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Cognitive control and attentional functions

Melissa-Ann Mackie [a,b], Nicholas T. Van Dam [b,c], Jin Fan [b,c,d,*]

[a] The Graduate Center, City University of New York, New York, NY 10016, USA
[b] Department of Psychology, Queens College, City University of New York, Flushing, NY 11367, USA
[c] Department of Psychiatry, Mount Sinai School of Medicine, New York, NY 10029, USA
[d] Department of Neuroscience, Mount Sinai School of Medicine, New York, NY 10029, USA

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ABSTRACT

Cognitive control is essential to flexible, goal-directed behavior under uncertainty, yet its underlying mechanisms are not clearly understood. Because attentional functions are known to allocate mental resources and prioritize the information to be processed, we propose that the attentional functions of alerting, orienting, and executive control and the interactions among them contribute to cognitive control in the service of uncertainty reduction. To test this hypothesis, we examined the relationship between cognitive control and attentional functions. We used the Majority Function Task (MFT) to manipulate uncertainty in order to evoke cognitive control along with the Revised Attention Network Test (ANT-R) to measure the efficiency and the interactions of attentional functions. A backwards, stepwise regression model revealed that performance on the MFT could be significantly predicted by attentional functions and their interactions as measured by the ANT-R. These results provide preliminary support for our theory that the attentional functions are involved in the implementation of cognitive control as required to reduce uncertainty, though further investigation is needed.

1. Introduction

Cognitive control is required for the flexible allocation of mental resources in the service of goal-directed behavior (Badre, 2008; Kouneiher, Charron, & Koechlin, 2009; Miller, 2000; Posner & Snyder, 1975; Solomon et al., 2009). The terms "cognitive control", and "executive control" are frequently used interchangeably in the literature. For the purpose of this paper we define cognitive control as the broader construct of information prioritization for goal-driven decision-making (Posner & Snyder, 1975). Executive control of attention, on the other hand, is defined as a specific component of attention for conflict processing (Posner & Fan, 2008). Although the term cognitive control is widely used in the literature, how control is achieved is not clearly understood and its underlying mechanisms are not entirely known. In this paper, we present our theory regarding the role of the attentional functions in cognitive control, along with data from a preliminary study investigating the relationship between the attentional functions and cognitive control.

1.1. Defining cognitive control

Previous attempts to model cognitive control have resulted in several definitions, which describe cognitive control in terms of performance on specific tasks. For example, the popular conflict monitoring theory (Botvinick, Braver, Barch, Carter, & Cohen, 2001) and a recently proposed variant of this theory (Yeung, Cohen, & Botvinick, 2011) are based on performance models of tasks such as the Stroop Color-Word task (Stroop, 1935) and the Eriksen flanker task (Eriksen & Eriksen, 1974). The guided activation model (Miller & Cohen, 2001) is based on a model of the Stroop task, while the error-likelihood model (Brown & Braver, 2005) and its updated version, the prediction response outcome model (Alexander & Brown, 2011), are based on modified stop-signal and flanker tasks. These models are meant to capture control functions considered to be most relevant to cognitive control, but models of control are disproportionately based on tasks tapping response inhibition. As a result, existing models yield theories of cognitive control whose parameters are constrained to the particular function being measured by the specific tasks in which the theories are grounded. This is clearly problematic for defining an ontology of a construct as heterogeneous as cognitive control (Morton, Ezekiel, & Wilk, 2011; Stout, 2010), which is not limited to response inhibition, but is also required for complex information processing, which we will later discuss.

Another approach to defining cognitive control is inspired by functional anatomy (Stout, 2010), with focus predominantly on the anterior cingulate (Botvinick et al., 2001) or prefrontal (Miller & Cohen, 2001) cortices, both shown to be associated with tasks widely considered as cognitive control functions. To test anatomical hypotheses, specific tasks known to elicit activation in

* Corresponding author. Address: Department of Psychology, Queens College, The City University of New York, 65-30 Kissena Blvd., Flushing, NY 11367, USA.
E-mail address: jin.fan@qc.cuny.edu (J. Fan).

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pre-specified neuroanatomical areas are chosen, rather than tasks that may tap the more integrative, heterogeneous construct. The difficulty that arises when attempting to pinpoint the neural geography of complex cognitive functions is that often a one-to-one mapping of structures to functions is elusive. Instead, we may find a range of cognitive processes emerging from a mélange of brain structures (Price & Friston, 2005), as well as a mélange of processes emerging from single structures (Shackman et al., 2011). While narrow definitions of cognitive control may lead to the identification of associated discrete functional anatomy, considering the construct as dynamic and flexible produces a far more complex picture.

A definition of cognitive control in terms of its underlying psychological processes has yet to be developed. Existing models are limited in their scope, confining application of the construct to specific individual functions. As such, existing task- and anatomy-based models fall short of capturing the broad nature of cognitive control. In order to arrive at a satisfactory description of the construct and its nature, a more integrative examination is necessary.

1.2. Cognitive control: componential, emergent, or both?

The ontology of cognitive control has been overwhelmingly such that the constructs described as comprising it (e.g., response selection, response inhibition, and task-set switching, among others) are described as discrete functions, measured by different tasks, with no interactions between them (Lenartowicz, Kalar, Congdon, & Poldrack, 2010). Although a previous study aiming to determine the organization and possible dissociability of the executive functions found them to be both diverse and unified (Miyake et al., 2000), it is only very recently has it been suggested that cognitive control is achieved via the interactions of control components (Badre, 2011). There is now emerging debate regarding whether cognitive control is better defined as comprising discrete functional components attributable to unique functional anatomy, whether it emerges from more basic psychological functions that often serve other purposes or whether it is best conceptualized as being both componential and emergent (Cooper, 2010; Juvina, 2011).

The componential view has been investigated by neuroimaging studies. One approach attempts to isolate a control component and identify the neural structures uniquely associated with that function (Aron, 2007). Another approach attempts to dissociate several components (Lenartowicz et al., 2010) derived from previous task-based definitions (Miyake et al., 2000) and identify their discrete functional anatomy. There is much evidence to suggest considerable overlap in control functions (Sabb et al., 2008), which is problematic for mapping these constructs onto neural networks (Lenartowicz et al., 2010), and ultimately suggests that in terms of cognition, these functions share something more fundamental (Juvina, 2011). Control components are often found to be related (Juvina, 2011) and difficult to completely dissociate (Lenartowicz et al., 2010; Miyake et al., 2000), suggesting that they share a fundamental commonality. It is our hypothesis that this commonality lies with the attentional functions, underlying a critical basis of cognitive control.

From another perspective, the emergent view of cognitive control suggests that control functions arise from the goal-directed integration of neural resources otherwise dedicated to non-control processes (Cooper, 2010; Juvina, 2011). Support for this view has thus far come from computational models employing Adaptive Character of Thought-Rational (ACT-R) cognitive architecture, demonstrating that the mechanisms implemented to deal with cognitive control tasks (e.g., Stroop) are also employed in other, non-control tasks (Nomura et al., 2010; Pacheco-Unguetti, Acosta, Callejas, & Lupiáñez, 2010). In terms of brain-based models, network-oriented theories of cognitive control provide a more integrative view of control functions by suggesting the existence of distinct networks responsible for the execution of control functions (Corbetta & Shulman, 2002; Dosenbach, Fair, Cohen, Schlaggar, & Petersen, 2008). A more recent brain network approach suggested that the instantiation of cognitive control may occur via the interactions of defined task-related networks (Power et al., 2011). Together, these findings suggest the need for departure from a strictly componential view of cognitive control (Juvina, 2011). Of note, an emergent view need not dismiss the contributions of various components of cognitive control and the theories that have developed around them (Alexander & Brown, 2011; Botvinick et al., 2001; Brown & Braver, 2005; Miller & Cohen, 2001). Rather, the emergent view builds on these components of cognitive control, with new system-level properties emerging when component interactions are examined in a specific framework.

1.3. Cognitive control for uncertainty reduction

In order to define cognitive control, it is essential to understand its function(s). We propose that cognitive control serves as the basis for the reduction of uncertainty. Uncertainty may be conceptualized at several levels, ranging from sensory processing to outcome prediction (Bach & Dolan, 2012). One way to quantify uncertainty is in terms of Shannon *entropy*, which takes into account the amount of information that must be gained before a correct decision may be made (Shannon, 1948). In Shannon's information theory, *entropy*, in bits, can also represent higher-level uncertainty associated with, for example, selection of letters or words in a message. Uncertainty can arise from conflict between perceptual and behavioral processes, such that the amount of uncertainty is proportional to the number of competing responses from which one must choose (Hirsh, Mar, & Peterson, 2012). As previously mentioned, cognitive control is widely considered as necessary for conflict processing. We propose that the condition of conflict is a special case of uncertainty (Hirsh et al., 2012; Mushtaq, Bland, & Schaefer, 2011), such that the quantifiable uncertainty one faces in conditions of conflict lies within a limited range. Uncertainty can, however, be manipulated without conflict, as it is in the Majority Function Task (MFT; Fan, Guise, Liu, & Wang, 2008), requiring the recruitment of cognitive control not in the service of conflict processing (as it is typically thought to be) but rather for uncertainty reduction.

Cognitive control is most important when there is competition for limited mental resources, a relatively common condition in the brain (Desimone & Duncan, 1995). Cognitive control serves to reduce uncertainty in decision-making, at various levels, by controlling what information reaches focused awareness. Under such circumstances, a considerable amount of computation is required in order to generate accurate responses. For example, when processing information in the presence of task-irrelevant distracters (as in the Color Stroop (Stroop, 1935) or the Eriksen flanker (Eriksen & Eriksen, 1974) tasks), individuals must actively screen out distracting information or inhibit competing responses in order to accurately implement a response. Efficient performance on these tasks is due to the mental flexibility that cognitive control allows.

As distracting information and/or the number of possible responses increase, uncertainty also increases. One way to examine information uncertainty and consequently the implications for cognitive control is within the framework of information theory (Fan et al., 2008; Hirsh et al., 2012). If we consider uncertainty in terms of *entropy*, or the amount of information that needs to be processed before a response can be made, we can investigate cognitive control in explicitly computational terms. Considering the overlap in neural networks associated with cognitive control and dealing with uncertainty, uncertainty can be viewed as one context that triggers the implementation of cognitive control (Mushtaq et al., 2011). Conflict detection and resolution is therefore a special case of cognitive control, functioning to reduce uncertainty and facilitate decision-making.

Other control 'components', or as we consider them, functions, can also be explained from an uncertainty reduction perspective. For example, the "switch cost" associated with set-shifting can be considered to be due to increased uncertainty associated with the task switch. Underdetermined responding and response selection also induce uncertainty, as uncertainty increases with the number of potential responses. For inhibition of prepotent responses, a low frequency event can be conceptualized in terms of dealing with increased uncertainty (for a specific trial type termed as *surprise* in Shannon's information theory) when a required response is not the most readily accessible one.

1.4. An attentional function theory of cognitive control

From the inception of the term "cognitive control", it was described as a limited capacity system employed in the form of cognitive strategies (particularly attentional strategies) consistent with task instructions (Posner & Snyder, 1975). Early theories of attention, such as expectancy theory (Deese, 1955), the early filter model (Broadbent, 1958), the attenuation model (Treisman, 1960, 1964), the pertinence model (Deutsch & Deutsch, 1963), and feature integration theory (Treisman & Gelade, 1980) are all related to the selection of a subset of sensory information due to a limited capacity for information processing. One early model featured a 'supervisory attention system' to account for the willed and automatic control of behavior (Norman & Shallice, 1986). Attention can thus be thought of as subserving cognitive control by modulating information processing in a goal-consistent manner, via the attentional functions. Further, control processes have been described as being implemented via attention, and since active attention is required, only one process can be controlled at a time without interference from other processes (Shiffrin & Schneider, 1977).

One view of attention is that it consists of separable, yet interconnected brain networks (alerting, orienting, and executive control) that influence computational priority, controlling what information enters conscious awareness (Fan et al., 2009; Posner & Fan, 2008). Alerting allows for an increase in vigilance to an impending stimulus and orienting refers to the mechanisms by which information is selected from various sensory inputs. Executive control of attention refers to those processes involved in detecting and resolving conflict in information processing among competing mental processes (Bush, Luu, & Posner, 2000). Previous investigations of cognitive control have focused almost exclusively on the orienting function of attention: "top-down" control is analogous to endogenous (voluntary and goal-directed) orienting and "bottom-up" attentional control is analogous to exogenous (involuntary and saliency-driven) orienting (Folk, Remington, & Johnston, 1992; Theeuwes & Burger, 1998). We argue that other aspects of attention also contribute to the emergence of cognitive control, and that these functions are not exclusive to top-down control.

We propose an attentional function theory of cognitive control in which the attentional functions operate to serve cognitive control in the reduction of uncertainty in temporal, spatial, and process/response domains. In this theory, alerting increases the predictability (reduces the uncertainty), in time, of the upcoming information that is to be processed. Orienting acts to select the most relevant and important information, in space, to be processed. Orienting and executive control of attention are differentiated in that orienting acts at the input stage to filter (or attenuate) task irrelevant information whereas executive control acts to bias the task-relevant process at the processing and response stages when there is competition between processes. For example, on the Stroop Color-Word task, the color and word meaning are processed simultaneously and compete with each other to be the potential response. The attentional functions play a role in resolving the conflict by biasing the color naming process, and by inhibiting the competing response. In the flanker task, because orienting cannot filter out (or attenuate) the flankers perfectly, the flankers may be processed as target and the incongruent flankers and target compete for the response. The executive control function solves this conflict, interacting with the orienting function, to focus the computations more on the task-relevant dimension or target location. The objective of cognitive control is thus the prioritization of computations of specific input information so that uncertainty can be minimized.

We hypothesized that attention plays a critical role in cognitive control via the functions of alerting, orienting and executive control, and their interactions, to influence the priority of computations of cognitive processes for access to consciousness or response. To test the hypothesis, we examined individual differences on our well-established measure of attention (Fan et al., 2009) in relation to our newly developed task (Majority Function Task, MFT) which involves the implementation of cognitive control (Fan et al., 2008; Wang, Liu, & Fan, 2011). We therefore used the MFT as an index of the general capacity of cognitive control, and the ANT-R to index the individual attentional functions and their interactions. We predicted that performance on the ANT-R would be predictive of efficiency cost with increasing uncertainty on the MFT.

2. Methods

2.1. Participants

Sixty-two adult volunteers participated in this study. After excluding those with lower than 70% accuracy on the ANT-R, and those who performed less than 2 standard deviations below the mean on accuracy on the MFT, the final sample size was 44 (33 females; mean age, 21.6 years; *SD* 4.4 years). The protocol was approved by the Institutional Review Board of Queens College of the City University of New York, and written informed consent was obtained from each participant.

2.2. Tasks

2.2.1. The majority function task

We developed the MFT to parametrically manipulate cognitive load, and to capture the effects of cognitive control by manipulating uncertainty, rather than conflict only (Fan et al., 2008). In this task, participants are randomly presented with groups of arrows (set sizes 1, 3 or 5) at 8 possible locations arranged as an octagon around a central fixation cross (see Fig. 1). The arrows are presented simultaneously, pointing either left or right, and participants must indicate the direction in which the majority of arrows point. There are six conditions, with the ratios of arrows pointing in the same direction to arrows pointing in the opposite direction as: 1:0 for set size 1; 3:0 and 2:1 for set size 3; and 5:0, 4:1, and 3:2 for set size 5. The stimuli are presented for 2500 ms, followed by a variable fixation period of 2000–3000 ms and each trial lasts 5 s on average. Participants are instructed to respond as accurately and as quickly as possible. There are three runs with six blocks each (two for each set size), each block has 12 trials, and each run has 72 trials. Each run lasts 395 s. There are 5 s fixation periods before and after each block. The order of the blocks is counterbalanced with reversed repetition

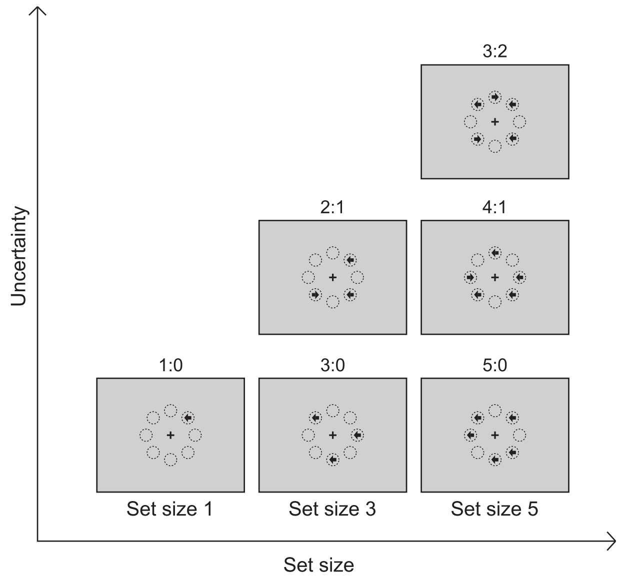

Fig. 1. Schematic of the Majority Function Task (MFT). In this task, arrows with set sizes of 1, 3, or 5 are randomly presented at 8 possible locations arranged as an octagon centered on a fixation cross. The arrows point either left or right, and are presented simultaneously. Participants' task is to indicate the direction in which the majority of arrows point. For example, if three arrows are presented, and two point to the left and one to the right (see the "2:1" panel in the "Set size 3" column), the correct response should be "left". The eight circles are all for illustration of the locations and are not displayed during the experiment. The label for each condition is the ratio of the number of arrows pointing in the same and other directions in each set size.

for each run. The total trial number in this task is 216 and it takes approximately 20 min to complete.

From an information theory perspective, the MFT systematically manipulates uncertainty with computational load, so that uncertainty is defined as *entropy*, or the average information value in bits that participants need to process in order to make a decision. By manipulating set size (1, 3 or 5 arrows) and set content (ratio of leftward to rightward pointing arrows), computational load of each condition can be quantified based on algorithms of information processing and RT variation. Previous algorithmic and computational modeling analyses of performance on the MFT revealed that a grouping search, rather than exhaustive or self-terminating search, exhibited the best fit to the data (Fan et al., 2008; Wang et al., 2011). The grouping search, whereby participants sequentially sample groups of arrows out of the set (e.g., 2 arrows for set size 3 and 3 arrows for set size 5) until they arrive at a sample in which all arrows are pointing in one direction, allowing them to find the majority, has been shown to be the most plausible algorithm for searching for the majority on this task. The computational loads for the six conditions, based on the grouping search strategy are 0, 1.00, 2.58, 1.58, 2.91, and 4.91 bits, respectively. Zero bits is a relative value and does not mean that there is no information to be processed. Because all arrowheads possibly need to be processed in order to make a decision on majority, unlike in a flanker task where flankers can be filtered out, this task requires dynamic and flexible cognitive control.

2.2.2. The revised attention network test

The ANT-R (Fan et al., 2009), based on the original version of the Attention Network Test (ANT) (Fan, McCandliss, Sommer, Raz, & Posner, 2002), was developed to assess the efficiency and the interactions of the three dissociable attentional functions: alerting, orienting and executive control (see Fig. 2). Stimuli consist of a row of 5 horizontal black arrows (one central target plus four flankers), pointing either to the left or right, against a gray background. Participants are asked to identify the direction of only the center arrow by pressing the left button of a computer mouse if the target points left, and the right mouse button if the target points right, and to respond as quickly and as accurately as possible. A cue, in the form of an increase in brightness of one or two boxes at either/both locations of the target stimuli, may appear prior to target onset, and may either be temporally or spatially informative. There are three different cue conditions: (1) no-cue (no box flashes prior to target onset); (2) double-cue (both cue boxes flash prior to target onset and so this only provides temporal information); and (3) spatial-cue (one cue box flashes prior to target onset and so is temporally and possibly spatially informative).

The alerting function is measured via the performance (e.g., RT) difference between the no- and double-cue conditions. For the orienting component, a spatial-cue is followed by a target presented either to the left or right of a centered fixation crosshair, requiring participants to shift their attention from the crosshair to the target in order to respond. The validity of the spatial cues is manipulated to measure the disengaging and moving aspects of the orienting function, so that 75% of the 48 spatial cues are valid, and 25% are invalid. To measure the conflict effect, the target (center) arrow is flanked both sides by two arrows that either point in the same direction as the target (congruent condition) or different direction from the target (incongruent condition). To further challenge the executive control function, the flanker conflict effect is combined with a location conflict (Simon) effect (Simon & Berbaum, 1990) so that there are 2 flanker congruency (congruent, incongruent) and 2 location congruency (congruent, incongruent) conditions.

A fixation cross is visible at the center of the screen throughout the task. In each trial, depending on the condition, a brief cue is either presented for 100 ms (cued conditions) or the display of the boxes remains unchanged (no-cue condition). Cue-to-target intervals are manipulated to measure the alerting and orienting speeds. After a variable duration (either 0, 400, or 800 ms, mean = 400 ms), the target and flankers are presented for 500 ms. The duration between target offset and onset of the next trial is varied systematically with a mean trial duration of 4000 ms. Participants must respond within 1700 ms after the onset of the target. The mean trial duration is 5000 ms, with 72 test trials each over 4 runs, mean run duration = 420 s. The total time require to complete this task is approximately 30 min.

Each attentional function is operationally defined as a comparison of the performance (RT and accuracy) between conditions, providing a score for each attentional function:

1. Phasic alerting benefit can be measured by:

$$Alerting = RT_{no\text{-}cue} - RT_{double\text{-}cue}$$

.

2. Orienting operations can be separately measured as:

$$\begin{aligned} Validity\ effect &= Disengaging + (Moving + Engaging) \\ &= RT_{invalid\text{-}cue} - RT_{valid\text{-}cue} \\ Moving + Engaging & \\ &= RT_{double\text{-}cue} - RT_{valid\text{-}cue} \end{aligned}$$

Here, the Moving + Engaging is equivalent to the "orienting" effect described in our previous studies e.g., (Fan et al., 2002).

$$Disengaging = RT_{invalid\text{-}cue} - RT_{double\text{-}cue}$$

for the cost of disengaging from the invalid cue. Disengaging was not listed and included in the regression model because it is not independent of the validity effect.

$$\begin{aligned} Orienting\ time = & RT_{valid\text{-}cue,\,0\ \mathrm{ms}\ cue\text{-}to\text{-}target\ interval} \\ & - RT_{valid\text{-}cue,\,800\ \mathrm{ms}\ cue\text{-}to\text{-}targetinterval} \end{aligned}$$

for the benefit of the target response due to advanced orienting.

3. The conflict (cost) effects are defined as:

$$\textit{Flanker conflict effect} = RT_{\textit{flanker-incongruent}} - RT_{\textit{flanker-congruent}}.$$
$$\textit{Location conflict effect} = RT_{\textit{location-incongruent}} - RT_{\textit{location-congruent}}.$$
$$\textit{Flanker by location interaction} = (RT_{\textit{flanker-incongruent, location-incongruent}} - RT_{\textit{flanker-congruent, location-incongruent}}) - (RT_{\textit{flanker-incongruent, location-congruent}} - RT_{\textit{flanker-congruent, location-congruent}}).$$

4. The interactions between the various attentional functions can be calculated by comparing the conflict scores under different cue conditions:

$$\begin{aligned}\textit{Alerting by flanker conflict} = {} & (RT_{\textit{no-cue, flanker-incongruent}} - RT_{\textit{no-cue, flanker-congruent}}) \\ & - (RT_{\textit{double-cue, flanker-incongruent}} - RT_{\textit{double-cue, flanker-congruent}})\end{aligned}$$

A negative value here indicates that alerting had a negative impact on flanker conflict processing.

$$\begin{aligned}\textit{Orienting by flanker conflict} = {} & (RT_{\textit{double-cue, flanker-incongruent}} - RT_{\textit{double-cue, flanker-congruent}}) \\ & - (RT_{\textit{valid-cue, flanker-incongruent}} - RT_{\textit{valid-cue, flanker-congruent}}).\end{aligned}$$
$$\begin{aligned}\textit{Validity by flanker conflict} = {} & (RT_{\textit{invalid-cue, flanker-incongruent}} - RT_{\textit{invalid-cue, flanker-congruent}}) \\ & - (RT_{\textit{valid-cue, flanker-incongruent}} - RT_{\textit{valid-cue, flanker-congruent}}).\end{aligned}$$
$$\begin{aligned}\textit{Alerting by location conflict} = {} & (RT_{\textit{no-cue, location-incongruent}} - RT_{\textit{no-cue, location-congruent}}) \\ & - (RT_{\textit{double-cue, location-incongruent}} - RT_{\textit{double-cue, location-congruent}}).\end{aligned}$$
$$\begin{aligned}\textit{Orienting by location conflict} = {} & (RT_{\textit{double-cue, location-incongruent}} - RT_{\textit{double-cue, location-congruent}}) \\ & - (RT_{\textit{valid-cue, location-incongruent}} - RT_{\textit{valid-cue, location-congruent}}).\end{aligned}$$
$$\begin{aligned}\textit{Validity by location conflict} = {} & (RT_{\textit{invalid-cue, location-incongruent}} - RT_{\textit{invalid-cue, location-congruent}}) \\ & - (RT_{\textit{valid-cue, location-incongruent}} - RT_{\textit{valid-cue, location-congruent}}).\end{aligned}$$

The network effects in accuracy were computed using similar formulae as above, with the proportion of correct trials replacing RT.

2.3. Data analysis

Means and standard deviations of RT, accuracy, and efficiency (defined below) were calculated for each task. Cases with missing data (individuals for whom efficiency on one or more of the ANT-R functions could not be computed, due to missed trials or error response under any conditions) were excluded in this analysis (final n = 38) since our prediction uses "and" rather than "or" logic, and we could only include those with complete data sets on both tasks in the *efficiency* computations. The significance of the attentional effects and their interactions was tested using one-sample *t*-tests (two-tailed). The wide range of scores obtained on the MFT (difference between the easiest and most difficult conditions in RT and accuracy) indicated a substantial impact of the speed-accuracy trade-off. To take both speed and accuracy into account, we also computed an efficiency index across conditions and tasks for the variables in our regression model:

Efficiency (E) = Accuracy/RT, in which accuracy is the ratio of correct responses and RT is in seconds. The rationale for using this division rather than the inverse is to obtain higher scores for better performance (Machizawa & Driver, 2011).

For the MFT, we calculated efficiency for each individual on each condition and then estimated the best-fit regression line to obtain a slope and intercept. That is, the slope of efficiency as a function of cognitive load (Fan et al., 2008; Wang et al., 2011) was computed for each participant:

$MFT_E = b_0 + b_1$ *entropy*, in which b_1 is the slope and b_0 is the intercept.

To compute the attentional effects in the ANT-R, we computed efficiency scores for each condition and then calculated the attentional effects for each individual based on the formulae presented above, using efficiency scores rather than RT or accuracy separately. For example, to compute efficiency on the flanker conflict effect for each participant:

$$\textit{Flanker conflict}_E = E_{\textit{flanker-incongruent}} - E_{\textit{flanker-congruent}},$$

We then performed a backwards stepwise regression analysis using MFT efficiency slope as the dependent variable and the ANT-R efficiency scores for all attentional effects as independent variables. As previously mentioned, the MFT manipulates information (*entropy*) parametrically. We therefore employed MFT_E slope as our dependent variable since it quantifies performance per unit increase of entropy, and is a useful indicator of how MFT performance varies with increased information. The overall regression model was as follows:

$$\begin{aligned}MFT_E slope = {} & b_0 + b_1 Alerting_E + b_2 Validity_E + b_5 Orienting_E \\ & + b_6 FlankerConflict_E + b_7 Location\ Conflict_E \\ & + b_8 Alerting \times Flanker_E + b_9 Orienting \times Flanker_E \\ & + b_{10} Validity \times Flanker_E + b_{11} Flanker \times Location_E \\ & + b_{12} Alerting \times Location_E + b_{13} Orienting \times Location_E \\ & + b_{14} Validity \times Location_E.\end{aligned}$$

To maximize predicted variance of the model, we focused on the first regression model to reach significance at $p < 0.05$. A significant model would indicate that cognitive control efficiency could be predicted by attentional functions.

3. Results

3.1. Cognitive control as measured by the MFT

We first examined model fit for the grouping search. The R^2 values ($M = 0.91$, $SD = 0.04$, 95% confidence intervals = 0.90–0.92) of the individually fit regression lines for the efficiency computations for the various conditions of the MFT was a large effect. The large proportion of variance accounted for by this method demonstrates that quantifying MFT performance in terms of efficiency is both valid and useful, as well as providing further support for the grouping search as the most likely strategy for participants in this task.

The overall average RT was 964 ms (SD = 150 ms), overall accuracy of task performance was 94% (SD = 2%), and overall efficiency was 1.17 (SD = 0.18). RTs, accuracy, and efficiency scores for each condition of the MFT are presented in Table 1. Fastest response times (M = 539 ms, SD = 72 ms) and highest accuracy (M = 99%, SD = 1%) were observed for the 1:0 condition, indicating that this was the least difficult condition at which participants were the most efficient (M = 1.87, SD = 0.25). Slowest response times (M = 1516 ms, SD = 279 ms), lowest accuracy (M = 75%, SD = 8%), and lowest efficiency rates (M = 0.52, SD = 0.12), were observed for the 3:2 condition, indicating that this was the most difficult condition. If we consider RT and accuracy cost as an indicator of level of cognitive load, then the 3:2 condition was the one with the greatest level of cognitive load, as one would expect from the level of uncertainty generated by the high incongruence ratio of the arrows.

Fig. 3a shows the increase in RT for each MFT condition as a function of computational load, or the amount of information in bits that need to be processed, in order to make a decision. Note that RT increased not as a function of the number of arrows within the set, but the information value of the set. As such the 2:1 condition had longer average RT than the 5:0 condition. Fig. 3b

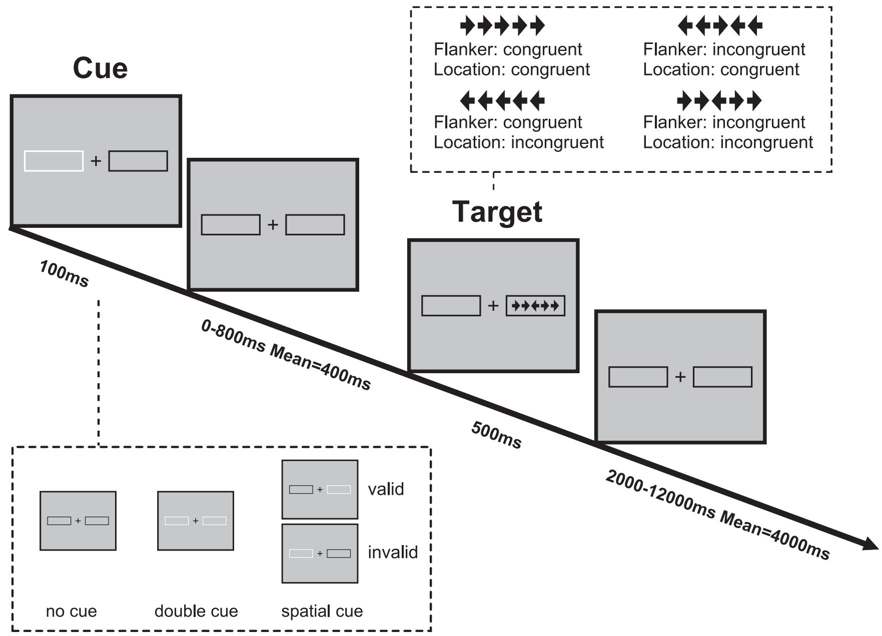

Fig. 2. Schematic of the Revised Attention Network Test (ANT-R). In each trial, depending on the cue condition (none, double, and valid or invalid), a cue box flashes for 100 ms. After a variable duration (0, 400, or 800 ms), the target (the center arrow) and two flanker arrows on the left and right side (congruent or incongruent) are presented for 500 ms. The participant makes a response to the target's direction. The post-target fixation period between 2000 and 12,000 ms.

Table 1
MFT means (*SD*) in RT (ms), accuracy (%) and efficiency for all conditions.

Set size	Condition	Entropy (bits)	RT (ms)	Accuracy (%)	Efficiency
1	1:0	0	539 (72)	98.83 (1.31)	1.87 (0.25)
3	3:0	1	672 (126)	100 (0)	1.54 (0.31)
	2:1	2.58	1114 (189)	93.20 (6.48)	0.86 (0.13)
5	5:0	1.58	733 (125)	100 (0)	1.40 (0.25)
	4:1	2.91	1208 (218)	98.03 (3.96)	0.84 (0.16)
	3:2	4.91	1516 (279)	75.44 (8.43)	0.52 (0.12)

shows the accuracy for each trial type of the MFT. Accuracy decreased not only with ratios of uncertainty within arrow sets, but also as a function of computational load. Efficiency scores also decreased with increasing levels of uncertainty, as illustrated in Fig. 3c. The overall effect of the MFT, computed as the RT difference between the easiest condition (1:0) and the most difficult condition (3:2), showed an average RT difference of 977 ms (SD = 249 ms), and an average difference in accuracy of 23% (SD = 9%). The efficiency difference was 1.35 (SD = 0.21), representing a 72% average decrease in efficiency between the 1:0 and 3:2 conditions.

3.2. Attentional functions as measured by the ANT-R

The overall average RT was 653 ms (SD = 82 ms), overall accuracy of the task performance was 91% (SD = 9%), and overall efficiency was 1.51 (SD = 0.17). RTs, accuracy and efficiency scores for each of the attentional effects are presented in Table 2. Fig. 4a–c shows effects of the attentional functions and their interactions in RT, accuracy, and efficiency, respectively. The flanker conflict effect had the largest average RT difference (168 ms, SD = 37 ms), and an average accuracy cost of 13.5% (SD = 13.5%). The average efficiency discrepancy for the flanker conflict effect was −0.55 (SD = 0.20), representing a 32% average decrease in efficiency between the flanker congruent and flanker incongruent conditions.

The comparison between the no-cue and double-cue conditions for the alerting effect showed a significant difference for RT ($t(37) = 9.33$, $p < 0.001$) and efficiency ($t(37) = -8.34$, $p < 0.001$) but not for accuracy ($t(37) = -1.74$, *ns*), indicating that alerting improved overall response speed and efficiency, but not accuracy. There were also significant differences for RT ($t(37) = 19.59$, $p < 0.001$), accuracy ($t(37) = -5.00$, $p < 0.001$) and efficiency ($t(37) = -12.62$, $p < 0.001$) for target response under the invalid-cue condition compared to the valid-cue condition for the validity effect, indicating a cost by invalid cueing. The orienting time effect showed significant differences for RT ($t(37) = 12.28$, $p < 0.001$), accuracy ($t(37) = -5.73$, $p < 0.001$) and efficiency ($t(37) = -12.83$, $p < 0.001$) under the 0 ms-cue-to-target interval compared to the 800 ms-cue-to-target interval, indicating better attentional performance under the longer cue to target interval condition. The flanker conflict effect on RT ($t(37) = 27.97$, $p < 0.001$), accuracy ($t(37) = -7.29$, $p < 0.001$) and efficiency ($t(37) = -17.06$, $p < 0.001$) were significant when flanker congruent and flanker incongruent conditions were compared, demonstrated the performance cost of incongruent flankers. The location conflict effect was significant for RT ($t(37) = -4.19$, $p < 0.001$) and accuracy ($t(37) = -2.28$, $p < 0.05$) but not for efficiency ($t(37) = 0.378$, *ns*).

The alerting by flanker conflict and the alerting by location conflict interactions were not significant on RT ($t(37) = 0.03$, *ns*), accuracy ($t(37) = -0.99$, *ns*), or efficiency ($t(37) = 0.96$, *ns*) indicating that whether participants were provided with double cues or no cues did not have a significant effect on either flanker or location conflict processing. The orienting by flanker conflict interaction was significant for RT ($t(37) = 5.26$, $p < 0.001$) and efficiency ($t(37) = -2.88$, $p < 0.01$), but not for accuracy ($t(37) = -1.53$, *ns*), indicating that orienting facilitated flanker conflict processing in terms of speed and efficiency. The orienting by location conflict interaction was not significant for RT ($t(37) = 0.592$, *ns*), accuracy

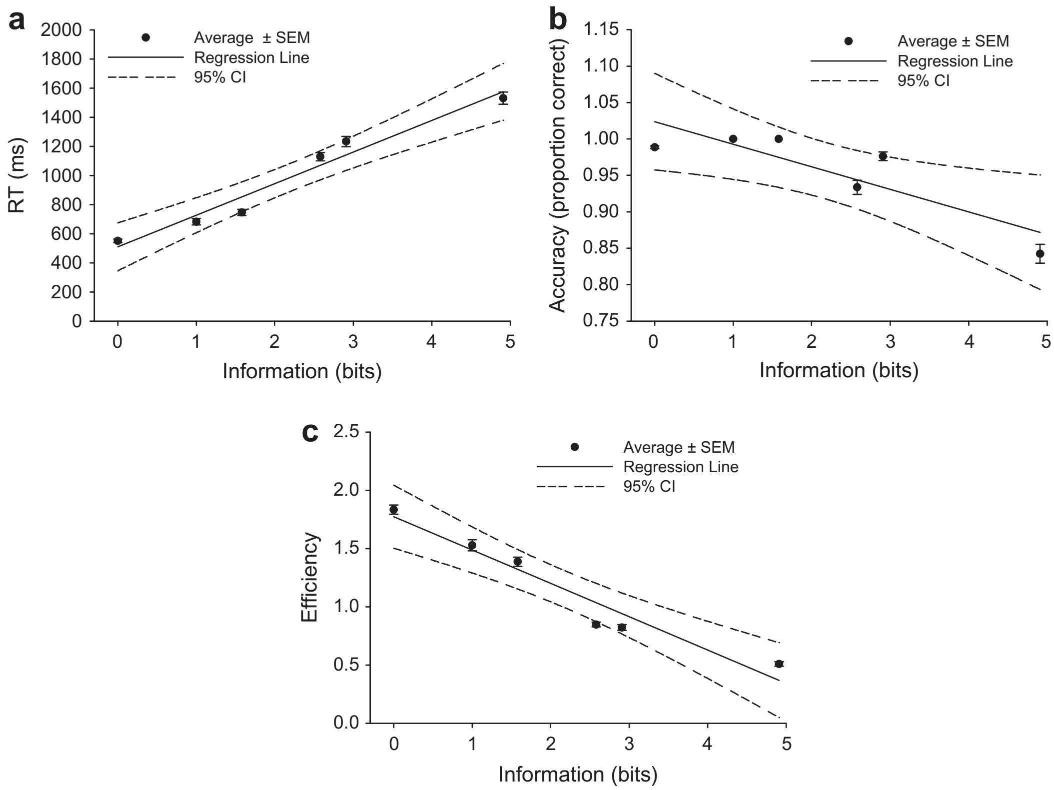

Fig. 3. (a) RT, (b) accuracy, and (c) efficiency change as a function of computational load in MFT.

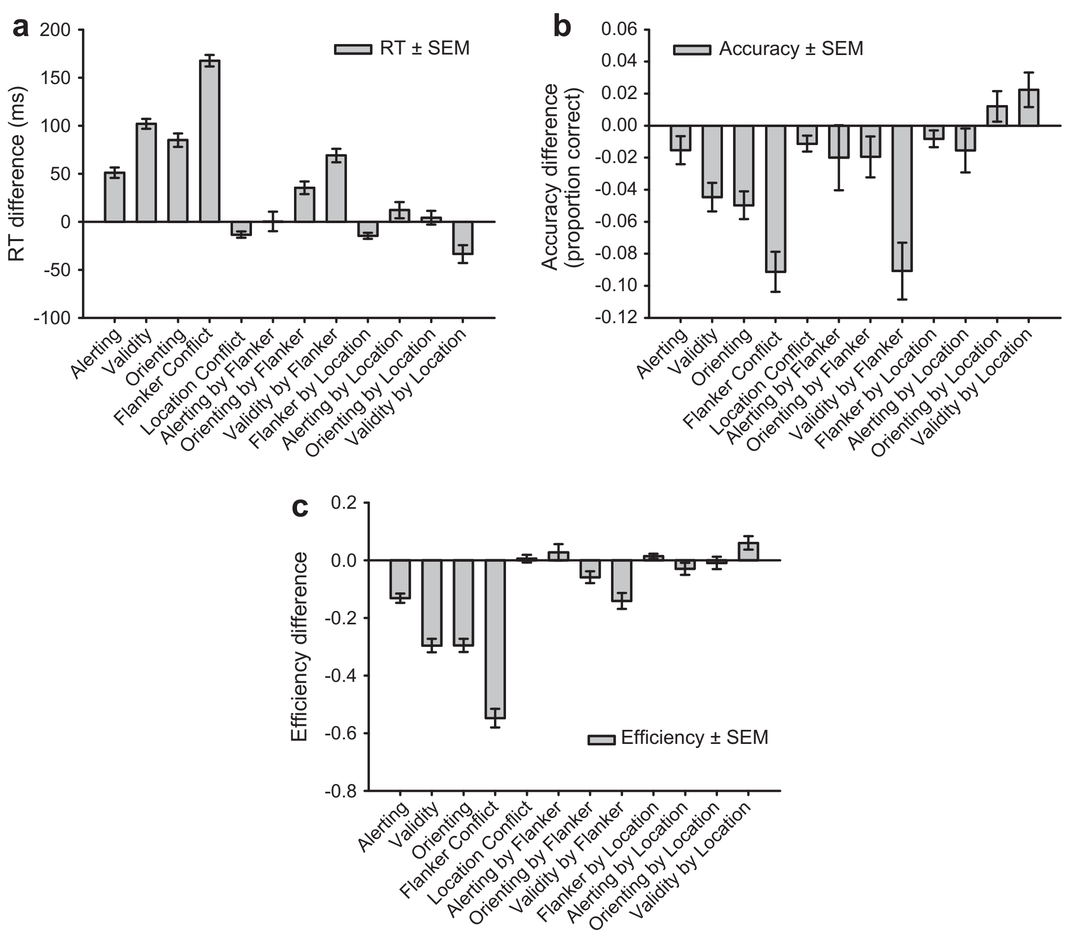

Fig. 4. (a) RT, (b) accuracy, and (c) efficiency for the various attentional functions and their interactions on ANT-R.

Table 2
Means (*SD*) of the attentional function effects in RT, accuracy, and efficiency difference scores.

Attention function effect	RT (ms)	Accuracy (%)	Efficiency
Alerting	51 (34)***	1.67 (5.29)	−0.13 (0.10)***
Validity	102 (32)***	4.92 (5.57)***	−0.30 (0.15)***
Orienting time	85 (43)***	5.78 (5.96)***	−0.32 (0.16)***
Flanker conflict	168 (37)***	13.54 (13.55)***	−0.55 (0.20)***
Location conflict	−13 (20)***	0.63 (3.34)*	0.01 (0.08)
Alerting by flanker	0.25 (63)	1.19 (12.8)	0.03 (0.18)
Orienting by flanker	35 (41)***	2.68 (8.89)	−0.05 (0.13)**
Validity by flanker	69 (43)***	10.10 (10.81)***	−0.15 (0.17)***
Flanker by location	−15 (19)***	0.39 (3.49)	0.01 (0.05)
Alerting by location	12 (52)	3.41 (10.45)	−0.05 (0.16)
Orienting by location	4 (44)	−1.87 (5.87)	0.00 (0.13)
Validity by location	−34 (57)**	−1.38 (6.87)*	0.06 (0.14)*

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

($t(37) = 1.27$, *ns*) or efficiency ($t(37) = -0.45$, *ns*). The validity by flanker conflict interaction was significant for RT ($t(37) = 9.90$, $p < 0.001$), accuracy ($t(37) = -5.13$, $p < 0.001$), and efficiency ($t(37) = -5.91$, $p < 0.001$), indicating invalid cueing generated a further cost for the target response beyond the conflict effect. The validity by location interaction was also significant for RT ($t(37) = -3.62$, $p < 0.01$), accuracy ($t(37) = 2.08$, $p < 0.05$), and efficiency ($t(37) = 2.56$, $p < 0.05$), indicating that orienting to an invalid cue reduced the location conflict effect. The flanker conflict by location interaction, produced a significant negative RT difference ($t(37) = -4.68$, $p < 0.001$), but the differences for accuracy ($t(37) = -1.56$, *ns*) and efficiency ($t(37) = 1.67$, *ns*) were not significant. This indicates that the RT cost of the flanker conflict effect under the location incongruent condition was less than under the location congruent condition, which is counter-intuitive but consistent with our previous findings (Fan et al., 2009).

3.3. Cognitive control performance as a function of attentional functions

To examine relationships between MFT_E slope and the ANT-R attentional effects in *efficiency*, we first conducted an exploratory correlation analysis (see Table 3). None of the ANT-R attentional effects and interactions in *efficiency* were significantly correlated with MFT_E slope. To determine the main contributions of integrative attentional functions to cognitive control, we regressed MFT_E slope on efficiency scores of the ANT-R effects (using backwards stepwise regression). Evaluation of assumptions showed that normality, linearity and homoscedasticity of residuals were satisfied. Further, the Durbin–Watson test (2.43) indicated independence of residuals within the model.

Table 3
Correlations between efficiency on the various ANT-R attentional effects and MFT efficiency (MFT_E) slope.

	MFT_E slope	A_E	V_E	O_E	F_E	L_E	AxF_E	OxF_E	VxF_E	FxL_E	AxL_E	OxL_E	VxL_E
A_E	−.22	1											
V_E	.29	.01	1										
O_E	.23	.17	.49**	1									
F_E	.24	.12	.66**	.64**	1								
L_E	−.03	.17	.01	.05	.20	1							
AxF_E	−.10	.51**	−.01	.21	.18	0.21	1						
OxF_E	.11	−.45**	.32*	.34*	.26	−0.16	−.45**	1					
VxF_E	.07	.24	.54**	.21	.54**	0.05	.32*	0.11	1				
FxL_E	.04	−.04	.26	.32*	.24	0.26	0.11	.34*	0.27	1			
AxL_E	−.22	.27	−.14	.08	.16	−0.19	0.06	0.01	−0.04	−0.04	1		
OxL_E	−.18	−.22	−.09	−.14	−.06	0.05	−0.22	0.18	0.11	0.29	−.36*	1	
VxL_E	−.25	−.08	.06	−.21	.09	0.17	−0.23	−0.07	0.07	0.12	0.06	.41**	1

A = Alerting; V = Validity; O = Orienting time; F = Flanker Conflict; L = Location Conflict; AxF = Alerting by Flanker; OxF = Orienting by Flanker; VxF = Validity by Flanker; AxL = Alerting by Location; OxL = Orienting by Location; VxL = Validity by Location.
* $p < 0.05$.
** $p < 0.01$; (2-tailed).

Table 4
Correlations between RT on the various ANT-R attentional effects and MFT RT slope.

	MFT RT slope	A	V	O	F	L	AxF	OxF	VxF	FxL	AxL	OxL	VxL
A	.21	1											
V	.15	.08	1										
O	.10	.18	.44**	1									
F	.13	.04	.26	.38*	1								
L	−.07	.02	.03	−.26	.15	1							
AxF	−.18	.29	.24	−.10	−.13	.05	1						
OxF	.28	−.28	.15	.12	.09	−.08	−.41**	1					
VxF	.25	.06	.54**	.16	.38*	.07	.06	.29	1				
FxL	−.12	.08	.05	−.06	−.30*	.28	.33*	−.02	−.21	1			
AxL	0	.05	−.11	−.30*	.17	.24	−.11	.04	.01	−.20	1		
OxL	−.19	−.09	.05	.16	−.01	−.01	−.04	−.10	−.09	.28	−.64**	1	
VxL	−.28	−.16	−.12	−.10	.29	.12	.03	−.21	−.07	−.02	.09	.12	1

A = Alerting; V = Validity; O = Orienting time; F = Flanker Conflict; L = Location Conflict; AxF = Alerting by Flanker; OxF = Orienting by Flanker; VxF = Validity by Flanker; AxL = Alerting by Location; OxL = Orienting by Location; VxL = Validity by Location.
* $p < 0.05$.
** $p < 0.01$; (2-tailed).

Table 5
Correlations between accuracy on the various ANT-R attentional effects and MFT accuracy slope.

	MFT accuracy slope	A	V	O	F	L	AxF	OxF	VxF	FxL	AxL	OxL	VxL
A	.11	1											
V	−.05	.05	1										
O	−.12	.19	.19	1									
F	−.17	.16	.48**	.51**	1								
L	.09	.19	.04	.19	−.10	1							
AxF	.05	.78**	−.03	.17	.03	.33*	1						
OxF	−.19	−.38*	.41**	.30	.38*	.01	−.44**	1					
VxF	.02	.14	.91**	.24	.52**	.07	.04	.29	1				
FxL	.17	.14	.14	.07	−.01	.83**	.27	.08	.19	1			
AxL	−.22	.01	−.02	.47**	.48**	−.15	−.03	.39**	.05	−.17	1		
OxL	.37*	−.03	.01	−.37*	−.32*	.06	.22	−.23	.03	.19	−.56**	1	
VxL	.08	−.03	.11	−.07	.19	−.03	−.15	.27	.003	−.03	.18	0	1

A = Alerting; V = Validity; O = Orienting time; F = Flanker Conflict; L = Location Conflict; AxF = Alerting by Flanker; OxF = Orienting by Flanker; VxF = Validity by Flanker; AxL = Alerting by Location; OxL = Orienting by Location; VxL = Validity by Location.
* $p < 0.05$.
** $p < 0.01$; (2-tailed).

Table 6
Initial model and first model to reach significance in backward regression analysis predicting MFT efficiency slope from ANT-R attention effects.

Predictor	MFT_E slope				
	B	SE B	β	t	r
Model with 12 predictors					
Alerting$_E$	−0.12	0.11	−.26	−1.12	−.22
Validity$_E$	−0.00	0.09	−.01	−0.03	.29
Orienting$_E$	0.03	0.09	.08	0.31	.23
Flanker Conflict$_E$	0.08	0.08	.34	1.11	.24
Location Conflict$_E$	−0.05	0.12	−.09	−0.43	−.03
Alerting by Flanker$_E$	−0.08	0.07	−.29	−1.17	−.10
Orienting by Flanker$_E$	−0.11	0.10	−.30	−1.11	.11
Validity by Flanker$_E$	0.01	0.07	.05	0.21	.07
Flanker by Location$_E$	0.14	0.19	.16	0.73	.04
Alerting by Location$_E$	−0.10	0.09	−.28	−1.17	−.22
Orienting by Location$_E$	−0.09	0.08	−.26	−1.09	−.18
Validity by Location$_E$	−0.08	0.07	−.26	−1.19	−.25
Model with 5 predictors					
Alerting$_E$	−0.12	0.08	−0.26	−1.62	−.22
Flanker Conflict$_E$	0.07	0.04	0.31	2.05*	.24
Alerting by Location$_E$	−0.10	0.06	−0.28	−1.64	−.22
Orienting by Location$_E$	−0.09	0.06	−0.25	−1.35	−.18
Validity by Location$_E$	−0.06	0.06	−0.19	−1.07	−.25

Note: R^2 for Model with 12 predictors = .34 ($p > 0.05$), R^2 for Model with 5 predictors = .28 ($p < 0.05$).
* $p < 0.05$.

Table 7
Initial model and first model to reach significance in backward regression analysis predicting MFT RT from ANT-R attentional effects.

Predictor	MFT_E slope				
	B	SE B	β	t	r
Model with 12 predictors					
Alerting	0.49	0.28	.31	1.75	.21
Validity	0.24	0.36	.14	0.65	.15
Orienting	−0.27	0.27	−.23	−1.00	.10
Flanker Conflict	0.29	0.29	.22	0.99	.13
Location Conflict	−0.15	0.49	−.06	−0.30	−.06
Alerting by Flanker	−0.24	0.18	−.28	−1.34	−.18
Orienting by Flanker	0.20	0.26	.16	0.79	.28
Validity by Flanker	0.06	0.24	.05	0.23	.25
Flanker by Location	0.09	0.55	.03	0.16	−.12
Alerting by Location	−0.27	0.21	−.29	−1.28	0
Orienting by Location	−0.35	0.26	−.29	−1.34	−.19
Validity by Location	−0.17	0.15	−.19	−1.10	−.28
Model with 3 predictors					
Alerting	0.53	0.24	.34	2.20*	.21
Alerting by Flanker	−0.13	0.14	−.15	−0.92	−.18
Orienting by Flanker	0.40	0.21	.31	1.94	−28

Note: R^2 for Model with 12 predictors = .30 ($p > 0.05$), R^2 for Model with 3 predictors = .18 ($p < 0.05$).
* $p < 0.05$.

In our regression analysis of MFT_E slope, the initial model including all ANT-R predictors explained 34% of variability in scores. For the initial model and the first model to reach significance at the $p < 0.05$ level, unstandardized regression coefficients (B), standard error of B, standardized regression coefficients (β), t-statistics (t) and correlations (r) with the dependent variable for the predictors are presented in Table 6. Regarding the first model to reach significance at the $p < 0.05$ level, R for regression was significantly different from zero, $F(5,37) = 2.53$, $p < 0.05$, with $R^2 = 0.28$, 95% CI = .08–.49. The adjusted R^2 value indicates that 17% of the variability in MFT_E slope can be explained by *Alerting$_E$*, *Flanker Conflict$_E$*, *Alerting by Location$_E$*, *Orienting by Location$_E$* and *Validity by Location$_E$*. *Flanker Conflict$_E$* ($\beta = .31$) was the one regression coefficient that differed significantly from zero ($p < 0.05$). While 17% explained variance may not seem like a large amount, it is by definition, close to a large effect (see Cohen, 1988). A medium effect corresponds to approximately 10% of the variance, while a large effect corresponds to approximately 25% of the variance. For the first model to reach significance, tolerance (range: .671–.959, $M = .815$, $SD = .116$) and variance inflation factor values (range: 1.042–1.491, $M = 1.247$, $SD = .178$), were well within typically recommended ranges. We therefore concluded that multicollinearity was not a significant threat to inference based on the regression model.

The rationale for focusing on the first regression model to reach significance is that we aimed to balance the parsimony of the model with maximizing the amount of explained variance in the MFT_E slope by the combination of predictors. While it is true that the backwards step-wise approach could be progressed to simpler models (final model had only 3, rather than 5 predictors), this comes at a substantial cost in variance of MFT_E slope predicted (R^2 (model with 5 predictors) = .283; R^2 (model with 3 predictors) = .203; $\Delta R^2 = .08$).

Although we were mainly interested in the relationship between MFT_E slope and efficiency scores, we also conducted analyses in which we regressed MFT_E slope on RT and accuracy scores for all ANT-R predictors. See Tables 4 and 5 for the bivariate correlations between the MFT slope and the network effects (in RT and accuracy, respectively). For the initial models and the first models to reach significance at the $p < 0.05$ level, unstandardized regression coefficients (B), standard error of B, standardized regression

Table 8
Initial model and first model to reach significance in backward regression analysis predicting MFT accuracy from ANT-R attentional effects.

Predictor	MFT_E slope				
	B	SE *B*	*β*	*t*	*r*
Model with 12 predictors					
Alerting	0.59	0.09	.18	0.65	.11
Validity	−0.10	0.15	−.32	−0.68	−.05
Orienting	0.39	0.06	.13	0.61	−.12
Flanker Conflict	−0.03	0.03	−.19	−0.79	−.17
Location Conflict	−0.10	0.17	−.19	−0.57	.09
Alerting by Flanker	−0.25	0.04	−.18	−0.63	.05
Orienting by Flanker	−0.26	0.05	−.13	−0.52	−.19
Validity by Flanker	0.06	0.07	.35	0.77	.02
Flanker by Location	0.14	0.16	.28	0.87	.17
Alerting by Location	0.00	0.41	−.02	−0.08	−.22
Orienting by Location	0.08	0.06	.28	1.38	.37
Validity by Location	0.05	0.05	.18	0.98	.08
Model with 2 predictors					
Validity	−0.02	0.05	−.06	−0.41	−.05
Orienting by Location	0.11	0.04	.36	2.60*	.37

Note: R^2 for Model with 12 predictors = .23 ($p > 0.05$), R^2 for Model with 2 predictors = .14 ($p < 0.05$).
* $p < 0.05$.

coefficients (β), *t*-statistics (t) and correlations (r) with the dependent variable for the predictors are presented in Tables 7 and 8.

In terms of RT, the initial model explained 30% of the variability in MFT scores. For the first model to reach significance at the $p < 0.05$ level, R was significantly different from zero, $F(3,40) = 2.93$, $p < 0.05$, with $R^2 = 0.18$, 95% CI = −0.01 to .37. The adjusted R^2 value indicates that 12% of the variability in MFT_E slope can be explained by *Alerting*, *Alerting by Flanker* and *Orienting by Flanker*. For the first model to reach significance, tolerance (range: .797–.883, $M = .827$, $SD = .048$) and variance inflation factor values (range: 1.133–1.255, $M = 1.212$, $SD = .069$) were within normal limits.

For accuracy, the initial model explained 23% of the variability in MFT scores. For the first model to reach significance at the $p < 0.05$ level, R was significantly different from zero, $F(2,41) = 3.44$, $p < 0.05$, with $R^2 = 0.14$, 95% CI = −0.04 to .32. The adjusted R^2 value indicates that 10% of the variability in MFT_E slope can be explained by *Validity* and *Orienting by Location*. For the first model to reach significance, tolerance and variance inflation factor values were equal to 1 for each predictor.

4. Discussion

Our results support the idea that cognitive control (as implemented for the MFT) is at least partially supported by various attentional functions and their interactions. Of the attentional effects discussed above, our final regression model included alerting, flanker conflict, and interactions of alerting, validity, and orienting with location conflict. It is worth noting that all three interactions were with the location effect. The location conflict effect of the ANT-R, which is essentially a Simon effect (Simon & Berbaum, 1990), may be relevant to the complex way in which cognitive control is implemented in the MFT. The location effect represents a taxing of executive control when the direction of the center arrowhead is opposite the location of the actual stimuli (e.g., arrowhead pointing left when stimuli are to the right side of the fixation cross). The alerting and validity by location effects demonstrate the importance of the alerting function as they facilitate the implementation of cognitive control during a Simon-like effect. Likewise, the orienting function is similarly an effective predictor when it is considered under different Simon-like effects. Given that the MFT requires one to process stimuli in 8 possible stimuli locations, it is not surprising that alerting and orienting play a role in MFT performance. Somewhat interesting is that the regression suggests that executive function related to a Simon-like conflict resolution, when interacting with cue validity, alerting, and orienting, are also relevant to predicting the way in which uncertainty is reduced during executive control for the MFT.

We presented a theory that describes processes supporting cognitive control, and suggests that the need for control is indicated when an individual is faced with uncertainty in the form of increased information processing demands (quantifiable in units of bits). It follows from our theory that once engaged, control would be withdrawn when uncertainty and its accompanying conflict are resolved. However, this idea requires further empirical examination. When faced with uncertainty, the attentional functions, possibly in concert with other functions, interact to give rise to the control necessary to constrain what information reaches conscious awareness for processing. Further, attentional functions do not operate independently of other systems, but rather interact with perceptual and cognitive functions in the service of cognitive control. For example, attention my bias or enhance processing across sensory modalities (Corbetta, Miezin, Dobmeyer, Shulman, et al., 1990; Desimone & Duncan, 1995; Egner & Hirsch, 2005; Gazzaley, Cooney, McEvoy, Knight, & D'Esposito, 2005; Moran & Desimone, 1985), and working memory (Awh, Vogel, & Oh, 2006; Gazzaley & Nobre, 2012).

4.1. Attention and cognitive control

Our results suggest a role for the attentional functions in cognitive control. In the present study, this was reflected by low efficiency in attentional functions and their interactions predicting decreased efficiency in cognitive control, under increasing levels of uncertainty. We predicted that all three attentional functions would be implicated in cognitive control as measured by the MFT. Examination of zero-order correlations revealed that the main three attention functions were not individually correlated with performance efficiency on cognitive control in this study. This may appear to suggest that there is no relationship between these functions and cognitive control on the MFT task. However, considering the attentional functions in concert within the regression model revealed their predictive value, as each attentional function (alerting, orienting, and executive control) was represented to some extent in the final model.

As previously mentioned, there has been debate over whether cognitive control can be considered as comprising discrete control components or an emergent property from other psychological functions that usually serve more basic functions (Cooper, 2010; Juvina, 2011). Our data may suggest that cognitive control is at least partially emergent from the interactions of the attentional functions as they are recruited to deal with uncertainty reduction and conflict resolution in the service of efficient information processing. This conclusion is especially evident in the regression model wherein it is the linear combination of attentional functions that is predictive of performance on the MFT.

One criticism of existing task-based models of cognitive control is that while they report associations between control functions and specific tasks, they do not detail how the functions allow for performance on these tasks (Cooper, 2010). Our theory states that cognitive control is recruited in order to reduce uncertainty associated with cognitive tasks, and that this is accomplished via the recruitment of the attentional functions and the interactions between them. Our findings are consistent with neural and behavioral findings on tasks that reflect interactions between the main attentional functions (Badre, 2011; Callejas, Lupiàñez, Funes, & Tudela, 2005; Walsh, Buonocore, Carter, & Mangun, 2011).

4.2. The MFT as a measure of cognitive control

The MFT systematically manipulates uncertainty, resulting in a much higher level of computational load than other tasks such as the Stroop Color-Word and Flanker tasks. The implementation of cognitive control is thus greatly required to reduce uncertainty in order to make the correct response (Fan et al., 2008; Wang et al., 2011). Unlike the Stroop Color-Word and flanker tasks, the nature of the MFT is such that it does not solely require participants to screen out distracting information or inhibit a prepotent response. Instead, participants must also process the conflicting information in order to choose the correct response, and they may do so several times before arriving at a response (Fan et al., 2008). For example, in the flanker task, a correct response is derived from a single processing of the stimulus: the participant must ignore flanker direction and determine whether a single target arrow is pointing to the left or to the right. Similarly, for the Stroop task, participants must determine the color of the ink in which the word is printed, while inhibiting the impulse to read or respond to the color word instead. With practice, however, participants may learn how to screen out the distracting information, and reduce the reaction time and accuracy costs associated with conflict on these tasks. This effect is associated with participants' expectation that conflict will occur. In contrast, to reach a decision on the majority in the MFT, participants may need to process all arrows to ultimately generate the appropriate response and, unlike the Stroop or flanker task, the amount of information can vary in a quantifiable fashion for the MFT.

The MFT has properties of the flanker task (determining directionality in the presence of conflicting information), but requires stronger cognitive control as indicated by the almost tenfold RT cost on average for the hardest condition of the MFT versus the flanker incongruent condition (conflict effect) of the ANT-R (Fan et al., 2008, 2009). Greater computational load of the MFT can be inferred from longer RT and decreased accuracy of responses (Fan et al., 2008). We observed large variability in performance on the MFT, indicating that as a task of cognitive control, it may allow for greater flexibility in examining this construct. The range of task complexity and the accompanying intra- and inter-individual variability in performance may allow for a broader understanding of the increased recruitment of cognitive control in dealing with increased complexity. This wide range of variability also makes the MFT suitable to studying differences in cognitive control performance between healthy individuals and patient populations.

4.3. Efficiency as an index of behavioral performance

The increased variability in RT and accuracy under the higher uncertainty conditions of the MFT appear to indicate the involvement of a speed-accuracy trade-off. When this occurs, RT and accuracy are working against each other. Therefore, combining RT and accuracy into an efficiency score allows for the examination of overall levels of performance across conditions (Townsend & Ashby, 1983). In studies of cognitive control, it is common to look at RT and/or accuracy separately. However, as complexity increases, as in the MFT, participants may opt to favor speed over accuracy, or vice versa. This may result in effects being missed at the individual level due to participants' switching strategies under different conditions. Combining accuracy and RT (both are ratio scores) therefore controls for the effects of favoring one strategy over the other. It is for this reason that we focused primarily on regressing MFT efficiency scores on ANT-R attentional effects. Results of the separate regression analyses for RT and accuracy demonstrated that alerting and orienting functions accounted for the majority of the variance in these performance indices, likely reflecting the speed-accuracy trade-off. Looking at performance in terms of efficiency then, is more likely to reflect the psychological processes involved in cognitive control, as the combination of speed and accuracy likely reflects the adjustment of cognitive control under the demands of the task.

4.4. Summary

We argue that there is a limit to the amount of information that can reach focused awareness (Posner & Fan, 2008), and that cognitive control is thus implemented, at least partly, via integrative attentional functions in order to prioritize the important information to be processed. We propose a theory of cognitive control that is, at least in part, emergent from attentional functions. It is the computational mechanisms of distinct attentional functions and their interactions that influence information processing for access to consciousness or to output. Considering the incredibly flexible nature of cognitive control, varying combinations of interactions of fundamental components, such as attentional functions, seems a more plausible explanation than discrete control functions localized to specific brain areas.

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