this study used a number of attention tasks such as those from the Test for Attention Performance (Zimmermann & Fimm, 2000), and from the Multidimensional Attention Test Battery (Heyden, 1999) to assess executive attention. Although completing these attention tasks requires executive control, Ren’s study has not identified particular attention functions that characterize these attention measures. Therefore, it remains an open question which one of the EFs (e.g., updating, inhibition, and shifting) is related to the position component of an intelligence measure. Furthermore, it is unclear whether new results considering the item-position effect are in line with previous results regarding the relationship between EFs and fluid intelligence.

1.3. The present study

The major objective of this study is to provide new insights into the
relationship between EFs and fluid intelligence. There have been developments during the last years that are not reflected appropriately by the old studies on the relationship (e.g., De Jong & Das-Smaal, 1995; Friedman et al., 2006; Rockstroh & Schweizer, 2001; Salthouse et al., 2003). The structural investigation by Miyake et al. (2000, 2012) has provided a framework for organizing the functions of executive control, with a focus on updating, shifting, and inhibition. Furthermore, there is the split of fluid intelligence scores, into the basic ability component and the item-position component. Because of these developments the relationship needs to be studied in considering the functions of executive control on one hand and the basic ability and item-position components of fluid intelligence scores on the other hand.

A battery of six cognitive tasks was employed to measure updating, shifting, and inhibition. Each task was designed to tap a single EF while placing minimal demands on other EFs. Fluid intelligence was assessed by APM (Raven, Raven, & Court, 1997), and Horn’s reasoning scale (scale 4) taken from the Leistungsprüfsystem (LPS), a frequently used intelligence test (Horn, 1983). APM is the most prominent indicator of fluid intelligence (Carpenter et al., 1990; Carroll, 1993). Horn’s reasoning scale mainly assesses abstract reasoning that is at the core of fluid intelligence (Horn, 1997).

Data on the EF tasks were analyzed by CFA models to represent the three EFs and to examine the intercorrelations between them. Decomposition of the variance of intelligence data into ability and item-position components was achieved by a special CFA model denoted as the fixed-links model. A major characteristic of the fixed-link model is that the factor loadings are constrained according to theoretical considerations, and the variances of the latent variables are estimated (Schweizer, 2012; Schweizer et al., 2011). The fixed-links model shares the basic mathematical foundations with the early growth curve model (McArdle, 1988) and also with the tau-equivalent model (Lord & Novick, 1968, p. 97).

2. Method

2.1. Participants

A total of 205 university students participated in this study. They were 134 male and 70 female participants aged between 17 and 32 years ($M = 20.56, SD = 2.32$). One participant’s data on sex and age were missing. Written informed consent was obtained from each participant before experimental testing. Participants were either paid or recruited as part of a requirement for an internship experience in undergraduate public service programs.

2.2. Measures

2.2.1. Executive functioning tasks

2.2.1.1. Star counting task (SCT). This task was modified from the original star counting test to measure working memory updating (De Jong & Das-Smaal, 1995). Updating is a fundamental process in completing this task since one has to continuously update the number of stars in working memory. A computerized version of this task has already revealed a substantial relationship with other working memory updating tasks such as the exchange test (Ren et al., 2013). The current task asked participants to count the number of stars from a starting number in forward or backward directions. The starting stimulus included a starting number and 8 triangles symmetrically arranged around the center of the screen (see part 1 of Fig. 1 for an example). The counting stimuli were similar to the starting stimulus but one or two triangles were replaced by stars. Meanwhile, a plus or a minus sign appeared in the center of the screen (see part 2 and part 3 of Fig. 1). In the beginning of each trial, a starting stimulus appeared on the screen for 750 ms, followed by a succession of 6 counting stimuli each lasting for 750 ms. Participants were prompted to enter the final result of the counting immediately after the removal of the last stimulus. This task included 24 trials. In 12 trials including only the plus signs, the starting number or the just reached number needed to be increased by one for each star. In the other 12 trials including only the minus signs, the staring number or the just reached number needed to be decreased by one for each star. A correct outcome of counting was coded as 1 and an incorrect outcome as 0 for each trial.

2.2.1.2. N-back task (N-back). The N-back paradigm has been frequently used to assess working memory updating (e.g., Jaeggi, Buschkuehl, Jonidas, & Perrig, 2008; Schmiedek, Hildebrandt, Lövde’n, Lindenberger, & Wilhelm, 2009). The stimuli were 9 single digits (1–9). A sequence of digits was presented on the screen and participants were asked to decide whether each digit in a sequence matched the one appearing two items (2-back) or three items (3-back) before. The first two or three digits were preparatory since they had no reference item to be compared with. Participants were asked to press “F” if the digits were identical or “J” if they were not. This task included 2-back and 3-back versions each including two blocks. There were 8 practice trials and 72 formal trials. The dependent variable was the proportion of correct responses.

2.2.1.3. Antisaccade task (Anti). This inhibition task was modified from Unsworth and Spillers (2010). The stimuli were black squares and arrows. Each trial started with a fixation point displayed on the screen for a random time from 200 ms to 2200 ms. A black square was then flashed either to the left or to the right of the fixation point for 300 ms. Following the disappearance of the square, an arrow (left, right, or up) was immediately presented to the opposite side of the black square for 60 ms, which was followed by a masking stimulus (a gray square). Participants were asked to determine the direction of the arrow. There were 10 practice trials and 60 formal trials. The proportion of correct responses was recorded.

2.2.1.4. Stroop task (Stroop). The original color-word Stroop task (Stroop, 1935; Unsworth & Spillers, 2010) was adapted to measure inhibition. The stimuli were color words (i.e., red, green, and blue) printed with colors. Participants were asked to name the color of a word by pressing corresponding keys (1 = red, 2 = green, and 3 = blue) as quickly as possible without sacrificing accuracy. After completing 21 practice trials, participants were asked to complete 75 formal trials, in which 33% were incongruent and 67% were congruent. The dependent variable was obtained by computing the reaction time (RT) differences between trials in the congruent condition and those in the incongruent condition.

2.2.1.5. Number-letter task (Nr-L). This shifting task was modified from Miyake et al. (2000). The stimuli were number-letter pairs presented individually in one of the four quadrants of the screen (see Fig. 2 for example trials). The numbers were either even (2, 4, 6, and 8) or odd (3, 5, 7, and 9). The letters were either consonants (g, k, m, and r) or vowels (a, e, i, and u). Participants were asked to indicate whether the number was odd or even when the pair appeared in one of the top quadrants whereas they needed to indicate whether the letter was consonant or vowel when the pair appeared in one of the bottom quadrants. This task included four blocks. In the first two blocks the pairs appeared only in the top two quadrants (block 1) or only in the bottom two quadrants (block 2). These two blocks served as the baseline condition where shifting was not involved. In block 3 and 4, however, the number-letter pairs appeared in a clockwise rotation around all four quadrants. Half of the trials required participants to shift between the two types of categorization operations. After completing 8 practice trials, participants needed to complete 16 trials for each of the first two blocks and 32 trials for each of the last two blocks. The difference between the average RT of the trials in the last two blocks and that of the first two blocks were computed as the shifting cost.
2.2.2.1. Raven’s Advanced Progressive Matrices (APM)

The set II of APM (Raven et al., 1997) was adapted for computer administration. The 36 test items were presented successively by the computer with an ascending order of difficulty, just as in the paper-and-pencil version. Each item consists of a display of a 3 × 3 matrix composed of geometrical elements, one of which is missing. Participants were instructed to choose an appropriate element out of 8 alternatives by pressing the number key. Responses to each item were recorded as binary data. Because of technical problems, 40 participants were allowed only 20 min to complete the test. The other 165 participants were allowed 30 min. In order not to complicate the results because of the difference in testing time, statistical analyses involving APM were based only on data of participants who completed the 30 min version.

2.2.2.2. LPS reasoning scale (LPS)

This study employed the 4th scale of Leistungsprüf syst em (Horn, 1983). It was an ability test with a time limit of 8 min. The scale consists of 40 individual items presented in an ascending order of difficulty. Each item is composed of a series of 9 numbers or letters in which 8 follow a rule but 1 does not. Participants were asked to figure out the underlying rule and identify the target number or letter that does not fit the rule. Responses to each item were recorded as binary data.

2.3. Apparatus and procedure

Participants were tested in pairs in a quiet lab. Data on the LPS scale were obtained by the paper-and-pencil testing. The other tasks were computerized measures, which were presented on a computer monitor using the E-Prime software. Testing took around 90 min. The measures were administered in a fixed order to minimize any measurement error due to changes of sequences. The order was as follows: SCT, Dot-T, N-back, Stroop, Nr-L, Anti, APM, and LPS. Participants had an opportunity to take a short break between measures.

2.4. Statistical analysis

Outliers were identified by examining between-subject distributions. Any observation exceeding 3 standard deviations from the means were replaced with a value that was 3 standard deviations. This procedure affected no > 5% of observations.

Modeling the item-position effect by means of the fixed-links model was conducted separately for the APM and LPS data. Each model included two latent variables representing the ability component and the item-position component. Individual items served as manifest variables and each loaded on both latent variables. Loadings on the ability component were kept constant. Loadings on the item-position component were determined by a quadratic function that has been proved to be effective in modeling the item-position effect of intelligence items (Zeller, Krampen, Reiß, & Schweizer, 2016). Next, a link function was used to overcome the difference between data and model with respect to scale and distribution (Schweizer, 2012; Troche, Wagner, Schweizer, & Rammsayer, 2016):

\[ w_i = \sqrt{p_i (1-p_i)} \]

where \( p_i \) represents the probability of correct responses for the \( i \)-th item. The link function is realized as weights that modify the constrained factor loadings. It is obtained as the square root of the variance of the item showing the binomial distribution, i.e., \( p (1-p) \) which links the standard deviation of the normal distribution to the binomial distribution. That’s to say, the link function establishes links between the variance of a latent variable that follows a normal distribution and the variances of a manifest variable showing a binomial distribution, and
therefore created correspondence between important aspects of data and model. The link function that is realized as a set of weights adapts the factor loadings to the specific properties of data used for computing the empirical variance-covariance matrix that includes probability-based covariances. Otherwise the model-implied matrix would only fit to an empirical matrix computed from continuous data but not from binary data. Finally, a one-factor model that was actually a tau-equivalent model including only the ability component was also examined.

LISREL8.8 (Jöreskog & Sörbom, 2006) was used for modeling analyses. Since the difficulties varied among the intelligence items, scores of the very easy items were negatively skewed. Therefore, the robust maximum likelihood method (Satorra & Bentler, 2001) was used for evaluating the models including the intelligence items as manifest variables. The covariance matrix used as input to the models was special since some of the variables were dichotomous and others continuous. Probability-based covariances were computed for the binary items, and in all the other cases sums of squared deviations were used. Computing sums of squared deviations is the standard procedure; the computation of probability-based covariances is described in Schweizer, Ren, and Wang (2015).

3. Results

3.1. Descriptive statistics, reliability, and correlation analysis

Table 1 shows the descriptive statistics, reliability estimates and Pearson correlations between the variables. Regarding the reliability, the internal consistency based on Cronbach's alpha was computed for each EF task, and the split-half reliability on the basis of odd and even items. Data on APM were based on 165 participants and the other data based on 205 participants. The means of the SCT, N-back, Anti, LPS, and APM were proportion accuracy scores, and those for the Stroop, Nr-L and Dot-T were raw RT scores. All variables showed normal distributions with values of skewness and kurtosis < 2 (see Kline, 2005). Most estimates of reliability were larger than 0.70, indicating reasonable reliability. The relatively small estimate of SCT was probably due to the limited number of trials within the task. In spite of that, this updating task exhibited substantial correlations with the other updating measure and with the intelligence measures.

Most correlations listed in Table 1 reached significance at the 0.05 level. Unfortunately, the Stroop task showed no significant correlation with any other measure. Previous research collecting the Stroop task data showed, at least, low to modest correlations with other EF and intelligence measures (e.g., Friedman et al., 2006; Unsworth & Spillers, 2010; Xu et al., 2013). The score of the Stroop task in this study showed virtually no correlation with other EF measures and with the intelligence measures. This was mainly because that the Stroop task was so easy (M = 0.89, SD = 0.09) that it did no more reflect individual differences. One reason for the low degree of difficulty was that the current Stroop task mainly required a manual response while the Stroop effect depends heavily on verbal responses (Hilbert, Nakagawa, Bindl, & Bühner, 2014; White, 1969). Therefore, the Stroop data were excluded from further analysis.

3.2. The relationship between EF and Gf without considering the item-position effect

CFA was firstly applied to the EF data for representing the three EFs and intercorrelations among them. Since the Antisaccade task was a single inhibition task to be used in modeling analyses, we computed two sub-scores (Anti 1 and Anti 2) of this task as indicators of inhibition. Anti 1 was achieved by averaging the former 30 trials and Anti 2 by the latter 30 trials of the task. In addition, scores of Dot-T and Nr-L were reversed so that higher scores mean higher levels of performance in the models.

Inspection of the fit indices reveals that the fit of the three-factor EF model based on data of 205 participants was excellent, χ²(6) = 5.63, p = 0.47, RMSEA < 0.001, SRMR = 0.027, CFI = 1.00, IFI = 1.00, NNFI = 1.00. The insignificance of the χ² suggests that the model's prediction did not significantly deviate from the data pattern. As is shown in Fig. 4A, the standardized correlation coefficients between the latent variables exhibited moderate to moderately strong correlations, indicating that the three EFs were distinguishable but still shared some underlying commonality. The same model based on data of 165 participants showed also an excellent fit, χ²(6) = 3.66, p = 0.72, RMSEA < 0.001, SRMR = 0.021, CFI = 1.00, IFI = 1.00, NNFI = 1.03. As is shown in Fig. 4B, the correlation pattern between the latent variables was similar to that presented in Fig. 4A.

Next, in order to examine the relationships between EFs and Gf, the three-factor EF model was extended to a comprehensive correlation model by adding a latent variable representing Gf that was loaded by scores of APM and LPS. Correlations between the EF components and Gf were estimated. This model showed a very good fit, χ²(14) = 17.17, p = 0.25, RMSEA = 0.037, SRMR = 0.041, CFI = 0.99, IFI = 0.99, NNFI = 0.98. As is shown in Fig. 5, updating and inhibition yielded moderate to strong correlations with Gf (updating with Gf: Z = 4.02, p < 0.01; inhibition with Gf: Z = 4.26, p < 0.01). However, the correlation of shifting with Gf was small and insignificant (Z = 1.45, p > 0.05).

3.3. Modeling the item-position effect of fluid intelligence measures

The ability-position model and the one-factor model were examined for APM and LPS separately. The 36 items of the APM were used for modeling analyses as over 95% of the sample attempted all items within 30 min. The item set of the LPS had to be reduced for two reasons: (1)

<table>
<thead>
<tr>
<th>Measure</th>
<th>M</th>
<th>SD</th>
<th>Skew</th>
<th>Kurtosis</th>
<th>Reliability</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. SCT</td>
<td>0.76</td>
<td>0.17</td>
<td>−0.75</td>
<td>0.38</td>
<td>0.58</td>
<td>−</td>
<td>−</td>
<td>−</td>
<td>−</td>
<td>−</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td>2. N-back</td>
<td>0.64</td>
<td>0.13</td>
<td>−0.20</td>
<td>−0.15</td>
<td>0.72</td>
<td>0.32</td>
<td>−</td>
<td>−</td>
<td>−</td>
<td>−</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td>3. Anti</td>
<td>0.77</td>
<td>0.18</td>
<td>−1.28</td>
<td>0.62</td>
<td>0.94</td>
<td>0.30</td>
<td>0.28</td>
<td>−</td>
<td>−</td>
<td>−</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td>4. Stroop</td>
<td>151.70</td>
<td>96.73</td>
<td>1.10</td>
<td>3.28</td>
<td>0.97</td>
<td>0.10</td>
<td>0.10</td>
<td>0.05</td>
<td>−</td>
<td>−</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td>5. Nr-L</td>
<td>579.10</td>
<td>295.55</td>
<td>0.38</td>
<td>1.28</td>
<td>1.01</td>
<td>−0.01</td>
<td>−0.18</td>
<td>−0.13</td>
<td>−0.11</td>
<td>−</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td>6. Dot-T</td>
<td>189.80</td>
<td>142.14</td>
<td>0.67</td>
<td>1.28</td>
<td>1.06</td>
<td>−0.20</td>
<td>−0.16</td>
<td>−0.19</td>
<td>−0.02</td>
<td>−0.16</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td>7. LPS</td>
<td>0.82</td>
<td>0.08</td>
<td>−0.15</td>
<td>0.69</td>
<td>0.71</td>
<td>0.29</td>
<td>0.26</td>
<td>0.32</td>
<td>−0.04</td>
<td>−0.11</td>
<td>−0.14</td>
<td>−</td>
</tr>
<tr>
<td>8. APM</td>
<td>0.68</td>
<td>0.14</td>
<td>−0.47</td>
<td>0.47</td>
<td>0.83</td>
<td>0.35</td>
<td>0.21</td>
<td>0.37</td>
<td>−0.08</td>
<td>−0.04</td>
<td>−0.10</td>
<td>0.44</td>
</tr>
</tbody>
</table>

Note. Reliabilities for the executive functioning tasks were computed using Cronbach's alpha. Reliabilities for the intelligence measures were split-half reliabilities computed on the basis of odd and even items. SCT = Star counting task; N-back = N-back task; Anti = Antisaccade task; Nr-L = Number letter task; Dot-T = Dots-triangles task; APM = Raven's Advanced Progressive Matrices; LPS = LPS reasoning scale.

p < 0.05.
because of the strict time limit imposed on this scale, 38% of the sample haven't attempted the last two items, which resulted in high levels of difficulty and low variances for the items. (2) The first 20 items were too easy for university students so that these items were completed almost faultlessly. Without variance, however, it was not possible to observe the item-position effect. Therefore, only items 21–38 of the LPS were used for modeling the position effect. The average total score \((M = 12.69, SD = 2.87)\) of these 18 items had a virtually perfect correlation \((r = 0.98, p < 0.01)\) with the average total LPS score.

The upper part of Table 2 presents the fit statistics for the models of APM. The fit results indicate that the ability-position model yielded an acceptable fit while the one-factor model was not good according to the CFI, IFI, and NNFI. The parameter estimates of the variances of the latent variables within the ability-position model reached significance (ability: \(Z = 3.20, p < 0.01\), position: \(Z = 4.44, p < 0.01\)), suggesting that both components represented important sources of individual differences. The measurement models of LPS were also examined. It needs to be noted that 3 pairs of neighboring items (item 33 and item 34; item 36 and item 37; item 37 and item 38) within the LPS showed excessively high correlations among each other, which suggests an inhomogeneity of the scale. Such inhomogeneity would likely cause model misfit. Therefore, models of the LPS were estimated
3.4. The relationship between EF and the two components of fluid intelligence scores

This section examines the correlations of EFs with the ability and position components of the intelligence score by combining the three-factor EF model and the ability-position model of each intelligence measure into a comprehensive model. The fit statistics of the comprehensive model associated with APM showed an acceptable fit, although the SRMR was a bit high, robust \( \chi^2 \) (844) = 989.88, \( p < 0.001 \), RMSEA = 0.032, SRMR = 0.115, CFI = 0.93, IFI = 0.93, NNFI = 0.92. Fig. 6 presents the correlations between EFs and components of APM. All correlations were significant except those between inhibition and the position component \( (Z = 1.51, p > 0.05) \), and between shifting and the ability component \( (Z = 0.67, p > 0.05) \). Updating showed a moderately strong correlation with the position component and a relatively small correlation with the ability component, but no significant difference was found between the two correlations \( (Z_{\text{difference}} = 1.71, p > 0.05) \). The correlation of inhibition with the ability component reached significance \( (Z = 3.47, p < 0.01) \), and this correlation was not significantly larger than that between inhibition and the position component \( (Z_{\text{difference}} = 1.09, p > 0.05) \). The correlation of shifting with the position component was significantly larger than that with the ability component \( (Z_{\text{difference}} = 4.74, p < 0.01) \).

The fit statistics of the comprehensive model associated with LPS showed also an acceptable to good fit, robust \( \chi^2 \) (256) = 327.44, \( p < 0.001 \), RMSEA = 0.037, SRMR = 0.078, CFI = 0.92, IFI = 0.92, NNFI = 0.92. Fig. 7 presents the latent correlations between EFs and components of LPS. All correlations were significant except those between updating and the ability component \( (Z = 1.47, p > 0.05) \), and between shifting and the ability component \( (Z = 0.00, p > 0.05) \). The correlation pattern exhibited a high degree of similarity to that associated with APM. Specifically, the correlation of updating with the position component was larger than that with the ability component \( (Z_{\text{difference}} = 3.23, p < 0.01) \). Inhibition showed a relatively large correlation with the ability component compared to that with the position component, but no significant different was found between the two correlations \( (Z_{\text{difference}} = 0.99, p > 0.05) \). With respect to shifting, the correlation with the position component was larger than that with the ability component of the LPS \( (Z_{\text{difference}} = 6.21, p < 0.01) \).²

4. Discussion

The research work regarding the relationship between measures of EFs and fluid intelligence has provided new insights. So far it has been known that working memory is a major ingredient of fluid intelligence (e.g., Ackerman et al., 2005; Colom et al., 2004). The consideration of the subprocesses of executive function on one hand and the components of the intelligence tests on the other hand now reveals a more complex picture. It turns out that shifting and updating mainly contributed to the component of fluid intelligence tests that represents the item-position effect whereas the executive process referred to as inhibition was mainly associated with the ability component of each fluid intelligence test. There are two other relationships (i.e., the correlation of updating with the ability component of APM, and the correlation of inhibition with the item-position component of LPS) that, however, were restricted to either APM or LPS. These additional relationships were probably due to specificities of the processing stimulated by respective measures, and it is an open question whether they are replicable because of their not so large size. It was also possible that the lack of an association between inhibition and the item-position component of APM and the lack of an association between updating and the ability component of LPS were also due to specificities of the intelligence measures.

The item-position effect has been perceived as an expression of...

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¹Please note that the comprehensive model based on the ability-position model was structurally different from that with only one factor for GI since the former was estimated based on individual item scores while the latter base on sum scores of the two intelligence tests. Therefore, the fit between the two models cannot be compared with each other.

²These results were based on the 205 participants. We also computed the results based on the same 165 participants as the APM analyses. The results were similar to these reported here.
learning, as was proposed by Embretson (1991) and Verguts and De Boeck (2000) and was empirically corroborated by Ren et al. (2014). Complex problems like intelligence items implicate a number of rules that must be detected and considered in solving the problems (Carpenter et al., 1990; Stankov, 2001). Since the number of basic rules is small, test-takers may infer these rules and thus improve their ability to solve items as testing continues. This notion fits very well with updating as the necessity to repeatedly reach new but similar states in the human information processing. Updating that is restricted to a specific kind of contents may actually become more and more efficient. The same argument applies to shifting since the kinds of cognitive operations to be performed are usually quite restricted so that there is frequent shifting between similar cognitive operations. Furthermore, because of individual differences in learning in combination with individual differences in the capacity of working memory (Wang, Ren, Altmeyer, & Schweizer, 2013), improvements in the efficiency of the updating and shifting processes are likely to occur in the course of completing items of an intelligence test. Such a learning interpretation of the item-position effect provides a further argument for the relationship between executive functioning and intelligence.

In contrast, the executive process referred to as inhibition appears to be unrelated to changes in the demands to human information processing. The major contribution of this executive process to completing intelligence items appears to provide protection from deviations from the task-relevant course of human information processing. The challenge to this process appears to originate from the environment, and the environment stays the same for all items unless a disturbance is introduced. However, if the testing is conducted in a controlled environment, such a disturbance is rather unlikely. Therefore, a correlation with the ability component should be more likely than otherwise.

Nevertheless, inhibition is an important process of human information processing. The ability to inhibit non-functional information from influencing information processing and to focus the processing on the processing plan and the demands that need to be accomplished is very important for solving all kinds of intelligence test problems. A high degree of inhibition appears to be prerequisite for reaching high scores in all kinds of problems. Accordingly inhibition is important for fluid intelligence. There is even a claim that the inhibition process is a candidate for the source of the g factor (Jensen, 1998). However, it needs to be noted that the observation of a modest correlation between inhibition and fluid intelligence in our study is far from conclusive in supporting inhibition as a source of the g factor.

Finally, it needs to be mentioned that the rationality of the results underlines the usefulness of decomposing fluid intelligence data into the ability and item-position components. Specifically, the finding that updating and shifting correlating mainly to the item-position component of fluid intelligence data went a further step than previous studies that reported a relationship of these processes with intelligence without considering the item-position effect. It also suggests that the relationship between measures of inhibition and intelligence tests was less influenced by the item-position effect. Consequently, the distinction of the two components of an intelligence measure provides an opportunity to explain research results that otherwise may be perceived as contradictory.

References


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