The interplay between automatic and controlled processes:

Experimental contributions to dual-process theories of cognition

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Abstract

Since its beginnings, psychological science has frequently used dichotomous categories to describe behavior and mental phenomena. The most traditional dual models have impactfully equipped both the scientific and folkloristic psychological vocabularies of such dichotomies (e.g., conscious vs. unconscious, logic vs. creative, rational vs. emotional). However, while offering an affordable account of how the human cognitive system works, these models appear too simplistic. Substantially, they are grounded upon the findings obtained in decades of results in almost all the psychological fields, from perception to social processes, which have been later merged into a broad systemic theory of human cognition. However, this dual-system theory, which proposed to unify all cognitive dualities into System 1 (automatic, unconscious, fast, effortless, intuitive, and so on) and System 2 (controlled, conscious, slow, effortful, rational, and so on) entities, lacks a systematic investigation of its basic assumptions: for instance, that the features are aligned within and complementary between the two systems. These properties are essential for the tenets of the theory since a systemic theory should postulate the interdependence and interrelation of the elements constituting a system. In this view, the central thread linking all the experimental contributions in the present work is that the dual-system theory should resist when investigating cognitive performance either at low- and at high-level of complexity (complexity defined as the variety of mechanisms implicated in the phenomena of interest).

Through seven studies conducted in three research lines, addressing temporal attention, task-switching, and decision-making, the interaction between automatic and controlled features in each process has shown to be the rule rather than the exception. Thus, the results presented in this work support the idea that the dual-system theory current formulation has a weak explanatory power, suggesting that decomposition approaches aimed at disentangling the contribution of qualitatively and quantitatively different mechanisms in each cognitive process are needed to advance or put aside dual-process theories.

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Introduction

Automatic and controlled, implicit and explicit, intuitive and rational, associative and analytical, habitual and voluntary, bottom-up and top-down, exogenous and endogenous, parallel and serial, unconscious and conscious, fast and slow, hot and cold, System 1 and System 2, and so on: the dichotomization of the human mind's processes is old as the psychological science, partially reflecting even older debates like body-mind and nature-nurture.

Since William James essays (1890), will and habit represent the two functional modes that govern mental functioning. This duality has been the central point of many theories in almost the totality of psychological fields. The meanings of the various couples of adjectives are slightly different one each other, sometimes more and sometimes conceptually less. Most of the reasons for such a wide vocabulary mostly belong to the variety of psychological fields in which they were born and, consequentially, the theoretical contexts in which they have been used. For example, decision-making and reasoning literature has focused on intuitive and rational strategies; research on attention has investigated bottom-up and top-down processes; research on memory has disentangled implicit and explicit material. How all these dichotomous categories coexist among different cognitive functions is currently unclear.

Up to now, the dual nature of mind has been broadly accepted in psychological science. However, critiques exist, and debates are still going on.

The success of dual-process theories (DPT) has extended to many applied fields, highlighting the implications that they can widely have in human contexts. Generally, these fields have found in DPT an excellent framework to investigate and reduce the impact of fast and automatic strategies on human errors.

For instance, DPTs have been used within medical settings, specifically in the diagnostic process (Rotgans et al., 2019; O'Sullivan and Schofield, 2018; Phua and Tan, 2003). Medical organizations, involved in improving the power of health care systems, have paid much attention to the processes subtending professional decisions, intending to avoid biases in diagnoses and, thus, in subsequent actions. Making diagnoses or other kinds of relevant health choices for individuals is a process for which the only professional expertise often is not enough: professional experts also need to be decision experts. The impact of expertise in decision-making has been widely investigated at different levels, with experts showed to have a better understanding about the fallacies involved in decisional processes, to be equipped with a furnished toolbox aimed at avoiding common biases and with a marked capacity of expertise-based intuition (Salas et al., 2010). Avoiding common biases, which are known to be a product of intuitive judgments, also has paramount importance in scientific research. Researchers may indeed implicitly use cognitive shortcuts in the hypothesis-testing and results' interpretation processes, such as confirmation and method biases (Klayman and Ha, 1987; Fanelli et al., 2017; Podsakoff et al., 2012; Wilholt, 2009).

Another field in which a massive use of cognitive biases has been strongly recognized is the forensic and criminal investigative context (Budowle et al., 2009; Van Gelder and de Vries, 2014). A similar impact has also been shown in political science. Systematic cognitive biases are also studied in the context of policy-making and communication, allowing for the development of several tools to influence people's decisions, such as "nudging" (Thaler and Sunstein, 2003; Gigerenzer, 2015). Concepts such as ideology, stereotypes, and prejudice are widely studied in the context of DPT in social psychology (e.g., Yilmaz et al., 2016), and represent the bricks of voting behavior: contemporary politics strongly rely upon these pieces of knowledge, for instance, in the implementation of political campaigns (Arceanaux, 2012; Taber and Lodge, 2016). DPTs have also been shown to be useful in cultural analysis (Lizardo et al., 2016). Again, DPTs are prominently part of data regulation and privacy policies (Phelan et al., 2017; Aivazpour et al., 2017). In an information-based society, the data breach is at the top of significant risks. However, even if almost everyone is sensible to their own private data, reading long informed consents is very effortful, and the time available is often scarce: then, in most cases, clicking on "Accept" without reading looks out to be the more reasonable action, generating the well-known "privacy paradox".

Finally, a promising line of research regards Artificial Intelligence. Computational methods are often implemented to understand human information processing, and complex neural networks sometimes seem to be among our significant understandings of the human mind. Certain machine learning fields, such as reinforcement learning, (Sutton and Barto, 1998; Daw et al., 2011) aim to implement algorithms that can mimic intuitive forms of human learning from feedback, enabling them to generate predictions about the future.

Notwithstanding the spreading of DPTs and the importance they have obtained in a vast set of applied fields, many different issues in their usage and definition have been highlighted throughout more than 50 years of research. Since the cognitive revolution, much effort has been made to describe the mechanisms underlying the two ways of information processing, and what can be ascribed as "controlled" or "automatic". Problems mostly arose when the need for the construction of a general framework encompassing the whole cognitive functioning, able to contain all the DPT results obtained in specific psychological fields, came out, evidencing a sort of "too-short-blanket-dilemma". Several results, indeed, have put in doubt that this conceptualization is robust and reliable enough to support such a broad theorization. Given the great popularity that DPTs have obtained in several human contexts, they need to be systematically destructured to test the reliability of their fundamentals and predections, providing human contexts with a strong and useful framework.

From this point, the main objectives of the present thesis are to shed new lights on the dual processes underlying human cognition, investigating the different impacts of the two across different levels of complexity. The principal aim is to test the basic assumptions of dual-process theories and their generalizability.

In the first chapter, the current debate on DPTs and the most relevant issues will be reviewed. Problems in the definition of automaticity and cognitive control will also be considered separately, highlighting the most influential conceptualizations.

The experimental part that will follow is divided into three sections. The results obtained from two experiments on temporal attention will be presented in the first, investigating that evidence of high-level processing at early processes such as the identification and discrimination of two rapidly presented stimuli exists. In the second experimental section, the phenomenon of interest is in the domain of control processes, and the findings obtained in three experiments will be presented. The focus here is on task-switching performance, an excellent example of the interplay between automatic and controlled mechanisms, requiring a more complex performance in the sense of greater coordination of different processes. Finally, the last session regards decision-making, which is at the top, for complexity, of the cognitive functions investigated in these works. Indeed, decision-making requires individuals to make inferences and calculations integrating many factors, such as alternatives, probabilities, outcomes, task structure, and own's affective state. According to the decisional environment and the degree of uncertainty presented to subjects, decision-making processes can be determined by bottom-up, intuitive, or top-down, analytical strategies.

CHAPTER 1

Dual-process theories: the long-lasting debate

Some early influential works have been credited to be among the pioneers of the experimental investigation on the human mind's duality. Atkinson and Shiffrin (1968) firstly termed as "control" the ability of an individual to put under its will some psychological phenomena and the set of functions that allows for the guidance of behavior as "control processes". Following the authors, control processes are pervasively represented in sensory, short-term, and long-term memory; they can guide performance mostly through the active implementation of strategies; they are sensitive to the instruction set, the experimental task, and the history of the subject. Several years later, the fundamentals of the automatic/controlled dichotomy were posed in a series of elegant experiments (Schneider and Shiffrin, 1977; Shiffrin and Schneider, 1977), demonstrating how extensive practice allows for the automatization of a task, but only when the mapping between stimuli and responses remains fixed, whereas controlled processes are engaged when this mapping is inconsistent. The essential distinction between the two processes relies upon the investment of attention over the sequence of nodes that guide information processing to action execution. When attention is set over this sequence of nodes, allowing the individual to start or guide its execution voluntarily, the "controlled processes" occur.

In contrast, the unchanging environment, with the strengthening of the relations between nodes in memory through learning, allows for the gradual disengagement of attention. Progressively, all the events become directly instantiable by stimuli without the intervention of the subject's control: thus, these processes consist of the automatic activation of a sequence of nodes with no need for serial search through memory sets, becoming faster and more efficient. The following research has provided additional strong evidence that two different modes of information processing exist (Logan et al., 1980; 1992; Fisk and Schneider, 1981; Schneider and Fisk, 1982; Anderson et al., 1992; Hancock et al., 1986; Pashler et al., 2001), enriching the spectrum of attributes belonging to the two processes. Schneider and Chein (2003) outlined several different phenomena described by these studies: automatic processing develops after consistent training in a constant mapping between stimuli and responses, is fast and parallel, requires little effort and does not interfere with other concurrent tasks, is robust to stressors, is inflexible, and is context-independent. Differently, all the opposite characteristics define controlled processes: they are flexible, slow, serial, effortful, sensitive to stressors, and context-dependent. Assuming an evolutionary advantage for this duality of processing

(Schneider and Chein, 2003), it is quite easy to conceive why the two processes are useful in everyday cognition. Driving a car while paying attention to the road is one of the most typical examples.

Research on dual-process theories (DPT) continued throughout decades and has found in reasoning a very flourishing field. Since the suggestion of an individual bounded rationality (Simon, 1955) that upset the *homo oeconomicus* view of the expected utility theories (Von Neumann and Morgenstern, 1953), much work has been done in the description of the irrationality underlying human choices and actions. Biases and heuristics, i.e., effortless cognitive shortcuts, have been extensively described in the Kahneman and Tversky prospect theory (1979). The existence of numerous systematic biases in human decision-making has provided direct evidence that two types of reasoning exist, evidence supported by several influential authors (Kahneman and Frederik, 2002; Evans, 2003; Gigerenzer and Gaissmaier, 2011).

The spreading of attributes, phenomena, and fields in DPTs has moved authors to start to conceptualize a broad and promising theoretical framework of a dual cognition. The successful definition of two systems of reasoning is generally attributed to Stanovich and West (2000): System 1 is implicated in associative, fast, and intuitive judgments and behavior, mostly responsible for individual biases, prejudice, and stereotypes, while System 2 is deliberate, analytical, and slow, allowing for cost-benefit analyses. Research on reasoning suggested that competition for the action control exists between the two systems and that the role of System 2 is intrinsic in its capacity to override automatic System 1-type behavior (Evans, 2003).

With this categorization, DPTs moved from a functional to a systemic definition of information processing. The systemic definition covers almost the totality of the dimensions of human phenomena distinguished into two different ways of processing, subtending common mechanisms and functions within all the processes belonging to each category, from attention and memory to decision-making and reasoning.

Currently, DPTs are very pervasive in psychological literature: a search on SCOPUS resulted in more than 2k papers, with a sharp increase after 2000 (Figure 1).

Notwithstanding the DPTs' long tradition and their impact on psychological science, the debate about their nature and fundamentals is still going on. Indeed, while the existence of two qualitatively different processes appears to be quietly demonstrated, several recent observations have led authors to reconsider the reliability of an all-inclusive theory of dual processes.

A letter exchange between two relevant groups of academics on *Trends in Cognitive Science* highlighted several weaknesses of the most prominent dual-theories, especially in the so-called dual-typology (Melnikoff and Bargh, 2018a; 2018b; Pennycook et al., 2018).

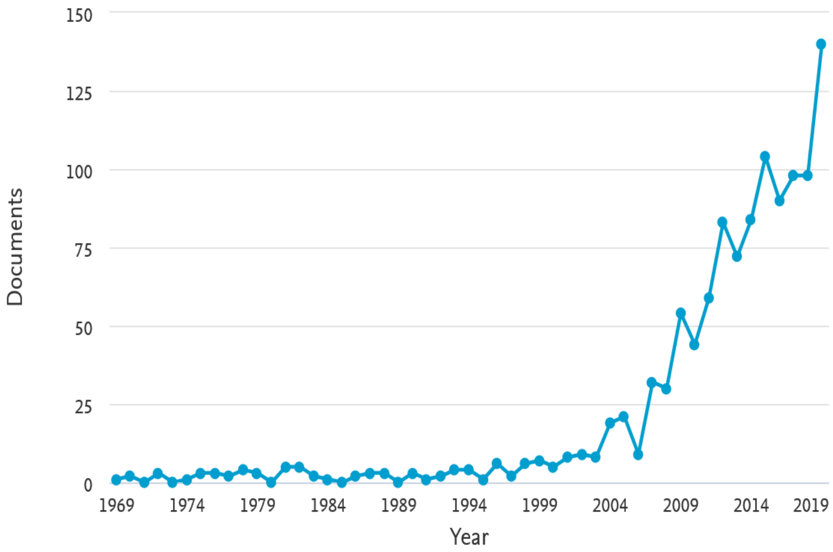


Figure 1. Documents published by year (1969-2019) for a "dual-process theor*" search on Scopus.

Melnikoff and Bargh (2018a) argument was prominently that dual-process theories, as conceived by several authors, suffer by an alignment problem, also suggested by other influential authors (Kruglanski and Gigerenzer, 2011; Keren and Schul, 2009). More specifically, based on the coexistence of their defining features, processes can be at the same time made up of automatic and non-automatic characteristics. Arguing against the all-or-none dimension of automaticity, the authors suggested that no correlation exist or has been experimentally proved, among the different traditional antinomian dimensions of the automatic-control distinction, i.e., awareness, controllability, intentionality, and efficiency (Bargh et al., 1994). For instance, according to Melnikoff and Bargh, dual-process theories implicitly state that if a process is non-intentional must be necessarily automatic, taking for granted all the other features (unconscious, uncontrollable, and efficient). However, as they reported, literature presents a vast number of disclaiming results, highlighting the non-correlation and, thus, the misalignment between features.

A reply to this argument soon came from a group of relevant advocates of DPTs (Pennycook et al., 2018). In their view, the correlation among types is not fundamental, because one dichotomous defining feature is enough to assume the duality of cognition against a continuous unimodal conceptualization, and that the statement of a “list of features” view is outdated and researchers in the field often use this wrong implicit assertion. However, as Melnikoff and Bargh answered (2018b), the rejection of the correlational view among features does not reflect the authors’ actual assumptions, providing several examples of works where the typology has been perpetrated by them.

According to Melnikoff and Bargh, the dual typology seems to be quite insidious. However, it looks reasonable that rejecting the dual typology does not mean to abandon DPTs and that critiques to DPTs must not be generalized to a critique of a dual view of cognitive processes. Conversely, what is debatable should be how the results suggesting a duality of processes have been unified in a large theoretical framework.

Besides the different attributes and names given to dichotomies and their relation, authors in the field of DPTs have also differently interpreted the duality as functional or structural, in terms of modes, processes, and systems, often in interchangeable ways. In a meaningful methodological paper, Keren and Schul (2009) analyzed the variable terminology in dual-theories, highlighting the differential interpretation that may arise by arguing a dual-process or a dual-system conceptualization. Keren and Schul warranted over the possible confusion exerted by the interchangeable definitions of systems or processes, each describing a very accurate picture, somehow comparable to computer's hardware and software. They have primarily focused on systemic theories, highlighting some implicit assumption of such characterization. For instance: the failure in the isolability of the two systems, a critical feature for a system to be defined in this way; the misuse of binary features, which can be in some cases continuous in other dichotomous; the lack of an explanation for the hypothesized switch between systems, for instance after extended practice; the non-alignment of features, highlighting the inability of the two-system theories to include hybrid phenomena.

While DPTs have been widely accepted in the psychological literature, they present a high number of problematic issues. Regarding defining features, it has been shown that the dichotomies do not always work when distinguishing between the two processes, providing evidence for their non-correlation: as it will be shown in the next sections, several phenomena indicate that a mixture of these features can be simultaneously observed. These arguments raise the question of the nature of the dual processes. Theories differentiated in the terminology used for defining them, sometimes assuming a functional, sometimes a structural view of their nature. The confusion generated by this variety of terminology has led research to wrongly assume that these terms are, in some way, overlapping, often neglecting the problem. Finally, the urge to construct a comprehensive theoretical framework has hidden the specificity of DPs in the singular mental processes investigated. It is certainly conceivable that a variable range of phenomena shares the same underlying mechanisms. However, abandoning a specific theorization in favor of a more general one may erroneously overlook essential details in constructing such a relevant general theory of broad cognition. As Gigerenzer warranted (2011b), converging several specific theories into a more general theory of dual processes may move backward these theories to surrogates, rather than forward to an integrated theory of cognition. Such issues leave many questions still open in DPT research.

The problematic definition of automaticity

Automaticity has been traditionally tied up with attention: the more resource-consuming a process is, the less it is automatic. The view that links automaticity and its opposite throughout a continuum is one of the most influential in early cognitive psychology, which has given rise to many models and theories of attention and performance. Briefly, it is assumed that the cognitive system has a limited amount of energy to invest in mental processes, which can be distinguished between processes that require no energy to be run (i.e., automatic) and processes that, instead, require a certain degree of resources to be controlled (i.e., non-automatic). The capacity model (Kahneman, 1973) posited that non-consuming processes could be run simultaneously (i.e., in parallel) with others without resulting impoverished, while consuming processes may interfere with one each other and could be run just one at a time (i.e., serially). In contrast to the effortful ones, automatic processes were defined to have a constant level of performance and do not improve with practice (Hasher and Zacks, 1979).

Given that a continuum has two poles, this view gave rise to the view mentioned above of a dichotomized cognition. Indeed, many features of cognitive processes, such as consciousness or intentionality, were hard to conceive as continuous dimensions, and the all-or-none definition of automaticity became predominant. However, advances in research on automaticity subsequently challenged this all-or-none view (Kahneman and Treisman, 1984; Bargh, 1994; Moors and De Houwer, 2006). Moreover, the single-capacity view of attention was challenged. Indeed, the lack of co-occurrence between features, the non-mutual exclusivity of modes, the problematic definition of learning, and the rise of multiple-resource models (Baddeley, 1996) added relevant elements to the unreliability of the all-or-none definition of automaticity.

The solutions adopted were, in turn, to abandon the concept of automaticity (Regan et al., 1981), to support a gradual view of automaticity with different learning paths for the different features (Logan et al., 1985), or to allow for a free alignment of the related-features except for automaticity itself (Bargh et al., 1994).

Given that abandoning the automatic categorization means throwing away decades of research and speculation on it, and that this probably might help hiding the problem rather than solving it, a more flexible definition of what is automatic appears to be the best way, at least at a conceptual level. However, this approach does not clarify what is the essential dimension of automaticity. According to Bargh (1992), a process might be automatic in the case it started either with or without intentionality, a position already promoted by Shiffrin and Schneider, opening the question if “learned” automaticity can be considered to some extent as “pure” automaticity. In this case, “learned” automaticity (for example, through repetition) rises from intention, which is a more controlled dimension, and getting inside the mechanisms that govern the shift from one to another is intriguing and suggestive. Studies on practice have shown other interesting, even mixed, results. The central question is how the practice might effectively improve performance: by speeding up central stages of processing or eliminating the attentional bottleneck (Pashler et al., 2001)? The relevance of understanding the mechanisms of practice and learning has numerous advantages for DPTs. It allows clarifying whether automatization or skill learning determines a parallelization of processes, a switch from one system to another, or an economization of the same action control patterns. To go further into the discussion, the literature on habit and their formation can come in support.

In psychology, habit is a topic very close to automaticity, and it is not surprising if it suffers from the same definitional issues. Habits are defined as overlearned behavioral patterns, to some extent, automatic, that rapidly start in response to a triggering external or internal specific stimulus and are detached from goals. However, they are not purely reflexive: they may have initially been effortful, conscious, or intentional (and it is not assumed that they necessarily lose all these features after habituation). In this sense, the process of habit formation has been conceived as automatic (Wood and Neal, 2007). Once started, habits are quite rigid and are hard to stop or alter.

Simple S-R associations of behaviorist tradition had governed for a long time the literature on habits. However, they are not necessarily stimulus-driven. Indeed, they may pursue a goal, even if unintentionally (Moors and De Houwer, 2006), giving them the characterization of learned goal-directed automatic responses (Verplanken and Aarts, 1999). Logan (1992) argued that learning could be explained in an episodic model: differently from S-R associations set up irrespectively from the causal relation between events and behavior, experience creates episodic traces. With repeated behavior following the exposure to the same or similar stimuli, the multi-step retrieval of these traces economizes to single-step direct memory retrieval. While in Logan’s view this shift happens in the quality of processes, the Adaptive Control of Thought Theory (Anderson et al., 1992) postulated that learning generates a more quantitative strengthen of the production rules that control the cognitive steps of behavior.

The relation between the agent and the environment in learning and habit formation has been widely formalized, especially in the reinforcement learning accounts (Sutton and Barto, 1998) which explains habit formation as a strengthening of the state-action patterns according to the history of reward signals provided by the environment and prediction errors, offering evidence of a model-free action controller (Daw et al., 2011; Dolan and Dayan, 2013). This view has been applied to many contexts but has also been criticized as too simple, arguing for a prominent role of action-sequences

(Dezfouli and Balleine, 2012; Morris and Cushman, 2019) or self-reinforcing repetitive pattern of behavior in the sensorimotor space (Egbert and Baradiaran, 2014).

Instead, a highly influential recent approach that included Bayesian thinking in his theorization is the Friston's predictive coding theory (Hohwy, 2013) that has been proposed as a formal explanation of automatic learning. It assumes that individuals possess internal models of the world that are constantly and inferentially updated through automatic and effortless hypothesis-testing to minimize errors. In this context, learning happens because of the accumulation of prediction errors generated in a bottom-up fashion. This model found broad consensus in a variety of fields, especially perception, and can include a previous model of learning such as S-R associations.

Similar issues concern heuristics in decision-making literature. These have been described as implicit and effortless cognitive shortcuts, aimed at reducing cognitive load, mostly responsible for decision biases (Tversky and Kahneman, 1974), even if their evolutionary advantage has been acknowledged (Gigerenzer and Brighton, 2009). However, the connection between heuristics and habits is still not clarified: although they are often used as synonyms, they might represent different stimulus-driven strategies (Wood and Runger, 2016).

Following the literature, automaticity has been equipped with a very heterogeneity of definitions, paradigms, and functional mechanisms (Fiedler and Hutter, 2014). Consequently, the automatic, the heuristic, the implicit, and the habitual fell into the large family of System 1, that Stanovich (2004) proposed to call more explicatively as TASS (The Autonomous Set of Systems). This set of subsystems shares some characteristics with the modularity of some mental processes theorized by Fodor two decades before (1983): they are fast and mandatory (i.e., they can be turned on by relevant stimuli, without the interference of the central system). However, other sets of characteristics described by Fodor for modular processes (such as domain-specific, informationally encapsulated, and cognitively impenetrable) were not involved by the authors in the set of defining features of TASS, because of the difficulty to test them (informationally encapsulated) or because of their non-exhaustiveness (domain-specific). The encapsulation assumption requires modules to be independent, a condition not likely met by the TASS.

In conclusion, the variety of the operational definitions of automatic processes has led to a conceptualization of a broad set of specific features, rather than a precise operationalization, showing all its limitations (Fiedler and Hutter, 2014). Thus, the puzzling conceptualization of automaticity, the difficulty in search of its central feature, and the reluctance in throwing away decades of research encouraged several authors to follow a decomposition approach, in order to avoid the use of overlapping explanations and definitions of automaticity (Moors and De Houwer, 2006).

Does automaticity, habits, and heuristics belong to the same family? Do they reflect overlearned behavior and experience, and do they act similarly in different contexts and mental activities? Such a decomposition approach seems to represent an excellent way to answer these questions.

Similar problems on the other side

Definition issues are not limited to automatic processes. Non-automatic processes, especially cognitive control, which is their guarantor inside the mind, must deal with their troubles, which in part overlap with the ones of their counterparts. Like automatic processes, cognitive control also has its primary condition in the investment of attention, and through this, it exerts multiple roles. Its abilities, such as planning, monitoring, inhibition, and mental sets updating, are a set of neurocognitive mechanisms, often defined as executive functions, allowing for the flexible adjustment of behavior in a context-dependent manner to achieve specific goals.

The analytical, rule-based, Type 2 system has been supposed to be dependent upon the evolution of language. It is viewed as a central executive, from the Baddeley's Working Memory model (Baddeley and Hitch, 1974), even if Stanovich (2004) warned to be cautious in interpreting this centrality to avoid a homunculus-like fallacy. Indeed, in the current characterization of control in DPTs, System 2 looks out to be both the referee (of autonomous responses) and an independent agent, based on its resources.

The flexibility guaranteed by cognitive control has been described for a long time with unitary and almost monolithic conceptions. Indeed, the most influential psychological literature has provided a description of cognitive control as a unique high-level entity. An illustrious theorization (Norman and Shallice, 1986) described it as a "Supervisory Attentional System" which acts over an automatic Contention Scheduling process. Subsequently, in his famed conceptualization of working memory, Baddeley posits the cognitive control, named as "central executive" over two different subsystems, relying upon specific resources, auditory-verbal and visuo-spatial. In this conception, cognitive control with the mental functions looks like the orchestra's maestro, giving it personified abilities and features. This kind of personification has led throughout the years to the insidious homunculus problem: in brief, the assumption of a little man's existence inside the human mind that governs mental processes. Arguably, the homunculus is invoked as an easy way to cover some weaknesses in the *explanans,* allowing for its best, even if artificial, conceptual fit to the *explanandum.* This assumption leads to the strained settlement of another little man inside the little man's mind, and so on until infinity. Being aware of the problems hidden in this kind of explanation is of paramount importance in cognitive control interpretation.

The central function of control has been suggested by several results throughout the years, mostly in the neuroscience field (Alvarez and Emory, 2006). On the one hand, neuroimaging techniques allowed for the visualization in vivo of the activated areas during task performance, showing that prefrontal areas, mostly PFC (prefrontal cortex), were almost always activated during the performance in different executive tasks; on the other hand, clinical tradition showed that PFC damage might lead to impairments in inhibition as well as in planning, monitoring, and shifting.

This evidence is very robust and hardly debatable. However, the central definition of cognitive control has been questioned even by its proponents. For instance, Baddeley (1996) advises that executive control is a post-hoc label of the problem, not the real explanation and that fragmenting the homunculus into more explanative processes is necessary for dealing with the problem. The fragmentation proposed by Baddeley led to the inclusion of the episodic buffer in its multicomponent model (Baddeley et al., 2000), a multidimensional capacity-limited store that can chunk information from the visuospatial and phonological WM subsystems and long-term memory. However, subsequent research has shown that the addition of the buffer in the model has not been able to aid in fragmenting the executive: indeed, contrarily to the first assumptions, studies investigating both the WM subsystems with concurrent tasks showed no effects of cognitive load on binding processes, suggesting a passive rather than an active role of the episodic buffer (Baddeley et al., 2010).

Other strategies have been implemented to study the nature of executive processes. For instance, Miyake et al. (2000) tried to rule out the problem by simultaneously investigating various well-known executive paradigms, assumed to represent three different executive functions (i.e., set-shifting, inhibition, and updating) analyzing the results through structural equation modeling. Data showed a reasonable degree of reliability, and the model revealed three latent factors, related to the tasks hypothesized to rely upon. However, the three factors were not independent one each other, the model was weak, and the authors concluded arguing both a unitary and multiple nature of executive processes. Moreover, dual-task performance, which was also part of the investigation, did not correlate with any of the factors hypothesized and was suggested by the authors to represent an additional executive component to coordinate between processes. Higher mental functions such as reasoning, planning, and problem-solving seem to be dependent upon these three core EFs and present their specific developmental path (Diamond, 2013).

The development of finer neuroimaging techniques and experimental paradigms has led the field to converge into an idea of a divisible PFC into more localized areas, which are thought to be responsible for domain-specific EFs (Yuan and Raz, 2014). Evidence supports the unitary and multiple nature of

EF, thus maintaining a superordinate cognitive control network, consisting of a broader network of areas (Niendam et al., 2012). Indeed, growing evidence is highlighting the role of other cortical areas in the circuits responsible of high-order mental functions, such as parietal cortices (e.g., Gruber and Goschke, 2004; Collette and Van der Linden, 2002; Sdoia et al., 2020), cerebellum (e.g., Stoodley, 2012; Picazio et al., 2020), and basal ganglia (e.g., O'Reilly and Frank, 2006; Hazy et al., 2007). Moreover, models addressing a distributed control have been constructed (Hazy et al., 2006; Vandierendonck, 2016). For instance, in their WM model, Vandierendonck et al. (2015) suggested substituting to the central executive a distributed "production system", which consists of a procedural knowledge base, made up of rules in long-term procedural memory, and a processing engine, which can execute these procedures when these patterns fit in the constraints stored in a specific passive component of WM, the executive memory.

Interestingly, in the Vandierendonck et al. 's model, learning is represented by the strengthening of the production rules caused by cumulative activation and experience. It is highly plausible that prediction error can participate in these learning mechanisms by updating a model contained in the supposed executive WM store. The authors also proposed that a procedure is activated given its relevance and specificity: the more complex the rule, the more specific it is. Learning by practice might act in simplifying the rules, according to Logan, from a multi-step to a single-step procedure, leading the behavior to be less specific and more general, i.e., with a reduced instantiation of control. Although the idea that the executive is distributed rather than central is getting a broad consensus, the homunculus conception seems to be deeply rooted. Indeed, the problem looks too much often to be neglected.

Besides the robust traditional conception of unitary mechanisms, other points might be identified for the problems arisen in the definition of control processes. First, executive functions are not purely observable processes. They operate over a plethora of underlying mental phenomena. This has been defined as a "task-impurity problem" (Miyake et al., 2000): differences in the non-executive processes required by task performance can be critical when distinguishing among functions. Secondly, and relatedly, Verbruggen et al. (2014) argued that researchers have often confounded tasks with mechanisms. Indeed, different executive processes might act in concert to determine the actual performance in a task. Consequently, tasks traditionally implemented for measuring "executive functioning" as a whole or more specific mechanisms such as inhibition or switching between task sets might not merely assess "executive functioning", "inhibition", or "task-switching". For instance, the performance in a simple task-switching paradigm requires individuals at least to process certain sensory information, maintain the goal representation, update task sets, inhibit previous irrelevant sets, create associations between stimuli and responses, and learn from feedback. Indeed, it is possible to assume that the automatization of performance in a task requiring an initial degree of control, might develop over some but not all the aspects that compose the whole task execution, following different paths, and that some processes are more resistant to automatization or cannot be automatized at all.

Research on trial-compatibility effects in highly used paradigms such as the Stroop and the Simon tasks revealed other interesting effects. The two tasks exert a response conflict, but in the first case, that conflict is generated by a stimulus-stimulus conflict, while in the second from a stimulus-response conflict. These two kinds of conflicts are found to be independent, suggesting modularity rather than a centrality of cognitive control (Egner et al., 2007; Hommel et al., 1997).

In conclusion, even in this case, it seems that a clear definition of the mechanisms underlying control processes are still not clear. A unitary and monolithic conceptualization of control appears to be outdated, even though most of the results are still seen under this lens. As for the automatic processes, control processes vary greatly depending upon the cognitive functions investigated, the tasks used, and the theories taken as supportive. Only specific dissociations between tasks and functions, through the implementation of specific methodological designs, might shed light on how control is exerted over the whole mental functioning.

Interactions

The conceptual limitations in the definition of automaticity and control put in doubt a simplistic view of two separate systems and the substantial distinction of their features. Indeed, ample evidence suggests that bottom-up and top-down processes interact in a way that does not fit with a continuous or dichotomic conception.

Pashler et al. (2001) described how different processes, traditionally defined as bottom-up (such as attentional capture) or top-down (such as task-switching), might indeed be influenced and thus, rely upon both ways of strategies. Results on involuntary attentional capture strongly suggest that the ability to be interfered by distractors in a search is mostly explained by the relation between distractor-target features rather than by the concrete features of distractor stimuli itself (Folk et al., 2002). It seems that irrelevant information does not merely draw the subject’s attention implicitly, but it draws attention relatedly to the subject’s voluntary goals aimed at detecting target-related features. Voluntary and stimulus-driven processes might be integrated in orienting selective attention: equally salient distractors showed not to have the same attractiveness if one of the two possesses some of the to-be-attended target-features. This effect has also been confirmed in neuroimaging studies, which showed a more massive BOLD response in temporoparietal junction and ventral frontal cortex for target-colored distractors rather than for non-target-colored ones presented in to-be-ignored peripheral locations (Serences et al., 2005). Even though this contingent capture hypothesis has been recently challenged (Belopolsky et al., 2010), suggesting that the prominent role of top-down processes is the rapid disengagement from salient stimuli rather than filtering them out and that top-down processes have been shown to modulate later stage of attention rather than early ones (Parrott et al., 2010). However, research on priming effects in attentional paradigms have firmly indicated that unconscious processing can be modulated by the top-down effects instantiated by subjects' intentions (Ansorge and Neumann, 2005), task instructions (Nakamura et al., 2007), and expectancy (Kunde et al., 2003; Eckstein and Perrig, 2007). An attentional sensitization model over unconscious information processing has been proposed (Kiefer et al., 2012), suggesting that automatic influences can be enhanced or attenuated depending upon the match between their task-relevancy and internal task-sets, arguing for "conditional" automaticity in which at least some unconscious processes are constrained to the amount of attentional resources. This model is supported by results in single-cell studies revealing that the neuron's firing probability is increased if the stimulus feature processed by the neuron is being attended to (Treue and Martinez Trujillo, 1999). Thus, it seems that low order processes might not be so inflexible. Even the cognitive impenetrability of a low process such as perception has been questioned, but further research in this field is required (Firestone and Scholl, 2016).

This concept of conditional automaticity can also be described according to the SNARC effect (Fischer et al., 2003). The SNARC effect is the automatic activation of a mental spatial number line, following a left-to-right direction, at least in Western individuals (Zebian, 2005), resulting in a preference response for left/right-sided targets when cued by unpredictable small/big digits. However, more recent research has extensively shown that this activation is slow and that top-down processes exerted by instructions and culture might generate and change this preference (Ristic et al., 2006; Núñez, 2011).

As regards controlled processes, task-switching paradigms have been extensively used as measures of top-down influences on performance. In the standard version of the task, where participants are asked to perform two different tasks in an unpredictable sequence, reaction-times are typically slower when participants are required to switch from one task to another compared to when the two tasks are repeated. The switch cost (i.e., the difference between RT switch and repetition trials) is traditionally taken as a control engagement measure, reflecting time-consuming top-down reconfiguration processes between high-order task sets. Indeed, numerous findings revealed that the switch-cost depends on the cue-stimulus interval (Rogers and Monsell, 1995), which is the time available to subjects to switch between task sets: the longer the interval, the lower the switch cost. However, even at long intervals, when participants have enough preparation, a residual switch cost is still observed

(Rogers and Monsell, 1995; Liefooghe et al., 2009), suggesting that other than top-down processes may concur in determine the switch-cost. Then, some authors suggested that rather than think about why switch trials are slower than repetition trials, in this case, it could be more useful to think about why repetition trials are faster than switch ones, indicating the role of priming effects (Schneider and Logan, 2005). Several results showed a different role of task recency and contingencies in task-switching paradigms (van't Wout, 2018; van't Wout et al., 2015), evidencing additive and combining weights for bottom-up and top-down attentional mechanisms (Summer and Ahmed, 2006; Koch and Allport, 2006; Ruthruff et al., 2001).

One strong evidence that controlled and automatic processes interact in guiding behavior comes from the investigation of cognitive adaptation to conflicts. The conflict-monitoring hypothesis argued that top-down mechanisms are responsible for reconfiguring task sets after incompatible trials because of the higher effort requested by the task. This reconfiguration is known to adjust performance on the following task, depending upon its congruency. Especially after incongruent trials, congruency effect (i.e., faster response for congruent trials) is reduced, eliminated, or reversed (incongruent trials became faster than congruent ones). Control-based views of conflict adaptation highlighted the role of task-relevant information (Botvinick et al., 2001), the specificity of conflict type (Egner, 2008; Notabaert and Verguts, 2008; Zhao et al., 2015), local task sets (Hazeltine et al., 2011), active representations (Verguts and Notebaert, 2009), and just weak evidence exists that working memory resources and conflicts resolution are functionally interrelated (Moss et al., 2020). Other authors suggested that this sequence effect is dependent upon the number of features that change from one trial to another (i.e., word and ink color in the Stroop task), with faster responses when both or no stimuli change, compared to trials when features are partially repeated (for instance, the ink color is repeated but not the word). Again, this evidence has suggested that besides top-down reconfiguration processes, also bottom-up repetition influences congruency effects. Indeed, other conflict adaptation views have focused on feature integration (Hommel et al., 2004) and stimulus-response contingency learning (Schmidt, 2013). Notabaert et al. (2006) found that the congruency effect was reduced in a complete alternation Stroop version only when participants were given enough time to reconfigure the task set (coherently with the time-consuming feature of top-down processes). Differently, in a partial repetition version it was eliminated even with a little response stimulus interval.

Feature and control-based theories regarding the nature of the congruency sequence effect exist, both supported by many results. The results indicating that bottom-up and top-down strategies may cooperate rather than compete for behavior have led authors to reconsider their interactive functioning and propose integrative accounts (Egner, 2014; Braem et al., 2014). For instance, Egner (2014), suggested that bottom-up and top-down processes act complementarily intending to reach the same goal: learning to bind external features of stimuli and contextual cues to internal task sets and states into episodic traces, useful for optimal adaptation (in terms of speed and accuracy) to future events. Egner proposed a multi-level account of learning, operating at different levels of abstraction, from concrete features to abstract goal representations, able to consider both conflict-specificity among tasks (Egner et al., 2007) and generalization to new events.

Besides, in reasoning research, the interplay between intuitive and logical reasoning has been conceptualized in a different number of ways. In brief, the Default Interventionist model (Evans, 2007) asserts that Type 2 processes started later, and their role is to override fast and impulsive responses emerging from the Type 1 system. Differently, in the Parallel model of Sloman (1996), associative and ruled-based processes start in parallel, a suggestion supported by the number of studies reporting that the detection of conflict between responses is detected very early in the task. However, this model has been strongly criticized: indeed, it assumes that controlled processes are always active, a feature that seems to be quite not economically adequate for our neurocognitive system. Then, an integrated model of the two (De Neys, 2012) described that Type 2 processes are activated only when a conflict is detected. However, an intuitive logical component is activated early and can respond logically in a fast way, allowing for some logical judgments to be made quickly, some knowledge-based responses to be effortful, and both Type 1 and Type 2 processes to lead to biases. Similarly, computational and neurobiological research in decision-making provides evidence that the binary view of mind does not precisely reflect what happens when a statistical brain is making choices and planning behavior (Daw, 2018). Alternatives to the System 1/System 2 theory of cognition proposed to split the processes differently, for instance, according to the type of representation used by individuals, as in the Fuzzy Trace Theory (Brainerd and Reyna, 2001).

The described results are just some findings showing that a combinatory rather than discrete role must be integrated into DPTs. Further research from different paradigms may integrate and add results in this converging evidence.

From simple to complex tasks

The issues presented in the DP frameworks are strictly dependent upon the intrinsic problematic definitions of automaticity and control. For instance, assuming an all-or-none or a continuum conceptualization of automaticity or a central vs. a distributed view of cognitive control has substantial consequences on DP’s theoretical foundation. As outlined above, the reasons for such a tricky issue can be mostly found in the middle of the two processes: the link between automatic and controlled processes is more than just a slider, and their interplay might be more profound than it can be distinguished through the current theoretical lenses. Also, besides the misalignment observed in the process features within a cognitive field, it remains to be investigated the misalignments between cognitive functions. As Monsell and Driver argued (2000), control research has focused more on what is controlled rather than on how control is exerted, and the same can be addressed to research on automaticity. To get out of the dichotomy, which appears to be effective in explaining what is automatic or controlled but not how, a right approach, according to Logan (2003), could be the investigation of how control acts over mental processes by studying how the underlying psychological mechanisms can be controlled and in what extent. In doing this, the study on the interplay between automatic and controlled processes in different contexts and tasks might be an excellent path to follow. The need to understand how these mechanisms are exerted and interact according to the environment's different levels of complexity has already been indicated (Monsell and Driver, 2000). Simple and complex tasks do not merely differ in a low vs. high cognitive level supposed. Even though in most cases simple processes strongly rely upon automatic functions, and complex processes upon controlled ones, they also differ in the sense of contextual complexity and number of cognitive processes required to play a role. In this sense, cognitive processes are required to interact in order to optimize behavioral performance according to goals and sub-goals, integrating the information generated by the two processes. For instance, research on reasoning has shown that more complex logical arguments with conflicting responses are more sensitive to produce belief-biased responses, providing evidence that the task's structure determines the timing in which a response is available (Handley and Trippas, 2015). If the whole cognition works in a duality mode, the notion of a broad DPT makes necessary also to assume that the same interactive way works for all cognitive function, either if one is asking subjects to report two digits embedded in a stream of letters or to infer an implicit probabilistic structure. The two situations differ in the complexity (do not read difficulty) of the task. However, it is arguable that, in the context of a DPT, this optimizing interaction can be seen in simple perceptual and attentional processes, as well as in more complex reasoning tasks, in ways determined by the task considered.

The central point of the current debate on DPTs is represented by the utility of having a dual-process typology. However, what is not clear is whether a defining feature exist and, consequently, if it can be coherently operationalized in an extensive set of cognitive functions. Even with the rejection or acceptance of the dual-process typology (which is not equal to the rejection or acceptance of the dual-process theory), the question about whether mental phenomena share or not single- o multiple-process allowing for its automatization or control remains open.

Eventually, one solution in experimental paradigms is to look at how manipulations that are known to give rise to automaticity (for example, through practice) or cognitive control (for example, exerting conflicts between a set of mental representations) can modulate the studied phenomenon, taking in consideration its structural and conceptual complexity. Moreover, to not bump into confirmation biases, an opposite approach must be taken. If it is assumed that dual processes always interact, this approach gives us a picture of the specific task performance changes. Conversely, it appears strictly necessary to investigate negative conditions, such as observing the effects over a controlled process by knocking out the features that render it controlled, as it is done through stress induction. Therefore, does the given performance turn out to get opposite features (automatic)? Or do specific features of the phenomenon vary while others remain stable? A reductionist approach seems necessary, especially when the focus of the investigation are the most complex mental functions.

Up to now, several dual-process theories have been proposed, mostly lacking exhaustiveness and exclusiveness of explanation. Attempts to unify them in a broader framework have also been made, but the way in which these relate is still ignored. Evans (2009) posed a question: “How many dual-process theories do we need?”. If possible, integration appears to be a real need in psychological research: however, the risk to be redundant and confusing as knowledge increases is actual. The efforts to unify the dual-process theories will be beneficial in the understanding of human cognition, either for supporting a functional or an architectural view of the mind. How did higher cognition evolve, how it interacts with low-level abilities, and how do habits develop are just a few of the number of questions that can be faced with a more solid theoretical background. However, integration does not mean to theorize just a broader label for all the dual processes described. Instead, in the present view, it requires to be investigated through a sort of directional approach: from the most simple, earliest, and lower stage to the most complex, latest, and higher level of information-processing. Making adequate and precise progress in psychological theories is more urgent than having a totalized theory of dual-cognition and advancing knowledge in this way could be quite useful in avoiding big jumps or the construction of surrogates (Gigerenzer, 2011b). Thus, the Evans’ question can be reformulated as “How many dual-processes do we have?” or “Have we developed a higher cognition for each (default) ability?”.

CHAPTER 2

Controlled processes in temporal attention: an experimental contribution to Attentional Blink theories

The most peculiar capacity of attention is that it can be oriented not only to environmental stimuli but also to the deployment of information processing. Its pivotal role in qualifying cognitive processes through the engagement and disengagement of cognitive control made it one of the fundamentals of dual process theories since the beginnings (Schneider and Shiffrin, 1977).

Simultaneously, attention is a cognitive process itself, and, like the others, it also possesses a dual nature: it can be oriented exogenously or endogenously, reflecting bottom-up and top-down processing directions (Posner, 1980).

Consequently, attention may be subjected to the same contingencies observed in other cognitive functions. Indeed, the top-down modulation of attentional phenomena has been extensively observed (e.g., Gazzaley and Nobre, 2012; Burnham, 2019).

Interestingly, this top-down modulation can be observed both in spatial orientation and in the temporal resolution of attention, which this section is focused on. Results highlighting the interactive role of bottom-up and top-down processes in temporal aspects of attention will be outlined, and an experimental contribution to the field will be presented.

The Attentional Blink: a blind spot in temporal attention

In the broad set of limitations of the human cognitive system that arise in the everchanging world, the temporal resolution capacity of information processing plays a pivotal role. Indeed, most individuals exhibit an evident impairment in detecting relevant subsequent stimuli among irrelevant ones if a short temporal window separates them. When individuals must detect two or more stimuli target embedded in a rapid serial stream of distractors, the accurate detection of the second one, having correctly identified the first, is severely impaired. This drop in performance is usually found when the interval (Lag) between the two targets lasts about 200-500 msec, describing a U-shape function. This interesting phenomenon is named Attentional Blink (AB; Raymond et al., 1992), and is usually investigated in a Rapid Serial Visual Presentation (RSVP) paradigm in which every stimulus (usually digits and letters) is presented in the foveal vision for about 80-100 msec with or without an interstimulus blank interval (ISI). In the standard task, the RSVP is presented at the center of the screen, and subjects must report the targets' identity after the RSVP. The factorization of the interval between the two stimuli (T1 and T2) is defined as Lag, which is the number of positions in the stream, after which T2 appears relatively to T1 (i.e., Lag 3 is three positions after T1, 240-300 msec of interval). One curious and paradoxical phenomenon is that when T2 is presented immediately after T1, with no intervening distractors (Lag 1), the performance is usually spared, even though several alternative paradigms have been shown to eliminate the Lag 1 sparing effect.

Notwithstanding the AB is a very robust effect, some issues are still not clarified. First, it is not currently known why some individuals do not present the standard AB. Secondly, there is no broad consensus about the parametrization of the AB. Even though the standard scoring method is generally used (the proportion of T2|T1 over T1-only accurate responses), an effective change of the whole curve may happen, for instance, in its amplitude or extension, making difficult to link specific predictions for specific changes. Thirdly, several variants of the standard paradigm are often made, such as the lags used, their number, or the timing parameters, sometimes rendering impossible a comparison between results. Finally, there is still confusion about the processes underlying the whole AB phenomenon. Indeed, since the early ‘90s, literature has flourished of theories explaining the functional and structural mechanisms responsible for this phenomenon (Dux and Marois, 2009).

Even though with different mechanisms, capacity-limited theories posit that resource limitations in central processing are responsible for the drop in T2 performance. In the interference theory (Shapiro et al., 1994), both targets enter the working memory according to their featural template, as well as the following items (T1+1 and T2+1) due to their proximity to targets. In working memory, these items receive an attentional weighting, according to which they compete for their successful retrieval. The processing of the items started with the T1 detection lasts about 500 msec: the AB takes place when the temporal proximity of the target is short because the attentional weight of T2 is not able to overcome the stronger one of T1. Differently, in the bottleneck models, such as the two-stage theory of Chun and Potter (1995), before entering the working memory, features of stimuli in the RSVP are first processed in parallel. When relevant features are detected, the target item undergoes encoding and consolidation, a serial and effortful process. Due to the temporal proximity of the two targets, T2 is not able to enter Stage 2 because it is already busy in the consolidation of T1.

Similarly, in the more recent eSTST (episodic Simultaneous Type/Serial Token) model (Wyble and Bowman, 2009), the failure in reporting T2 is determined by the time-consuming consolidation stage. The difference with the two-stage model relies upon types and tokens: items in the RSVP activate high-level types that must be bound to working memory tokens by an attentional blaster to be correctly identified, generating episodical information aimed at distinguishing separate objects. The attentional enhancing function of the blaster is slow and is transiently suppressed after the first target, to allow for the construction of episodes aiming at avoiding otherwise overlapping and overwhelming information. A conceptually different capacity limited component can also be found in the Temporary Loss of Control (TLC) theory (Di Lollo et al., 2005), which suggested that a central processor is responsible for monitoring the RSVP in search of targets switching to a consolidation mode at the detection of T1. Since this central processor is serial, while it is engaged in the consolidation of T1, the monitoring of the stream is made by exogenous processes sensitive to stimuli category features. Then, the different category of the T1+1 item leads to a disruption of the filter, and the consolidation of T2 becomes less efficient. Other theories subtending capacity limitations to be responsible for the AB focused on physiological processes, as in the Locus Coeruleus-Norepinephrine model (LC; Nieuwenhuis et al., 2005), which explained the AB according to the dynamic of the phasic noradrenergic responses of the LC to target stimuli.

Conversely, other theories do not rely upon capacity limitations to account for the AB, instead of focusing on the temporal deployment of attention. For instance, the gating theory (Raymond et al., 1992) proposed that an inhibitory mechanism prevents physical features of T1+1 to interfere with target features and, thus, at a short interval, T2 is still inhibited and cannot be processed. This mechanism acts as a gate: with the detection of physical target features (e.g., the color) the gate opens for identification and closes when different features are presented in the RSVP. Similarly, in the Boost and Bounce model (Olivers and Meeters, 2008), T1 detection exerts an attentional boosting prolonged to the T1+1 item. If the T1+1 item turns out to be a distractor, then a transient suppression of the attentional enhancement (bounce) takes place, preventing a proximal T2 from reaching consciousness. Differently from the gating model, this mechanism is aimed at inhibiting distractors rather than to prevent features binding errors between T1 and the following item. The inhibition in the Boost and Bounce model acts at a late stage of visual processing: sensory and semantic information provides the items with an attentional strength modulated by the precedent and successive items. Working memory encodes item information, binds them to the response, and maintains the attentional set, promoting an input filter aimed at enhancing target-like and suppressing distractor-like features.

This brief presentation of theories on AB roughly shows that, whatever it is considered, a duality of processes is described (e.g., early and late-stage, parallel and serial processing, enhancement and inhibition, exogenous and endogenous). However, even though much research has been produced, the question of how top-down processes might influence performance and the relative weight of the two processes in determining the AB phenomenon remains speculation.

The notion that the AB phenomenon is not purely bottom-up is known, and evidence exists indicating the role of top-down modulations. The interplay between the two processes has been extensively documented, even if a summarizing and theoretically relevant joint of results has not been made. This unified view of AB-related phenomena can be outlined through several effects and manipulation used in literature.

Dual processes in the Attentional Blink

Attention and, specifically, its visual component, is well-known to be controlled by at least two mechanisms, top-down cognitive-driven, and bottom-up stimulus-driven, each suggested to rely upon separate neural networks (Corbetta and Shulman, 2002).

Top-down mechanisms are known to be deployed when conflicts between representations or processes arise. More finely, in the visual system, the degree of top-down attentional investment seems to depend upon the number of conflicts that remain unsolved by bottom-up mechanisms (McMains and Kastner, 2011). Interestingly, feedback signals from the frontal to the occipital cortex are essential for visual detection and awareness. However, interference between bottom-up occipital feedforward and top-down frontal feedback signals may arise when individuals are attending to RSVPs, allowing for bottlenecks to take place (Martin et al., 2019).

The interactive effects of top-down and bottom-up processes in the AB have been sparsely investigated through several different manipulations.

Training and practice effects have been an object of interest in the AB literature due to their possible theoretical relevance. In a capacity-limited interpretation, practice effects should not eliminate the AB, addressing this phenomenon to a more structural view. Indeed, studies investigating the effects of training found only an attenuated AB (Maki and Padmanabhan, 1994; Braun et al., 1998).

Choi et al. (2012) found that a short T2-colour salient training leads to a long-term elimination of the AB, together with changes in prefrontal areas. The authors suggested that practice effects induced by the salient color training might have improved the temporal resolution of attention through top-down signals. However, the specific role of salient bottom-up features was not extensively investigated, which could have a role in explaining some of the differences with previous studies. Similar results have been obtained by using temporal cues (Martens and Johnson, 2005, Badcock et al., 2013) and rhythmic entrainment (Ronconi et al., 2016), suggesting that presumably, the expectations and the learning of the contingencies of the environment (and the reward of a behavioral success, as Choi et al. argued), otherwise hidden by the standard AB, could have played a role improving the structural knowledge of the task. In turn, this understanding could have strengthened the working memory set (or the filter) to suppress distractors and enhance target features, especially if just two lags are designed in the task as in Choi et al.'s study. Indeed, Tang et al. (2014) failed to replicate their results varying the number of stimuli before T1 or the lags between T1 and T2. In contrast, Willems et al. (2018) obtained a similar improving effect even through a non-salient training paradigm but with a constant lag, suggesting that the Choi et al.'s results must be read in terms of increased expectations rather than improved attentional control. Differently from these top-down accounts of training, other studies on effects of practice have shown that training can increase a T2-related N2 component of ERPs, evidencing the improvement in the temporal selectivity processes rather than top-down mechanisms of reallocation of resources between the targets (Nakatani 2009; 2012). Relatedly, Enns et al. (2017) controlled ceiling effects in the training program, evidencing that the improvements are linked to more general perceptual cognition rather than on specific AB processes. In addition, training in a response selection paradigm has also shown to reduce the AB (Garner et al., 2014; Verghese et al., 2018), suggesting that irrelevant training might improve generalized sensory consolidation. This transfer effects have also been interestingly investigated concerning video-games training beneficial effects (Olfers and Band, 2018): studies looking for transfer effects of video-game training found that training in action games reduces the AB (Oei and Patterson, 2013; Baniqued et al., 2014), even though some methodological issues have been highlighted (Kristjànsonn, 2013).

In summary, there is no consensus about the components on which training exerts its beneficial effects, with other literature showed that learning effects are more related to a late stage of processing rather than a strengthening of sensory information (Kelley and Yantis, 2010; Parrott et al., 2010). In any case, both stages may exhibit different changes, which only specific investigation may highlight.

Besides training, other manipulations have been implemented to shed light on the processes that govern the AB. Several studies aimed at investigating the top-down modulatory contingencies in the AB, evidence that intentional task-related top-down modulations can be rapid and intervene at an early stage of processing (Hilkenmeier et al., 2009). These may, in turn, be processed as task relevance (Nieuwenstein, 2006), target identity expectations (Meijs et al., 2018), temporal cues (Martens and Johnson, 2005, Badcock et al., 2013), and goals (Ferlazzo et al., 2007; 2008).

Moreover, the impact of top-down mechanisms in this paradigm has been studied through several other manipulations, aimed at reducing cognitive control engagement. For instance, evidence has produced indicating that the over-investment of attention may favor the raise of the AB (Olivers and Nieuwenhuis, 2005; 2006; Arend et al., 2006; Taatgen et al., 2009; Wierda et al., 2010; Lapointe-Goupil et al., 2011): engaging a more distributed attention through concurrent irrelevant activity was paradoxically found to reduce the AB. Similarly, meditation training may be effective in inducing changes in the investment of attentional resources and have been linked to several beneficial outcomes in cognition (Raffone and Srinivasan, 2010) and reduce the AB (Slagter et al., 2007; van Leeuwen et al., 2009; Colzato et al., 2015). Again, another manipulation that turned out to be effective in modulating attentional blink is stress. Conversely to the overinvestment hypothesis and following resource depletion theories, acute stress produced a greater AB compared to non-stressed participants (Kawahara and Sato, 2012; 2013) that, as explained by the interaction between condition and Lag, was an AB specific modulation rather than a general spreading of attention. The effects of stress on AB have also been studied using the Emotional Attentional Blink paradigm (EAB) in which, regardless of the target valence (positive or negative), T2 detection was instead improved (Schwabe and Wolf, 2010; Kan et al., 2019). Again, if stress induces changes in temporal attention by modulating early attentional capture or late stage of processing is still unknown.

Further research aimed at adding evidence of top-down modulations of the AB and at deconstructing the two processing stages is necessary.

This experimental chapter

In this first experimental chapter, a line of research focused on temporal attention will be described. Using the Attentional Blink paradigm, it will be described how literature can be read by examining the intervention of the dual processes, highlighting that even low-order processes may be influenced by top-down mechanisms. In the first study, the role of high order goals, namely task instructions, are described in the determination of the attentional blink phenomenon, providing theoretical and methodological evidence for the support of a goal-switching account. In the second study, the focus is shifted on the lag-1 sparing phenomenon, i.e., the sparing of the attentional blink performance when the second target appears immediately after the first one, and specifically over the frequent order reversals made by subjects in this condition. When using ordinal stimuli as targets, such as numbers, automatic mechanisms may underly the response both in both the coding and the recovery stage of target processing, which appear to be flexible if more controlled strategies are required. These results parallel research in the SNARC effects, confirming that duality of processes is involved in such paradigms and suggests that these effects may not only cover spatial but also temporal dimensions. Additionally, they showed that even the processes underlying a very low-level ability, such as the temporal discrimination of two briefly presented stimuli, is flexible and not impenetrable by high-order influences.

Manipulation of goals in the Attentional Blink: methodological implications in the goal-switching hypothesis

Abstract

The attentional blink (AB) refers to the impairment in accurately detecting two targets embedded in a stream of distractors as a function of the interval between them. While several models of the AB exist, little is known about how high-level representations may play a role in determining the AB effect. In [Ferlazzo, F., Lucido, S., Di Nocera, F., Fagioli, S., and Sdoia, S. (2007). Switching between goals mediates the attentional blink effect. *Experimental Psychology*, 54, 89–98; Ferlazzo, F., Fagioli, S., Sdoia, S., and Di Nocera, F. (2008). Goal-completion processes affect attentional blink. *European Journal of Cognitive Psychology*, 20, 697–710] a goal-switching hypothesis was suggested, consisting in an attenuation of the AB when participants can rely upon a single-goal (reporting the sum or the pair of targets) instead of a dual-goal (i.e., reporting the two targets separately). Recently, in [Lagroix, H. E., Talib, G., Di Lollo, V., and Spalek, T. M. (2018). Questioning the goal-switching account of the AB: comment on Ferlazzo et al. (2007). *Journal of Cognitive Psychology*, *30*(1), 122-128] this account has been criticized due to several methodological issues, such as the scoring method, the range of inter-target intervals, and the level of the standard condition. In this work, we replicated the studies in object and discussed the points raised in Lagroix et al. 's work. While these factors may affect the direction of effects, differently from Lagroix et al., indications emerged about the existence of effects related to goal manipulations.

Introduction

Research in experimental psychology has widely shown that human beings are limited in the ability of temporally processing information emerging from the outside world. Some of those limits had been intensively investigated through Attentional Blink paradigms (AB; Raymond, Shapiro and Arnell, 1992). In those paradigms, a rapid serial visual presentation task (RSVP) is presented in foveal vision with a presentation rate of about 10 stimuli/s. Participants are asked to identify two target stimuli (T1 and T2) while ignoring other stimuli (distractors). The AB effect changes performance as a function of the time interval between the two targets. Specifically, given the correct identification of T1, the ability to detect T2 drops when presented 200-500 ms after T1. Longer intervals (lags) between T1 and T2 usually result in a progressive recovery of performance. Moreover, the drop in performance does not happen if T2 is presented immediately after T1 (Lag-1 sparing effect).

Several AB paradigms and models exist in literature (Dux and Marois, 2009). One topic in the AB literature concerns the role of high-level top-down processes in determining at least part of the AB effect (Olivers and Nieuwenhuis, 2005; Hommel et al., 2006; Di Lollo et al., 2005). Relatedly, Ferlazzo et al. (2007; 2008) found that when participants are asked to report T1 and T2 in a combination rather than separately (i.e., as one rather than a dual goal-task), the AB effect decreases significantly. Using digits as targets, the instructions given in their studies were to report the pair or the sum of the two digits, instead of the two targets separately. It is known that task-switching can exert an effect on AB performance (i.e., when T1 and T2 are qualitatively different) (Sdoia and Ferlazzo, 2012; Kawahara, Zuvic, Enns, and Di Lollo, 2003; Visser, Bischof, Di Lollo, 1999), but little is known about how these processes might interact with early temporal stimuli processing. Top-down processes and goal-switching mechanisms may determine post-completion errors (Altmann and Trafton, 2002), which could affect AB performance even when T1 and T2 belong to the same overlearned category (digits or letters). Investigating the role of such high-level mechanisms may represent a step toward an improved theoretical understanding of the AB and its underlying processes.

Recently, the results of Ferlazzo et al. (2007; 2008) have been questioned by Lagroix et al. (2018). Indeed, using a different method of scoring, the authors did not replicate the results. Moreover, they pointed out some methodological issues, opening useful questions for the AB research.

Scoring method

The most relevant issue raised by Lagroix et al. (2018) regards the scoring method adopted by Ferlazzo et al. (2007; 2008). They argued that the AB conventional scoring method (the proportion of T2|T1 correct trials upon the T1 only correct trials) is unreliable if used for a Sum task. Since wrong sums could be the consequences of many different errors and there is no possibility to determine if wrong sums contain the correct identification of T1 or not, Ferlazzo et al. (2007;2008) calculated the accuracy as [correct sums/correct sums + T1 only correct responses].

According to Lagroix et al. (2018), this scoring method provides an underestimated AB effect, making not comparable the different instruction conditions, an issue already mentioned in Ferlazzo et al. (2008), due to the smaller difference between the nominator and the denominator for Sum instructions than for Standard one. Thus, Lagroix et al. (2018) suggested the use of an equivalent score for all three conditions, calculated as the proportion between the number of T2|T1 correct (T1+T2 correct for the Sum condition) on the total number of trials. In this way, they found no differences between the three conditions (Standard, Pair, and Sum). It should be noted that in their work, Ferlazzo et al. (2008) used two scoring methods for the Sum condition: a first one based upon T1 only correct responses and a more conservative one as the proportion of the correct sums. The authors considered the problem of underestimation/overestimation (respectively) of the two scoring methods, finding that both led to the same results, i.e., the attenuation of the AB effect in a single-goal task-set.

However, coherently with the theoretical accounts of AB, the performance of T2 must be calculated upon the performance on T1: attentional blink happens when the identification of T1 is made (Shapiro et al., 1994). Thus, the inclusion of the incorrect responses in the proportion could be misleading since it does not consider the different difficulties in identifying T1 for the different lag conditions and results in an overestimated pattern.

Range of inter-target trials

In agreement with Lagroix et al. (2018), the choice of a correct inter-target lags range is of great importance in AB paradigms. To simplify the AB paradigms, AB researchers tend to reduce the number of lags, i.e., cutting off the Lag-1 or having just one lag in the AB period and one outside. The lag-1 sparing effect, even if many authors suggested its independence from the AB, has been investigated in several studies, which described how its presence or absence gives some essential indications about the nature of the task used (Visser, Bischof, Di Lollo, 1999). More generally, the lack of a standardized paradigm for the range of lags makes comparisons of AB magnitudes between studies quite unreliable. For instance, MacLean and Arnell (2012) suggested calculating the AB magnitude as the difference between the highest and the lowest lags in terms of accuracy. Several studies have been implemented upon this method of calculus, by using only two lags, one in and one out the 200-500ms T1-T2 interval (e.g., Vogel and Luck, 2002; Zhang et al., 2008; Dux and Marois, 2008) in order to measure the AB magnitude. Many critical points must be addressed with regards to this method. Firstly, even though each design is implemented upon specific hypotheses, this method does not control the trend of performance and design any typical AB curve. Secondly, the severest drop of performance does not always fall on the same point, but within an interval. Thus, the lag in which the performance should be more impaired cannot be operationalized *a priori*. Thirdly, it is known that different patterns of AB can be exhibited and vary due to individual differences (Maciokas and Crognale, 2003; Lahar et al., 2001; Russo et al., 2016).

However, methodological choices are made for each experimental design, and many reasons could account for them, which are far from the will to explain the AB trend, from the beginning to the recovery. In Ferlazzo et al. (2007), there was no intention of investigating changes in performance recovery at longer lags. Then those were not included in the task.

Level of the standard condition

Lagroix et al. (2018) reported as an issue the level of the standard conditions of the different experiments presented in Ferlazzo et al. (2007), arguing for the unreliability of the AB reduction observed in the Pair instruction conditions. As they reported, comparing the Pair condition of the Exp.1 (Ferlazzo et al., 2007) with the Standard performance in each of the three experiments reported, the AB did not appear attenuated if compared to the performance with Standard instructions in the experiments 2 and 3. However, experiments 1, 2, and 3 varied not only for the experimental instructions (pair in Exp.1 and Exp.2, Sum in Exp.3), but also for the type of targets/distractors stimuli used (digits/letters in Exp.1 and Exp.3, letters/digits in Exp.2), for the lags used (1 to 4 in Exp.1, 1 to 6 in Exp.2 and Exp.3), for the number of trials (240 in Exp.1 and Exp.2, 360 in Exp.3), and the number of targets presented in each stream (2 in Exp.1 and Exp.2, 1 or 2 in Exp.3). All these variations may have exerted some effects in each experimental design. Stretching interpretations by making comparisons among conditions from different experimental designs can be strongly misleading.

In addition, it is well known that AB magnitude presents wide individual differences (Martens and Wylbe, 2010; Dale et al., 2010; Willems et al., 2013; Willems and Martens, 2016; Colzato et al., 2007; Dale and Arnell, 2010; Maclean and Arnell, 2010; Martens and Valchev, 2009; Dux and Marois, 2008): some individuals show a significant amount of AB effect, many others show a smaller amount and many others do not show any AB at all. This variability in the general population can affect the experimental samples, producing mean performance patterns depending on the individuals that constitute each sample group and partially explaining differences between control conditions.

Other issues

Another point discussed by Lagroix et al. (2018) concerns the experimental design. As Ferlazzo et al. (2008) argued, an experiment where the independent variable is operationalized by the instructions, avoiding carry-over effects exerted by the first instruction given to the participants, the use of a between-subject design, rather than a within-subjects one (Dell’Acqua et al. 2007), is strictly recommended. Moreover, participants’ goal representations may vary despite the different instructions: it seems impossible to evaluate the experimental manipulation's actual effectiveness, at least with this task.

One more aspect must be mentioned. Differently from Ferlazzo et al. (2007), the Lagroix et al. 's (2018) RSVP streams constituted a varying number of items since RSVP ended after one distractor following T2. In contrast, in Ferlazzo et al. 's experiments, these were fixed and were made of 10 (2007) or 14 (2008) stimuli. Moreover, the different length of RSVPs makes T2 backwardly masked by one or more distracters. This fact represents another discordance point between the two experiments, probably making also not comparable the different streams in the same experiment.

Finally, an additional general issue regards the baseline measure. A correct task design should contain trials with no T2 to control the participants' performance in identifying T1 trials only (Raymond et al., 1992; Shapiro et al. 1994).

The present experiment

In this experiment, four groups of observers performed an AB task, upon different instructions. Participants in the Standard group were told that they had to identify and report separately the two digits (T1 and T2) embedded in a series of letters, replicating a typical AB paradigm with two different goals. Participants in the Pair group were told they had to report the pair of digits embedded in a series of letters, while participants in the Sum and the Sum Extended groups were told they had to report the sum of the two digits, but the latter group performed a more extended task, in which streams with no T2 were also presented. The different instructions were aimed to manipulate the task goal-representation: participants in the Pair group and in both the Sum groups would achieve the task goal only after T2 was presented, and the pair/sum of digits was completed. The Sum Extended condition aimed to consider the variability of performance in a task where only-T1 trials were presented. Furthermore, to control a possible effect of backward masking on the identification of T2, fixed streams (18 items, all-masks condition) and streams where only one distractor followed T2 (one-mask condition) were randomly presented instructions condition. Finally, both the scoring methods (Ferlazzo et al., 2007;2008; Lagroix et al., 2018) were used to highlight differences between the two and replicate the results of Lagroix et al. Besides the experimental manipulations, visual processes and motor responses involved in the RSVP tasks were the same for all the group of observers.

Methods

Participants

Participants were 80 Psychology students (49 females; mean age 24.81 years, s.d. 4.61 years). They had a correct or corrected-to-normal vision. The study was approved by the Institutional Review Board of the Department of Psychology at the Sapienza University of Rome and conducted in accordance with its policies and with the Declaration of Helsinki. All participants provided written informed consent.

Stimuli

The AB task was programmed in E-Prime. All the stimuli were white alphanumeric characters, centrally displayed on a black background on a 17-inch computer monitor with a refresh rate of 60Hz. The target items were the digits 1 to 9; the distractor items were capital letters (A, B, C, D, E, F, G, H, L, M, P, Q, R, S, T, and U).

Procedure

Each trial began with a fixation cross at the center of the screen. Participants started each trial by pressing the spacebar. After 500 ms, an RSVP was presented. Each item was displayed for 83 ms (yielding a presentation rate of about 12 items/s) and immediately replaced by the following item. On any given trial, the distractors and two target digits were selected randomly without replacement from the set of letters and digits, respectively. The first target (T1) appeared on half of the number of streams in the third position and on the other half in the fourth position. The position of the second target (T2) unpredictably varied on each trial. The intervals (lags) between the two targets were: 1 (83 ms after the presentation of T1), 3 (249 ms), 4 (332 ms), and 9 (747 ms), to get an indication of the whole AB span. The different lag streams were randomly presented 80 times each, 40 for each T1 position. At the end of the streams, participants were asked to report the two digits or the sum of the two digits, depending on the group. Participants were told that they could type the two digits in any order they wish; they had no time limits and were asked to be as accurate as possible.

Participants were randomly assigned to one of three instructions group. Standard instructions required participants to identify and report the two digits in response to two separate and sequential prompts.

“Pair” instructions required participants to report the pair of the two digits in response to a single prompt. “Sum” instructions required participants to report the sum of the two digits in response to a single prompt. The entire task for these three groups consisted of 320 trials plus 20 practice trials. Finally, an additional “Sum extended” instruction group was created. Participants in this group got the same instructions of the “Sum” group, but their task comprised 160 additional experimental trials (480 total trials), where no T2 was presented. For all the groups, on half of the trials, the RSVP consisted of 18 items (all-masks RSVP condition), while on the other half, the RSVP ended after the presentation of the first distractor following T2 (one-mask RSVP condition). The trials in the two RSVP conditions were the same for each Lag condition, and each group consisted of 20 participants. Participants were told to have a little break if they wished, by waiting to press the spacebar to begin the new trial.

Statistical analyses

Accuracy was calculated as the standard score for AB, i.e., the proportion of correct T2|T1 responses on the T1 correct responses. Swaps were calculated as correct responses. For the “Sum” and the “Sum extended” group, we calculated the score as the proportion of the correct sums on the correct sums plus the trials in which participants reported only the T1. To compare results with Lagroix et al. ’s scoring method, we also calculated accuracy as T2|T1 on the total number of trials. For the Sum extended instructions, only two-target trials were included in the analyses. Accuracy scores were then analyzed in mixed ANOVAs with Lag (1,3,4,9), RSVP (one-mask and all-masks) as within-subjects factors, and Instructions (Standard, Pair, Sum, Sum extended) as between-subject factor. Mauchly tests of sphericity were conducted for all ANOVAs. In the case of significant tests ($p<0.05$), Greenhouse-Geisser corrections were applied to the ANOVAs’ results.
One participant in the Standard condition, two in the Sum condition, and two in the Sum Extended condition were excluded due to low performance (less than 20% total accuracy for T2|T1).

Results

T1 Accuracy

Proportion of T1 correct responses in the Standard condition were 83.5%, 91%, 87.5%, and 88.5% for lags 1, 3, 4, and 9, respectively. Proportion of T1 correct responses in the Pair condition were

77%, 88.5%, 86%, and 88% for lags 1, 3, 4, and 9, respectively. The calculation of correct sums plus T1 only responses gave lower proportions for the two sums condition. Indeed, T1 responses in the Sum condition were 74%, 72%, 74%, and 75.5% and in the Sum extended condition 74.5%, 48%, 62% and 70% for lags 1,3,4, and 9, respectively. Differences between the Standard and the Pair condition in T1 calculus is certainly determined by the different scoring method. However, it seems that another difference exists between the two Sum conditions, with the extended ones presenting lower percentages in the two Lags inside the AB (Lags 3 and 4).

T2 Accuracy

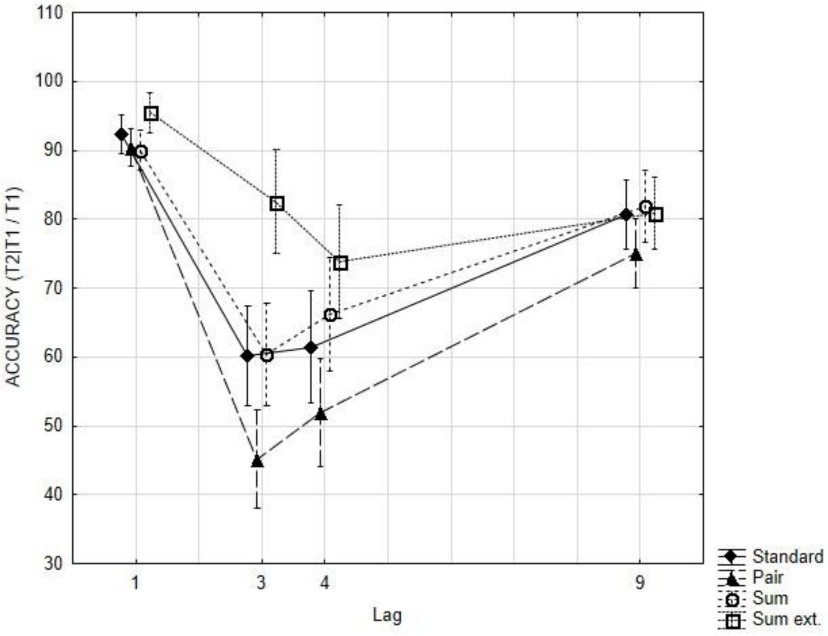
Even though the calculation proposed in Ferlazzo et al. (2007) is the only calculation comparable to the standard one, this would lead to underestimating the T2|T1 score, as the authors and Lagroix et al. (2018) argued. Using the standard scoring method, we proceeded to compare the Standard and the Pair condition only, since in these two conditions there were no doubts about attributing T1 only responses. Afterward, we analyzed the four conditions using the method proposed by Lagroix et al. (2018), i.e., the proportion of correct T2|T1 on the total number of trials.

The mixed ANOVA with lag and RSVP as within-subjects and condition (Standard vs Pair) as between-subject factors showed significant main effects of RSVP ($F_{1,37}$=6.151, $p < 0.05$, partial η2 = 0.14) and Lag ($F_{2.05,75.93}$=117.503, $p < 0.0001$, partial η2 = 0.76). The greater accuracy explained RSVP effect for participants in all-masks streams (mean=68.41, d.s.=2.24, and mean=70.87, d.s.=2.2, for one-mask and all-masks RSVP respectively). The typical AB pattern explained the lag effect. Instructions' main effect was not significant (p= 0.07, partial η2 = 0.08), although participants in the Standard group were more accurate than those in the Pair group (mean=73.64, d.s. = 3.1, mean=65.63, d.s. = 3.02 for the Standard and Pair group, respectively. The interaction between RSVP and Lag was also significant ($F_{3,111}$=3.597, $p < 0.05$, partial η2 = 0.09), aiming that in all-masks RSVP participants AB recovered slightly better than in one-mask RSVP. The interaction between Lag and Instructions was also significant ($F_{3,111}$=2.2762, $p < 0.05$, partial η2 = 0.07), revealing that participants in the Pair instructions had a deeper AB curve (Figure 1). Indeed, Fisher LSD post-hoc tests showed a significant difference between instruction conditions in Lag 3 (p = 0.005). No other significant effects in the ANOVA were found ($p > 0.05$). Even though they have not been inserted into the ANOVA, Table 1 showed accuracies in all four instruction conditions, showing an increased accuracy in Lag 3 and Lag 4 in the Sum extended condition.

The second mixed ANOVA was conducted over T2|T1 on the total proportion of trials (Figure 2), allowing the comparison among the four instruction conditions.

The ANOVA showed a significant main effect of Lag ($F_{2.3,163.55}$=132.1505, $p < 0.0001$, partial η2 = 0.65), and significant interactions between RSVP and Instructions ($F_{3,71}$=6.1713, $p < 0.001$, partial η2 = 0.21), and between Lag and Instructions ($F_{3,71}$=3.5772, $p < 0.001$, partial η2 = 0.13). Fisher LSD post-hoc comparisons (table) revealed significant differences between Sum extended and Standard instructions in Lag 3 (p=0.048), Lag 4 (p=0.038), and Lag 9 (p=0.001) but no differences in Lag 1 (p>0.05); significant differences between Pair and Standard instructions in Lag 3 (p=0.017); finally, Sum extended was the only instruction condition in which a significant difference between Lag 9 and Lag 1 (p<0.0001) was observed.

Figure 1.

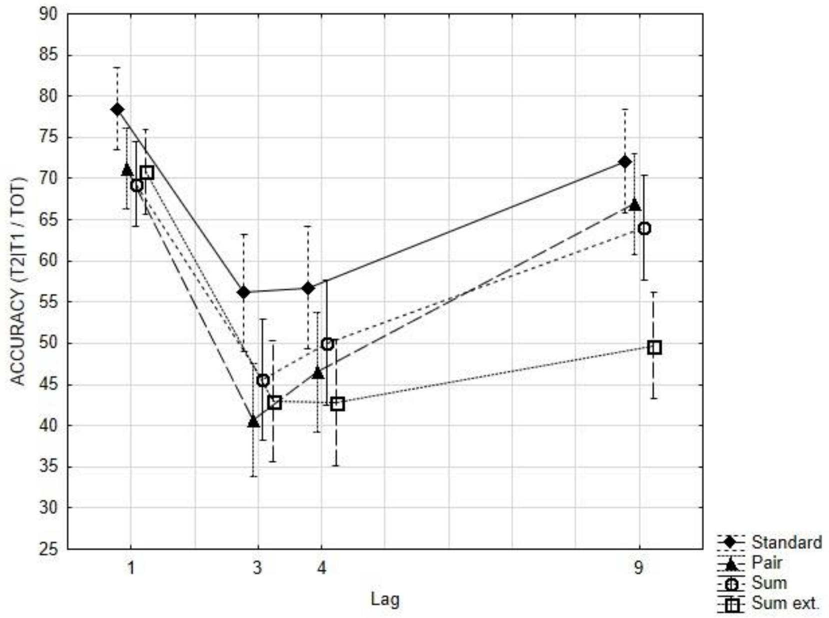


The effect of Instruction manipulation on the Attentional Blink.

Accuracy is the percentage of correct T2 given correct T1 on the total number of correct T1.

Error bars denote standard errors.

Figure 2.



The effect of Instruction manipulation on the Attentional Blink, when accuracy is calculated as the percentage of correct T2|T1 (correct sums for the “Sum” and the “Sum extended” conditions) on the total number of trials. Error bars denote standard errors.

Table 1. T2|T1 / T1 accuracy means and standard errors for Instruction x RSVP condition x Lag.

	ONE MASK RSVP				**ALL MASK RSVP**			
	Lag 1	**Lag 3**	**Lag 4**	**Lag 9**	**Lag 1**	**Lag 3**	**Lag 4**	**Lag 9**
Standard	92.49 (2.33)	60.11 (5.22)	59.18 (5.82)	80.24 (3.67)	92.16 (1.99)	60.18 (5.68)	63.73 (5.92)	81.07 (3.95)
Pair	91.06 (2.27)	43.35 (5.08)	48.42 (5.67)	72.47 (3.58)	89.73 (1.94)	47.01 (5.54)	55.41 (5.77)	77.65 (3.85)
Sum	88.36 (2.39)	60.46 (5.36)	65.31 (5.97)	80.4 (3.77)	91.58 (2.05)	60.37 (5.84)	67.09 (6.08)	83.49 (4.06)
Sum ext.	95.96 (2.39)	92.19 (5.36)	73.87 (5.97)	79.33 (3.77)	94.95 (2.05)	72.94 (5.84)	73.83 (6.08)	82.46 (4.06)

Table 2. T2|T1 / Tot accuracy means and standard errors for Instruction x RSVP condition x Lag.

	ONE MASK RSVP				**ALL MASK RSVP**			
	Lag 1	**Lag 3**	**Lag 4**	**Lag 9**	**Lag 1**	**Lag 3**	**Lag 4**	**Lag 9**
Standard	78.03 (4.07)	54.87 (5.2)	52.89 (5.41)	71.58 (4.39)	78.95 (3.51)	57.5 (5.1)	60.53 (5.42)	72.63 (4.78)
Pair	70 (3.97)	39.38 (5.07)	43.25 (5.28)	64.5 (4.28)	72.5 (3.43)	42 (4.97)	49.75 (5.29)	69.38 (4.66)
Sum	67.22 (4.18)	45 (5.34)	49.44 (5.56)	62.36 (4.52)	71.39 (3.61)	46.25 (5.24)	50.69 (5.57)	65.69 (4.91)
Sum ext.	71.81 (4.18)	45.56 (5.34)	44.44 (5.56)	53.61 (4.52)	69.86 (3.61)	40.42 (5.24)	41.25 (5.57)	45.83 (4.91)

Finally, participants’ in the two sum conditions may differ in their reporting strategy when they did not detect T2. Indeed, some participants may have tried to guess the sum, while others may have preferred to report T1 only. The two types of strategies may have considerable consequences over the scores’ proportions. Participants who preferred to report T1 only will certainly have lower proportions when using Ferlazzo et al.’ (2007) scoring method than participants who guessed the sums (because these trials will not be part of the denominator). We split participants in the Sum and the Sum Extended groups separately by the median of the T1 only reports, i.e., when they correctly reported only T1 instead of the sum. Then, we merged the two sum conditions into two new groups, “Sum low T1” and “Sum high T1”, to have comparable groups with the Standard and the Pair ones. The mixed ANOVA (Group x RSVP x Lag) over the relative scoring method revealed significant main effect of Group ($F_{3,71}=20.08$, $p < 0.0001$, partial $\eta2 = 0.46$), of Lag ($F_{2.173977,154.3524}=125.3256$, $p < 0.0001$, partial $\eta2 = 0.64$), and of the interactions between RSVP x Lag ($F_{2.555501,181.4406}=7.0853$, $p < 0.001$, partial $\eta2 = 0.09$), Group x Lag ($F_{9,213}=9.589$, $p < 0.0001$, partial $\eta2 = 0.29$) and Group x RSVP x Lag ($F_{9,213}=4.290$, $p < 0.0001$, partial $\eta2 = 0.15$). The Sum low T1 group obtained the expected overestimated pattern of the AB, whereas the Sum High T1 group showed a stronger AB than in the Standard condition (Figure 3).

The same ANOVA over the absolute scoring method showed significant main effects of Group ($F_{3,71}=6.2583$, $p < 0.001$, partial $\eta2 = 0.21$) and Lag ($F_{2.341964,166.2794}=125.8434$, $p < 0.0001$, partial $\eta2 = 0.64$). and significant RSVP x Group ($F_{3,71}=3.2779$, $p < 0.05$, partial $\eta2 = 0.12$) and Group x Lag ($F_{9,213}=2.2769$, $p < 0.05$, partial $\eta2 = 0.09$) interactions. In this case the Sum low group exhibited the same AB trend as the Standard group, as in Lagroix et al. (2018) and the Sum High T1 group had lower performance in all targets than the Standard group (Figure 4).

Figure 3.

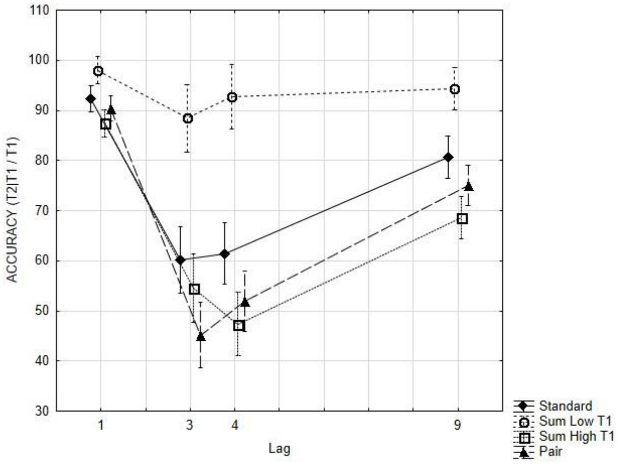
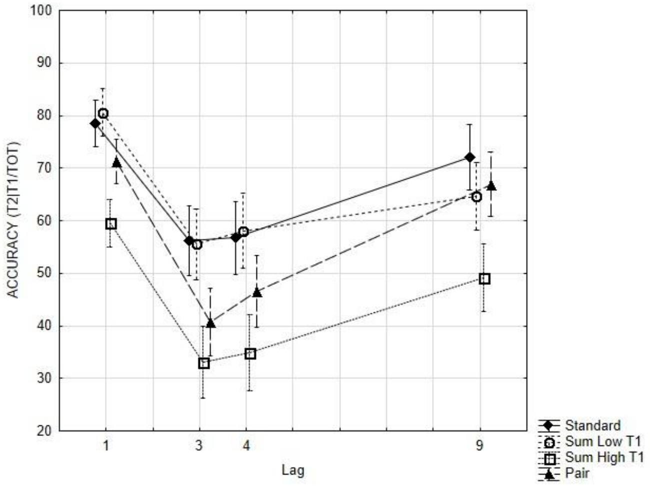


Figure 4.



The effect of Instruction manipulation on the Attentional Blink when the “Sum” and the “Sum extended” conditions’ participants are split into two new groups according to their reporting strategy (“Low T1 only” are assumed to guess the sums when they did not detect the two targets while the “High T1 only” had a high proportion of T1 only reported).
In **Figure 3**, accuracy is the percentage of correct T2|T1 on correct T1. In **Figure 4**, accuracy is the percentage of correct T2|T1 on total number of trials per condition. Error bars denote standard errors.

Discussion

In this study, we aimed to respond to Lagroix et al. (2018) questions addressed to the Ferlazzo et al. ’s (2007) paper. In that and in a later paper (Ferlazzo et al., 2008), the authors suggested a goal-switching hypothesis to explain part of the typical Attentional Blink (AB) pattern (i.e., the drop in detecting two subsequent targets when the Lag between them is approximately 200-500 ms). Their hypothesis concerned the role of high-level goal switching when participants must separately report two targets. They suggested that in standard AB paradigms, participants must accomplish two separate goals in each RSVP stream (i.e., reporting the T1, report the T2), and part of the AB curve can be explained by high-level switch costs between the two different goal representations. Indeed, they observed that varying the task instructions, when participants have just one goal to achieve (i.e., report the pair of targets, or their sum in case of digits), the AB is attenuated. Lagroix et al. (2018) commented on these results addressing several methodological points that we are going to discuss according to the results of the present replication study, in which we tested participants in four conditions: Standard, Pair, and Sum instructions, plus an additional Sum condition (Sum extended) where T1 only streams were also presented.

Accuracy in AB paradigms is typically calculated as the proportion of T2|T1 correct trials over the number of T1 correct responses. However, this kind of calculus leads to an underestimation of the AB in Sum conditions. Since the AB is an impairment in T2 performance rising from T1 identification-related processes, as most AB theories suggested (e.g., Shapiro et al., 1994; Chun and Potter, 1995; Di Lollo et al., 2005; Wyble and Bowman, 2009), calculating this proportion over the total number of trials, as Lagroix et al. (2018) suggested, is mainly wrong with the AB assumptions, resulting in overestimated AB. However, Lagroix et al. (2018) showed that the opposite results are obtained by using the two methods: no differences exist when the absolute proportion is used.

In the present study, using the standard scoring method (Figure 1), we found an attenuation of the AB in the Sum Extended condition, which is the replication of the Sum condition in Ferlazzo et al. (2007), but not in the Sum condition, which was the replication of the Sum condition in Lagroix et al. (2018). However, since the Sum and the Sum Extended conditions were equal in terms of the task to be accomplished (do the sum) and the number of the two-target trials, we found no indication of a reduced AB in the Sum compared to the Standard condition. If the underestimation of the AB is only the consequence of the scoring method used, it was expected in the Sum Extended and the Sum condition.

A different picture emerged when using the Lagroix et al. ’s (2018) scoring method (Figure 2). The amplitude of the AB curve expanded in the Sum extended condition, with lower accuracy in Lag 3 and 4 and 9, compared to the Standard condition. Again, this finding was not observed in Lagroix et al. (2018). The Sum condition was not significantly different from the Standard one but exhibited an AB similar to the Pair one, which presented a significantly reduced accuracy in Lag 3 compared to the Standard condition.

In Sum Instructions conditions, individual differences may emerge in the strategy they use in the task. Instantly, when participants failed to notice one or both the targets, they may use at least two different strategies: 1) trying to guess the sum or 2) report the only target they have seen. The two kinds of strategies provide different results because, in the first situation, the difference between the numerator and the denominator in the proportion is undoubtedly smaller than in the second situation. Accordingly, in the second subset of analyses, we split the Sum and the Sum Extended samples by the median of the T1 only reports (for the two-target trials only in the Sum extended group) and merged the subgroups in a Low T1 (guessing participants) and in a High T1 (T1 only preference) group. We then analyzed the dataset with both the scoring methods with these new subgroups. With the standard method, we replicated the Ferlazzo et al. (2007) findings for the guessing participants while the opposite results (a deeper AB) were observed for the High T1 group. Differently, with the absolute scoring method, we observed no differences in performance between the Standard and the

Sum Low T1 groups and lower performance, irrespective of the Lag, for the Sum High T1 group compared to the Standard one.

Very different results in each of the four combinations have been observed. Indeed, the individual strategy used by participant numerically affects the results, but in a way not accountable by the Lagroix et al. 's scoring method. By combining the two different scoring methods, goal manipulations seem to influence the amplitude of the AB. However, the direction and the interpretations of these effects need more extensive investigations.

Undoubtedly, choosing enough and reasonable lags in AB paradigms is of paramount importance for detecting effects throughout the whole span of AB pattern, consisting of the lag-1 sparing, the drop in performance, and the recovery. Lagroix et al. (2018) employed a three lags-design (lag 1, lag 4, and lag 9), whereas Ferlazzo et al. (2007) a six-lags design (ranging from Lag 1 to Lag 6). Nevertheless, it can be noted that in Ferlazzo et al. 's, no indication of AB recovery can be drawn. However, since only one Lag was used from the Lagroix et al. 's no precise estimation of performance in the AB window can be estimated.

Due to the scoring issues, we conducted statistical analyses for the standard scoring method over the Pair and the Standard instructions separately, finding a deeper AB in the Pair condition. This deepening was due to lower accuracy in Lag 3. This result was opposite to the one found in Ferlazzo et al. (2007) but also different from the one obtained by Lagroix et al. (2018), which did not find any performance variations. Namely, differences may have emerged due to the chosen range of inter-target trials (the Lag 3 was not assessed in the Lagroix et al. 's study). Regarding the Ferlazzo et al. 's findings of a reduced AB in the Pair condition, longer lags (i.e., increased performance in some trials) and a mixture of fixed and variable RSVPs might have played a role in altering expectancy in the position of T2.

Conclusions

The present study aimed to replicate the questions opened by Lagroix et al. (2018) to Ferlazzo et al. (2007). We highlighted that several methodological and strategical dimensions might account for the two works' results, supporting different interpretations of the Attentional Blink's goal-related processes. Such findings posit that the direction of effects showed may not be just an artifact only created by methodological choices but may represent subtle effects that need to be further clarified. Additional research is needed to improve our understanding of high-level mechanisms underlying temporal attention, which must employ precisely replicated experimental procedures to get reliable results.

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The role of number representation in the Attentional Blink order reversals

Abstract

The psychological research has extensively shown that individuals are limited in their ability to temporally process environmental information. The attentional blink is the drop in performance observed when individuals must detect two targets in a sequence of distractors as a function of their interval. Lag-1 sparing refers to the relative and paradoxical sparing of the performance when the second target immediately succeeds the first one. Precedence and integrative approaches have been suggested in the explanation of this phenomenon. In four experiments, we demonstrated that features of the stimuli relation (the ordinality of numbers, presented as targets) and task-instructions play a role in the regularization of lost temporal information. The prior entry account seems not to be generalizable in explaining order reversals: integration processes are flexible and depend on both encoding and retrieval mechanisms.

Introduction

Identifying the correct temporal order of two or more events has a paramount importance for the optimal adaptation of individuals to the environment. However, the human cognitive system is often limited in uni- and multi-sensorial temporal segregation (Sternberg and Koll, 1973), an ability requiring a complex integration of spatiotemporal information, especially when environmental stimuli appear shortly in time one after the other. These limitations have been extensively studied in healthy and pathological individuals, investigating constructs currently defined as "Subjective Simultaneity", "Just Noticeable Difference", and "Temporal Binding Window" (Wallace and Stevenson, 2014; Spence and Parise, 2010). Research in experimental psychology has indicated non-attentional and attentional responsible mechanisms (Matthews and Meck, 2016), even though no clear consensus has been reached about which processes are mostly implicated. Indeed, both characteristics of stimuli (bottom-up) and voluntary attention (top-down) may play a pivotal role in guiding the perceived succession of two events (Pöppel, 1997; Schneider and Bavelier, 2003).

In the context of visual perception and attention, one phenomenon that has been revealed useful to investigate human temporal limitations is the Attentional Blink (AB, Raymond et al., 1992). When individuals are asked to detect two target stimuli (e.g., numbers) in a rapid serial visual presentation (RSVP) of distractors (e.g., letters), performance is usually impaired when the second target appeared about 200-500 ms after the first one. Interestingly, in most conditions, when T2 directly follows T1, with an interval of about 100 ms, performance is relatively spared (a phenomenon named Lag-1 sparing). Lag-1 sparing is dependent on whether T2 requires dimensional or spatial switching (Visser et al., 1999), on the presence of pre-T2 distractors (Olivers et al., 2011), and the timing between T1 and T2 (Bowman and Wyble, 2007). Moreover, Lag-1 sparing is "spreadable" on additional targets following T2 if there are no intervening distractors in between (Olivers et al., 2007; Kawahara et al., 2006; Di Lollo et al., 2005). However, literature is still debating upon whether a distractor between the targets is a determinant factor for the occurrence of the AB, a debate that has significant consequences for the theorization of the whole AB phenomenon (Chen and Zhou, 2015; Lagroix et al., 2012; Brisson et al., 2011; Nieuwenstein et al., 2009).

The sparing observed at lag-1 usually happens with costs: the performance on T2 is usually better than the performance on T1, and, when the two targets have been correctly identified, the right perception of their temporal order is lost, and the two targets are often reversed.

Literature presents two different approaches for the explanations of order errors in visual attention. The first one gravitates around the precedence effect (Reeves and Sperling, 1986): a strong attentional enhancement on an item strengthens its representation in visual short-term memory, and the stronger the representation, the faster it is processed. Regarding the AB, the attentional gate opened by the identification of T1 enhances the identification of T2. However, the strength of T2 allows for it to win the race for working memory access, prioritizing its entry (Schneider and Bavelier, 2003; Spence and Parise, 2010): the more salient the target, the earlier its perception. Then, several studies accounted for prior entry in the explanation of reversals in the AB. This view has been supported by several studies in which, by strengthening T1 through a pre-cue, a significant decrease in order reversals was found (Olivers et al., 2011; Hilkenmeier et al., 2012a; 2012b). According to the Boost and Bounce model (Olivers and Meeters, 2008), individuals report the two targets in the order these enter in working memory. Differently, in the eSTST model (Wyble and Bowman, 2009), targets need to be bound to different WM tokens, a process that requires a consolidation time: here, the strength of the items and the competitive race between the targets has a role in determining the consolidation sequencing. The eSTST model is an evolution of the STST model (Bowman and Wyble, 2007), which has been modified mostly because of the "spreading the sparing" phenomenon (Olivers et al., 2007; Kawahara et al., 2006). The most noticeable difference for Lag-1 sparing between the two models is that, differently from the eSTST, the STST model allowed for T1 and T2 to be bound to the same token, when presented at Lag-1. At this point, the STST model raises the possibility that the two events may result in an integrated representation. Integration has also been widely investigated in the literature of Attentional Blink in a perceptual sense (Hommel and Akyurek, 2005; Akyurek et al., 2008). For instance, the short time interval between the two targets makes them be perceived as simultaneous, and, when possible, integrated into a unique percept. Evidence shows that when participants combine different features of two targets into one, e.g., integrating the two, the number of reversals notably decreases (Akyurek et al., 2012). Integration accounts have been mostly criticized because they explained the reversals as a loss of order. However, data frequently reported a percentage of swaps that barely reach the 50 % of correctly identified targets, which indicates a chance level performance, a level that appears to be logical when participants do not have any idea of what target came first. However, as Akyurek et al. (2012) argued, integration, reversals, and correct order reports represent only possible temporal order perception outcomes.

However, a possibility exists that this integration hides a response bias, i.e., integrated responses can be more produced when the alternative is to guess about their order. Similar kind of response biases have also been studied with temporal order and simultaneity judgments tasks, making important the question provided to participants about what they have attended to and what type of judgment they must make ("Which target came first?" vs. "The targets were simultaneously presented or not?") (Spence and Parise, 2010).

The effects predicted by precedence and integrative accounts regard consolidation processes. However, both consolidation (Chun and Potter, 1995) and retrieval mechanisms (Shapiro et al., 1994) have been differently considered responsible for the Attentional Blink phenomenon in AB's first theories. The weights of the two processes are still not fully understood, and how the two interact in determining the lag-1 sparing phenomenon is not yet been investigated.

In addition, in each of the two approaches, the stimuli' features can be determinant for their temporal discriminability. However, these features are not yet extensively investigated. The precedence and the integration approaches, by explaining the reversals according to the prior entry principle in one case, and to perceptual integration in the other, do not consider the possibility that items in working memory can be temporally represented in a way which is not entirely predicted by stimulus strength or its integrative properties.

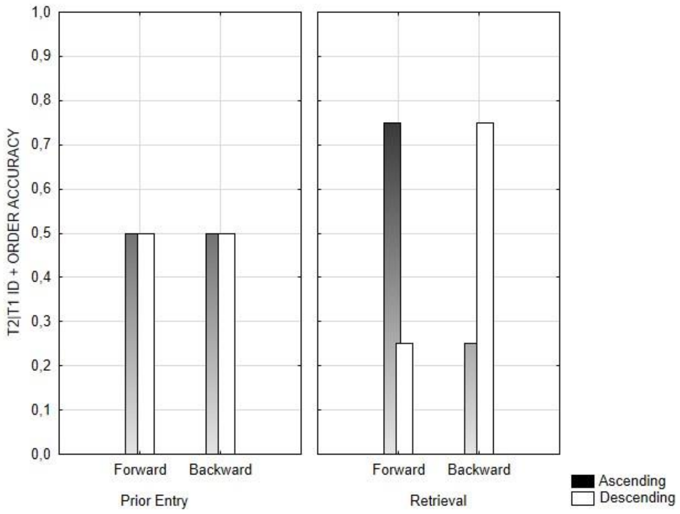
Among the plethora of stimuli used in attentional paradigms, numbers are among the most employed, and their cognitive organization has been widely investigated. For instance, the representation of numbers has been extensively studied in spatial paradigms. These studies allowed to highlight that numbers are organized in a mental number line (Spatial-Numerical Association of Response Codes, SNARC; Dehaene et al., 1993; Wood et al., 2008). According to this evidence, a left-to-right preference in the representation of digits exists, on which the reading habits are a strong determinant

(Shaki et al., 2009). Even though this representation seems to rely on automatic processes, it has also been shown that it is task-dependent and flexible (Zhang et al., 2020; Moro et al., 2017; Pfister et al., 2013). This kind of organization has also been found in the pitch height (SMARC effect; Rusconi et al., 2006), in quantities in general (Dalmaso and Vicovaro, 2019), and in other ordinal dimensions such as time representation (Bonato et al., 2012). Response codes have also been associated with spatial-temporal dimensions (Vallesi et al., 2008; 2011). Indeed, these magnitudes are behaviorally, cognitively, and neurally linked in the ATOM theory of magnitude (Walsh et al., 2003). Besides the association between numbers and space, the association between time and numbers has also been documented. Even if not widely investigated, such as spatial representation, the evidence upon the numbers' temporal organization highlighted a preference for ascending sequences of digits. For instance, in a serial comparison task, faster RTs were found ascending than descending ordered digits (Muller and Schwarz, 2008; Kaan et al., 2005).

Consequently, the evidence on the temporal organization of numbers can help the advancement of knowledge about the mechanisms on which the order reversal in the AB relies on.

In the present study, the incidence of an irrelevant dimension (the order of digits presented in the RSVP) on the number of reversals at Lag-1 has been investigated through 4 experiments. All the experiments have the aim to investigate if the principle of prior entry in explaining order errors can be viewed as a general principle or if other features can be part of the results observed. In experiment 1a, we investigate if a natural preference for ascending digits in an RSVP paradigm exists, hypothesizing that digit order might not affect reversals by assuming a prior entry hypothesis. Differently, according to a retrieval/response bias hypothesis, descending digits might be more swapped than ascending digits (Figure 1). The same predictions were made for experiment 1b, in which we asked participants to report the two targets backwardly respect their presentation order. The order of responses, in that case, allows us to monitor a possible forward ordered response preference. In experiment 2, we use a within-subjects design to disentangle any possible expectancy effects in coding strategies through uncued randomization of forward and backward trials. Finally, in experiment 3, we used longer lags in addition to lag-1 to verify that *a)* the possible effects are distinctive for lag-1, and *b)* these effects are not altered when participants cannot predict the position of T2.

Figure 1.



Expected results for the two different assumptions. If the prior entry hypothesis is generalizable, then we should observe no effects of digits magnitude on reversals. Differently, assuming a response bias retrieval hypothesis, we should observe a preference for naturally ordered (ascending) responses, then targets presented in descending order should be more frequently swapped in the Forward condition with the opposite true for the Backward condition.

Experiment 1a

In experiment 1, we tested the hypothesis that the magnitude of numbers has an impact on the temporal order perception of two target digits presented one immediately after another in an RSVP among letter distractors. Specifically, we first hypothesize that a natural preference exists for ascendingly ordered digits: according to our hypothesis, ascending sequences might be better temporally ordered than descending ones.

Method

Participants

Fifteen university students (females = 10; mean age = 25.4, s.d. = 4.08) from Sapienza University of Rome participated in the study. All of them have a normal or corrected-to-normal vision. The study was approved by the Institutional Review Board of the Department of Psychology at the Sapienza University of Rome and conducted in accordance with its policies and with the Declaration of Helsinki. All participants provided written informed consent.

Stimuli

Participants performed an RSVP task. Among a sequence of letters, used as distractors, one or two target digits might appear. Letters were randomly selected without replacement from a Latin letter list (excluding B, G, I, O, S, and Z). Digits were pseudo-randomly selected without replacement from a list of Arabic digits from 2 to 9. A totality of 225 trials was presented to participants; in additional 40 trials, only one digit was presented. Digits and letters were presented for 80 ms each, with no interstimulus interval (ITI). Each sequence was made of 25 characters. The first digit (T1) might randomly appear between the 5th and the 13th position. The second digit (T2), if present, always appeared immediately after T1, with no intervening distractors in between. The second digit might be bigger/smaller than the first (ascending/descending trials) in approximately half of the trials. No repeated digits were presented in the same trial. Each character was displayed in white on a black background, with a 2 cm of width and 2 cm of height. The task was programmed on e-Prime 2.0 and launched on a Dell PC.

Procedure

Participants read and signed the informed consent and seated at approximately 60 cm from the monitor, in an illuminated room, and were instructed. Each sequence began with a fixation cross at the center of the screen. When the participants pressed the spacebar, the fixation cross disappeared, and the RSVP sequence started at the center of the screen after 500 ms. At the end of the sequence, the question "What was the first digit?" appeared. After participants made their response on the keyboard, the question "What was the second digit?" appeared. After participants made their second response, a blank interval of 1000 ms was displayed, and a new fixation cross appeared. Unspeeded responses were required to participants. They were explicitly asked to report the digits in the order they appeared and guess if they were unsure about their identity. In any case, they had to report two digits in each trial. After each response, no feedbacks were provided.

Results

Mean individual proportions of correct identification of T1 were analyzed in a one-way ANOVA, with Digits order as a factor (within-subjects, Descending vs. Ascending). The analysis did not reveal any significant effect ($F_{1,14} = 1.493$, $p = .242$).

Mean individual proportions of correct identification of T2 upon the correct identification of T1 (T2|T1), regardless of order, were analyzed in the same ANOVA design, showing a small but significant decrease of performance when digits were presented in descending order ($F_{1,14} = 12.309$, $p < .01$, partial $\eta2$ 0.47) (Figure 2).

The same analysis of T2|T1, but considering only responses made in the correct order, revealed a significant decrement for accurate reports of temporal order for targets presented in descending order ($F_{1,14}$ = 28.0182, $p < .001$, partial η2 0.67). Thus, digits presented in descending order were more frequently swapped than ascending digits (Figure 2).

Finally, a t-test was performed to compare the number of ascending or descending responses made by participants in the totality of trials. The t-test revealed a significant difference between ascending and descending responses (*t*(14) = 4.830643, $p < .001$), showing that participants made more ascending than descending overall responses.

Experiment 1b

The same predictions made for experiment 1a were also made for experiment 1b. Differently from 1a, in the 1b, the order of report was reversed (participants had to report the digits backwardly, i.e., the last first) to test the hypothesis that task goals may modulate order inversion, as a function of Digits order. We hypothesized that, if the order preference depends upon early processes, we must find the opposite pattern in experiment 1a. Indeed, descending digits might be preferred in the backward report condition. Differently, if this preference acts presumably in a late phase, then the pattern might be the same. Indeed, in the present backward version, descending digits must be reported in ascending order.

Methods

Participants

Fifteen university students (females = 7; mean age = 24.86, s.d. = 2.53) from Sapienza University of Rome participated in the study. The study was approved by the Institutional Review Board of the Department of Psychology at the Sapienza University of Rome and conducted in accordance with its policies and with the Declaration of Helsinki. All participants provided written informed consent.

Stimuli

Stimuli were the same used in experiment 1a.

Procedure

The procedure was identical to the one of experiment 1b, except for the order of reports. At the end of each sequence, the sentence "Report the second digit" appeared before "Report the first digit". Thus, participants were asked to report the digits in the opposite order concerning their presentation order.

Results

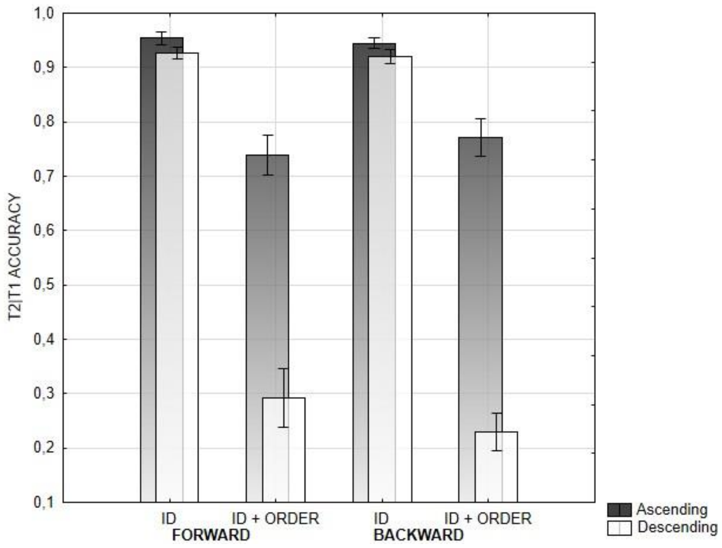
One-way ANOVA for T2|T1 regardless for correct order as a function of ascending or descending order of digits showed again a little but significant decrease of performance when digits were presented in descending order ($F_{1,14} = 5.351$, $p < .05$, partial η2 0.28) (Figure 2). However, the same one-way ANOVA for T1 performance did not reveal any difference between conditions ($F_{1,14} = 2.5438$, $p = .133$).

The ANOVA for T2|T1 performance, considering only responses made in the correct order, revealed a significant decrement for accurate reports of temporal order for targets presented in descending order ($F_{1,14} = 82.5678$, $p < .0001$, partial η2 0.85). Thus, digits presented in descending order were more frequently swapped than ascending digits (Figure 2). Differently from experiment 1a, in this case, accuracy for descending digits means to report an ascending pair, with the opposite valid for ascending digits.

Conversely from the experiment 1a, the t-test between the total number of ascending/descending responses revealed a significant difference between ascending and descending responses (*t*(14)= -9,10035, $p < .0001$), showing that participants made more descending than ascending overall responses (mean = 24% and mean = 74% for ascending and descending responses, respectively).

Data from experiments 1a and 1b were also analyzed in a mixed ANOVA with Report Order (Forward and Backward) as a between-subjects factor and Digits Order (Ascending and Descending) as a within-subjects factor. The ANOVA for the T2|T1 regardless of the correct order revealed a significant main effect of Digits Order ($F_{1,28} = 15.55$, $p < .0001$, partial η2 0.36), and no other significant effect ($p > 0.05$). Similarly, the ANOVA on correctly ordered T2|T1 showed a significant main effect of Digits Order (($F_{1,28} = 91.503$, $p < .0001$, partial η2 0.76), and no other significant effects ($p>0.05$), confirming the results obtained in the separate analyses.

Figure 2.



Accuracy (correct T2|T1 / correct T1) in the Forward (Exp. 1a) and in the Backward (Exp 1b) instruction conditions for Ascending and Descending ordered targets. ID = Identification only (regardless of order). ID + ORDER = Identification in the correct order (according to the instructions). Error bars denote standard errors.

Experiment 2

The between-subjects design of experiments 1a and 1b might have played a role in determining the results obtained: a possible effect of expectancy might have guided performance. Indeed, if the order of reports (forward or backward) is the same for the whole experiment, participants know in advantage what is the report order required, and thus they might implicitly encode digits in a serial order accordingly to the task goal. Experiment 2 was designed to exclude this possibility. We hypothesize that if the match between the order of numbers and the order of reports has a role in the encoding phase, the pattern of results of experiments 1a and 1b might change or disappear. Differently, if the representation of digits and the perception of time act in a later phase, i.e., when participants must retrieve and report the two digits perceived, then we expect to find the same pattern of the previous experiments.

Methods

Participants

Fifteen university students (female = 5; mean age = 26.27, s.d. = 4.85) from Sapienza University of Rome participated in this study. The study was approved by the Institutional Review Board of the

Department of Psychology at the Sapienza University of Rome and conducted in accordance with its policies and with the Declaration of Helsinki. All participants provided written informed consent.

Stimuli

Stimuli were the same used in the previous experiments. A totality of 234 dual-target trials was presented to participants, equally divided for each report order condition ("forward" and "backward"). Additional 20 single-target trials per Report order condition were administered.

Procedure

The procedure was identical to the previous experiments, except for the design. In this experiment, the two report conditions ("forward" and "backward") are treated as within-subjects. Each participant performed the same task with the "forward" and "backward" trials randomly intermixed. The report order was not declared or cued before the sequence; thus, participants knew how they had to report the digits only after each sequence ended. Indeed, at the end of each sequence, the sentence "Report the second digit" appeared half of the trials before "Report the first digit".

Results

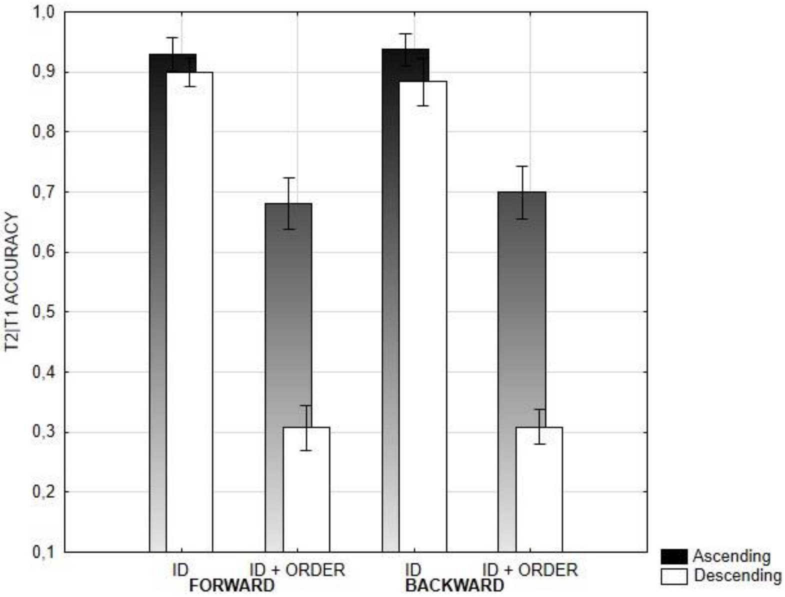
A two-way within-subjects ANOVA was performed over T1 performance for all four combinations of Report order (backward and forward) and Digits order (ascending and descending). The analysis showed no significant differences in the ability to detect T1 ($p > 0.05$ for all effects).

The same analysis was performed upon T2|T1 performance, regardless of correct order, showing a significant main effect of Digits Order again, with a little increment of performance when targets were presented in ascending order ($F_{1,14} = 16.927$, $p < .01$, partial $\eta 2$ 0.55), and no other significant effects ($p > 0.05$) (Figure 3).

The ANOVA upon T2|T1 performance, considering accurate only the responses given in the correct order, showed a significant main effect of Digits Order ($F_{1,14} = 49.0383$, $p < 0.0001$, partial $\eta 2$ 0.78) and no other significant effects ($p>0.05$) again, successfully replicating results in experiments 1 and 2 (Figure 2).

As well as in experiments 1a and 1b, ascending responses were more frequent in the Forward trials (mean = 55% and mean = 26% for ascending and descending responses, respectively; $t(14) = 5.693385$, $p < 0.0001$) while the opposite was true for Backward trials (mean = 25% and mean = 56 % for ascending and descending responses, respectively; $t(14) = -5.40746$, $p < 0.0001$).

Figure 3.



Accuracy (correct T2|T1 / correct T1) in the Forward and in the Backward instruction conditions in the Exp. 2 for Ascending and Descending ordered targets. ID = Identification only (regardless of order). ID + ORDER = Identification in the correct order (according to the instructions). Error bars denote standard errors.

Experiment 3

In the previous experiments, the second target, if present, was always presented immediately after the first one (i.e., at lag 1). In experiment 3, we repeated the same procedure with additional lags to reduce global task expectations about the T2 position and control if the numerical magnitude effect disappeared at longer lags.

Method

Participants

Fifteen students (females = 3; mean age = 26.27, s.d. = 4.22) were enrolled in the Sapienza University of Rome. The study was approved by the Institutional Review Board of the Department of Psychology at the Sapienza University of Rome and conducted in accordance with its policies and with the Declaration of Helsinki. All participants provided written informed consent.

Stimuli

The task and the stimuli were the same as the previous experiment. The only difference with experiment 2 is the manipulation of lags (i.e., the distance between T1 and T2). Three different lags were used: Lag 1, 3, and 9 (80, 240, and 720 ms after T1, respectively). Thirty trials for each combination among digits order (ascending and descending), report order (backward and forward), and lag (1,3, and 9), plus 28 single-target trials (14 each Report order condition) gave a totality of 388 randomly presented trials. In the dual-target trials, T1 was equally presented between the 5th and the 10th position. In the single-target trials, T1 was equally presented between the 6th and the 19th position (i.e., the same positions where T2 might be presented in the dual-target trials).

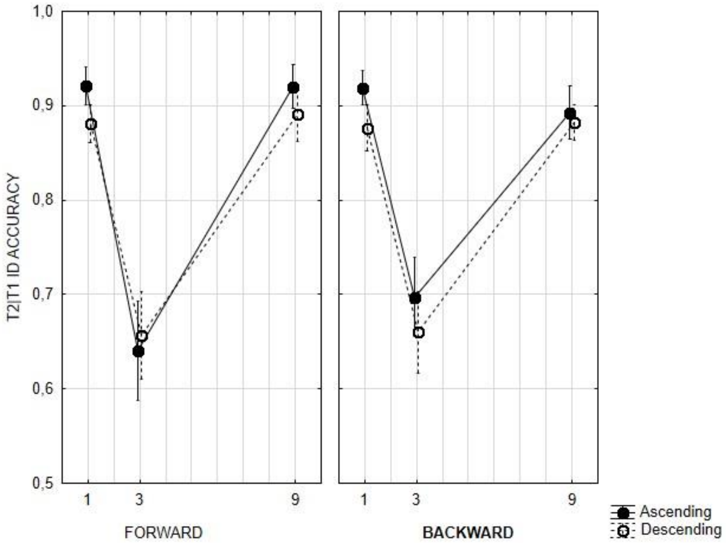
Procedure

The procedure was identical to the one in experiment 2.

Results

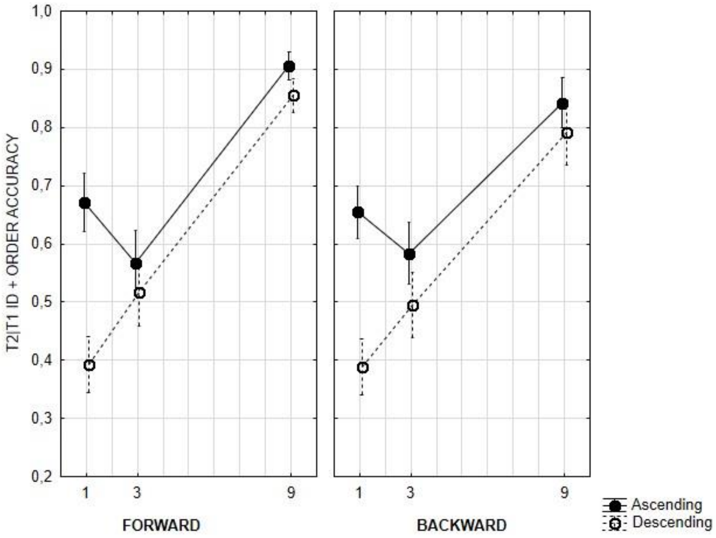
Data were firstly analyzed in a three-way within-subjects ANOVA with Report order (Forward vs. Backward), Digits Order (Ascending vs. Descending), and Lag (1,3, and 9) upon t2|t1 performance regardless of order. The analysis showed a significant main effect of Lag ($F_{2,28} = 46.769$, $p < .000001$, partial η2 0.769618), revealing a typical AB effect for all conditions (Figure 4). No significant effects ($p > 0.05$) were found for Report order and Digits order, nor for the Report Order x Digits order, the Report order x Lag, the Digits order x Lag, the Report order x Digits order x Lag interactions.
Subsequently, t2|t1 in the correct order were analyzed in the same ANOVA design. The analysis showed a significant main effect of Digits order ($F_{1,14} = 28.6198$, $p < .001$, partial η2 0.671514), of Lag ($F_{2,28} = 45.9618$, $p < .000001$, partial η2 0.766518), and of the Digits order x Lag interaction ($F_{2,28} = 9.73$, $p < .001$, partial η2 0.410029). Main effect of Report order and the Report order x Digits order, the Report order x Lag, and the Report order x Digits order x Lag interactions were not significant ($p > .05$). Duncan's post-hoc test for the Digits order by Lag interaction showed all comparisons but Forward Lag 3 vs. Backward Lag 3 and Forward Lag 9 vs. Backward Lag 9 were significant ($p < 0.05$). Specifically, the performance was better for ascending digits than descending ones, at lag-9 compared to lag-1 and lag-3, and at lag-1 for ascending digits compared to descending digits at lag-1 (Figure 5).

Figure 4.



Lag variations for accuracy (correct T2|T1 / correct T1) regardless of correct order, in the Forward, and the Backward instruction conditions in the Exp. 3 for Ascending and Descending ordered targets. Error bars denote standard errors.

Figure 5.



Lag variations for accuracy (correct T2|T1 / correct T1) in the correct order (according to instructions) in the Forward and in the Backward instruction conditions in the Exp. 3 for Ascending and Descending ordered targets. Error bars denote standard errors.

A two-way ANOVA with Report order and Lag (1,3, and 9) as factors, upon the percentage of overall descending responses, revealed a significant main effect of Report order ($F_{1,14}$ = 18.727, $p < .001$, partial η2 0.57), and a significant interaction ($F_{2,28}$ = 7.392, $p < .01$, partial η2 0.34), and a non-significant main effect of Lag ($p > .05$). Indeed, participants made more descending responses in the backward compared to the forward instruction condition. The difference between the two instruction conditions was evident when T2 immediately followed T1 (Lag-1) and progressively decreased at longer lags. The opposite was obviously true for overall ascending responses ($F_{1,14} = 18.578$, $p < .001$, partial η2 0.57 and $F_{2,28} = 7.998$, $p < .01$, partial η2 0.36, for the main effect of Report order and the interaction, respectively).

Table 1a. Percentages of overall descending responses.

Descending Responses	Single	Lag 1	Lag 3	Lag 9
Forward	42.86 (3.12)	38.33 (3.57)	45.78 (2.3)	48.78 (0.7)
Backward	59.05 (2.56)	62.33 (2.77)	56.56 (2.15)	52.89 (1.67)

Table 1b. Percentages of overall ascending responses.

Ascending Responses	Single	Lag 1	Lag 3	Lag 9
Forward	56.19 (3.03)	60.67 (3.67)	53.67 (2.27)	50.78 (0.67)
Backward	40.48 (2.58)	36.11 (2.65)	42.89 (2.19)	46.56 (1.83)

Discussion

The present study aimed to investigate the presence of regularizing mechanisms in the perception of the temporal order of targets in the Lag-1 sparing phenomenon of the Attentional Blink. Several works explained order reversals at Lag-1 as a precedence phenomenon, e.g., prior entry (Olivers et al., 2011), or through an integrative account (Hommel and Akyurek, 2005).

In the present study, reversals have been studied using numerical targets. Digits are quite often employed as stimuli in Attentional Blink paradigms. However, despite the considerable evidence regarding number processing's spatial and temporal dimensions, their impact in the AB performance has never been investigated. Even though numbers have been studied in this context, other studies might focus on different kinds of stimuli categorization.

The organization of numbers might be a relevant feature in understanding reversals. Thus, we hypothesized that if prior entry is a general principle in guiding performance at Lag-1, the magnitude of numbers and their order should not be relevant. Differently, the order of digits might have an impact in determining the order of their presentation, even though response bias for naturally ordered preference can be observed. We investigated these assumptions through 4 experiments, controlling for report-order instructions, asking subjects to report the target in the forward (Exp. 1a), and in the backward (1b) order; expectancy due to between subject-design of the Exp. 1a and 1b (Exp. 2); use of longer lags (Exp. 3). Because of the stimuli used, we were not able to make predictions about integration processes.

A clear effect of digits order was found throughout all the experiments: the digits presented in descending order were significantly more reversed than digits presented in ascending order. At first glance, that result can be addressed to a response bias. However, this preference in response is inverted by the manipulation of task instructions. When asking to report the two digits in backward order (i.e., the second first, Exp 1b, 2, and 3), participants seem to prefer to type the two digits in descending order. Since the digits presented in descending order must be reported in ascending order in the backward condition, this inverted preference gave the same pattern of the forward condition trials. Interestingly, it can be hypothesized that participants move along the number line's mental representation in the two directions according to task instructions. As evidence shows, the SNARC effect is flexible and can be modulated (Zhang et al., 2020; Moro et al., 2017; Pfister et al., 2013).

However, experiments 1a and 1b, due to their between-subjects design, cannot disentangle the effects of expectancy over the RSVP: indeed, it is possible to argue that task instruction may modulate the encoding strategy for the current trial.

When the possibility to expect in advance the report instructions for the current trial was eliminated (Experiment 2), the digits order effect found in Experiment 1a and 1b was confirmed, thus revealing that in this case, the task instruction does not entirely act at the encoding level. It seems that a preference for ascending ordered digits in the encoding phase exist, but that this preference can be modulated by task instructions operating at a later stage (e.g., when the digits must be recalled).

In addition, in Experiment 3, we tested the hypothesis that the reversals pattern did not change when employing a standard AB task with more than one lag condition. Accordingly, the better performance for ascending ordered digits was found only at Lag-1, with no differences between the digits order conditions at Lag-3 and 9. A response-bias interpretation should have assumed that the report-order preference might persist in all the lag conditions.

The results of the present study may have different implications for the theories on Lag-1 sparing phenomenon. First, the principle of prior entry in explaining order reversals seems not entirely to fit when considering digits as stimuli. The present results suggest that the percentage of reversals commonly found can be split into two significantly different percentages when factorizing a task-irrelevant feature such as the magnitude of digits. If prior entry acts independently of the magnitude of numbers, we should have been found no effects for digits order. It is possible to argue that the fewer reversals observed for ascending responses may be due to the greater local salience of little numbers than large numbers (even more if they follow a larger number), requiring less time to be processed. Further research is required to test this interpretation.

Differently, even though our paradigm is unable to test the integration account, it looks theoretically more helpful in explaining the present results. Losing the order information of stimuli might subtend participants' proneness in regularizing them, presumably using the most economical and natural strategy. Here, the impossibility to integrate the two targets may have led participants to encode them in the most effortless order to recall, which is the ascending one. Under uncertainty, individuals have been shown to use low-effort strategies, such as the availability or the representativeness heuristic (Tversky and Kahneman, 1974). Intriguingly, heuristics might also act in low-level processes, such as temporal order judgments, in the early stages of encoding information. At the retrieval phase, i.e., when individuals must produce a behavioral output, the encoded information is modified accordingly to task-goals. If the instruction matches the encoded information, then the encoded order of events is reproduced; if not, control processes may intervene by reverting the encoded information, favoring the inverted sequence. This point adds to evidence about the goal-related changes in AB performance, which has been elsewhere reported (Kawahara, 2003; Olivers and Nieuwenhuis, 2006; Akyurek and Hommel, 2005; Ferlazzo et al., 2007; 2008).

In summary, the present results highlighted the importance of investigating the possible different roles of encoding and retrieval processes in the Attentional Blink. Regularizing mechanisms may be responsible for reversals at Lag-1, guiding the temporal order perception. Task-irrelevant features, such as the magnitude of numbers and their ordinality, have been shown modulating the number of order reversals. Procedural choices, such as the employment of stimuli, should be primarily considered in implementing AB tasks.

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Chapter 3

The multiple facets of backward inhibition

When facing tasks, the large variety of stimuli and contexts encountered by individuals necessitates an exceptional ability to respond to them accurately and quickly through the integration of goals and external requirements. This integration must subtend the interaction between mechanisms of different nature and its analysis might help in shedding new lights on the complex interplay of automatic and controlled processes.

Human beings evolved in a high-demanding world, which often requires them to solve multiple problems at once. However, the rapid environmental change often does not allow for an efficient switch between goals and costs in accuracy and reaction times are usually observed. Human performance in task-switching paradigms has been extensively investigated, showing that individuals are faster in responding following a repetition than a switch of tasks. The difference between performances on repetition and switch trials is termed “switch cost” and has been traditionally ascribed as an indicator of cognitive flexibility. Indeed, the switch cost is known to reflect the additional time required by the cognitive system to update its mental task representation to perform the new task accurately. Classical theories of task-switching are traditionally divided between a task-set reconfiguration account and a task-set inertia account. The first one suggested, through alternating-runs paradigms and manipulations of the cue-stimulus interval, a task-set reconfiguration hypothesis (Rogers and Monsell, 1995), depicting the switch-cost as the product of the more time needed by cognitive control to reconfigure the relevant task set before the stimulus classification. On switch trials, additional processes must intervene, such as the retrieval of the new task set from long-term memory to working memory (Arbuthnott and Woodward, 2002). However, evidence has shown that even with long preparation interval a residual switch cost is still obtained (Rogers and Monsell, 1995; Liefooghe et al., 2009). Different concurrent processes might also reflect the slower RT in switch compared to repetition trials (Koch and Allport, 2006; Ruthruff et al., 2001), and not all of them can be considered high-level processes.

Conversely, the task-set inertia account (Allport et al., 1994) stated that the mechanisms responsible for switch cost rely upon bottom-up proactive interference generated by previous task sets and experienced associations between stimulus, response, and task sets (Allport and Wylie, 2000; Waszak et al., 2003). Evidence supporting the task-set inertia hypothesis came from studies manipulating the proportion of stimuli associated with competing task-sets (Wylie and Allport, 2000) and studies investigating sequential switch-cost asymmetries between less or more dominant tasks (Allport and Wylie, 2000). Moreover, results in three-tasks paradigms highlighted that previous task sets might continue to interfere with concurrent performance, demonstrating a backward inhibition mechanism, which is the focus of this experimental section.

Currently, a multiple-component model (Mayr and Kliegl, 2003) integrating the task-set reconfiguration model, based on top-down updates of task-set representations, and the task-set inertia model, relying upon bottom-up proactive mechanisms, is mostly accepted. The multiple-component model explains the task-switching process as made up of different phases: task set processing, stimulus processing, and response selection/execution. By using 2:1 mapping between cues and tasks, research evidenced that earlier stages of task-switching are governed by top-down cue-related reconfiguration processes. In contrast, later stages are dependent upon bottom-up mechanisms stimulus-triggered, aimed at applying task rules to stimuli and selecting correct responses among the available ones.

The N-2 repetition cost

In task-switching, backward inhibition (Mayr and Keele, 2000) is an inhibitory mechanism that allows for the suppression of the representation of a just executed task, to facilitate performance in a new and different incoming task. This mechanism is thought to guarantee flexibility in a rapidly changing environment by inhibiting previous irrelevant task sets. At a behavioral level, this inhibition causes a reaction time (RT) cost: when switching back to a recently inhibited task (A – B – A sequences), RTs on the third task are slower than when switching back to a less recently inhibited task (C – B – A sequences), an effect named “N-2 repetition cost”.

The relevance of the backward inhibition effect for task-switching and, in general, cognitive control research, is due to its specific role in operating at a high-level task set representation. Its functionality relies on its ability to counteract perseverative tendencies: the capacity of backward inhibition to operate with persisting activation strengths of cue-stimulus-responses associations within task-sets renders it a sort of lateral inhibition mechanism, though functioning under endogenous control (Hübner et al., 2003). BI deficits have been observed in several clinical conditions, such as obsessive-compulsive disorder (Wolff et al., 2018), Parkinson disease (Fales et al., 2006), depression (Whitmer and Gotlib, 2012; Chen et al., 2016), insomnia (Ballesio et al., 2018), Williams syndrome (Foti et al., 2015a; 2015b), and in other conditions such as Developmental Topographical Disorientation (Palermo et al., 2014), alcohol intoxication (Zink et al., 2019), and prolonged isolation (Van Baarsen et al., 2012), and genetic hypotheses have been proposed (Markett et al., 2011). As well as switch cost, N-2 repetition cost is thought to reflect the concurrent deployment of different processes, and the mechanisms underlying its nature are still under debate. However, the difference between the processes relying upon switch cost and N-2 repetition cost has been suggested (Hartmann, 2019), making the BI an exceptional and additional phenomenon in the investigation of dual-processes into the inhibitory mechanisms that govern human choices and actions. Indeed, several results pointed out that backward inhibition cannot be assumed as a pure controlled process but that it seems to possess features reflecting both a bottom-up and a top-down functioning.

First, it is not clear the critical stage in which backward inhibition occurs even though most research aims to shed light on this point. Following Koch et al. (2010), task inhibition is assumed to occur when conflicts between task stimuli or responses are detected, suggesting that it is exerted by the monitoring of performance interferences made by cognitive control. Evidence has shown that backward inhibition may arise at every task processing stage, requiring only a conflict to be detected (Houghton et al., 2009). In turn, research has abundantly but not resolutely investigated the differential role of cues and tasks in determining the N-2 repetition cost. Regarding cue processing, using 2:1 cue-mapping paradigms N-2 repetition costs have been observed both with cue repetition and switch, thus providing evidence that the cost associated with task inhibition is presumably dependent on task performance (Altmann, 2007; Gade and Koch, 2008). Thus, cue-related task set retrieval appears to be differently implicated in BI from task set application processes (Mayr and Kliegl, 2003). However, cue-type temporal and spatial characteristics (Druey and Hübner, 2007; Grange and Houghton, 2009; Arbuthnott and Woodward, 2002, Arbuthnott, 2005; 2008; 2009) can modulate backward inhibition through exerting conflicts even at the level of task cues. Recent works argued that cue related processes are essential for N-2 repetition cost to occur. They do so by controlling that stimuli/responses associations were univalent (Prosser et al., 2020) or asking participants to made responses related to task identity (Regev and Meiran, 2017), evidencing robust costs. These results doubt the task-set application view, suggesting a multicomponent account of backward inhibition that has nothing to do with task conflicts, a position already promoted by Costa and Friedrich (2012).

Another main topic in task switching research is the preparation time available to subjects to reconfigure the mental task-set. It can be manipulated by modulating the time between the cue's presentation and the appearance of the imperative stimulus (CSI, Cue-Stimulus Interval). Research on standard task-switching paradigm has extensively shown that a prolonged CSI significantly reduces switch-cost but not eliminates it, suggesting that switch cost can be partially modulated at a top-down reconfiguration level, but other low-processes contribute to the effect. At first glance, the same arguments can be used for backward inhibition. However, it has been confirmed by several findings that increasing the CSI does not lead to a reduction of the N-2 repetition cost (Gade and Koch, 2008; Bao et al., 2006; Schuch and Koch, 2003; Mayr and Keele, 2000). This result appears in high contrast to the opposite effect observed for switch costs advocating that top-down reconfiguration processes do not prominently interact with backward inhibition. However, more recent findings showed that N-2 repetition cost could be affected by manipulating CSI in N-1 and N-2 trials or by using more abstract cues (Scheil and Kleinsorge, 2014) revealing that preparatory processes in backward inhibition are complex phenomena. A long CSI has also been found to reduce N-2 repetition cost in the context of language-switching (Philipp et al., 2007b; Guo et al., 2013a; 2013b). Differently, the manipulation of RCI (Response-Cue Interval) gave more indicative findings on BI's nature. Indeed, several results stated the temporal decay of BI with prolonged RCI associated with reduced N-2 repetition costs (Grange and Houghton, 2009; Koch et al., 2004; Mayr and Keele, 2000). However, as Gade and Koch (2005) reported, this effect is more related to the interval in the switch between N-2 and N-1 trial. Koch et al. (2010) suggested that rather than a passive decay of inhibition, BI reflects more the trial-by-trial conflicts in task processing. According to the authors, when switching between tasks, not only the previous task set is inhibited, but also the other irrelevant task-set. In C-B-A sequences, faster performance occurred because the C-set has already been inhibited in the transition from N-2 to N-1 trial. Differently, in A-B-A sequences, both B- and C-sets must be suppressed at the Nth trial.

In task-switching paradigms, conflicts may also arise at the stimulus processing level and at the response-preparation and -execution phases. According to Koch et al. (2010), the most crucial contribution to backward inhibition comes from this late stage of task processing, i.e., when task set retrieved from cued are activated through the match with the stimulus and the performance is concluded through the response. Through the combination of a task-switching and a Go/NoGo paradigm, Schuch and Koch (2003) and Philipp et al. (2007a) highlighted the prominent role of response selection and response execution (of the N-1 task) in determining the N-2 repetition cost. When the N-1 trial required participants not to respond, N-2 repetition cost disappeared. The same results were obtained when the N-1 trial required a double-press (Schuch and Koch, 2003), evidencing that task-execution is much more involved.

Similarly, Gade and Koch (2007) implemented a four-tasks paradigm, three with overlapping response-set and one univalent. Accordingly, no N-2 repetition cost was observed when the N-1 task was univalent. The valence of response mappings appears to be a fundamental dimension to exert interference in task sets and, thus, requiring BI to be triggered. Moreover, N-2 repetition cost was found even when participants were engaged in covert responses in trial N-1 in a motor imagery task (Scheil et al., 2019). However, interference at the response stage does not take into consideration the role of stimulus-related processing. Sdoia and Ferlazzo (2008) interestingly provided evidence that a task only requiring stimulus encoding in N-1 can trigger inhibition. Crucially, in their study, the N-2 repetition cost was observed only when this task presented overlapping stimuli but not when these were univalent, arguing for the prominent role of stimulus-related interference.

One possibility for clarification is the use of electrophysiological techniques. However, just a few studies implemented electrophysiological techniques in the investigation of BI processes. Until now, only a few studies investigated backward inhibition processes by using event-related potentials (ERP). Sinai et al. (2007) and Zhang et al. (2016) found increased negativity over parietal sites in BI trials. Sinai et al. (2007) found increased response-locked negativity over parietal sites, and an earlier onset of lateralized readiness potential, suggesting the role of conflict resolution in triggering the BI. Moreover, they found a reduced/enhanced N2/P3 cue-locked activity over centroparietal sites.

Recent evidence (Giller et al., 2019a; 2019b; Wolff et al., 2018; Zink et al., 2019; Zhang et al., 2017) reported that mostly at early stages processes involved in suppressing task-irrelevant information at the target level (P1/N1 components at inferior-frontal gyrus) are modulated in BI trials.

Electrophysiological techniques highlighted that parietal (Sinai et al., 2007; Zhang et al., 2016) and frontal (Giller et al., 2019a; 2019b; Wolff et al., 2018) regions are concurrently involved in the generation of BI effect. Similarly, neuroimaging studies highlighted the involvement of frontal regions (Dreher and Berman, 2002; Mayr et al., 2006) but also basal ganglia and premotor areas (Whitmer and Banich, 2012) and supplementary motor areas (Zink et al., 2019). Recent results also found that continuous theta-burst stimulation on the cerebellum selectively decreased RT on A-B-A sequences (Picazio et al., 2020). Up to now, research on brain mechanisms involved in task inhibition is still at its first steps. More knowledge on this point is paramount to address the research on cognitive control mechanisms underlying sequential task-switching and helps in understanding the central or distributed nature of control and executive functions. In the same field, several other intriguing answers necessitate more investigation. For instance, it is unclear whether backward inhibition represents a domain-general or -specific mechanism, partially reflecting the question on the multiple or unitary nature of controlled processes. In a series of studies, Arbuthnott et al. (2002; 2005) observed a dissociation between spatial and verbal cues, with spatially featured cues unable to trigger BI. However, verbalizing cues were found to increase competition even with spatialized cues (Arbuthnott et al., 2005). Arguably, the spatial location of cues may reduce the competition of albeit automatically activated response codes, especially when targets are digits, as shown in the SNARC effect (Dehaene et al., 1993). The dissociation between a visuospatial and a verbal task-switching paradigm was also found in individuals with Williams Syndrome (Foti et al., 2015a; 2015b), supporting a domain-specific model of BI. Other evidence comes from language-switching investigations, even though in this field research has produced opposite results and interpretations (Babcock and Vallesi, 2015; Branzi et al., 2016; Guo et al., 2013a; 2013b; Philipp and Koch,2009; 2007b), and in the context of ego-depletion hypothesis, observing that switching-based depletion and not choice-based depletion is capable of reducing BI effect as a domain-specific process (Zhang et al., 2017).

Characteristics of controlled processes are their flexibility and sensitivity to contexts and research has investigated the modulation of BI relatively to sequence effects. Nevertheless, Philipp and Koch (2006) reported that the mere presence of repetitions in the task could reduce the BI-related cost. Moreover, as well as standard task-switching performance, N-2 repetition cost is subject to asymmetric costs (Arbuthnott, 2008). Schuch and Grange (2015) also observed that it depends on N-3 trials, in that A-B-A sequences preceded by a B trial are faster than the same sequences preceded by a C trial. Also, task dominance has been found to increase N-2 repetition cost (Jost et al., 2017), a result in line with the one of Sexton and Cooper (2017), who found slower performance on hard-easy-hard compared to easy-hard-easy sequences even though their finding was the opposite of the ones by Arbuthnott (2008), who found higher cost for easy-hard-easy sequences. Accordingly, Schneider (2007) found a reduced BI when manipulating task-goals by inducing participants to chunk sequences compared to between chunks.

Another main topic regarding BI is if, as controlled processed, it is subject to practice effects. In fact, research has shown that BI is reduced after extensive practice (Grange and Juvina, 2015; Scheil, 2016; Zink et al., 2019) with more substantial effects when participants have weaker cue-target associations (Houghton et al., 2009) and showing the same behavior of controlled processes (Schneider and Shiffrin, 1977) with variable-constant response mappings (Scheil, 2016). The results observed identify the strengthening of task-related memory elements as a critical factor in reducing the impact of inhibitory mechanisms, as predicted by computational models (Grange et al., 2013). Nevertheless, the role of episodic retrieval in determining BI-related costs have been evidenced (Grange et al., 2017; Mayr, 2002).

While practice effects appear to be quietly demonstrated, supporting the notion of controlled processes, research on the development of BI during the lifespan is not conclusive. Whereas Li and Dupuis (2008) found no age-related effects on BI between young and old adults, Pettigrew and Martin (2016) found a higher cost in older adults and Giller et al. (2019) in adolescents. The very few studies do not permit to conclude possible age-related deficits in BI, but a recent metanalysis on several inhibition paradigms reported that N-2 repetition cost is not affected by aging (Rey-Mermet and Gade, 2018).

Despite the growing collected evidence on backward inhibition processes, the mechanisms underlying are still not precise. What can be assumed is that it is not a unitary phenomenon, but different processes are involved, probably evidencing differential roles of top-down and automatic processes, and different contribution among different controlled mechanisms. Indeed, literature has shown that backward inhibition: do not depend upon preparatory processes, but it is reduced by practice and can be modulated by sequence effects; it is modality independent but appears to be domain-specific about the materials that constitute task sets; cue- and task-sets related processes are differently involved in the triggering of and overcome from BI; frontal areas involved in flexible cognitive control are strongly implicated in determining the N-2 repetition cost but also other brain areas such as parietal cortices, premotor areas, basal ganglia, and cerebellum, are found to be strictly associated; evidence of modulations with aging are inconsistent. This variety of results makes the BI a fascinating phenomenon to study, necessarily through a multicomponent account. However, even though it represents a robust effect, at an inter-individual level, it looks not reliable (Kowalczyk and Grange, 2017) and analysis considering individual differences are being preferred in the investigation of multiple aspects of BI mechanisms.

This experimental chapter

The focus in this chapter is on task-switching performance, an excellent example of the interplay between automatic and controlled mechanisms. Specifically, the three experiments in this section regard the investigation over the processes responsible for the backward inhibition phenomenon or the N-2 repetition cost, which is the slow performance in a three-tasks paradigm for the third task of the A-B-A sequences compared to the C-B-A ones. At least two phenomena are implicated in this kind of inhibition: the triggering of inhibition (which in part overlap the one seen in the standard switch-cost) and the overcome from that inhibition. Differently from switch-cost, of which participants might be aware, backward inhibition is usually unconscious and might indicate the influence of a lateral rather than a central cognitive inhibition mechanism. That point already reflects a misalignment existent in backward inhibition: i.e., a controlled process that presents characteristics of the System 1 (non-conscious). The studies conducted and reported in this section aimed at further highlighting similar misalignments. Indeed, a dual-system account should provide evidence that controlled processes (such as task-switching) is simultaneously unitary, domain-general, and dependent on late cognitive and electrophysiological mechanisms. The findings obtained report that this is not the case.

In the first study (Sdoia et al., 2020), subjects were tested in the backward inhibition task in three different transcranial direct current stimulation (tDCS) sessions. Results showed that the parietal or frontal cortex's stimulation led to a dissociation of effects, suggesting a differential, and probably interacting, functional role, relying upon a distributed rather than central network. In the second study, to investigate if the backward inhibition acts at a higher-, semantic-level, the standard behavioral task was manipulated by changing the format of the target stimulus in the N-1 task, comparing triplets with format change and unchanged. N-2 repetition costs was abolished in the format change condition, evidencing that task-set inhibition operate at low-, perceptual, stimulus-related levels rather than on abstract, high-level material. Finally, in the last study the task-switching paradigm was integrated with a Go-NoGo/Stop Signal paradigm, and scalp event-related potential were recorded, to investigate at a more fine-grained level the mechanisms underlying backward inhibition. Data has shown that backward inhibition does not rely upon only late processes but that differential electrophysiological sequential changes for cue- and target-related processes, possibly highlighting a dual-pattern of bottom-up/top-down effects.

Anodal tDCS over the right parietal but not frontal cortex enhances the ability to overcome task set inhibition during task switching

Abstract

Switching between tasks requires individuals to inhibit mental representations of the previous task demands and to activate representations of the new task demands. The inhibition of the executed task remains active for a while so that when the inhibited task set must be re-activated shortly after, the need to overcome residual task set inhibition leads to behavioral costs.

In a sham-controlled balanced-order within-subjects experimental design we investigated whether applying right anodal/left cathodal transcranial direct current stimulation (tDCS) over the dorsolateral prefrontal or parietal cortex modulated the ability to overcome persistent task inhibition during task switching. Results showed that right anodal/left cathodal tDCS over the parietal cortex improves performance selectively when switching back to a recently inhibited task that requires previous inhibition to be overcome. Right Anodal/left cathodal tDCS over the prefrontal cortex improves performance during task switching in general, either when re-engaging in a inhibited task or when engaging in a noninhibited task. Results suggest a different contribution of prefrontal and parietal regions to task switching, with parietal cortex being selectively involved in overcoming persistent task inhibition and prefrontal cortex being more generally involved in the control of task set during task switching.

Introduction

The ability to flexibly adjust behavior to a changing environment by promoting the processing of current goal-relevant information at the expense of the no longer relevant one is a key factor for efficient adaptation and survival, particularly when irrelevant information interferes with current intention, eliciting conflicting responses. Behavioral adaptation to external changes is supported by cognitive control processes, a set of neurocognitive mechanisms that, based on current goals establish internal constraints on the way we process external information, defining—for instance—the information to attend to at the perceptual level (e.g., the color), at the motor level (left hand movement), and the association between potential stimuli and responses (e.g., if red press the left button). Thus, cognitive control grants behavioral flexibility by establishing and strategically modifying the task set, that is the transient and arbitrary associations between mental representations of stimuli and responses in accordance with current goals (i.e., task set; Monsell, 2003).

Response adaptation to changing task demands has been often studied in laboratory by means of the task switching procedure, wherein participants typically alternate between performing each of two or more possible tasks afforded by the same stimulus (see Kiesel et al., 2010 and Vandierendonck et al., 2010 for reviews). In this procedure, the control settings appropriate for one task become no longer relevant when a new task is required, so that cognitive control is necessary for the instantiation of the appropriate task set (e.g., defining the new relevant information at perceptual and motor levels). The need to reconfigure the internal control settings required to perform a new task is considered a source of the so-called switch cost (Rogers and Monsell, 1995; Rubinstein et al., 2001; Sohn and Anderson, 2001), that is the reaction time (RT) difference that typically results from the slower performance on trials where the participant has to switch to a different task (switch trials) compared to trials where the participant has to repeat a task (no-switch trials). Interestingly, no-longer-appropriate task sets remain active after their instantiation (Allport et al., 1994; Allport and Wylie, 1999; Altmann and Gray, 2008; Yeung and Monsell, 2003; Goschke, 2000), interfering proactively with the new task set, so that when rapidly shifting from one task to another inhibition could be necessary to counteract this persistent activation and to switch efficiently to the new task (see Koch et al., 2010 for a review).

Importantly, the inhibition of the executed task remains active for a while so that when the inhibited task set (e.g., task A) is reactivated shortly after, as in an A–B–A task sequence, it is unlikely that it has fully recovered from previous inhibition. The need to overcome this suppressed state leads to a behavioral cost, named n-2 task repetition cost, which has been demonstrated by showing that switching back to a task that has been executed very recently (e.g., A-B-A task sequences) is harder than switching back to task that has been executed a less recently (e.g., C-B-A task sequence; e.g., Mayr and Keele, 2000; Arbuthnott and Frank, 2000).

This form of inhibition (also known as backward inhibition; Mayr and Keele, 2000) has attracted interest in cognitive psychology mostly because it seems to target high-level mental representations, such as the whole task set, rather than individual perceptual features (e.g., red color; e.g., Tipper, 2001) or motor responses (e.g., left-hand button press; e.g., Logan, 1994). On these grounds, task inhibition has been subject to intense research in cognitive psychology, but its neural mechanisms remain unclear.

Neuroimaging studies consistently suggest that both frontal and parietal regions play a crucial role in task switching (e.g., Braver et al., 2003; Crone et al., 2006; Dove et al., 2000; Liston et al., 2006; Sohn et al., 2000; Sylvester et al., 2003; Yeung et al., 2006) but the individual contribution of these brain regions to task set inhibition has remained largely uninvestigated. Dreher and Berman (2002) reported larger activity in the right lateral prefrontal cortex, as assessed by functional magnetic resonance imaging, when switching to a task recently performed compared when switching to a task less recently performed (i.e., ABA versus CBA task sequence), and suggested that the right prefrontal cortex plays a role in overcoming task inhibition. Consistent with this result, a reduced task inhibition was also reported in participants with damage to the right, but not to the left, lateral prefrontal cortex (Mayr et al., 2006). However, larger activity during task switching was also reported in other brain regions in participants who were good at inhibiting previous task sets, such as the basal ganglia and supplementary motor area/premotor area, compared to participants who were less good at inhibiting an irrelevant task (Whitmer and Banich, 2012). On the other hand, electrophysiological studies consistently reported increased negativity at parietal sites when switching back to a recently executed task (Sinai et al., 2007; Zhang et al., 2016) suggesting that the parietal cortex also plays a role in task inhibition. Hence, findings from neuroimaging and electrophysiological studies reported modulation of brain activity at both frontal and parietal sites related to inhibition of irrelevant task set, and converging evidence are still needed to clarify the specific contribution of these regions.

Insight into the neural mechanisms of task set inhibition can be obtained by actively manipulating the neural activity of specific brain regions that are supposed to be involved in task inhibition and assessing the impact of this perturbation on behavioral performance (i.e., n-2 task repetition cost). One possibility to non-invasively modulate the cortical excitability is offered by transcranial direct current stimulation (tDCS; Priori et al., 1998). tDCS allows transient modulation of spontaneous neuronal excitability through the delivery of a low constant electric current flow through two electrodes applied to the scalp. This electric current flow alters the polarization of the resting membrane potential, such that cortical excitability is increased in the region below the anode electrode and decreased in the region below the cathode electrode (Nitsche and Paulus, 2000; 2001; Wassermann and Grafman, 2005).

The goal of the present study was to investigate whether applying tDCS at frontal and parietal sites modulates the ability to overcome the persistent inhibition during task switching, as assessed by the n-2 task repetition cost. Specifically, in a sham-controlled, balanced-order within-subject experimental design, right anodal/left cathodal tDCS was applied over prefrontal or parietal scalp sites during a task switching procedure. The mean accuracy and reaction times (RTs) were recorded to assess performance on trials wherein participants had to switch back to a previously inhibited task (ABA switch sequence), wherein they had to switch back to a non-inhibited task (CBA switch sequence), and wherein they had to repeat the same task they performed on the previous trial (AA no-switch sequence).

Methods

Participants

20 healthy subjects with a mean age of 26.3 years (s.d. 3.64; 12 women) participated in the study. All participants reported normal or corrected-to-normal vision, no history of neurological or psychiatric disorders, and no ongoing medication. They all were naïve to the aims of the study. The sample size was defined through power analysis, using a medium to large partial eta2 of 0.2 for the higher order interaction and a power of 0.90 to increase the chance of replicability.

The study was approved by the Ethics Committee of the Department of Psychology at the Sapienza University and conducted in accordance with its policies. All participants provided written informed consent.

Procedure

Task cues were black geometrical frames (a square, a diamond, and a circle) with a size of about 6 cm by 6 cm, centrally presented on a grey background. Stimuli were digits from 1 to 9, except for the digit 5 that was never presented. Each digit was about 2 cm in height and 1cm in width, and was centrally presented, superimposed on the task cue.

Participants performed three different numerical judgment tasks: a magnitude task, requiring participants to indicate whether the digit was smaller or larger than five; a parity task, requiring participants to indicate whether the digit was an odd or an even number; and a position task, requiring participants to indicate whether the digit was centrally or peripherally positioned along the number line (3, 4, 6, and 7 were considered central digits; 1, 2, 8, and 9 were considered peripheral ones). The magnitude task was cued by the diamond, the parity task by the square, and the position task by the circle.

Participants responded by pressing the A key of a standard QWERTY keyboard to the smaller-than-5, even, and centrally positioned digits, and with the L key to the larger-than-5, odd, and peripherally positioned digits. Participants were tested individually in a dimly lit testing room. The cues and the stimuli were centrally presented on a 17-inches computer monitor (refresh rate: 60 Hz) placed 60 cm from the participant. The experiment was programmed in E-Prime on a computer running the Microsoft Windows XP operating system.

Instructions about the tasks, the cue-task associations, and the category-response associations were displayed on the screen and verbally detailed to each participant at the beginning of the experiment.

The experiment consisted of four blocks of 96 trials each. On each trial, the task cue was presented first. After 600 ms, the stimulus was presented over the task cue. Participants were required to respond to the stimulus as fast as possible, according to the task rules indicated by the task cue. In case of an error, an auditory error feedback was provided for additional 50 ms. Error feedback was also provided for reaction times slower than 2500 ms. The experiment started with the participant pressing the space bar.

Task sequences were pseudo-randomized with the constraints of having approximately 100 ABA switch trials, 100 CBA switch trials, and 100 AA no-switch trials. No-switch trials were included as a control condition, as we expected the tDCS to selectively affect performance on switch trials (ABA and CBA) and not on no-switch trials, and also to reduce potential expectancy-related effects due to having only switch trials.

Transcranial direct current stimulation

In three separated task-switching sessions one week apart, all participants underwent three different right anodal/left cathodal stimulation conditions: frontal, parietal, and sham tDCS during the task performance (online stimulation). In the frontal stimulation condition the anode was placed over the right dorsolateral prefrontal cortex (F4 according to 10–20 EEG International System) whereas the cathode electrode was placed over the left dorsolateral prefrontal cortex (F3). In the parietal stimulation condition the anode was placed over the right parietal site corresponding to P4 and the cathode electrode over P3. In the sham condition, electrodes placement was the same of the frontal condition. Session order was randomized across participants.

During the two active sessions, a direct current of 1.5 mA was induced by two saline-soaked circular sponge electrodes (3 cm diameter, density 0.2 mA/cm2) and delivered by a battery-driven constant current stimulator (BrainStim E.M.S., srl Bologna, Italy) with a fade in/fade out ramp of 45 s. In the sham condition, the stimulation only involved the fade in/fade out phase and 2 seconds of stimulation.

Results

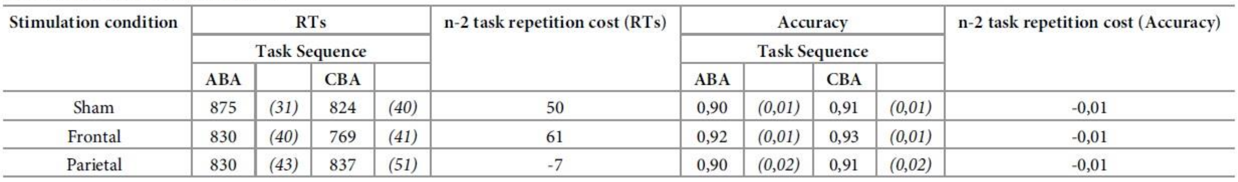
Mean individual reaction times (RTs) and error rates (ERs) were analyzed in a 3 X 2 repeated measures ANOVA design using Stimulation (frontal, parietal, and sham) and Sequence (ABA and CBA) as independent variables. The first block was considered as practice and excluded from the analyses. Only ABA and CBA task sequences with correct responses on trials n, n– 1, and n– 2 were included in the RTs analyses. One participant was excluded from the analyses because of poor task accuracy and extremely slow RTs (percent of correct responses was more than two standard deviations below the group mean and the RTs average was more than two standard deviations above the group mean in the frontal session). Mean RTs and ERs for all the conditions are reported in Table 1.

For RTs data, the ANOVA revealed a significant main effect of the Sequence (F(1, 18) = 12.987, p = 0.002, ηp 2 = 0.419), showing slower RTs for sequences ABA (846 ms) compared to CBA (810 ms), indicating that a significant n − 2 repetition costs occurred. The main effect of the Stimulation was not significant (F(2, 36) = 0.576, p = 0.567). Importantly, the Sequence by Stimulation interaction turned out to be significant (F(2, 36) = 4.137, p = 0.024, ηp2 = 0.187), indicating that the n-2 repetition cost was modulated by the tDCS. Specifically, Duncan post-hoc tests revealed that the RTs were significantly shorter during the right anodal/left cathodal tDCS of the prefrontal cortex than during the sham stimulation on both the ABA (p = 0.025) and CBA sequences (p = 0.004). This indicated that tDCS over the frontal cortex affected the performance on trials where participants switched back to an inhibited task set as well as where they switched to a non-inhibited tasks. Furthermore, Duncan post-hoc test also showed that the RTs on the CBA sequences during the right anodal/left cathodal tDCS of the parietal cortex were not significantly different from those observed during the sham stimulation (p = 0.535). Interestingly, the RTs on the ABA sequences during the right anodal/left cathodal tDCS of the parietal cortex were significantly shorter than those of the ABA sequence during the sham stimulation (p = 0.027). This indicated that tDCS over parietal cortex affected selectively the performance on trials where participants switched back to an inhibited task. To further specify tDCS modulation of performance we also tested for change in the size of the n-2 task repetition cost in a one-way ANOVA according to the stimulation condition (Sham, Frontal a nd Parietal; see Fig 1). The significant effect of the stimulation condition (F(2,36) = 4.137, p = 0.024) revealed that there were no significant differences between the n-2 task repetition cost under the sham and frontal tDCS (51 and 62 msec, respectively; p = 0.668 Duncan test). Importantly, the n-2 task repetition cost during parietal tDCS (- 7 msec) was significantly different from the n-2 task repetition cost during both sham (51 msec) and frontal (62 msec) tDCS (parietal vs sham: p = 0.031; parietal vs frontal: p = 0.015). This indicated that the right anodal/left cathodal tDCS of the parietal cortex significantly reduced the n-2 task repetition cost.

We also analyzed the effects of tDCS on the repetition trials in a one-way ANOVA in order to ruled out the hypothesis that tDCS affected the performance in an unspecific way, for instance by globally reducing or increasing the RTs regardless of the switch or repetition requirements. Results revealed that RTs were the same on sham, frontal and parietal tDCS (F(2, 36) = 0.695, p = 0.505), indicating that tDCS had no effects on no-switch trials.

The ANOVA on mean individual error rates did not reveal any significant main effect or interaction (Stimulation: F(2, 36) = 1.372, p = 0.266; Sequence: F(1, 18) = 1.323, p = 0.265; Stimulation X Sequence: F(2, 36) = 0.101, p = 0.903), indicating that the accuracy was the same regardless of the type of stimulation and the type of task sequence.

Table 1. Mean reaction times, accuracy and n-2 task repetition costs as a function of the stimulation (sham, frontal and parietal) and the task sequence (ABA and CBA). Standard errors are in brackets.



Stimulation condition	RTs				n-2 task repetition cost (RTs)	Accuracy				n-2 task repetition cost (Accuracy)
	Task Sequence					Task Sequence				
	ABA		CBA			ABA		CBA		
Sham	875	*(31)*	824	*(40)*	50	0,90	*(0,01)*	0,91	*(0,01)*	-0,01
Frontal	830	*(40)*	769	*(41)*	61	0,92	*(0,01)*	0,93	*(0,01)*	-0,01
Parietal	830	*(43)*	837	*(51)*	-7	0,90	*(0,02)*	0,91	*(0,02)*	-0,01

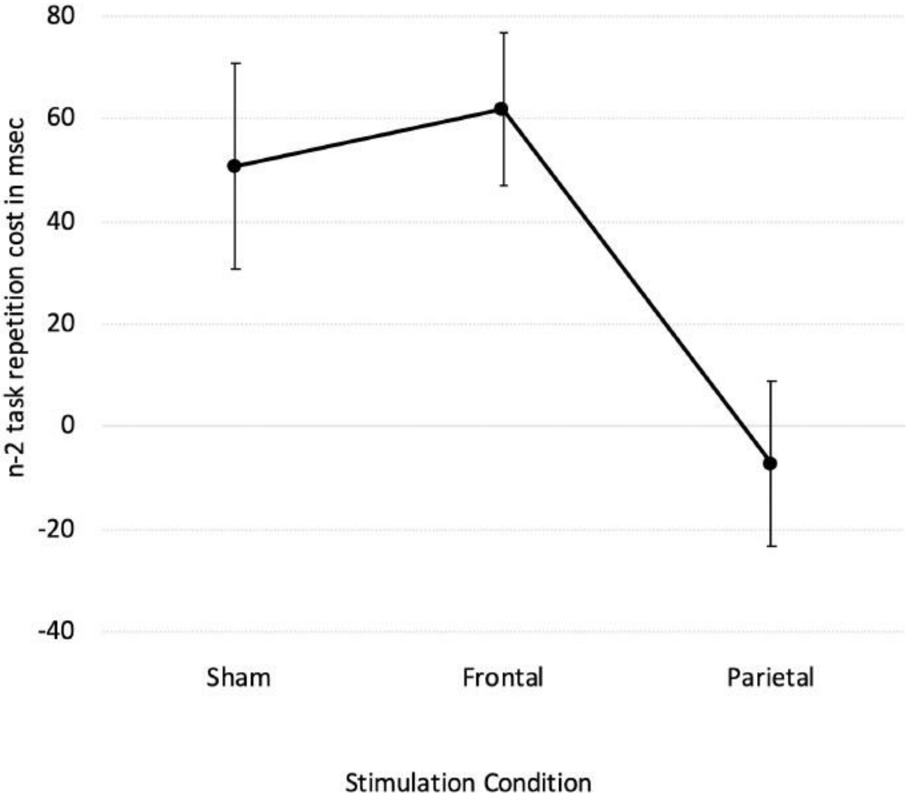


Fig 1. n-2 task repetition costs as a function of the tDCS conditions (Sham, Frontal, Parietal). Bars denote standard errors.

Discussion

In the present study we investigated whether applying right anodal/left cathodal tDCS over the dorsolateral prefrontal or parietal cortices improves the ability of overcoming persistent task inhibition during task switching.

Results revealed that right anodal/left cathodal tDCS of the dorsolateral prefrontal cortex did not affect the ability of overcoming persistent task inhibition. Indeed, tDCS of the prefrontal cortex determined a general improvement when a task switching was required compared to when the same task was repeated, but the size of this improvement was the same either when re-engaging an inhibited task, and thus the previous inhibition had to be overcome, or when switching to a task that did not suffer from previous inhibition. Importantly, right anodal/left cathodal tDCS of the parietal cortex improved the performance selectively when re-engaging a previously inhibited task, without affecting the performance when switching to a task that did not suffer from previous inhibition, eliminating the n-2 task repetition cost completely (Fig 1).

This suggests that the parietal cortex has a role in overcoming persistent inhibition of a previously executed task when re-engaging it. Of importance, neither the frontal nor the parietal tDCS affected the performance on the no-switch trials, indicating that the effects of the tDCS over the prefrontal and parietal cortices did not determine a general performance modulation, but selectively influenced the processes involved in task set switching. The findings that prefrontal stimulation improved the task switching ability and that this improvement equally affected the performance when switching to a non-inhibited task as well as when re-engaging an inhibited task (without affecting no-switch trials) support the idea that the prefrontal cortex has a role in cognitive control processes involved in task set switching, and they are consistent with previous imaging and ERPs studies. The role of prefrontal cortex in task switching has been largely documented (see Worringer et al., 2019 for a review), and neuroimaging studies have shown prefrontal activations across a variety of stimuli and paradigms (see Kim et al., 2012 for a meta-analysis). The lateral PFC activity has been frequently interpreted as reflecting transient cognitive control operations associated with task switching, such as the endogenous task-set reconfiguration (Sohn et al., 2000). Indeed, the prefrontal cortex has been suggested to exert top-down control to maintain or to update task representations (Yeung et al., 2006; Desimone and Duncan, 1995; Miller and Cohen, 2001). Importantly, the present findings suggest that the role of prefrontal cortex is not selectively related to the ability of overcoming persistent task inhibition. Although caution is necessary when comparing findings from different techniques, this result appears inconsistent with the fMRI result reported by Dreher and Berman (2002), who found that the right lateral prefrontal cortex was more activated when switching back to a task recently performed compared to a task less recently performed. However, methodological differences exist between the experimental procedure used by Dreher and Berman (2002) and our present procedure that may explain the different results. For instance, the experimental procedure used by Dreher and Berman (2002) involved the presentation of triplets of tasks that were constructed with the constraints of having only three possible task sequences, namely the ABA, CBA and BAA, instead of a randomized sequence of tasks. Presenting stimuli in specific triplets allowed to maximize the occurrence of task sequences that are relevant for the intended comparisons (e.g., ABA and CBA) but it could incidentally induce implicit expectancy about the identity of the upcoming task or about the sequence of task presentation. For instance, due to the heuristic of representativeness (Tversky and Kahneman, 1974), in a situation where three tasks are possible and the tasks are presented in separated triplets of trials, people may judge on each triplet the CBA sequence as more probable than the ABA sequence of tasks. This may induce participants to expect the CBA triplets more than the ABA triplets or to expect a n-2 task switching (i.e., CBA) more than a n-2 task repetition (i.e., ABA). If that were the case, the ABA task sequence would also represent a violation of an implicit expectancy and thus, the prefrontal activation reported by Dreher and Berman (2002) could reflect an expectancy-related effect. Consistent with this hypothesis, evidence has been recently provided that internally generated predictions about the likelihood of a change in task demand are represented in dorsolateral prefrontal cortex (Jiang et al., 2018). In the present study, this type of expectancy-related effects can be ruled out because, unlike the procedure used by Dreher and Berman (2002), we used a cued-task switching procedure where the occurrence of a task cue on each single trial informed participants about the identity of the upcoming task before each stimulus presentation and without uncertainty; most importantly, each trial was presented one after another and in a randomized order of task presentation, so that the effects that incidentally may induce the occurrence of specific sequences of tasks can be controlled for.

Crucially to the goal of the present study, right anodal/left cathodal tDCS of the parietal cortex improved the performance only when re-engaging in a task that has been recently inhibited, without affecting the performance when switching to a task that did not suffer (or suffered less) of previous inhibition. This suggests that the parietal cortex has a specific role in overcoming task set inhibition during task switching. Prior findings provide support to this idea. The parietal cortex has been found to be consistently activated during task switching (compared to task repetition) in fMRI studies (Braver et al., 2003; Crone et al., 2006; Dove et al., 2000; Liston et al., 2006; Sohn et al., 2000; Yeung et al., 2006; Le et al., 1998; Rushworth et al., 2001). A common region of the superior parietal lobule has been also identified as a source of cognitive control during shifts between perceptual, mnemonic, and rule representations, indicating that the parietal lobe plays a domain-independent role in the instantiation of a new task set (Esterman et al., 2009). This domain-independent feature is what would be required to a brain structure that is supposed to be involved in inhibitory control and that operates at the level of the whole task set representation rather than on individual stimulus or response features. The superior parietal cortex was also found to be more active for bivalent than for univalent stimuli (Crone et al., 2006), that is when stimuli elicit multiple competing tasks, and the need for inhibition is strong, than when stimuli are uniquely associated with a single task and there is no task interference and, thus, no need of task inhibition. The domain-independent feature, together with the high neural activity for bivalent stimuli strongly suggests the parietal cortex as a potential candidate for hosting neural population involved in overcoming persistent task inhibition.

Converging evidence to the involvement of parietal cortex in task inhibition also comes from electrophysiological studies. An increased negativity at parietal sites has been reported when switching back to a recently executed task than when switching to a less recent task (Sinai et al., 2007; Zhang et al., 2016). More generally, the hypothesis that the parietal cortex is involved in overcoming task inhibition during task switching fits well with findings showing the involvement of parietal cortex in conflict resolution (e.g., Liston et al., 2006). For instance, the neural activity in posterior parietal cortex has been shown to vary with a physiologic index of conflict in competing processing neural pathways and to predict an enhanced behavioral adjustment (Liston et al., 2006).

However, cognitive and neural processes that mediate the overcoming of inhibition remain largely unclear. Evidence exists that task inhibition can be observed when interference between competing task sets occurs at the stimulus processing level (e.g., Arbuthnott and Woodward, 2002; Hübner et al., 2003; Sdoia and Ferlazzo, 2008) as well as when it occurs at the response level (e.g., Schuch and Koch, 2003; Gade and Koch, 2007). Several studies suggest that posterior parietal cortex is anatomically well suited to detect stimulus conflict (e.g., stimuli eliciting multiple tasks), as it receives input from the extrastriate visual cortex and sends projections to lateral prefrontal cortex (Wise et al., 1997). Previous studies have also emphasized a role for posterior parietal cortex in facilitating goal-directed attention to task-relevant aspects of a visual stimulus (Corbetta et al., 2000; Corbetta and Shulman, 2002). Thus, overcoming task inhibition could be mediated by biasing attention processes toward the current stimulus set, enhancing processing of task-related stimulus dimensions. Alternatively, the parietal cortex may support overcoming of inhibition by enhancing control over response-related features of the task set, for instance by enhancing representations of category-response rules (e.g., Philipp et al., 2013).

Evidence for involvement of parietal cortex in representations of stimulus-response associations or action rules do exist (Philipp et al., 2013; Brass and von Cramon, 2004). However, parietal cortex has been also involved in stimulus categorization (e.g., Liston et al., 2006). Since in our present procedure the task conflict occurred at both stimulus and response level (i.e., stimuli could elicit all the three possible tasks and the same motor responses were used for all the three possible tasks) it is not possible here to disentangle whether the role of parietal cortex in overcoming persistent inhibition is related to stimulus processing or to response-selection. Future studies could investigate whether frontal and parietal tDCS differently affect stimulus-related and response-related aspects of task inhibition.

One limiting factor of the current study was that on-line changes of neural activity in prefrontal and parietal cortex were not directly assessed during tDCS. This leaves open the possibility that tDCS also affected neural activity of other cortical regions.

In summary, our results show that experimentally-induced alterations of neural activity via right anodal/left cathodal tDCS of the dorsolateral prefrontal cortex and parietal cortex modulates performance during task switching, supporting previous observations about the involvement of both parietal and frontal cortex in cognitive control of task set. Importantly, right anodal/left cathodal tDCS of the parietal cortex improves performance only when switching back to a recently inhibited task and that thus requires previous inhibition to be overcome.

Right anodal/left cathodal tDCS of the prefrontal cortex improves performance during task switching in general, either when re-engaging in a inhibited task or when engaging in a noninhibited task, thus without affecting the ability to overcome task inhibition. This suggests a different contribution of prefrontal and parietal regions in task switching, with parietal cortex being selectively involved in overcoming persistent inhibition and prefrontal cortex being more generally involved in the control of task set during task switching.

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The impact of stimulus format on task inhibition during cued task switching

Abstract

Inhibiting mental representations of tasks that are no longer relevant is essential for an optimal adaptation of behavior in a rapid-changing environment. However, switching back to recently inhibited tasks is more demanding than switching to a less recently inhibited task (i.e., backward inhibition). Such mental representations are named task-sets, representing stimuli-response associations bound to contextual information. Although backward inhibition is assumed to operate on task-sets, it is not currently known if it acts on a conceptual/abstract representation of task-sets' meaning or on low-level objects' properties. Then, we addressed this question by implementing a typical task-switching paradigm with three different tasks, manipulating the stimulus format (Arabic or verbal numbers) in the N-1 task without changing its meaning. In two experiments, we found that N-2 repetition costs are eliminated if the stimulus format in the N-1 task changed, suggesting that backward inhibition occurs when interference is detected between overlapping object properties. Furthermore, our results supported the idea that stimulus processing plays a pivotal role in inhibitory mechanisms in a cued task-switching environment.

Introduction

Switching between tasks requires to inhibit mental representations of the previous task demands and to activate representations of the new task demands. The inhibition of the executed task remains active for a while so that when the inhibited task-set must be re-activated shortly after, the need to overcome residual task-set inhibition leads to behavioral costs. In task-switching paradigms, where participants must perform three different tasks sequentially, an N-2 task repetition cost can arise. That has been demonstrated by showing that switching back to a task that has been executed very recently (e.g., A-B-A task sequences) is more demanding than switching back to the task that has been executed a less recently (e.g., C-B-A task sequence). Interestingly, this form of inhibition (also known as backward inhibition; Mayr and Keele, 2000) is assumed to act on high-level mental representations, such as the whole task-set, rather than on low-level perceptual features of stimuli (Tipper, 2001) or motor responses (Logan, 1994). The peculiarity of backward inhibition has intrigued the psychological scientific community, making the N-2 repetition cost a broad interest phenomenon in cognitive control research.

Recently, the N-2 repetition cost has been subject to investigations aimed at clarifying the causes and processes underlying backward inhibition and the necessary conditions for the phenomenon to occur or be influenced by.

For instance, literature has shown that task-set inhibition is modulated by many factors, including the preparatory interval in trial *N-1*, the response-cue interval (RCI), the cue type, and the overlapping of stimuli and/or responses. Instantly, transparent cues that provide a clear link to the upcoming task and the to-be applied response significantly reduced $n-2$ task repetition costs (Gade and Koch, 2014). Differently, N - 2 task repetition cost has been observed under bivalent stimuli (overlapping stimulus sets) and not under univalent stimuli, that is when stimuli univocally afford only one of the possible tasks (non-overlapping stimulus sets) (Costa and Friedrich, 2012). Conversely, N-2 repetition cost has been found when the same task-set might be instantiated by two different cues, reporting no differences between a cue-switch (a-B-*A*) and a cue-repetition (A-B-*A*) (Altmann, 2007; Gade and Koch, 2008). Moreover, longer CTIs (Cue-Target Interval) lead to stronger inhibition (Scheil and Kleinsorge, 2014). Instead, prolonged RCIs produced small costs (Grange and Houghton, 2009; Koch et al., 2004; Mayr and Keele, 2000) and large costs when the preceding interval was very short (Gade and Koch, 2005), suggesting that strong residual activation of the preceding task triggers strong inhibition and that trial-by-trial conflicts are much more responsible for the mechanisms underlying backward inhibition than passive temporal decay. Indeed, sequential modulations of trials' dimensions have been largely fruitful in observing modulations of task-set inhibition. Generally, manipulations at the stimulus/response level (i.e., when the task-set must be applied) in the N-1 task have been shown to reduce or eliminate the N-2 repetition cost. For instance, when participants in the N-1 trial were required to not respond (Schuch and Koch, 2003; Philipp et al., 2007), to make an unspecific response (e.g., double-press; Schuch and Koch, 2003), to produce a covert response in a motor imagery task (Scheil et al., 2019), to perform a univalent task (Gade and Koch, 2007), or to solely encode a univalent stimulus (Sdoia and Ferlazzo, 2008), inhibition was not triggered and no need to overcome it was present (no difference between A-B-*A* and C-B-*A* sequences).

Then, evidence indicates that a sort of overlapping at the level of the stimuli and/or responses (e.g., the different tasks share the stimuli or the responses) or between-task interference due to stimuli affording more than one task is necessary for inhibition to be triggered, suggesting that backward inhibition occurs in case a conflict is detected (Koch et al., 2010; Houghton et al., 2009).

Here, we further investigated the boundaries conditions of stimulus overlapping (or interference) under which task inhibition occurs. Specifically, we aimed to investigate the impact of stimulus format on the inhibition of competing task-sets during cued task switching.

The role of stimulus format on task inhibition during task switching has never been investigated, though it is informative regarding the underlying nature of the task-set and its cognitive representation. For instance, it is informative about the processing level at which task inhibition does operate (e.g., semantic) or whether a high- or low- level representation of task stimuli is included in the task-set (e.g., semantic or perceptual, respectively).

Stimulus overlapping might produce interference at many different levels of information processing. For instance, overlapping or interference can occur at a high-level stimulus processing, such as the semantic level, or a more low-level stimulus processing, such as the perceptual or sensorial level. Stimuli that have the same meaning might produce task interference regardless of the sensory input or the format they are presented (semantic overlapping). I.e., stimuli can have the same meaning despite the difference in the sensorial input (visual vs. auditory) or the format (digit vs. word number) they are presented. Differently, stimuli must have the same perceptual code for inhibition to be triggered, such as they must have the same format (perceptual overlapping). For instance, dissociations for brain areas subtending the processing of verbal and Arabic numeral codes have been found (Skagenholt et al., 2018).

The present study's goal was to investigate the differential effect of stimulus format on task inhibition as assessed as the N-2 task repetition cost. Specifically, we aimed at assessing whether inhibition of the previous task-set is triggered during a cued switching of task despite the change of stimulus format between the previous and current tasks.

To this aim, we manipulated the sequence of tasks (ABA vs. CBA) in order to assess the basic N-2 task repetition cost together with the stimulus format on trial N-1 (digit - D vs. word - W), which could be the same or not as the stimulus format of the trial N-2 and N, resulting in a 2 (ABA and CBA) X 2 (DDD vs. DWD) experimental design.

If inhibition of the interfering task-set is triggered regardless of the perceptual code or stimulus format (e.g., symbolic or verbal) of the two competing task-sets, then the transition from A to B (AB) should trigger the same amount of inhibition than the transition from A to b (Ab). That should result in the same amount of N-2 task repetition cost when switching back to the inhibited task regardless of the perceptual code of the triggering stimulus (ABA vs. AbA). On the other hand, if the inhibition of the interfering task-set is only triggered when the perceptual code is the same on the current and the interfering task-set, then the transition from A to b should trigger a less amount of inhibition (or trigger no inhibition at all) than the transition from A to B. Conversely, that should result in a reduced

or even abolished N-2 task repetition cost when switching back to the inhibited task regardless of the perceptual code of the triggering stimulus (ABA vs. AbA).
Note that regardless of whether the format of the target stimulus was a digit (“3”) or a number word (“three”), the stimulus itself remained bivalent as it could afford each of the three possible tasks equally, meaning that the stimulus set remained overlapping even if the stimulus format changed.

Experiment 1

Methods

Participants

Thirty students (females = 14, mean age = 22.93, s.d. = 3.2) were recruited at the Faculty of Psychology of Sapienza University of Rome to participate in the study. All participants had a normal or corrected-to-normal vision. They all were naïve to the aims of the study and provided written informed consent. The study was approved by the Ethics Committee of the Department of Psychology at Sapienza University.

Procedure

Participants performed a cued switching task (similar to ones used in many previous studies). In each of the 570 trials, a task cue appeared at the center of the screen. Task cues were black geometrically shapes (a square, a diamond, and a circle) with a size of about 6 cm by 6 cm. Stimuli were numbers from 1 to 9 (except for the number 5) presented as digits or as their relative Italian words (e.g., “3” or “TRE”). After 600 ms from the cue presentation, the stimulus was presented, and the cue disappeared. Stimuli had a height of about 2 cm, with a width of about 1 cm for digits, whereas words ranged from a width of about 3 cm for the shortest number words (e.g., “SEI”) to a maximum of about 9 cm for the longest number word (“QUATTRO”). Participants had to respond to the target by pressing the key “A” or “L” over a standard QWERTY keyboard according to the current task-cue rule with their left or right index finger, respectively. Each of the three possible cues corresponds to a rule: the square cued a parity task (press “A” for even, “L” for odd numbers); the diamond cued a magnitude task (press “A” for smaller, “L” for numbers greater than 5); the circle cued a position task (press “A” for centrally, “L” for peripherally numbers positioned along the number line; 3,4,6, and 7 were considered central numbers).

The cues and the stimuli were black and centrally presented over grey background. The task was programmed in E-Prime 2.0 and was ran on a 17-inches computer monitor (refresh rate: 60 Hz) placed approximately 60 cm from the participant.

Instructions about the task were verbally provided and displayed on the screen to each participant before the experiment.

The task consisted of three blocks of 190 trials each. A trial started with the presentation of a task-cue. After 600 ms, the cue disappeared, and the stimulus was presented over it. Participants were required to respond as fast and accurately as possible. If participants made an error or took longer to respond (> 2500 ms), auditory error feedback was provided for an additional 50 ms. After the participant’s response, the stimulus disappeared, and the next cue was presented with 200 ms of blank interval.

Stimuli in the 25% of trials were presented as number words. We will refer to capital letters for the trials with the dominant code (digits in the present experiment) and lowercase letters for the infrequent code (number words in the present experiment). Task sequences were randomly intermixed for each participant with the constraints of having approximately 65 trials each for ABA, CBA, AbA, and CbA switch conditions, and AA repetition trials. Repetition trials were included as a control condition and to reduce potential expectancy-related effects due to having only switch trials. In addition, the randomization makes it possible to have approximately 40 trials each for ABa, CBa, aBA, and cBA switch conditions. Triplets of tasks were not explicit to participants in order to avoid any expectancy effects.

Participants performed 72 practice trials. The practice trials were constructed in this way: 30 digit-trials (10 for each task, non-intermixed), 30 mixed digits/words trials (75% / 25%) (10 for each task, non-intermixed), and 12 trials (4 for each task) wholly intermixed. If necessary, participants repeated the practice phase for a maximum of one additional time.

Results

We removed from the analyses three subjects since they presented a very high inverted N-2 repetition cost.

Mean individual reaction times (RTs) and error rates (ERs) were analyzed in a 2 X 2 repeated measures ANOVA design using the task sequence (ABA and CBA) and the stimulus format on trial

N - 1 (i.e., digit vs. number word, respectively - DDD vs. DWD) as independent variables. Task sequences in which an error occurred on trials N, N − 1, or N − 2 were excluded from RTs analyses. For RTs data, the ANOVA revealed non-significant main effects of the sequence ($p > 0.05$). Importantly, the sequence by stimulus format interaction was statistically significant ($F_{1, 26}$=15.3888, $p < 0.001$, partial eta squared = 0.37). Post-hoc test showed that RTs were significantly slower on ABA than CBA sequences on digit triplets, revealing an N-2 task repetition cost of 53 msec. Most important to the purpose of the present experiment, RTs on ABA sequences were significantly faster in the context of a change in stimulus format from Digit to Word from trial N-2 to N-1 (DWD) than when stimulus format remained a digit (DDD; 924 vs. 966 vs. msec, respectively; $p < 0.01$). Also, RTs on ABA sequences in the context of a change in stimulus format from trial N-2 to N-1 (DWD) did not differ significantly from RTs on CBA sequence when a change in stimulus format occurred ($p > 0.05$) (Figure 1).

Together these results indicated that when a change in stimulus format occurred in the context of a task switching, the inhibition of the abandoned task is not triggered, and switching back to the abandoned task after a change of stimulus format (AbA) is easier than when stimulus format remained the same (ABA), as indicated by the fact that N-2 task repetition cost was abolished.

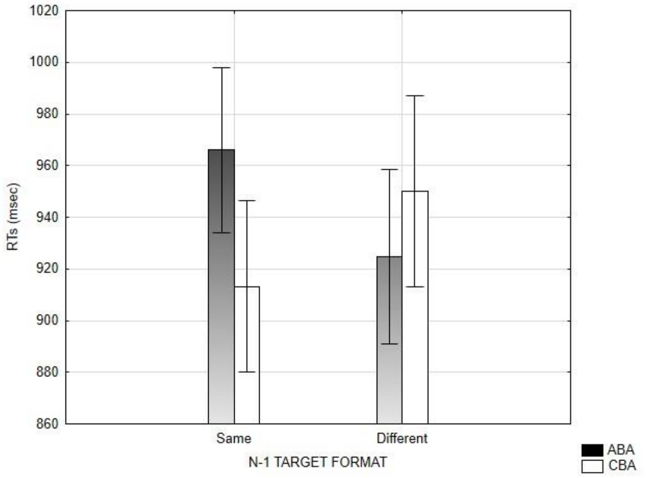
Participants responded significantly faster on digit than word trials (936 vs. 1019 msec, respectively; $F_{1, 26}$=81.1839, $p < 0.0001$). Note that in the present experiment the 75% of the task stimuli consisted of digits (e.g., “7”), and the remaining 25% were number words (e.g., “seven”).

Mean accuracy was 85.6%. The ANOVA on mean individual error rates did not reveal any significant main effect or interaction ($p > 0.05$)

Participants responded significantly faster to parity and magnitude tasks (905 and 925 msec) than to position task (1043 msec; $F_{2, 52}$=14.5681, $p < 0.0001$). RTs were also significantly faster on task repetition trials (AA, 750 msec) than both ABA and CBA trials (963 and 946, respectively; $F_{2, 52}$=107.1811, $p < 0.0001$). Subjects were slower in switching from a number to a word trial (1008 msec) than from a word to a number (943 msec) and from a number to a number (941 msec) ($F_{2,52}$=25.6202, $p < 0.0001$).

We also directly tested whether the N-2 task repetition costs observed in the two format conditions (change or not) were significantly different from zero: results revealed that when the stimulus format did not change, the N-2 task repetition cost was significantly different from zero (t_{26}= 3.84, $p<0.001$) while it did not when the format changed from trial N-2 to N-1 (t_{26} = -1.14, $p=0.26$).

Figure 1. Mean reaction times for ABA and CBA trials in each of the two format conditions in Experiment 1. Error bars denote standard errors.



Experiment 2

Intending to control the possibility that eliminating the N-2 repetition cost in the format change condition (AbA-CbA) was not dependent upon a worse performance when participants are engaged in word trials, in Experiment 2, we replicated Experiment 1 by reverting the proportion of trials.

Methods

Participants

Thirty students (females = 19, mean age = 22.42, s.d. = 3.24) were recruited at the Faculty of Psychology of Sapienza University of Rome to participate in the study. All participants had normal or corrected-to-normal vision. They all were naïve to the aims of the study and provided written informed consent. The study was approved by the Ethics Committee of the Department of Psychology at Sapienza University.

Procedure

The task and the procedure were identical to the ones in Experiment 1. The only difference is in the proportion of trials: in this case, word-trials were 75% of the total trials. Thus, here the dominant code is the word and the digit the infrequent one.

Results

Five participants were excluded from the analyses since they presented a very low accuracy (less than 70%). The pattern RTs for the three different tasks was similar to the pattern observed in Experiment 1. Participants responded significantly faster to the parity and the magnitude tasks (979 and 1038 msec) than to the position task (1161 msec; F(2, 48)=17.5217, p<0.0001). RTs were also significantly faster on task repetition trials (AA, 869 msec) than on ABA and CBA trials (1061 and 1042, respectively; $F_{2,48}$=56.935, p < 0.0001).

The mean RTs on word trials did not differ from the mean RTs on digits trials (1053 and 1059, respectively (p>0.05). Reaction times when switching between trials was not significantly different among the number to word, word to number, and word to word switch trials (p > 0.05).

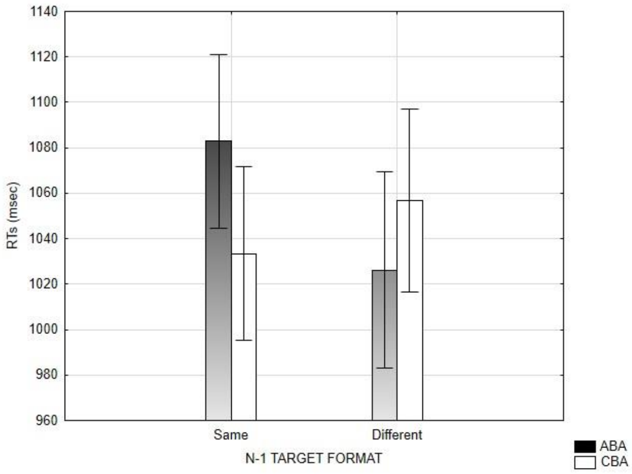
Importantly, the 2 (Sequence) X 2 (Format) ANOVA revealed non-significant main effects of the sequence $F_{1,24}$=0.34900, p=0.56 or stimulus format (Current effect: $F_{1,24}$=1-3828, p=0.25116) but a significant sequence by stimulus format interaction (Current effect: $F_{1,24}$=7.6445, p=0.01, partial eta squared = 0.24). Duncan post-hoc test showed that RTs were significantly slower on ABA than CBA sequences on the same format trials (1083 and 1033, respectively, p = 0.03), revealing an N-2 task repetition cost of 50 msec. Crucially, RTs on the ABA sequences were significantly faster for the change format triplets (WDW) than for the same format trials (WWW, 1026 vs. 1083 msec, respectively; p = 0.01). Also, on the change format condition, RTs on ABA sequences (WDW) did not differ significantly from RTs on CBA sequences regardless a change in stimulus format occurred (p = 0.17) or not (p = 0.725979) on CBA triplets (Figure 2).

We also tested whether the N-2 task repetition costs were significantly different from zero in the two format conditions (change or not): results revealed that when the stimulus format did not change, the N-2 task repetition cost was significantly different from zero (t_{24}= 2.29, p=0.031142) while it did not when the format changed from trial N-2 to N-1 (t_{24}= -1.43, p=0.164752)

Mean accuracy was 84.1%; The ANOVA on mean individual error rates did not reveal any significant main effect or interaction (p > 0.05).

These results are similar to those from Experiment 1 and indicate that when the stimulus format changes from one trial to the next, the competitor task's inhibition is not triggered.

Figure 2. Mean reaction times for ABA and CBA trials in each of the two format conditions in Experiment 2. Error bars denote standard errors.



Combined Analysis of Experiments 1 and 2

Results were consistent across the Experiment 1 and 2 in showing that the typical N - 2 task repetition cost was abolished when the stimulus format changed during the task transition from trial N - 2 to trial N - 1.

To test potential differences between experiments 1 and 2, we ran a combined ANOVA on mean RTs, including Experiment as a factor. The 2 (Experiment) X 2 (Sequence) X 2 (Format) ANOVA revealed a significant main effect of the experiment (Current effect: $F_{1, 50}$=5.034, p=.03, partial eta-squared = 0.09) due to RTs being significantly faster on Experiment 1 than on Experiment 2. The Sequence X Format interaction was also significant (Current effect: $F_{1, 50}$=20.778, $p< 0.0001$, partial eta squared = 0.29). This interaction was evidenced in both Experiment 1 and 2 and showed that RTs on the ABA sequence were significantly slower than RTs on the CBA condition only on the same format condition (1022 and 971 msec, respectively, $p < 0.001$), revealing an N - 2 task repetition cost of 51 msec. Conversely, ABA RTs of the change format condition were as fast as those of the CBA sequence of the same format condition (p = 0.84) and even faster than CBA RTs of the change format condition (p = 0.02). Importantly, the Experiment by Sequence by Format interaction was not statistically significant (Current effect: $F_{1, 50}$=0.003 , p=0.95), indicating that the pattern of results was consistent across the experiments (Table 1).

Table 1. Mean reaction times in Exp. 1 and 2 for ABA and CBA trials and the mean N-2 repetition costs in each format condition.

N-1 Target Format	**Experiment 1**			**Experiment 2**		
	ABA	**CBA**	**N-2 rep. cost**	**ABA**	**CBA**	**N-2 rep. cost**
Same	965.96 (34.4)	913.13 (34.93)	52.83	1082.91 (35.75)	1033.4 (36.3)	49.51
Different	924.66 (37.71)	950.07 (37.98)	-25.41	1026.12 (39.19)	1056.84 (39.47)	-30.71

Discussion

The present study addressed the impact of stimulus format on task inhibition during cued task-switching. Specifically, we investigated if changes in stimulus code (verbal and Arabic numbers) in the trial N-1 might reduce or eliminate the N-2 repetition cost, to increase knowledge about the processes that govern backward inhibition. Indeed, such manipulation can give indications about the possibility that backward inhibition operates at a high-level (e.g., semantically), or low-level specific features trigger it. In two experiments, we observed that perceptual changes of stimulus format (i.e., at low-level), despite the maintenance of the same meaning (high-level), is enough for the backward inhibition not to occur, even if the change was from verbal to Arabic code (Exp. 1) or vice-versa (Exp. 2).

As the literature on backward inhibition has shown (Schuch and Koch, 2003; Philipp et al., 2007; Scheil et al., 2019; Gade and Koch, 2007; Sdoia and Ferlazzo, 2008), our results are consistent with the evidence that manipulations in the N-1 task at the stimulus level are able to eliminate N-2 repetition cost compared to conditions in which such changes have not been implemented. However, these studies have mostly required participants to perform a qualitatively different task in N-1, such as inhibiting the response, producing a double-press or a covert response, performing a univalent task, or merely encoding the stimulus. In the present work, there were no changes in tasks, and no different goals were cued in experimental conditions: just changing stimulus properties is enough to eliminate the N-2 repetition cost.

More importantly, our results highlighted that task-set inhibition does not operate on general representations linked to conceptual meanings of stimuli-response associations. Notwithstanding, interference at target dimensions such as stimulus format is necessary for the N-2 repetition cost to occur.

Target stimulus' dimensions, such as perceptual features, are bound together with cues' codes, goals, and responses, into an object (Kahneman et al., 1992) or event (Hommel, 2004) file. Recent evidence (Kowalczyk and Grange, 2020; but also, Mayr, 2002) has suggested that episodic retrieval mechanisms of these files are responsible for much of the N-2 repetition cost. Indeed, when the event file of the N-2 task matches the one in the N task, the cost is reduced or absent, while the N-2 repetition cost is typically observed when there is an episodic mismatch in one or more features between the two. Current research has highlighted that cue-, stimulus-, and response-related interference might explain behavioral costs in cued task-switching, highlighting the complex interplay between episodic interference and inhibitory processes underlying backward inhibition and task-switching in general. Therein, in the present study, we manipulated the stimulus format of the N-1 task. Since we left randomized the stimulus-response sets in the N-2 and N task (i.e., the N-2 repetition sequences in the two Format conditions are balanced between N-2 episodic matches and mismatches), our results do not indicate that task-preparation and episodic retrieval played a role in the observed effects. Incidentally, results suggest that pure task preparation is not sufficient to trigger task inhibition. Otherwise, inhibition costs would have appeared in the format change condition too. Instead, since our manipulation regards the N-1 trial, an episodic mismatch occurs in each switch of the sequence (from N-2 to N-1, and from N-1 to N trials). Thus, our results might be related to task-set inhibition in the first switch (N-2 to N-1), which does not occur or is less robust than in episodic matches. Consequently, the overcome from that inhibition in the second switch (N-1 to N) became more facilitated due to the weakest inhibition in the previous trial.

Also, the effects of episodic retrieval of task-set due to the stimulus format can be ruled out because the infrequent format did appear on each of the three different tasks with the same frequency and AbA (or CbA) represents a theoretical N-2 task repetition occurring for each of the tasks. Moreover, the format was not associated with a specific task. Similarly, the cues' format remained the same across trials so that cue-related task-set retrieval processes cannot be a source for the observed effects. However, the role of preparatory processes in backward inhibition has produced various findings. Recent evidence arguing for the role of cue-related processes in task-switching performance is growing (Gade and Steinhauser, 2020), and further research to disentangle preparatory and inhibitory processes is required.

Another possible explanation is that observed effects are exerted by repetition priming mechanisms of the precedent task-set. Indeed, since the code in each of the two sequences (AbA and CbA) switches from b to A pro-active interference might be less strong, and less inhibition might be required than in switch sequences where the stimulus format does not change (ABA and CBA). However, if it was the case, we should have been observed a faster performance in switch trials (BA) with a format change (both Arabic to verbal code and vice-versa) than in switch trials with no format change (verbal to verbal and Arabic to Arabic format), due to less proactive interference. We found only in experiment 1 increased RTs when switching from numbers to words, but not from words to numbers, compared to numbers to numbers. Indeed, we were confident in excluding such an interpretation.

The present findings supported the task-set application view (Schuch and Koch, 2003; Los and Burg, 2010), which argued that the task-set application triggers inhibition and the switching cost (and the N-2 repetition cost) is the behavioral outcome of that inhibition. Indeed, when competing representations of task-sets in working memory are activated with the target onset, which has been recently performed and inhibited, it requires more effort to gain access to working memory. However, the paradigm used is not able to punctually disentangle if the present results might be interpreted as an effect on the triggering of inhibition (switching to the b task does not inhibit the A task) or to the recovery from that inhibition (after a b task is easier to recall the A task set than after a B task). Further research on this point is needed.

According to our results, task-sets competitions do not interfere if stimulus codes change. Task-set inhibition seems not to operate at a conceptual, high-level, but are embedded into specific low-level objects’ properties. Accordingly, previous studies have found that parietal regions, which are traditionally involved in conflict monitoring and detection of stimuli categories and properties (Corbetta and Shulman, 2002; Liston et al., 2006), are specifically involved in backward inhibition (Sdoia et al., 2020; Zhang et al., 2016; Sinai et al., 2007).

In a recent model, task-sets lie in a procedural component of Working Memory (Oberauer, 2009). In their view, a task-set is a stimulus-response mapping representation specific for a confined set of conditions, able to automatically exert a cascade of responses (like a “prepared reflex”; Hommel, 1998) when in the declarative component of Working Memory (through attention) that specific condition is represented. Regarding backward inhibition, it is conceivable that the update of procedural WM when switching back to a recently inhibited task (ABA) requires more effort due to inhibitory mechanisms that occur on the application of precedent task-sets. However, it is not known if these inhibitory mechanisms affect general meaning representations or exact properties of stimulus features. Following our results, stimuli targets, and in general objects representations, are embedded into task-sets not only by their meaning but by their specific (perceptual) properties. In this context, the same-meaning/different-format stimuli seem to be rather embedded into different and not interfering task-sets, on which inhibitory processes are not triggered since they are not “competitors” for the dominant code.

Intriguingly, our results suggest that backward inhibition processes appear to act on verbatim rather than on gist mental representations (Reyna et al., 2012). According to the Fuzzy-Trace Theory (Brainerd and Reyna, 2001), information can be stored independently but parallelly as a gist (i.e., meaning-based intuitive information regardless precise consideration of stimuli) and/or as verbatim (i.e., exact, superficial, and symbolic representation of the stimulus) representation. In the cued task-switching paradigm implemented, individuals might use verbatim and gist representations to perform the three tasks. Indeed, participants must recognize meanings of digits/numbers and then compare them (e.g., "6" or "six" is greater than "5"). Intriguingly, when the format changes in N-1, individuals must use the same gist (e.g., in the magnitude task, "6" requires the same response than "six", since they have the same meaning) but with a different verbatim exact representation (e.g., the number 6 is different from the word "six"). Interestingly, since in task sequences successive trials may present the same (e.g., "6" and "4") or different (e.g., "6" and "four") format, verbatim representations may overlap. The same verbatim representation in successive trials (number/number or word/word) may produce interference, whereas different representations (number/word or word/number) do not. Then, recall (i.e., overcome the inhibition of) the N-2 task-set can be facilitated when such interference has not been produced. It is worth noting that specific format facilitation is excluded since we observed the same effects reverting, in Exp 2, the control and experimental conditions of the Exp 1 (by manipulating the proportion of numeral and verbal format trials).

In conclusion, our findings highlighted that task-set inhibition in cued-task-switching paradigms does not act at a high, conceptual level, but changes in perceptual dimensions, such as the stimulus format, are sufficient for inhibition to not occur. These findings supported the view that preparatory processes alone are not fully responsible for N-2 repetition cost and that stimulus level processing, in the sense of task-set application, plays a pivotal role in task-switching.

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Cue- and target-related mechanisms interact to overcome backward inhibition: an ERP study.

Abstract

Inhibition of task-sets allows for the flexible contextual adaptation of cognitive processes. However, performing a task that has recently been inhibited requires stronger effort than switching to a task that has been less recently performed. In a cued task-switching paradigm, both cue-related preparatory and post-target reconfiguration processes have shown to play a role in both the triggering of and overcoming from the backward inhibition effect. In the present work we aimed at advancing evidence on the differential roles of cue- and target-related processes by combining a task-switching procedure with a Go/NoGo task and recording electrophysiological activity for the analysis of event-related potentials. N-2 repetition trials showed a reduction in the cue-locked P2 and a target-locked P3 enhancement. That dual pattern of effects appears to be dependent on the overcoming from backward inhibition, since when the previous task was a NoGo trial the sequence effects in both ERPs and RTs were not observed. Our results suggest that the post-target stage is essential for the triggering of inhibition and that cue- and target-related mechanisms reflect additive and compensatory task-set activation/reconfiguration processes crucial for the overcoming from backward inhibition.

Introduction

Switching between tasks is a complex ability requiring fine cooperation of cognitive mechanisms to guarantee a flexible and optimal adaptation of individuals to the environment. Literature has extensively shown that inhibitory mechanisms are the foundation of this ability, which may be uncovered and studied in multiple-tasks experimental procedures. Indeed, when individuals are asked to switch back to a recently performed task (A-B-A sequences), their reaction times are slower than when they must switch to a less recently performed one (C-B-A sequences). This difference has been named *N-2 repetition cost*, known as the behavioral index of a backward inhibition mechanism. Essentially, the N-2 repetition cost reflects the more effort spent by individuals to overcome an inhibition triggered in the switch between the N-2 and N-1 trial. Theoretically, backward inhibition indicates a high-level inhibition over task sets, i.e., the internal sets of goals, stimuli dimensions, and task-specific stimulus-response associations (Mayr and Keele, 2000; Monsell, 1996). However, multicomponent accounts of task-switching (Mayr and Kliegl, 2003) advocated that task-set reconfiguration (Rogers and Monsell, 1995), based on top-down updates of task-set representations, and task-set inertia (Wylie and Allport, 2000), relying upon bottom-up proactive mechanisms, may interact in producing task-switching performance. A behavioral combined with Event-Related Potentials (ERP) research (see Karayanidis and Jamadar, 2014) has shown that not only both proactive (cue-related preparatory mechanisms) and reactive (related to post-target interference) control processes may account for task-switching costs (switch-repeat trials' RTs), but also their interaction. Additionally, proactive and reactive control processes are not unitary but consist of different components that must be disentangled. Since the task-switching paradigm, and its variations, allows for the investigation of the cue-, target-, and response-related mechanisms, it represents an excellent way to investigate inhibitory processes underlying human cognitive flexibility and task-set updating.

Unlike switch-cost, N-2 repetition cost allows for the investigation of switch-sequence effects (ABA vs. CBA trials), allowing testing how proactive and reactive control processes interact, what roles the inhibition triggering and overcoming play in this interaction, and at what level (task-set or stimulus processing). Backward inhibition has been found to occur in every case cognitive control detects a conflict during the task performance, which may occur at every stage of information processing (Houghton et al., 2009; Koch et al., 2010). Instantly, temporal and spatial characteristics of cues may modulate the BI (e.g., Druey and Hübner, 2007; Grange and Houghton, 2009; Arbuthnott and Woodward, 2002) even though research using neither 2:1 mappings, univalent stimulus/response associations nor task identity responses did not find evidence for these modulations (Altmann, 2007; Gade and Koch, 2008; Regev and Meiran, 2017; Prosser et al., 2020). Similarly, stimulus- and response-related manipulations of the N-1 stimulus have shown to eliminate the BI (Schuch and Koch, 2003; Philipp et al., 2007; Gade and Koch, 2007; Sdoia and Ferlazzo, 2008; Koch et al., 2010). Despite the number of studies, the specific role of each stage is still uncleared.

Koch et al. (2010) advocated that BI has to do with trial-by-trial conflicts in task-processing, relating temporal decay of inhibition and lateral suppression's mechanisms of task-sets. Indeed, research manipulating Response-Cue Interval (RCI) has found that prolonged intervals reduced N-2 repetition cost (Grange and Houghton, 2009; Koch et al., 2004; Mayr and Keele, 2000), especially in the switch between N-2 and N-1 trials (Gade and Koch , 2005). The trial-by-trial account is strengthened by findings obtained in studies manipulating the Cue-Target Interval (CTI; Gade and Koch, 2008; Schuch and Koch, 2003; Mayr and Keele, 2000), evidencing that N-2 repetition cost is not reduced with more preparation. However, interactive effects are showed when manipulations regarded N-2 and N-1 trials or the abstractness of cues (Scheil and Kleinsorge, 2014). It is worth noting that for task-switching increasing preparatory intervals results, instead, in a substantial reduction of switch costs, even though residual switch costs remain presumably related to carry-over interference effects.

However, how these mechanisms interact in producing N-2 repetition costs is not still understood. One limitation of behavioral studies of backward inhibition is that they rely upon unidimensional measures (i.e., reaction times and error rates), often reducing the two prominent conditions of BI paradigms (ABA and CBA sequences) into one single measure (the N-2 repetition cost), not allowing for a detailed investigation of changes that may happen within trials' processing stages. Indeed, since behavioral data from task-switching paradigms allow for the analysis of the final product of these multiple processes, i.e., RT costs, other techniques are necessary for the investigation of specific hypotheses. ERP research has provided several intriguing results in task-switching literature due to its ability to temporally inspect cognitive processes in a trial-by-trial and a stage-by-stage fashion. Most results showed evidence for a larger switch-related P3 for cues and the opposite effect for targets, reflecting the more effort spent in task-set updating and the weaker target-rule matching in switch compared to repeat trials (Karayanidis and Jamadar, 2014; Han et al., 2018). Other components have also been shown to be modulated by task-set shifting, as N2, related to monitoring processes, P2, reflecting the perceptual activation of stimuli, and pre-target negativity, accounting for preparatory processes (Karayanidis and Jamadar, 2014).

Unfortunately, only a couple of studies investigated ERPs in backward inhibition. Sinai et al. (2007) found increased response-locked negativity over parietal sites and an earlier onset of the lateralized readiness potential. Moreover, they found an enhanced P3 cue-locked activity over centroparietal sites in ABA compared to CBA sequences. Additionally, the response- and cue- locked effects they have found were associated with high- and low- interference sequences, respectively, with behavioral data showing significant differences between ABA and CBA trials in high interference condition only. The authors have discussed the results suggesting a role of attentional mechanisms in the sequential ability to switch from non-dominant to dominant task (low interference) during preparatory cue-related processes; differently, in a high interference condition, BI is suggested to occur after response selection, when the overcome of inhibition is finalized.

Instead, Zhang et al. (2016) found that BI trials exhibited a larger post-target N1 at parietal and centro-parietal sites than control trials, suggesting that more robust attentional allocation is required re-activate recently inhibited tasks and overcome backward inhibition. However, Zhang et al. did not find any effect on the N2 and P3 post-target components. Even though the two ERP studies came to the same conclusions, i.e., that BI trials require strong attentional effort, the former found the effect at cue-locked ERPs and on later stages (P3) while the latter at stimulus-locked and at an earlier component (N1). Moreover, the difference between the paradigms, such as the different sequential manipulations and/or, more substantially, the different CTIs (1130 ms and disappearance of the cue at target's presentation in Sinai et al.; 100 ms and no cue disappearance at target's presentation) may have strongly affected results. In addition, Zhang et al. (2016) implemented a task-switching paradigm in which one of the three tasks was univalent (a double-press), comparing ABA and DBA sequences, neglecting possible effects of the non-overlapping of responses. Other studies (Giller et al., 2019a; 2019b; Wolff et al., 2018; Zink et al., 2019a; 2019b) which used the same task as in Zhang et al. (2016), reported that mostly at early stages processes involved in suppressing task-irrelevant information at the target level (P1/N1 components at inferior-frontal gyrus) are modulated in BI trials. Finally, the possibility that both cue-related top-down mechanisms and target-related bottom-up processes may coexist and observed depending on the paradigm used.

In this framework, we hypothesized that the interaction of dissociable cue-related preparatory and target-related associative processes, as reflected in ERP components, are needed to exert N-2 repetition cost. To do so, we used a CTI of 600 ms already used in previous studies (Sdoia et al., 2020) to give participants a reasonable but not excessive time to shift task-sets and observe any variations in event-related potentials. Additionally, we used a fixed RCI interval of 200 ms given precedent evidence has shown that the time-course of backward inhibition reaches its peak with about 200-300 ms time window after the response has provided (Scheil and Kleinsorge, 2014).

Since N-2 repetition cost is exerted in trial-by-trial modulations of conflict interferences, we hypothesized that these components should not be observed when the preceding task-set is not inhibited. Following the literature, we expect not to find any behavioral and related electrophysiological indication of the occurrence of backward inhibition when N-2 and N-1 tasks do not require an overt response. Moreover, our experimental set allows for the visualization of ERPs component in Stop trials to have a more precise picture of the consequences of the backward inhibition’s resolution even in the absence of an overt response.

Methods

Participants

Twenty-nine Leiden University’s students were enrolled to participate in the study. Participants were required to be between 16 and 35 years old, and to not have never received a diagnosis of neurological/psychiatric diseases. Two of them were excluded due to technical issues in the EEG recording. Three additional participants were successively removed from the analyses due to low accuracy (less than 75%) at the behavioral task. The final sample consisted of 24 participants (age: mean = 20.29, s.d. = 2.76; 3 males; 5 left-handed). Participants received SONA credits as compensation for their participation. The study was approved by the Psychology Research Ethics Committee of the Institute of Psychology at the Leiden University and conducted in accordance with its policies and with the Declaration of Helsinki. All participants provided written informed consent.

Behavioral task

Participants performed a standard three-tasks switching paradigm. At the beginning of each trial a cue (with a size of about 6 cm by 6 cm) was presented, followed by an imperative stimulus after 600 ms. The stimuli might be digits from 1 to 9 except the number 5. The cues were geometrical shapes and were informative of the task participants must accomplish at the presentation of the imperative stimulus (the digit). A square cued a parity task (odd or even), a diamond cued a magnitude task (smaller or bigger than 5), and a circle cued a centrality task (centrally or peripherally positioned along the number line; central digits were 3-4-6-7). Participants had 2500 ms to respond to the imperative stimulus pressing with their index fingers on button boxes attached to the two chair arms. Left responses were required for odd, smaller than 5, and central digits, right responses for the opposite dimensions. If participants made an error or take longer to respond a 50 ms acoustic feedback was provided. After the participant's response, the stimulus disappeared, and the next cue was presented after 200 ms of blank interval. Both cues and stimuli were black and centrally presented over a grey background. The task was programmed in E-Prime 3.0 and was ran on a 24-inches computer monitor (refresh rate: 60 Hz) placed about 60 cm from the participant.

In approximately 25% of total trials, a NoGo/Stop signal was presented informing participants that they must try to inhibit their response. The NoGo/Stop signal was a clear reduction of the cue/digit's width and the font wast turned to *italic,* and might be presented simultaneously with the cue (i.e., the cue is directly presented as a "NoGo Cue"), simultaneously with the stimulus (i.e., the digits is directly presented as a "NoGo target"), or after 200 ms the presentation of the digit (i.e., the digits is presented as a Go target but turned to a NoGo target after 200ms, a condition we referred as "Stop target").

Task sequences were randomly intermixed for each participant with the constraints of having comparable amounts of (we will refer to NoGo/Stop trials with lower letters and to Go trials with capital letters): ABA, CBA, AbA, and CbA switch sequences; AbA, CbA, ABa and CBa switch sequences for each time of NoGo/Stop signal presentation ("NoGo Cue", "NoGo Target", and "Stop Target"). Triplets of tasks were not explicit to participants, and task repetitions (AA) were allowed for about the 5% of trials to reduce possible expectancy effect.

Twelve blocks of 96 trials each were administered, providing a totality of 1152 trials. Between each block participants were allowed to take a short break, without standing up from the chair.

EEG data acquisition and pre-processing

Electroencephalographic (EEG) activity was measured with active BioSemi electrodes over 32 positions: Fp1, Fpz, Fp2, F7, F3, Fz, F4, F8, FT7, FC3, FCz, FC4, FT8, T7, C3, Cz, C4, T8, TP7, CP3, CPz, CP4, TP8, P7, P3, Pz, P4, P8, POz, O1, Oz, and O2. Six additional external electrodes were positioned over the left and right outer canthus (horizontal ocular activity), above and below the right eye (vertical ocular activity), and over the left and right mastoid. Monopolar recordings were referenced to the common mode sensor (CMS) and drift was corrected with a driven right leg (DRL) electrode (for details see http://www.biosemi.com/faq/cms&drl.htm). EEG activity was recorded with a sampling rate of 512 Hz. Offline analyses were performed with Brain Vision Analyzer. Linear derivations of electro-oculogram (EOG) signals were calculated for horizontal and vertical ocular activity.

EEG raw data was down-sampled to 256 Hz and re-referenced to the mastoids. Data was filtered through a 0.1 Hz (order 4) high-pass, 30 Hz (order 4) low-pass, and a 50 Hz notch filter. Then, a target-locked segmentation was applied (± 800 ms), and an Infomax Independent Component Analysis was run for ocular correction. Cue- and target-locked segments (from -200 to +800) were generated and baseline (-100 to 0) was subtracted. A maximal allowed voltage step of 10 µV/ms and a Max-Min difference of 100 µV were set for artifact rejection. Segments were then differentiated per condition and averaged.

Residue Iteration Decomposition (RIDE)

The large inter-trial and inter-subject variability in the latency of late ERP components is a paramount problem in ERP research. Indeed, traditional average-based methods usually provide strongly blurred measures of ERP, especially their late components.

Residue Iteration Decomposition (RIDE; see Ouyang et al., 2011; 2015; 2016) has been implemented to encompass this issue.

RIDE is a technique aimed at decomposing ERPs waveforms into stimulus-locked (S) and response-locked (R) clusters, which latencies are locked to stimulus- and response-onsets.

Importantly, RIDE allows for the extraction of a central cluster (C), nor stimulus- or response-locked, which latency is assumed to be highly variable within trials and within subjects, accounting for intertrial and inter-subjects differences in ERPs high-order cognitive control components (such as the P3) primarily involved in task-set reconfiguration processes. Using stimulus-onset, response times, and components latencies, (estimated through iterative cross-correlative processes), RIDE firstly remove the S and R and then estimate the C cluster. The decomposition, distinguishing the three clusters, gives the opportunity to work on these clusters separately.

In the present work, the S cluster is estimated between 0 and 500 ms from stimulus-onset, the C cluster between 100 and 800 ms from stimulus-onset, and R components between -300/+300 from response-onset. Since cues do not require a subsequent response and RIDE gives opportunity to choose what clusters, in addition to the S, can be estimated, R components have been calculated only in target-locked ERPs except for the NoGo/Stop trials where no response was required.

RIDE was conducted using the appropriate MATLAB toolbox and following the developers' manual (http://cns.hkbu.edu.hk/RIDE.htm).

ERPs analyses

After visual inspection of individual- and grand-averages and consistently with previous literature on ERPs in backward inhibition (Sinai et al., 2007), we chose to focus on the mid-line central position (Cz) for statistical analyses except for late components in R clusters and in NoGo/Stop trials that we measured at the mid-line frontal site (Fz).

After RIDE decomposition, cue-locked S cluster revealed an N1 (interval: 70-170 ms) and a P2 (180-240 ms) components, whereas C cluster showed a P3 (230-320 ms) and a N4 (400-570 ms) components. Same components were extracted from S and C clusters in target-locked ERPs (70-130 ms, 160-260 ms, 250-400 ms, and 450-650 ms for N1, P2, P3, and N4 components, respectively). For target-locked ERPs we have also measured a late positivity (LP) component (500-800 ms) in the C cluster of NoGo/Stop trials. Instead, target-locked R components showed a late positivity (480-680 ms). Mean amplitudes for each components' interval were calculated.

Furthermore, lateralized-readiness potentials (LRPs) were measured. Response-locked segments were generated on the pre-processed EEG data from -800 to +100 ms and baseline (-800 to -600 ms) was corrected. LRPs were calculated by averaging the differences between the grand-average contralateral to the response and the ipsilateral in C3 and C4. Jackknife resampling was applied for the measurement of LRP onsets (Miller et al., 1998; Ulrich and Miller, 2001), determined as the first value exceeding the 50% of the most negative peak in each subsample.

Procedure

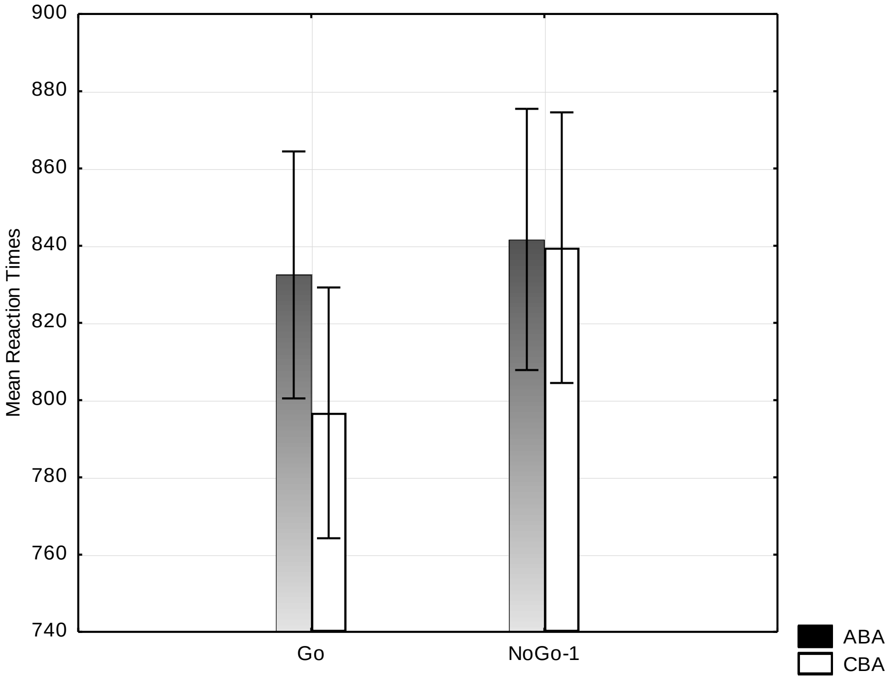
Participants came to the lab and signed the informed consent. They removed earrings, bracelets, and any metal accessory. Participants were required to sit comfortably over the chair in front of the screen and were prepared for the EEG montage. After the electrode positioning, the task's instructions were orally provided and displayed on the screen. Participants were asked to stay as still as possible during the performance and informed that they could relax during each block's short breaks. Participants underwent thirty practice trials. The experimenter made sure participants understood the instructions and, in need, administered other practice trials. After the task performance, participants were properly cleaned and debriefed.

Results

Behavioral task

Mean individual reaction times (RTs) and accuracy were analyzed in a 2 X 2 repeated measures ANOVA design using Sequence (ABA and CBA) and NoGo Condition (Go, NoGo-1) as independent variables. Task sequences in which an error occurred on trials N, $N - 1$, or $N - 2$ were excluded from RTs analyses. The analysis of accuracy failed to reveal any significant difference ($p > 0.05$ for all effects). Differently, the ANOVA on RTs revealed a significant Condition by Sequence interaction ($F_{1,23}=4.3325$, $p = 0.048$, partial $eta^2 = 0.16$). Both the main effects of Sequence and Condition were non-significant ($p > 0.05$). Duncan’s post-hoc tests showed a significant difference between ABA and CBA trials in the Go Condition ($p < 0.01$), between ABA in the NoGo-1 and CBA in the Go condition ($p < 0.01$), and between CBA in the NoGO-1 and CBA in the Go condition ($p < 0.01$), but no statistically significant difference between ABA and CBA in the NoGo-1 condition ($p>0.05$) (Figure 1).

Figure 1. Mean RTs for ABA and CBA task sequences in Go/NoGo conditions. Error bars denote standard errors.



Mean individual RTs and accuracy for the NoGo-1 condition were also analyzed in a 3x2 repeated measures ANOVA design, using NoGo Timing (CueNoGo, TargetNoGo, TargetStop), and Sequence (ABA, CBA) as independent variables. The ANOVA on accuracy revealed no significant difference (p>0.05 for all effects), whereas the ANOVA on RTs only revealed a significant main effect of NoGo Timing ($F_{2,46}$=4.9737, p = 0.01, partial eta squared = 0.18). Specifically, participants responded significantly slower in the TargetStop (mean= 847.70, s.d. = 36.94) and in the TargetNoGo (mean = 851.76 s.d. = 36.51) conditions than the CueNogo (mean = 808.39 s.d. = 30.84) condition when the NoGo trial was the N-1, as revealed by Duncan’s Post-Hoc tests (p < 0.01 and p = 0.01, respectively). Finally, mean individual accuracy for NoGo/Stop trials was analyzed in a 3 x 2 repeated measures ANOVA design, using NoGo Timing (CueNoGo, TargetNoGo, TargetStop) and Sequence (ABA, CBA) as independent variables. The ANOVA showed a significant main effect of NoGo Timing ($F_{2,46}$=37.07, p < 0.0001) due to a lower accuracy observed when participants are engaged in a Target Stop trial (mean = 0.83 s.d. = 0.02) compared to the optimal performance in TargetNoGo and in CueNoGo conditions (mean=0.97 s.d. = 0.01 and mean = 0.99 s.d. = 0.003, respectively). The ANOVA showed neither a significant main effect of Sequence nor for the interaction (p > 0.05).

ERPs

As behavioral data, mean amplitudes at site Cz were analyzed in 2x2 repeated measures ANOVA designs. Go/NoGo condition (Go, NoGo-1) and Sequence (ABA, CBA) were treated as independent variables.

Cue-locked ERPs

The cue-locked S and C cluster, and the reconstructed ERPs after RIDE are displayed in Figure 2. For the S cluster of cue-locked ERPs, the ANOVA on the N1 component revealed a significant main effect of Condition ($F_{1,23} = 6.38314$, $p = 0.01$, partial eta squared = 0.22) due to a reduced negativity in the NoGo-1 condition (mean = -1.997 μV, s.e. = 0.39 μV) compared Go (mean = -2.774 μV, s.e. = 0.51 μV) condition. Main effect of Sequence and the interaction were both non-significant ($p > 0.05$). Differently, the ANOVA on the P2 component revealed again a significant main effect of Condition ($F_{1,23} = 11.26303$, $p < 0.01$, partial eta squared = 0.33) and a significant interaction of Condition x Sequence ($F_{1,23} = 9.07377$, $p < 0.01$, partial eta squared = 0.28), while the main effect of Sequence was not significant ($p = 0.06$). The main effect of Condition was due to an increased positivity in the NoGo-1 condition (mean = 0.411 μV, s.e. = 0.37 μV) compared to the Go (mean = -0.736 μV, s.e. = 0.34 μV) condition. Duncan’s post-hoc tests on the interaction showed a significant difference ($P < 0.001$) in all but for the ABA vs. CBA in the NoGo-1 condition comparison (Figure 3 and 4).

To investigate why the NoGo-1 condition exhibited no P2-related Sequence effects, we further analyze P2 mean amplitudes in a 3x2 repeated measures ANOVA design, using NoGo Timing (CueNoGo, TargetNoGo, TargetStop), and Sequence (ABA, CBA) as independent variables. We observed a significant main effect NoGo Timing ($F_{2,46} = 22.65577$, $p < 0.0001$, partial eta squared = 0.49), showing a progressive reduction in amplitude from the CueNoGo to the TargetStop conditions (mean = 1.03 s.d. = 0.41, mean = 0.57 s.d. = 0.53, and mean = -0.93 s.d. = 0.43 for CueNoGo, TargetNoGo, and TargetStop conditions, respectively). No other significant effects were showed ($p > 0.05$)

Figure 2. Cue-locked reconstructed ERP, S cluster, and C cluster waveforms at Cz.

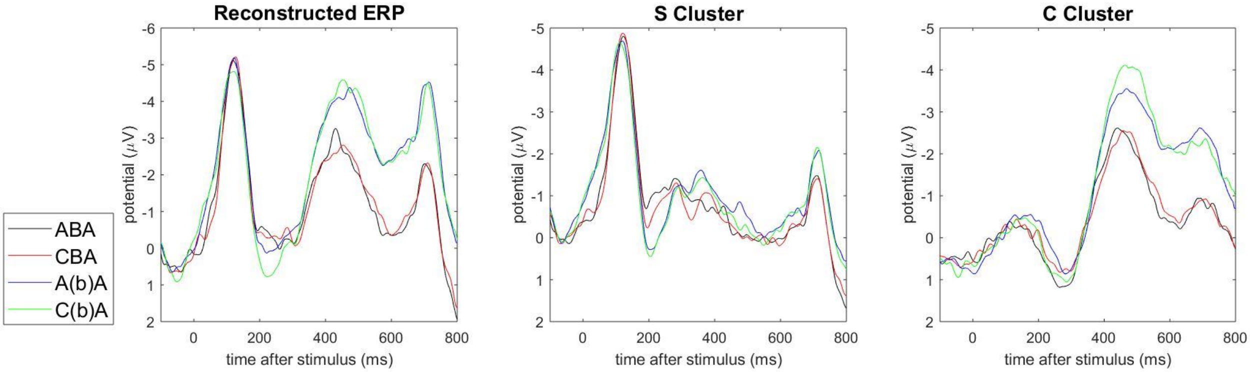


Figure 3. Mean amplitudes for P2 in cue-locked S cluster ERP. Error bars denote standard errors.

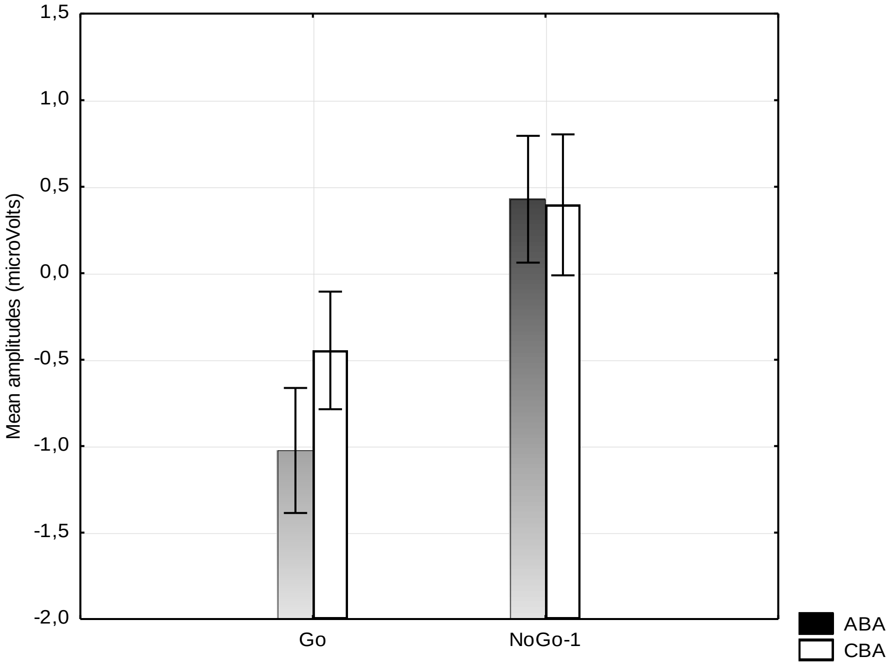
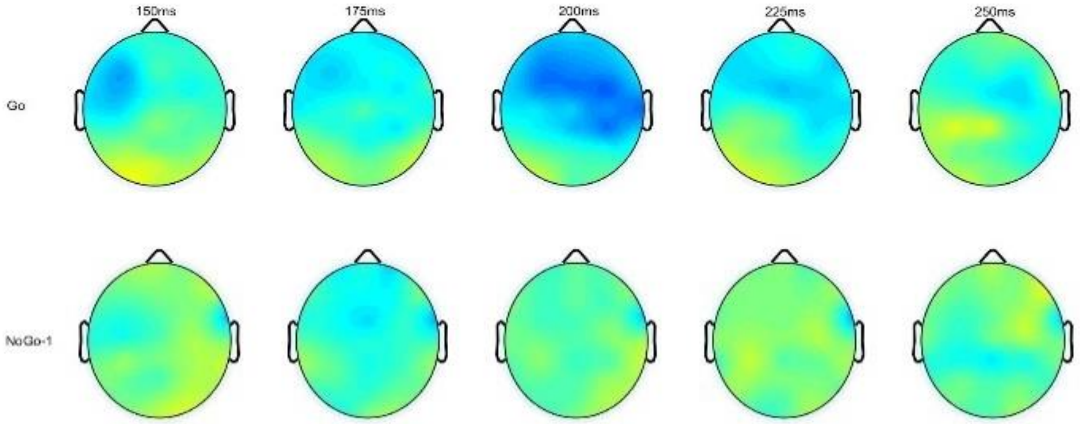


Figure 4. Topography evolution of ABA-CBA difference waves for cue-locked P2 in S cluster (range -1.5/1.5 microVolts) in the Go (above) and NoGo-1 (below) conditions.



As regards the C cluster, the ANOVAs on the P3 and the N4 components did not reveal any significant effect ($p > 0.05$ for all effects).

Target-locked ERPs

The cue-locked S and C cluster, and the reconstructed ERPs after RIDE are displayed in Figure 5. For the S cluster of target-locked ERPs neither N1 nor P2 components revealed significant differences in the ANOVAs ($p>0.05$).

Conversely, for the C cluster, the P3 component revealed no significant main effects ($p > 0.05$) but a significant Condition by Sequence interaction ($F_{1,23} = 4.67913$, $p = 0.04$, partial eta squared = 0.17). Specifically, P3 in ABA trials was more pronounced than in CBA trials in the Go condition only (Duncan's post-hoc tests: $p = 0.05$) (Figure 6 and 7).

Finally, the N4 component revealed a significant main effect of Sequence ($F_{1,23} = 4.709272$, $p = 0.04$, partial eta squared = 0.17) evidencing a stronger negativity for ABA compared to CBA trials (mean = 0.12 s.d. = 0.43 and mean = 0.99 s.d. = 0.43 for ABA and CBA trials, respectively). No significant main effect of Condition nor the interaction were significant ($p > 0.05$).

As in cue-locked ERPs, we have further analyzed the peculiarity of NoGo Timing sub-conditions in a repeated-measures ANOVA 3x2 design, using NoGo Timing (CueNoGo, TargetNoGo, TargetStop), and Sequence (ABA, CBA) as independent variables. No significant effects were showed for both P3 and N4 were observed ($p > 0.05$).

Figure 5. Target-locked reconstructed ERP, S cluster, and C cluster at Cz.

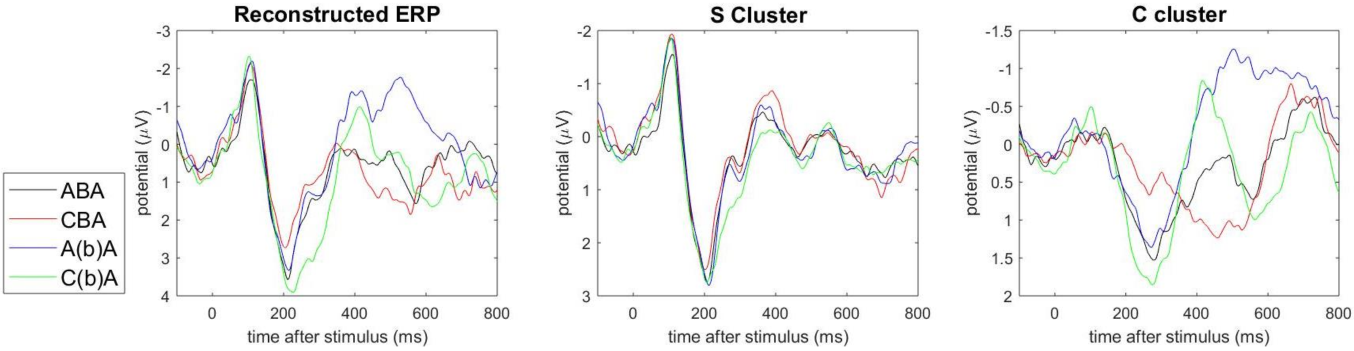


Figure 6. P3 Mean amplitudes in the C cluster of target-locked ERP. Error bars denote standard errors.

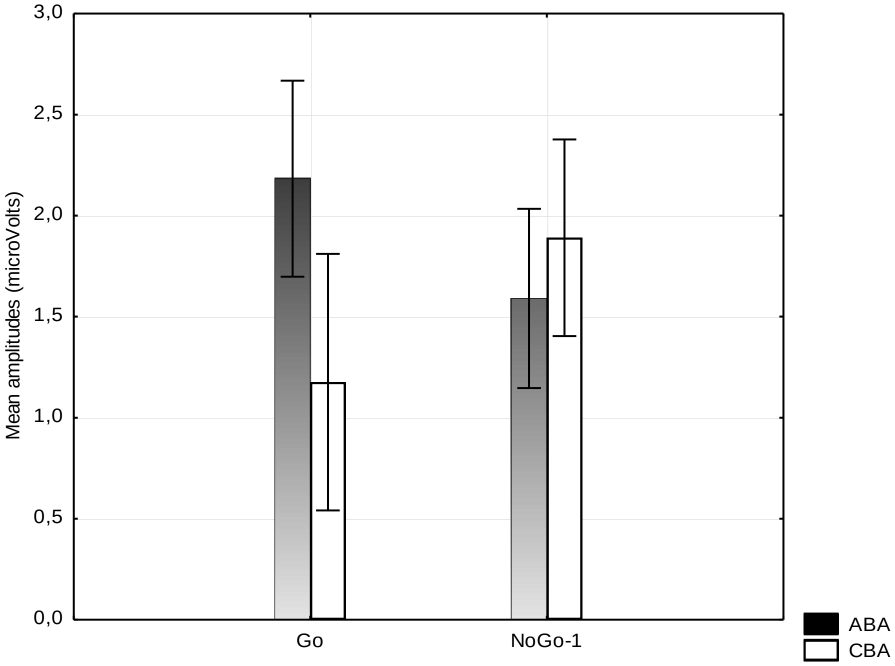
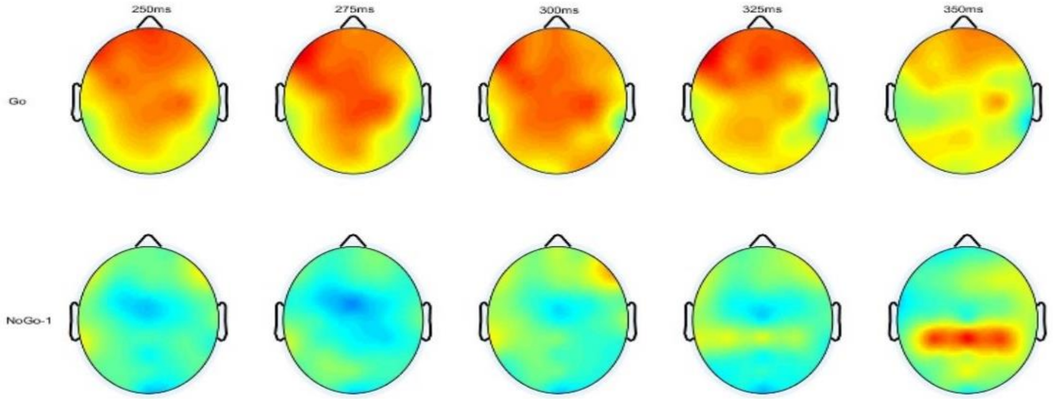


Figure 7. Topography evolution of ABA-CBA difference waves for target-locked P3 in C cluster (range -1.5/1.5 microVolts) in the Go (above) and NoGo-1 (below) conditions.



For target-locked C cluster we have also analyzed at Fz a late positivity (LP) component in NoGo/Stop trials in a 3x2 repeated measure ANOVA design, using NoGo Timing (CueNoGo, TargetNoGo, TargetStop) and Sequence (ABA,CBA) as independent variables. At Fz, participants exhibited (Figure 8) a stronger late positivity in CBA than ABA trials (main effect of Sequence: $F_{1,23}$= 4.31201, p = 0.049, partial eta squared = 0.16) and a progressively increased positivity from CueNoGo to TargetStop conditions (main effect of Condition: $F_{2,46}$ = 59.06937, p < 0.0001, partial eta squared = 0.72). However, the Condition by Sequence interaction was not significant (p > 0.05). The reconstructed ERPs, the S, and the C cluster for NoGo/Stop trials are displayed in Figure 9. The stronger positivity observed when participants must inhibit the response when the signal was provided after the target’s appearance might represent an increased effort spent in inhibiting that response, as also manifested in the reduced accuracy in the behavioral task. In addition, even not significant, behavioral data report a slight decrease in accuracy for CBA trials compared to ABA stop trials. Even if speculative, the reduced positivity observed in ABA sequences might represent the less strong effort in inhibiting that response, since an inhibition on that task has already been triggered, compared to the CBA trials.

Figure 8. LP mean amplitudes in target-locked C cluster ERPs in a NoGo/Stop trial. Error bars denote standard errors.

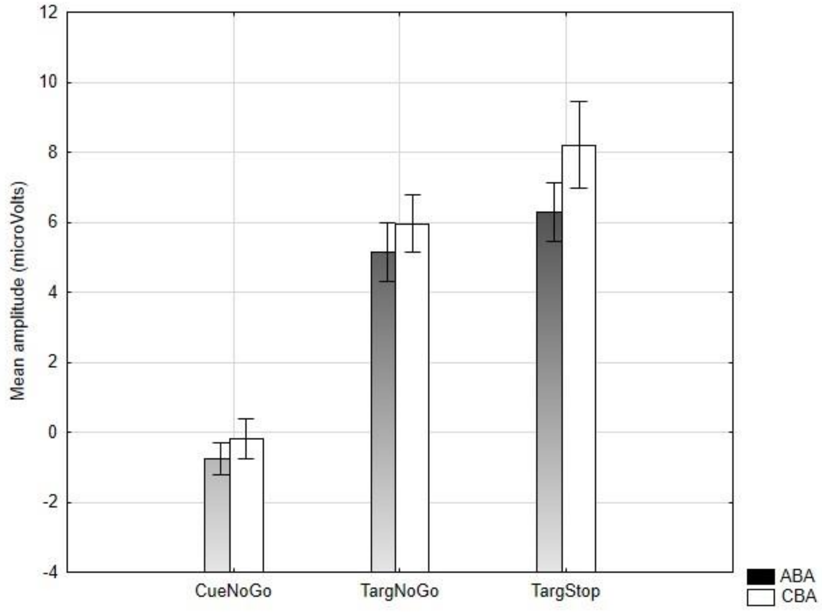
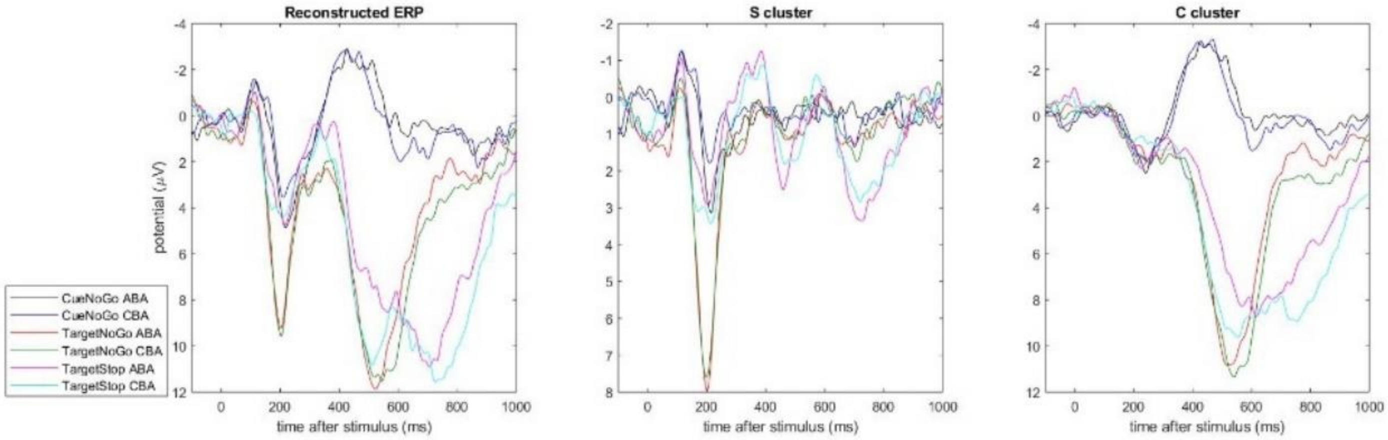


Figure 9. Target-locked reconstructed ERP, S cluster, and C cluster for NoGo/Stop Trials at Fz.



Regarding the R cluster, the mean amplitudes of the LP component at Fz were analyzed in a repeated-measures ANOVA design, using Go/NoGo Condition (Go, NoGo-1) and Sequence (ABA, CBA) as independent variables. The analysis failed to find any significant effect ($p > 0.05$).

Lateralized Readiness Potentials (LRPs)

LRPs Onsets (Figure 10 and 11) were analyzed in a repeated-measures ANOVA design, with GoNoGo condition (Go, NoGo-1) and Sequence (ABA, CBA) as independent variables. *F*s were corrected according to Ulrich and Miller (2001) (Equation 1), and *p values* were then recalculated. The analysis revealed a non-significant main effect of Condition, a non-significant Condition by Sequence interaction (p*corr* > 0.05), and a quasi-significant main effect of Sequence (p*corr* = 0.069). However, the difference between ABA and CBA trials in the Go condition, was larger than the same difference in the NoGo-1 condition (Figure 11). Note that since LRPs were response-locked and starting from 0 (the stimulus onset), a reduced onset means a delayed response.

$$\mathrm{Fcorr} = \frac{\mathrm{F}}{(\mathrm{n}-1)^2} \qquad (1)$$

Figure 10. LRPs for the different GoNoGo conditions (left: Go; right: NoGo-1). Continuous lines represent ABA trials, dashed lines CBA trials. Grey squares depict the differences in onsets between ABA and CBA trials.

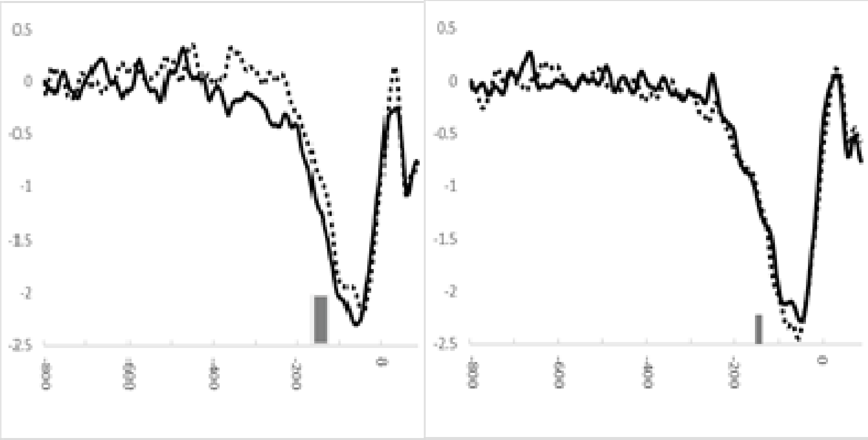
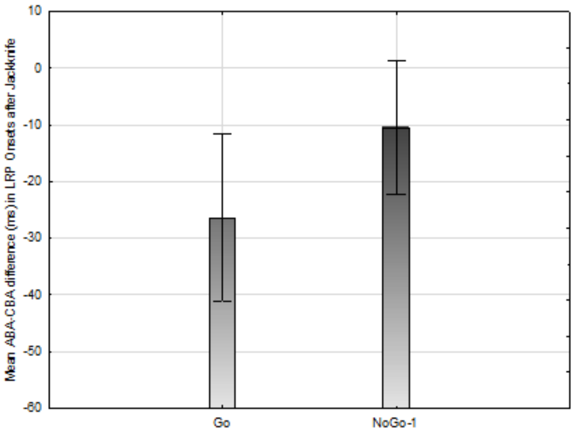


Figure 11. Mean difference (ms) between ABA and CBA trials' LRPs onsets in Jackknifed subsamples at C3/C4. Error bars denote standard errors, corrected as in Miller et al. (1998).



Our finding is consistent with the one obtained by Sinai et al. (2007) for LRP onsets. The absolute differences between ABA and CBA trials in LRP onsets (26.36 ms, calculated on Jackknifed subsamples) and in RTs (35.74 ms) are similar and represent the delayed preparatory processes occurring in N-2 repetition trials. However, we did not find a significant interaction between condition and sequence for LRP onsets even though in NoGo-1 the difference was smaller than in Go trials. Presumably, a larger sample size and a greater statistical power would have highlighted such interaction.

Discussion

Research on the N-2 repetition cost in cued task-switching has extensively shown that several processes underlying backward inhibition exist. For instance, literature presents various findings aimed at disentangling the differential role of preparatory, cue-related mechanisms, and task-set application-, stimulus- and response-related phenomena. To do so, authors have efficaciously manipulated tasks' variables such as the Response-Cue and the Cue-Target intervals (e.g., Gade and Koch, 2008; Bao et al., 2006; Schuch and Koch, 2003; Mayr and Keele, 2000, Scheil and Kleinsorge, 2014; Grange and Houghton, 2009; Koch et al., 2004), several features of cue and target stimuli (Altmann, 2007; Gade and Koch, 2008; Gade and Koch, 2014; Druey and Hübner, 2007; Grange and Houghton, 2009; Arbuthnott and Woodward, 2002, Arbuthnott, 2005), the stimulus-response mappings (Prosser et al., 2020; Regev and Meiran, 2017; Gade and Koch, 2007), or the response requirements (Scheil et al., 2019; Sdoia and Ferlazzo; 2008; Schuch and Koch, 2003; Philipp et al., 2007). Such manipulations have efficiently shown that inhibitory processes that govern the ability to switch between tasks cannot be solely ascribed to, for example, preparatory or applicative processes alone but that a mixture of psychological mechanisms are involved. Intriguingly, that mixture of mechanisms regards both high- and low-level processes (Ruthruff et al., 2001; Tieges et al., 2007).

In the present study, we aimed investigating the role of particular processing stages (preparation, stimulus processing) combining behavioral and electrophysiological (event-related potentials) measures. To inspect if differences in ERP components between ABA and CBA are peculiarly related to backward inhibition processes and not to purely sequential effects, we used a standard three-task-switching paradigm, combined with a Go/NoGo task, as already used in Schuch and Koch (2003) and Philipp et al. (2007). Following their results, we hypothesized that, when in the N-1 trial no response must be provided, the N-2 repetition cost is abolished. In addition, manipulating the timing of the NoGo, we expected different results if participants are asked to stop preparatory or post-target reconfiguration processes.

Consistently with the literature (Schuch and Koch, 2003; Philipp et al., 2007), our results showed that the N-2 repetition cost was eliminated when the N-1 trial was a NoGo task. Also, the N-2 repetition cost was not observed in the NoGo-1 condition either if the NoGo signal was provided at the presentation of the cue, of the Target, or 200 ms after the Target. By previous interpretations of the N-2 repetition cost (Koch et al., 2010), our results support the view that stimulus-processing and response preparation/execution stages play a major role in the triggering of BI. Indeed, if preparation processes alone were enough for the occurrence of the task-set inhibition, we should have observed the typical slowing of RTs in ABA trials when the NoGo signal in the N-1 task was given in concomitance with or after the target's appearance. However, since the task-set might require more than 200 ms to be reconfigured after the target presentation, our findings cannot precisely disentangle target- and response-related roles.

ERP investigations on backward inhibition are few and implemented different versions of the standard behavioral paradigm. For instance, Sinai et al. (2007) have compared episodic and semantic switching, while others (Zhang et al., 2016; 2019; Giller et al., 2019; 2020; Wolff et al., 2018; Zink et al., 2019) have used a double-press (univalent) as a third task and a very short CSI (100 ms).

In the present study, ERP results have prominently shown two patterns of effects, consistent with the view that backward inhibition is a dual-process involving both cue- and target-related processes. Instantly, most important findings in our work showed that sequence effects (ABA vs. CBA trials) are modulated by a decreased central positivity for ABA trials for cue-locked waveforms after about 200 ms the cue-onset, and an increased central positivity for target-locked ERPs after about 300 ms the target-onset, reflecting changes in P2- and P3-like components, respectively. Implementing the

RIDE technique (Ouyang et al., 2011), we were able to show that those changes occurred respectively at the early, stimulus-related and at the later central clusters.

In task-switching studies, an early switch-related cue-locked fronto-central positivity is reliably observed, peaking approximately at 200 ms after cue-onset, which has been suggested to be involved in the rapid detection of changes in the upcoming task (e.g., Finke et al., 2012; Karayanidis and Jamadar, 2014; De Baene and Brass, 2014).

In our findings, the N-2 repetition-related reduction of P2 might be explained as the fewer resources required by the task-rule to be activated. Indeed, ABA cues might require less strong activation than CBA cues, since their representation is still active in working memory. During CBA trials, the N task has been less recently performed than the ABA task; then, it entails a stronger attentional enhancement for its retrieval. At first glance, this may seem a simple recency effect. Indeed, several authors have attributed to switch-costs memory interference processes from the precedent task-sets (Wylie and Allport, 2000): if a task has not been recently performed, its goal requires a more robust enhancement to be re-activated relative to a recently performed one. However, we are confident in excluding such interpretation due to the absence of this sequence effect in NoGo-1 trials. Since ABA and CBA sequences did not change in the NoGo-1 condition, we should have expected a similar pattern of results for the NoGo-1 condition. Instead, results provide evidence that inhibitory processes may affect this early but flexible component: the task-set inhibition triggered at the N-1 task on the N-2 task weakened the activation of the task-set during this stage. Intriguingly, research has evidenced that the P2, besides underlying stimulus evaluation, also represents a task-relevant rather than a general “change detector” (Finke et al., 2012; Gajewski et al., 2008). Our ERPs results did not replicate findings from Sinai et al. (2007), which found a reduced/enhanced N2/P3 for backward inhibition compared to control waveforms. However, several points should be addressed. First, Sinai et al. employed a very long CSI (1130 ms), which may have reduced the need for subjects to prepare for the upcoming task rapidly. Secondly, the authors have employed semantic/episodic conditions, analyzing alternating triplets of tasks (e.g., semantic-episodic-semantic) in experimental and control sequences. Third, since we use the RIDE technique to decompose stimulus-related, central, and response-related clusters, it is possible that individual variability might have played a role in hiding the effects we found.

At the opposite, we observed an increased target-locked P3 for ABA trials compared to CBA trials. Again, this sequence effect was not observed in the NoGo-1 condition. This N-2 repetition-related positivity presumably underly task-set reconfiguration processes that occur during stimulus processing. Following traditional accounts of the P3 (Donchin and Coles, 1988), enhancement can be interpreted as the more effortful updating processes required in ABA trials, i.e., when the inhibition triggered over the task-set must be overcome. Indeed, it is plausible that switching back to an inhibited task requires a stronger effort than switching back to a non-inhibited task. Frequency accounts (e.g., oddball) of the P3 enhancement are discarded since the number of ABA, and CBA trials were balanced, and the number of task repetitions was kept at a minimum. Similarly to the P2 effect arguments, we discarded pure retrieval interpretations (because the effects were not observed for NoGo-1 trials) and an implicit expectancy of sequences. Indeed, since P3 has been largely related to novelty and surprise effects (Friedman et al., 2001), CBA might be implicitly more expected than ABA sequences due to cognitive biases (i.e., the representativeness heuristic; Tversky and Kahneman, 1974). However, if no inhibitory processes were present, we should have observed the same pattern in the NoGo-1 condition. In addition, novelty and task-switching P3 have been shown to share common networks (Barcelò et al., 2006). While Sinai et al. (2007) did not measure target-locked ERPs, we have already argued that the difference in the paradigms employed in other ERP studies of backward inhibition (Zhang et al., 2016; 2017; Giller et al., 2019; 2020; Zink et al., 2019; Wolff et al., 2018) make the results not fully comparable. However, these studies found mixed and controversial results.

A combined interpretation of the present findings regards the possibility that the more substantial post-target effort in updating the task-set (i.e., the enhanced P3) is a compensatory process generated by the weaker attentional engagement during task-set activation in ABA compared to CBA trials (i.e., the reduced P2). This evidence may speak in support of a sort of threshold model for the overcome from backward inhibition. Task-set inhibition can be triggered at the post-target stage, whereas overcoming from that inhibition does reflect cue-related activation and target-related reconfiguration processes, operating at different levels on the representation of task-sets.

Furthermore, we observed other interesting non-interactive effects between Go/NoGo conditions and sequence. Instantly, we found stronger cue-locked N1/P2 components when the previous trial was a NoGo than it was a Go task. These effects were prominent when the NoGo signal was provided simultaneously to the cue. Indeed, in that condition, we assume that the task has not been processed at all, and the decrement/increment in N1/P2 components might reflect the detection of changes in perceptual cue-related properties and task-set activations occurring in the switch from a NoGo to a Go task. In fact, when the NoGo signal was presented later (e.g., simultaneously to the target or after the target), the cue was of the same category (Go), and the task-set was activated.

We also observed a main effect of sequence for the target-locked N4, with increased negativity for ABA compared to CBA trials. The N4 waveform has been traditionally linked to semantic processing violations and meaning processing (Kutas and Federmeier, 2014; Vachon and Jolicoeur, 2011). However, other findings (Hoen and Dominey, 2000; Niedeggen et al., 1999; Barrett and Rugg, 1990) have suggested that the N4 responds to the detection of a rule/sequence violations on a more general level, involving also nonverbal stimuli. A subcomponent of the N4 is the centro-parietal N450, which is typically found in the Stroop task (e.g., Szűcs and Soltész, 2012; West and Alain, 2000). More precisely, N450 is characterized as a negativity in the incongruent-congruent difference potentials and represent a marker of stimulus-related conflict detection/resolution processes. Interestingly, our findings do suggest that even in the absence of a response in the N-1 task, sequences and conflicts might still be processed after task-set reconfiguration. Speculatively, overcoming from inhibition may require the combination of reconfiguration (P3) and conflict resolution (N4) mechanisms. However, that result requires further investigations.

In summary, our results speak against a pure retrieval account and support a dual-processes interpretation of task-set inhibition. According to the task-set application view of the N-2 repetition cost, our findings showed that target processing is essential for the backward inhibition. Both behavioral and electrophysiological data support this. Instantly, when the previous task is a NoGo, we observed no N-2 repetition cost and no differences in either cue- or target-related ERP components. These differences in standard Go runs were prominently reflected in cue- and target-related ERP components, possibly reflecting an additive and compensatory role of task-set activation/reconfiguration processes.

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CHAPTER 4

Beyond outcomes and probabilities: stress and decision-making in controlled and complex environments

Decision-making has been one of the research fields most influenced by dual-process theories. Particularly, DPTs represented an attractive solution to the problem of finding the source of errors in human choices and judgments.

Making good choices is often of paramount importance for survival and, generally, for well-being. However, the right choices (if they exist) are often not immediately available to individuals. Decision-making processes are quite hard to operationalize. Indeed, they are strictly dependent upon a large number of features and dimensions belonging to both the environmental context and the individual state, on which rigorous experimental control is not always simple to put. Outcomes, probabilities, structures, number of alternatives, time available, but also intentions, goals, motivations, emotions, and feelings are just some of the factors that play a pivotal role in determining the strategy used by individuals to express preferences, learning from feedback, and use previous experience.

Decision-making theories roots cover broad aspects of human knowledge, from psychology and neuroscience to social sciences and economics. Many attempts to formalize human decision-making have been made, especially in the flourishing behavioral economics context.

Until Simon's bounded rationality (1955), the Von Neumann and Morgenstern's expected utility theory (1953) was the primary view in the field, suggesting human rationality. With the rational limitations highlighted by Simon (1955), the literature on decision-making has moved toward the discovery of biases and heuristics in human rationality and choices. With their Prospect Theory (1979), Kahneman and Tversky, revolutionized the idea of human beings as rational individuals, evidencing with a formal description that errors in decision-making strategies are systematic rather than casual. The limited computational resources move individuals toward the massive use of effortless cognitive shortcuts. The adaptivity of these fast and frugal strategies has been widely suggested, promoting the mind's view as an adaptive toolbox (Gigerenzer and Todd, 1999).

Intuitive and rational strategies here partially reflect the automatic-controlled view of cognitive processes. Indeed, as described in previous sections, even in the case of decision-making, the separated dichotomy is theoretically attractive but not powerfully demonstrated. Individuals are undoubtedly capable of making high-speed choices, but also to operate very hard cost-benefit analyses. What are the conditions in which one strategy is preferred over the other? If two different systems, networks, or information processing modes exist, what differentiates the two?

Stressing the control: does control failures necessarily prompt habitual behavior?

Even if it is still not fully clarified how, stress is known to profoundly affect cognition and behavior. Since the Selye's discoveries, the stress response has been considered as a non-specific physiological response to any kind of stressor (Selye, 1974). Successively, a specificity account has reached more consensus: different stressors activate different responses of the same physiological mechanism (Pacak and Palkovitz, 2001). For instance, Herman and Culliman (1997) differentiate between systemic and processive stressors. Systemic stressors are those generated by an immediate threat of physiological nature: these are, for example, a sudden lack of oxygen or an exaggerated temperature drop or rise; instead, processive stressors require high-order processing of stimuli. Processive and systemic stressors rely upon different neural responses and produce different outputs (Pacak and Palkovitz, 2001).

This dual nature of stressors partially reflects the duality of physiological responses exerted by a stressor in the organism, measured by rising levels of catecholamines (such as epinephrine, norepinephrine, and dopamine) and glucocorticoids (such as cortisol). The formers are sympathomimetic hormones, mainly released by the adrenal medulla and the synaptic terminations of both sympathetic and central nervous systems. They give rise to a rapid physiological response, aimed at increasing arousal for an immediate fight-flight response to a stressor, by inhibiting all the processes not necessary in that situation, such as visceral and digestive activity. Glucocorticoids, instead, are hormones released by adrenal glands as a product of the activation of the top-down hypothalamus-pituitary-adrenal (HPA) axis, a circuit in which are involved structures related to emotional and salient stimuli processing, such as the amygdala and the hippocampus. The hormonal response is a slower than the sympathetic one, with a peak 15-20 minutes after the stressor, and a recovery (without stressor repetitions) about 60 minutes later. Chronic stress is supposed to dysregulate the HPA activity, exerting long-lasting negative consequences for many physiological systems, such as the immune and the reproductive systems.

Behavioral stress responses are known to rely upon the connectivity between the amygdala and the prefrontal cortex, specifically the medial prefrontal cortex (mPFC), through the transmission of serotonin and GABA (Andolina et al., 2013). Specifically, the mPFC modulates the amygdala responses to environmental salient and emotional stimuli, which has led some authors to conceptualize a default stress response normally inhibited by prefrontal activity (Brosschot et al., 2016). Stress and perceived unsafety may disrupt the normal function of PFC and thus impair the amygdala's inhibitory regulation pathway.

The effects of stress on performance can be described in a cognitive-energetical model, which suggests that task performance can be partially saved thanks to high-consuming compensatory processes at the cost of latent decrements in other aspects of the cognitive system (Hockey, 1997; Mandrick et al., 2016). In general, these decrements have been broadly described as a narrowing of attention (Chajut and Algom, 2003; Baddeley, 1972), limitation of working memory resources (Shields et al., 2016; Arnsten, 2009; Schoofs et al., 2008; 2009; 2013), and behavior adjustment to more habitual and low-effortful strategies (Schwabe and Wolf, 2011; 2013). Traditionally, the resource depletion hypothesis is the principal interpretation for adverse effects of stress on cognitive performance and prefrontal functions, supported by several confirmatory neuroscientific findings (Liston et al., 2009; Qin et al., 2009; Bogdanov and Schwabe, 2016).

Coherently, stressful events have been found to change neurobiological mechanisms shifting the allocation of resources from the executive to a salience network, a change supported by the sharp increase in dopamine levels (Hermans et al., 2014), and to impair reward-related activity in PFC (Ossewaarde et al., 2011). These effects reflect an imbalance between the functioning of the two cognitive systems in a dual processes account (Stanovich and West, 2000; Evans, 2008): stress is known to shift cognition from top-down control to bottom-up automatic processing mode (Vogel et al., 2016; Möschl et al., 2017), hypothesizing an impairment in explicit memory and an improvement in implicit memory (Sandi, 2013), a hypothesis also supported by several neuroimaging studies (Arnsten, 2009; Gold et al., 2015). This duality of effects is also explicated in preserved automatic functioning, with habit formation processes improved. Skilled individuals suffer less than non-skilled ones the effects of stress on performance, a result consistent in the view of automatization of processes: novice operators or emergency/novel situations rely upon the use of controlled processing, which can be profoundly disrupted by stress (Hancock, 1986). However, several results pointed to the beneficial effects of stress on cognitive performance, such as in inhibitory mechanisms (Plessow et al., 2011; 2012; 2017), according to the view of narrowed attention against a simplified resource depletion hypothesis and promoting the view of a shift within rather than a shift away from control strategies.

Several factors influence how individuals act under stressful situations: in their COPE model, Cohen et al. (2016) described a circular relationship between work content, cognition, and action. Work content is constituted of goals and task demands: goals are assumed to be organized in a hierarchical manner, where the fit between high-level goals and sub-goals is essential for optimal engagement in the task. Task instructions have been found to influence performance. For instance, Plessow et al. (2017) found that a repeated reminder of the requested performance strategy mitigates the adverse effects of psychosocial stress on cognitive control. Finally, performance scheduling after stress experience could exert different effects. For instance, in a risky decision-making task, the delay between the stressor and the task was found to induce risk aversion 5 or 18 minutes after stressors and risk-taking 28 minutes after (Pabst et al., 2013). Also, short delays were found to impair working memory and enhance inhibition while longer delays cause the opposite pattern, suggesting a double-time effect of rapid non-genomic effects and cortisol secretion's slow genomic effects (Shields et al., 2015). The COPE model also comprises endogenous intervening factors. Individual emotional state and coping strategies (Folkman and Lazarus, 1984) have been largely shown to affect physiological stress response and task performance (Ben-Zur, 1999; Janson and Rohleder, 2017).

Additionally, several studies have described that the cognitive appraisal of a stressful event as a challenge or a threat influences motivation and self-efficacy, which can predict better or worse performance (Trotman et al., 2018). Finally, stress is known to increase physiological arousal, which has been extensively related to cognitive performance. As Keren and Schul (2009) argued, the continuum of arousal does not fit well with a continuous or dichotomous theorization of affect in DPT. Indeed, it is often assumed that processes relying upon System 1 are "hot" while processes relying upon System 2 are "cold". Nevertheless, what does "cold" mean in the arousal continuum? The lowest or the mid-point? Alternatively, as Keren and Schul discussed, is an interpretation implying affect to be a peculiar characteristic of System 1 reasonable? However, emotional valence has shown to have differential effects on cognitive control, showing that pleasure and not arousal vary the level of conflict adaptation in a flanker task (van Steenbergen et al., 2010; 2011).

Evidence shows that the exposure to stress can disrupt the modulatory role of control over habitual behavior. Although low-order processes seem to remain intact, if not improved, high order cognition is profoundly impaired. However, this impairment seems to be dependent upon factors such as type of stressor, timing, affect states, goals, and coping strategies. Additionally, stress has found to affect in a different way cognitive functions that are suggested to rely upon overlapping brain structures, such as working memory, inhibition, and decision-making. Moreover, different paradigms for each cognitive assessment have revealed controversial results.

The non-unitary nature of stress effects on cognitive control again suggests that the general binary view of the controlled and automatic process is not exhaustive in explaining the several interactive phenomena. Stress manipulations are useful techniques in the investigation of these interactions, aiding in the advances of knowledge of the functioning of the human cognitive system.

Decision-making and stress

Assuming the dual nature of the cognitive mechanisms underlying decision-making processes (Dolan and Dayan, 2013; Tversky and Kahneman, 1983; Reyna, 2004; Evans, 2008), in line with research on reasoning and judgment, stress-related effects are well known to impair analytical in favor of habitual strategies of choice.

The "shift", as it is frequently called, reflects two different primary behavioral outcomes in decision-making functioning: at one side, the working memory overload, suggesting the decrement in control processes, and the augmented saliency of environmental stimuli, revealing an increased tendency to process information in a bottom-up fashion. Accordingly, literature has shown that stress: affects flexible decision-making, making individuals less sensitive to outcome devaluation (Schwabe and Wolf, 2011), increasing the tendency, exacerbated by trait impulsivity, to perseverate choices (Raio et al., 2020), reducing model-based learning, with working memory capacity and processing speed having a protective role (Otto et al., 2013; Friedel et al.; 2017), and altering reward-related dimensions, such as valuation, learning, and risk-taking (Porcelli and Delgado, 2017). At the same time, stress is known to alter feedback sensitivity, blunting reward prediction error (Zhang et al., 2020), and supposedly reducing the use of negative feedbacks (Petzold et al., 2010), facilitating model-free reinforcement learning after adverse outcomes (Park et al., 2017). Numerous findings have also reported higher risk-taking after stress exposure, even though with sex differences (Lighthall et al., 2009; 2012) and increased disadvantageous choices in both risk and uncertainty conditions (Porcelli and Delgado, 2009; Preston et al., 2007; van de Bos et al., 2009). The task's reward contingencies have a prominent role in determining the presence of the effect: situations in which a risk-prone behavior leads to disadvantageous outcomes are more affected by stress than when the same behavior does not lead to better performance (Starcke and Brand, 2016).

Moreover, according to Starcke and Brand, the worst performance is observed in uncertainty compared to risk conditions. The degree of ambiguity has a pivotal role in decision contexts. It generally indicates how much probabilities and outcomes associated with the available alternatives are explicit to decision-makers, ranging from complete ignorance to absolute certainty of outcomes, through uncertainty (probabilities of outcomes are not known) and risk (probabilities are known, but outcomes are still not sure). Decision-making assumptions have been made upon several different experimental paradigms, ranging in the continuum of ambiguity. It is assumed that, in normal conditions, decision-making under risk is mostly supported by rational processes and executive functioning (Brand et al., 2006) aimed at maximizing expected reward whereas decision-making under uncertainty by intuitive strategies and implicit learning, relying upon gut feelings and history of reward experiences (Bechara et al., 1997). This consideration leaves open the question whether the same behavioral outcome (e.g., more disadvantageous choices) reflects the same or different underlying processes when situations presented to individuals are dimensionally distinguished. However, research has frequently neglected the differential role of paradigms and conditions, and a systematic study of decision-making components, with or without stress, is lacking.

Stress-related effects on decision making follow the more general contribution of stress on cognitive performance, stating that under stress individuals tend to act in a less-demanding way, promoting non-consuming processing. However, it is worth noting that all the phenomena observed regard two very distinctive systems, and little is known about how they interact or how the shift from one to the other system seems to happen. Instead, the famous metaphor of the continuum is strictly related to the current availability of resources, with less the resources, the less consuming processes must be used. When the fuel of a car is running low, it is necessary to switch off all electronic devices connected to the car battery, saving more fuel as possible to reach the nearest petrol station. Then, if the GPS cannot work, the driver must use its previous knowledge and follow already known routes, if these are available.

In the same way, under overload, the cognitive system temporarily cut off unnecessary processes to reach the goal and start following already known patterns and avoiding effortful analyses, according to the degree of available resources. This explanation is simple, easy, and clear. However, it does not seem to answer questions such as why individuals frequently use cognitive shortcuts even when there is no energetic reason to use them, how the degree of the contribution of the two processes can be measured, or at which point the switch happened.

A promising line of research aimed at simultaneously assessing the contribution of dual processes to decision-making comes from reinforcement learning. Reinforcement learning aims to formalize cognitive mechanisms in the interaction between an agent and the environment through computational models. This suggests that an agent constantly updates its value representation of choices according to the feedback collected and implements decisional models to explore the world. In this context, Daw and colleagues (2011) have developed a two-step task which is supposed to evaluate two different learning strategies: a model-free, reward-sensitive, and inflexible versus a model-based, structure-sensitive, and flexible strategy. The parametrization of the computational model of this task assumes that a weighting parameter is responsible for the degree of model-free/model-based contribution to behavior encountered in subjects, hypothesizing that a hybrid model is the best fit for the human participant in normal conditions. This approach, coupled with the use of many standard decision-making paradigms, appears to be a good solution for the increase of knowledge about the multiplicity of stress-related effects on cognition. A dual control view of learning and decision-making has been suggested in RL's field of RL also uses neuroimaging techniques, providing evidence for competition between prefrontal and dorsolateral striatal networks (Daw et al., 2005).

Unfortunately, most current knowledge relies upon studies investigating the effects of laboratory-induced acute stress. Apart from the clinical population, as individuals with Post-Traumatic Stress Disorder, and individuals with early stress exposure, such as victims of infant violence, not part of the present work, very few studies investigated the impact of everyday stress and chronic stress exposure on cognition and, to a greater extent, on decision-making. Despite the complexity of chronic stress and its complicated controlled investigation, results similar to those obtained through acute stress manipulations have been shown. Indeed, it has been found that decision-making shifts toward more habitual strategies (Soares et al., 2012; Lenow et al., 2017), unbalancing the activation of underlying networks from the associative to the sensorimotor circuits and atrophying medial prefrontal cortex and putamen (Soares et al., 2012). Cortisol levels seem to be an important predictor of this effect. Insensitivity to losses and increased reward dependence were suggested in individuals with lower cortisol basal levels (van Honk et al., 2003) providing additional evidence for the determining role of cortisol amount rather than the stress manipulation per se in other contexts (Otto et al., 2013; Starcke et al., 2011): individual variability in stress reactions matters.

In conclusion, although the results obtained indicate that decision-making can be strongly affected by stress, a general framework in the context of known dual-process theories is hard to draw. Experimental studies aimed at integrating findings are needed, eventually positing the concerting, rather than complementary, roles of low and high-order processes.

This experimental chapter

Overall, data in this last section regard decision-making, which is at the top of the cognitive functions here investigated in terms of complexity. Indeed, decision-making requires individuals to make inferences and calculations integrating a lot of factors, such as alternatives, probabilities, outcomes, task structure, and own's affective state. According to the decisional environment, and the degree of uncertainty presented to subjects, decision-making processes can be determined by bottom-up, intuitive, or top-down, analytical strategies. It will be shown that affective states and environmental conditions, but also individual differences and tasks type may determine the prevalence of one or the other strategy. In the first study, decision-making research in the laboratory is described. In the experiment will be shown how different decision-making processes are differentially affected by an acute stress induction procedure. Decision-making is assessed through three paradigms, and the data showed that they are not equally affected by stress and that individual differences in impulsivity have a substantial role in determining the strategy used by individuals after the manipulation. In a second study the differential impact on different decision-making and controlled processes have been shown during a prolonged stressful condition, due to the social isolation caused by the COVID-19 pandemic lockdown in Italy. In both studies, a complementary or a continuum account of the relation between the two systems is not fully supported.

Psychosocial acute stress affects model-free/model-based learning strategies in human decision-making: individual risk propensity matters.

Abstract

Human decision-making is widely sensitive to stress exposure. Literature has extensively shown that stress may strongly affect decision-making, prompting individuals to inflexibly rely upon habitual strategies. However, research has mostly focused on single paradigms, neglecting the multidimensional construct of cognitive processes underlying decision-making.

In this experiment, we investigated decision-making through three paradigms: the Markov Decision Task (MDT), the Balloon Analogue Risk Task (BART), and a Wheel of Fortune Task (WFT), aimed at detecting simultaneously different components of decisional processes. Through a within-subject controlled design, we administered a stress induction procedure through a variant of the Trier Social Stress Test, verifying its efficacy through autonomic (HRV) and biological (salivary cortisol) measures. The results showed that the shift from a model-based to a model-free reinforcement learning strategy in the MDT was exacerbated by risk-seeking propensity: individuals with higher scores at BART were more prone to increase the use of model-free learning. Intriguingly, learning of task-contingencies, as measured by decision time cost as a function of task transitions, was found to be less coupled with model-based behavior under stress. Finally, performance at the WFT interacted with daily subjective stress in producing choice behavior changes, with no apparent relations with the other two paradigms. The results obtained present a promising picture for the study of decision-making under stress exposure.

Introduction

There is ample and growing consensus about the existence of two qualitatively different information processing strategies in the human mind and brain. This evidence has been demonstrated over a broad set of cognitive functions, among which decision-making represents one of the most productive fields. Dual-process theories currently use and misuse the terms System 1 and System 2 to differentiate between the two (Melnikoff and Bargh, 2018; Pennycook et al., 2018): the first one concerns habitual, associative, fast, and effortless strategies, whereas the second one, at the contrary, is rational, analytical, slow, and effortful. Evidence has shown that two different mechanisms exist, tapping different strategical and learning dimensions of decision-making (Brand et al., 2008; 2005). However, decision-making is a multi-component process, where both systems, or strategies, may interact in producing behavior, according to the nature of the decisional problem: in an uncertain environment (where there is no explicit information about options' outcomes and probabilities) decision-making strongly rests on intuitive strategies (i.e., System 1) while the opposite being true under risk.

A recent account for duality in decision-making models (Daw et al., 2011; 2018) has differentiated between two computational learning strategies. Under uncertainty, the performance in a sequential choice task can be mediated by the different contributions of a model-free (where choice behavior is dependent upon previous trial's outcomes observed) and a model-based (where outcomes are integrated into the representation of the task's probabilistic structure) component. Indeed, humans have shown to use hybrid strategies, suggesting that both may influence behavior, through the activity of different brain networks, in which areas such as the ventral striatum and the prefrontal cortex are involved (Daw et al., 2005; 2011).

Investigating the peculiar role of decision-making components is essential in the understanding of how these dimensions are interrelated. One manipulation which can induce changes in the weight of the two ways of information processing is acute stress, which is known to shift this balance toward habitual and less effortful responses (Schwabe and Wolf, 2011; 2013). Indeed, stress is known to modify the amygdala-prefrontal brain network, resulting in the reduced supply of high-order prefrontal processes (e.g., Andolina et al., 2013). This temporary impairment induced by acute stress has been widely demonstrated in decision-making literature, even though the variety of paradigms and the lack of systematic multi-component studies undermined a unified knowledge of stress's effects over the whole decisional process. For instance, it has been shown that in paradigms where increased risk-taking means increased disadvantageous choices, the effects of stress is more substantial than in other decisional contexts (Starcke and Brand, 2016). Moreover, decision-making dimensions, as measured by different paradigms, have shown to be uncorrelated (Bishara et al., 2009) and to produce dissociations among several conditions (Deisenhammer et al., 2018; Sun et al., 2020; Zhang et al., 2017; 2015; Adjeroud et al., 2017; Trotzke et al., 2015; Kim et al., 2015; Gorini et al., 2014; Goudriaan et al., 2010; Starcke et al., 2009), as well as overlapping brain areas despite divergent behavioral performance have been demonstrated (Pletzer and Ortner, 2016)

Furthermore, decision-making abilities and the effects of stress on it may vary as a function of individual differences, even though the literature on this point is controversial. For instance, personality characteristics have provided mixed evidence for decision-making performance in standard paradigms (Buelow and Cayton, 2020; Brunell and Buelow, 2017; Brand and Altstötter-Gleich, 2008), but these have not been tested under stress exposure. Instead, other individual functional variables provided promising results. Indeed, literature has shown that individuals with high working memory capacity are more protected from the aversive effects of stress, showing less or no reduction in model-based strategies (Otto et al., 2013). Recent work has found that individuals presenting high trait impulsivity have shown to be more perseverative in their choices than low trait impulsivity participants and speed up their decision times irrespective of reward (Raio et al., 2020). Coherently, a previous study using the same two-stage task, has found an increment of model-free learning in high-impulsivity individuals, showing reduced prefrontal model-based signatures (Deserno et al., 2015). However, impulsivity is a multidimensional construct, since interrelations between impulsivity, risk-taking, and decision under ambiguity have been observed (Giustiniani et al., 2019). It is indeed possible that other forms of impulsivity may interact differently with decision-making and stress effects. Moreover, while the use of questionnaires as a measure of impulsivity helps in clarifying individual or personality differences in choice behavior and stress reactions, it does not shed new light on how different decision paradigms are interrelated. Also, the use of different stress manipulations (generally distinguished in processive or systemic) may exert peculiar effects on cognitive performance.

In this picture, this study aimed at more systematically investigate how decision-making components (under uncertainty, under risk) can adjust themselves to the unbalance of the two strategies, considering individual risk-propensity as a possible intermediate factor.

Three decision-making paradigms have been used: the two-stage decision task (Daw et al., 2011) aimed at quantifying model-free and model-based contributions in an uncertain environment; the Balloon Analogue Risk Task (Lejuez et al., 2002), aimed at evaluating individual risk-propensity; the Wheel of Fortune Task (Camille et al., 2001), aimed at investigating the emotional role of regret under risk.

Methods

Participants

The sample size was defined through an a-priori power analysis conducted with MorePower, showing that 34 participants were sufficient to reach 0,9 power to increase the chances of replicability with a large effect size (0.25) in a repeated measures design.

Thirty-eight students from courses different from Psychology were enrolled in the study. Of these, 2 participants were excluded due to their drop out after the first session. Four additional participants were excluded because of contraceptives' or medications' use or because they refused to ultimately carry out the stress induction procedure. Data from 32 participants (14 females, age: mean= 22.81, sd=3.18) were finally included in the analyses. All participants were not aware of the hypotheses of the experiment. The study was approved by the Institutional Review Board of the Department of Psychology at the Sapienza University of Rome and conducted in accordance with its policies and with the Declaration of Helsinki. All participants provided written informed consent.

Stress induction procedure

The stress induction was done through a variant of the TSST, in which the speech was not performed but only anticipated (Starcke et al., 2008). Participants were told they had to prepare a 5-minutes speech, without papers and pencil, about their personality related to their academic choice, to motivate the fact that they are the right persons for what they chose to study. They were told that after the tasks, they would give the speech in front of a committee, composed of a psychologist and a professor. Additionally, they were told that the speech would be recorded through a camera to analyze their verbal and non-verbal behavior further. The committee would pose questions and highlight possible discrepancies between participants' verbal and non-verbal behavior, and personality tests would be administered. Participants were asked to fill a fake consent form for videotaping, and an off-camera was mounted in the room. Participants were then left 5 minutes thinking about their speech, and then a 5-minutes arithmetic task was performed aloud in front of the experimenter. The arithmetic task consisted of the progressive subtraction of 13 starting from 1022. Any wrong response was explicitly signalled by the experimenter, who asked the participant to start again from 1022. In the control condition, participants were left resting after the explanation of the procedure, and the arithmetic task consisted of the progressive summation of 15, starting from 0, without any explicit feedback. The complete procedure, in both sessions, lasted for 15 minutes.

Heart Rate Variability

Heart rate variability was recorded throughout the entire duration of each experimental session through a Polar chest belt. As a measure of HRV, pNN50 was calculated, i.e., the percentage of absolute differences in successive normal sinus interval (NN) values > 50 ms, known as a measure of parasympathetic activity (Mietus et al., 2002).

Salivary cortisol

Saliva samples were collected in each experimental session in three time-points: after 5 minutes resting (t0), immediately after the stress/control procedure (t1), and immediately after the completion of the last decision task (t2). Saliva samples were collected through standard *Salivette*® (Sarstedt), collection swabs centrifuged at 1000 rpm for 15 minutes, and then stored at -80°C into Eppendorf tubes. Cortisol concentrations were determined through immuno-enzymatic kits (ELISA, DiaMetra), with within assay variability of ≤ 10% and a between assay variability ≤ of 8.3%. Microplates were read at 450 mm filter. Duplicate assays were conducted for each sample interval, and the average of the two was used for analyses. Cortisol concentrations were log-transformed and interpolated against the standard-curve, calculated for each plate.

The areas under the curve respect to the ground (AUCg, equation 1) and respect to the increase (AUCi, equation 2) were calculated for each session to have measures of total cortisol production and changes in time, respectively. Due to the difference in t2 between participants, the areas were parametrized for each session as follows:

$$(1)\quad AUCg = \frac{\left(\left(\frac{s0+s1}{2}\right)*(t1)\right)+\left(\left(\frac{s1+s2}{2}\right)*(t2-t1)\right)}{t2}$$

$$(2)\quad AUCi = \frac{\left(\left(\frac{s0+s1}{2}\right)*(t1)\right)+\left(\left(\frac{s1+s2}{2}\right)*(t2-t1)\right)-\left(s0*(t2)\right)}{t2}$$

where s0, s1, and s2 were log-cortisol concentrations expressed in nMol/l at three time-points in each session and for each participant. t0, t1, and t2 are the time expressed in minutes of each sample for each time-point relative to t0 (which was kept at 0).

Also, participants were equally divided by the median of the peak-baseline measure in the stress condition into responders and non-responders.

Two-stage decision task

The two-stage decision task or Markov decision task (Daw et al., 2011) consists of two decision stages on each trial (see Figure 1a for the task scheme). The first decision stage involves two choice options associated with different transition probabilities (common, rare) to two second-stage states, each consisting of a specific pair of options. Indeed, each option in the first stage is commonly (70%) and rarely (30%) associated with each of the two second-stage states. Each of the four second-stage options is linked to a specific probability to get or not get a reward (1 Euro image), according to a randomly assigned Gaussian random walk, which varies independently throughout the task with s.d. 0.025 and reflecting boundaries 0.25 and 0.75 (Figure 1b).

In this task, participants must constantly update reward predictions at the second stage (model-free decision making) and use this information prospectively to make goal-directed (model-based) decisions at the first decision stage on the next trial.

In the task, stay-switch behavior is defined as the probability to repeat a choice on the first stage as a function of the transition (common or rare) and the outcome (reward, no reward) on the previous trial.

Participants underwent instructions and training (firstly differentiated for both stages, then together) with different symbols, colors, and reward probabilities. The experimental task consisted of 201 trials without breaks. The first 20 trials were considered as practice and were removed from analyses. Participants used the "f" and "j" keys on the keyboard to choose between the left and right options. The position of the choices was not fixed as they varied randomly in each trial.

Scores are calculated as differences measures for model-free behavior [(common reward + rare reward) − (common no reward + rare no reward)] and model-based behavior [(common rewarded + rare unrewarded) − (rare rewarded + common unrewarded)].

Figure 1.

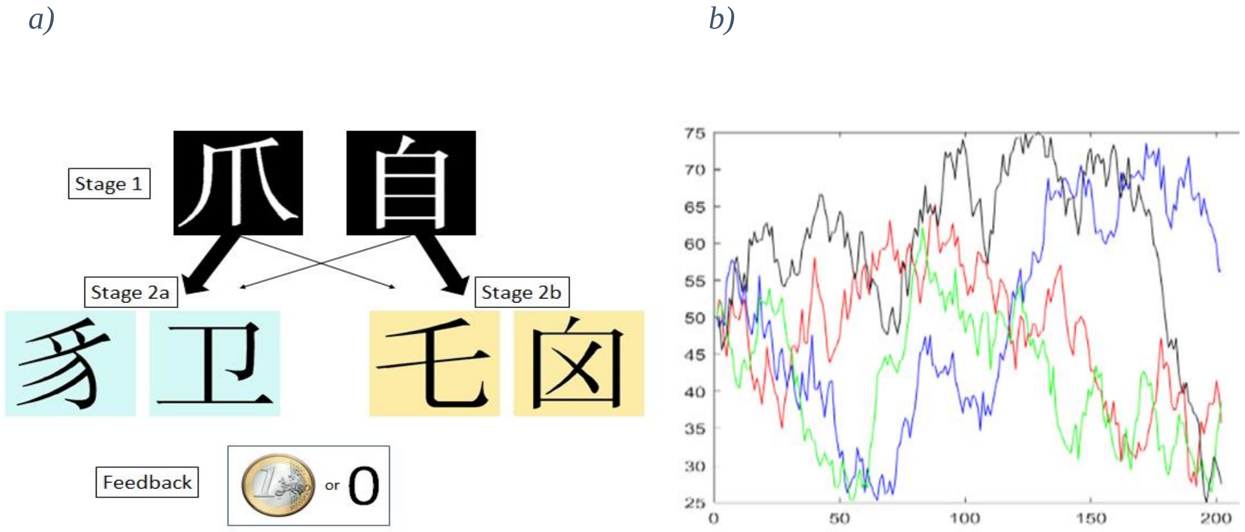


Figure 1. a) Inner structure of the two-stage decision-task. Thick and thin lines represent common (70%) and rare (30%) transitions, respectively. b) Independent Gaussian random walks randomly associated to the four 2-stage options (trials and reward probabilities on the x and the y axes, respectively).

Balloon Analogue Risk Task

In the Balloon Analogue Risk Task (BART; Lejuez, 2002), participants must inflate a balloon on the screen using the spacebar as much as they want to increase their score of 0.05 at each pump. As they wish, they can capitalize on the score obtained at each balloon by pressing "enter" on the keyboard. Participants were told that the balloon might explode at any time since the first pump, make them lose the points they were collecting for that balloon without affecting already capitalized points and that its size may cover the entire screen. The maximum number of pumps allowed were 128 for each balloon, and the explosion probability linearly increased from 1/128 at the first pump. After a single practice balloon, 30 balloons were presented in the task. Scores were calculated as mean pumps adjusted for non-exploded trials. Additionally, the median of the BART score obtained in the control condition was used to differentiate between low and high risk-propensity participants.

Wheel of Fortune Task

In the Wheel of Fortune Task (Camille et al., 2004), participants were asked to choose in each of the 64 trials composing the task between two wheels. The two wheels explicitly presented outcomes and their related probabilities (table 1), aiming at evaluating decision-making under risk. Each wheel's outcome probabilities were kept constant at -50/+50% (safe option) and -25/+75% (risky option).

Participants clicked on the "OK" button under each wheel to choose it. After they clicked, the wheel-needle started rotating, and participants were required to click again on the "OK" button to stop it. In half of the trials, both the outcomes (chosen, unchosen) were displayed (complete feedback), whereas, in the other half, only the outcome of the chosen wheel was presented (partial feedback). All the outcomes were predetermined to have a similar number of losses and wins. Participants might observe outcomes as long as they wish and then click again on a button to go further, allowing for calculating the time spent in analyzing the outcomes. Then, participants were asked to rate on a -50/+50 Visual Analogue Scale their happiness at that moment. Finally, they clicked on the button again, and a new trial started.

Scores were calculated as the number of risky choices made. Decision (time between the beginning of each trial and the choice of the wheel) and feedback (time between the presentation of the outcomes and the click to go further) times were also recorded, as well as the happiness ratings for losses and wins.

Questionnaires

Participants were required to fill two questionnaires at the end of the two sessions. These were Italian versions of the Coping Strategies Inventory (Tobin et al., 1989) and the Daily Hassles Stress Scale (Kohn and Macdonald, 1992), in order to control for habitual coping strategies used by subjects and subjective stress levels in the month before the experiment.

Procedure

The study implemented a within-subjects design. Participants performed two experimental sessions (control and stress) approximately one week apart. They were asked not to eat, drink coffee, tea, or other stimulants, assume drugs or any other substance, smoke, wash teeth, and use make-up cosmetics at least two hours before the scheduled experimental session. All sessions were scheduled between 1:30 and 5:30 PM to control for circadian rises and falls of cortisol levels. Also, the sessions' time was approximately the same in the two sessions of each participant, and the two sessions' order was counterbalanced within participants.

Participants came to the lab and signed the first informed consent. This informed consent lacked correct information about the study's real objectives to keep participants naïve about the hypotheses of the study. Indeed, the experiment was presented as a general investigation of decision-making abilities and self-evaluation processes. Then, participants were asked to switch off their phones, wore the HR belt (Polar) and were asked to rest for five minutes and fill a short anonymized demographic questionnaire (providing information about sex, age, use of contraceptives, drugs, stimulants, smoking and alcohol attitudes), during which baseline HR was registered. After these 5 minutes, the first saliva sample was collected (t0), the stress/control procedure was implemented, and the second saliva sample was collected (t1). Participants were told that at the end of the two sessions, they would receive a book voucher. The value of the voucher would vary according to their performance at the three decision tasks. Then, participants performed the three decision tasks in counterbalanced randomized order, and the last saliva sample was collected (t2). Participants in the first session were then dismissed, whereas participants in the second session were asked to fill the two questionnaires, the real informed consent, and were debriefed before leaving the laboratory. All participants received the same 10 euros book voucher for their participation.

Results

Physiological response to stress

The pNN50 was taken as an index of Heart Rate Variability (Mietus et al., 2002). A first one-way ANOVA was conducted with condition (control and stress) as repeated measures factor. The results reported a non-significant decrease of pNN50 in the stress condition (mean=0.48, sd= 0.03) than in the control condition (mean=0.53, sd=0.03), even though it tended to significance (F1,31=3.6887, p=0.064, partial eta2=0.11). In a separate two-ways ANOVA, with condition as repeated measures and risk-propensity group as between-subjects factor, the main effect of condition became significant ($F_{1,30}$=4.5218, $p < 0.05$, partial eta2=0.13), while all other effects were non-significant ($p > 0.05$) (Figure 2).

Planned comparisons for the mean pNN50 for each 5 minutes time-point have shown that conditions significantly differ at the 4th time-point, i.e., between 10 and 15 minutes after the beginning of the stress procedure (t(6)= 2.49, $p < 0.05$).

To assess total cortisol levels and change with time, AUCg and AUCi were calculated. For the AUCg, an ANOVA was run with condition as a repeated measure factor and sex as a between-subjects factor. The analysis did not show significant differences ($p > 0.05$ for all effects), even though participants showed higher cortisol production during the stress condition (mean= 0.94, sd= 0.06 and mean 1.02, sd=0.08, for control and stress condition respectively, p for the main effect of condition = 0.08) (Figure 3a).

The same analyses were run using AUCi as a dependent variable. A non-significant effect of condition was observed in the first one-way ANOVA, and the same was true in a second two-way ANOVA with condition and gender as factors, and in all the ANOVAs with self-report scores as continuous predictors (p >0.05 for all effects). Due to the interindividual variability of hormonal response, the same analyses were repeated by considering responders and non-responders as a between-subjects factor. For the AUCg, no significant differences were again highlighted (p> 0.05 for all effects). Conversely, for the AUCi, the ANOVA reported a significant main effect of response (F1,30=11.69089, p < 0.01, partial eta2= 0.28) and no main effect of condition (p > 0.05). The interaction was also significant (F1,30=7.76675, p < 0.01, partial eta2= 0.2), explained by the increased AUCi in responders compared to non-responders in the Stress but not in the Control condition (Figure 3b).

High interindividual variability for physiological data has presumably played a role in all the analyses. A larger sample size might have possibly produced significant effects due to the increase of statistical power.

Figure 2. pNN-50 index for Heart Rate Variability in the Control and Stress conditions. Vertical bars denote standard errors.

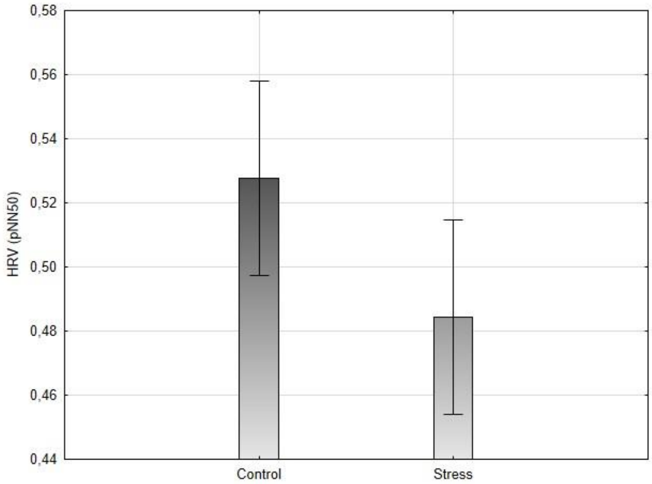
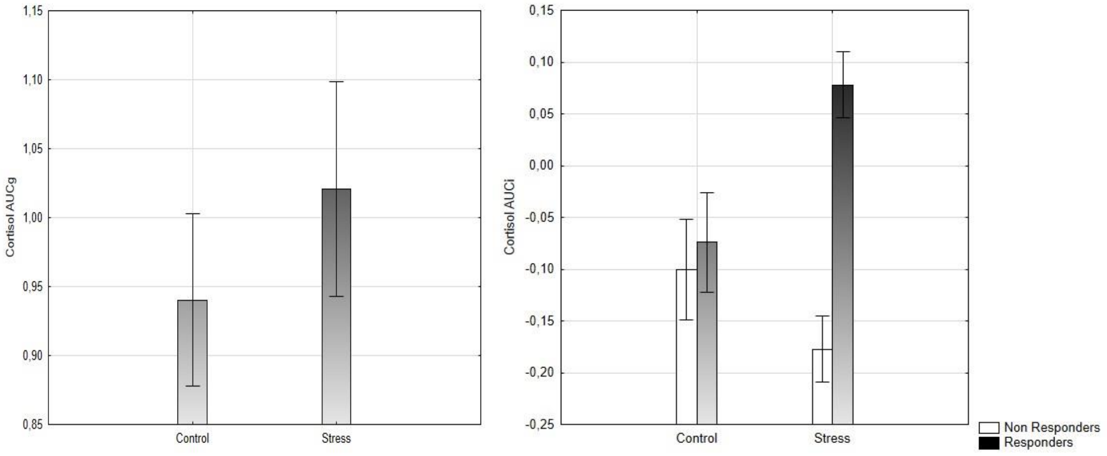


Figure 3. a) Area under the curve with respect to the ground of cortisol production in the Control and Stress conditions. b) Area under the curve with respect to increase of cortisol production in the Control and Stress conditions. Vertical bars denote standard errors.

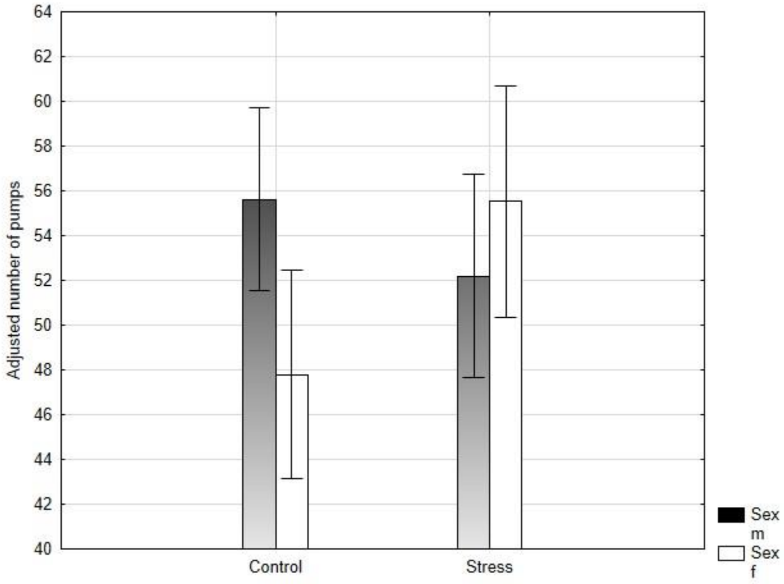


a) *b)*

Balloon Analogue Risk Task

Mean adjusted pumps were analyzed in a two-way ANOVA with condition (control and stress) as within- and gender as between-subjects factors, since previous research has shown gender differences in response to stress (Lighthall et al., 2009). Results showed a significant effect of the interaction ($F_{1,30}$=4,8720, $p < 0.05$, partial eta2= 0.14) and non-significant main effects of condition and gender ($p > 0.05$). Duncan's post-hoc contrasts reveal ed that the interaction effect was due to a significantly higher score in the stress than in the control condition ($p < 0.05$) in females (mean= 47.79, sd=4.66 and mean= 55.52, sd=5.15 for the control and stress condition, respectively), while no difference was observed in males (mean= 55.62, sd=4.11 and mean= 52.2, sd=4.54 for the control and stress condition, respectively) (Figure 4). That is an opposite result compared to literature (Lighthall et al., 2009; Deuter et al., 2017; Kluen et al., 2017), which showed that rather stress increases differences between females and males, with males being more risk seekers than females under stress. However, existing studies have implemented between-subject designs and might have been unable to explain individual pre-existent differences that have been observed in this case.

Figure 4. Mean adjusted number of pumps in Control and Stress conditions for men and womens. Vertical bars denote standard errors.



Two-stage decision task

A first ANOVA was run on stay probabilities in the first stage with condition (control and stress) and learning strategy (model-free and model-based) as repeated measures factors and risk-propensity group as between-subjects factor (low and high). The ANOVA showed a significant effect of the third-order interaction (F1,30=4.20911, $p < 0.05$, partial eta2= 0.12) and no significant differences for all the other effects ($p > 0.05$). Duncan's post-hoc tests revealed a significant difference in model-free indices in the stress condition between low and high-risk seekers, with the latter presenting a higher score ($p < 0.05$), while the increment in the model-free index in high-risk seekers between control and stress condition tended to significance ($p = 0.07$) (Figure 5).

To additionally test the effects of stress and risk propensity over the probability of repeating the first stage action as a function of previous reward and transition state at a population level, logistic generalized mixed models were implemented with all within-subjects factors as random coefficients, using the lme4 package for R (Bates et al., 2014). The model confirmed the significant reward by condition by risk-propensity group interaction (β (SE) = 0.24 (0.1), $p < 0.05$) and showed a significant reward by transition by risk-propensity group interaction (β (SE) = 0.16 (0.07), $p < 0.05$). Wald test revealed a significant main effect of reward ($p< 0.0001$), of reward by transition ($p<0.0001$), reward by risk-propensity group ($p<0.05$), reward by transition by risk-propensity group ($p< 0.05$), and reward by condition by risk-propensity group (p<0.05) interactions, confirming the role of individual risk-seeking levels in eliciting the effects of stress over model-free learning (Figure 6).

Due to the results of previous studies, RTs at both stages have been analyzed in separate ANOVAs. An ANOVA was then run over decision times in the first stage, with condition, choice (stay vs. switch) as within-subjects factors, and risk propensity group as between subjects. The analysis revealed only a significant main effect of condition (F1,30=4.7179, p < 0.05, partial eta2= 0.13), because stress participants were slower than in control condition (mean= 569,21, s.d.=32,2 and mean= 620,37, s.d.= 30,82, for control and stress condition respectively), irrespectively of type of choice and risk propensity (p > 0.05 for all other effects). The same analyses were run over stage 2 decision times, with the same factors, except for the stay-switch choice was substituted by transition type (common vs. rare). As expected, the analysis revealed a significant main effect of transition ($F_{1,30}$=56.0220, p < 0.0001, partial eta2= 0.65), with rare trials slower than common trials, and again a significant main effect of condition ($F_{1,30}$=5.9801, p < 0.05, partial eta2= 0.16), with the same direction as the first stage decision time. No other significant differences were found (p> 0.05 for all the other effects). Since previous literature showed a correlation between Model-Based indices and the transition effect in RTs, an analysis of covariance was run over 2nd stage RTs with model-based indices at control and stress condition. The two main effects of condition and transition were preserved (F1,26=10.0952, p < 0.01, partial eta2= 0.28 and F1,26=29.6714, p < 0.0001, partial eta2= 0.53, respectively), and the model-based index in control condition interacted significantly with condition (F1,26=8.7572, p < 0.01, partial eta2= 0.25) and with condition x transition (F1,26=7.8706, p < 0.01, partial eta2= 0.23). No other interactions were observed (p>0.05). Then, to further clarify the relation between learning strategies and the 2nd stage decision-cost, Pearson's correlations were calculated. In the control condition, the decision-cost was significantly positively correlated with MB index (r= 0.6465, p< 0.001) but not with the MF index (r = 2.449, p> 0.05). Instead, in the stress condition both indices were significantly positively correlated with the decision cost (r = 0.4565, p <0.01, and r=0.4389, p <0.05 for MB and MF respectively) (Figure 7a and b).

Figure 5. Probabilities to repeat the same first stage choices: indices of model-free and model-based behavior. Model-free = [rewarded common + rewarded rare] - [unreward common - unrewarded rare]. Model-based = [rewarded common + unrewarded rare] – [rewarded rare + unrewarded common]. Vertical bars denote standard errors.

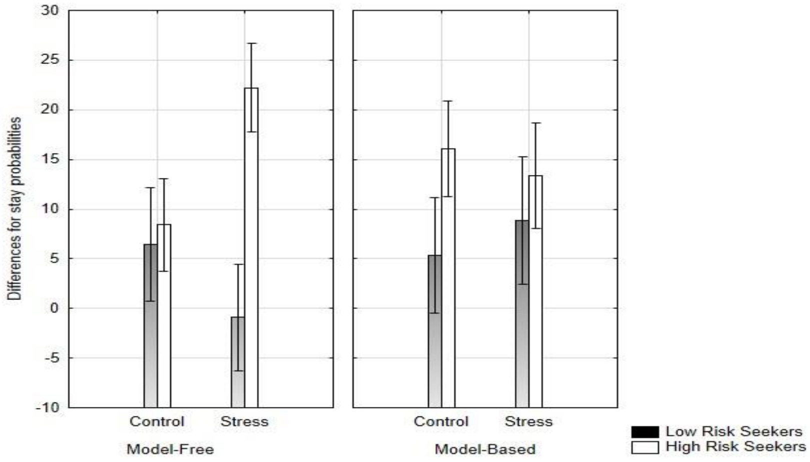


Figure 6. Coefficient plot for generalized mixed models, separately for Control and Stress conditions.

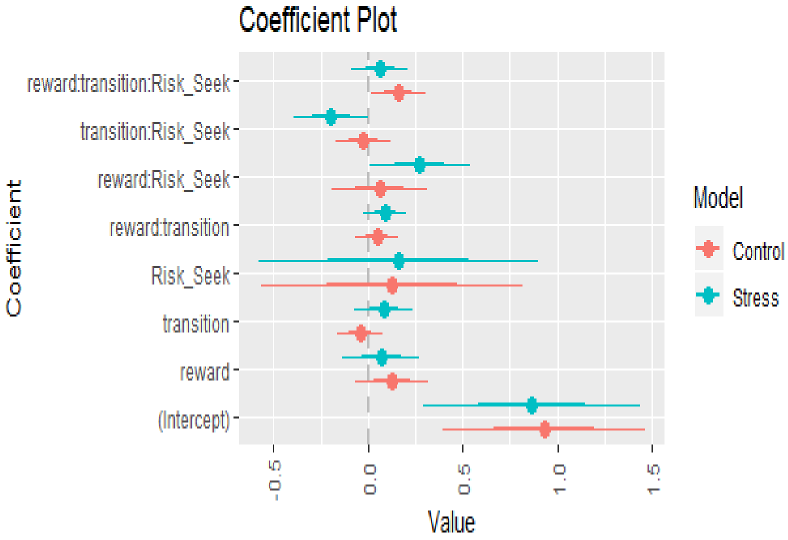
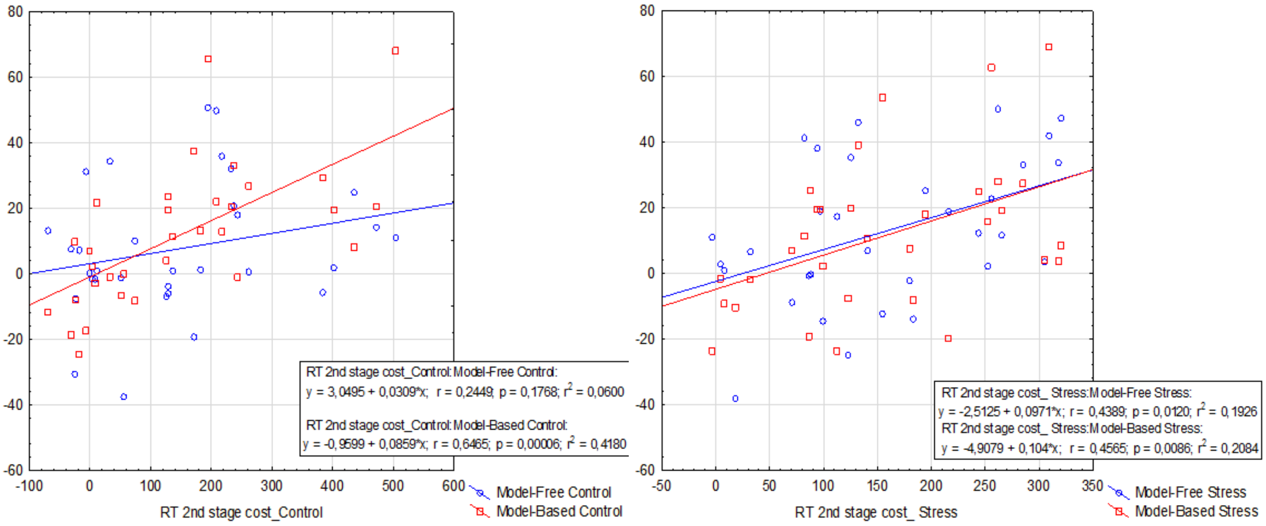


Figure 7. Pearson's correlations between model-free/model-based indices with the second stage RT-cost (RTs after rare – after common transitions) in the Control (a) and in the Stress (b) conditions.



a) *b)*

Wheel of Fortune Task

The number of risky choices was firstly analyzed in a two-way ANOVA with condition (control and stress) and feedback (complete and partial) as repeated measures factors. The analysis failed to show any significant differences ($p > 0.05$ for all effects), even in a second ANOVA where gender was considered a between-subject factor. Then, the scores at the Daily Hassles Stress Scale were inserted as continuous predictors in a separate analysis, to test if individual differences in daily experienced stress may play a role. With the DHS score, the interaction between condition and feedback turned out to be significant (F1,30= 8.40807, $p < 0.01$, partial eta2= 0.22), together with the interaction between condition, feedback, and the DHS (F1,30= 10.12793, $p < 0.01$, partial eta2= 0.25). All the main effects were non-significant except for a quasi-significance reached by the main effect of the DHS score ($p=0.054$), with more daily stressed participants were more risk-prone, regardless of the experimental conditions. Reduced risky choices in the partial feedback in stressed participants compared to the other three conditions explained the effect of the second-order interaction as tested by Duncan's post-hoc tests (Stress Partial vs. Control Complete, $p < 0.05$, Stress Partial vs. Stress Complete $p < 0.05$, Stress Partial vs. Control Partial $p=0.057$) (Figure 8).

Then, to test if the engagement in the evaluation of outcomes in the complete and partial feedback conditions was altered by stress, a repeated-measures ANOVA was conducted over feedback times with condition (control and stress) and feedback (complete and partial) as within-subjects factors. The analysis revealed a main effect of feedback (F1,31= 23.9019, p < 0.0001, partial eta2= 0.43), indicating that participants spent more time inspecting outcomes in the complete feedback (mean = 1833.75 ms, sd= 92.08ms) than in the partial feedback condition (mean= 1627.48 ms, sd=87.09 ms). The analysis also revealed no other significant effects (p>0.05 for all others). We repeated the same analysis controlling for the DHS score in the analysis of choices in an analysis of covariance. The interaction between condition and feedback turned out to be significant (F1,31=8.94358, p<0.01, partial eta2=0.23), as well as the third-order interaction (F1,31=7.51988, p<0.05, partial eta2=0.2). Duncan's post-hoc test revealed that participants spent less time inspecting outcomes in the Stress Partial condition compared to all the other three (p < 0.05 for all the contrasts except for the "Control Complete" vs. "Stress Complete" one, p = 0.08). The same ANOVA, with or without the DHS scores continuous predictor, or Risk-Propensity factor, over decision-times did not reveal any difference between conditions (p>0.05 for all effects).

Finally, emotional ratings were analyzed in a three-ways ANOVA with condition (control vs. stress), outcome (loss vs. win), and feedback (complete vs. partial) within-subjects factors. The analysis showed significant differences in all the three main effects (F1,31=4.9591, p<0.05, partial eta2=0.14; F1,31=114.4044, p<0.0001, partial eta2=0.79; F1,31=4.3930, p<0.05, partial eta2=0.12, for condition, outcome, and feedback main effects respectively), showing that participants rated more negatively the outcomes in the stress compared to control condition, after losses compared to wins, and in partial compared to complete trials. No other significant effects were found (p>0.05). Controlling for DHS score eliminated all significant differences (p>0.05) except for the outcome main effect (F1,31=7.869674, p<0.01, partial eta2=0.2). Instead, adding Risk Propensity group as a between-subjects factor, a significant condition x group was found (F1,29=4.719151, p<0.05, partial eta2=0.14), since participants in the low risk-propensity group evaluated more negatively outcomes in the stress condition compared to the control condition (Duncan's post-hoc, p<0.01) (Figure 9). In contrast, high risk-propensity group did not show any difference (p>0.05), and a significant outcome x group interaction (F1,29=5.183142, p<0.05, partial eta2=0.15), since more negative evaluations were made by high compared to the low risk-propensity group in the domain of losses (p<0.05) but not in the domain of wins (p>0.05).

Figure 8. Number of risky choices in Control and Stress conditions for Complete and Partial Feedback trials, using the DHS score as a covariate. Vertical bars denote standard errors.

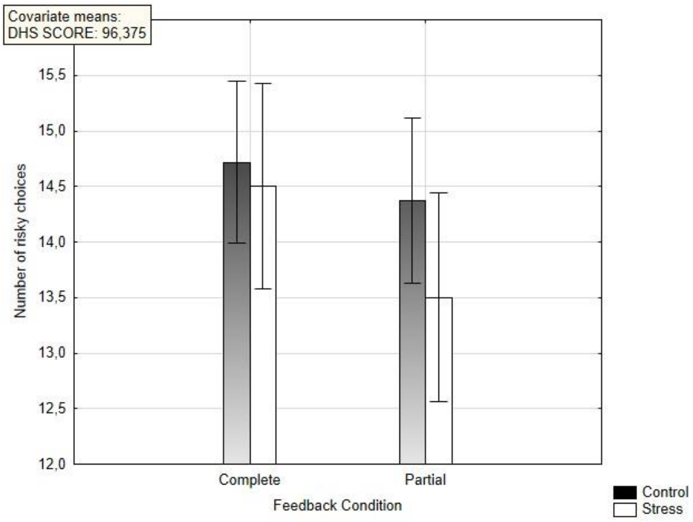
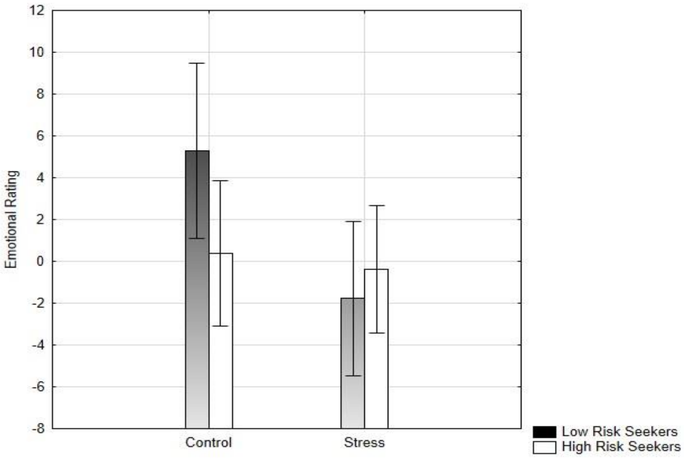


Figure 9. Mean emotional ratings in the Control and Stress conditions for low and high risk-seekers. Vertical bars denote standard errors.



Discussion

The literature on decision-making has extensively shown that individuals tend to modify their decisional strategies to deal with the threatening situation under stress exposure. However, despite the broad number of results, conclusions about the precise mechanisms underlying this shift are still not clear. Among the possible causes of this vagueness, there are: the large variety of decisional paradigms existent, the different stress manipulations, and the lack of systematic studies considering together these dimensions and the interrelations of decision-making constructs. Moreover, individual differences in decision-making strategies and response to stress may represent an important additional factor in determining the direction of the effects, which may play a pivotal role in exerting dissociations between variables and dimensions.

With this in mind, we hypothesized that acute stress induction might differently affect the connections among decision-making components, between and within paradigms. To do so, we used two "hybrid" decision-making paradigms, able to theoretically detect the influence of habitual/emotional and rational/analytical strategies in two different decisional environments, i.e., uncertain and risky conditions. Indeed, the Two-Stage Decision Task (Daw et al., 2011) can show model-free and model-based learning contribution in sequential decision-making, while the Wheel of Fortune Task (Camille et al., 2004) requires individuals to use counterfactual emotions in a risky environment. Furthermore, since literature has shown that decision-making is sensitive to impulsivity, we used a well-known decision-making paradigm, the Balloon Analogue Risk Task (Lejuez et al., 2002), to control wheter risk propensity is able to modulate the connections between decision dimensions and stress effects.

Firstly, the results have shown that acute stress prompts habitual behavior through the selective increase in model-free learning strategy in the two-step decision task, but only in high risk-propensity participants, as measured by the BART score in the control condition. We observed no complementary reductions in model-based learning, indicating that presumably, the relation between the two strategies does not take the form of a continuum. The studies that investigated the effects of acute stress on this task reported unclear findings: a model-based reduction has been shown only in Otto et al. (2013), where the reduction was linked to cortisol increase rather than to the experimental condition. Differently to us, Otto et al. implemented a between-subject design, where the role of individual differences in hormonal levels, in response to stress, and task performance might have played a role. Radenbach et al. (2015), found a reduction in model-based behavior under acute stress for more chronically stressed participants, while Park et al. (2017) found that stress enhanced model-free learning but using a different task design, implementing a reversal-learning task with fixed probabilities, where linking rewards to choices is quite more effortless. Furthermore, Otto et al. (2013) have used a systemic stressor (the Cold Pressor Test), and possible differential effects between stressor types might be present.

Following recent evidence (Raio et al., 2020), trait impulsivity has been found to account for stress-related effects in the two-step task's performance. Raio et al. found that stress-related effects in impulsive individuals account for choice perseveration and time to make decisions, without consequences on the balance between model-free and model-based. As the authors argued, impulsivity is a vast construct consisting of several dimensions. Here we evidenced for the first time that risk-propensity, as measured by the BART, can have an impact in determining stress-related changes in model-free behavior, extending their results, and making a step toward the knowledge of the relation between impulsivity and decision-making. Trait impulsivity and risk-propensity have been shown to produce different behaviors and are suggested to account for performance in decision-making tasks differently (Upton et al., 2011). However, we did not measure trait impulsivity since it was not part of our hypothesis, but future research should highlight possible dissociations between constructs.

Interestingly, literature provided evidence about an RT indicator of model-based learning in the two-step task (Shahar et al., 2019; Deserno et al., 2015; Decker et al., 2016). In the 2nd stage, participants might encounter a common or a rare transition, and the difference of decision times between the two has been found to correlate with the model-based index. As expected, we found the same correlation in the control condition, while model-free was not linked to this indicator. Intriguingly, we found that in the stress condition, the correlations obtained between the RT indicator and the two indices were both significant but were not different one each other: the correlation with the MB was reduced while the one with MF was increased. Conversely, from the results on choice behavior, in this case, the relation between the two strategies seems to follow a continuum model. The RT difference between rare and common transition trials can be ascribed as a cost, quite similar to the costs usually observed in task-switching paradigms. This cost has traditionally been used as a measure of cognitive flexibility, describing high-order processing's functioning, where smaller costs are an indicator of highly flexible individuals. In this context, a link between the rare-common cost and the model-based index, which subtend the construction of internal models of task contingencies, appears to be theoretically sustainable. It might be that in normal conditions, these two dimensions are somehow "coupled". During stress, since it is widely known that it impairs the functioning of high-order, controlled processing in the frontal areas, this coupling is weakened, and habitual MF learning prompts out taking his complementary part of this relation. Finally, due to compensatory strategies, choice behavior in this task might be preserved, or more precise indicators must be developed. Undoubtedly, further research on this point is needed.

Secondly, in the risk task, the Wheel of Fortune, we found no effects over choice behavior or individual risk-propensity interaction. However, we found that the Daily Hassles Stress Scale's pre-existent stress levels generally increased risky choices. Furthermore, controlling for DHS score, acute stress was found to reduce risky choices, but only in partial feedback trials (i.e., when participants anticipately know that they will experience only the chosen wheel's outcome). The literature presents controversial findings of the direction of stress-related changes in risk-taking (Starcke and Brand, 2016). As Starcke and Brand argued (2016), factors inherent to the particular paradigms' condition play a pivotal role in the risk-taking changes' directionality. According to the regret theory, complete feedback trials might lead participants to generate counterfactuals and anticipated experience of regret or elation. The generation of counterfactual emotions require individuals to use top-down processes and deal with a larger amount of information than in partial feedback trials, which are assumed to generate disappointment-like emotions. Since participants in these trials do not have the chance to compare their choice to a counterfactual, during stress a "cognitive closure" mechanism might be instantiated as a need to eliminate the ambiguity and select the safest option. Coherently, the analysis of the feedback times (i.e., the time between the presentation of the outcomes and the click to go further) clearly indicated that a cognitive closure account might be consistent: obviously, participant spent less time in analysing outcomes in the partial feedback trials compared to complete feedback trials, but this reduction was more considerable in the stress condition. Differently, no effects were found for decision times (i.e., the time between the two wheels' presentation and the participants' choice). Thus, even in this case, stress effects are associated with feedback-related processes.

In conclusion, acute stress appears to disentangle feedback-learning processes from high-order representations in an uncertain sequential environment. In more risk-prone individuals, this effect appears to be more considerable, to the extent which stress may prompt otherwise hidden differences or compensatory effects might obscure explicit choice performance. That is explicated in augmented model-free learning behavior. One possible responsible mechanism might be represented by a reduced emotional stress reactivity (Smits et al., 2020) to environmental feedbacks and outcomes under stress. Relatedly but conversely, feedback-learning processes seem to change performance in a risky paradigm, where choice behavior turned out to be affected by acute stress according to an adjusted ability to anticipate and experience choice outcomes.

The obtained results open different and intriguing questions in the systematic investigation of the whole decision-making process and its relations to stress. Future research should: a) link these results to the performance of other standard paradigms, such as the Iowa Gambling Task, the Game of Dice Task, and the Delay Discounting Task, aimed at providing evidence about the interrelations between decision-making components and paradigms; b) propose new and better performance indicators; c) differentiate the stress effects through the use of processive and systemic procedures; d) provide evidence about the mediating role of individual factors.

Conclusions

In this within-subjects balanced design, a processive acute stress induction has been effective in producing differential choice-behavior changes depending on the decisional environment presented to participants and individual factors such as risk-propensity and daily subjectively experienced stress. Instantly, participants who presented high risk-propensity levels showed increased Model-Free learning strategy when stressed in the Two-Step Task, and no stress-related modulations of emotional ratings in a risky environment (in the Wheel of Fortune Task) compared to low risk-propensity individuals. Model-based modulation determined by stress was found in the "coupling" between choice and RT indicators, evidencing that learning from task contingencies shifted toward a model-free learning strategy. Differently, in a risky environment, a decrease in disadvantageous choices and in time spent observing outcomes is observed when participants have less feedback information to process, possibly related to a need for early cognitive closure. Future research must go further into these points, to systematically investigate the connections between and within decision-making components, by implementing transversal research by different paradigms and experimental methods.

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Decision-making under uncertainty and risk-propensity changes during COVID-19 pandemic lockdown in Italy: a longitudinal study.

Abstract

During the COVID-19 acute pandemic phase, many national governments claimed strict lockdowns, imposing billions of individuals to stay confined at home. Factors such as the social isolation, fear of contagion, worries for the loved ones, and the economic slump acted as prolonged stressor over individuals. Here, we present the findings of the cognitive part of a longitudinal study remotely conducted during and after the lockdown in Italy. Results from behavioral tasks have shown: a) a decrease in decision-making under uncertainty (Iowa Gambling Task) throughout the lockdown with a recovery in the follow-up; b) low risk-seeking (Balloon Analogue Risk Task) levels that increased as the lockdown continued, with a partial reduction in the follow-up; c) an acute decrease of cognitive control efficiency in task-switching in the first-time point measured. Under uncertainty, individuals are required to optimally connect with their gut feelings to guide behavior. Negative affect, generated by the social isolation and all the pandemic-related harmful issues, may reduce this ability modifying individuals' behavioral strategies. Short- and medium-term interpretations of the COVID-19 stressful experience are provided. Results from behavioral science during emergencies may be highly helpful to understand and prevent people's potentially dangerous conduct.

Introduction

The outbreak and spreading of the Severe Acute Respiratory Syndrome Coronavirus 2 (COVID-19) have had a tremendous worldwide impact on societies, getting governments in the position to make impressive decisions, especially about economics and healthcare.

Many national governments have implemented many extraordinary measures to counteract the diffusion of the COVID-19 and relieve the pressure on intensive care units. During the acute pandemic phase, millions of individuals were limited in their movements, with the closure of many national and regional borders. Considerably, in several countries, national or territorial lockdown was imposed.

Italy has been among the first nations to undergo a national lockdown since it has been the first Western country dealing with the COVID-19 pandemic. The first COVID-19 cases were reported at the end of February in Northern Italy, where little territorial lockdowns have been implemented. On March 9th, the government proclaimed the "*Io resto a casa*" (I stay at home) decree, imposing a forced quarantine for the entire country. Schools, universities, and almost the totality of the economic activities were closed, with only a minor part of individuals continued to go out for work, while smart working became a standard for both workers and students. Social and physical distancing was also imposed, prohibiting individuals from gathering. The lockdown was prolonged until May 4th.

The pandemic profoundly impacted individuals' mental health (Czeisler et al., 2020). Instantly, rates of suicides (e.g., Sher, 2020), sleep disturbances (e.g., Marelli et al., 2020; Blume et al., 2020), eating disorders (e.g., Fernàndez-Aranda et al., 2020), anxiety and depressive symptoms (e.g., Tang et al. 2020; Huang and Zhao, 2020), alcohol and substance abuse (e.g., Kar et al., 2020), and auto- and hetero-directed violence (e.g., WHO, 2020) increased in the population, to the point that some authors have outlined a COVID Stress Syndrome (Taylor et al., 2020). Central features of the COVID Stress Syndrome are the fear of the dangerousness of COVID-19, the worry about socioeconomic costs of COVID-19, xenophobic fears that foreigners are spreaders, traumatic stress symptoms, compulsive checking, reassurance-seeking, avoidance, panic buying, and coping difficulties during self-isolation. The adverse outcomes on mental health can be mostly ascribed to the economic slump, with many persons who lost their jobs, the death or sickness of loved ones, the fear of contagion, and the social isolation due to lockdown and social distancing politics. The pandemic lockdown period might have represented a prolonged stress condition, of which related acute and carry-over psychological effects are not already known.

Psychological research on COVID-19 flourished in the last months. As far as we know, the totality of studies implemented one-shot or longitudinal designs assessing mental outcomes through online surveys and self-report questionnaires. Already published research is showing interesting phenomena about psychological adaptation to the pandemic-related situation. For instance, studies have shown that the detrimental impact COVID-19 on mental health can be mitigated by psychological flexibility (Pakenham et al., 2020), i.e., the ability to adjust behavioral responses according to the environmental demands, possibly disposing individuals to adaptive coping strategies (Dawson and Golijani-Moghaddam, 2020). As plausible, during the emergency-related twisting of individuals' lives, adapting to the new and unpredictable changing situation is essential for good health. Besides, individuals during the pandemics must deal with massive but unclear and ambiguous information provided by media, preventing themselves from an invisible enemy whose developments are unknown. Instantly, intolerance to uncertainty was found to significatively account for depression and anxiety outcomes (del Valle et al., 2020). Intolerance to uncertainty can produce unhealthful behavioral outcomes, aimed at reducing the feeling of uncertainty. Indeed, individuals with a high need for cognitive closure were found to be engaged in more stockpiling food behavior during the COVID crisis (Brizi and Biraglia, 2020). In uncertain conditions, i.e., when risks are not explicit, people must rely upon previous experience and gut feelings to move in the environment and make decisions. According to the somatic marker hypothesis (Damasio et al., 1996; Bechara et al., 2000), the ability to learn from an uncertain environment is implicit and unconscious and is strictly compromised when the ability to recognize emotions is somehow impaired. During the pandemics, individuals with high trait emotional intelligence showed reduced negative emotions (Moròn and Biolik-Moròn, 2020).

Since other research has shown that changes can be observed in cognitive performance during the permanence in isolated and confined environments (see Kanas and Manzey, 2008; Lipnicki and Gunga, 2009; Strangman et al., 2014), our goal was to investigate how cognitive functions can adapt to this exceptional situation, possibly highlighting providing precious behavioral evidence useful for policymakers and prevention programs during pandemics (Van Bavel et al., 2020).

Up to now, to our knowledge, this is the first longitudinal study assessing cognitive functions through the repeated administration of behavioral tasks during the COVID-19 spreading.

Specifically, we investigated changes in decision-making and high-order executive functions, using standard decision and task-switching paradigms throughout and after Italy’s pandemic lockdown.

The importance of making fast and optimal decisions is essential during an emergency crisis. Indeed, good decision-making ability is essential to maintain citizen social responsibilities (such as using individual protection devices, keeping social and physical distancing, practicing regular personal hygiene, staying home during the lockdown), and to prevent harmful individual outcomes. Similarly, the consequence for bad decisions made by medical professionals or policymakers can be fatal both in short- and in the long-term. Since the pandemic development and the risks for being infected are not known (for instance, due to a large number of infectious asymptomatic individuals), being able to make decisions under uncertainty and having optimal capacities of cognitive flexibility is of paramount importance. Assessing risk-propensity levels is also crucial to predict possible violations of dispositions, making it possible to structure good and efficacious policies, and prevent or treat bad mental health outcomes during a prolonged emergency state. Indeed, knowledge on decision-making and cognition in general, changes during the current pandemic is essential in helping to understand how to manage threats across different social communities, improve the scientific and political communication, and align individual and collective interests (Van Bavel et al., 2020; Lunn et al., 2020; Betsch, 2020). The cognitive processes underlying decision-making, learning, and flexibility also reflect individuals’ ability to select and use only the information necessary to interpret reality. The ability to correctly evaluate risks and moderate one’s behavior is recurrent during the emergency and previous pandemics (Soper, 1919).

Much evidence exists on the effects of stress on cognitive and decision-making processes, though most of the studies do not focus on isolation and confinement conditions. In general, literature reports that under stress, people exhibited limitations of working memory resources (e.g., Shields et al., 2016; Arnsten, 2009; Schoofs et al., 2008), narrowing of attention to central information neglecting peripheral cues (e.g., Chajut and Algom, 2003; Baddeley, 1972), and tend to use more habitual, simple, and low-effortful behavioral strategies at the expenses of controlled and flexible ones (e.g., Schwabe and Wolf, 2011; 2013; Payne et al., 1988). Most of the studies investigating decision-making under stress have focused on its acute effects, generally evidencing increased risky decision-making (see Starcke and Brand, 2012). However, literature presents mixed results, possibly due to the different complexity of tasks, individual differences, and intensity and nature of stressors (e.g., Morgado et al., 2015; Porcelli and Delgado, 2009; Lighthall et al., 2009; van der Bos et al., 2009; Otto et al., 2013; Bourne and Yaroush, 2003; Lupien et al., 2009). Unfortunately, only a few studies investigated decision-making under chronic stress conditions, reporting both increased/decreased risky behavior associated with increased levels/administration of cortisol (i.e., the hormonal marker of the stress response) (van Honk et al., 2003; Kandasamy et al., 2014) and biased decision-making toward habitual and automatic strategies (Soares et al., 2012; Lenow et al., 2017; Baradell and Klein, 1993). Similarly, stress has been shown to induce task-switching performance changes, even though findings are controversial (Plessow et al., 2012; Tona et al., 2020; Deuter et al., 2019). Social isolation and feelings of loneliness have been shown to reduce cognitive control processes' efficiency (Van Baarsen et al., 2012) and overall cognitive performance (Cacioppo and Hawkley, 2009).

In the present work, we present the cognitive decision-making part of a longitudinal study on the psychological impact of the COVID-related lockdown in Italy. Data presented here are indeed part of a broader study, also evaluating sleep and other subjective indices. Through three different behavioral tasks administered online, we sought to investigate decision-making under uncertainty, risk-propensity, and cognitive flexibility.

Method

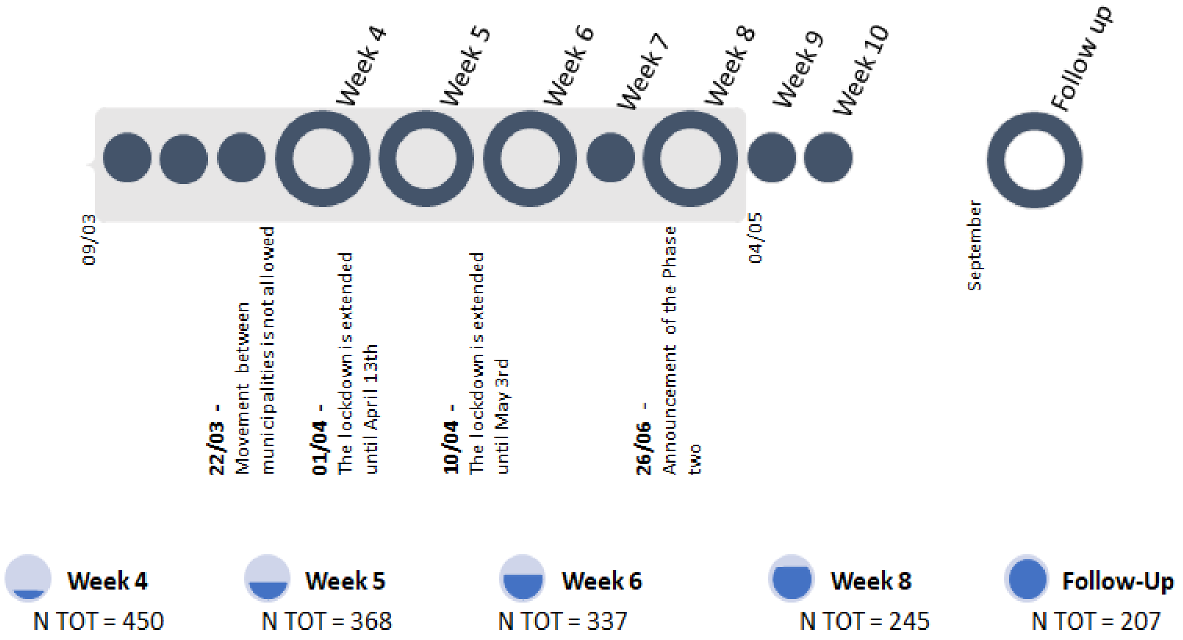
We started this longitudinal online study on March 28, 2020, enrolling participants through social media and university networks. We initially planned to have one time-point every week. However, since the Italian lockdown was prolonged, after three weeks, we asked participants to not respond in the successive one and to respond the week after. Since some participants made their first responses in the second week of the study, we maintained the same sequence of weekly intervals (1 – 1 – 1 –

2). Then, globally, our study covered from the end of March until mid-May. After six months since the begin of the lockdown, we contacted participants to respond again to have a follow-up measure. The number of total respondents for the cognitive part of the e-COVID study for each time-point, together with the study's timeline and the relevant events for the COVID-19 pandemic lockdown in Italy, are depicted in Figure 1.

Since we implemented a longitudinal within-subject design, we reduced sample size by excluding all the respondents that did not complete all the five time-points. Due to the small number of respondents who completed the study starting from the second or the third week since the beginning of the study, we used only data from respondents who completed the study and the tasks starting from the first week. Thus, we had three time-points during the lockdown (March 29 to April 19), one as the last-week of lockdown (April 26 to May 3), and one follow-up (September). If the same participant responded more than once at the same time-point, only the first response was considered.

The study was approved by the Institutional Review Board of the Department of Psychology at the Sapienza University of Rome and conducted in accordance with its policies and with the Declaration of Helsinki. All participants provided written informed consent.

Figure 1.



Above, the timeline of the study period. The grey area represents the lockdown period, from 09/03 to 04/05. Each circle represents a week. Circle labelled referred to the study time-points. Empty circles represent the time-points of the group considered in the present study (respondents who started at the beginning of the study). The major government's dispositions are reported under the timeline. Below, the total number of respondents in each of the considered time-points. The remaining time-points had low or very low number of respondents (50 in Week 7, 20 in Week 9, and 13 in Week 10).

Cognitive tasks

The three cognitive tasks we administered were implemented on the Inquisit platform (www.millisecond.com), modifying the parameters of existing scripts. All the scripts were Copyrighted © Millisecond Software. Participants were told to perform the tasks using their laptops.

Iowa Gambling Task

The Iowa Gambling Task (IGT; Bechara et al., 1994) is a behavioral task aimed at assessing decision-making under uncertainty. In this task, respondents must choose a card from one of four decks through their mouse in each trial. After they chose, each card provides feedbacks about the euros obtained, the euros lost, and the net gain. Unknown to participants, the four decks differ for the frequency and magnitude of losses. In two decks (A and C), losses are more frequent but smaller than in the other two decks (B and D). However, A and B are high-paying decks, presenting a higher magnitude of losses and equivalent overall net loss throughout the task. The opposite is true for the low-paying decks (C and D), which present a lower magnitude of losses, and they also are equivalent in the long run. Thus, decks A and B are categorized as “disadvantageous”, whereas decks C and D as “advantageous” decks.

Literature showed that healthy participants usually learn throughout the task what are the two advantageous decks and prefer to choose between them in the last blocks.

Following the Bechara’s standard paradigm (1994), gains were always equal to 100 euros for decks A and B and 50 euros for decks C and D. Losses were selected randomly without replacement from values in Table 1. To control for learning effects throughout the study period, we randomly manipulated the decks’ order into four possible combinations and decks’ reward by multiplying gains and losses (Table 1) by a factor of 1, 2, or 3, across subjects.

Table 1.

Deck A	0	0	0	0	0	150	200	250	300	350
Deck B	0	0	0	0	0	0	0	0	0	1250
Deck C	0	0	0	0	0	50	50	50	50	50
Deck D	0	0	0	0	0	0	0	0	0	250

Magnitude of losses in the Iowa Gambling Task across 10 trials for each of the four decks.

The task consisted of 100 trials not explicitly divided into 5 blocks. Participants started with 2000 virtual euros and are told to win as much as possible.

The standard IGT score was calculated as the number of advantageous minus the number of disadvantageous choices in each of the five blocks of trials. We also calculated the number of switches (i.e., when participants switch from one deck to another in successive trials) and latencies (i.e., the time between presenting a new trial and the subsequent choice).

Participants with 1 or less than 1 standard deviation of choice proportions among decks were excluded to control for casual performances. We excluded performances with 2 or less than 2 switches in the entire task to control for excessively perseverative participants. Latencies exceeding 2 standard deviations below/above the individual mean at each time-point were considered outliers and excluded from the analyses.

Balloon Analogue Risk Task

The Balloon Analogue Risk Task (BART; Lejuez et al., 2002) is an uncertainty-based decision-making task aimed at assessing risk-propensity. In this task, respondents are presented with one of 30 balloons in each trial. For each balloon, respondents must decide to inflate the balloon as much as they want, and temporarily gain money for each pump or permanently collect their winnings and skip to the next balloon. The payoff for each pump was set to 0.05 points. Participants are told that the balloon may explode after any pump, making them lose the potential winnings for that balloon. The maximum number of possible pumps for each balloon is 127, then the probability that a balloon might explode after the first pump is 1/128. This probability increases after each pump. Participants are unaware of the maximum number of pumps or the explosion probabilities. They do know that a balloon might explode after the first pump or that a balloon might fill up the entire screen without exploding. Participants are told that their goal is to earn as much as possible.

The adjusted average number of pumps was calculated as the mean number of pumps in unexploded balloons. The number of explosions and the time between pumps (except for the time before the first pump and between the last pump and the collect choice) were also calculated. The time between pumps exceeding 2 standard deviations below/above the individual mean at each time-point were considered outliers and excluded from the analyses.

Category Switch Task

In the Category Switch Task (Friedman et al., 2008; Mayr and Kliegl, 2003), participants are presented with a word in each trial, and they must respond as fast and accurately as possible according to one of two categorization rules. The "living" task is cued by a heart and requires participants to categorize words as living or non-living objects; the "size" task is cued by an arrow-cross and requires participants to categorize words on their size (bigger or smaller) relative to a basketball. Half of the trials are switch trials, and half are repetitions. Congruent and incongruent (same/different response required by the tasks) switch and repetition trials are equally balanced. Participants are required to respond on their keyboard using left and index fingers on 'E' and 'I' keys. Responses were randomly assigned to keys.

The entire task consisted of a practice and an experimental phase. The practice phase was made up of 32 separately unmixed trials for the "living/size" task, presented in random order. An additional 16 mixed trials were presented. If participants' accuracy was lower than 80%, additional practice trials were presented. The experimental phase consisted of 64 trials. RTs less than 100 ms were not possible. The intertrial interval was set at 500 ms for correct responses and 1500 ms for errors, while there was no cue-target interval.

RTs in the experimental phase were calculated for repetition and switch trials. We measured the switch-cost as the mean RT on switch trials minus the mean RT on repetition trials. Also, we calculated N-2 repetition cost (i.e., the persistent interference of previous task sets in current performance) see Mayr and Keele, 2000) by separately calculating RTs for AB*A* (e.g., "living" – "size" – "living") and BB*A* (e.g., "size" – "size" – "living") trials. RTs smaller/larger than 2 standard deviations below/above the individual mean at each time-point were considered outliers and excluded from the analyses.

Procedure

In the whole study, besides cognitive tasks, also sleep indices and questionnaires were administered. In each experimental day, participants entered the research website and launched the Inquisit link for cognitive tasks. The order of the tasks was fixed. The BART was the first task to complete, then the IOWA Gambling task, the Category Switch task, and finally, the Psychomotor Vigilance Task (which findings will be reported elsewhere). Informed consent was provided at the first experimental session through Qualtrics. Participants entered the tasks using a personal code. If they wish, they could provide their e-mail address to remind them of the successive time-points. Only the research team had access to e-mail addresses and other personal data.

Results

Iowa Gambling Task

After the correction of the IGT's database, data from 107 respondents (females = 71; mean age = 36.71, s.d. = 16.43) were analyzed.

Mauchly sphericity tests were conducted in each ANOVA. When significant, ps were adjusted according to Greenhouse-Geisser correction.

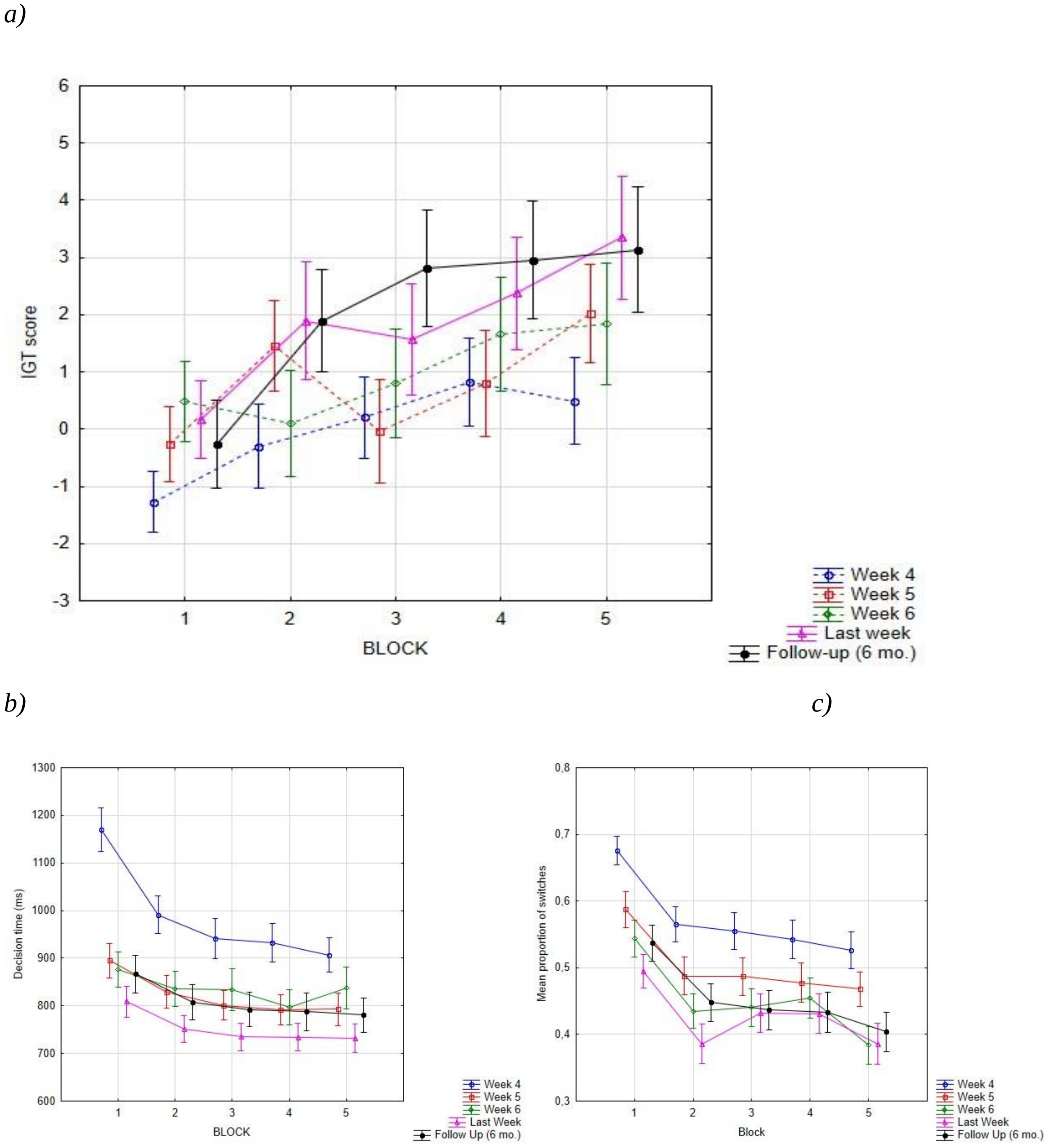
A first 5x5 repeated measures ANOVA on the IGT score was conducted using Week (Week 4, 5, 6, Last Week, and Follow Up) and Block (1 to 5) as independent variables. The ANOVA revealed significant main effects of Week and Block ($F_{4,424}=2.393764$, $p < 0.05$, partial eta squared = 0.02 and $F_{4,424}=8.121497$, $p < 0.0001$, partial eta squared = 0.07, for Week and Block effects, respectively) and no effect of the interaction ($p> 0.05$). However, since we observed differences in the trends throughout the blocks in each time-point (Figure 2a), we conducted separate ANOVA (Bonferroni corrected alpha = 0.01) and trend analyses for each session.

The ANOVA in the first time-point did not show a significant effect of block ($p>0.05$). Polynomial comparisons showed a significant linear component ($F_{1,106}=6.098288$, $p = 0.01$, partial eta squared = 0.05) and no significant quadratic or cubic components ($p>0.05$). The second time-point it showed a non-significant effect of block (G-G adjusted $p>0.05$) following a cubic trend ($F_{1,106}=4.240791$, $p=0.04$, partial eta squared = 0.04). The third time-point did not show a significant effect of block nor significant linear, quadratic, or cubic components (G-G adjusted $p>0.05$). Also, the fourth time-point did not show a significant effect of block ($F_{4,424}=2.638131$, G-G adjusted $p=0.04$, partial eta squared = 0.02), but revealed a significant linear trend ($F_{1,106}=5.908443$, $p=0.01$, partial eta squared = 0.05). Differently, performance on the follow-up showed a significant effect of block ($F_{4,424}=4.385032$, $p< 0.01$, partial eta squared = 0.04), following a linear ($F_{1,106}=10.84087$, G-G adjusted $p<0.01$, partial eta squared = 0.09) and a quadratic trend (F1,106=4.308984, p=0.04, partial eta squared = 0.04).

Latencies (decision times between the presentation of the new trial and the choice of a deck) were analyzed in a 5x5 repeated measures ANOVA, using Week and Block as factors. The ANOVA revealed both significant main effects (F4,424=16.8030, G-G adjusted p< 0.0001, partial eta squared = 0.14 and F4,424=56.0459, G-G adjusted p< 0.0001, partial eta squared = 0.35 for the main effects of Week and Block, respectively). In addition, also the interaction was significant (F16,1696=7.2042, G-G adjusted p< 0.0001, partial eta squared = 0.06). Instantly, Duncan’s post-hoc showed that respondents spent more time in analyzing option before choosing in the first week compared to all the others (p< 0.0001) and less time in the fourth week compared to the first three (p <0.05), in the first (p<0.0001) and in the second (p<0.05) block compared to all the others, and in the first block in the first week compared to the first blocks of the other time-points (p < 0.0001). Then, respondents showed to learn at each time-point and throughout the blocks how to perform the task (Figure 2b).

The proportion of switches were also analyzed in a 5x5 repeated measures ANOVA, using Week and Block as factors. The analysis showed significant main effects of Week and Block factors (F4,424=13.7899, G-G adjusted p< 0.0001, partial eta squared = 0.11 and F4,424=47.9521, G-G adjusted p< 0.0001, partial eta squared = 0.31 for Week and Block, respectively) and no significant interaction (p>0.05). Duncan’s post-hoc tests of the main effects showed that the respondents in the first and in the second week switch significantly more than in the other time-points (p< 0.05) and more/less in the first/last block compared to all the others (p < 0.01). We performed this analysis due to findings obtained by Lipnicki et al., (2009) in a confined environment. However, differently from Lipnicki et al., we did not find any significant variations in switch strategies between blocks except an expected decrease of switches from the first to the last block of the task (Figure 2c).

Figure 2.



Performance in the IGT in each block of the task at each study time-point. a) Mean IGT score (advantageous – disadvantageous choices). b) Mean latencies (time to make decisions). c) Mean proportion of switches among decks. Bars denote standard errors.

Balloon Analogue Risk Task

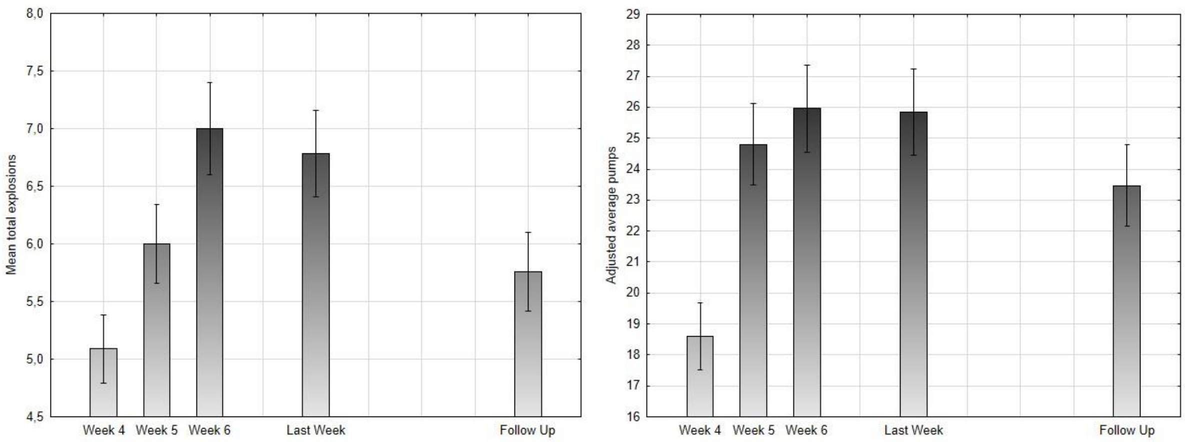
For the BART, data from 124 respondents (females = 77; mean age = 36.71, s.d. 16.47) were analyzed. Mauchly sphericity tests were conducted in each ANOVA. When significant, ps were adjusted according to Greenhouse-Geisser correction.

The total number of explosions was analyzed in a one-way ANOVA, using Week as a within-subject factor. The ANOVA revealed a significant effect of Week (F4,492=9.24872, G-G adjusted $p< 0.0001$, partial eta squared = 0.07). As shown by Duncan's post-hoc tests, the number of total explosions significantly increased ($p< 0.05$) throughout the study, reaching its peak at Week 6 and 8 (non-different, $p > 0.05$), and then bouncing back to a lower level at follow-up.

The same ANOVA was conducted for adjusted average pumps, showing a significant effect of Week Week (F4,492=13.6702, G-G adjusted $p< 0.0001$, partial eta squared = 0.1). The adjusted number of pumps significantly increased after the first time point for all the successive sessions ($p < 0.001$) and decreases significantly from Week 6 and Last Week at Follow-Up ($p< 0.05$), as shown by Duncan's post-hoc tests. Explosions and adjusted number of pumps then followed the same pattern (Figure 3a and 3b).

Also, the time between pumps was analyzed in the same ANOVA design. Although outliers at individual levels were removed, we still observed aberrant values at the group levels. Participants presenting more than 10000 ms mean values were removed. Finally, data from 111 participants were analyzed. Again, the analysis showed a significant effect of Week (F4,440=30.9478, G-G adjusted $p< 0.0001$, partial eta squared = 0.22), explained by a significant reduction between Last Week and all the other time-points and between the Follow-Up and all the other time-points ($p< 0.0001$). Time between pumps, differently from the other BART indices, followed a trend similar to the one observed in latencies and RTs in the IGT and in the CST (Figure 3c).

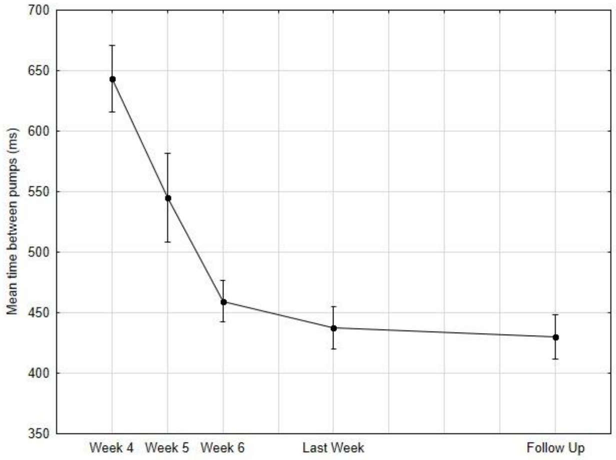
Figure 3.



a)

b)

c)



Performance in the BART score at each time-point of the study. a) Mean total explosions. b) Mean adjusted average pumps (number of pumps for unexploded balloons). c) Mean time between pumps (for all but the first pump and the time between the last pump and the collect choice). Bars denote standard errors.

Category Switch Task

Data from 128 respondents (females = 84, mean age = 36.34, s.d. = 16.5) were used for the analysis of the Category Switch Task. Mauchly sphericity tests were conducted in each ANOVA. When significant, ps were adjusted according to Greenhouse-Geisser correction. Participants in all time-points had an optimal level of performance, as can be seen by the mean accuracy for each time-point (90%, 90.2%, 92.9%, 92.9%, and 90.2% for Week 4, Week 5, Week 6, Last Week, and Follow Up, respectively).

The ANOVA on RTs revealed significant main effects of Week (F4,508=40.508, G-G adjusted p< 0.0001, partial eta squared = 0.24) and Transition (F1,127=286.340, G-G adjusted p< 0.0001, partial eta squared = 0.69), and a significant interaction (F4,508=16.760, G-G adjusted p< 0.0001, partial eta squared = 0.11). The significant effect of week was explained by the reduced RTs throughout the study, whereas the significant effect of transition showed that switch cost was observed in all time-points (mean RTs for repetition trials: 1019.362 ms, s.d. 20.56 ms; mean RTs for switch trials: 1308.9 ms, s.d. 31.57 ms). Mean RTs for repetition- and switch-trials at each time-point are reported in Table 1.

In order to inspect the changes in switch-cost, we planned a second ANOVA on the switch cost difference, using Week as a within-subjects factor. The analysis clearly showed a significant effect of Week (F4,508=16.7598, G-G adjusted p< 0.0001, partial eta squared = 0.11). Duncan's post-hoc test on the principal effect showed that the switch-cost in the first time-point was significantly different from all the others ($p<0.0001$ for all comparisons). No other significant differences were observed.

The same ANOVA was run to inspect the effect of time-points on the N-2 repetition cost. The ANOVA showed significant main effects of Week (F4,508=40.788, G-G adjusted $p< 0.0001$, partial eta squared = 0.24) and of Transition (F1,127=52.038, G-G adjusted $p< 0.0001$, partial eta squared = 0.29). The effect of Week was explained by the reduction of RTs throughout the task, whereas the effect of Transition showed that the N-2 repetition cost was present in each time-point (mean RT for BBA trials: 1275.14 ms, s.d. = 30.98 ms; mean RT for ABA trials: 1348.1 ms s.d., 34 ms). A significant interaction was also observed (F4,508=5.787, G-G adjusted $p< 0.001$, partial eta squared = 0.04). Mean RTs for BBA- and ABA-trials at each time-point are reported in Table 2. Even in this case, we analyzed in a one-way ANOVA the N-2 repetition cost, using Week as a within-subjects factor, showing the same significant comparisons already observed in the switch cost analysis (F4,508=5.78654, G-G adjusted $p< 0.001$, partial eta squared = 0.04, $p<=0.01$ for the differences between the first time-point and all the others, $p > 0.05$ for all other comparisons).

Table 2.

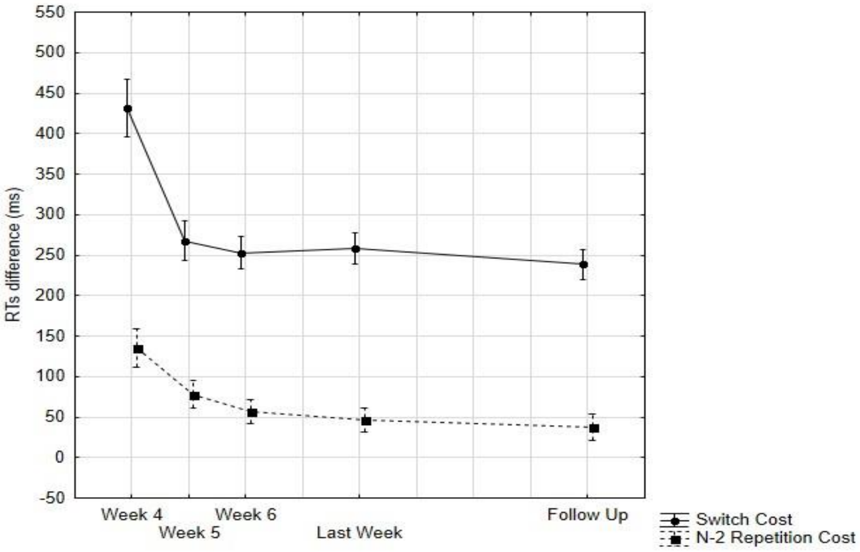
	Week 4	**Week 5**	**Week 6**	**Last Week**	**Follow-Up**
Repetitions	1197.18 (35.07)	1048.06 (34.82)	976.3 (21.12)	941.78 (21.14)	933.49 (20.18)
Switch	1628.54 (60.22)	1315.68 (40.77)	1228.82 (32.91)	1199.68 (33.85)	1171.95 (30.02)

Table 3.

	Week 4	**Week 5**	**Week 6**	**Last Week**	**Follow-Up**
BB*A*	1564.91 (58.37)	1276.03 (41.55)	1200.98 (33.11)	1178.09 (33.63)	1155.72 (29.14)
AB*A*	1700.66 (64.61)	1353.96 (41.92)	1258.11 (34.28)	1224.53 (35.11)	1193.26 (33.66)

Mean RTs (s.d.) of repetition- and switch-trials (Table 1) and BBA- and ABA-trials (Table 2) at each time-point of the study.

Figure 4.



Mean switch cost (continuous line) and N-2 repetition cost (dashed line) at each time-point of the study. Bars denote standard errors.

Discussion

Dealing with psychological distress due to the COVID-19 pandemic lockdown can be very hard for individuals. Social confinement has been and continues being a common condition in worldwide nations, especially for those more stricken with the diffusion of COVID-19. Italy has been among the first countries afflicted by the pandemic, and it was the first Western country imposing a strict lockdown all over the national territory. Due to the severity of dispositions taken by the Italian government, millions of people were confined at home for almost 2 months with no possibility of visiting parents or loved ones. The psychological outcomes of the lockdown's exceptional condition have been studied both in Italy and in other countries. However, most of these studies mostly employed subjective measures and surveys, reporting changes in several general indices such as mood, sleep, and unhealthy behaviors, attempting to relate harmful consequences to more specific dimensions such as coping strategies, tolerance to uncertainty, need for cognitive closure, flexibility, and emotional intelligence.

In the present study, we planned to conduct a longitudinal research to monitor cognitive, subjective, and sleep indices throughout the whole period of the Italian lockdown. The e-COVID study started at the end of March and ended at mid-May, with a follow-up measure obtained in September. To give credit to the richness and variety of indices, subjective and sleep findings were elsewhere reported, while the present work focuses only on the cognitive performance data. As far as we know, the present work is currently the first longitudinal study investigating cognitive processes adaptation during the pandemic lockdown using behavioral tasks. Instantly, we measured changes in decision-making under uncertainty (Iowa Gambling Task, IGT), risk-propensity (Balloon Analogue Risk Task, BART), and cognitive flexibility (Category Switch Task, CST) in 5 time-points ranging from the fourth to the sixth week of lockdown, the last week of lockdown (the eighth week after the lockdown imposition), and a follow-up in September (six months after the begin of the lockdown). We hypothesized that decisional processes and high-order functioning. Risk-propensity, learning and choosing under uncertainty, and rapidly adapt to environmental demands have been paramount abilities during the pandemic lockdown, possibly explaining adverse psychological outcomes, failures in the adaptation to the situation, and the production of risky and unhealthy behaviors. We also hypothesized a differential impact for low-level, automatic (IGT) and high-level, controlled (CST) processes.

Our findings globally showed short- and medium-term changes in cognitive performance.

Instantly, we found that the IGT performance was worst during the three central lockdown time-points than in the last week, especially in the follow-up measure. The reduction in performance was observed in the lack of expected decisional trends during the task blocks, with no optimal implicit learning of the task structure, resulting in less advantageous choices. Indeed, whereas performance appeared to increase throughout the task in all time-points, significant effects of block were observed only in the last two time-points. Moreover, only in the follow-up, we observed a quadratic trend, which is expected in a standard performance from the firsts to the last blocks, i.e., when participants unconsciously learn the advantageous decks and avoid bad decks. A practice effect interpretation is excluded since participants should not have optimally performed the task in the first measures accordingly to the standard performance (Bechara et al., 1994). For instance, the IGT net score in the first time-point was proximal to zero, despite a slight increase throughout the blocks, providing no clear learning evidence.

We have also found an increased risk-seeking in the BART throughout the lockdown period, peaking at Week 6 and 8, with a partial reduction in the follow-up. This finding can be accounted for by two explanations. First, it can be conceived as an increased risk-seeking related to lockdown. That result can be interpreted as the progressive urge for individuals to take risks to escape the isolation, which progressed as the time in lockdown was prolonged, explaining the partial reduction observed in the follow-up. Indeed, it is plausible to argue that individuals used more risk-avoidant behaviors during the acute phases of the COVID-19 pandemic. After individuals spent several weeks in lockdown, they observed reductions of personal risks for contagion because they were confined at home. Together with the fact that home confinement can be a monotonous and boring condition, they might have felt a progressive, increased impulse to risk. That is in line with the elsewhere observed augmentation of risky-related behaviors (e.g., Czeisler et al., 2020; Sher, 2020; Kar et al., 2020). Moreover, it is worth noting that the end of the lockdown period was not known to Italian citizens when it was imposed. Indeed, several decrees have succeeded in prolonging the lockdown period (the last one was on April 10th, proclaiming lockdown until May 3rd). Then, the mismatch between the expectations of a short lockdown period and the updates of national dispositions might have increased the urgency to be impatient of future better outcomes preferring less delayed rewards (i.e., risk-seeking). Not being under lockdown, together with the increase of infection observed in September, might have reduced this urgency in the follow-up. Secondly, since a risky behavior in the BART can instead be advantageous, it is possible to argue that the task's repeated administrations might have allowed respondents to understand that risking was more profitable than saving. Indeed, evidence exists that repeated administration of the BART led to increased scores as the study progressed (MacLean et al., 2018). However, the MacLean study observed the performance over 7-days. Moreover, we did not find any increase between the third and the fourth time-point and do find a decrease in the follow-up. Also, compared with the previous literature data, the adjusted average of pumps observed by respondents in this study was much lower. Furthermore, we observed the same trend for the number of explosions. In the first time-point, that represents a very low risk-seeking behavior, providing support for the contagion-related risk-reduction interpretation.

Finally, we found a steep decrease in the switch and N-2 repetition cost in the CST between the first and the other time-points. Studies implementing repeated administration of task-switching paradigms have provided evidence for practice effects due to training, observing reduced switch, and N-2 repetition costs (e.g., Meiran, 1996; Scheil, 2016), even though literature lacks systematic longitudinal data. Then, in this case, we cannot completely rule out this interpretation. However, the reductions observed were significant, only comparing the first with all the other time-points. If we were exploring only switch-costs, we would have been interpreted this finding as an increase in performance due to a strengthened association of stimulus-response mappings since the switch cost measures switch and repetition trials. Still, we also measured N-2 repetition cost, which is given by two qualitatively different switch trials (ABA and BBA, in this case), and we found an effect like the switch-cost. We can then argue against the interpretation that the higher costs observed at the first-time points are entirely due to a switch-related greater difficulty than repetitions. Furthermore, we observed similar and optimal total accuracies among all the time-points. Importantly, we still observed residual switch and N-2 repetition costs in the last sessions.

Hence, according to our findings, we suggest a dual pattern of pandemic lockdown effects. The first one is explicated in a medium-term trend observed in decisional processes. The described changes in decision-making under uncertainty and risk-seeking might reflect processes related to reduced emotion-based learning and the persisting isolation faced by individuals during the pandemic lockdown. Unfortunately, the literature lacks studies useful for comparisons. However, studies reporting the effects of stress exposure over decision-making abilities generally reported a shift toward the use of habitual strategies (Schwabe and Wolf, 2011; Friedel et al. 2017), an increase in the rate of disadvantageous and risky choices (Porcelli and Delgado, 2009; Preston et al., 2007; van de Bos et al., 2009; Lighthall et al. 2009; 2012; but see Starcke and Brand, 2016), and an alteration of sensitivity to feedbacks (Porcelli and Delgado, 2017), especially for losses (Petzold et al., 2010; Park et al., 2017). Decision-making under uncertainty in the IGT has been largely shown to be impaired by stress administration (e.g., Preston et al., 2007; Simonovic et al., 2018; van den Bos et al., 2009; Starcke et al., 2017). Theoretically, the Somatic Marker Hypothesis, on which the IGT was traditionally based (Damasio et al., 1994), relies upon intuitive and associative strategies. Stress has been shown to impair the connections between the prefrontal cortex (which is known to be involved in high-level cognitive functioning, such as working memory) and the amygdala (e.g., Andolina et al., 2013). Recent evidence has questioned the IGT's intuitive account, suggesting that a dual-process framework, implicating the intermixing between automatic and controlled processes, is better suitable in explaining performance in such a task (Brevers et al., 2013). Accordingly, the SMH suggested that during the decisional process, immediate and delayed prospects of the available options are driven by subcortical and cortical mechanisms, respectively, possibly exerting conflicts between the several somatic responses produced (Reimann and Bechara, 2010). Thus, dissociations between such "impulsive" and "reflective" networks can be observed when considering short- and long-term effects of stress and negative affect on decision processes.

Relatedly, the second one is instead exacerbated as a short-term effect of the stressful situation, eventually reflecting the "shock" experienced by individuals in the first week after the massive outbreak of COVID-19 and the awareness that the lockdown period and the spreading of the contagion would be slower and prolonged as expected. As a processive stressor (Hermann and Culliman, 1997; Pacak and Palkovitz, 2001), the COVID situation does not necessarily present an immediate threat to the organism, but it can be recognized, interpreted, and anticipated as a possible threat by higher-order cognitive processes. Cognitive flexibility is acutely affected by stress (Plessow et al., 2012). However, cognitive-energetical stress models suggested that high-consuming, compensatory processes may intervene to spare performance at the cost of latent decrements (Hockey, 1986). This model seems to fit our data. As the stressful experience progressed, these compensatory processes stabilized cognitive flexibility to an acceptable level.

Executive functions have been distinguished in cool (necessary for the flexible and strategical organization of behavior, and the maintenance of goals and information in working memory) and hot (related to self-monitoring, emotion regulation, and inhibition of impulsive conducts), with dissociable underlying neural networks (Brevers et al., 2013). It can be argued that during acute stress exposure, the effects may not or maybe slightly distinguished. In contrast, when the stress and adverse condition is prolonged, the intervening compensatory processes might make visible the changes in low-level cognitive functioning, which is much more related to the emotional information that supports the production of behaviors and it is slower to readapt.

Evidence from behavioral science, even in an exceptional and weakly controlled condition, might be precious in understanding individuals' conduct during the contagion and in other similar emergency crises, providing useful information for the prevention and implementation of effective countermeasures (Van Bavel et al., 2020). In that sense, our work provides significant findings regarding the possible mechanisms involved in risky, counter-productive behaviors during an emergency, which might be highly dangerous for individuals and social communities.

Limitations

Three major limitations of the present study can be highlighted. First, due to the unexpected rise of infections and the imposing of a lockdown, we could not collect a pre-lockdown baseline measure, which would have been very useful in interpreting the lockdown-related effects, controlling for practice effects, and making possible pre-post lockdown comparisons. Moreover, the follow-up measure is undoubtedly a baseline from the lockdown condition, but it did not occur during a normal situation. Indeed, in September, COVID-19 infections in Italy were rising again, and preventive measures (such as physical distancing, prohibited gathering of people, mandatory use of individual protective devices) were still imposed. Fear of contagion, smart-working, and light social isolation was maybe still affecting individuals' lives. Second, the design of the study was planned weekly due to the constant update of preventive measures. Third, since it was an online study, we had no complete control over respondents. Furthermore, we observed large numbers of dropouts or non-consistent following of weekly administration.

Conclusions

We investigated in this longitudinal within-subjects study decision-making and cognitive flexibility performance through online behavioral tasks during the COVID-19 pandemic lockdown in Italy.
Our findings report that individuals during the lockdown were affected by changes in decision-making under uncertainty and risk-seeking, making individuals less able to learn from feedbacks when information about options is unexplicit. Accordingly, negative emotions and information overload might have reduced the ability to use experience in behavior guidance. Individuals might have been coerced to use less habitual strategies and rely upon risk-avoidant behaviors. The prolongation of the isolation period might have increased the urge to take risks and engage in unhealthy and impulsive conduct. These effects have been shown to have time-dependent lockdown-related changes. Parallelly, a short-term effect of the first weeks after the COVID-19 outbreak is discussed in terms of a decreased ability to flexibly switch cognitive representations according to the changing of task-demands, evidencing acute changes in top-down, controlled, cognitive processes. The COVID-19 pandemic and the related countermeasures imposed to fight its diffusion may represent exceptional threats for individuals' health, promoting dysfunctional behavior changes.

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General Discussion and Conclusions

The present work aimed to investigate dual-process theories of cognition in distinct cognitive functions operating at different levels of complexity. Here, complexity is referred to as the number and variety of cognitive mechanisms assuming to interact in producing a behavioral performance. The studies presented here belong to three research lines, examining the interplay between automatic and controlled processes in temporal attention, cognitive flexibility, and decision-making.

Advocates and critics of dual-process theories are still debating about the nature of the two processes and their interaction, the scientific terminology to be used, and the methodology to employ to disentangle their role in behavior efficaciously (Melnikoff and Bargh, 2018a; 2018b; Pennycook et al., 2018). Most of that theoretical framework issues regard the systemic or functional nature of the two processes, the alignment of their characteristics, and the continuous or dichotomous relation between them (e.g., Kruglanski and Gigerenzer, 2011; Keren and Schul, 2009). These still unsolved problems moved several authors to doubt the real utility and the explanatory effectiveness of dual-process theories (Gigerenzer, 2011). As can be seen in literature (Evans, 2009), the result is the rise of a large number of dual-process theories, each one addressing specific cognitive and behavioral phenomena with weak or no apparent relations to the others. Despite these challenges, some authors are still working toward the generalization of the theory to the whole cognitive functioning (Evans and Stanovic, 2013; Pennycook et al., 2018). While that goal is far-reaching, the "whatever-it-takes" conceptualization of two separate systems might represent an obstacle toward the ambitious description of a dual-process mind.

Questions regarding dual-process theories are rooted in the difficulties intrinsic in the definitions of automaticity and cognitive control. On the one hand, automatic processes have been described in many different ways, but the core concept of automaticity has not yet been addressed (e.g., Fiedler and Hutter, 2014). What is it that makes an automatic process automatic? On the other hand, cognitive control supremacy in cognitive research is encountering similar defining crises, with much recent evidence undermining its traditional unitary, central, and domain-general features (e.g., Engel et al., 2007). However, while research in cognitive science is providing exceptional and contradictory findings, the cliffs of tradition seem hard to be climbed over. If dual-process theories benefit the clarification of the puzzling conceptions in automaticity and cognitive control literature is not known, but, indeed, reasoning in a dual-way can be highly helpful for several reasons. First, it allows for the possible qualitative and quantitative identification or categorization of a hypothesized phenomenon as a non-alternative one. Relatedly, it also allows for the verification that if a process does not present the features of a modality (e.g., controlled), it cannot be necessarily ascribed to the other one (e.g., automatic). Secondly, it permits the decomposition of known and unknown mechanisms into several peculiar phenomena. For instance, do executive functions make part of the same conceptual entity (Miyake et al., 2000; Verbruggen et al., 2014)? Thirdly, it may consent to make inferences about the interrelations among cognitive processes sharing the same features but traditionally or structurally belonging to other fields.

With that in mind, the findings obtained in the studies presented in this work move critiques to the view that automatic and controlled processes are two separate systems at a function-level of exploration. Instantly, I showed that the two processes or strategies or modalities are not necessarily balanced in decision-making, with stress (acute or prolonged) causing a non-complementary shift between the two. Indeed, in a first study, an acute stress induction procedure has been shown to induce differential changes in decision-making, in interaction with individual risk-propensity levels, in the way of a shift toward the use of more habitual and less flexible strategies, possibly related to an impairment in the ability to process feedback. Similarly, in a second study, a prolonged stressful experience (the isolation due to the COVID-19 pandemic lockdown) has been found to prolongedly reduce the ability to learn from feedbacks in uncertain conditions. That effect was found without an apparent complementary reduction in model-based strategies and controlled processes. As regards the COVID study, instead, the efficiency of controlled processes showed a short-term decrease.

I have also highlighted that what we conceived as cognitive control in task-switching performance is not necessarily central, unitary, operating at high-levels, and domain-general, but consists of a mixture of subtended qualitatively different mechanisms. Instantly, in a tDCS study, the anodal stimulation differentially affected cognitive control processes, by generally improving the ability to switch between tasks (frontal stimulation) and specifically improve the ability to overcome the inhibition of previous task sets (parietal stimulation). A second study shown that task-set inhibition does not operate at an abstract semantic level, but it is triggered by stimulus changes at a lower, perceptual level. Indeed, manipulating the stimulus format was enough for backward inhibition to not occur. Finally, in the last study of the section, the mechanisms involved in backward inhibition have been investigated by recording event-related potentials. The results obtained shed new lights over the differential roles of cue- and target- related processes, where task-set retrieval and reconfiguration have been disentangled, both accounting for the N-2 repetition cost (the behavioral outcome of backward inhibition).

Furthermore, in mechanisms that regulate the access to consciousness of two rapidly presented stimuli, even in the early processes involved in temporal discrimination and judgment, traces of the influence of high-level goals and flexibility can be observed. More specifically, the first study of the section showed that goals and instructions might modulate the attentional blink performance. Asking individuals to reduce the goals otherwise required to perform a Rapid Serial Visual Presentation task modulates the ability to detect the targets embedded in the distractors' stream. Moreover, in the second attention study, findings showed that the ability to judge the correct order of two rapidly and subsequently presented stimuli (at Lag 1 sparing phenomenon of the attentional blink) is flexible and strategic, rather than inescapably dependent upon bottom-up saliency mechanisms. Ascending ordered digits were less frequently swapped than descending ones, but participants showed to flexibly adapt their reporting preference according to instructions given.

Overall, the presented data account for the non-alignment of System 1- and System 2-like processes. Indeed, the relations both within and between the two systems characteristics (e.g., automatic, unconscious, and associative, and controlled, conscious, and analytical for System 1 and System 2, respectively) appear to be less peculiar and compartmental than most of the dual-process theories (implicitly and explicitly) assume. Differently, it seems that bottom-up and top-down dimensions are strongly interdependent in producing behavior, at whatever level of complexity one is observing. That has a consequence for the terminology used (as Systems Theory postulates, a system is defined as a set of interrelated and interdependent parts), the interpretations of specific phenomena (e.g., if a process is controlled is not necessarily analytical), and the overall cognitive functioning (e.g., if the behavior is habitual is not necessarily less flexible).

The dichotomization of mental processes has, due to kind of associative heuristics, led to a match of each of the two features of a dichotomy with each feature of other dichotomies (e.g., if a behavior can be [habitual OR voluntary] AND [fast OR slow], it has not necessarily to be [habitual AND fast] OR [voluntary AND slow]). In many theoretical positions, it seems that other folkloristic dichotomies, such as good/bad, have been absorbed in this associative process, spreading the idea that System 1 is error-prone while System 2-behavior leads to good outcomes (Melnikoff and Bargh, 2018a).

Since evidence-based policies aimed at reducing errors and disadvantageous conducts are becoming significant in operative contexts and financial settings, that dichotomization has led interventions to be primarily focused on boosting deliberative and rational procedures (World Bank Group, 2015; Balogh et al., 2015). However, the literature indicates that errors are not peculiarly related to Type 1 processes (e.g., Kruglansky and Gigerenzer, 2011). Similarly, some current techniques are based on the mechanisms that govern individuals' automatic processes by promoting specific interventions in the environment. Behavioral economists and choice architectures populate control rooms today. Their advice is becoming more and more central in the public policies supposed to modify individuals' disadvantageous behavior and have an impact on socially relevant issues (e.g., nudging, Thaler and

Sunstein, 2003). However, such techniques observed only modest and fickle results (and presented ethical issues, too).

Automatic and controlled processes might not be complementary: the efforts made in boosting Type 2 strategies alone do not necessarily lead to a reduction of biases. At the same time, nudging individuals do not make people more aware of the consequences of their behavior. The picture is more intricated and certainly need more investigation.

Future perspectives in applied contexts should integrate results in cognitive and behavioral psychology. For instance, findings in the framework of the Fuzzy Trace Theory (FTT; Blalock and Reyna, 2016) have shown that biases arise due to an incomplete or inaccurate formation of intuitive and nonconscious gist representations of facts. Indeed, how information is presented dramatically matters in the correct understanding of data. For instance, during the COVID-19 pandemic, the scientific communication has been predominant in every kind of media and, thus, in the assumption of safe/risky conducts in citizens (Van Bavel et al., 2020). Even more so, since stress has been shown to have a differential impact of different decision-making strategies, rather than overloading citizens with tons of not-sufficiently-explained data, interventions should have been focused on simplifying their ability to choose and judge in uncertain contexts. As well as civil people, this is true for individuals living and working in operative contexts, who should also be trained in using their intuition or creativity in new and ever-changing contexts.

However, without new evidence on the automatic-controlled relation, all the techniques based on DPTs can be currently considered atheoretical. To overcome the issues in dual-process theories, systematic research aimed at investigating the specific contributions of automatic and controlled processes in each cognitive function (e.g., decision-making, cognitive inhibition, attention) are required. Such systematic studies should consider the differential mechanisms assessed by the several tasks commonly used to investigate cognitive processes. For instance, in decision-making literature, many paradigms have been developed and are often interchangeably employed in the evaluation of choice behavior. However, the differences among them (e.g., uncertainty and risky conditions, advantageous or disadvantageous nature of risk-propensity) make the results not directly comparable. Indeed, what does a risky behavior mean in different contexts? Are we sure that we can infer that such results should predict a less advantageous behavior?

While it is useful to study systematic relations between paradigms, it is indeed true that correlational approaches might have low efficacy in confidently highlight such relations. Differently, the combination of systematic studies and effective manipulations known or supposed to induce effects over the contribution of controlled or automatic processes (e.g., stress) might be more powerful in evidencing such dissociable changes. Besides the interrelations between processes and paradigms, the implementation and use of paradigms able to contemporarily show the roles played by the two modalities should be a good practice to reach that goal. Indeed, most behavioral tasks use uni-dimensional dependent variables (e.g., reaction times, error rate, number of risky choices) that are not appropriate when investigating multi-dimensional effects. Furthermore, the use of *delta*-like indices (e.g., switch-costs or other difference scores) might additionally confound the interpretations, since they hide potentially theory-relevant dissociations inside datasets.

In conclusion, besides the specific contribution provided by each experiment presented in this work in its related theoretical field, the findings obtained speak against a compartmentalized distinction of automatic and controlled processes, suggesting that cognitive functioning’s conceptual systemic distinction is fuzzy. Indeed, such a rigid dual-system theory does not necessarily fit when investigating at a processes-level. Rather than stretching phenomena to the theory, the specific cognitive functions should be systematically investigated concerning each other, studying the differential effects on dual processes produced by specific conditions. Decomposition and reductionist approaches posit as possible fruitful methodologies in addressing whether dual-process theories of cognition should be maintained and advanced, and in providing reasonable directions to dual-process research.

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