Global difficulty modulates the prioritization strategy in multitasking situations

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Abstract

There has been a considerable amount of research to conceptualize how cognition handle multitasking situations. Despite these efforts,it is still not clear how task parameters shape attentionnal resources allocation. For instance, many research have suggested that difficulty levels could explain these conflicting observations and very few have considered other factors such as task importance. In the present study, twenty participants had to carry out two N-Back tasks simultaneously, each subtask having distinct difficulty (0,1 or 2-Back) and importance (1 or 3 points) levels. Participants's cumulative dwell time were collected to assess their attentional strategies. Results showed that depending on the global level of difficulty, attentional resources of people were driven either by the subtask difficulty (low-global-difficulty) or the subtask importance (high-global-difficulty), in a non-compensatory way. We discussed these results in terms of decision-making heuristics and metacognition.

Highlights

- During multitasking, resources allocation is driven either by the difficulty or the importance of the subtasks.
- Task importance biases resources allocation when the global difficulty is high.
- Task attributes drive resources allocation in a non-compensatory fashion.

Keywords: dual task, attentional processes, metacognition, working memory, decision-making

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Introduction

Multitasking refers to those situations where multiple tasks must be simultaneously executed in a limited time window. It covers various cases from routine activities like driving or preparing the venue of a large number of guests, to more complex system management, like space shuttle piloting, air traffic control or aircraft piloting. In these situations, the simultaneous execution of the tasks is hardly possible because of immutable bottlenecks in central processing (Pashler, 1994), response competition (Eriksen, 1995), limited processing resources (Kahneman, 1973) or overlaps in resource solicitation (Wickens, 2002). Therefore, it compels people to build on executive processes (Baddeley, 2012) like task sequencing (Schumacher et al., 1999), plan-remembering (Burgess, Veitch, de Lacy Costello, & Shallice, 2000), task switching (Monsell, 2003; Pashler, 2000) or attentional control (Baddeley, 2012; Norman & Shallice, 1986), so as to maintain performance at an acceptable level.

There has been a great deal of effort to compile knowledge about multitasking performance into formal models that predict the sequence of operations, under various conditions of multitask structure, and with a high degree of timing precision (Meyer & Kieras, 1997; Pashler & Sutherland, 1998; Salvucci & Taatgen, 2008). However, as raised recently by Wickens, Gutzwiller, and Santamaria (2015), these canonical models somewhat ignore meta-cognitive or strategical processes. Rather, they support that performance mainly results from the correspondence between the structure of the task and the availability of human resources. For instance, the *Threaded Cognition* theory (Salvucci & Taatgen, 2008) posits that one primarily allocates resources in a "*greedy and polite*" fashion: as soon as they are requested, resources are used *if available* (*greedy*), and are immediately released once the operation is ended (*polite*).

The prioritization process

Nonetheless, many studies have highlighted the strategic dimension of resources allocation and the possibility to *deliberately* influence it, depending on the respective importance (or priority) of the available tasks, i.e. prioritization (Gopher & Brickner, 1982; Gopher & Navon, 1980; Matton, Paubel, Cegarra, & Raufaste, 2016; Wang, Proctor, & Pick, 2009). Its role has been shown in many applied fields like task management (Barabasi, 2005; Freed, 1998), air-traffic control (Ho, Nikolic, Waters, & Sarter, 2004; Loft, Sanderson, Neal, & Mooij, 2007), aircraft piloting (Iani & Wickens, 2007; Raby & Wickens, 1994), car driving (Brumby, Salvucci, & Howes, 2009; Levy & Pashler, 2008) or simulated office (Sauer, Wastell, Robert, Hockey, & Earle, 2003). Each time, task importance, given either explicitly or implicitly, is shown to significantly influence resources allocation or task sequencing, especially under fatigue or increased difficulty conditions, where it tends to preserve performance on the more important tasks. For instance Raby, Wickens, and Marsh (1990) showed that, during a simulated flight, as difficulty increased (e.g., time constraint, extra-communications), proportion of time spent on high-priority subtasks increased at the expense of other low-priority subtasks.

If observable consequences of prioritization have been well addressed, less effort has been dedicated to describe prioritization at a cognitive level. For instance, when Meyer and Kieras (1997) stated that task priorities are one main determinant of executive processes (p. 14), they did not provide an explanation of how these priorities might be computed. In the same vein, when Gopher and Brickner (1982) showed the impact of priorities upon voluntary control of resources, they did so to better understand the structure of human resources, not to understand prioritization itself. In their experiment, the authors manipulated the priority of two subtasks by assigning them a level of desired performance. Doing so, they overlooked prioritization since it cannot be reduced to one's ability to allocate resources according to a varying performance target. Prioritization also includes the ability to *compute and store* internally the respective priorities of the subtasks according to their various attributes. The same comment can be made about Norman and Bobrow (1975)'s work, who manipulated task priorities by assigning "percentages of attention" (e.g., "task A must receive 80% of your attention"). Hence, assigning performance is neglecting one essential stage of prioritization, that is priorities computation. There is a need to distinguish the construct of "importance" from the construct of "priority". "Importance" refers to an objective task attribute that characterizes the relationship of the task to the assigned goal, whereas "priority" refers to an agent's internal representation resulting from prioritization, and biasing resources allocation in a top-down fashion. Some other terminological choices have been observed elsewhere (Wickens et al., 2016), but the crucial point here is to distinguish *external* from *internal* priority constructs.

Actually, this perspective is close to that of Wickens et al. (2015, 2016), who have proposed that prioritization – although not naming it so – is akin to a multi-attribute decision process. According to their model of Strategic Task Overload Management (STOM; Wickens et al., 2015), in a multitask environment, people would continuously process several attributes of each subtask, that are its *salience*, its *priority* (i.e., "*the relative importance of a task"*), its *interest*, the *effort* attached to it, and its *difficulty*. Each of these attributes would influence the relative attractiveness of the corresponding subtask, with a specific *weight* and a specific *polarity*. For example, it was found that, given a cognitive effort avoidance principle (Kool, McGuire, Rosen, & Botvinick, 2010), the attractiveness of an easier task will be positively biased, with a weight of 0.63. This weight means that *ceteris paribus* the easier task will be chosen 63% of the time. Seemingly, according to empirical findings, people tend to avoid the effort attached to task switching (Arrington & Logan, 2005), with a probability of 0.60. Nevertheless, in a recent paper Wickens et al. (2016) pointed out that the polarity of the difficulty attribute could be reversed under specific experimental conditions. They highlighted that the attraction to an easier task was found in studies using simple tasks or comparing easy and hard versions of the same task. On the contrary, attraction to the more difficult task was found with more complex tasks, which have been related to a longer "giving-up time", described by Kool et al. (2010).

Moreover, there's a need to understand further how multiple attributes might interact in the process, especially if contradictory. For example, which task would be prioritized between a hard important one and an easy unimportant one? In a recent study, Wickens and colleagues 2016 clearly asked the question of "how [these attributes] would trade off against one another" (p. 325). In their first experiment, people had to execute multiple tasks at once using the revised Multi-Attribute Task Battery environment (MATB-II ; Santiago-Espada, Myer, Latorella, & Comstock Jr, 2011). Two groups of participants were told either to prioritize one particular task (the *tracking* task) or to perform all tasks as best as possible. The difficulty attribute of the *tracking* task was manipulated within groups by changing the update rate. The authors found that the *tracking* task was less switched to (12% less often) when it was more difficult, and no effect of assigned priorities on switches was found. Moreover, when subjects had to choose between two other alternative tasks (resources management or communication), they chose twice as frequently the easier and less important task (communication) than the more difficult and more important task (resources management). It is noteworthy that difficulty and importance attributes of these two tasks were rated subjectively after the final experimental trial, i.e. they were not manipulated. Moreover, as noted by the authors, the easier less important task was also the most salient, so that multiple attributes manipulations were confounded.

Even though marginal, these contradictory results call for new investigations about the interactions that may exist between task attributes, to explain prioritization. More specifically there is a need for more controlled experiments, embedding identical and simple subtasks so as to avoid structural effects and concentrate the analysis on the potential effects of the difficulty–importance interaction. In the vein of Raby and Wickens (1994), we propose that the effect of the importance attribute over the resources allocation depends on the difficulty level. Under low-global-difficulty scenarios, individuals would tend to allocate their resources as a function of tasks difficulty, in a *greedy and polite* fashion (Salvucci & Taatgen, 2008). Under high-global-difficulty scenarios, they would invest in top-down processes so as to evaluate the respective priorities of the various available subtasks, and allocate their resources accordingly. This could explain that under low-global-difficulty circumstances, subtask importance does not have a great influence over resources allocation, since a difficulty-driven strategy would be sufficient to attain a satisfying level of performance.

The objective of the present study is to test these hypotheses by assessing prioritization strategies in a controlled situation, whereby two attributes could present opposite polarities. In our experiment, participants had to handle two N-Back subtasks simultaneously ("dual N-Back task"), which level of difficulty and importance levels were manipulated. Importance was implemented through the use of two possible payoff values. Complementary eye tracking data were collected to assess attentional strategies through the proportion of cumulative dwell time on the different areas of interest. Indeed, ocular movements are functionally related to attentional movements, and studies have highlighted the existence of a wide overlap between overt and covert attention phenomena (Hoffman & Subramaniam, 1995; Klein, 1980; Peterson, Kramer, & Irwin, 2004; Rafal, Calabresi, Brennan, & Sciolto, 1989; Sheliga, Craighero, Riggio, & Rizzolatti, 1997; Shepherd, Findlay, & Hockey, 1986). These considerations have been reinforced by neuroanatomical observations that showed that the brain regions specifically involved in overt and covert attentional movements widely overlap (Nobre, Gitelman, Dias, & Mesulam, 2000; Perry & Zeki, 2000). To rephrase Shepherd et al. (1986), while it is possible to move one's attention without realizing ocular movement, it is not possible to make an ocular movement without, at the same time, moving one's covert attention in the corresponding direction. Thus, we thought that ocular metrics would provide us with relevant information about participants' attentional strategies, regardless of the performance levels they would achieve.

At an operational level, we hypothesized that resources allocation would be explained by an interaction of the two task attributes, and that the impact of importance over the resources allocation would depend on the global difficulty level. More specifically, we thought that (H1) under low-global-difficulty conditions, (H1a) subtask performance and (H1b) visual resources allocation toward the two subtasks would be explained by their respective level of difficulty, whatever their importance. Conversely, we hypothesized that, (H2) under high-global-difficulty conditions, (H2a) subtask performance and (H2b) visual resources allocation would be explained by the respective importance of the two subtasks, whatever their level of difficulty.

Method

Participants

Twenty participants were recruited ($M_{age} = 23.45, SD = 3.9$). All were volunteers and were engineering students of the National Higher School of Aeronautics and Space (ISAE-SUPAERO). Before the experiment, all the participants read and signed a consent form. Their participation was not rewarded. The present method has been validated by the French Ethics Committee on Non-Interventional Research, and was given the following code name : CERNI-Université fédérale de Toulouse-2016-010.

Apparatus and materials

The experiment took place in an isolated experimental room. All the tasks were run on a Dell computer attached to a 22" monitor (1680 × 1250 pixels). Participants sat approximately at 70 cm from the screen. During the test phase, eye gazes were recorded using an SMI RED 500 system (SensoMotoric Instruments). Responses were recorded with a Cedrus RB-530 pad. Reaction time and stimuli presentation were recorded with Python 2.7 and the PsychoPy 1.83 library (Peirce, 2009). Participants successively passed through a single and a dual version of the N-Back task. For the single version, black digits were successively presented at the center of the screen, within a white 5° square. The instruction to apply (“N-BACK”) was continuously displayed at the top left of the screen. Responses were made using the center button of the response pad. Participants had to press this button when the displayed digit corresponded to the target.

In the dual version, the two digits sequences were presented within two respective 5° squares, 2° below the center of the screen. The two digit centers were horizontally separated by 12.2° (6.1° from the horizontal center). Each subtask was characterized by two attributes. The subtask difficulty was indicated by a number corresponding to the N-back level of the task (0, 1 or 2), located 1.5° below the subtask’s square. The subtask importance was indicated by the quantity (1 *vs* 3) of yellow circles, located 0.8° above the squares. A quantitative feedback was displayed at the middle of the two subtasks between two trials : it was green when points were won (e.g., $+3$) and red when lost (e.g., -1). When the result was null, it was a black equal sign. The left and right buttons of the response pad were respectively used to signal a target in the left or the right subtasks. In any version of the task, errors were signaled by a red circle displayed at the center of the corresponding square area, during the inter-trial-interval (Figure 1).

Procedure

After they signed the consent form, participants sat in front of the computer. Before each phase, participants were given written instructions, yet they were allowed to ask the experimenter for clarifications. In any phase, participants were told to initiate the incoming block by pressing the bottom button (labeled “OK”) of the response pad.

Single condition. Participants saw a digit sequence, and were instructed to judge whether each digit matched the digit presented N times ago (N-Back). If so, they had to press the center button of the pad. For the 0-Back condition, they had to detect any 0 digit. There were two successive blocks of 30 trials per difficulty level. Each block included 30% of target trials, randomly distributed. Each trial began with the presentation of a digit for 800 ms, during which participants could signal it as a target. Then, a blank 1000 ms inter-trial-interval (ITI) was presented. Error feedback potentially appeared at the center of the square throughout the ITI. Then the next digit appeared for 800 ms and so on.

This single condition phase always started with the 0-Back difficulty level. Participants were informed that as long as they detected at least 50% of the targets for a given difficulty level, training would continue with an increased difficulty level, and that the training would stop otherwise. All the participants reached the 2-Back level, with at least 50% of target detected.

Dual condition. Participants were then instructed they would undergo *two* N-Back subtasks simultaneously. They were asked to apply the same rules as in the single N-Back task, for each independent subtask. They were informed that each subtask would have an independent difficulty level (0, 1 or 2-back) and an independent importance level (1 or 3 points). They were told that for any hit, they would earn the number of points (1 or 3) attached to the subtask, and that for any mistake (*miss* or *false-alarm*), they would lose it – the initial score being zero. Participants were instructed to achieve *the highest overall score possible*, i.e., on the combined score of both subtasks. Importantly, they were not biased towards any executive strategy. For instance, they were free to abandon one subtask.

Each block consisted of 15 trials, that is two simultaneous sequences of 15 digits. Within a block, each subtask included 4 targets ($\approx$ 30%). A trial began with the simultaneous presentation of two digits for 1600 ms, during which participants could press either the left or the right button of the response pad, to signal a target in the left or the right subtask respectively. Then, the digits disappeared for 1000 ms while the feedback was displayed and potential errors were signaled (red circle). Then the next two digits appeared for 1600 ms and so on (Figure 1). Each block was preceded by a pause screen which displayed the score for the previous block. Importantly, the difficulty and importance attributes of the incoming block were visible during the pause screen so that participants could process available information before they began.

Before the test phase, participants were given 8 training blocks of various difficulty-importance associations. As for the test phase, each block consisted of 15 trials. This training lasted for 10 minutes approximately. Calibration of the eye-tracker was then performed. The test phase consisted in 36 blocks, resulting from the product of all the possible combinations of difficulty (3 levels) and importance (2 levels) between the two subtasks ($3 \times 2 \times 3 \times 2 = 36$). The test session always began with two 0-Back subtasks of Low importance (1 point). The following 35 conditions were presented in a random order. Each block lasted 50 seconds.

Measures and design

For each dual-task condition, performance and visual resources allocation were assessed. For performance, hit rates were systematically compared with their equivalent single condition. The resulting difference (cost) allowed to distinguish the effect due to difficulty or importance manipulations, from those due to the concurrence in itself ("concurrence cost"; see Navon & Gopher, 1979). The overall hit rate was also computed, that consisted in the total proportion of targets detected for both subtasks. Visual resources allocation was assessed through measures of cumulative dwell time. There were three areas of interest (AOI) : one for each subtask that corresponded to its white square, and one in the middle of both subtasks (Figure 1). Cumulative dwell time was computed as the total duration of eye fixations that fell within a given AOI. Fixations had a minimum duration of 80 milliseconds and a maximum dispersion of 2°. Cumulative dwell time was expressed as the percentage of the overall cumulative dwell time for the three AOIs.

Data was analyzed according to two distinct plans. Data describing the subtask level, like the hit rate cost and the dwell time proportion, were submitted to a $3 \times 3 \times 3$ within-subject analysis of variance (ANOVA), with the subtask difficulty (0-Back *vs* 1-Back *vs* 2-Back), the concurrent subtask difficulty (0-Back *vs* 1-Back *vs* 2-Back) and the subtask relative importance (less *vs* same *vs* more) as repeated measures. On the other hand, general data like the overall hit rate and the cumulative dwell time for the central AOI, were submitted to a 6×3 within-subject ANOVA, with the difficulty association ($0-0$ *vs* $0-1$ *vs* $0-2$ *vs* $1-1$ *vs* $1-2$ *vs* $2-2$) and the relative importance ($A > B$ *vs* $A = B$ *vs* $A < B$) as repeated measures. This last plan was obtained by flipping and merging data from symmetrical conditions.

Analyses were performed using R (version 3.2.1.). Unless otherwise noted, means are reported with their standard deviation. The significance level was set at .05 and generalized eta squared ($\widehat{\eta}^2_G$) is reported. All p-values were corrected for non-sphericity (Greenhouse-Geisser correction). When appropriate, analyses were completed with the Holm's multiple pairwise comparisons method. For reasons of space, only the more relevant levels of the analysis are reported. Exhaustive inferential statistics are available in supplementary materials.

Results

Hit rate analysis

Overall hit rate. The ANOVA revealed that the overall proportion of detected targets mainly depended on the difficulty association [$F(5, 95) = 86.62, p < .001, \widehat{\eta}^2_G = .65$]. Post-hoc tests brought out two main groups of difficulty association : $1-2$ and $2-2$ conditions were considered as equivalents ($p = 1.0$) and triggered a lower overall hit rate ($M = .59 \pm .04$) than the four other demand associations ($M = .94 \pm .02; p < .001$). Some slight differences were found among these last four conditions (Figure 2). No main effect of the priority association [$F(3, 57) = 1.40, p = .27$] nor interactional effect [$F(15, 285) = 1.06, p = .38$] were found. These results highlighted that the $1-2$ and $2-2$ N-Back associations induced higher global difficulty than the other associations.

Hit rate cost. At the subtask level, the magnitude of the hit rate cost (Figure 3) was influenced by a second order interaction involving the ongoing difficulty, the concurrent difficulty, as well as the relative importance [$F(8, 152) = 9.58, p < .001, \widehat{\eta}^2_G = .08$]. Under each low-global-difficulty condition ($0-0$, $1-1$, $0-1$, $0-2$), the importance level had no effect on costs ($p \geq .84$). Conversely, under high difficulty scenarios ($1-2$ and $2-2$), costs were modulated by the importance level, confirming the H2a hypothesis. Post-hoc showed that *less* > *same* and *same* > *more* differences were significant ($p < .001$). For instance, when facing a 1-Back difficulty, costs for a 2-Back subtask were greater when the latter was less important ($M = .50 \pm .28$), compared to when it had the same importance ($M = .26 \pm .32$), or when it was more important ($M = -.03 \pm .27$). There was one exception though, with the 1-Back facing a 2-Back, triggering equivalent costs when it was either *more* or *equally* important ($p = .34$).

Resources allocation analysis

Proportion of cumulative dwell time. Proportion of cumulative dwell time (Figure 4) was affected by a second order interaction between the ongoing difficulty, the concurrent difficulty, and the subtask relative importance $[F(8, 152) = 9.08, p < .001, \hat{\eta}^2_G = .06]$.

Under low-global-difficulty scenarios ($0-0$, $1-1$, $0-1$, $0-2$), the relative importance had no impact over resources allocation ($p = 1.0$ for 12 comparisons), which mainly depended on the difficulty association. In particular, much more resources were allocated to a 2-Back ($M = .77 \pm .18$) or a 1-Back ($M = .82 \pm .16$) facing a 0-Back, than any other subtask ($p < .001$, for 4 comparisons). This confirmed our H1b hypothesis.

Conversely under high-global-difficulty scenarios ($1-2$ and $2-2$), the more important the subtask, the more it received visual resources ($more > same > less; p < .01$; see Figure 5), whatever its level of difficulty. For instance, when against a 2-Back, a more important 1-Back received more resources ($M = .68 \pm .27$), compared to when it had the same importance ($M = .44 \pm .28$), which was significantly higher than under lower importance ($M = .13 \pm .14$). These results confirmed our H2b hypothesis though we noted one exception: for a 2-Back against a 1-Back, less ($M = .15 \pm .17$) and same

($M = .28 \pm .09$) importance levels triggered a difference that was marginally significant ($p = .058$).

It cannot escape the attention that certain subtasks were allocated only a small proportion of resources but resulted in a good level of performance. This being the case of $0 - 0$ and $1 - 1$ difficulty associations. Suggesting that in these conditions participants may have exhibit specific visual patterns, which are detailed below through central dwell time measurements.

Central dwell time. The proportion of visual resources that was allocated to the central AOI (Figure 5) mainly depended on the difficulty association [$F(5, 95) = 29.75, p < .001, \hat{\eta}^2_G = .41$]. The $0 - 0$ ($M = .60 \pm .53$) and the $1 - 1$ ($M = .53 \pm .31$) associations triggered equivalent ($p = .15$) and greater dwell times than all the other associations ($p < .001$). In turn, the $2 - 2$ association triggered more central dwell time ($M = .28 \pm .33$) than the $0 - 1$ ($M = .10 \pm .09; p < .001$) or the $0 - 2$ ($M = .11 \pm .11; p < .001$) conditions. Moreover it triggered only a marginally significant difference with the $1 - 2$ association ($p = .07$). From these results it is clear that when response rules were identical participants favored peripheral processing of both subtasks, especially under low-global-difficulty conditions ($0 - 0$ and $1 - 1$).

There was also a main effect of the relative importance [$F(3, 57) = 5.15, p < .01, \hat{\eta}^2_G = .01$], that did not result in any pairwise significant difference ($p \geq .47$). Finally, there was no difficulty-importance interaction [$F(10, 190) = 1.12, p = .35$].

Discussion

The main objective of the present study was to test the hypothesis that resources allocation is modulated by task importance and difficulty when facing multitasking situations. More precisely, we hypothesized that subtasks attributes would not systematically bias the allocation of visual resources and that individuals would rely on the importance attribute as long as the global difficulty would be high. The present results are consistent with our starting hypothesis : under low-global-difficulty, proportion of cumulative dwell times was mainly explained by the subtask difficulty, whereas under high-global-difficulty, proportion of cumulative dwell times was explained by the subtask relative importance. Moreover, the various attributes defining the two subtasks did not linearly bias the resources allocation but rather, the participants switched from a *difficulty-driven* strategy to an *importance-driven* strategy, depending on the difficulty level. Finally, under low-global-difficulty conditions, two types of ocular behaviors were observed. When response rules were identical ($0 - 0$ and $1 - 1$), peripheral processing of both subtasks was favored, which resulted in an increase of dwell time proportion in the central AOI. On the other hand, when rules were incompatible ($0 - 1$ and $0 - 2$), they visually favored the most difficult subtask. Thus, depending on the difficulty level, the two subtask attributes did not systematically contribute to visual resources allocation. In other words, the importance attribute did not direct their attentional strategy when a *greedy and polite* policy (Salvucci & Taatgen, 2008) led to optimal levels of performance.

These results are in line with a significant body of work demonstrating the importance of prioritization to drive attentional strategy (Anderson, 2013; Chelazzi et al., 2014; Gopher, Armony, & Greenshpan, 2000; Gopher & Brickner, 1982; Janssen & Brumby, 2015; Kurzban, Duckworth, Kable, & Myers, 2013; Matton et al., 2016; Schumacher et al., 2001), and more generally in human regulation (Loft et al., 2007). More particularly, it shows that resources allocation is prone to top-down modulations, which may take precedence over a “greedy and polite” resources allocation policy. Consistently with other works in learning or problem solving, we propose that these modulations are supported by a meta-cognitive level that monitors the current state of performance, and makes decisions about resources allocation accordingly (Nelson, 1990). In these fields, it has been shown that resources allocation was influenced by task processing fluency (data-driven) when the task was simple but was more sensitive to goal-related information (e.g., task importance), when more complex (Ackerman, 2014; Koriat, Ackerman, Adiv, Lockl, & Schneider, 2014).

Although this type of modulation is not in the scope of the STOM model (Wickens et al., 2016; see the Introduction, p. 5), our results could help to enrich it. For instance, we showed that the interaction of task attributes is not linear but instead might be mediated by voluntary adaptations, in order to “protect” the achievement of the assigned goal.

In terms of the STOM model, it could be that attributes weights or polarities are modified, depending on dynamical factors such as perceived performance, with the possibility, for instance, to increase the weight of the importance attribute in case the assigned objective can not be optimally satisfied.

Decision-making heuristics and prioritization

The present experiment is one illustration of how decision-making processes and executive control are entangled (Coutlee & Huettel, 2012). Once one is facing the “simultaneity problem” (Kurzban et al., 2013), executive control partly relies on the evaluation of the tasks involved and their scheduling. But what is the criterion of the decision ? And can the evaluation process be described ? Our findings advocate in favor of the implementation of decision-making heuristics, as the two attributes have alternately driven visual resources allocation.

In the decision field, considerable evidence has shown that when facing several alternatives, individuals rely on heuristics rather than on a rational “weight and sum” policy (Gigerenzer & Gaissmaier, 2011; Payne, Bettman, & Johnson, 1993). For instance, according to the *take-the-best* heuristics (Brandstätter, Gigerenzer, & Hertwig, 2006), one firstly determines the most important attribute (e.g., the price) and sees if the alternative values of that attribute allow for a decision. If not, the second most important attribute is considered and so on, until a decision can be made. Not only do these kinds of heuristics often give equivalent (if not more) accuracy as more rational models, but it is also more plausible as it yields to less computation cost and protects agent from resources depletion

(Brandstätter et al., 2006).

In this study, such heuristics may have been at work, as the importance attribute did not exert any significant influence when a *difficulty-driven* strategy was satisfying. Therefore it can be accounted that complex *task management* can rely on decision-making heuristics, and more particularly that not all the task attributes are considered before an executive decision is made. In a multi-attribute environment, one could firstly rely on the most relevant attribute of each task to select an appropriate executive strategy, and switch to the second most relevant feature in cases the first attribute does not allow to select a satisfying executive strategy.

However, we would not argue that difficulty-driven and importance-driven strategies are mutually exclusive, as the structure of the task never ceases to influence activity. Rather, we focus on the strategic level of execution, and on the choice of the criterion that *globally* biases the strategies employed in the context of multitasking.

If this is correct, this heuristic hypothesis could provide a fundamental explanation of how the operator can cope with the informational complexity of the task or work environments despite his or her limited resources (Kahneman, 1973; Norman & Bobrow, 1975; Sperandio, 1971). Moreover, it would be consistent with an emerging view that people tend to avoid costly mental operations (Kool et al., 2010) and favor "fast and frugal" heuristics (Gigerenzer & Gaissmaier, 2011). From a computational point of view, it corresponds to the idea that human agents favor strategies that come along with a minimal number of control stages (if→then operations, see *the minimal control principle*, Taatgen, 2007). It would also provide a potential explanation for how one can prioritize between competing tasks when they present multiple and potentially contradictory attributes. In that case, instead of assuming a rational and continuous integration between two or more attributes, our study suggests that the various attributes are first ordered and browsed accordingly until one or few of them can reliably leads to a satisfactory strategy. How these attributes are precisely ordered, and why, is a question of a great interest in need for further investigations.

Practical implications

Our task, albeit basic, manipulated working memory - an executive function that is highly sollicited in complex environments like cockpits (Gateau, Ayaz, & Dehais, 2018; Sohn & Doane, 2004), ATC (Morrow et al., 2003; Taylor, O'hara, Mumenthaler, Rosen, & Yesavage, 2005) or surgical operating rooms (Hedman, Klingberg, Enochsson, Kjellin, & Felländer-Tsai, 2007). Our results suggest that in such operational situations, operators might not only consider task difficulty but also other attibutes such as task importance attributes. This contribution is all the more valuable as modern work environments are increasingly integrating automation, a technology that generate a *decorrelation between difficulty and importance*. For instance, in the cockpit, an automated device like the autopilot reduces the difficulty of the aviating task, but does not reduce its importance. Therefore, the difficulty/importance dissociation represents a relevant insight into the fundamental understanding of operators strategic behavior, in such environments.

This reinforces the idea that, in any partially or fully automated system, operators should dispose of prioritization rules taking task importance into account, like the "Aviate > Navigate > Communicate > manage Systems" (ANCS) rule, in the aviation domain. As a matter of fact, violations of such rule have been found to lead to inappropriate monitoring patterns (i.e., prioritization errors; Jonsson & Ricks, 1995; Wilson, 1998), and to be involved in numerous aviation incidents or accidents (Colvin, Funk, & Braune, 2005; Funk, 1991; see Rosvall & Karlsson, 2010 for a recent case). Therefore, efforts should be made to ensure that operators have a correct representation of the relative importance of the different tasks that make up their environment, especially when these are likely to change over time (e.g., in a cockpit, the relative importance of each instrument depends mainly on the flight phase).

Acknowledgments

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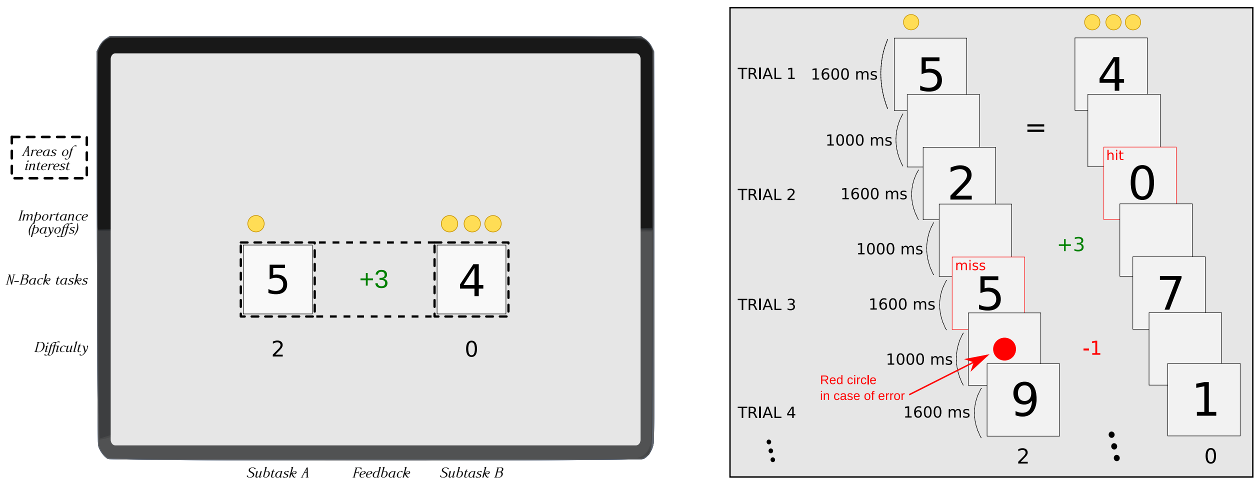

Figure 1. The “dual N-Back task”. Left : the environment of the task. Each subtask is characterized by a difficulty attribute and an importance attribute. Dashed lines and information outside of the screen are for illustrative purpose only. Right : four potential trials of the dual-task phase. Under a 0-back difficulty, participants had to detect any 0 digit.

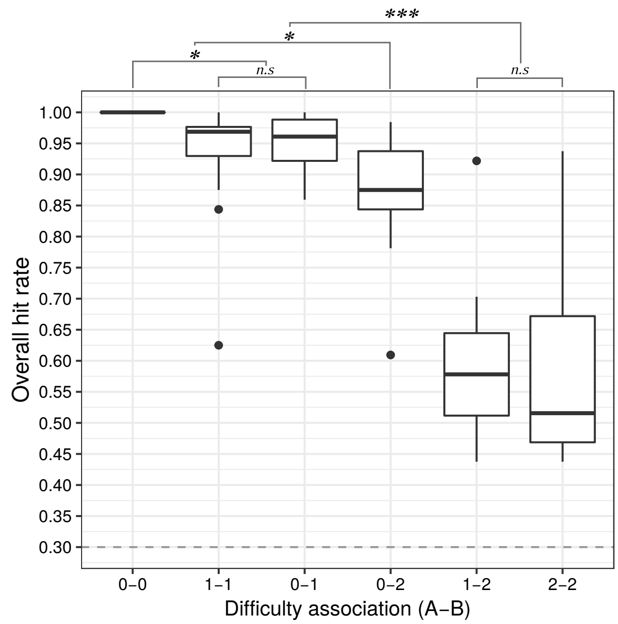

Figure 2. Overall hit rate per difficulty association. Boxplot with whisker bold band represents median values of hit rate. The upper and lower end of the boxes represent 95% confidence intervals. Whiskers represent ranges. Points are outliers. (*n.s: not significant*, * < .05, *** < .001)

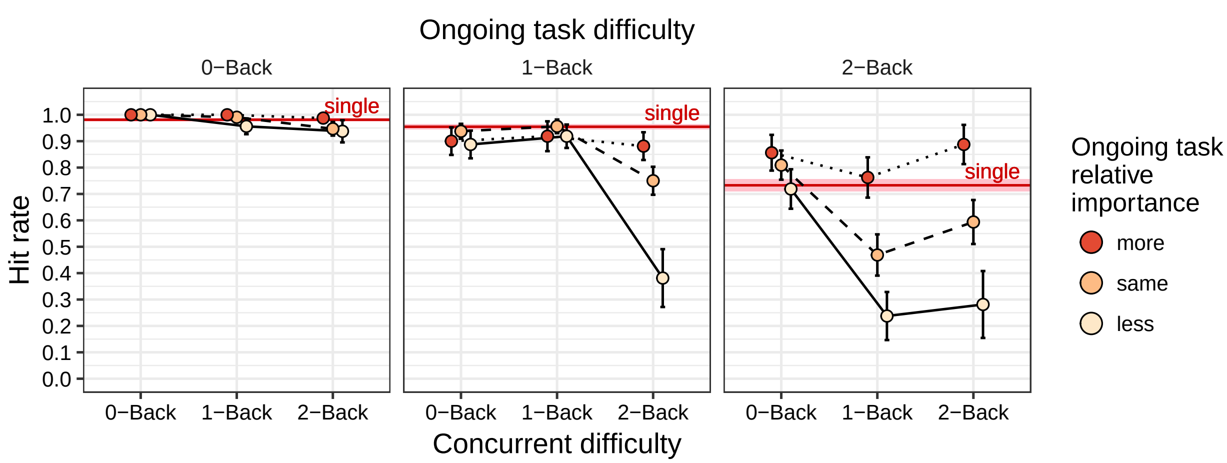

Figure 3. Hit rate costs as a function of ongoing and concurrent difficulty levels, as well as subtask relative importance. Points are dual-task conditions and red lines are single condition. Error bars and red shaded areas are the confidence interval.

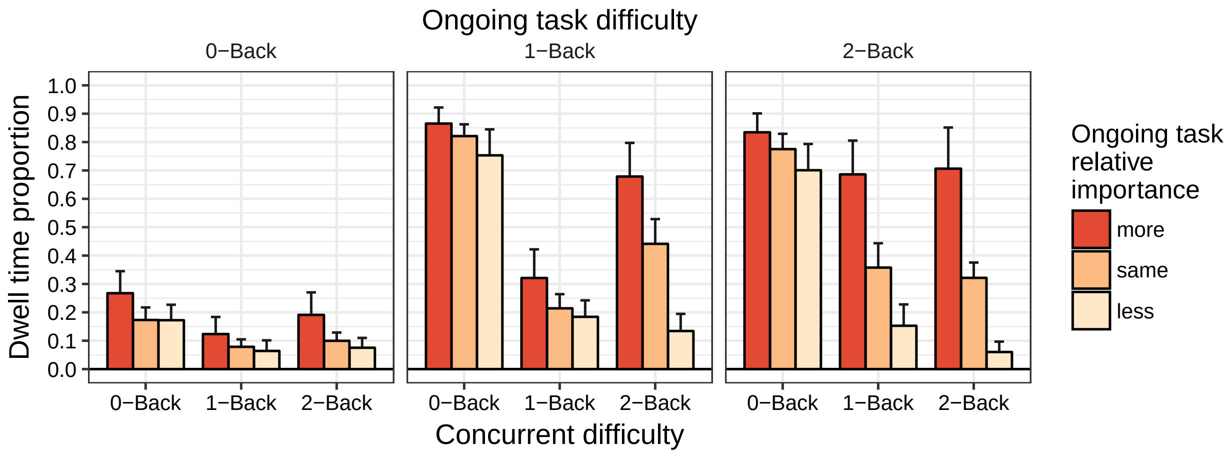

Figure 4. Dwell time proportion as a function of ongoing and concurrent difficulty levels, as well as the ongoing task relative importance. Error bars are the confidence intervals.

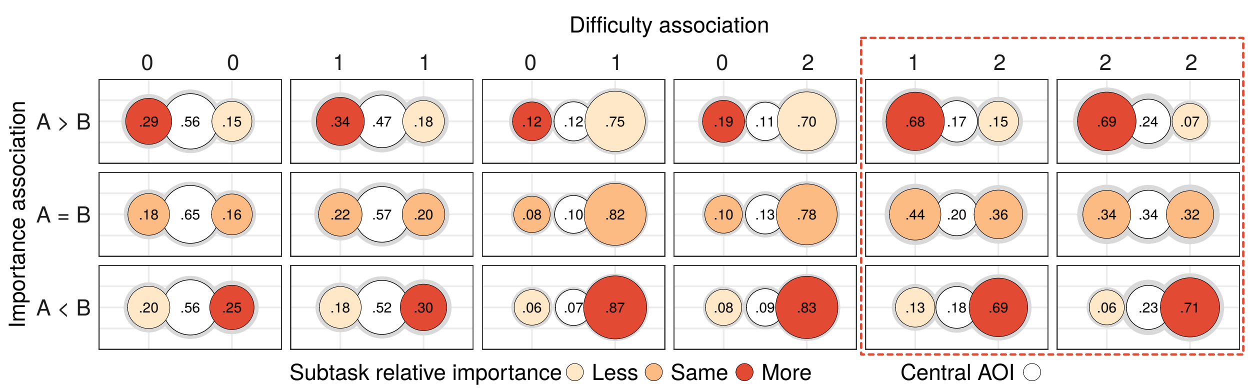

Figure 5. Dwell time proportion along the three AOIs. Each column represents an association of difficulties, and each row an association of importance levels. The size of each circle is proportional to the amount of visual resources allocated. The gray shaded area stands for the standard deviation. As can be seen, relative importance had an effect over visual resources allocation *only under* $1-2$ and $2-2$ difficulty associations (surrounded by a red dashed line).

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Supplementary materials

Inferential results

Table 1

Inferential results for subtask specific metrics

Metrics	**Effect**	**F(df)**	**p**	$\hat{\eta}^2_G$
Hit rate costs	Ongoing Difficulty (OD)	$(2, 38) = 11.16$	$< .001$	0.09
	Concurrent Difficulty (CD)	$(2, 38) = 39.23$	$< .001$	0.14
	Importance (I)	$(2, 38) = 60.21$	$< .001$	0.21
	OD:CD	$(4, 76) = 30.57$	$< .001$	0.17
	OD:I	$(4, 76) = 23.96$	$< .001$	0.14
	CD:I	$(4, 76) = 17.02$	$< .001$	0.10
	OD:CD:I	$(8, 152) = 9.58$	$< .001$	0.08
Dwell time	OD	$(2, 38) = 115.52$	$< .001$	0.48
	CD	$(2, 38) = 78.27$	$< .001$	0.44
	I	$(2, 38) = 66.90$	$< .001$	0.27
	OD:CD	$(4, 76) = 29.87$	$< .001$	0.19
	OD:I	$(4, 76) = 28.02$	$< .001$	0.10
	CD:I	$(4, 76) = 23.20$	$< .001$	0.09
	OD:CD:I	$(8, 152) = 9.08$	$< .001$	0.06

Table 2

Inferential results for general metrics

Metrics	**Effect**	**F(df)**	**p**	$\hat{\eta}_G^2$
Overall hit rate	Difficulties association (DA)	$(5, 95) = 86.63$	$< .001$	0.65
	Importances association (IA)	$(2, 38) = 1.40$	0.26	0.01
	DA:IA	$(10, 190) = 1.06$	0.40	0.02
Central dwell time proportion	DA	$(5, 95) = 29.75$	$< .001$	0.41
	IA	$(2, 38) = 5.14$	0.01	0.01
	DA:IA	$(10, 190) = 1.12$	0.35	0.01