Acta Psychologica 221 (2021) 103448

Contents lists available at ScienceDirect

Acta Psychologica

journal homepage: www.elsevier.com/locate/actpsy

The dual mechanisms of cognitive control and their relation to reasoning and the item-position effect☆

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ARTICLE INFO

Classification codes:
2223
2340
3120

Keywords:
Dual mechanism of cognitive control
Fluid intelligence
Item-position effect
Reasoning
AX-CPT

ABSTRACT

Braver's (2012) *dual mechanisms of cognitive control* differentiate between proactive control (PMC; i.e. early selection and maintenance of goal-relevant information) and reactive control (RMC; i.e. a late mobilization of attention when required). It has been suggested that higher cognitive capacities (as indicated by reasoning ability as a major characteristic of fluid intelligence) facilitate using the more resource-demanding PMC. We propose the following alternative explanation: engagement in PMC during the completion of reasoning tests leads to better test performance because gained knowledge (i.e. rules learned) during completion of early items is better maintained and transferred to later items. This learning of rules during the completion of a reasoning test results in an item-position effect (IPE) as an additional source of individual differences besides reasoning ability. We investigated this idea in a sample of 210 young adults who completed the AX-Continuous Performance Task (AX-CPT) and the Vienna Matrices Test (VMT). Using fixed-links modeling, we separated an IPE from reasoning ability in the VMT. Based on reaction time (RT) patterns across AX-CPT conditions, we identified three different groups by means of latent-profile analysis. RT patterns indicated engagement in PMC for Group A, mixed PMC and RMC for Group B, and RMC for Group C. With the consideration of the IPE, groups did not differ in their reasoning abilities. However, Group A (engaging in PMC) had a more pronounced IPE than Group C (engaging in RMC). Therefore, we conclude that PMC contributes to a stronger IPE, which in turn leads to higher scores in reasoning tests as measures of fluid intelligence.

1. Dual mechanisms of cognitive control

The ability to control our behaviour in order to achieve our goals is an important ability to master everyday life. We can plan into the future and suppress actions when anticipating future consequences (e.g. Sodian & Frith, 2008). The ability to register and maintain context information is assumed to play a crucial role and is also often referred to as cognitive control or attention control (Paxton et al., 2008).

Within the framework of the dual mechanisms of cognitive control (DMC), Braver (2012) put forward the idea that context representation and maintenance during information processing are the key components of cognitive control. As the name implies, there are two distinguishable mechanisms of cognitive control (Braver, 2012). Maintaining goal-relevant information in anticipation of a certain event or stimulus is referred to as a *Proactive Mechanism of Control* (PMC). This mechanism of control means early selection and maintenance of goal relevant information in anticipation of a challenging event in order to ideally guide attention. A *Reactive Mechanism of Control* (RMC), on the other hand, describes stimulus or event driven activation of goal-relevant information. With this mechanism of control, specific information is processed when it appears, but not anticipated to prepare processing in advance. This can be seen as late correction of past occurrences, as this mechanism depends on the occurrence of a specific event rather than its anticipation. It was suggested that RMC places less demands on cognitive resources than PMC, which is rather cognitively demanding (Braver, 2012).

Evidence in favour of two dissociable mechanisms of cognitive control stems from different areas of research. For example, neurophysiological studies provided evidence for different brain areas associated with PMC and RMC (Braver et al., 2009; Paxton et al., 2008). On

☆ Initial results of the latent profile analysis and the multilevel model analysis were presented at the 63rd conference for experimental psychologists (2021, TeaP, Ulm).

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https://doi.org/10.1016/j.actpsy.2021.103448
Received 8 September 2021; Received in revised form 5 November 2021; Accepted 9 November 2021
Available online 13 November 2021
0001-6918/

the behavioural level, Gonthier, Braver, and Bugg (2016) analysed reaction times (RTs) of different variations of the Stroop task and showed that the effects of the two mechanisms of control could be dissociated by experimental manipulation. Furthermore, Braver et al. (2001) reported that young adults showed more PMC than RMC while the opposite was found in older adults. It should be noted, however, that – although using PMC seems to be more advantageous than RMC – successful cognition is assumed to depend on a mixture of both mechanisms (Braver, 2012).

2. Dual mechanisms of cognitive control and intelligence

Burgess and Braver (2010) observed RMC-related brain activity when interference expectancy was low but an increase in PMC-related brain activity when interference expectancy was high in a recent-probes task. These results indicated that individuals shifted from one mechanism of cognitive control to the other when the situation required such a shift and cognitive capacities were available. In their behavioural data, Burgess and Braver (2010) also compared individuals with high and low fluid intelligence with fluid intelligence (Gf) defined as the ability to solve novel problems (Jensen, 1998). Overall high Gf individuals outperformed low Gf individuals in the recent-probes task (Burgess & Braver, 2010).

Gray et al.'s (2003) investigation of neural mechanisms of Gf lead to a similar observation. These authors applied an n-back task and systematically varied the amount of interference between conditions. Results showed stronger event-related neural activity in brain areas associated with PMC in the high interference condition. Most importantly for the present purpose, individuals with higher Gf did not only outperform individuals with lower Gf in the high interference condition but also showed stronger PMC-related brain activity. These results suggested that high Gf individuals engaged more strongly in PMC than low Gf individuals, which might be the reason for their better performance when being confronted with high interference (Gray et al., 2003).

The Gf-related differences reported by Burgess and Braver (2010) were not larger in the high than in the low interference condition, which was the case in the study of Gray et al. (2003). However, Burgess and Braver (2010) reported that, in a pilot study, high Gf individuals were indeed less affected by interference than low Gf individuals, especially when the inference expectancy was high.

These previous results on the relationship between Gf and the dual mechanisms of cognitive control (Burgess & Braver, 2010; Gray et al., 2003) have been taken as evidence that the higher cognitive capacities of individuals with high Gf facilitate or enable the use of PMC. Individuals with lower Gf, on the other hand, are more likely to engage in the less capacity-demanding RMC (Braver, 2012). The aim of the present study was to investigate an alternative explanation of the link between Gf and the dual mechanisms of cognitive control, which assumes a reversed direction of the effect. More specifically, we assumed that the engagement in PMC in contrast to RMC during the completion of a reasoning test leads to better performance on a reasoning test (and thereby to a higher estimation of Gf). To substantiate this assumption, we will outline in the following paragraphs how performance on reasoning tests is not only influenced by reasoning ability but also by an item-position effect (IPE) and how this IPE might be influenced by the use of PMC/RMC.

3. The item-position effect

Both previous studies on Gf and the dual mechanisms of cognitive control (Burgess & Braver, 2010; Gray et al., 2003) assessed Gf with Raven's Advanced Progressive Matrices (APM; Raven & Raven, 2003). With this type of test, participants have to identify a rule within a presented matrix per item and use this rule to choose one out of eight alternatives to fill the empty cell in the matrix correctly. Such psychometric reasoning tests are well-established and valid measures of Gf (Gustafsson, 1984; Kan et al., 2011; Schweizer et al., 2011) since reasoning ability is the main component of Gf (Carroll, 1993). However, there is also growing evidence that these reasoning tests are not homogeneous and therefore are no pure measures of Gf or reasoning ability. Confirmatory factor analyses (CFA) on the items of reasoning tests and primarily on the APM (e.g. Sun et al., 2019; Zeller et al., 2017) pointed to an IPE. This IPE could be dissociated from reasoning ability by means of bifactor measurement models, in which the factor loadings of the latent variable representing the IPE were fixed to increase monotonically from the first to the last item. The IPE explained a substantial portion of individual differences in test performance in addition to the latent variable reflecting reasoning ability and also improved the measurement model substantially (Schweizer, 2013; Troche et al., 2016). The IPE indicates that the processing of earlier items influences the processing of later items and the strength of this influence varies strongly between individuals, which is depicted by the amount of variance of the latent variable representing the IPE. At first sight, it might be assumed that the IPE just reflects the increasing item difficulty in a reasoning scale. This explanation could be ruled out with simulation studies (Schweizer & Troche, 2018) and empirical studies (Zeller et al., 2017). For example, in the study by Zeller et al. (2017) items were presented in random order. This manipulation of item order led to a dissociation of item position and item difficulty, and the IPE could still be clearly observed but not anymore explained by item difficulty. Importantly, the two components of the APM (i.e. reasoning ability and IPE) were not only separable on a statistical level, but also showed different correlations with several psychological constructs. Ren et al. (2017), for example, highlighted that when IPE and reasoning ability were both being considered, reasoning ability was moderately related to updating and inhibition, while the IPE was associated with updating and shifting abilities but not with inhibition.

To date, the most plausible explanation for the IPE is, that it reflects the learning of rules underlying the matrices during the processing of an item series (Ren et al., 2014; Ren et al., 2015; Sun et al., 2019; Zeller et al., 2017). This explanation is based on the finding that the IPE but not reasoning ability was strongly related to complex learning (Ren et al., 2014). According to the learning hypothesis, the underlying rules have to be identified and correctly applied to correctly solve a reasoning test item. If an individual can successfully carry over this newly gained knowledge to the next items, solving the next items can benefit increasingly from the processing of previous items. It is reasonable that individuals do not only differ in their ability to detect the rules underlying the matrices but also in their ability to use knowledge gained during the solving of earlier items or, stated differently, in their ability to use context information when an item is seen as an element of an item series. It is this ability, which is assumed to underlie individual differences in the IPE.

4. Item-position effect and cognitive control

The insights into the meaning of the IPE also provide a functional link with the dual mechanisms of cognitive control since the core of PMC is the use of context information to ideally guide attention during current information processing. Individuals engaging in PMC would already have previously learned rules on hand. Their first inspection of an item would already include the direct comparison of a new item with the experience from previous items. Since they show a disposition that supports maintenance of information, they are less likely to miss a connection or loose trace of a rule already learned. This should lead to a clear and increasing advantage when solving a series of similar items.

On the contrary, an individual engaging primarily in RMC might be expected to first process each reasoning item separately without taking previous experience into consideration, and only then accesses prior experience during previously solved items. These individuals would only benefit from prior knowledge, if a rule is correctly detected during the first inspection and the connection between this rule and an earlier rule can be made. This approach is less likely to be successful, since it depends on the successful retrieval and connection of previously applied rules.

In other words, individuals using PMC might benefit from this mechanism of cognitive control during experimental tasks as well as during the completion of a reasoning test, while individuals using RMC do not. This would lead to a positive correlation between performance on the experimental task assessing PMC/RMC and the reasoning task that is not due to reasoning ability but the IPE in the reasoning task. This would suggest, the previously observed relation between higher Gf as measured by a reasoning test and engagement in PMC by Braver and his colleagues (Burgess & Braver, 2010; Gray et al., 2003) can be interpreted in different ways. One interpretation refers to the original explanation that high compared to low Gf individuals possess higher cognitive capacities, which facilitate engagement in PMC during cognitively challenging situations (Burgess & Braver, 2010; Gray et al., 2003). Alternatively, it might be possible that individuals differ in their extent of engagement in PMC and that stronger engagement in PMC has a positive influence on the learning of rules and their later application when completing a reasoning test. This should become evident in a stronger IPE (rather than higher reasoning ability) resulting in better performance on the reasoning test.

5. Current research

The goal of the present study was to investigate this alternative explanation. More specifically, the goal was to examine, whether individuals that have a predisposition to engage in PMC differ from individuals that have a predisposition to engage in RMC during their performance on a reasoning test, due to higher reasoning abilities (as an indicator of Gf and, thus, of cognitive capacities) or due to a more pronounced IPE.

For this purpose and to identify individuals using PMC and or RMC, we used the AX-Continuous Performance Task (AX-CPT) paradigm (e.g., Gonthier, Macnamara, et al., 2016). In each trial of the AX-CPT, participants are presented with a cue letter followed by a probe letter (see Fig. 1). The task has four conditions, which differ in the combination of cue and probe letters. If the cue letter "A" is followed by the probe letter "X" (AX condition), participants are supposed to give a target response, by pressing a designated button with the right index finger. For all other cue-probe combinations, a non-target response is required, and participants are instructed to press another button with the left index finger. These conditions are often abbreviated as BX condition, BY condition and AY condition. Whereas "B" always indicates any letter but "A" as cue, "Y" any letter but "X" as probe, and the letters "X" and "A" represent themselves as probe or cue respectively.

Several studies mentioned RT differences between single conditions of the AX-CPT (e.g. Braver et al., 2001; Gonthier, Macnamara, et al., 2016; Paxton et al., 2008; Redick, 2014) which were interpreted as markers or identifiers of a certain mechanism of control. Overall, individuals strongly engaging in PMC should give a nearly immediate response upon appearance of the probe in the BX and BY condition as the cue letter holds sufficient information to prepare a correct non-target response. Also, when only applying PMC no significant RT difference

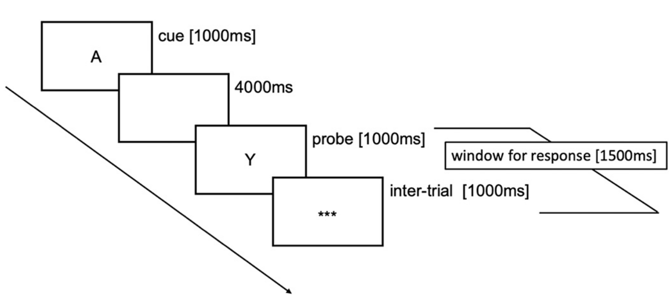

Fig. 1. Simplified display of one trial of the AY condition of the AX-CPT.

between the BX and BY condition should arise. The target response for the AX condition should be somewhat slower, as the individual has to wait for the probe to appear, since it is relevant for the response. RTs in the AY condition should also be notably slower when compared to the BX and BY condition, since the appearance of the probe letter has to be awaited before giving a correct response.

For individuals applying predominantly RMC, a different RT pattern should emerge, since responses are only formed after the probe has been presented. These individuals would give their fastest response in the BY and AY conditions, since the probe letter Y contains all information necessary to respond and no further processing of the cue letter is necessary. Additionally, there is no reason for a difference in RT between these two conditions. In the AX and BX conditions, RTs should be longer because the cue letter has to be retrieved after the probe letter X has been presented. Only then a response can be prepared. Since AX trials are presented more frequently, a target response could have a small advantage when compared to a non-target response. This advantage would be noticeable in faster RTs in the AX condition when compared to RTs in the BX condition.

For the present study, we expected that, in line with Burgess and Braver (2010), individuals showing an RT pattern with all the markers described above for PMC would achieve higher test scores on a reasoning test than individuals with an RT pattern coinciding with the markers described for RMC. However, when dissociating the IPE from reasoning ability, we expected that this PMC-related advantage would be obvious in a more pronounced IPE rather than in higher reasoning ability. There were several obstacles to investigating this idea. We had to first identify individuals who show a disposition to engage in PMC or RMC according to their RT pattern in the AX-CPT. Additionally, correlational analyses between RTs in specific conditions of the AX-CPT and reasoning test scores would be difficult to interpret since shorter RTs are consistently related to higher reasoning test scores regardless of the specific processes for which RTs are obtained (e.g. Der & Deary, 2017). Engaging in PMC or RMC, however, should lead to different variations of RTs across the four AX-CPT conditions (i.e. different RT patterns) and not only in faster RTs per se. Therefore, to identify possible underling groups of individuals that show similar dispositions in their use of cognitive control when completing the AX-CPT, we applied latent profile analyses (LPA). This approach enabled us to detect different groups without coercing certain structures (e.g., assuming exactly two groups) based on theoretical assumptions. Grouping individuals by means of LPA ensured that the groups were allowed to vary in their RT pattern. The LPA proved to be an objective approach to identifying unique groups of individuals showing different RTs during the completion of the AX-CPT, which also facilitates the replication in future studies. To characterize the identified groups in terms of PMC/RMC, multilevel modeling (MLM) was applied to analyse RT differences within the groups (between the AX-CPT conditions) and compare these RT differences between groups (i.e. cross-level interactions). In a last step, we investigated whether an IPE could be extracted in addition to reasoning ability from a reasoning test and whether the groups differed in their factor scores on reasoning ability and/or IPE. With this procedure the overarching objective could be specified by the following research questions:

1. Do the groups identified by means of LPA show RT patterns across the four conditions of AX-CPT that coincide with the markers assumed for PMC or RMC?
2. Can the IPE be detected in the reasoning test scores of the present sample in addition to a latent variable representing reasoning ability?
3. Do individuals that show the most PMC-consistent RT patterns have higher reasoning abilities and/or a more pronounced IPE than individuals with RMC-consistent RT patterns?

6. Method

6.1. Participants

A total of 210 individuals participated in the present study. While 161 participants described themselves as female, and 48 as male, one participant did not declare gender, age nor highest level of education. Mean age of the sample was 22.4 years (SD = 4.6 years). One hundred sixty-nine participants reported having university entrance qualification as their highest level of education, 21 a Bachelor's degree or higher, and 19 participants had neither. All participants reported normal or corrected-to-normal vision and gave written informed consent. The study protocol was approved by the local ethic committee of the University of Witten/Herdecke (No. 175/2017).

6.2. Vienna matrices test

The Vienna Matrices Test (VMT; Formann et al., 2011) is a measure of Gf, similar to Raven's APM, and consists of 18 items. Each item contains a 3 × 3 matrix, with each cell containing a geometric figure. The right cell on the bottom right is filled with a question mark. Participants are instructed to choose one out of eight possible response alternatives, which completes the matrix according to the underlying rule when substituting the question mark. In line with the manual, no time limitation was used and each participant gave a response to each item.

According to the manual, Cronbach's Alpha is approximately $\alpha = 0.80$. Each item was coded with 1 or 0 when a correct or an incorrect response was given, respectively. To obtain information on the representativeness of the sample regarding fluid intelligence, correct responses were summed up and transformed into age-stratified IQ scores as suggested by the manual.

6.3. AX continuous performance task

6.3.1. Apparatus and stimuli

The AX-CPT was adapted from Gonthier, Macnamara, et al. (2016) and programmed with E-Prime 2.0 Software. Participants completed the task on a Lenovo Thinkpad T510 with a 15.5″ monitor, which was positioned approximately 50 cm from participants' eyes. Responses were given via an external Cedrus response pad (Model RB-830; Cedrus Coporation; n.d.) with a registration accuracy of ±1 ms. Stimuli were black letters presented in the centre of the white monitor. Each letter had a height of 1 cm and a width of 0.8 cm.

6.3.2. Procedure

The task consisted of four conditions (AX-, AY-, BX-, and BY condition). In the 80 trials of the AX condition, the cue letter A was followed by the probe letter X. The AY condition contained 20 trials with the letter A as cue and any letter but X as probe. In the 80 trials of the BY condition, cue and probe letters were neither A nor X. In the 20 trials of the BX condition, the cue was any letter but A and the probe letter was X. The trials of the four conditions were presented in random order.

Each trial started with the cue letter presented for 1000 ms, followed by a blanc screen lasting 4000 ms and then the probe letter was presented for 1000 ms (see Fig. 1). Afterwards, three black asterisks were presented in the centre of the screen for 1000 ms before the next trial started. Participants were instructed to press a designated key with the right forefinger in response to trials from the AX condition and to press another designated key with the left forefinger in response to trials from the three other conditions. The instructions emphasized speed but to avoid errors. As dependent variable, mean RT of correct responses given within 150 to 1500 ms after the onset of the probe was recorded for each of the four conditions.

The task was preceded by written instructions and 10 practice trials to ensure that participants had understood the instructions. The duration of the task was approximately 20 min.

6.4. Time course of the study

In a first session, the VMT was completed as paper-pencil test in groups of two to five participants. In this session, further tests were administered, which are irrelevant for the present purpose. The second (individual) session took place within four to seven days after the first session, where each participant completed the AX-CPT followed by two other experimental tasks.

6.5. Statistical analysis

All analyses were run with R software using the packages *tidyLPA* (Rosenberg et al., 2019), *lmerTest* (Kuznetsova et al., 2017), *lavaan* (Rosseel, 2012), and *MBESS* (Kelley, 2007).

6.5.1. Identification of groups

In order to identify different groups according to the RT patterns across the four conditions of the AX-CPT, the mean RT for each participant in each condition was calculated and submitted to a latent profile analysis that used an expectation–maximization algorithm. Four types of models were computed. The four LPAs differed from each other by the assumption of equal (Model 1 and 3) or varying variances (Model 2 and 4) and by the assumption of zero covariances (Model 1 and 2) or varying covariances (Model 3 and 4). For each model, solutions for two up to eight possible groups were calculated resulting in 32 solutions. The best solution was identified by an analytic hierarchy process (AHP, Akogul & Erisoglu, 2017). The AHP took the information of various fit indices (AIC, AWE, BIC, CLC, KIC, see Table 1) into account and inverted their values to create a decision matrix, whereof it computed a composite relative importance vector (C-RIV) for each solution. According to Akogul and Erisoglu (2017), the solution with the highest C-RIV should be regarded as the best solution.

6.5.2. Group characteristics

In order to examine whether the response patterns of the identified groups could be distinguished, we applied multilevel modeling (MLM) to analyse RT differences between and within the identified groups for all four conditions of the AX-CPT. As our hypothesis would be reflected in cross-level interactions (different slopes between groups, meaning different RT differences between groups and conditions) a Slope-as-Outcome model[1] with group affiliation (Level 2) and condition (Level

Table 1
Mean and standard deviation (in parentheses) of IQ and reaction times (RT in milliseconds) in the four AX-CPT conditions for the full sample as well as the subsamples identified by the latent profile analysis.

	VMT raw scores	IQ scores[a]	RT_{AX}	RT_{AY}	RT_{BX}	RT_{BY}
Full sample	13.69	98.40	408	507	393	384
(N = 210)	(3.06)	(14.34)	(99)	(100)	(139)	(129)
Group A (n	14.19	100.75	357	445	305	307
= 114)	(2.92)	(13.62)	(30)	(40)	(34)	(31)
Group B (n	13.61	97.98	416	532	418	400
= 67)	(2.93)	(13.70)	(48)	(55)	(56)	(53)
Group C (n	11.90	90.07	594	693	683	654
= 29)	(3.30)	(15.77)	(130)	(88)	(110)	(115)

[a] IQ calculations were based on age-based norms, therefore the information of one participant in the full sample as well as Group B is missing.

[1] Complete equation of the slope-as-outcome model Aa in Table 3: $RT_{ij} = \gamma_{00} + \gamma_{01}GroupB + \gamma_{02}GroupC + \gamma_{10}AY + \gamma_{20}BX + \gamma_{30}BY + \gamma_{11}AY{:}GroupB + \gamma_{21}BX{:}GroupB + \gamma_{31}BY{:}GroupB + \gamma_{12}AY{:}GroupC + \gamma_{22}BX{:}GroupC + \gamma_{32}BY{:}GroupC + \varepsilon_{ij} + \upsilon_{0j} + \upsilon_{1j}$. With i indicating the individual within a Group and j the Group, υ_{0j} the random effects of the intercept, υ_{1j} the random effects of the slope, ε_{ij} the residual variance.

1) as a predictor of RT was calculated. Here, cross-level interactions can be seen as an indicator of different engagement in cognitive control. Models were calculated with Restricted Maximum Likelihood estimation (REML). This is preferable, as it is less prone to Type I errors compared to Maximum Likelihood estimation and well suited for small groups ($n < 50$; McNeish, 2017).

6.5.3. Identification of an item-position effect

For the separation of the IPE from reasoning ability, the 18 items of the VMT were analysed by a CFA using the robust maximum likelihood estimation. In a first (congeneric) model, one latent variable was derived from the 18 items with all factor loadings being freely estimated. This latent variable is assumed to reflect reasoning ability as an indicator of Gf. In a next step, the IPE was added to this model as a second latent variable. The correlation between the two latent variables (reasoning ability and item-position effect) was set to zero in order to avoid overlap of the variances. The factor loadings of the second latent variable were fixed to describe a quadratic increase from the first to the last item according to the following equation (cf. Troche et al., 2016):

$$f(i) = \frac{i^2}{k^2}$$

In this equation *i* represents the position of a given item, *k* the total number of items in the test, and *f* (*i*) the factor loading calculated for item *i*. This enables to account for the increasing variance appearing within the items throughout test completion. The gap between the distribution of binary manifest data and normal distribution of the latent variables was bridged by weighting each factor loading with the standard deviation of the respective item (Schweizer, 2013). The statistical significance of the variance of the latent variable representing the IPE was tested to investigate whether the IPE indeed represented a substantial amount of variance in the VMT items. The congeneric and the bifactor model were evaluated by means of model fit indices (χ^2, SRMR, RMSEA, CFI). As recommended by DiStefano (2016), values below 0.06 and 0.08 for the Root Mean Squared Error of Approximation (RMSEA) and for the Standardized Root Mean Square Residual (SRMR), respectively, indicated a good model/data fit. Further, a χ^2/df ratio of less than 2 (Wang & Wang, 2020) and a Comparative Fit Index (CFI) larger than 0.95 were regarded as evidence for a good fit. Models were compared by means of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) where lower values indicate better fit.

6.5.4. Relation of item position effect, reasoning and cognitive control

In a final step, the groups identified by the LPA were compared regarding differences in reasoning ability and the IPE. For this purpose, factor scores for the reasoning ability and the IPE were extracted. Factor scores depict for each individual the standing on the latent variable in relation to the whole sample. Factor scores are *z* standardized, therefore interpretation of values are always in relation to the mean of the whole sample. Afterwards, the factor scores were compared between the groups by means of pairwise independent *t*-tests. Data used for this analysis can be requested from the corresponding author.

7. Results

For the analysis of RTs, observations below 150 ms and above 1000 ms were excluded (1.39% of all observations). As in Gonthier, Macnamara, et al. (2016), only correct answers were included, this reduced the total of observations by another 2.17%. Table 1 gives descriptive statistics of RTs in the four conditions of the AX-CPT for the full sample (first row). Also reported in Table 1 are means and standard deviations of VMT raw scores and IQ scores. The IQ scores were close to the mean of 100 and the standard deviation of 15 in the representative norm sample reported in the manual of the VMT. Cronbach's alpha was $\alpha = 0.75$, which was close to $\alpha = 0.80$ as reported in the manual.

7.1. Identification of groups

To identify whether different groups of individuals can be found within the RT data, LPAs for the four types of models were run. For each model, the fit indices for solutions with two up to eight groups were computed (see Table 2). The above mentioned AHP (Akogul & Erisoglu, 2017) was used to determine the best solution. According to this process, a model with three groups with variances and covariances allowed to vary between groups and conditions yielded the best description of the data.

This solution assigned 114 participants to Group A, 67 participants to Group B, and 29 participants to Group C. The RT patterns across the four AX-CPT conditions of the three groups are given in Table 1 and are illustrated in Fig. 2. This solution also made sense from a theoretical point of view, as the additional groups in solutions with more than three groups showed response patterns, which were similar to and overlapping with the response patterns of the groups identified in the solution with three groups.

To describe the three groups according to their RT patterns across the four AX-CPT conditions (see Fig. 2), a MLM analysis was conducted. The fully unconditional intercept-only model revealed that participant effects explained 71% of the variance in the RTs as indicated by the intraclass correlation coefficient (ICC[2] = 0.714).

7.2. Group characteristics

To compare all conditions between (3×3 intercepts, 3×6 slopes) and within groups (3×6), a total of nine Slope-as-Outcome models had to be calculated, releveling the group or condition variable for each model. Detailed information about the calculated models is presented in Tables 3, 4, and 5. With releveling we were interested in a total of 45 comparisons. To avoid alpha inflation, we used the conservative Bonferroni correction and adjusted alpha to $\alpha = 0.0011$.

In Models Aa, Ab, and Ac (Table 3) Group A and the AX, AY and BX condition represent the intercept, respectively. In Models Ba, Bb and Bc, intercepts were again the AX, AY, and BX conditions, respectively, but for Group B (see Table 4). Finally, the intercept was releveled to Group C and the AX, AY, and BX condition, respectively (Models Ca to Cc in Table 5). Most relevant results are highlighted below while the full information can be taken from the tables.

When comparing the RT differences between conditions, Group A showed the strongest similarity to the RT pattern expected for individuals using PMC. Group A had significantly faster RTs in the BX and BY conditions compared to the AY and, most importantly, to the AX condition. Noteworthy is also, that the difference between RTs in the BX and in the AY condition, which has been interpreted as a strong indicator for PMC by Braver et al. (2001), was significantly larger in Group A than in the other two groups. RTs in the BX and BY conditions did not differ from each other in Group A, which was another marker for PMC.

In Group B, RTs in the AY condition were significantly longer than RTs in the other three conditions. RTs being longer in the AY condition when compared to the BX and the BY condition, fit the predicted outcome for individuals engaging in PMC. Group B showed similar RTs in the AX condition as in the BX and BY conditions. This did neither fit the assumptions made for PMC nor RMC, since with PMC responses in the BX and BY condition should be the fastest, and with RMC the RT of the BY and AX condition should be significantly different. Interestingly, in Group B (and in contrast to Group A), RTs in the BX condition were significantly longer than in the BY condition, which was consistent with the assumptions made for RMC. While the difference between the BX and BY condition was significant, it did not significantly differ from the

[2] Intraclass Correlation Coefficient (ICC) is defined as the Level-2 variance (participant effects) in proportion to the overall variance of the dependent variable (reaction time) in the intercept-only model: ICC = ${\sigma_{\upsilon0}}^2/({\sigma_{\upsilon0}}^2 + {\sigma_\varepsilon}^2)$

Table 2
Fit indices for all the estimated models by the latent profile analysis. Model number indicates model type and Groups the number of groups set for the estimation.

Model	Groups	AIC	AWE	BIC	CLC	KIC	C-RIV
1	1	10,371.05	10,462.61	10,397.83	10,357.05	10,382.05	0.02721
1	2	9617.78	9767.83	9661.29	9593.75	9633.78	0.02930
1	3	9276.20	9484.76	9336.44	9242.13	9297.20	0.03034
1	4	9075.63	9342.74	9152.62	9031.50	9101.63	0.03097
1	5	8969.77	9295.38	9063.49	8915.60	9000.77	0.03129
1	6	8978.42	9362.70	9088.88	8914.05	9014.42	0.03122
1	7	8988.38	9431.30	9115.57	8913.85	9029.38	0.03115
1	8	8998.08	9499.61	9142.00	8913.40	9044.08	0.03108
2	1	10,371.05	10,462.61	10,397.83	10,357.05	10,382.05	0.02721
2	2	9424.59	9621.50	9481.49	9392.47	9444.59	0.02987
2	3	9058.05	9360.24	9145.08	9007.92	9087.05	0.03100
2	4	8876.24	9283.64	8993.39	8808.14	8914.24	0.03156
2	5	8776.47	9289.10	8923.74	8690.38	8823.47	0.03185
2	6	8751.00	9368.94	8928.39	8646.85	8807.00	0.03187
2	7	8741.91	9465.18	8949.43	8619.69	8806.91	0.03183
2	8	8742.14	9570.62	8979.78	8601.94	8816.14	0.03176
3	1	8982.36	9144.08	9029.22	8956.36	8999.36	0.03136
3	2	8831.93	9052.14	8895.53	8795.91	8853.93	0.03185
3	3	8799.38	9078.23	8879.71	8753.19	8826.38	0.03193
3	4	8809.78	9147.71	8906.85	8752.99	8841.78	0.03185
3	5	8783.56	9179.60	8897.36	8717.12	8820.56	0.03190
3	6	8793.47	9248.22	8924.01	8716.79	8835.47	0.03182
3	7	8803.45	9316.85	8950.72	8716.59	8850.45	0.03175
3	8	8763.15	9334.87	8927.16	8666.45	8815.15	0.03185
4	1	8982.36	9144.08	9029.22	8956.36	8999.36	0.03136
4	2	8706.76	9044.31	8803.83	8650.34	8738.76	0.03222
4	**3**	**8651.97**	**9164.86**	**8799.25**	**8565.63**	**8698.97**	**0.03230**
4	4	8651.98	9340.42	8849.46	8535.51	8713.98	0.03218
4	5	8629.96	9493.74	8877.65	8483.55	8706.96	0.03214
4	6	8601.54	9640.53	8899.44	8425.34	8693.54	0.03213
4	7	8618.66	9833.11	8966.76	8412.40	8725.66	0.03195
4	8	8598.55	9988.32	8996.85	8362.38	8720.55	0.03191

Note. Model 1: Equal variances and covariances fixed to 0; Model 2: Varying variances and covariances fixed to 0; Model 3: Equal variances and equal covariances; Model 4: Varying variances and varying covariances; "Groups" indicates the number of Groups considered in the model; AIC = Akaike's Information Criterion; AWE = Approximate Weight of Evidence; BIC = Bayesian Information Criterion; CLC = Classification Likelihood Criterion; KIC = Kullback Information Criterion, C-RIV = Composite Relative Importance Vector. Based on an Analytic Hierarchy Process (AHP, see Akogul & Erisoglu, 2017) taking the mentioned fit indices into account, Model 4 with 3 groups (given in bold) showed overall the best fit (highest C-RIV).

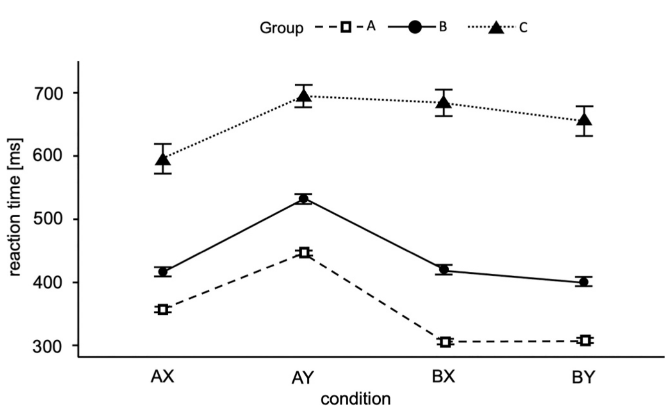

Fig. 2. Observed reaction time pattern and standard errors in the four conditions of the AX-CPT for the three groups identified by latent profile analysis.

difference that emerged for participants in Group A. This led to the conclusion that the difference for Group B between the BX and BY conditions, albeit significant, was so small that it could not be properly distinguished from the non-significant one that emerged for Group A. Summarized, Group B showed two RT differences that fit PMC, one that was RMC-consistent and some that did not comply with either. This implied that Group B engaged in a mix of PMC and RMC.

Group C participants had longer RTs in the BX condition than in the AX condition. Additionally, RTs in the BX condition were significantly longer than in the BY condition. These were both defined as markers for the engagement in RMC. For Group C the difference between the BX and BY condition was also significantly larger as the one that emerged in Group A, clearly distinguishing the two Groups.

Summarized, the RT pattern of Group A portrayed the expected PMC-consistent RT pattern while the RT pattern of Group C coincided with the RMC- consistent RT pattern. Although the interpretation of the RT pattern of Group B was less clear it seemed to have some similarities with PMC- and RMC-consistent patterns. It should also be mentioned that Group C was significantly slower in all AX-CPT conditions compared to the other two groups, and Group B was significantly slower than Group A.

7.3. Identification of an item-position effect

To analyse whether an IPE could be identified in the responses across the 18 items of the VMT, fixed-links modeling was applied. A congeneric model with the assumption of one underlying latent variable was compared to a bifactor model with a first latent variable representing reasoning ability and a second latent variable representing the IPE. Factor loadings on the latter were fixed with a quadratic increase to describe the increasing influence of the IPE from the first to the last item. The model fit statistics of the two models are given in Table 6.

According to Kenny (2015), the Comparative Fit Index (CFI) is seen as non-informative, when the RMSEA in the baseline model is lower than 0.158. The RMSEA of the baseline model was 0.112, therefore the CFI is listed in Table 6 but not used for model evaluation. The χ^2/df ratio was smaller than two for both models indicating good model fit (Wang & Wang, 2020). Also, according to SRMR and RMSEA, both models described the data well. However, the bifactor model had a lower AIC and BIC than the congeneric model indicating that it described the data better than the congeneric model. Additionally, in the bifactor model

Table 3
Estimates, t-values and *p*-values displayed for each Slope-as-Outcome model estimated with Group A as intercept and reaction time as dependent variable.

Model Aa			
Fixed effects	Estimate	t	*p*
Level 1			
Intercept (γ_{00})	356.87	67.14	<0.001
AY (γ_{10})	88.2	22.26	<0.001
BX (γ_{20})	−51.92	−13.11	<0.001
BY (γ_{30})	−50.11	−12.65	<0.001
Level 2			
Group B (γ_{01})	59.08	6.76	<0.001
Group C (γ_{02})	237.11	20.09	<0.001
AY:Group B (γ_{11})	27.67	4.25	<0.001
BX:Group B (γ_{21})	54.38	8.35	<0.001
BY:Group B (γ_{31})	34.22	5.26	<0.001
AY:Group C (γ_{12})	11.12	1.26	0.206
BX:Group C (γ_{22})	140.58	15.98	<0.001
BY:Group C (γ_{32})	110.08	12.51	<0.001

Model Ab			
Fixed effects	Estimate	t	*p*
Level 1			
Intercept (γ_{00})	445.07	83.73	<0.001
AX (γ_{10})	−88.2	−22.26	<0.001
BX (γ_{20})	−140.12	−35.37	<0.001
BY (γ_{30})	−138.31	−34.91	<0.001
Level 2			
Group B (γ_{01})	86.75	9.93	<0.001
Group C (γ_{02})	248.23	21.03	<0.001
AX:Group B (γ_{11})	−27.67	−4.25	<0.001
BX:Group B (γ_{21})	26.72	4.1	<0.001
BY:Group B (γ_{31})	6.56	1.01	0.314
AX:Group C (γ_{12})	−11.12	−1.26	0.206
BX:Group C (γ_{22})	129.46	14.72	<0.001
BY:Group C (γ_{32})	98.95	11.25	<0.001

Model Ac			
Fixed effects	Estimate	t	*p*
Level 1			
Intercept (γ_{00})	304.95	57.37	<0.001
AX (γ_{10})	51.92	13.11	<0.001
AY (γ_{20})	140.12	35.37	<0.001
BY (γ_{30})	1.81	0.46	0.648
Level 2			
Group B (γ_{01})	113.46	12.99	<0.001
Group C (γ_{02})	377.69	32	<0.001
AX:Group B (γ_{11})	−54.38	−8.35	<0.001
AY:Group B (γ_{21})	−26.72	−4.1	<0.001
BY:Group B (γ_{31})	−20.16	−3.1	0.002
AX:Group C (γ_{12})	−140.58	−15.98	<0.001
AY:Group C (γ_{22})	−129.46	−14.72	<0.001
BY:Group C (γ_{32})	−30.5	−3.47	<0.001

Note. Model Aa: Group A and condition AX as Intercept.
Model Ab: Group A and condition AY as Intercept.
Model Ac: Group A and condition BX as Intercept.
Bonferroni adjusted alpha value: 0.0011.

Table 4
Estimates, t-values and *p*-values displayed for each Slope-as-Outcome model estimated with Group B as intercept and reaction time as dependent variable.

Model Ba			
Fixed effects	Estimate	t	*p*
Level 1			
Intercept (γ_{00})	415.95	59.99	<0.001
AY (γ_{10})	115.87	22.42	<0.001
BX (γ_{20})	2.46	0.48	0.633
BY (γ_{30})	−15.89	−3.07	0.002
Level 2			
Group C (γ_{01})	178.03	14.11	<0.001
Group A (γ_{02})	−59.08	−6.76	<0.001
AY:Group C (γ_{11})	−16.55	−1.76	0.078
BX:Group C (γ_{21})	86.19	9.17	<0.001
BY:Group C (γ_{31})	75.85	8.07	<0.001
AY:Group A (γ_{12})	−27.67	−4.25	<0.001
BX:Group A (γ_{22})	−54.38	−8.35	<0.001
BY:Group A (γ_{32})	−34.22	−5.26	<0.001

Model Bb			
Fixed effects	Estimate	t	*p*
Level 1			
Intercept (γ_{00})	531.82	76.7	<0.001
AX (γ_{10})	−115.87	−22.42	<0.001
BX (γ_{20})	−113.4	−21.95	<0.001
BY (γ_{30})	−131.75	−25.5	<0.001
Level 2			
Group C (γ_{01})	161.48	12.8	<0.001
Group A (γ_{02})	−86.75	−9.93	<0.001
AX:Group C (γ_{11})	16.55	1.76	0.078
BX:Group C (γ_{21})	102.74	10.93	<0.001
BY:Group C (γ_{31})	92.4	9.83	<0.001
AX:Group A (γ_{12})	27.67	4.25	<0.001
BX:Group A (γ_{22})	−26.72	−4.1	<0.001
BY:Group A (γ_{32})	−6.56	−1.01	0.314

Model Bc			
Fixed Effects	Estimate	t	*p*
Level 1			
Intercept (γ_{00})	418.41	60.35	<0.001
AX (γ_{10})	−2.46	−0.48	0.633
AY (γ_{20})	113.4	21.95	<0.001
BY (γ_{30})	−18.35	−3.55	<0.001
Level 2			
Group C (γ_{01})	264.22	20.95	<0.001
Group A (γ_{02})	−113.46	−12.99	<0.001
AX:Group C (γ_{11})	−86.19	−9.17	<0.001
AY:Group C (γ_{21})	−102.74	−10.93	<0.001
BY:Group C (γ_{31})	−10.34	−1.1	0.271
AX:Group A (γ_{12})	54.38	8.35	<0.001
AY:Group A (γ_{22})	26.72	4.1	<0.001
BY:Group A (γ_{32})	20.16	3.1	0.002

Note. Model Ba: Group B and condition AX as Intercept.
Model Bb: Group B and condition AY as Intercept.
Model Bc: Group B and condition BX as Intercept.
Bonferroni adjusted alpha value: 0.0011.

both the reasoning latent variable ($\varphi = 0.211$, $z = 7.034$, $p < .001$) as well as the latent variable representing the IPE explained a significant portion of variance ($\varphi = 0.210$, $z = 4.856$, $p < .001$). The reported variances were scaled as suggested by Schweizer and Troche (2019). The scaled variances clearly showed that the IPE and reasoning ability both explained an equal amount of variance in the bifactorial model, further emphasizing the relevance of considering the IPE as a latent variable in the measurement model.

7.4. Relation of item position effect, reasoning and cognitive control

In a next step, factor scores for each participant were extracted from the bifactor model (see Fig. 3). To examine whether the three groups differed in their reasoning ability and/or in the extent of the IPE, six pairwise *t*-tests were calculated (see Table 7). To account for the multiple comparisons, alpha was adjusted to $\alpha = 0.0083$. The reasoning factor scores did not differ between the three groups (see Table 7). Also, the IPE did not differ significantly between Group B and C nor between Group B and A. However, in Group A, the IPE was significantly more

Table 5
Estimates, t-values and *p*-values displayed for each Slope-as-Outcome model estimated with Group C as intercept and reaction time as dependent variable.

Model Ca			
Fixed effects	Estimate	t	*p*
Level 1			
Intercept (γ_{00})	593.98	56.36	<0.001
AY (γ_{10})	99.32	12.64	<0.001
BX (γ_{20})	88.66	11.29	<0.001
BY (γ_{30})	59.97	7.63	<0.001
Level 2			
Group B (γ_{01})	−178.03	−14.11	<0.001
Group A (γ_{02})	−237.11	−20.09	<0.001
AY:Group B (γ_{11})	16.55	1.76	0.078
BX:Group B (γ_{21})	−86.19	−9.17	<0.001
BY:Group B (γ_{31})	−75.85	−8.07	<0.001
AY:Group A (γ_{12})	−11.12	−1.26	0.206
BX:Group A (γ_{22})	−140.58	−15.98	<0.001
BY:Group A (γ_{32})	−110.08	−12.51	<0.001
Model Cb			
Fixed effects	Estimate	t	*p*
Level 1			
Intercept (γ_{00})	693.3	65.79	<0.001
AX (γ_{10})	−99.32	−12.64	<0.001
BX (γ_{20})	−10.66	−1.36	0.175
BY (γ_{30})	−39.35	−5.01	<0.001
Level 2			
Group B (γ_{01})	−161.48	−12.8	<0.001
Group A (γ_{02})	−248.23	−21.03	<0.001
AX:Group B (γ_{11})	−16.55	−1.76	0.078
BX:Group B (γ_{21})	−102.74	−10.93	<0.001
BY:Group B (γ_{31})	−92.4	−9.83	<0.001
AX:Group A (γ_{12})	11.12	1.26	0.206
BX:Group A (γ_{22})	−129.46	−14.72	<0.001
BY:Group A (γ_{32})	−98.95	−11.25	<0.001
Model Cc			
Fixed effects	Estimate	t	*p*
Level 1			
Intercept (γ_{00})	682.63	64.77	<0.001
AX (γ_{10})	−88.66	−11.29	<0.001
AY (γ_{20})	10.66	1.36	0.175
BY (γ_{30})	−28.69	−3.65	<0.001
Level 2			
Group B (γ_{01})	−264.22	−20.95	<0.001
Group A (γ_{02})	−377.69	−32	<0.001
AX:Group B (γ_{11})	86.19	9.17	<0.001
AY:Group B (γ_{21})	102.74	10.93	<0.001
BY:Group B (γ_{31})	10.34	1.1	0.271
AX:Group A (γ_{12})	140.58	15.98	<0.001
AY:Group A (γ_{22})	129.46	14.72	<0.001
BY:Group A (γ_{32})	30.5	3.47	<0.001

Note. Model Ca: Group C and condition AX as Intercept.
Model Cb: Group C and condition AY as Intercept.
Model Cc: Group C and condition BX as Intercept.
Bonferroni adjusted alpha value: 0.0011.

pronounced than in Group C. This difference was statistically significant even after alpha adjustment.

To be able to compare our results with previous research (e.g., Burgess & Braver, 2010; Gray et al., 2003), we also calculated pairwise *t*-tests for the VMT raw scores between the groups. Group A had significantly higher VMT scores when compared to Group C, $t(40) = -3.65$, $p < .002$, $d = -0.71$, while the VMT scores of Group B did not differ significantly from Group A, $t(138) = -1.295$, $p = .199$, $d = -0.19$, nor from Group C, $t(48) = 2.42$, $p = .019$, $d = 0.53$, when adjusting the alpha value for the three comparisons ($\alpha = 0.017$).

8. Discussion

In the present study, we found three clearly distinguishable groups of individuals by analysing RTs across the four conditions of the AX-CPT. Group A and Group B showed similar RT patterns, yet only the RT pattern of Group A directly coincided unambiguously with the one assumed for PMC indicating strong engagement in PMC. Group B exhibited mixed engagement in PMC and RMC. Group C had an RT pattern that resembled the one expected for RMC. Across all

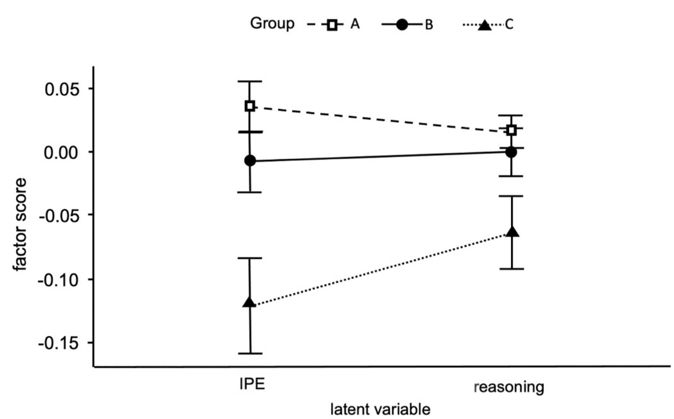

Fig. 3. Factor scores on the latent variables representing the item-position-effect (IPE) and reasoning ability in the Vienna Matrices Test for the three groups identified. Error bars represent standard errors.

Table 7
Results for two-tailed *t* tests to compare factor scores for the latent variables reflecting the item-position effect (IPE) and reasoning ability between the three groups with different engagement in PMC and RMC.

	t	df	*p*	*Cohen's d*
IPE				
Group B – C	2.55	51.23	.014	0.57
Group B – A	−1.44	148.55	.151	0.22
Group C – A	3.72	44.94	.00056	0.76
Reasoning				
Group B – C	1.84	51.76	.071	0.41
Group B – A	−0.73	129.62	.471	0.11
Group C – A	2.51	40.14	.016	0.54

Note. Bonferroni adjusted alpha value: 0.0083.

Table 6
Chi-square (degrees of freedom), *p*-value, and various fit indices to compare the congeneric model and the bifactorial model which includes latent variables representing reasoning ability and item-position effect.

Model	χ^2 (*df*)	*p*	RMSEA	SRMR	CFI	AIC	BIC
Congeneric	217.28 (135)	< .001	0.054	0.064	0.794	2999.44	3119.93
Bifactorial	208.99 (134)	< .001	0.052	0.063	0.812	2993.15	3116.99

Note. Root Mean Squared Error Approximation (RMSEA); Standardized Root Mean Square Residual (SRMR); Akaike Information Criterion (AIC); Bayesian Information Criterion (BIC); Comparative Fit Index (CFI) is non-informative as the RMSEA of the baseline model is lower than 0.158.

participants, we identified an IPE in the VMT data indicating that individuals differed in the extent they could benefit from the completion of previous items during the completion of later items. Although the effects were partly of medium size, the three groups did not differ significantly in their reasoning ability. The IPE, however, was more pronounced in Group A compared to Group C, which is in line with the assumption, that engagement in PMC is associated with a larger IPE.

8.1. Classification of groups

The LPA on RTs in the four conditions of the AX-CPT identified three groups of individuals. Results of the MLM led to the following characterization of the groups: Participants in Group A had shorter RTs than the other two groups and the RT pattern was a straightforward match with the expected pattern for individuals applying PMC. Participants in Group B had somewhat slower RTs than Group A. Unlike Group A, their fastest RTs were in the AX, BX and the BY condition and there was a significant, albeit very small difference between the BX and BY condition. The RT pattern of Group B showed features typical for PMC as well as features typical for RMC. Therefore, we interpreted the RT pattern of Group A as engagement in PMC, and the RT pattern of Group B as a mixture of engagement in PMC and RMC.

Group C had not only slower RTs compared to the other two groups but also a very different RT pattern. The difference between RTs in the AY and in the BX condition, which has been previously emphasized as an indicator for using PMC (Braver et al., 2001), was significantly smaller in Group C than in the other groups, indicating that Group C engaged less in PMC than the other two groups. Also, the expected difference between RTs in the BX and BY condition was significantly larger in Group C compared to Group A. The emergence of a difference between the BX and BY condition is a clear marker for engagement in RMC. A further marker would have been similar RTs in the AY and BY conditions. This was not the case for any group. Yet the differences between the conditions were notably larger for Groups A and B, and significantly smaller for Group C. This difference between the AY and BY conditions, albeit significant, is very small for Group C. Further support for the assumption that Group C most likely engaged in RMC can be taken from the findings reported by Gonthier, Macnamara, et al. (2016). The authors explicitly manipulated the AX-CPT to make individuals engage more strongly in RMC. The RT pattern which resulted from this manipulation was similar to the RT pattern observed in the present study for Group C with longer RTs in the AY condition than in the other three conditions. The above-mentioned difference between RTs in the AY condition compared to the BX and BY conditions was even more pronounced in the study by Gonthier, Macnamara, et al. (2016) than in our Group C.

In sum, three clearly distinguishable groups could be identified in the present study, which did not only differ in overall RT or their RTs in single conditions, but in their RT patterns across the four AX-CPT conditions. The RT pattern of Group A clearly matched the assumed pattern for PMC, the RT pattern of Group B indicated mixed engagement in PMC and RMC while the RT pattern of Group C indicated engagement in RMC.

8.2. Relation of item position effect, reasoning and cognitive control

When examining the association between reasoning ability and the two mechanisms of cognitive control, previous studies (Burgess & Braver, 2010; Gray et al., 2003) split the sample of participants into subgroups according to their reasoning ability score and declared the groups as high and low Gf individuals. Then behavioural data and/or neural activity between these subgroups were compared regarding their engagement in PMC/RMC. The results of these previous studies suggested that high Gf individuals engaged more strongly in PMC than low Gf individuals. Results were seen as evidence for the idea that the larger cognitive resources of individuals with high Gf facilitated the use of the resource-demanding PMC (Braver, 2012). When we directly compared the VMT raw scores between the three groups identified in the present study, we obtained similar results: Group A, which most strongly engaged in PMC, had significantly higher reasoning scores (as indicator of Gf) compared to Group C which had the weakest or no engagement in PMC and showed strong evidence for using RMC. This is worth to mention since we used the VMT in the present study to measure reasoning ability while Burgess and Braver (2010) as well as Gray et al. (2003) used Raven's APM. Thus, the outcome of a functional relationship between reasoning ability as a measure of Gf and the dual mechanisms of cognitive control seems not to depend on the instrument with which reasoning ability is assessed.

In contrast to previous studies, however, we extracted an IPE from the present reasoning test. The existence of an IPE in reasoning test data in addition to a latent variable representing reasoning ability was in line with an increasing body of research on the IPE in reasoning measures (Ren et al., 2014; Ren et al., 2015; Sun et al., 2019; Troche et al., 2016; Zeller et al., 2017). Both latent variables explained an equal proportion of variance in the measurement model indicating that the IPE cannot be neglected when reasoning ability is correlated with other variables. To date, the most plausible explanation for the IPE states that some individuals strongly benefit from already completed items, while others do not (Ren et al., 2014). Therefore, some individuals are better at using knowledge gained during the completion of earlier items to ideally bias their information processing for the completion of later items. Proceeding from this interpretation of the IPE, we assumed that individuals using PMC showed a larger IPE than individuals using RMC due to their early selection and maintenance of (context) information to bias attention in an ideal manner during the completion of the task at hand (cf. Braver, 2012). This idea was supported by our empirical results as individuals who strongly engage in PMC (Group A) exhibited a more pronounced IPE compared to individuals who engage in RMC (Group C), while the groups did not statistically differ in their reasoning ability. This result is remarkable as it suggests that the direction of the relationship between the engagement in RMC/PMC and fluid intelligence might be interpreted differently than previously proposed by Braver and his colleagues (Burgess & Braver, 2010; Gray et al., 2003). These authors argued that higher Gf as a reflection of higher cognitive capacities facilitates applying the resource demanding PMC. On the contrary, our results suggest that using PMC rather than RMC leads to higher reasoning test scores because of a more adaptive behaviour during test completion. Individuals engaging in PMC seem to use context information, knowledge gained from solving previous items, to solve later items. This leads to a stronger IPE, while individuals engaging in RMC seem to benefit less from previously solved items and therefor have a smaller IPE. It is important to mention that, although Group A and Group C did not differ significantly in their reasoning ability, the effect size was quite large with Cohen's $d = 0.54$ so that the size of Group C was perhaps not large enough to reveal a significant difference in reasoning ability when compared to the other groups. A more tentative interpretation, therefore holds, that Group A and C differed primarily in their IPE and only subordinately in their reasoning ability. The differences between Group B and Group C in the IPE and reasoning ability might be similarly interpreted against the obtained effect sizes presented in Table 7.

8.3. Limitations

From this point of view, the rather small size of Group C might be considered a limitation of the present study since it resulted in larger standard errors when compared to the other two groups. In contrast, more than half of the sample belonged to Group A showing a typical PMC pattern. This was surprising as we composed the sample not only from university students but also from individuals without university entrance certification to spread the range of intelligence. As a result, the IQ distribution in our sample was highly similar to the distribution in the norm sample. Nevertheless, the portion of individuals identified as applying RMC was rather small. Therefore, it could be interesting to see whether a similar group classification would be obtained in a sample with a larger age range or in a sample of older adults for whom Braver et al. (2001) reported more engagement in RMC compared to younger individuals. Additionally, a combination of a classification approach as introduced in the present study based on behavioural data and a neurophysiological approach using fMRI might illuminate whether the groups would show brain activation patterns reported to be PMC- or RMC-specific (Braver et al., 2009; Paxton et al., 2008).

Since the experimental approach as well as the statistical methods of our study do not allow for a strong causal interpretation of the relationship between PMC and IPE, a more straightforward hypothesis test is called for to further confirm our interpretation. Nevertheless, our results suggest that another causal relationship might be conceivable between measures of Gf and the dual mechanisms of cognitive control than suggested by Burgess and Braver (2010).

9. Conclusion

To summarize, three clearly distinguishable groups could be identified, which differed in their engagement in PMC and RMC and in their VMT test scores. Albeit, under the consideration of the IPE in the VMT data, the identified groups did not differ in their reasoning ability. Instead, the difference in the test scores could be explained by a more pronounced IPE in the group with strong engagement in PMC compared to the group that engaged in RMC. These results present first evidence for the notion that using PMC rather than RMC can lead to better reasoning test scores due to a stronger IPE. In other words, compared to individuals who engage in RMC, individuals engaging strongly in PMC benefit more from solving previous items when they solve later items in a reasoning test.

CRediT authorship contribution statement

Helene M. von Gugelberg: Conceptualization, Methodology, Data curation, Formal analysis, Visualization; Writing - original draft, Writing - review & editing; **Karl Schweizer**: Conceptualization, Validation, Methodology, Writing - review & editing; **Stefan J. Troche**: Conceptualization, Methodology, Supervision, Writing - review & editing, Resources, Project administration.

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