Effortful control is associated with executive attention: A computational study

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Effortful Control is associated with executive attention: a computational study

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Abstract

Introduction. Effortful control (EC) is the self-regulatory aspect of temperament that is thought to reflect the efficiency of executive attention (EA). Findings on relationship between EC and performance on EA tasks among adults are still contradictory. This study used a computational approach to clarify whether greater self-reported EC reflects better EA.

Methods. Four-hundred-twenty-seven healthy subjects completed the Adult Temperament Questionnaires and the Attention Network Task-revised (ANT-R), a conflict resolution task that gauges EA as the Flanker Effect (FE), i.e., the difference in performances between incongruent and congruent trials. Here we also employed a drift-diffusion model in which parameters reflecting the actual decisional process (drift rate) and the extra-decisional time are extracted for congruent and incongruent trials.

Results. EC was not correlated with the FE computed with the classic approach, but correlated positively with drift rate for the incongruent trials, even when controlling for the drift rate in the congruent condition and the extra-decisional time in the incongruent condition.

Conclusion. This study demonstrates an association between self-reported EC and EA among adults. Specifically, EC is not associated with overall response facilitation but specifically with a greater ability to make goal-oriented decisions when facing conflicting information.

Keywords: Executive Attention, Effortful Control, Drift Diffusion Model, Temperament, self-regulation.

Introduction

Personality differences arise, at least in part, from biological, constitutionally-based temperament traits. According to Posner and Rothbart (Posner & Rothbart, 2007; Derryberry & Rothbart, 1997), temperament reflects individual differences in reactivity and self-regulation. “Reactive” aspects of temperament are represented by Extraversion and Negative Affectivity. These dimensions reflect the activity of the appetitive and defensive motivational systems, which serve appetitive or defensive needs and respectively mobilize approach and inhibition behavior as well as underlie individual dispositions toward positive and negative emotions. (Derryberry & Rothbart, 1997). These motivational aspects of temperament provide initial forms of self-regulation by enabling individuals to attend to both rewarding and threatening information in the environment. However, these processes are involuntary and automatic, and might not allow for flexible adaptation to external circumstances. Conversely, Effortful Control (EC) represents the “voluntary” aspect of temperament that allows individuals to resolve successfully conflicts between immediate reactive tendencies and long-term demands, and to overcome a dominant response in order to produce a more appropriate, valued and goal directed non-dominant response (Casey, Tottenham & Fossella, 2002; Derryberry & Rothbart, 1997; Posner & Rothbart, 2009; Posner & Rothbart, 2018; Rothbart, Ellis & Posner, 2011). EC includes the abilities to voluntarily shift and focus attention (attentional control) and to inhibit or initiate behavior (inhibitory and activation control, respectively) as needed for adapting to circumstances even if one does not feel like doing so. In this way, EC promotes the capacity for effective and flexible self-regulation, which is central for adaptive functioning: limitations in EC are associated with greater psychological and interpersonal maladjustment in both youth (see Eisenberg, Smith & Spinrad, 2011; and Posner & Rothbart, 2018 for a review; Kim-Spoon et al, 2019) and adult samples (Ayduk et al, 2008; Cain et al., 2013; Cain et al, 2018; Claes et al, 2010; De Panfilis et al., 2013; De Panfilis et al, 2016; Fosco et al, 2012; Meehan et al., 2013; Meehan et al, 2017; Sleuwagen et al, 2018).

Infant research demonstrated that the development of EC in childhood parallels the increasing efficiency of executive attention (EA), i.e., the capacity to detect and solve conflicts between opposing information (Gerardi Caulton, 2000; Rothbart et al, 2003; Rothbart & Rueda, 2005; Chang & Burns, 2005; Simonds, Kieras, Rueda & Rothbart, 2007; Kim-Spoon et al, 2019). EA can be studied by means of tasks that compare responses under a congruent condition, in which a single response tendency is present, with those under an incongruent condition, in which two conflicting response tendencies are elicited by a stimulus. Specifically, the Attention Network Test (ANT) has been developed to reliably evaluate the EA brain network in both children and adults (Posner & Rothbart, 2018; Fan et al, 2002; Fan et al, 2009; Rothbart & Rueda, 2005). In the adult version of the ANT, subjects are asked to identify the direction of a central arrow pointing rightward or leftward (target) that is surrounded by two flanker arrows on each side. Flanker arrows may point in the same direction of the target on either side (congruent condition) or in the opposite direction (incongruent condition). Typically, incongruent conditions yield prolonged reaction times (RTs) (Fan et al, 2002; Fan et al, 2009). The flanker conflict effect (FE), defined as the difference in RTs between flanker incongruent and flanker congruent conditions, represent an index of EA – the greater the FE, the lower the efficiency of the EA network (Fan et al, 2009). At the brain level, resolving conflicts on the ANT is associated with increased activation in the anterior cingulate cortex, a key region for signalling and solving cognitive conflict (Fan et al, 2005), as well as with intrinsic activity of some resting state networks, suggesting that the brain also owns intrinsic functional organization to support the executive network of attention (Visintin et al, 2015; Markett, Reuter, Montag et al, 2014).

While current theories on attention and self-regulation posit that an individual's EC directly relates with one's ability to resolve conflicts on EA tasks such as the ANT (Posner & Rothbart, 2009, 2018; Nigg, 2017), there is yet limited evidence of an empirical association between self-reported EC and behavioural measures of EA among adults. A few studies evaluated whether EC in non-clinical adults was related with performance on some EA tasks, such as the Simon task, the flanker task and the Stroop task, but results were mixed, with findings of either a positive (Kanske & Kotz, 2012) or null (Bridgett et al, 2013) association. With respect to performance on the ANT, FE was negatively related with EC in a study involving borderline personality disorder patients, temperamentally matched low-EC individuals, and healthy controls (Posner et al, 2002). However, no association between EC and FE was reported in a mixed community and clinical sample of remitted depressed patients (Marchetti, Shumake, Grahek, Koster, 2018). These contrasting findings may be explained by sample diversity (i.e., larger range of EC scores and ANT performances in the study by Posner et al, 2002 due to sample selection), but are also consistent with concerns, from a psychometric view, on reliably calculating the efficiency of the attentional networks as differences scores between raw RT on the ANT (MacLeod et al, 2010).

Indeed, in the context of two-choice decision tasks, such as the ANT, an individual's RT represent a combination of decisional and extra-decisional time. While the decisional time is a measure of the decisional process, the extra-decisional time reflects perceptive and motor components of the response time interval. The classic approach computing EA as the FE at the ANT leaves unclear whether an individual have a small FE because is particularly fast in making cognitive decisions upon incongruent trials, or has just a fast motor response.

Computational modelling applies mathematical methods to empirical data with the aim of estimate latent behavioural and cognitive variables, named parameters, that underlie neural process that generates empirical observations (Bennet et al., 2019; Browning et al., 2020). Ideally, the extracted parameters should better relate with observations (e.g., clinical symptoms, neural substrates) that are not easily captured by traditional analysis (Huys et al., 2016).

The Drift Diffusion Model (DDM) (Ratcliff & McKoon, 2008) is a form of computational modelling that allows breaking down these two different components. Based on each individual's distribution of RTs for correct and incorrect responses, the DDM quantify a set of parameters that produce the best fit to the actual subject's responses, including the drift rate, which is a measure of the decision process, and the extra-decisional time. A greater drift rate reflects better performances whereas a greater extra-decisional suggests longer non-decisional intervals. DDM is widely validated (Voss et al., 2013), fits to the data from neural network simulations (Mueller et al., 2017), and has been successfully applied to some attentional tasks (Merkt et al., 2013; Lefferts et al., 2019; O'Callaghan et al., 2017; White, Ratcliff & Starns, 2011; White Servant & Logan, 2018; Dillon et al, 2015; Price et al., 2019).

Thus, the present study evaluated whether EA, as assessed by the ANT, is associated with good self-reported temperamental EC in a large multicultural sample of adults. In addition to compute EA as the FE using the classic approach, we employed the DDM to evaluate which part of an individual's choice (i.e., decisional and extra-decisional) required to respond to congruent and incongruent trials on the ANT was precisely related with temperamental EC. Specifically, we hypothesized that good self-reported EC would directly relate to greater drift rate for the incongruent trials on the ANT, indicating greater ability to solve conflicts between opposing information (i.e., greater EA) but not to the FE using the classic approach as this could reflect the inter-individual variability in the different components of the response time.

We further hypothesized that the association with EA would be specific of EC, so that the efficiency of EA, would not be related to reactive aspects of temperament such as negative affectivity and extraversion, reflecting the voluntary and self-regulatory nature that characterizes EC.

Material and Methods

Participants.

This study involved 427 non-clinical subjects (33.7% males, mean age: 25.06; sd=6.57). The a-priori sample size estimation is detailed in the Supplementary material. Two-hundred-fifty-four (38.6% males; mean age: 27.6; sd=5.52) were recruited in an urban area in Northern Italy through advertisements in meeting places in the local community. Among these 189 (37.6% males; mean age: 27.1; sd=4.00) were part of a previous study (De Panfilis et al., 2019). A hundred-seventy-three subjects (26.6% male; mean age: 21.45; sd=6.23) were undergraduates from a multicultural U.S. university enrolled in another study (Meehan et al., 2017).

Sample Size. The a-priori sample size calculation (G*power, Faul et al., 2007) suggested that the required sample size to detect an effect size of 0.15 with an alpha $p<.05$ (two-tailed) and a power (1-beta) of 95% would be of 470 participants. We considered such a low effect size because of the limited and contrasting evidence of association between self-reported EC and behavioural measures of EA among adults.

The studies were approved by the Local Ethical Authorities. Subjects enrolled in Italy participated for no compensation whereas those recruited in the USA were compensated with course credits. After giving informed consent, all included subjects completed the inclusion assessment and self-report measures in a separate appointment from the ANT task. Exclusion criteria were substance abuse, and having received any prior or current psychiatric diagnosis or treatment. For all the experiments, we reported all the measures, conditions and data exclusions.

Assessments

Temperament

Temperament was assessed with the Adult Temperament Questionnaire (ATQ; Evans and Rothbart, 2007), that comprises 77 items that are rated on a 7-point Likert-scale (1 = "extremely untrue of you", to 7= "extremely true of you").

Items refer to Negative Affectivity (NA; i.e., "I become easily frightened"), Extraversion (E; i.e., "It doesn't take much to evoke an happy response in me"), and Effortful Control (EC; i.e., "I can keep performing a task even when I would rather not do it"). The questionnaire also includes a fourth scale, Orienting Sensitivity, which was not used in the current study because unrelated to the study aims.

Participants could skip items they did not feel comfortable responding to. Missing items within a subscale were imputed using the mean scores of the respective subscale, if they represented less than 10% of all the items. Four-hundred-fifteen subjects were then included in the temperamental analyses.

The internal consistency of the NA, E and EC subscales was good (Cronbach's alpha, respectively .798, .706, and .828).

Executive Attention

Subjects performed the Attention Network Test Revised (ANT-R; Fan et al., 2009), a behavioural task designed to measure the efficiency of the three attentional networks: alerting, orienting and executive attention (EA).

Subjects are asked to indicate as quickly and accurately as possible the direction of the target that is the central arrow. The target is accompanied on both side by a couple of arrows. These can point in the same (congruent condition) or in the opposite direction (incongruent condition). The task is composed of 288 trials (n=144 congruent and n=144 incongruent) and for each trial it computes the RT and the correctness. Accuracy represents the rate between correct and incorrect trials. The difference in RT and accuracy between the incongruent and congruent conditions is named Flanker Effect (FE) and measures the executive control network of attention: the lower the FE, the greater the efficiency of EA.

A cue can be presented at 0, 400, or 800 ms before the target. When present, it acts through temporal facilitation, reflecting the alerting network of attention. Based on its spatial location (left or right), instead, the cue can be informative of the location of the upcoming target. This can be on the same (valid) or on the opposite (invalid) side of the target. The contrast between the valid and the invalid conditions, called location effect, explores the orienting network of attention. Because in the ANT-R the cue manipulations are balanced between the congruent and incongruent target conditions and the focus of our study was on EA, we simply classified the 288 trials in congruent and incongruent.

Statistical Analysis

First, we assessed the two approaches (i.e., classic and DDM) singularly, evaluating their performances in measuring EA; second, we compared the two models. Lastly, we evaluated the association between EA as measured by the ANT-R and temperament dimensions.

Sample characteristics

Descriptive statistics were performed to detail demographic variables and temperament dimensions in the study sample.

Executive Attention assessment

We next assessed the efficiency of EA by means of two different approaches: the classic approach and the drift diffusion model.

Classic approach

We calculated first the FE with the classic approach (Fan et al., 2009) that computes it as the difference in the average RT on correct responses between the congruent and incongruent trials.

$$\mathbf{FE = RT_{incongruent} - RT_{congruent}}$$

We also adopted a correct score of the FE (FE_c), as suggested by Wang and colleagues (Wang et al., 2014) that represents the ratio between the FE and the mean RT across all trials.

$$\mathbf{FE_c = FE/RT_{mean},}$$

where FE= Flanker Effect and RT= reaction times

Classic approach Performance. As for the performance on the ANT-R, we first evaluated whether the experimental manipulation yielded the expected results in the selected model (i.e.

slower RT and lower accuracy in the incongruent than the congruent condition). To do so we compared the two conditions using a one-sample t-test on the FE calculated both with the classic approach and in its corrected form. A FE positive and significantly different from 0 suggests faster RT for the congruent trials compared with the incongruent trials. In the same way, a positive and significantly different from 0 difference in accuracy, suggest a greater ratio of correct responses in the congruent than incongruent trials.

We then evaluated the speed-accuracy trade-off as the correlation between the RT and the accuracy of the FE. A lack of positive correlation guarantees that the effect in reaction time cannot be explained by a speed-accuracy trade-off, that is, by the tendency for decision speed to covary with decision accuracy so that low speed means higher accuracy.

Drift Diffusion Model

Second, we used a Drift-Diffusion Model (or Diffusion Decision Model, DDM) (Ratcliff & McKoon, 2008; Ratcliff et al., 2016). DDM has been recognised as one of the best model when describing decision-making strategies (Bogacz et al., 2006). This computational model of decision making allows to explain behaviours in two-choices discrimination tasks beyond mean RT and data accuracy. DDMs describe decision making as an accumulation of evidence, a noisy process that seems to mirror the behaviours of populations of neurons before a recruiting threshold is reached.

Being a two-choice decision model the two possibilities are depicted by two opposing thresholds, that in our model are the correct answer (upper threshold coded as 1) and the wrong answer (lower threshold coded as 0).

DDM quantifies a set of parameters using the distribution of RTs and errors across the trials, including the drift rate and the extra-decisional time.

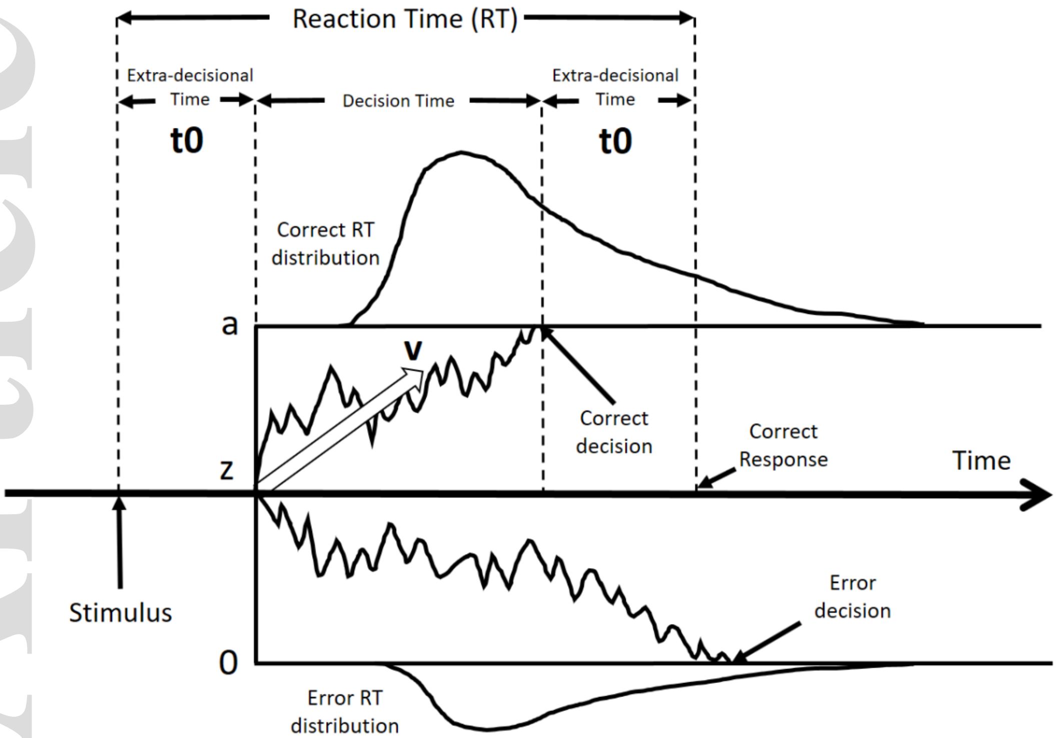
Evidence accumulates in a noisy manner, and the average rate of accumulation is called drift rate. The drift rate reflects the decisional process as the probability of a step towards the one of the two thresholds, in ours model the right (coded as 1) and the wrong (coded as 0) answers. We expect that overall, the subjects are more likely to make the right decision and hence the drift rate will be positive. Tasks harder to solve such as the trials in the incongruent condition in which the probability of making the right choice is lower have a smaller drift rate. The extra-decisional time encompasses all those processes that happen before and after the decision is made, namely encoding of the stimulus and execution of the motor response (Figure 1).

Thus, we evaluated the drift rate and the extra-decisional time in two separate models for both congruent and incongruent trials on the ANT-R. We regarded the drift rate for incongruent trials as an index of an individual's EA (i.e., the higher the drift rate, the greater the probability of making the right choice, the better the efficiency of EA).

The DDM also includes a decisional threshold separation (a) that reflects the response caution. Because a decision is made when the evidences accumulated in favour of one option reach a decisional threshold, a greater boundary separation means that more evidences (i.e. more time) are needed to reach a threshold (i.e. decision). In an attentional task it reflects the speed/accuracy trade-off so that subjects with larger boundaries are more prone to conservative decisions and hence to fewer errors.

Three more parameters that can vary in the model are (1) the percentage of contaminants (p) that account for short and long outlier RTs; (2) a parameter quantifying the differences in non-decisional time for correct and incorrect responses (d); and (3) the starting point (z) (Figure 1). The starting point reflects how the individual is a priori biased toward one of the two decisional options. Because during the execution of the task, the parameters might change, the inter-trial variability of three parameters is also computed: variability in drift rate (sv), variability in extra-decisional time (st0) and variability in the starting point (sz). The across-trial variability in drift rate, for example, is explained by the fact that, even if the stimulus is identical, the way that the individual accumulates the decision-relevant information can change with the repetition of the stimulus over the task execution.

Figure 1. The diffusion decision model



Note: A greater value of the drift rate (v) correspond to better performances towards the correct answers. The extra-decisional time (t0) is the component of RT that is not due to evidence accumulation that encompasses all those processes that happen before and after the decision is made. The model also included a parameter quantifying the decisional threshold separation (a) that reflects the response caution. A greater boundary separation means that more evidences (i.e. more time) are needed to reach a threshold (i.e. decision). The starting point (z) reflects how the individual is a priori biased toward one of the two decisional options.

DDM Analysis and Performance. DDM analyses were conducted using a Fast-dm software (Voss & Voss, 2007). Information regarding how the model was run and how we tested its performance (i.e. model fit and model recovery) are detailed in the **Supplementary** file.

Comparison between the classic and the DDM models of EA

Because this was the first study to apply the DDM to the performance on the ANT-R, as an exploratory analysis we also evaluated the association between the classic indexes of EA of the ANT-R (i.e., FE and FE_c) and the DDM parameters of drift rate and extra-decisional times for both incongruent and incongruent trials using Spearman's correlations. This analysis would allow to disentangle whether a smaller FE on the ANT-R precisely reflects greater ability for conflict resolution (i.e., better decisional process for the incongruent trials) rather than a generic overall response speed (i.e., better decisional process also for congruent trials) or faster extra-decisional time intervals unrelated to the pure cognitive task.

Associations between EA and temperament dimensions

We then explored whether the FE, the FEc as well as the drift rates and the extra-decisional times in both the congruent and incongruent conditions correlated with the temperamental dimensions, namely EC, NA and E. Because the parameters were not normally distributed, we explored these associations through Spearman's rho. When doing so, we also controlled in a partial correlation for the variability in drift rate (sv), since this parameter might have consequences for the relative speeds of correct and error responses.

Lastly, since the study aim was to evaluate which part of an individual's choice (i.e., decisional and extra-decisional) required for responding to congruent and incongruent trials on the ANT is precisely related with temperamental EC we built the following linear model with EC as a dependent variable.

$$\textbf{Effortful Control} = \mathbf{b0} + \mathbf{b1*v_{incongr}} + \mathbf{b2*v_{cong}} + \mathbf{b3*t0_{incong}} + \textit{error}$$

where v= drift rate and t0= extra-decisional time

This analysis would allow to confirm that EC precisely parallels the ability to resolve conflicts between opposite information, irrespectively of an overall faster decisional process (i.e., drift rate for congruent trials) and of those time intervals not due to evidence accumulation (i.e., extra decisional time for incongruent trials).

Results

Sample characteristics and performance at the ANT.

As for ANT-R performance, consistent with previous reports (Fan et al, 2009; Visintin et al, 2015) both the RT and the accuracy for the FE were significantly different from zero (Reaction Times: FE=137.69; t=41.73; $p<.001$; FE_c=.252; t=50.83; $p<.001$; Accuracy: FE=-0.173; t=-14.301; $p<.001$) confirming a faster RT and a greater accuracy when flanking arrows to the target pointed in the same direction compared to when they pointed to a different direction. Furthermore, there was no speed accuracy trade-off as indicated by the lack of correlation between the accuracy and the RT of the FE (r=.074; p=.277). Subjects' mean scores at ATQ and their mean FE at the ANT-R are depicted in **Table 1.**

Table 1. Demographics, ATQ scores and FE values in the whole sample

	n=427
Male	n=144 (33.7%)
Age (years)	25.07 (6.57)
Education (years)	15.19 (2.59)
Negative Affectivity	3.78 (.72)
Extraversion	4.54 (.72)
Effortful Control	4.53 (.83)
Reaction Times (ms)	
Congruent	552.56 (89.6)
Incongruent	691.31 (126.4)
Flanker Effect (FE) (ms)	138.58 (61.54)
Flanker Effect/mean RT (FE_c)	0.252 (0.09)

Note. values as mean (standard deviation) if not otherwise specified. Missing subjects: sex: n=5; age: n=22; For the temperamental dimension n=412 subjects included.

DDM performance. Confirming previous results using the same drift-diffusion model on an attentional task (Price et al., 2019) the first model in which all the parameters were free to vary was the one that got a better fit. The model showed a good ability in recovering the parameters of interest (see **Supplementary**).

Comparison between the classic and the DDM models of EA

The classic ANT-R FE was associated positively with the extra-decisional times in all conditions (congruent: rho=.274; p<.001; incongruent: rho=.530; p<.001) and negatively with the drift rate in the congruent condition (congruent: rho=-.140; p=.005; incongruent: rho=.-.020; p=.690), while FE_c correlated only with the extra-decisional time in the incongruent condition (rho=.337; p<.001). This suggests that the EA indexes on the ANT-R, as assessed by the classic method, mainly reflect an association with faster extra-decisional times and faster decisional processes for the congruent trials, rather than with a faster decision process during incongruent trials.

Correlation between the parameters from both the classic approach and the DDM are depicted in **Table 2**.

Table 2. Pearsons Correlations between the parameters extracted both with the classic approach and through the DDM

incongruent	t0	.375 (p<.001)						
	RT	.122 (p=.014)	.826 p<.001					
congruent	v	.344 (p<.001)	-.282 (p<.001)	-.456 (p<.001)				
	t0	.353 (p<.001)	.755 (p<.001)	.659 (p<.001)	-.164 (p=.001)			
	RT	.198 (p<.001)	.789 (p<.001)	.899 (p<.001)	-.541 (p<.001)	.740 (p<.001)		
FE		.009 (p=.855)	.580 (p<.001)	.743 (p<.001)	-.146 (p=.003)	.317 (p<.001)	.422 (p<.001)	
FE_c		-.036 (p=.468)	.337 (p<.001)	.472 (p<.001)	.070 (p=.157)	.069 (p=.167)	.098 (p=.048)	.924 (p<.001)
		v	t0	RT	v	t0	RT	FE

incongruent	congruent	

Note. RT= mean Reaction Times. FE= Flanker Effect; FE_c= Flanker Effect divided by the mean RT; v= drift rate; t0= extradecisional time.

Association of EA measures with demographic and temperament variables

When exploring the association with the socio-demographic variables we did not considered age and year of education. Consistent with the sample selection (i.e. university students) these two variables were non-normally distributed and leptokurtic (age: d(405)=.141; p<.001; Skewness=1.831; Kurtosis= 5.55; years of education (d(405)=.320; p<.001; Skewness=.836; Kurtosis=1.05). For this reason, they were not included in the correlation analyses and in the regression models.

Overall the FE, but not the FE_c, was greater in females than males (t(328.071)=2.851; p=.005).

Compared to females, males were better in the decisional process only in the congruent condition (congruent: t=-2.839; p=.005; incongruent: t=1.591; p=.112), whereas had shorter non-decisional times (congruent: t=2.374; p=.018; incongruent: t=2.579; p=.010).

The temperamental traits were not associated with the FE calculated with the classic approach (Fan et al., 2009) nor with the mean RT for the congruent and incongruent conditions (**Table 3**).

Conversely, when exploring the association between temperament and the DDM decisional as well as extra-decisional parameters for congruent and incongruent trials, only the drift rate for incongruent trials correlated positively with EC (rho=.135; p=.006) (**Table 3; Figure 2**).

This association is significant even when testing for multiple comparisons with Bonferroni correction (Noble, 2009). Following our main hypotheses, in fact, we tested the association of three temperamental dimensions with two different EA measures for a total of six correlations. Even when dividing the p=0.05 threshold by the number of tests (new threshold for the p-value=0.05/6=0.008), EC is still significantly associated with drift rate for incongruent trials.

This remained significant even when controlling for the variability of the drift rate in a partial correlation ($r_{partial}$=.104; p=.034).

Table 3. Spearman's correlations between EA measures and temperamental dimensions

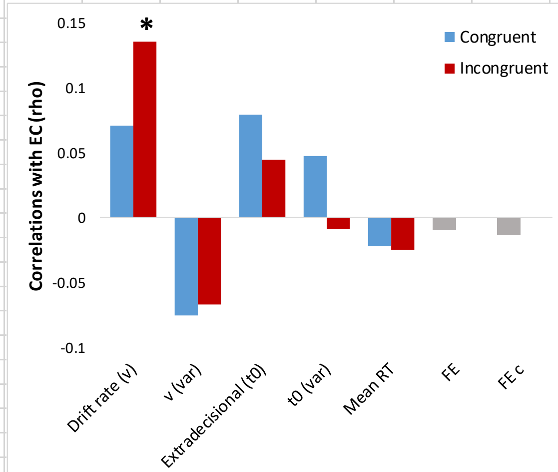
	EC	E	NA
ANT-R classic parameters			

Mean RT			
Congruent	-.022	-.082	.073
Incongruent	-.025	-.062	.058
Flanker Effect (FE)	-.010	-.028	-.042
Flanker Effect/mean RT (FE_c)	-.014	-.017	.004
DDM Parameters			
		Congruent	
Drift rate (v)	.071	.056	-.093
Variability in v (sv)	-.076	.011	.01
Extra-decisional time (t0)	.079	-.058	-.014
Variability in t0 (st0)	.047	-.039	.008
		Incongruent	
Drift rate (v)	.135*	-.075	-.081
Variability in v (sv)	-.067	.039	-.021
Extra-decisional time (t0)	.044	-.061	-.017
Variability in t0 (st0)	-.009	-.096	.063

Note. NA: Negative Affectivity; Ext: Extraversion; EC: Efforful Control. FE *p<.05

Figure 2. Association between Effortful control and the EA measures

	Congruent	Incongruent
Drift rate (v)	0.071	0.135
v (var)	-0.076	-0.067
Extradecisional (t0)	0.079	0.044
t0 (var)	0.047	-0.009
Mean RT	-0.022	-0.025
FE	-0.01	
FE c	-0.014	



Note. Each bar represents the magnitude of the Spearman correlation coefficient (rho) between that variable and EC. Bars are plotted separately for the congruent and incongruent conditions. var= variability in the parameter; RT= reaction times; FE= Flanker Effect, computed as the difference between the mean RT in the incongruent and congruent condition; FE_c = corrected Flanker Effect, computed as the ratio between FE and mean RT . *p<.05.

Having found that EC is associated with greater drift rate in the incongruent conditions, we next evaluated whether this association was independent from the drift rate in the congruent conditions as well as from the extradecisional time in the incongruent conditions. In a linear model with EC as dependent variable, the drift rate for incongruent trials was still the only significant variable associated with EC (R^2=.014; beta=.118; B=.065; 95%CI=.001, .133; t=1.894; p=.05). This was true even when controlling for the extra-decisional time in the same condition (beta=-.001; B=-.011; 95%CI=-.969, .947; t=-.023; p=.982) and the drift rate for congruent trials (beta=.001; B=.001; 95%CI=-.074, .074; t=-.001; p=.999). This confirms that EC is directly related to the decision process of solving cognitive conflicts.

Discussion

To our knowledge, this study is the first to evaluate whether temperamental effortful control is associated with greater executive attention, as measured by the ANT-R, in an adult community sample using a computational approach. To do that we used the DDM, which decomposes the performance on the ANT-R into separate parameters that reflect different aspects of an individual's decision making. EC was specifically related with the ability to solve conflicts between opposing stimuli (i.e., drift rate for incongruent trials). Conversely, EC was not associated with response efficiency in the absence of conflicting information (drift rate for congruent trials) nor with non-decision-time capturing encoding and motor execution of the task (extra-decisional time for both incongruent and congruent trials). Thus, EC is specifically associated with a sensitive measure of EA, i.e., the ability to inhibit a dominant response and activate a subdominant response when needed (Rothbart & Bates, 2006).

Interestingly, in the present study EC was not associated with EA as computed by the classic approach, as a simple difference in RT when responding to incongruent and congruent conditions (i.e, the ANT-R FE). Furthermore, the classic FE was not associated with decision time for incongruent trials as gauged by the DDM, but only with decision time in the congruent conditions and extra-decisional times across both conditions. Thus, in the present study the decision-making process of healthy subjects when solving conflicts between opposing information is better described by a drift diffusion model that allows to distinguish between the decisional and the non-decisional part of an individual's response. Conversely, the EA indexes on the ANT-R, as assessed by the classic method, mainly reflect an association with faster extra-decisional times and faster decisional processes for the congruent trials, rather than with a faster decision process during incongruent trials. When looking specifically at incongruent trials, the association between the extra-decisional time, but not the decision process, with the FE suggests that the classic approaches (Fan et al., 2008; Wang et al., 2014) might grasps mainly the perceptive and motor component of the time interval. In the same way, the observed association between the FE (Fan et al., 2008) and the decisional parameter in the congruent condition might reflect an individual variability in decision-making independently from the conflict resolution. Congruent with this hypothesis, the association between the decisional parameter in the congruent condition and the FE disappeared when controlling the latter for the individual's mean RT (Wang et al., 2014), a measure of individual variability.

These findings suggest that previous contrasting results on the association between the classic FE and EC (i.e., Posner et al, 2002; Marchetti et al, 2018) could be due to the high inter-individual variability in the different components of the response time, while a computational approach, which provides quantitative estimates of individuals' decision-making, can reliably capture the relationship between EA and EC. Indeed, in this study the association between the decisional process in the incongruent condition (i.e. the ability of solving a conflict) and EC remained significant even when controlling for the extra-decisional time and the decisional time in the congruent condition. Controlling for the extra-decisional time excludes that the association is due to longer encoding or motor processes. Similarly controlling for the decisional time in the congruent condition suggest that the association cannot be explained by the inter-individual variability in RTs.

We also demonstrated that a faster decisional time for incongruent trials was specifically related to the voluntary dimension of temperament, namely effortful control, but not with reactive aspects of temperament such as extraversion and negative affectivity. This confirms that the ability to employ deliberate top-down cognitive control to self-regulate precisely represent the neurocognitive correlate of EC, while the approach and avoidance motivational systems reflect bottom-up mental processes that automatically respond to external (i.e., sensory) stimuli, but are not activated by conflicting stimuli, as EA is (Nigg, 2017). Thus, the voluntary regulation of emotions, thoughts, and actions promoted by EC is rooted in the neurocognitive ability of conflict resolution.

The main study limitation relies in the sample selected. Enrolling only highly educated and young adults limits the generalisability of our results. Moreover, the linear model speaks of association between decision process and effortful control rather than of causality. Further, we cannot rule out the existence of other psychopathological dimensions mediating in this relationship.

In conclusion, the results of this study add to current research efforts aimed at clarifying the neurobehavioral bases of major domains of functioning, such as EC (NIMH RDoC, 2020). They also help bridging the gap between different frameworks that have historically been applied to study the field of self-regulation, i.e., the developmental temperament approach and the neurocognitive approach (Bridgett et al, 2013). Specifically, clarifying the processes that sub serve successful self-regulation is critical to understand the psychopathology of self-regulation failures (Nigg, 2017). Thus, the study finding that EC reflects the decision time to successfully solve conflicts between opposite information may have important clinical implications. Attentional and cognitive control training is effective in improving conflict resolution (Rothbart & Rueda, 2005; Posner, Rothbart & Tang, 2013; Siegle et al, 2007; Tang & Posner, 2009); therefore, individuals low in EC may benefit from interventions aimed at increasing the efficiency of their EA network, thereby buffering their risk toward self-regulation failures.

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