THE EDITOR'S CHALLENGE: COGNITIVE RESOURCES

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THE EDITOR'S CHALLENGE: COGNITIVE RESOURCES

Topic Editors:
Gesine Dreisbach, University of Regensburg, Germany
Bernhard Hommel, University Hospital Carl Gustav Carus, Germany

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Editorial: The editor's challenge: Cognitive resources

Bernhard Hommel[1]* and Gesine Dreisbach[2]

[1]Department of Biopsychology, Technical University Dresden, Dresden, Germany, [2]Institute of Psychology, University of Regensburg, Regensburg, Germany

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Marc N. Potenza,
Yale University, United States

*CORRESPONDENCE
Bernhard Hommel
bh@bhommel.onmicrosoft.com

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Editorial on the Research Topic
The editor's challenge: Cognitive resources

Many empirical and theoretical approaches in the cognitive sciences/neurosciences rely on the concept of *cognitive resources*. Selective attention and dual-task interference have been "explained" by resource limitations, thinking styles rely on the assumption that some cognitive processes are more resource-demanding than others, information integration is assumed to require precious cognitive resources, and so forth and so on.

And yet, no one knows what this resource is. Is it just a metaphor for something that we do not and can never really understand, or are we able to reveal its functional and/or neural basis? Is it just a shorthand for an emerging property of the dynamics of cognitive/neural processes and/or the interactions between competitive representations? How does that work, how do interactions deplete resources? Or does it really refer to some measurable "stuff" that is limited, like the amount of crosstalk/conflict between representations, sugar in the brain, dopamine, frequencies available for neural oscillations, or blood/energy? How can we measure this stuff, change its availability or dynamics? A truly mechanistic theory should offer testable assumptions about the structures/representations that are involved in embodying or generating resources and resource limitations, about the processes operating on these representations, and present a scenario explaining how the interactions between structure and process generate both resources and shortages thereof (Hommel, 2020)—at a level of detail that is open to empirical test and computational simulation.

Such a scenario is unlikely to be developed overnight, but we aimed to start this endeavor by inviting critical, ambitious, and courageous contributions of any kind, whether theoretical, conceptual, empirical, or computational, that provide important constraints for a better, truly mechanistic understanding of human cognitive resources. What are these resources, what do they stand for, where do they come from? We encouraged authors to throw all the homunculi out and take the next step, ideally in a broad, constructive discussion that transcends common communication bubbles.

Eleven authors or teams accepted our challenge. Two Systematic Reviews focused on working memory and attention, two areas in which resources play a particularly dominant role. Schumann et al. address a particularly modern topic: the relationship between multitasking and wellbeing. In particular, they are asking what experimental rest-break research is telling us about cognitive resources. They provide a taxonomy of rest breaks according to which empirical studies can be classified and then evaluate the theorizing in various fields, with an eye for popular concepts like ego depletion and opportunity costs. They distinguish between resource-based and satiation-based theoretical approaches and provide a set of guidelines for both theory building and future empirical approaches to the experimental study of rest breaks.

Vartanian et al. consider another obvious limitation of human information processing: working-memory (WM) span. While this span is often considered to be a structural limitation of the WM system, there is increasing evidence that WM capacity can be increased through individual training. The authors are asking whether training can change the neural substrates underlying WM and, if so, which systems are affected. Their meta-analysis of fMRI studies using WM training provides evidence suggesting that training is mainly targeting clusters within the fronto-parietal system, including the bilateral inferior parietal lobule (BA 39/40), middle (BA 9) and superior (BA 6) frontal gyri, and medial frontal gyrus bordering on the cingulate gyrus (BA 8/32). They discuss the functional and neural implications of these observations, as well as the implications for the construct of WM span as a limited resource.

In their Mini Review, Tagliabue and Mazza consider another limitation that will be affecting all of us sooner or later: the reduction of cognitive resources with increasing age. Age is assumed to be associated with a reduction of such resources, so that older individuals exhaust their resources more easily and more rapidly with difficult tasks. However, the authors emphasize that the most recent studies on neurophysiological markers of age-related changes are not overly consistent with respect to the relationship between neural and behavioral effects, which in turn suggests that neural indices may not be sufficiently diagnostic with respect to cognitive deficits. The authors further discuss possible confounds that might be responsible for the inconsistent picture and suggest possible ways to control them. They also suggest a theoretical alternative that considers age-related effects as qualitative, rather than quantitative, changes in the way cognitive resources are deployed at higher age.

In their Hypothesis and Theory article, Ansorge et al. compare traditional resource-limitation approaches to selectivity in human information processing to a functional approach that has a closer look at the necessities of information processing. The authors review various findings that have been taken to support the resource-limitation view, but point out that other interpretations are possible, sometimes even more plausible. Even apparent demonstrations of what looks like automatic processing, they argue, might be better understood from a functional point of view, and the same holds for what looks like neurophysiological evidence for resource limitations.

In the other Hypothesis and Theory article, Butz considers the nature of cognitive effort from a computational point of view. He suggests that a Bayesian brain approach has various advantages. The author describes how cognitive effort might be formalized in such an approach, and he develops a resourceful event-predictive inference model (REPI) that can successfully simulate effortful behavior. He discusses how the structure of this model accounts for interference effects, like in a Simon task, or for Task-switching costs. The further implications of the model are also considered.

In his Perspective article, Kleinsorge attributes the theoretical problems of the concept of cognitive capacity to Cognitive Psychology's failure to properly define the concept of representation in general and of task representation in particular. He emphasizes the central role of task instructions and describes how particular instructions can implement particular task spaces, as it were, the characteristics of which then generate what looks like capacity limitations as a side effect. He points out that a better understanding of these and related theoretical problems requires more research on instructions and how they shape the cognitive implementation of tasks.

In their Opinion article, Naefgen and Gaschler point out that cognitive research has tended to neglect variability of performance within individuals, and they argue that a stronger focus on this kind of variability might help us to understand the concept of cognitive resources in more depth. They present a method that allows distinguishing between cognitive resources and what they call common factors by using within-individual covariance patterns. They argue that resource limitations and common factors generate different data patterns, which they take as an important first step toward more mechanistic theorizing.

The Brief Research Report of Gallo et al. highlights the role of bilingualism in the development of cognitive resources and cognitive reserve. In their study, bilingual healthy seniors performed an online study, in which moderators of cognitive resource and second-language use were assessed. Structural Equation Modeling revealed facilitatory effects of L2 age of acquisition and L2 proficiency on executive performance and provided evidence for a moderating role of bilingual experience on the relationship between other factors known to promote cognitive reserve and cognitive integrity. Hence, bilingualism seems to play an important role in mitigating cognitive decline and promoting successful aging.

Three Original Research articles round up the Research Topic. Velasquez et al. focus on the conditions under which task-irrelevant stimuli can trigger involuntary conscious imagery. The authors presented their participants with video footage of events that one would observe from the driver's seat of a semi-automated vehicle, after having trained participants in such a way that street signs would be likely to induce involuntary imagery. Participants reported spontaneous involuntary imagery even if they were asked not to respond to the street signs and even under dual-task conditions. This suggests that imagery does not seem to underlie resource limitations.

Wang et al. are asking when and under which circumstances the completion of a task leads to the replenishment of cognitive resources. They show that the amount of replenishment depends on the current availability of resources and the cost-benefit trade-off at task completion. These observations provide further evidence for how people manage the investment of cognitive resources.

Finally, Senoussi et al. consider whether memory limitations reflect structural limitations of cognitive resources or a useful feature of human information processing. The authors suggest that flexible cognition requires time-based binding, which in turn necessarily limits the number of bound events that can be stored simultaneously. They believe that time-based binding is likely to be instantiated *via* neural oscillations and discuss supporting evidence.

Taken altogether, various avenues to specify, perhaps even to overcome the cognitive-resource concept exist, and the contributions to this Research Topic have suggested various theoretical, methodological and/or computational tools to make progress with respect to our understanding of the concept and its functional and neural underpinnings. Increasing doubts in the structural nature of possible resource limitations are obvious in many of the contributions, and various efforts to develop alternative interpretations have been made. As anticipated, these are only first steps and much more theoretical and empirical research will be necessary to really understand what the concept of resources is buying us, which theoretical alternatives are realistic and empirically supported, and whether it makes sense to replace the concept by more mechanistic descriptions. The interest in these questions seems to be widespread, as witnessed by the very substantial download rates for all 11 contributions. Hence, we are optimistic that research on this topic is moving forward.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Cognitive Capacity, Representation, and Instruction

*Thomas Kleinsorge**

Department Psychology and Neurosciences, Leibniz Research Centre for Working Environment and Human Factors at the TU Dortmund (IfADo), Dortmund, Germany

The central argument of the present article is that Cognitive Psychology's problems in dealing with the concept of "cognitive capacity" is intimately linked with Cognitive Psychology's long-lasting failure of coming to terms with the concept of "representation" in general, and "task representation" in particular. From this perspective, the role of instructions in psychological experiments is emphasised. It is argued that both a careful conceptual analysis of instruction-induced task representations as well as an experimental variation of instructions promises to broaden our understanding of the role of task representations as a determinant of limited cognitive capacity.

Keywords: cognitive capacity, representation, instruction, task space, cognitive resource

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Bernhard Hommel,
University Hospital Carl Gustav Carus,
Germany

Reviewed by:
Robert Gaschler,
University of Hagen, Germany
Alexander Nicolai Wendt,
Heidelberg University, Germany

Correspondence:
Thomas Kleinsorge
kleinsorge@ifado.de

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INTRODUCTION

The central argument of this article is that the concept of "cognitive capacity" suffers from Cognitive Psychology's long-lasting problems of coming to terms with the concept of "representation" in general, and "task representation" in particular. The notion of cognitive capacity refers to limits in cognitive processing and task performance that are thought to arise from limits intrinsic to an organism, with these limits being subject to intra- and interindividual variation.

In what follows, I will take the so-called "imagery debate" as a point of departure to discuss some fundamental problems of the concept of "representation." Then, I will discuss these problems with respect to the way instructions in psychological experiments may work. This will lead me to the distinction between the extension and the intension of a (task) representation, which I link to my own previous work regarding the concept of "task space." Ultimately, I will propose that the constraints inherent to task spaces may offer a representational account of some of the cognitive limitations that are usually discussed in terms of cognitive capacity. Due to its basically representational nature, this account sees limits of capacity not as a feature of an organism but as arising from organism-environment interactions as shaped by task representations.

Problems of the Concept of "Representation"

In the 70s and 80s of the last century, there had been rigorous debates around the concept of "representation" in Cognitive Psychology. One point of culmination was the "imagery debate" which centred around questions of representational format, i.e., whether or inasmuch cognitive representations are implemented in a propositional, symbolic format akin to language or should be conceived as a direct, analogue mapping of properties of the environment on brain states (cf. Pylyshyn, 2002). In hindsight, it seems that the analogue-mapping account won the palm, but this could have been a Pyrrhic victory as many of the fundamental problems remained unresolved (cf. Slezak, 2002). At the same time, the emergence of connectionist modelling promised to provide a solution to the problem of representation by transferring it to a "sub-symbolic" level (cf. Smolensky, 1988).

In many parts of Cognitive Psychology, these developments resulted in "models" of cognitive processes that are based on codes for environmental properties (without caring much about where these come from) that are interconnected by excitatory and inhibitory connections [which are based more on knowledge about the outer world than on knowledge about the brain; cf. the commentaries to the target articles of Smolensky (1988) and Pylyshyn (2002)]. What is largely neglected, however, are issues of representational format. Are there intrinsic limits to what can be represented within a single coherent representation that are not merely reflections of the incongruity of certain environmental states? And if there are such limits of "representational capacity," may they -at least in part- converge on limits of "cognitive capacity"?

From the perspective of instructable artificial systems, the distinction between symbolic and subsymbolic-connectionist systems has far-reaching consequences (cf. Noelle and Cottrell, 1995): While with symbolic systems "learning by being told" comes almost for free and boils down to a matter of translation between symbolic notations, this kind of rapid learning is hard to implement in a connectionist network due to its slow learning dynamics in terms of weight adaptation. This is not to say that it is impossible to implement such rapid learning into a (localist) connectionistic architecture, but this is usually done by assigning individual stimuli and responses to single units (cf. Ramamoorthy and Verguts, 2012). Thus, the mapping problem (see below) normally to be solved by the participant is solved by the designer of the connectionist architecture. On the other hand, within such an architecture inductive learning comes almost for free, which has to be formally implemented in symbolic architectures.

How are participants in psychological experiments disposed to (hopefully) implement those processes we aim to study? It is by instructions that are usually delivered in a verbal format. In some still largely mysterious way (most) participants are able to transform this verbal information into a format that allows them to perform the instructed task. Does this transformation preserve some of the structure of the verbal format of the original instruction? (To differentiate between verbal/symbolic and non- or sub-symbolic codes (more precisely, tokens of codes), the former but usually not the latter can be assumed to be endowed with some form of syntactical structure (i.e., not every token can enter into any relation with every other token) as well as compositionality (tokens with the same syntactical role are interchangeable in yielding legal expressions irrespective of whether the expressions refer to anything that exists).

Representation and Instruction

In one of my earliest studies (Kleinsorge, 1999), I investigated the "orthogonal compatibility effect" (cf. Cho and Proctor, 2003) by varying the format in which the stimulus-response mapping of the respective upcoming trial was instructed. (The general instruction at the beginning of the experiment was given verbally.) The (visual) mapping instruction was either presented verbally or by a segment of a circle connecting stimulus and response positions. It turned out that the orthogonal compatibility effect was only observed with verbal but not with pictorial instructions. In a subsequent experiment, it could be shown that it was not the format of the instruction *per se* but the way participants processed this information: when participants received only instructions regarding the response assigned to one of the stimulus locations but had to generate the complementary stimulus-response mapping, the compatibility effect showed up again. Nevertheless, participants responded much faster with pictorial as compared to verbal instructions even with incomplete information, ruling out that the missing information was inserted in a verbal format. These observations suggest that a sequential processing of information, which is intrinsic to verbal information but had to be imposed with pictorial information, was critical for the emergence of the orthogonal compatibility effect.

These findings point to the importance of representational format for the efficiency of performing a certain task by demonstrating that essentially the same task can be represented in different formats that result in different levels of performance including the presence vs. absence of a specific compatibility effect (which is often considered as a limitation of the capacity to inhibit irrelevant information)However, in most cases we have no control of the format in which participants represent an instructed task, which also implies limited control of the way task-relevant information is processed inasmuch this processing is determined by the format in which this information is coded.

What we can take for granted is that the build-up of a task representation by participants usually starts with a verbal instruction, but we know little about the format of the resulting processing structure by which participants perform the instructed task. One possibility would be that participants simply "copy" the critical parts of the instruction (e.g., individual stimulus-response mappings) and verbally rehearse these in the course of the experiment (Goschke, 2000). When the critical parts of the instruction consist of rules (e.g., "press the right key if the stimulus is a word and the left key if it is a pseudoword"), these may be encoded and rehearsed in verbal working memory. There is evidence that when instructed either by individual stimulus-response mappings or rules, participants stick to the original way they have been instructed (cf. Dreisbach and Haider, 2009). This observation would be in line with the "copying account" sketched before, which can be considered as the simplest form of "learning by being told." However, it is highly unlikely that such an account would be able to explain behaviour beyond the performance of simple lab tasks. Furthermore, recent evidence suggests that instructions that were initially stored in verbal working memory become rapidly stored in procedural memory by demonstrating that factors known to affect verbal working memory (phonological similarity, serial position) lose their impact after only a few trials of practice (Monsell and Graham, 2021).

When we assume that participants usually transform the verbal information of an instruction into some kind of internal format, two possibilities arise. Either, there is one -and only one- internal format enabling the formation of an effective task representation. This would mean that any situation directly determines its corresponding representation. This position would ultimately amount to a direct-coding account that comes along without any need for recoding the initially verbal information provided by the instruction. (This is not to say that the resulting task representation is verbal, but only that the representation formed on the basis of this information is solely dependent on situational affordances.) In this case, there would be no reason to worry much about instructions[1]: learning by instruction boils down to a straightforward mapping problem that requires from the system (the participant) to find out which input should be mapped onto the activation of a certain output pattern (cf. Noelle and Cottrell, 1995). Importantly, this view shifts the process of implementing an instruction into a black box without any behavioural correlate (perhaps apart from some erratic behaviour in the very first trials of an experiment). However, it is fully obvious that we constrain this process by "telling" our participants. Ignoring this corresponds to ignoring the problem of commensurability of symbolic and sub-symbolic codes, an ignorance that, as outlined above, accompanies Cognitive Psychology for decades.

On the other hand, if it is assumed that information conveyed by instruction can be represented in different formats, the question arises whether different formats result in differently efficient task performance, and why this is the case. From dual-task research it is known that participants' performance critically depends on whether the nominally two tasks allow to be represented as a higher-order single task (cf. Schmidtke and Heuer, 1997). If so, one may ask what it is that allows for the formation of such a higher-order task representation. At this point, it may be useful to refer to the distinction between the *extension* and the *intension* of a representation. This distinction goes back to Arnauld (1685/1972) and was applied to the problem of mental representations by Lundh (1981, 1982, 1995). The term intension refers to the relation of a mental (or neural) token to other tokens, or the relation of a concept to other concepts. Importantly, as such, intension lacks referential semantics, it is only about "connections" akin to connectionist networks. Referential semantics are provided by the extension of a representation, which is based on instantiations in perceptual and behavioural terms that link intensions to external referents. (On a neurophysiological level, intension seem to be represented primarily in the hippocampus (e.g., O'Reilly and Rudy, 2001)).

Interestingly, Lundh (1995) also proposed a solution to the above-mentioned imagery debate by assuming that intensions are stored in a unitary (one could also say: sub-symbolic) format, whereas extension is instantiated in different modality-specific codes. The latter assumption converges upon "embodied" accounts of cognition (e.g., Rosch et al., 1991; Wilson, 2002) that assume that cognitive processes are grounded in mechanisms of sensory processing and motor control that evolved for interaction with the environment (the extensional referential semantics in Lundh's terms). However, whereas embodiment accounts provide a quite successful solution to the problem how internal codes are grounded in organism-environment interactions, they tend to neglect the problem of syntactical structure of intension.

Task Representation and Cognitive Capacity

On these grounds, I suggest that the formation of a higher-order task representation critically depends on whether the lower-level tasks can concurrently be mapped on the same intensional configuration. This configuration is not to be confused with the much narrower concept of "task set" but corresponds more closely what Herbert Heuer and I (Kleinsorge and Heuer, 1999) termed "task space" (cf. Xiong and Proctor, 2018, for a thorough treatment of the distinction between task set and task space). Thus, metaphorically speaking, efficient performance of a complex task is dependent on being located in the same task space. However, as cogently explicated by Xiong and Proctor (2018), being located in the same task space also provides a basis for interference as the presentation of a stimulus may not only activate those aspects of a stimulus that are via instruction task relevant (as part of the task set) but activation may spread (via intensional relations) to task-irrelevant aspects that are thereby part of the task space. "Conflict tasks" of i.e. the Stroop- or Eriksen-type are specifically designed to induce interference which is then interpreted as indicating limits of cognitive capacity.

Beyond this conceptual level, the architecture of a certain task space may go along with certain ways of navigating it. One of our basic observations regarding a certain type of task combination (resulting from a factorial combination of two binary task dimensions) consisted of a certain pattern of costs for switching among the subtasks of this task space (cf. Kleinsorge et al., 2004). We accounted for this pattern by assuming a certain "hierarchical switching mechanism" that results in instantaneous "co-switches" when a higher-level task feature switched (cf. Korb et al., 2017, for recent neurophysiological evidence supporting the existence of such a mechanism).

To add another example from my own research: There is some quite compelling evidence that task switching proceeds much more efficiently when the next task is indicated by an explicit task cue as compared to mere foreknowledge of the task sequence (e.g., Koch, 2003). This comes along as a classical "capacity limitation" with respect to advance preparation. However, we have shown that this "capacity limitation" is restricted to switching among only two tasks. When switching among four tasks, this difference disappears, probably due to a richer "intensional" representation of the differences among four (as compared to two) tasks (cf. Kleinsorge and Apitzsch, 2012). Thus, what may be considered as a capacity limitation (in terms of endogenous preparation) may be due to a mismatch of (experimenter-presented) external stimulation and internal processing structure (in case of memory-based, task switching among two tasks).

CONCLUSION

If it is true that in psychological experiments all begins with instructions which then are to be transformed into an internal representation, it seems obvious that instructions strongly determine the general lay-out of a task space (cf. Xiong and Proctor, 2018). Given this, it seems to be surprising that we as

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[1] Apart from representational issues, instructions are also a social agent providing researchers and their participants with common ground for their interaction (cf. Gozli, 2019).

experimental psychologists pay so little attention to instruction, either by conceptual analyses as outlined above, or by way of varying (parts of) instruction in a systematic manner (e.g., Hommel, 1993; Kleinsorge, 1999, 2009; Dreisbach and Haider, 2009)[2].

In some way, we as experimental cognitive psychologists, are funny creatures: We lead our participants to perform awfully simple "tasks" to investigate the limits of "cognitive capacity," while at the same time we and the people around us routinely perform highly complex actions in the pursue of even more complex task goals—and it seems that we do not even wonder.

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[2] This is not to say that there is no relevant work on the effects of instructions. Much of this work centres around questions inasmuch representations of instructions are stored in verbal working memory (e.g., Monsell and Graham, 2021), or inasmuch interference exerted by a competing instructed task depends on executing this task as compared to being instructed to execute the task in the future (e.g., Liefooghe et al., 2012). I consider these approaches as complementary to the one presented here.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

TK contributed to this article.

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Procedural Control Versus Resources as Potential Origins of Human Hyper Selectivity

Ulrich Ansorge[1,2,3]*, Christian Büsel[4], Marlene Forstinger[1], Daniel Gugerell[1], Markus Grüner[1], Ulrich Pomper[1], Moritz Stolte[1], Rebecca Rosa Schmid[1] and Christian Valuch[5]

[1] Department of Cognition, Emotion, and Methods in Psychology, University of Vienna, Vienna, Austria, [2] Vienna Cognitive Science Hub, University of Vienna, Vienna, Austria, [3] Research Platform Mediatised Lifeworlds, University of Vienna, Vienna, Austria, [4] Department of Psychology, University of Innsbruck, Innsbruck, Austria, [5] Georg-Elias-Müller-Institut für Psychologie, University of Göttingen, Göttingen, Germany

In the current review, we argue that experimental results usually interpreted as evidence for cognitive resource limitations could also reflect functional necessities of human information processing. First, we point out that selective processing of only specific features, objects, or locations at each moment in time allows humans to monitor the success and failure of their own overt actions and covert cognitive procedures. We then proceed to show how certain instances of selectivity are at odds with commonly assumed resource limitations. Next, we discuss examples of seemingly automatic, resource-free processing that challenge the resource view but can be easily understood from the functional perspective of monitoring cognitive procedures. Finally, we suggest that neurophysiological data supporting resource limitations might actually reflect mechanisms of how procedural control is implemented in the brain.

Keywords: procedures, resources, cueing, Simon effect, dual-process (dual-system) models

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Gesine Dreisbach,
University of Regensburg, Germany

Reviewed by:
Wilfried Kunde,
Julius Maximilian University of Würzburg, Germany
Tobias Egner,
Duke University, United States

****Correspondence:***
Ulrich Ansorge
ulrich.ansorge@univie.ac.at

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INTRODUCTION

In the current review, we highlight that, in empirical research on cognitive resources, it is important to understand the specific reasons for the selectivity of human information processing before drawing conclusions about limited resources as the cause of such selectivity. We argue that many cases of selectivity reflect functional benefits rather than structural constraints. From the perspective of an updated selection-for-action view, we remind the reader that selectivity in human information processing is often functional rather than structural: it is often the consequence of an intentional restraint to focus on the most important information rather than a reflection of limited cognitive resources. Think of top-down search for a color-defined target, for instance, for your red suitcase on a baggage belt. Here, it is necessary to facilitate the processing of red colored objects relative to other objects of a different color. The reason for this type of selectivity is not limited resources in the sense of a time-invariant structural constraint. Instead, this selectivity serves a purpose and reflects a functional constraint that could vary over time, depending on what is intended and required by the task. In a different situation, it might be helpful to search for a different feature than red, such as when I look for my blue socks in a drawer. Functional selectivity can also take on additional limitations, for example, resulting in a tight focus on a single feature even where resource estimates would allow selection and processing of more features. Importantly, humans are typically concerned with some type of intentional, goal-oriented information processing. Following the pick-up of my suitcase at the airport, for example, I would next have to find the exit, navigate my way to my rental car booth, etc. As these examples show, functional selectivity in purposeful and goal-oriented behavior is abundant.

Importantly, we suggest that what applies to actions also applies to cognitive procedures in general, whether they result in overt behavior or not. In this context, procedures are the top-down controlled cognitive processes that humans conduct with a particular purpose or intention in mind (for a general architecture, see **Figure 1**). Thus, an updated selection-for-action view is better denoted a selection-for-procedures view. This perspective generalizes the distinction between functional and structural causes of selectivity from action control to the control of other vital cognitive processes lacking any obvious action correlates such as (latent) learning, reasoning, problem solving, comprehension, or the encoding and retrieval of knowledge.

At the outset, we sketch how top-down control of procedures is responsible for attention in its broadest sense: selectivity of human information processing. Next, we will give examples of hyper selectivity – how human information processing sometimes appears more selective than would be expected based on capacity limitations alone – and discuss how the selection-for-procedures view explains this discrepancy. In the course of our argument, we critically review dual-process theories of resource-demanding versus resource-free processing and, finally, point out how arguments for neuronal resources as the ultimate cause of selectivity in human information processing fall short of ruling out the selection-for-procedures view.

SELECTIVITY FROM A FUNCTIONAL PERSPECTIVE

When humans are confronted with several cognitive tasks at the same time, their performance is typically lower in terms of accuracy or speed than under single-task conditions (e.g., Navon and Miller, 1987; Pashler, 1994), and it takes time to switch between tasks (Rogers and Monsell, 1995). These observations laid the ground for the assumption that human information processing depends on limited resources (cf. Kahneman, 1973; Navon and Gopher, 1979; Wickens, 1980, 1984).

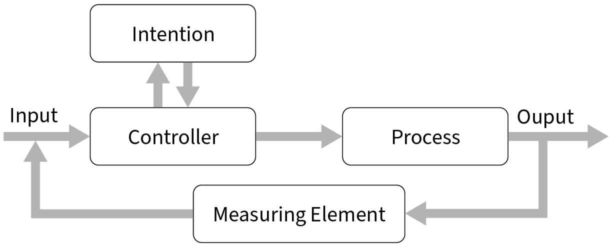

FIGURE 1 | Procedural control in a closed-loop system works similarly to any feedback loop. The input (e.g., a text) would be checked for fitting content by the controller (i.e., a steering value determined by, e.g., an intention to search for errors in a list of references) to be processed (e.g., read and correct references) until a measuring element signals that the purpose is fulfilled (e.g., no further errors could be found in a list).

However, we believe that all too often researchers jump to this conclusion without properly considering alternative interpretations of this basic finding. The rationale is that if only one task could be performed at a time, a capacity limit must have hampered performance of both tasks; since what should be wrong with solving more tasks at a time if this were possible? However, in our view, caution is advised in drawing this conclusion, as there is one alternative interpretation of the findings that should not be dismissed easily (cf. Navon, 1984). Selectivity could result from an intentional, functional limitation by the human agent rather than simply a structural resource limitation imposed upon human performance. According to this functional view, it is not a structural (i.e., time- and situation-invariant) limitation that causes selectivity. Instead, selectivity results from the fact that humans, often without noticing, focus on the most important aspects for controlling their actions and information processing in general. Which information is selected for prioritized processing ultimately depends both on human agent's current goals and prior experiences that have taught them how to efficiently complete similar tasks.

This has been emphasized, for example, in the selection-for-action view (Allport, 1987; Neumann, 1987). The selection-for-action view stresses that the necessity to carry out actions in time requires that top-down monitored information is processed continuously, so that information selection is optimally synchronized with the executed action as it unfolds. For example, think of the changing spatial input of a moving object you seek to keep track of via smooth pursuit eye movement. Another major emphasis of the selection-for-action view is that actions serve intended purposes that need to be top-down monitored for successful execution (cf. Lotze, 1852; von Holst and Mittelstaedt, 1950; Miller et al., 1960; Greenwald, 1972; Blakemore et al., 1998; Botvinick et al., 2001; Franklin and Wolpert, 2011; Janczyk and Kunde, 2020). Prioritized monitoring of the most important steering values and disregard for less important information is the major contender to a limited resources explanation of selectivity in human information processing (cf. Dreisbach et al., 2007; Dreisbach, 2012). This is especially true, where the number of currently top-down monitored features or objects is lower than would be expected based on known capacity limitations (cf. Eitam et al., 2013).

In fact, the human inclination to focus on the most relevant information – that is, information related to the success (or failure) of action goals – is not only a characteristic of overt actions but actually of any type of top-down controlled mental procedure, including those that do not manifest in overt behavior (cf. Anderson et al., 2004; see also **Figure 1**). As an example, consider the solution for a categorical syllogism. For a valid conclusion, humans have to select the major term of the major premise (e.g., "all bees are *insects*," with the major term in italics) and the minor term of the minor premise ("a *bumblebee* is a bee," with the minor term in italics). To draw a valid conclusion (such as "bumblebees are insects"), they would have to compare major and minor terms with the middle term (here, "bee"). Importantly, each step toward a proper conclusion – successful selection of each term in turn, plus the comparison at the end – must be monitored. That is, the steering value for monitoring covert processing would have to shift along with the successive steps of the operation. It might be argued that the first two selections could be conducted in parallel. However, this is unlikely, as typically the premises would be read, heard, or remembered in a phonological and, thus, sequential process. More importantly, this example shows that some of the selections require focusing on one particular feature or object, here, a term. Otherwise, errors would follow suit. For instance, mixing up the selection order of the minor term and the comparison would mean that the cognitive procedure – with the goal of a valid conclusion – would ultimately not be monitored appropriately for its success. This example of a sequentially unfolding procedure illustrates that sequential selections are often an inevitable constraint in the cognitive processing of meaningfully related information.

In addition, even where two features or two sources of information could be covertly processed in parallel, it is always possible to willingly focus on only one of them at a time if simply for reasons such as stopping short of a true capacity limitation (and, thus, not risking running into a capacity limitation, i.e., risk avoidance), endowing a mere content-wise "topical" difference between processed features or information with a redundant discriminating temporal tag within the processing sequence, or simply as a result of overgeneralization of sequential processing from situations where sequential processing is necessary to situations where it is not. In other words, "additional" cognitive control beyond what would be currently required to solve a task is not only associated with costs but also with value (cf. Dreisbach, 2012; Shenhav et al., 2017).

The general idea of closed-loop information processing also gained traction in theories of perception. Think of reentrant processing (Di Lollo et al., 2000; Pascual-Leone and Walsh, 2001), predictive coding (Friston and Kiebel, 2009; Clark, 2013; Press et al., 2020), or the sensorimotor hypothesis of vision (O'Regan and Noë, 2001). All of these theories share the central tenet that a past state of the cognitive system (e.g., a sensory activation, a memory trace, a motor command) is compared with a current state. Typically, this is done for purposes akin to monitoring or updating, such as deriving an "error" or "deviation" estimate (between initial and current state; Friston and Kiebel, 2009; De Lange et al., 2018), a refreshed impression (Di Lollo et al., 2000), or a particular qualitative experience (e.g., of seeing a particular color; O'Regan and Noë, 2001). Take the example of Bar's (2007) proactive-brain hypothesis: during visual recognition, an initial sensory state of low-spatial frequency information serves as a hypothesis, reducing the number of possible candidate objects for recognition through activation of potentially fitting templates in memory. In a subsequent step, more fine-grained high-spatial frequency information either confirms or revokes the initial hypothesis (or activated template) and, thus, objects are perceived more or less efficiently, respectively. Importantly, the function of such monitoring (e.g., of prediction, of gaining an error signal, of correction of an initial state, of experiencing a specific perceptual quality) would not be achieved if just any information would be selected for comparison. Instead, in all of these theories, functions are only served if past and current information are related to one another. Thus, selectivity, the human ability to prioritize some information – features, locations, "channels," modalities, or tasks – is an inevitable consequence of many, if not all, action, perception, and cognitive procedures serving an intentional goal. From this perspective, it appears grossly negligent to consider evidence of selectivity generally as proof for limited cognitive resources (cf. Duncan, 1980; Navon, 1984).

Skeptics might want to interject that these particular forms of selectivity could merely reflect information accumulation across time: for instance, more evidence supporting a particular prediction where past and, thus, "expected" inputs are more similar to one another than where they differ. This view, however, fails to account for the fact that goals or purposes are decisive for the "fate" of information accumulated across time. For example, while repeated visual input sometimes facilitates selection as in priming of visual attention (cf. Maljkovic and Nakayama, 1994; Kristjánsson and Campana, 2010; Valuch et al., 2017), humans also show the opposite tendency in other situations – that is, a preference for the selection of novel input that deviates the most from what is expected or what has been seen (Horstmann, 2002, 2005; Itti and Baldi, 2009; for a discussion of the principles in action control, see also Feldman and Friston, 2010; Jiang et al., 2013; Press et al., 2020). Whether repeated or novel information is selected for processing could, in many cases, depend on the requirements of the task at hand (cf. Müller et al., 2009; Gaspelin and Luck, 2018). Thus, framing perceptual selection in the context of purposeful and expectancy-based procedures allows understanding this malleable and flexible nature of relating past to present input. In contrast, a simple accumulation of input across time will not do.

EXAMPLES OF SELECTIVITY THAT CHALLENGE A LIMITED RESOURCES EXPLANATION

Are there any criteria that decide if a given case of selectivity reflects functional or structural constraints (see also **Box 1**)? This is indeed a thorny issue, and we are not certain that any criterion will be entirely convincing. In the following, however, we provide two simple examples that demonstrate hyper selectivity at variance with assumed resource capacity limitations: the flanker effect and switch costs associated with searching for two colors instead of a single one. Both instances are unexpected examples of hyper selectivity that is stronger than what would be expected on the basis of the assumption of limited resources, as the tasks impose seemingly low processing demands. From these examples, we derive general insights that might be of use for deciding if observed selectivity is due to functional or structural (i.e., resource limitations) constraints.

As a first example, we turn to flanker interference (Eriksen and Eriksen, 1974; Gratton et al., 1988; but see Franconeri, 2013). In the flanker task, one can observe increased interference between alternative letters – a central target letter and one or several peripheral flanking letters – simply by assigning alternative responses to the different letters (cf. Botella, 1996):

BOX 1 | There are some cases that challenge both the concept of resource limitations, and our notion of functional selectivity. While we explore evidence in favor of functional selectivity more in depth in the main text, we did not want to leave out conflicting evidence, which we mention here.

To prove resource theory wrong, some researchers sought to falsify selectivity and demonstrate processing abilities free of resource limitations under appropriate training or instruction conditions (cf. Allport et al., 1972). An impressive example is Schumacher et al.'s (2001) falsification of the "central bottleneck" (as a limiting resource that could only be used for one task at a time) or the resulting "psychological refractory period effect" – that is, the cost of performing two tasks simultaneously as compared to the same tasks alone (Pashler, 1994). Take a second example. While research on visual working memory suggests an upper capacity limit concerning how many objects can be remembered and reproduced from a memory set (e.g., Luck and Vogel, 1997; Cowan, 2010), other tasks suggest that humans can effortlessly surpass this limitation and represent perceptual information from large crowds of objects, well beyond what would be expected based on the suggested memory resource limitations. This is illustrated in the phenomenon of ensemble perception (Ariely, 2001; Alvarez and Oliva, 2008) which can be observed with tasks that do not require remembering and reproducing each object from a group individually but rather assessing summary characteristics of the group, such as the mean and range of features present across many object exemplars. Ensemble perception has been reported for relatively simple feature dimensions such as size, orientation, color, or motion direction but also more complex characteristics such as the gender or emotional expression of faces, or the apparent lifelikeness of objects (Whitney and Yamanashi Leib, 2018). Such results are not easy to explain from the perspective of limited processing resources. Thus, rather than reflecting limited processing or representational resources, the observed upper bound in explicit working memory capacity could stem from specific task requirements and the way that processing is probed at the end of each experimental trial. As a consequence, using the very same object arrays as stimuli, one could reach very different conclusions about capacity limitations, depending on how cognitive processing is assessed.

Given what we have argued for above – the functionality of selectivity, the benefits of concentrating on one steering value at a time – these findings are not entirely in line with the predictions of a selection-for-procedures view either. Therefore, we take the opposite perspective and point out two instances of unexpected hyper selectivity that is stronger than what would be expected on the basis of the assumption of limited resources, as the tasks impose seemingly low processing demands.

compared to a response-irrelevant condition, in which only one of two letters, say an *A* as a target presented together with a *T* as a flanker, requires a response, reaction times increase in a response-incongruent condition for responses to the same target letter *A*, now presented in the context of a flanker letter *T* that would require a different response if used as a target in another trial. Interestingly, increased response times under incongruent conditions are even reliably observed if the two alternative responses have to be given with the index fingers of the left and right hands, respectively (Gratton et al., 1988, 1992). This is puzzling, as it is, of course, possible to give responses with the two hands almost simultaneously (e.g., Mechsner et al., 2001). Think of pressing two keys on a piano simultaneously. How can it be that a simple instruction to use the two fingers to indicate different stimuli transform two commensurable (i.e., simultaneously executable) actions into alternatives that create a cost when activated at the same time? In our view, this is only possible if humans represent the corresponding actions intentionally as alternatives, which, in turn, requires monitoring whether the conditions for each of these alternatives are met. In other words, humans have to set up top-down control representations to twist "parallel processing" of motor program execution artificially into a sequential procedure of allowing the use of either one or the other finger. To note, this type of interference by assigning alternative responses to the letters is not the same as the psychological refractory period (cf. Welford, 1952; Pashler, 1994). The latter suggests that a decision in a Task *A* blocks a decision in a Task *B* until the decision in task *A* has been made. In contrast, interference by defining mutually commensurable responses as alternatives is more like creating the critical preconditions of a decision in a task in the first place. To note, however, the resulting cost of representation of responses as alternatives exceeds that of the decision itself. Botella (1996) showed that a decision between one response-associated target letter and an alternative "no-go" distractor, which was not associated with any response, created a cost and, thus, maybe a psychological-refractory period effect. However, this effect was substantially smaller than the interference by a response-incongruent flanker stimulus.

A second striking example comes from our own research where we found that asking participants to search for two instead of a single color in a visual search task incurred a processing cost (Büsel et al., 2019). Compared to a single-color block, in which participants had to search for one color-defined (e.g., red) target among differently colored distractors, dual-color blocks, where participants searched for two possible target colors (e.g., red or green) while presenting only one of these per trial, produced switching costs and mixing costs (cf. Kiesel et al., 2010). Here, switching costs mean that changing the target color from one trial to the next slowed target search compared to repeating target color in consecutive trials. Mixing costs mean that in dual-color blocks target search in target-color repeat trials was slower than in single-color blocks. The results suggest continued usage of a top-down search template for a specific color (e.g., a search template for red targets) in the dual-color blocks, just as if participants preferentially only searched for a single color at a time rather than for both colors simultaneously (see **Box 2**). Related to these findings, Van Moorselaar et al. (2014) reported that colored distractors that match an item held in visual working memory only capture attention in conditions where participants keep a single colored item in working memory but not when two items are held in working memory (see **Figure 2A**).

These findings are surprising in light of the assumed resource limitations in this situation. For instance, if working memory was used for the maintenance of the color-search templates, keeping two feature templates active should not have created a cost, as this number of features is well inside the typical resource capacity estimate of (visual) working memory (cf. Luck and Vogel, 1997; Cowan, 2010; but see Oberauer and Hein, 2012). In addition, this is also at variance with what others claim to have observed in a very similar experimental protocol: that participants can search for two colors simultaneously (Kerzel

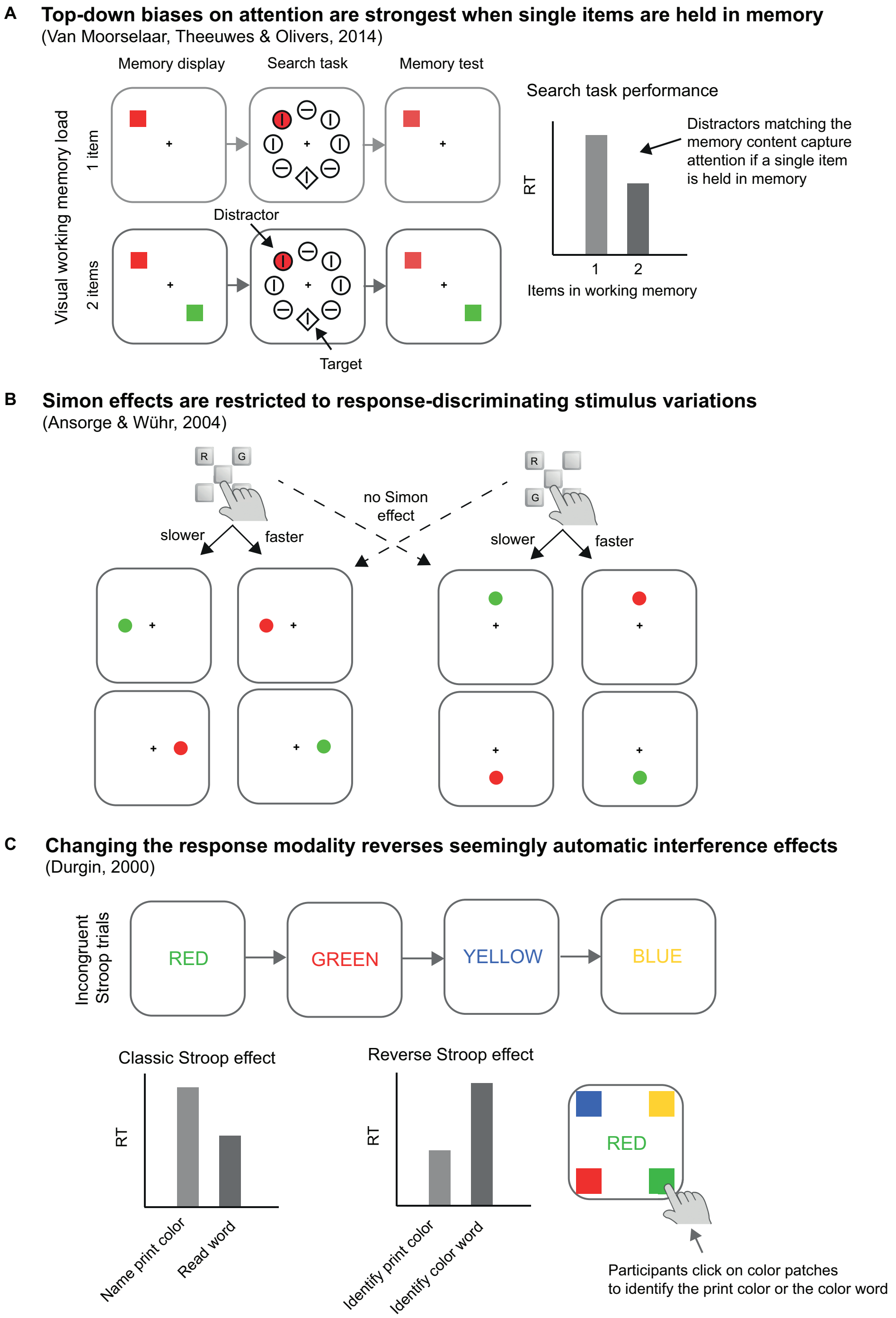

FIGURE 2 | Examples of empirical results that challenge a rigid limited resources view. **(A)** Top-down biases on attention are strongest when single items are held in memory. Related to the results of Büsel et al. (2019) described in the main text, the results of Van Moorselaar et al. (2014) illustrate that attention is captured by distractors that match the working memory content only if a single color is kept in memory, but this capture effect already vanishes if two colors are kept in working memory, even though this should not exceed generally assumed capacity limits. **(B)** Ansorge and Wühr (2004) found out that Simon effects are restricted to response-discriminating stimulus variations. The key mapping, that is, whether the alternative response keys for red (R) or green (G) stimuli were arranged in a horizontal or a vertical configuration varied between participants and red and green target stimuli occurred either along the horizontal or vertical meridian. Crucially, spatial stimulus-response compatibility effects (Simon effects) – facilitation for responses that shared location codes with targets (e.g., right responses to right targets) relative to responses and targets of different locations (e.g., right responses to left targets) – occurred only in those conditions where the axis of stimulus variations corresponded with the spatial response axis. The same compatibility effects were missing with regards to the non-varying spatial response axis, suggesting that location selection reflected response monitoring rather than response execution. **(C)** Changing the response modality reverses seemingly automatic interference effects. Durgin (2000) reversed the Stroop effect simply by asking participants to click on color patches corresponding to the word meaning rather than utter the print color names. For further discussion see main text.

BOX 2 | Here, we describe in brief a reanalysis of data originally published by Büsel et al. (2019). The purpose of this reanalysis was to investigate whether participants showed a preference for one of two colors while engaging in dual-color search. Presenting a non-predictive cue prior to the target display in a visual search experiment can facilitate target search with cues at target position (valid condition) relative to cues presented away from the target (invalid condition), especially or even selectively if the cue matches the search template for the targets (Folk et al., 1992; Folk and Remington, 1998). For instance, during search for red targets, a red but not a green cue would lead to a validity effect - with faster search in valid than invalid conditions - reflecting attention capture by the non-predictive cue (such that attention would be at target position from target onset in valid but not invalid conditions). During search for two target colors, we observed that only a single color was used as a search template at a time (Büsel et al., 2019). In the present textbox, we tested a novel hypothesis regarding the origin of this selectivity. If single-color search (e.g., for green targets) in one block before two-color search (e.g., for red and green targets) in a second block suggests to the participants a preference for the usage of the color used in both blocks (e.g., green), we expected to find more capture by top-down matching cues with a color used for targets in both blocks (e.g., green) than by top-down matching cues with a color used for targets in the two-color search block only (e.g., red).

Method

Participants. In total, 68 participants completed the experiment in Büsel et al. (2019).

Design and procedure. Participants were asked to complete four experimental blocks: two blocks in a single target-color version of the cueing task and two blocks in a dual target-color version of the same task. In single target-color blocks, the target was either always red or always green. The target-preceding cues could either match the searched for color (e.g., searching for a green target preceded by a green cue) or not (blue cue). In the dual target-color blocks, the target-color could randomly be either red or green. Consequently, preceding cues that were red or green matched the searched-for colors, whereas, again, blue colors did not match the task-relevant colors.

Participants' task was to report the orientation of the 'T' embedded within the circle carrying the target-color. The block order was balanced across participants and could be either A-B-A-B or B-A-B-A (here: A = dual; B = single; see **Figure 3**).

Analyses

In order to have a sufficient number of measurements per participant, we only analyzed participants in the A-B-A-B block order ($N = 32$). With these participants, we performed a repeated-measures analysis of variance (ANOVA), with the factors validity (valid, invalid) and whether the presented cue had the same color as the relevant color in the preceding single-color search block (yes, no). Non-matching cues were excluded from this analysis.

Response times. The interaction between both variables was significant, with $F(1,31) = 10.99$, $p < 0.01$, $\eta_p^2 = 0.26$. *Post hoc* paired *t*-tests revealed significant validity effects by cues that shared features with the previously relevant target-color in single-color search blocks, 22 ms, $t(31) = 3.43$, $p < 0.01$, $d = 0.31$. Conversely, top-down matching cues carrying features that were previously irrelevant even led to an inverted, albeit not significant, validity effect of −10 ms ($p = 0.12$).

Error rates. An identical ANOVA on arcsine-transformed error rates yielded identical results as response times.

Implications

This finding is yet another example of how subtle differences between tasks suggest to the participants different selective usages of features in monitoring – here, to monitor only one feature or several features at a time. A general resource limitation is obviously not responsible for the usage of only one feature during target search at a time, as visual working memory capacity is usually found to be around four items (Luck and Vogel, 1997).

and Witzel, 2019). Also noteworthy, using a similar experimental protocol as Van Moorselaar et al. (2014; cf. **Figure 2A**), a later study by Hollingworth and Beck (2016) found memory-driven capture also when multiple items were held in working memory, and both these studies were recently replicated, suggesting that both studies yielded robust results and the different outcomes were, thus, suggestive of an impressive flexibility of processing.

In our view, these findings jointly suggest that the observed selectivity could result from flexible cognitive procedures that depend on specific task representations rather than a structural limitation of cognitive resources. If we admit that humans are free to restrict their momentary monitoring focus to only a subset of all possible steering values, thus intentionally creating selectivity, it becomes easy to understand that expected capacity limitations can be violated by self-imposed restrictions. This might occur simply habitually as a consequence of prior experience (for an example, see **Box 2**).

Here, we discuss two related objections. First, why should participants accept processing costs (here, by searching for a single color at a time) if that could be prevented by a more clever choice of a task representation (here, by searching for two colors at the same time), if not because of a resource limitation forcing them to do so? The answer to this objection is simple: (Some) participants might simply not register the corresponding cost as something that they could prevent by a smarter task representation. For example, the necessity to keep different top-down features apart for the control of other procedures in different contexts (as we have discussed in the example of syllogistic reasoning above) might simply generalize to top-down search for two colors as a default. In line with this possibility, following learning, top-down control settings generalize to transfer tasks in visual search (e.g., Shiffrin and Schneider, 1977; Leber and Egeth, 2006). If participants do not notice the associated costs of this transfer, they would probably not change their task representations. In addition, if participants are generally more familiar with using different features for different purposes in many other situations, this might also create an implicit learning effect that is more difficult to overcome intentionally if that is required or advised (cf. Shiffrin and Schneider, 1977). (Below, we return to this issue).

Secondly, from the perspective of resource theory, selectivity for single features below capacity, as reflected in Büsel et al. (2019), might be particularly surprising (Lavie, 1995, 2005). Lavie (2005), for example, suggests that selectivity for a single feature under simple visual search conditions (e.g., for a single feature) is impossible, as under these conditions sufficient resources are available for the processing of additional input. And yet, this is what humans do: even during visual search for a single feature or while focusing on a single object, they can ignore additional input entirely, even if this is salient (e.g., Eimer and Kiss, 2008; Eitam et al., 2013; Schoeberl et al., 2019).

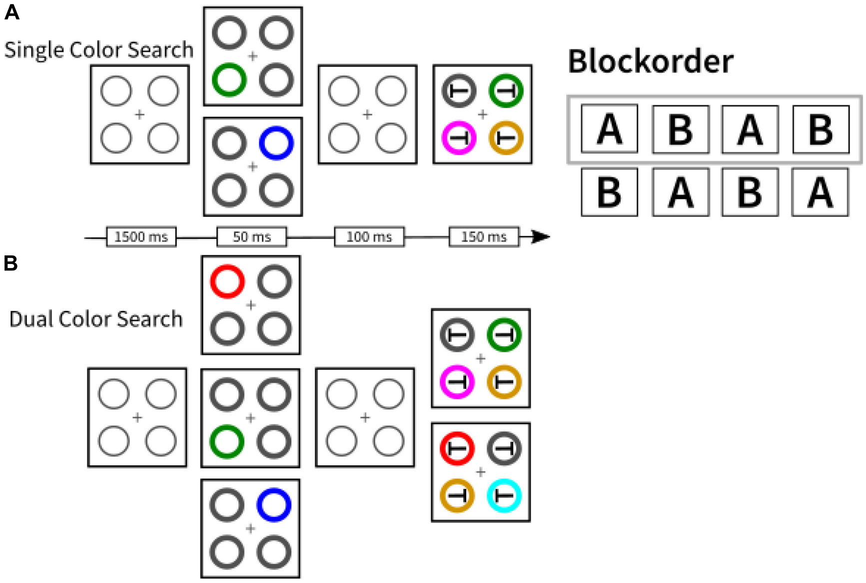

FIGURE 3 | A schematic depiction of the two search conditions used in Büsel et al. (2019). In single color search blocks **(A)**, participants were required to search for the same target feature throughout the whole block (here, for example, green). In dual color search blocks **(B)**, participants searched for a target that could randomly either be red or green. Block order was balanced across participants. For the analysis presented in **Box 2**, we used data from participants in the A-B-A-B block order condition (framed gray).

In fact, theoretically, any decision could always be taken by successively walking through the options at hand, one by one (cf. Kurzban et al., 2013). An interesting prediction that follows from this possibility is that under two-alternative choice response conditions, participants could consistently start with one of these options and test the hypothesis that the conditions for this option are satisfied – for example, that the current sensory input matches the searched-for feature. If one of two options is preferentially monitored first across trials of an experiment and across participants, one should observe a temporal advantage for this option relative to the alternative. In other words, it would be the less preferred, or secondary, option that would suffer from slowing when changing from a condition in which only one of the options is available to a condition in which either of these options can be available in every trial.

Interestingly, this is exactly what has been reported in some experimental situations: for example, if two features – one relevant and one irrelevant – lend themselves to humans' consistent coding as "positive" or prioritized versus "negative" or less prioritized (Proctor and Cho, 2006), one can find indeed that responses to positive features are faster (Lakens, 2012; Kawai et al., 2020). Take the example of the study by Kawai et al. (2020). Participants were asked to categorize words (e.g., enemy) as positive or negative. In one monochromatic block of trials, these words were all green, in a second monochromatic block, the words were all red, and in a heterochromatic block, red and green words were intermixed and each word was presented in red and green equally often. This was done to understand the origin of the congruence effect between color and affect – here, faster responses to positive words in green and to negative words in red (i.e., in the congruent condition) than to positive words in red and to negative words in green (i.e., in the incongruent condition) (Kuhbandner and Pekrun, 2013). As a consequence of the faster responses to the preferred option (typically the plus pole stimuli, positive words and green words) under choice conditions, a congruence effect (i.e., more efficient performance in congruent than incongruent conditions) based on the similarity versus dissimilarity of the participants' assigned polarities of two features of a stimulus (here, affect and color) is stronger for the plus pole than for the minus pole. For the plus pole, two positive features (i.e., the positive meaning of the word and its green color) and their polarity congruence (i.e., word meaning and color were both positive, fitting to one another) benefit responses to the congruent stimulus. At the same time, one positive (i.e., the positive meaning of the word) and one negative (i.e., the red color of the word) feature, as well as their polarity incongruence (i.e., word meaning was positive, but color negative, not fitting together) put responses to the incongruent stimulus at a disadvantage. Thus, the congruence effect is substantial. For the minus pole, however, in the congruent condition, two negative features (i.e., negative word meaning and red color) delay responding while their congruence (i.e., the word meaning and the color were both negative, thus fitting together) facilitates responding. Additionally, in the incongruent condition, one positive (i.e., the word meaning) and one negative (i.e., the color red) feature also reflect a mix of accelerating and slowing influences on response speed: facilitation by the positive feature (i.e., word meaning) and slowing of responses by the negative feature (i.e., the red color) as well as the incongruence between the feature polarities (i.e., the positive word meaning and the negative color). Thus, the congruence effect in this case is weaker (cf. Lakens, 2012; Kawai et al., 2020). Importantly, there was no congruence effect in the monochromatic blocks in which the colors did not differ and, thus, participants were not inclined to assign choice-elicited preferences to different colors. This is in line with the decisive nature of the alternative choice options for (1) the preference-dependent reaction time differences (or polarity assignments) and, thus, (2) the congruence effect based on these preferences (the polarity congruence effect). The fact that preferential processing of one color depends on the presence of the alternative color "option" is perfectly in line with the assumed possibility of solving choices by sequentially cycling through the alternative options.

DUAL-PROCESS THEORIES

So far, we have taken a skeptical stance regarding resource theories by looking at alternative origins of selectivity in terms of procedural control. However, a perhaps even stronger challenge for resource theory are instances of seemingly resource-free processing. Some types of stimulus selection seem to occur even against the human will to concentrate on a task. This is at variance with resource theory (but see Lavie, 1995, 2005, and the discussion further below). These forms of selectivity are interesting, as they are also puzzling from the selection-for-procedures view. The typical "solution" by resource theory has been to assume two types of processing – one depending on limited resources, the other free of resource requirements (e.g., Posner and Snyder, 1975). This is costly, as two rather than one type of processing have to be assumed. Below, we will explain that the functional selection-for-procedures view provides a more parsimonious explanation, showing that seemingly capacity-free processing is often simply an indirect consequence of the way a procedure is controlled and monitored (e.g., Ansorge and Wühr, 2004).

Let us start with typical examples of evidence for two modes of processing, one capacity-limited, depending on resources, and another one resource-free, running independently of capacity limitations (Posner and Snyder, 1975; Tversky and Kahneman, 1983; Petty and Cacioppo, 1986; Sloman, 1996). One famous example of resource-independent processing is "automatic reading" as reflected in the Stroop effect (cf. Stroop, 1935). When having to name the print colors of color words, participants are not able to ignore word meanings, so that an incongruence between word color and word meaning (e.g., the word green written in red), results in slower responses than congruence (e.g., the word blue written in blue) (MacLeod and MacDonald, 2000). It has been emphasized that the opposite is not true: when having to read the words, incongruent colors do not interfere with reading. Hence, it was assumed that reading is practiced to such an extent that it has been automatized and that it can proceed in a resource-free manner. Thus, reading can interfere with naming the word print or font colors (e.g., Posner and Snyder, 1975).

Take the Simon effect as a second example (Simon, 1990; Simon and Craft, 1970; Simon et al., 1970). When humans have to select and discriminate stimuli in their environment, stimulus position affects response efficiency even if the task does not require the processing of stimulus position. For instance, presenting red and green stimuli to the left and the right, and asking participants to discriminate between stimulus colors by left versus right responses, participants are typically faster and, on average, perform more correctly if stimulus and response side correspond to one another than when they do not correspond (e.g., Roswarski and Proctor, 1996): having to press the left key for green and the right key for red stimuli, responses are faster for green stimuli on the left and for red stimuli on the right than for green stimuli on the right and for red stimuli on the left. This Simon effect is very persistent and is also observed for other (e.g., vertical) stimulus-response correspondences (e.g., Stürmer et al., 2002). Originally, it has been interpreted to reflect a dual-process architecture, with a controlled processing route, responsible for the selection of task-dependent responses to the colors, and an automatic processing route, responsible for the automatic activation of response sides or positions by stimulus positions (Kornblum et al., 1990; De Jong et al., 1994; Zorzi and Umiltá, 1995; Zhang et al., 1999).

Let us take peripheral cueing of attention as a third example (Posner et al., 1980). During visual search for a target, presenting a peripheral cue prior to the target facilitates target search if the target is presented at the same position as the preceding cue (valid or cued condition), but interferes with target search if the target is presented away from the preceding cue (invalid or uncued condition). Originally, it was believed that this is due to automatic capture of attention by the peripheral cue, such that attention needed to be shifted to the target in uncued but not in cued conditions. Automaticity was assumed, as the cueing effect of peripheral cues (i.e., the advantage for targets at cued vs. uncued locations) was even found for cues that were not predictive of the upcoming target location. Furthermore, a short interval between cue and target and, thus, little time for cue processing enhanced the effect (Jonides, 1981; Müller and Rabbitt, 1989). In fact, participants could not suppress peripheral cues even when asked to do so (Jonides, 1981).

Later research, however, has proven all these initial interpretations as too simplistic. In all of these classic empirical cases for capacity-free selection of information, procedural control turned out to be responsible for the "automatic effects," too. Let us first look at the Stroop effect. Some studies noted that the Stroop effect is strongest if the color and the word belonged to the same object, implying that the word was selected inadvertently together with the color of an object, but not or less so if the word and the color were independent objects (Besner et al., 1997; Wühr and Frings, 2008). This observation suggests that in these situations, humans do not necessarily read a word automatically. Instead, the task of attending to the color of an object entails that the object carrying the color would also be processed to some extent. According to this interpretation, the functional task demands of having to select colors would be responsible for the inadvertent selection of the word meanings, too. However, one could argue that it is also possible that irrelevant words would be automatically read but that it is easier to suppress their influences or to actively filter out the words if they are represented in or as a different object (cf. Wühr and Frings, 2008). And yet, more or less Stroop interference depending on the presence of words and colors in the same objects is not the only evidence in favor of a functional origin of the selection of the word meanings. In a dramatic demonstration of the dependence of the Stroop effect on procedural control, Durgin (2000) reversed the Stroop effect simply by changing the response requirements (see **Figure 2C**). He asked participants to point to color patches corresponding to the word meanings rather than to utter the color names, thereby increasing the fit between irrelevant word colors and required responses (and decreasing the fit between word meanings and responses). As a consequence, Durgin observed that irrelevant but incongruent word colors interfered with word reading and that irrelevant word meaning's interference on discriminating between word colors was almost non-existent. These findings show that response requirements and the resulting match of stimuli to the responses differed in a way as to either facilitate color or word processing. In response to such findings, it is possible to identify different dimensions of potential overlap between stimuli and responses, all of which could interactively or additively determine the resulting net compatibility or correspondence effects based on automatic selection of stimulus features (cf. Kornblum et al., 1990). Critically, however, this description assumes that both stimuli and responses would be somehow discriminated from one another irrespective of the task at hand. Thus, this position leaves open as to why it would be possible to represent responses themselves differently.

The critical involvement of flexible representations of the responses (or, more generally, of the intended outcomes of a procedure) for interference by seemingly irrelevant feature or stimulus selection that is only predicted by the functional view and not by any kind of resource-free selection interfering with resource-demanding processing, was demonstrated in the Simon effect (Hommel, 1993; Ansorge and Wühr, 2004; Wühr and Ansorge, 2007). Consider the study of Hommel (1993). Participants had to discriminate the pitch of sounds presented from either the left or the right, responding left for low pitches and right for high pitches. Any button press additionally caused a light to turn on in the opposite hemifield. Crucially, in one condition, participants were instructed to respond with a button press, while in the other, they were instructed to turn on the light.

As a consequence, Hommel (1993) observed inverted Simon effects in the conditions in which lights had to be turned on: now stimuli on the right facilitated left-key presses and stimuli on the left facilitated right-key presses. Hommel (1993) reasoned that this was due to the flexible representation of the required responses in terms of their different potential sensory features (or, to be exact, sensory features of their effects or outcomes), such as the visually perceived or felt position of the response buttons (e.g., in a more traditional stimulus-response instruction, where the task was to press buttons) or as the visually perceived light positions (where the task was to turn on lights). As even the perceived light positions reliably discriminated between the required responses and, thus, could have been used to monitor the responses, participants included light positions in their response representations even prior to stimulus processing and, hence, a correspondence effect based on the intended and monitored responses resulted (or response effects, cf. Stoet and Hommel, 1999; Kunde, 2001; Ansorge, 2002).

That the flexible nature of the response representations rather than some pre-existing correspondence between stimuli and responses accounted for the Simon effect was substantiated by research of Ansorge and Wühr (2004). In each trial of their experiments (see **Figure 2B**), these authors presented a visual stimulus at one of four different positions, located above or below, left or right of the screen center. Critically, stimulus colors (red vs. green) were to be discriminated by two-alternative forced-choice responses varying on both axes – horizontal (left or right) and vertical (above or below), but responses differed from one another only on one of these axes. For instance, red required pressing a button to the left and above of a home key, while green required pressing a button to the left and below of the home key, meaning that the vertical but not the horizontal axis discriminated between the responses. In this way, participants' functional response representations were gauged to include the discriminative axis positions (e.g., in the example above on the vertical axis), but automatic effects of stimulus-response correspondence were possible for both axes. For instance, in the example above, stimuli on the vertical and on the horizontal axes could have exerted stimulus-response correspondence effects, as stimuli varied on both axes and both of these axes were part of a required response. In line with a flexible and functional perspective of response representations, however, the Simon effect was restricted to the response-discriminating stimulus positions. It was absent for the non-discriminating axis. For example, if red required a response to the left and above and green required a response to the left and below, participants were faster to respond to green stimuli below than above fixation, but their response was not affected by whether the green stimuli were presented left or right of fixation. This was the case, although only half of the green stimuli (the ones on the left) would have been presented on a side corresponding to the side of the required responses. Hence, only discriminative response features created a Simon effect, a finding much more in line with a functional view and flexible response representations (cf. Hommel, 2004) than with a view that assumes that somehow stimuli unfold their effects in a rigid and task-independent two-process architecture (e.g., Kornblum et al., 1990).

The same conclusion that has been drawn regarding the Stroop effect and the Simon effect – that the seemingly automatic selection of visual information depended on subtle forms of procedural control, has been reached for peripheral cueing. Specifically, in their contingent involuntary orienting hypothesis, Folk et al. (1992) tested if peripheral cues preceding targets at potential target locations might have captured participants' attention via matching the attentional control settings set up for the targets. These authors used two types of peripheral cues: abrupt onset cues, that is, a single white cue presented at one of several target positions, and color cues, that is, a single differently colored cue (e.g., a red cue) presented at one of several potential target positions along with color non-singletons (e.g., green non-singletons) at all other potential cueing (and target) positions. According to known bottom-up theories, all of these cues were salient – that is, they differed by strong local feature differences (e.g., in color) from their surroundings, and all of these cues should have therefore been in a position to capture attention automatically, in a stimulus-driven way (cf. Theeuwes, 1992; Nothdurft, 1993; Itti et al., 1998). To test if these cues captured attention automatically, Folk and Remington (1998) used two different blocked search conditions, matching the two possible cue-types in turn: targets were either abrupt-onset singletons (i.e., the single stimulus with an abrupt onset in the target display) in one blocked condition; or targets were color singletons (i.e., the single stimulus standing out by its odd color among homogeneously colored non-singletons of a different color). These authors found that color cues captured attention during search for color-defined targets but not during search for abrupt-onset targets and that abrupt-onset cues captured attention during search for abrupt-onset targets but not during search for color-defined targets. Later research confirmed that even the cue's color had to be similar to the searched-for color of the target (Folk and Remington, 1998). These results support the top-down contingency of the involuntary capture of attention by the cue on the cue's match to the top-down search settings (or the attentional control sets). Importantly, the evidence cannot be better explained by inter-trial priming of color (here, from a target in a preceding Trial $N-1$ to a cue in the current Trial N) and it is not better explained by quick capture of attention by just any salient cue – be it a top-down matching or a non-matching cue – and subsequent quick inhibition of capture by the non-matching cue only (cf. Ansorge and Horstmann, 2007; Eimer and Kiss, 2008; for a meta-analysis and review, see Büsel et al., 2020). For example, during search for two potential target colors, when both color-singleton cue and color non-singletons had a top-down matching color, there was no cueing effect, as all stimuli – singleton cue and non-singletons – matched the top-down control settings and, thus, attention was not captured to only the single more salient position of the singleton cue (Schoeberl et al., 2019).

In this context, it is worth noting that one particular variant of dual-process theories – namely load theory (cf. Lavie, 1995, 2005) was also not supported by the findings. According to load theory, stimulus-driven capture of attention as a form of selectivity prevails under conditions of low perceptual demands, whereas high perceptual demands would prevent stimulus-driven capture of attention. However, a salient but non-matching abrupt-onset singleton cue does not even capture attention when presented under very slightly perceptually demanding conditions: if presented alone – without concomitant competing distractors (Goller et al., 2016, 2020b). This failure of stimulus-driven capture of attention is evident in a continuous tracking of the cue's capture of attention by N2pc (e.g., Arnott et al., 2001; Goller et al., 2020b), an event-related potential that reflects shifts of attention to the left or the right (cf. Luck and Hillyard, 1994). In this context, the N2pc reflects more negative activity on the side contralateral than ipsilateral to an attended-to stimulus. The N2pc starts at about 200 ms post-stimulus and allows to continuously track the capture of attention with millisecond resolution, right from stimulus onset onward. Thus, it can be used to measure attention capture elicited by the cue itself, without having to rely on overt responses to the target (as would be the case for the cueing effect in target reaction times). Thus, the lack of any cue-elicited N2pc is particularly convincing evidence against any automatic capture of attention under conditions of slight or low perceptual demands (cf. Eimer and Kiss, 2008; Goller et al., 2020b).

In conclusion, many instances of seemingly resource-free processing can be more elegantly traced to subtle side effects of procedural control rather than a dual-process framework. In contrast, the only resort for explaining these effects from the perspective of resource theory is to allow a separate category of resource-free processes, as, otherwise, it would be hard to understand why humans would spend some of their precious cognitive resources on these seemingly irrelevant forms of selection. To note, participants might also avoid investing even more of their limited resources into active suppression of interfering stimuli. This, however, presupposes that something like resource-free processing existed in the first place. This assumption, we believe, is at least not always warranted given the subtle task-dependencies that we identified.

NEURAL RESOURCES

An obvious argument in favor of some form of resource limitation comes from neurophysiological data. Ultimately, the number of neurons in the human nervous system is finite and so is their upper limit of information processing. Whether, over the course of evolution, procedural demands shaped physiology or physiology determined cognitive abilities constitutes somewhat of a hen-and-egg problem. Interestingly, recent evidence on perceptual, attentional, or working-memory related limitations does fit exceptionally well with our proposed limitations via functional procedural control. In particular, several recent studies have demonstrated that environmental locations, objects or features seem to be 'sampled' by the brain in discrete steps rather than in a continuous fashion (for a review, see VanRullen, 2016). This sampling process likely originates from the ubiquitous rhythmic neural activity, which constitutes alternating phases of facilitated and suppressed information processing. Crucially, when this sampling process is directed to more than one location, feature or object at a time, the respective dimensions are sampled serially in alternation, rather than in parallel and at the same time. For instance, participants simultaneously monitoring two spatial locations for visual targets showed rhythmic fluctuations in target detection between 4 and 10 Hz. In line with a limited resource, temporal fluctuation profiles for the two locations were in anti-phase, suggesting that selection from two locations had to alternate between locations (Landau and Fries, 2012). Recently, we demonstrated a similar mechanism also for target-relevant templates held in working memory (Pomper and Ansorge, accepted): detection performance for targets corresponding to internally held templates was not continuous but fluctuated rhythmically over time. Importantly, performance fluctuations for two simultaneously held templates were in anti-phase, suggesting that a single working memory template is prioritized at any point in time. Critically, however, in our view, such selectivity does not imply that the ultimate origin of the alternating performance fluctuations was a limited neurophysiological resource. Instead, rhythmically alternating fluctuations could simply illustrate how monitoring of either of several locations, objects, or features at a time is realized at the physiological level. Concerning locations, this is particularly obvious, as even looking at a location – that is, the most natural response in a perceptual task – would require that we focus on one location at a time (cf. Rizzolatti et al., 1987), and what would be more natural than to rhythmically switch between single locations if more than one needs monitoring? In other words, an intention to preferentially monitor only one location at a time might simply be one way of how the task can be routinely solved at all. Thus, this intention for procedural control could be the ultimate reason behind this behavior, and oscillations may simply be one way in which brain processing could be used to fulfill these forms of procedural control.

DISCUSSION

Having argued for care in interpreting selectivity as reflecting structural capacity limits rather than functional selection imposed by top-down control of procedures, we want to emphasize that we do not want to question the possibility of limited resources or their counterpart – automatic processing – altogether. Certainly, some tasks are so difficult that they exceed limited human processing capacity while being easily performed by modern-day computers. Instead, our review highlighted examples of hyper selectivity in fairly simple tasks to caution against over-interpreting just any selectivity as evidence of an underlying structural resource limitation.

In addition, we took a skeptical stance toward dual-process theories as an explanation of several instances of seeming automatic or resource-free processing. Instead, we suggest taking a functional perspective and understanding these processes in terms of the top-down control of procedures. However, we believe that not all processes can be explained easily as forms of inadvertent processing through top-down control of procedures. For instance, flicker singletons with a flicker frequency deviating from that of their surrounding stimuli seem to capture attention in a truly bottom-up, automatic, or resource-free way (Cass et al., 2011; Stolte and Ansorge, 2021).

Another issue altogether are the types of learning-dependent automatic selection (cf. Shiffrin and Schneider, 1977). Highly trained forms of selection in the pursuit of persisting task demands are very likely under the selection-for-procedures view, as some of the types of controlled procedures that humans perform are very frequent in the everyday world. Again, think of looking at relevant locations as a strategy to support perception. These forms of selections may also spill over or generalize to situations in which they are not optimal or at least not necessary (Luchins, 1942; Goller et al., 2020a). Take the example of Goller et al. (2020a). These authors used Korean and German speakers in a test of language-induced tendencies to select visual inputs. Only the Korean language but not German (or English for that matter) strictly requires choosing a verb appropriate to discriminate tight- versus loose-fit relations between objects. Hence, Korean speakers should have practiced this particular procedure of selecting the corresponding visual information for an appropriate verbal description much more often than German speakers. In line with this hypothesis, even in a non-linguistic visual search for color-defined targets, Korean speakers showed a higher sensitivity for selecting a "fit singleton" than German speakers. Specifically, during search for a red target, presenting a differently colored fit singleton (e.g., a combination of loose cylinder around a piston presented among fit non-singletons, e.g., combinations of tightly fitting cylinders around pistons at all other positions) away from the target captured Korean speakers' but not German speakers' attention. This was evident in longer search times with interfering fit-singleton distractor than in a baseline condition without fit-singleton distractor (Experiments 4 and 5 of Goller et al., 2020a). This effect did not reflect simply more automatic attention capture among the Korean speakers, as capture and interference by a color singleton was the same for Korean and German speakers. Rather, it, reflected a generalization of a practice-dependent selection in the service of procedural control (here, depending on the practice with the language that one speaks) to a non-linguistic color-search task (cf. Baier and Ansorge, 2019). We cannot say if this selection reflected a form of more change-resistant gradual learning (cf. Shiffrin and Schneider, 1977) or a form of "Einstellung effect" (cf. Luchins, 1942), but we acknowledge the existence of these forms of "long-term procedural selectivity" that is not due to the task representation set up for procedural control in a current situation. Importantly, both of these factors are founded in the control of procedures rather than being due to resource limitations.

CONCLUSION

Humans are literally born in the saddle. They are born into a physically extended world, including their own bodies, which evolves over time. They have to control their bodily actions for successful coordination within a dynamically changing environment. Out of these constraints arises a necessity to select information appropriate to coordinated action in the temporally evolving spatial surroundings. This is a major reason for selectivity in processing, the consequences of which are often dismissed too easily as mere resource limitations. Therefore, in the current review, we have taken a skeptical stance toward the resource view, as selectivity can express how humans exert control over procedures in general, be these overt actions or covert processing. Importantly, this selection-for-procedures view is a functional, not a structural perspective. It emphasizes that selectivity is a benefit for information processing, not a deficit of it. Our view comes close to existing theories, such as Janczyk and Kunde's (2020) conclusion that anticipated action effects could explain psychological refractory period effects: what I as an agent expect to happen as a consequence of my processing or actions is responsible for the necessity to either deal with one task or the other at a time. However, in contrast to these authors, we do not think that the resulting bottleneck is of a structural nature – that is, the anticipation of procedural consequences does not draw on a limited resource that could be used for one or the other task. Instead, we think that a human's choice of the anticipated and monitored procedural consequences is her or his way to flexibly control her procedures itself.

DATA AVAILABILITY STATEMENT

The original contributions generated for this study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

UA, CB, MF, DG, MG, UP, MS, RS, and CV planned the outline and content of the present article. UA drafted a first version of the manuscript, with the exceptions of **Box 2** and of **Figure 2**, the first versions of which were crafted by CB and CV, respectively. All authors commented upon and revised the manuscript several times.

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Deriving Mental Energy From Task Completion

Xiang Wang[1], Chris Janiszewski[1], Yanmei Zheng[2], Juliano Laran[3] and Wonseok Eric Jang[4]*

[1]Warrington College of Business, University of Florida, Gainesville, FL, United States, [2]Shidler College of Business, University of Hawaii at Manoa, Honolulu, HI, United States, [3]Faculty of Business and Economics, University of Basel, Basel, Switzerland, [4]College of Sports Science, Sungkyunkwan University, Suwon, South Korea

Many tasks in everyday life (e.g., making an accurate decision, completing job tasks, and searching for product information) are extrinsically motivated (i.e., the task is performed to gain a benefit) and require mental effort. Prior research shows that the cognitive resources needed to perform an extrinsically motivated task are allocated pre-task. The pre-task allocation of mental resources tends to be conservative, because mental effort is costly. Consequently, there are mental energy deficits when the use of mental resources exceeds the allocated amount. This research provides evidence for post-task mental energy replenishment. The amount of resource replenishment is a function of the size of the mental energy deficit and the favorability of the cost-benefit trade-off experienced at the completion of the task (i.e., the value of the reward given the energy investment). The findings have implications for how cognitive resources management influences the availability of mental energy on a moment-to-moment basis.

Keywords: cognitive resources, mental energy, task rewards, task completion, extrinsic motivation

Edited by:
Bernhard Hommel,
University Hospital Carl Gustav Carus,
Germany

Reviewed by:
Ali Boolani,
Clarkson University, United States
Alexander Nicolai Wendt,
Heidelberg University, Germany

****Correspondence:***
Chris Janiszewski
chris.janiszewski@warrington.ufl.edu

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INTRODUCTION

Cognitive resources are a foundational concept in the cognitive sciences. Cognitive resource availability influences perception, comprehension, and elaboration in information processing models (Greenwald and Leavitt, 1984; Wingfield, 2016), the ability to engage in system 2 processes (e.g., rule-based reasoning, analytic thought, and planning) in dual-process models (Evans, 2008), and the effectiveness of behavior in models of self-control (Inzlicht et al., 2021). Exerting more cognitive effort improves decision accuracy (Bettman et al., 1998) and the effectiveness of behavior (Shenhav et al., 2017).

Resource-based models of cognition and behavior assume people expend cognitive resources in order to achieve a beneficial outcome, whether that outcome be a better decision, a more effective behavior, or a more rewarding consumption experience (Shenhav et al., 2017). Prior to engaging in a task, people assess the amount of cognitive effort (i.e., costs) needed to complete the task and the benefits that can be accrued from task completion (Brehm and Self, 1989; Boksem and Tops, 2008; Shenhav et al., 2017; Kool and Botvinick, 2018). If the anticipated benefits exceed the anticipated costs, people allocate cognitive resources into working memory (henceforth, mental energy) and engage in the task (see **Figure 1**; Navon and Gopher, 1979; Brehm and Self, 1989; Botvinick and Braver, 2015; Shenhav et al., 2017). During task engagement, mental energy is

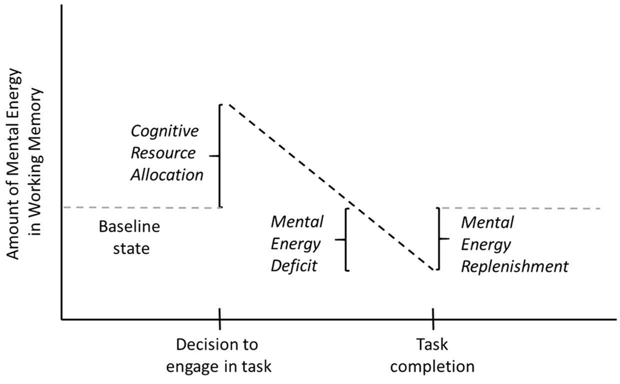

FIGURE 1 | Illustration of cognitive resource allocation, a mental energy deficit, and replenishment. The baseline level of mental energy is shown by the gray dashed line. The decision to engage in a task increases the level of mental energy (cognitive resource allocation). The amount of mental energy used during the completion of a task can be more than was allocated (mental energy deficit). Task completion provides an opportunity for mental energy replenishment.

expended to enhance mental focus (i.e., task performance) and facilitate mental intensity (i.e., task persistence; Shenhav et al., 2013).

In this paper, we ask the question, "What if a task is more demanding than expected?" If the actual cognitive resources needed to perform a task exceed the cognitive resources allocated for the task, post-task mental energy will be in a deficit state relative to baseline (i.e., the mental energy level prior to considering the task; see **Figure 1**). If mental energy allocation only occurs pre-task, and only depends on task characteristics, then sequences of tasks that result in an energy deficit should lead to degradations in cognitive performance. Accordingly, we posit that an adaptive response has emerged wherein automatic, post-task mental energy allocation can address a mental energy deficit. We further posit that this adaptive response should be sensitive to two factors: (1) the size of the mental energy deficit and (2) the favorability of the cost-benefit trade-off experienced at the completion of the task. Specifically, unexpected cognitive effort creates a mental energy deficit and a need to replenish the energy (Jansen et al., 2002, 2003; van Veldhoven and Broersen, 2003). A favorable cost-benefit trade-off (i.e., the task benefits are sufficient given the actual mental energy costs) will result in mental energy replenishment, whereas an unfavorable trade-off (i.e., the task benefits are insufficient given the actual mental energy costs) will not result in mental energy replenishment. In the latter case, the mental energy deficit acts as a signal that effort is being poorly invested and that corrective action should be taken (e.g., disengage from task, update priors about the mental energy requirements for the type of task performed, rest).

This research provides a more nuanced explanation of how mental energy is managed on a task-to-task basis and provides two insights into mental energy supplies. First, we know that mental energy varies on a moment-to-moment basis (Yeo and Neal, 2008). Yet, prior conceptualizations of cognitive resource management do not address the drivers of moment-to-moment changes in mental energy availability (Yeo and Neal, 2008; Shenhav et al., 2017). Our work provides insight into how unexpected effort affects (i.e., decreases and increases) mental energy, which in turn can influence performance on subsequent cognitive tasks. Second, the results provide insight into why people are cognitive misers (Navon and Gopher, 1979; Goldfarb and Henik, 2014; Kool and Botvinick, 2014; Sayalı and Badre, 2019). In general, people allocate the minimum amount of cognitive resources needed to complete a task. Consequently, resource allocation errors are primarily negative (i.e., there is a tendency toward an under allocation of resources). A resource allocation system characterized by under allocation can only be sustainable if there is a post-task correction mechanism. In the absence of this mechanism, the predominant experience of most people would be a perpetual deficit in mental energy. Our work provides insight into why this is not the case.

THEORY AND HYPOTHESES

Mental Energy

Mental energy has been conceptualized "as a subjective feeling about one's capacity to accomplish tasks in daily life" (O'Connor, 2006a). Within this conceptualization, mental energy is multi-dimensional construct consisting of (1) the mood of energy (i.e., the feeling that one can complete physical and mental tasks), (2) motivation (i.e., the desire to execute tasks), (3) cognitive resources (i.e., the ability to execute of cognitive tasks), and (4) quality of life (i.e., the degree to which life tasks are accomplished; O'Connor, 2006a). Mental energy researchers have focused primarily on the mood of energy and cognitive resource dimensions, with motivation being studied primarily in the goal literature and quality of life being studied primarily in the social welfare literature.

A considerable amount of research has focused on mental energy as a mood or feeling (O'Connor, 2004, 2006b; Lieberman, 2006). The *feeling of mental energy* is a general feeling that one is able to complete mental or physical activities (O'Connor, 2006b; Boolani et al., 2020). Common measures of the feeling of mental energy include the single-item visual analog scale (Wood and Magnello, 1992), the profile of mood states short form ("energetic," "full of pep," "vigorous," "active," and "lively;" Heuchert and McNair, 2012), and the mental energy state and trait scale (O'Connor, 2006b). The feeling of mental energy is impacted by sleep duration (Boolani and Manierre, 2019), time of day (Wood and Magnello, 1992), resistance exercise (Ward-Ritacco et al., 2016), illness (Loy et al., 2018), and food consumption (Lieberman, 2007; Maridakis et al., 2009), among other things. Experimental evidence shows that increasing this feeling increases vigilance (Maridakis et al., 2009) and decreases balance in the elderly (Boolani et al., 2020).

Considerable attention has also been devoted to investigating mental energy as a cognitive resource (James, 1907; Carver and Scheier, 1981; Lieberman, 2007; Goldfarb and Henik, 2014; Shenhav et al., 2017). The *mental energy as a cognitive resource* literature considers the amount of mental energy available to perform a cognitive task (e.g., mental energy at the moment).

Mental energy enables an executive control mechanism that "regulate(s) perceptual and motor processes in order to respond … to novel or changing task demands" (van der Linden et al., 2003, p. 47). This is especially true when people have to sustain engagement in a complex task that requires sustained attention, challenging analyses, dynamic planning, or disambiguating information (Broadbent, 1979; Bodenhausen and Lichtenstein, 1987; Campbell, 1988; Hockey, 1993; O'Connor, 2006a). In this perspective, changes in the availability of mental energy are inferred from changes in-task performance (Lieberman, 2007), including sustained attention (Schmeichel et al., 2003), organizing and evaluating information (Vohs et al., 2014), resolving choice trade-offs (Wang et al., 2010), compliance behaviors (Laran and Janiszewski, 2011), emotion regulation (Schmeichel et al., 2003), and impression management (Vohs et al., 2005). We investigate the mental energy as a cognitive resource dimension in this work.

Pre-task Allocation of Mental Energy Resources

The extant literature proposes that cognitive resources (i.e., mental energy) are allocated to working memory prior to engaging in an extrinsically motivated task (Brehm and Self, 1989; Boksem and Tops, 2008; Shenhav et al., 2017; Kool and Botvinick, 2018). There are three factors that influence the pre-task allocation of cognitive resources to working memory: the difficulty of the task (costs), the size of the benefit (rewards), and the cost-benefit trade-off.

Task Difficulty

A number of theories posit that expected task difficulty influences the amount of mental energy made available prior to initiating task pursuit. The theory of motivational intensity proposes that the amount of mental energy available prior to a task will increase as the expected difficulty of a task increases, but that mental energy will decline as it becomes apparent that a task is impossible to perform (Brehm et al., 1983; Brehm and Self, 1989). Similarly, goal-setting theory assumes that more aggressive goals require more mental energy for goal pursuit (Latham et al., 2011). Supporting this idea, working memory functions better when people can anticipate the difficulty of a task, suggesting that a difficulty cue allows a person to prepare for the task by allocating more cognitive resources to working memory (Manelis and Reder, 2015).

Task Benefits

A number of theories propose that the expected benefits associated with completing a task influence the amount of mental energy made available prior to engaging in task pursuit. For example, drive-reduction theory assumes that the motivation (i.e., the allocation of mental and physical energy) to pursue a task is a direct function of the reward potential of a behavior (Hull, 1943). Incentive theories of motivation propose that people will work harder for more positive outcomes (Bolles, 1972; Bindra, 1974; Wigfield and Eccles, 2000). Goal-systems theory assumes that motivated goal pursuit depends on the appeal and importance of the goal outcome (Kruglanski et al., 2002). The biopsychological theory of personality assumes that a behavioral activation system energizes behavior in accordance with a person's ability to appreciate the reward value of a behavior (Gray, 1970; Carver and White, 1994). In each model, more appealing, rewarding, or important goal outcomes generate more desire to engaging in the task, the implication being that more mental energy is available.

Cost-Benefit Analysis of the Task

A third factor that influences cognitive resource allocation is an analysis of the mental costs of engaging in a task vs. the benefits of task completion. Cognitive resources are allocated only when the reward is sufficient. This conceptualization assumes that mental effort is costly (Kahneman, 1973; Kurzban, 2016; Shenhav et al., 2017; Kool and Botvinick, 2018); hence, people are motivated to conserve cognitive resources (Navon and Gopher, 1979; McGuire and Botvinick, 2010; Kool and Botvinick, 2014; Dunn et al., 2016; Sayalı and Badre, 2019). People allocate the minimum amount of resources needed to complete a task, not the maximum amount of resources given the potential reward (Goldfarb and Henik, 2014). For example, cognitive energetics theory (Kruglanski et al., 2012) proposes that an allocation of cognitive resources should be equal to the "restraining force" – the resistance determined by task demands, the pull of competing goals, and one's inclination to conserve resources (i.e., allocate the minimal amount of resources to get the task done), provided that the magnitude of "restraining force" is lower than that of the "potential driving force," a function of goal importance and one's cognitive capacity. Similarly, the expected value of control (EVC) theory (Shenhav et al., 2013) proposes that the dorsal anterior cingulate cortex integrates information about the expected rewards and costs of a task to estimate its EVC and determine "whether it is worth investing control [effort] in a task, how much should be invested and, when several potential tasks are in contention, which is the most worthwhile."

Importantly, cost-benefit analyses that modulate the choice of tasks and the allocation of cognitive resources are considered to be subconscious (Boksem and Tops, 2008; Kurzban et al., 2013; Evans et al., 2016). Moreover, a growing literature suggests that a cost-benefit approach to choosing action is an adaptive advantage because it motivates behavior toward more rewarding activities and away from less rewarding ones (Boksem and Tops, 2008; Kool et al., 2010; Kurzban et al., 2013; Shenhav et al., 2013).

Post-task Mental Energy Replenishment

Existing accounts of the pre-task allocation of cognitive resources to working memory are not able to address how people avoid the cumulative effects of mental energy deficits. If the pre-task resource allocation system is designed to conserve cognitive resources (because mental effort is costly), then there will be more under allocation than over allocation of resources in a given time period. The under allocation of cognitive resources will inevitably lead to a deficit of mental energy and diminished cognitive performance. Thus, it would be advantageous for people to have a post-task mental energy replenishment system. A post-task mental energy replenishment system may not eliminate a mental energy deficit, but it would mitigate it.

Mental energy deficits are a common outcome in a conservative mental energy allocation system. The challenge for such a system is to determine how to address each mental energy deficit. We propose that post-task mental energy replenishment is one solution. Post-task mental energy replenishment is more likely to occur when the actual effort-reward trade-off is favorable. That is, if an accurate allocation of resources would still have resulted in engaging in the task (the reward justified the actual amount of mental energy invested), then the mental energy deficit will be replenished. Replenishment occurs because the error in pre-task mental energy allocation is acceptable given the reward. In contrast, when the actual effort-reward trade-off is unfavorable, mental energy replenishment should not occur. If an accurate estimate of the cognitive resources needed for the task would have resulted in rejecting the task or engaging in other tasks (the reward does not justify the unexpected amount of energy used), then the mental energy deficit should be a signal that cognitive resources estimates were miscalibrated and corrective action should be taken (e.g., update priors about energy requirements for this type of task, rest, and reassess behavior).

To illustrate these ideas, consider a situation where a person is shopping online. The person finds an acceptable product at a major retailer. She then determines it is worthwhile to invest additional cognitive effort in searching for a better deal (i.e., the anticipated benefits of additional search exceed the anticipated cognitive costs), allocates an appropriate level of cognitive resources, and engages in the search. If the search is more difficult than expected, there will be a mental energy deficit at the conclusion of the search. Post-task mental energy replenishment will occur if the reward (realized savings over original price) is sufficient given the actual amount of effort (i.e., the actual cost-benefit trade-off is favorable). Mental energy replenishment will not occur if the reward is insufficient given the actual amount of effort (i.e., the actual cost-benefit trade-off is unfavorable). An insufficient cost-benefit trade-off can occur because the unexpected amount of effort was too extensive (i.e., the additional search required much more cognitive effort than expected) or the reward was too small (i.e., the savings were minor).

As illustrated in the example, there are two forces that drive mental energy replenishment: the need for mental energy replenishment and the favorability of the cost-benefit trade-off (see **Figure 2**, high reward). First, unexpected effort creates a mental energy deficit and a need to replenish mental energy (Jansen et al., 2002, 2003; van Veldhoven and Broersen, 2003). The larger the amount of unexpected effort, the greater the need to replenish (Jansen et al., 2002, 2003). Second, replenishment should be strategic – it should be sensitive to the favorability of the actual cost-benefit trade-off from the completed task. This claim is consistent with the finding that people reinvest in tasks that are, on balance, rewarding (Boksem and Tops, 2008; Kool et al., 2010; Kurzban et al., 2013; Shenhav et al., 2013). An integration of the need for replenishment and favorability of the cost-benefit trade-off vectors predicts that energy replenishment will be an inverted-U function of the amount of unexpected effort when rewards are high (see the solid curve in **Figure 2**, high reward). Replenishment will not occur when unexpected effort is too low because the need to replenish would be negligible (see A1 in **Figure 2**, high reward) or when unexpected effort is too high because the cost-benefit trade-off would be unfavorable (see A3 in **Figure 2**, high reward). Replenishment occurs when unexpected effort is moderate because there is some need for replenishment and the cost-benefit trade-off would be favorable given the high rewards (see A2 in **Figure 2**, high reward). When rewards are low, the favorability of the cost-benefit trade-off declines because the rewards are less likely to be seen as worth the extra investment of effort, and thus, energy replenishment will be low (see the solid curve B1-B2-B3 in **Figure 2**, low reward).

Given that we are the first to propose post-task mental energy replenishment, there is little literature directly supporting the idea. Instead, one must assess if the predictions are consistent with how a conservative, pre-task cognitive resource allocation system would operate. The system we propose can not only guard against an insufficient amount of mental energy, but it can also help correct large energy allocation errors. Large mental energy deficits create a strong motivation to replenish. Consequently, a simple mental energy replenishment system could replenish energy any time there was a high need. Yet, this approach would not allow the system to learn – there would be no feedback. A better system, the one we propose, inhibits automatic mental energy replenishment when there are large energy investment errors. Unexpectedly large mental energy deficits are a signal that priors about the expected costs of completing a task need to be updated, as the anticipated effort for this type of task is highly miscalibrated (Inzlicht et al., 2015). Further, large deficits may signal that the present behavior should be abandoned or changed (Boksem and Tops, 2008; Kurzban et al., 2013). A mental energy deficit could even signal the need to switch from performing externally rewarding tasks to engaging in more intrinsically motivated activities (Inzlicht et al., 2015).

STUDIES

We conducted four studies to test our predictions. Studies 1, 3, and 4 directly measured mental energy replenishment and study 2 assessed mental energy replenishment *via* performance on a subsequent task. Study 1 showed mental energy replenishment after completing a high-reward task (i.e., A2 in **Figure 2**), but not after completing a low-reward task (i.e., B2 in **Figure 2**). Study 2 used a design similar to study 1 to show that mental energy replenishment can influence performance on a subsequent task. Study 3 manipulated expected effort and reward to show that a high reward increases mental energy replenishment when the amount of unexpected effort is moderate (i.e., A2 in **Figure 2**), but not when it is low (i.e., A1 in **Figure 2**). Study 4 manipulated actual effort and

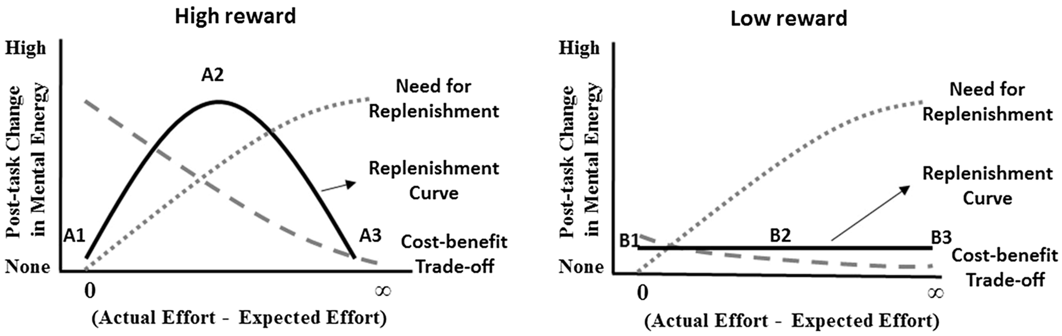

FIGURE 2 | Mental energy replenishment for extrinsically motivated tasks.

reward to show an inverted-U pattern of mental energy replenishment across different levels of effort when the reward is high (i.e., A1 vs. A2 vs. A3 in **Figure 2**), but not when the reward is low (i.e., B1 vs. B2 vs. B3 in **Figure 2**).

Study 1

The purpose of study 1 was to demonstrate that, when there is unexpected effort, mental energy is replenished upon completion of a high-reward task, but not a low-reward task. The procedure simulated online shopping behavior. The task involved finding online deals for five products, where reward value was manipulated by varying the bonus associated with finding deals. Participants were asked to find and record the deals. We predicted that participants in the high-reward condition would show mental energy replenishment at the completion of the shopping trip (i.e., A2 in **Figure 2**), but that participants in the low-reward condition would not (i.e., B2 in **Figure 2**).

Method

Participants and Design

The experiment used a two cell (reward value: low vs. high) between-subject design. An *a priori* power analysis using G*Power 3.1 (Faul et al., 2009) determined that at least 90 participants would be required to detect a medium-to-large effect (f = 0.30) with a power of 80%. We targeted a total sample of 100 on Amazon Mechanical Turk, and 101 participants completed the study in exchange for $1.20 in financial compensation (M_{age} = 32.99, 58.4% male). All participants completed the task correctly, likely because they were "master workers." Thus, no participants were removed from the analysis.

Procedure and Stimuli

The study took place in mid-December, during the holiday season. At the beginning of the study, we reminded participants that it was the holiday shopping season. Consequently, we would show them several products and have them find the best online deal (the lowest price) for each product. Participants in the high-reward condition were further told that at the end of the survey, we would show them the best price we found for each product. If the price they found was equal to or lower than our price, they would get a $0.1 bonus for the product. Participants in the low-reward condition were not told that they could earn a bonus and therefore would only receive the compensation for completing the study.

Next, we showed participants five products: a Bluetooth speaker, an electric toothbrush, a WiFi router, a hard drive, and a pair of headphones. For each product, we asked them to paste the link of the deal they found and enter the price. Before showing each product, we asked participants to indicate how much mental energy they had at that moment. To better capture changes in mental energy over time, we used the following measure (1 = "less energy than usual" and 7 = "more energy than usual"):

> We would like to know how much mental energy you have at this moment. People's mental energy fluctuates on a moment-to-moment basis. We will ask you to indicate how much mental energy you have at various times in this study. On the following scale, please indicate how much energy you feel you have AT THIS MOMENT.

We used a single-item measure because mental energy as a cognitive resource is a concrete, single-component construct (for similar measures, see Allen et al., 2014; Laran and Buechel, 2017; Cardini and Freund, 2020). Single-item measures of constructs have similar predictive validity to multiple-item measures provided (1) the construct is uni-component (e.g., mental energy) as opposed to multi-component (e.g., state and trait feelings of mental energy) and (2) the measure is of the construct (e.g., the amount of mental energy), not an attribute of the construct (e.g., the intent to use mental energy; Bergkvist and Rossiter, 2007; Diamantopoulos et al., 2012). Moreover, the single-item measure allows us to repeatedly assess mental energy in a short period of time, without introducing measurement-based rest periods that might allow mental energy to replenish (Masicampo et al., 2014; Helton and Russell, 2017).

After completing the fifth deal-finding task (i.e., the fifth product), participants saw the following message: "Congratulations! You have completed the task." Then, they responded to the same mental energy measure as shown above. To guard against the alternative explanation that greater pay leads to more mental energy, this last measure occurred after task completion but before disclosing the amount of the bonus.

To rule out the alternative explanations of felt achievement and competence (i.e., processes associated with intrinsic motivation), we also asked participants to indicate (1) the extent to which they thought completing the task felt like an achievement and (2) how effective they felt at the task, both on 7-point scales (1 = not at all and 7 = very much). Afterward, participants in the high-reward condition were shown the best deals. We compared the prices and awarded bonuses. The average bonus was $0.35 in the high-reward condition, with 98% of the participants receiving a bonus. Finally, all participants entered demographic information and were thanked for their time. The entire set of procedures and stimuli of this and all studies in the paper can be found in the **Supplementary Material**.

Results

Post-test of Unexpected Effort Assumption

A test was used to confirm that effort was higher than expected. An independent sample of participants ($N = 27$) engaged in the same task without mental energy measures. Participants indicated how effortful they thought the task would be on a 7-point scale (1 = not at all effortful and 7 = effortful) prior to engaging in the task (i.e., a measure of expected effort). Upon completion, participants indicated how effortful they thought the task was on the same 7-point scale (1 = not at all effort and 7 = effortful; i.e., a measure of actual effort). As expected, actual effort ($M = 5.63$, $SD = 1.39$) was higher than expected effort [$M = 4.96$, $SD = 1.48$; $F(1, 26) = 10.40$, $p = 0.003$, $\omega_p^2 = 0.251$].

Analysis of Mental Energy

Mental energy was measured six times in total. The average ratings across times and conditions are shown in **Figure 3**. T1 through T5 indicate the amount of mental energy reported before participants started to search for the first, second, … fifth product, respectively, and T6 was the amount of mental energy reported upon task completion. To examine mental energy replenishment pre- vs. post-task completion, we used a repeated measures ANOVA with reward value (low vs. high) as a between-subjects factor and time (T5: pre-completion vs. T6: post-completion) as a within-subjects factor.

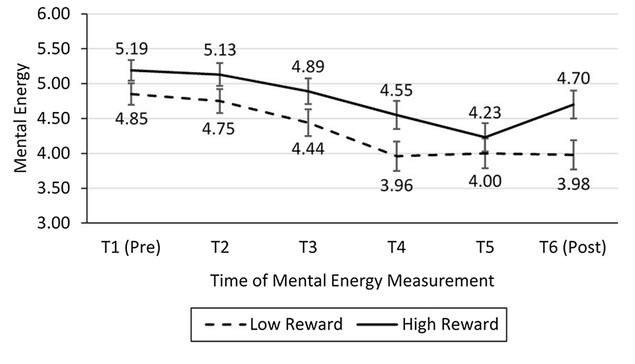

FIGURE 3 | Mental energy at different points in the task (study 1).

Mental energy replenishment was measured as the difference in mental energy at time T5 and time T6. This within-subject measure was better than analyzing mental energy at T6, because mental energy at T6 could not adjust for difference in mental energy at T5 (i.e., mental energy at T6 is not a measure of replenishment). Consistent with hypothesis 1, there was a significant interaction between time (T5 vs. T6) and reward value [$F(1, 99) = 6.71$, $p = 0.011$, $\omega_p^2 = 0.054$; see **Figure 3**]. Follow-up pairwise comparisons revealed that participants in the high-reward condition exhibited mental energy replenishment [$M_{T5} = 4.23$, $SD = 1.57$; $M_{T6} = 4.70$, $SD = 1.37$; $F(1, 99) = 12.95$, $p = 0.001$, $\omega_p^2 = 0.106$], whereas participants in the low-reward condition exhibited no mental energy replenishment [$M_{T5} = 4.00$, $SD = 1.37$; $M_{T6} = 3.98$, $SD = 1.54$; $F(1, 99) = 0.02$, $p = 0.880$].

A final set of analyses confirmed that mental energy generated as a consequence of extrinsic task completion did not depend on intrinsic task mediators like felt achievement or competence. The effect of reward value on felt achievement and competence was not significant [felt achievement: $M_{low} = 4.58$, $SD_{low} = 1.84$; $M_{high} = 5.04$, $SD_{high} = 1.51$; $F(1, 99) = 1.86$, $p = 0.176$; competence: $M_{low} = 4.92$, $SD_{low} = 1.69$; $M_{high} = 5.43$, $SD_{high} = 1.46$; $F(1, 99) = 2.73$, $p = 0.102$]. A follow-up test showed the interaction between time (T6 − T5) and reward on mental energy remained significant after controlling for felt achievement and competence [$F(1, 97) = 5.50$, $p = 0.021$, $\omega_p^2 = 0.043$]. The correlations between mental energy replenishment (i.e., T6 − T5 difference) and achievement or competence were not significant in the high-reward condition (achievement: $r = 0.028$, $p = 0.841$; competence: $r = -0.054$, $p = 0.699$) or low-reward condition (achievement: $r = 0.160$, $p = 0.276$; competence: $r = 0.257$, $p = 0.078$). The lack of a significant correlation in the high-reward condition is additional evidence that felt achievement and competence were not responsible for the increase in mental energy.

Replication With a Low-Reward Condition

One may argue that participants in low-reward condition received no reward, which is not equivalent to low reward. To address this concern, we reran study 1 ($N = 118$) using a low-reward condition, where participants received a $0.01 bonus for each best deal they found. The amount of bonus in the high-reward condition was $0.10. The results replicated the main findings of study 1: The significant interaction between time (T5 vs. T6) and reward value was significant [$F(1, 116) = 4.38$, $p = 0.039$, $\omega_p^2 = 0.028$] and participants in the high-reward condition exhibited mental energy replenishment [$M_{T5} = 4.33$, $SD = 1.42$; $M_{T6} = 4.62$, $SD = 1.41$; $F(1, 116) = 7.71$, $p = 0.006$, $\omega_p^2 = 0.054$] while participants in the low-reward condition did not [$M_{T5} = 4.32$, $SD = 1.66$; $M_{T6} = 4.30$, $SD = 1.74$; $F(1, 116) = 0.03$, $p = 0.873$; see the **Supplementary Material** for a full analysis]. Thus, using a low-reward condition instead of a no reward condition does not change our conclusions.

Discussion

Study 1 provides evidence that mental energy is replenished at task completion when the reward value is high, but not when the reward value is low. Further, it rules out the possibility that the influence of reward value on mental energy replenishment is due to intrinsic motivation mediators like feelings of achievement or competence. This null effect was anticipated because mental energy replenishment after an extrinsically motivated task should not be sensitive to drivers of intrinsic motivation.

Study 2

Study 2 demonstrates the behavioral implications of post-task mental energy replenishment. Specifically, study 2 replicates the findings of study 1 using a behavioral measure (e.g., task persistence) instead of a self-report of mental energy. A self-report of mental energy was not included in this study in order to avoid contamination across measures (i.e., directing attention to one's mental energy level may lead to demand artifacts on a behavioral measure; performance on a behavioral measure may lead to inferences about one's mental energy level).

Study 2 included an additional factor meant to address the possibility that mental energy replenishment is a consequence of intrinsic motivation contaminating an extrinsically motivated task. Energy management in intrinsic motivation occurs in-task (Csikszentmihalyi and LeFevre, 1989; Deci and Ryan, 2000). That is, if a task is enjoyable or engaging, mental energy can be allocated in-task so that the behavior is sustained. To address this possibility, task completion was manipulated across conditions. Using the same procedure as in study 1, participants were either told the task was completed or not after finishing the fifth part of the procedure. If intrinsic motivation was contaminating the extrinsically motivated task, this manipulation should not matter. If mental energy replenishment is a function of effort and reward at task completion (i.e., a post-task event), then there should only be mental energy replenishment in the high reward – task completion condition.

Method

Participants and Design

The experiment used a 2 (reward value: low vs. high) by 2 (completion: yes vs. no) between-subject design. An *a priori* power analysis using G*Power 3.1 (Faul et al., 2009) determined that at least 199 participants would be required to detect a small-to-medium interaction effect ($f = 0.20$) with a power of 80%. We targeted a total sample of 300 on Mechanical Turk, and 295 participants completed the study in exchange for \$1.30 in compensation. Forty-eight participants did not enter any relevant links throughout the task and, therefore, were excluded, leaving 247 participants ($M_{\text{age}} = 34.01$, 61.9% male).

Procedure and Stimuli

Participants completed a deal-search task, as in study 1, but with five changes. First, as the study was conducted in April (non-holiday season), we removed holiday-related words and pictures from the instructions. Second, we removed all measures of mental energy. Third, task completion was manipulated after participants completed the fifth deal-finding task. Participants in the completion condition saw the following message: "Congratulations! You have completed this task." On the next page, they read "Now we would like you to complete another task." Participants in the no completion condition saw a page saying "loading the next item" (all participants saw the same page after they finished the first, second, third, and fourth deal-finding task). On the next page, they read "Now we would like you to switch to another task." Fourth, the specifics of some products were changed (e.g., color and model type) due to product availability or deal availability. Finally, given the need to immediately measure task persistence, and the null effects in study 1, felt achievement and competence were not measured.

The availability of mental energy was measured using persistence on the second task (Braver, 2012). Task persistence owing to cognitive resources has been operationalized as sustained effort on unsolvable puzzles (Baumeister et al., 1998), time spent studying (Vohs et al., 2014), continued vigilance (See et al., 1995), product evaluation (Laran and Janiszewski, 2011), and discovering embedded figures (Vohs and Heatherton, 2000). In this study, participants did a "Book Evaluation Task." Specifically, participants were told as: "On the next few pages, we would like you to evaluate some newly released books and tell us whether you will consider adding them to your reading list. On each page, we will show you the book title, author, and a synopsis. After you evaluate some books, you can choose to quit the task. You can quit the task whenever you like." In this task, each book was presented on a separate screen and evaluated using two items: "Would you consider adding this book to your reading list?" (1 = yes or 2 = no) and "To what extent are you interested in reading this book?" (1 = not at all and 7 = very much). After evaluating each book, participants were offered the opportunity to "continue working on the task (i.e., evaluate more books)" or "quit." The number of books each participant evaluated before quitting the task was the measure of task persistence.

Results

Task persistence (i.e., number of books considered) was coded as the number of times each participant selected "continue working on the task (i.e., evaluate more books)," ranging from 0 to 20. There was a non-significant main effect of task reward [$F(1, 243) = 0.21$, $p = 0.65$] and completion [$F(1, 243) = 0.66$, $p = 0.42$], as well as a significant interaction between reward value and completion on task persistence [$F(1, 243) = 5.16$, $p = 0.024$; $\omega_p^2 = 0.017$; see **Figure 4**]. When reward value was low, participants in the completion ($M = 3.31$, $SD = 5.24$) and no completion ($M = 4.39$, $SD = 6.28$) conditions considered a similar number of books [$F(1, 243) = 1.04$, $p = 0.31$]. However, when reward value was high, participants in the completion condition ($M = 5.32$, $SD = 6.94$) considered more books than those in the no completion condition [$M = 3.05$, $SD = 4.32$; $F(1, 243) = 4.89$, $p = 0.028$; $\omega_p^2 = 0.016$].

Discussion

The results of study 2 provide evidence that post-task mental energy replenishment has consequences for subsequently

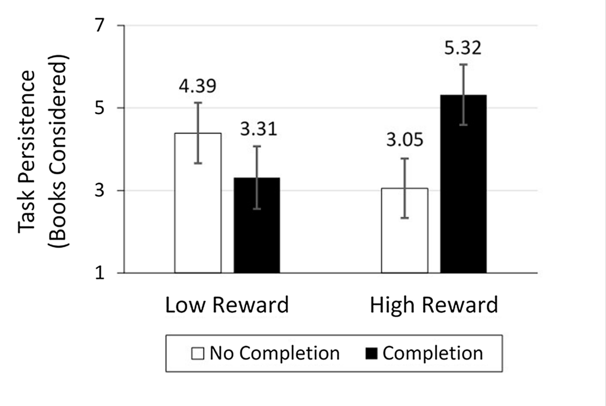

FIGURE 4 | Task persistence in study 2.

performed behaviors. When the reward value was high, task completion increased persistence in a subsequent, unrelated task. However, when the reward value was low, task completion did not increase persistence in the subsequent task. The task completion moderator provides further evidence that mental energy replenishment is a function of the unexpected effort invested and reward accrued from an extrinsically motivated task and that mental energy replenishment does not occur in-task. Study 2 also addresses the alternative explanation that measuring mental energy makes people more sensitive to mental energy. In study 2, there were no measures of mental energy, yet the results replicated study 1. Second, it could be argued that measuring mental energy creates a demand effect on reports of mental energy in high-reward conditions. In study 2, the high reward was kept constant, and no measure of mental energy was collected to make mental energy salient, yet the consequences of mental energy replenishment were still obtained in the completion condition. This should reduce concerns about demand effects.

Study 3

The x-axis in **Figure 2** is the difference between expected effort and actual effort. We hypothesize that people replenish mental energy after completing an extrinsically motivated task only when actual effort exceeds the expected effort by a sufficient amount (see A2 vs. A1 in **Figure 2**). One approach to providing evidence for this prediction is to alter the expected effort associated with a task. When actual effort sufficiently exceeds expected effort (i.e., there is unexpected effort), there should be mental energy replenishment when there is a high-reward value but not when there is a low-reward value (i.e., see A2 vs. B2 in **Figure 2**). This result would replicate the results of studies 1 and 2. In contrast, when actual effort does not exceed expected effort because the person has been led to believe the task will be more effortful (i.e., there is no unexpected effort), there should be no mental energy replenishment in a high or low-reward value condition (i.e., see A1 vs. B1 in **Figure 1**). This result would illustrate that the difference between expected and actual effort, not solely the amount of actual effort, is partially responsible for post-task mental energy replenishment.

Method

Participants and Design

The experiment used a 2 (reward value: low vs. high) by 2 (expected effort: low vs. high) between-subject design. An *a priori* power analysis using G*Power 3.1 (Faul et al., 2009) determined that at least 253 participants would be required to detect an effect of $f = 0.018$ (based on results of a pretest) with a power of 80%. We targeted a total sample of 260 on Mechanical Turk, and 263 Mechanical Turk participants completed the study in exchange for financial compensation ($M_{\text{age}} = 38.24$, 51.7% male). All participants were retained.

Procedure and Stimuli

At the beginning of the study, participants were told that they would complete a simple task where they would be asked to identify the correct synonym for a word. The synonym had to be chosen from four alternatives. Furthermore, participants learned that the task was programmed by Freerice – a 100% non-profit Web site that supports the United Nations World Food Program, and the aim of the task was to help end world hunger – for each answer they got right, the sponsors of Freerice would donate 1 grain of rice (low-reward condition) or 50 grains of rice (high-reward condition) to the United Nations World Food Program to help reach Zero Hunger.

Then, we manipulated the expected effort of the task. Participants in the high expected effort condition learned that the words they would see in the questions were not those frequently used in everyday life and, thus, they would need to invest extra cognitive effort. This description was intended to match their actual experience during the task (i.e., there should be no unexpected effort), as the questions were indeed moderately difficult and required some effort (see the questions listed in the **Supplementary Material**). Participants in the low expected effort condition were not provided information about expected effort and, thus, expected effort should be significantly below actual effort (i.e., there should be unexpected effort). Then, all participants rated the extent to which they thought the task would be effortful (1 = not at all and 7 = very effortful), which served as a manipulation check of anticipated effort.

Next, all participants started working on the task. The task involved five sets of questions, five questions in each set. To remind participants of the task reward, we put a banner at the top of the page saying "Free rice" and "For each answer you get right, we donate [1/50] grains of rice through the World Food Program to help end hunger." Upon completion of the fifth set of questions, participants saw the following message: "Congratulations! You have completed the task." As in previous studies, we measured mental energy prior to each set of five questions as well as after participants completed all sets of questions. After completing the task, participants completed a manipulation check of task reward, where they indicated the extent to which they thought the task was "valuable," "important," "rewarding," and "useful" (1 = not at all and 7 = very much; Cronbach's alpha = 0.96). Finally, participants responded to the achievement and competence measures used in studies 1 and 2.

Results

Manipulation Checks

As expected, there was a significant main effect of the reward value manipulation on perceived reward value [$M_{\text{high reward}} = 4.88$, $M_{\text{low reward}} = 4.37$; $F(1, 259) = 6.68$, $p = 0.010$, $\omega_p^2 = 0.021$]. There was no main effect of expected effort or a reward value by expected effort interaction on perceived reward value. In addition, a two-way ANOVA revealed a significant main effect of the expected effort manipulation on anticipated effort [$M_{\text{high expected effort}} = 5.78$, $M_{\text{low expected effort}} = 4.13$; $F(1, 259) = 92.67$, $p < 0.001$, $\omega_p^2 = 0.260$]. There was no main effect of reward value or a reward value by expected effort interaction on anticipated effort. Furthermore, consistent with our theory, there was a main effect of the expected effort manipulation on the amount of mental energy reported at T1, prior to engaging in the task [$M_{\text{high expected effort}} = 5.31$ $M_{\text{low expected effort}} = 5.04$; $F(1, 259) = 3.98$, $p = 0.047$, $\omega_p^2 = 0.011$], suggesting that participants allocated more mental energy to the task after they learned that the task would be effortful. There was no main effect of reward value or interaction on mental energy at T1.

Pretest

It was important to confirm that the low expected effort condition, but not the high expected effort condition, resulted in unexpected effort. An independent sample of participants ($N = 122$) engaged in the same task except that the mental energy measures were removed. Participants indicated how effortful they thought the task would be on a 7-point scale (1 = not at all effortful and 7 = effortful) before engaging in the task. Upon completion, participants indicated how effortful the task was on the same 7-point scale (1 = not at all effort and 7 = effortful; i.e., a measure of actual effort). The expected effort manipulation by expected vs. actual effort dependent measure interaction was significant [$F(1, 120) = 20.51$, $p < 0.001$, $\omega_p^2 = 0.138$]. As expected, in the low expected effort condition, the ratings of actual effort ($M = 5.10$, $SD = 1.54$) were higher than those of expected effort [$M = 4.30$, $SD = 1.49$; $F(1, 120) = 19.54$, $p < 0.001$, $\omega_p^2 = 0.132$]. In the high expected effort condition, however, actual effort ($M = 5.38$, $SD = 1.55$) was lower than expected effort [$M = 5.74$, $SD = 1.32$; $F(1, 119) = 3.94$, $p = 0.049$, $\omega_p^2 = 0.024$].

Mental Energy

Mental energy was measured six times. Consistent with our predictions, there was a three-way interaction of reward value, expected effort, and time [E5: pre-completion vs. E6: post-completion; $F(1, 259) = 4.49$, $p = 0.035$, $\omega_p^2 = 0.013$]. Further, there was a two-way interaction between reward value and time in the low expected effort condition [$F(1, 259) = 5.55$, $p = 0.019$, $\omega_p^2 = 0.017$; see **Figure 5**]. Specifically, there was mental energy replenishment in the high-reward value condition [$M_{\text{T5}} = 4.23$, $SD = 1.53$, $M_{\text{T6}} = 4.57$, $SD = 1.46$; $F(1, 259) = 11.67$, $p = 0.001$, $\omega_p^2 = 0.039$], but not the low-reward value condition [$M_{\text{T5}} = 4.67$, $SD = 1.25$, $M_{\text{T6}} = 4.69$, $SD = 1.21$; $F(1, 259) = 0.02$, $p = 0.881$]. In the high expected effort condition, there was no interaction between reward value and time [$F(1, 259) = 0.44$, $p = 0.51$] and no main effect of time [$F(1, 259) = 0.00$, $p = 0.992$; see **Figure 5**] on mental energy replenishment.

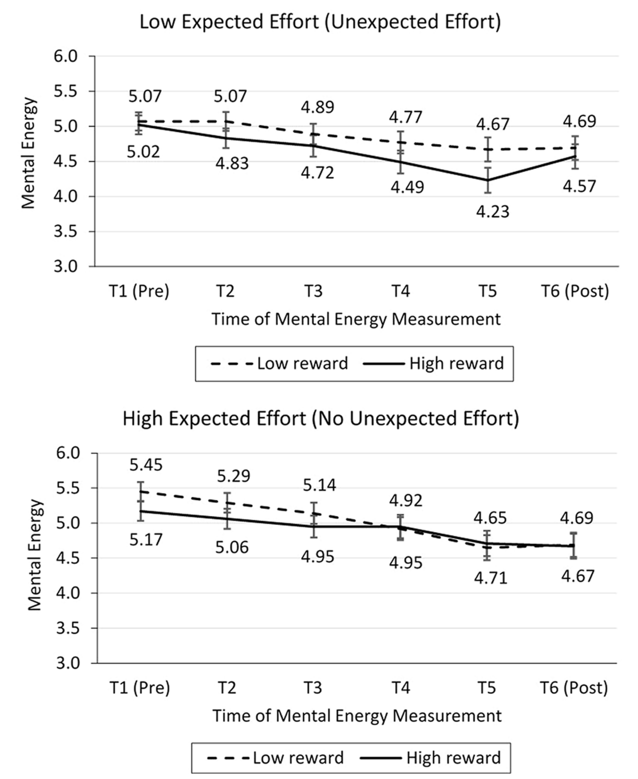

FIGURE 5 | Results of study 3.

Additional Analyses Using Felt Achievement and Competence

Similar to study 1, we anticipated that the mediators of intrinsic motivation would not explain mental energy replenishment for an extrinsically motivated task. Two-way ANOVAs revealed a main effect of reward value on felt achievement [$M_{\text{high value}} = 5.03$, $M_{\text{low value}} = 4.41$; $F(1, 259) = 9.40$, $p = 0.002$, $\omega_p^2 = 0.031$] and a marginally significant main effect of reward value on competence [$M_{\text{high value}} = 4.77$, $M_{\text{low value}} = 4.43$; $F(1, 259) = 3.47$, $p = 0.063$, $\omega_p^2 = 0.009$]. In the low expected effort condition, the correlation between mental energy replenishment (T6 − T5) and felt achievement or competence was not significant in the low-reward condition (achievement: $r = 0.047$, $p = 0.698$; competence: $r = -0.065$, $p = 0.594$) or the high-reward condition (achievement: $r = 0.123$, $p = 0.330$; competence: $r = -0.009$, $p = 0.945$). In the high expected effort condition, there was a marginally significant correlation between mental energy replenishment (T6 − T5) and felt achievement ($r = 0.151$, $p = 0.090$) while the correlation between mental energy replenishment (T6 − T5 and) competence was not significant ($r = 0.078$, $p = 0.383$). The lack of a significant correlation in the low expected effort – high-reward condition suggests that felt achievement and competence were not responsible for the replenishment of mental energy.

Discussion

Study 3 provides evidence that unexpected effort (i.e., the need to replenish), not actual effort, is responsible for post-task mental energy replenishment. When actual effort exceeded expected effort, and there was a high reward (i.e., a favorable cost-benefit trade-off), mental energy was replenished. When actual effort was less than the expected effort, and there was a high reward, there was no mental energy replenishment.

Study 3 helps rule out potential alternative explanations. For example, it could be argued that high rewards generate affect and this positive affect increases mental energy. This prediction is inconsistent with the results of study 3 because the low and high expected effort conditions both provided a high reward, but only the low expected effort condition resulted in increased mental energy. Similarly, it could be argued that high rewards encourage arousal, excitement, or anticipation that increase mental energy. Again, the interaction effect makes this unlikely. Study 4 creates a quadratic effect in the high-reward condition and, thus, provides additional evidence against these explanations.

Study 4

The x-axis in **Figure 2** is the difference between actual effort and expected effort. In study 4, we held expected effort constant, while manipulating actual effort and the size of the reward. When the reward was high, we expected to show the inverted-U pattern illustrated by A1, A2, and A3 in **Figure 2**. When the reward was low, we expected to show the flat pattern illustrated by B1, B2, and B3 in **Figure 2**.

Method

Participants and Design

The study was preregistered on AsPredicted.org.[1] An *a priori* power analysis using G*Power 3.1 (Faul et al., 2009) suggested a minimal sample size of 351 to detect an interaction effect of $f = 0.15$ (based on results of a pretest) with a power of 80%. We aimed to recruit 400 participants on Mechanical Turk, and a total of 401 participants completed the study in exchange for financial compensation. Eleven participants did not provide relevant responses and were therefore excluded from analyses using preregistered exclusion criteria, leaving a final sample of 390 participants ($M_{\text{age}} = 37.00$, 38.2% male). The experiment used a 2 (reward value: low vs. high) by 3 (actual effort: low vs. moderate vs. high) between-subject design.

Procedure

At the beginning of the study, participants were told that they would see information tags for electronic products and their task was to transcribe the product information into digital text. The transcription task required participants to transcribe five product descriptions.

To manipulate reward value, we told participants that they would either receive an extra 1 cent (low-reward condition) or an extra 5 cents (high-reward condition) for each information tag they accurately transcribed. Next, participants started working on the task. All participants transcribed a set of five information tags, with text length and blurriness varying across the three effort conditions. In the low effort condition, each information tag had two product attributes on it (about 40–50 characters) and text was clear (see **Figure 6** and the **Supplementary Material**). In the moderate effort condition, each information tag had five product attributes (about 100–120 characters) and the text was degraded a little, so participants had to spend more effort recognizing the text and typing it out. In the high effort condition, each information included eight product attributes (about 160–180 characters) and text was degraded to a greater extent (but still recognizable). A measure of mental energy was taken prior to starting the task (T1) and after each of the five sets of transcriptions (T2 – T6). After transcribing the fifth tag, just prior to the T6 measure of mental energy, participants saw "Congratulations! You have completed the task."

After completing the task, participants responded to several follow-up questions. First, as a measure of positive affect, they reported how happy they were at the moment. Next, participants responded to the achievement and competence measures used in studies 1 and 3. Finally, as a manipulation check of reward value, we measured how rewarding participants thought the extra payment for accurately transcribing the information tag was on a 7-point scale (1 = not at all and 7 = very much).

Results

Pretest

To assess if the actual task effort manipulation was successful, and if actual effort was higher than expected effort, a pretest had participants ($N = 192$) engage in the same procedure as in the main experiment, except that the information about the extra reward payment and the mental energy measures were removed. Participants indicated expected effort prior to engaging in the task using a 7-point scale (1 = not at all effortful and 7 = effortful). Upon completing the task, participants indicated actual effort using a 7-point scale (1 = not at all effort and 7 = effortful).

As predicted, the interaction between the actual effort manipulation and the difference between expected and actual effort (repeated measure) was significant [$F(2, 189) = 12.73$, $p < 0.001$, $\omega^2 = 0.116$]. Actual effort was lower than expected effort in the low effort condition [$M_{\text{expected}} = 4.77$, $SD = 1.48$, $M_{\text{actual}} = 4.21$, $SD = 1.62$; $F(1, 189) = 8.48$, $p = 0.004$, $\omega^2 = 0.038$], but higher than expected effort in the moderate effort condition [$M_{\text{expected}} = 4.72$, $SD = 1.70$, $M_{\text{actual}} = 5.14$, $SD = 1.96$; $F(1, 189) = 4.59$, $p = 0.034$, $\omega^2 = 0.018$] and the high effort condition [$M_{\text{expected}} = 4.92$, $SD = 1.30$, $M_{\text{actual}} = 5.79$, $SD = 1.60$; $F(1, 189) = 14.65$, $p < 0.001$, $\omega^2 = 0.067$].

Manipulation Check

A two-way ANOVA revealed a main effect of the reward value manipulation on perceived reward value [$M_{\text{high value}} = 5.14$, $M_{\text{low value}} = 4.18$; $F(1, 384) = 22.59$, $p < 0.001$, $\omega_p^2 = 0.053$]. There was also a marginally significant effect of actual effort

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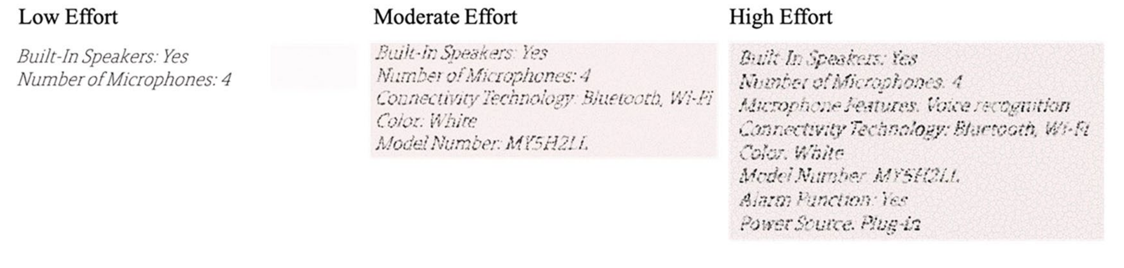
[1] https://aspredicted.org/blind.php?x=xf5pv8



Low Effort

Built-In Speakers: Yes
Number of Microphones: 4

Moderate Effort

Built-in Speakers: Yes
Number of Microphones: 4
Connectivity Technology: Bluetooth, Wi-Fi
Color: White
Model Number: MY5H2LL

High Effort

Built-In Speakers: Yes
Number of Microphones: 4
Microphone Features: Voice recognition
Connectivity Technology: Bluetooth, Wi-Fi
Color: White
Model Number: MY5H2LL
Alarm Function: Yes
Power Source: Plug-in

FIGURE 6 | Stimuli used in study 4.

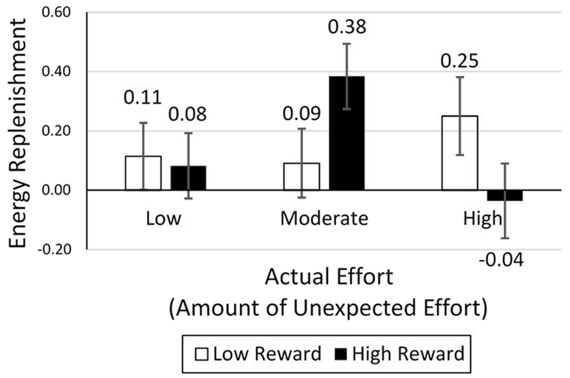


FIGURE 7 | Mental energy replenishment in study 4.

on perceived reward value [$M_{\text{low effort}} = 4.84$, $M_{\text{moderate effort}} = 4.78$, $M_{\text{high effort}} = 4.32$; $F(2, 384) = 2.44$, $p = 0.089$, $\omega_p^2 = 0.007$]. However, the interaction between reward value and actual effort was not significant ($F < 1$).

Mental Energy

As in study 1 and study 3, mental energy was measured six times. As preregistered, we first computed the amount of mental energy replenishment by subtracting pre-completion mental energy (T5) from post-completion mental energy (T6). Then, we created the planned quadratic contrast for the actual effort manipulation (e.g., low = −1, moderate = 2, and high = −1), which has a single degree of freedom associated with it. We used this planned contrast in the mental energy analyses. The means for the T6 – T5 difference (energy replenishment) are reported in **Figure 7**. The means for T1 through T6, for all conditions, are reported in the **Supplementary Material**.

The analysis was conducted using the preregistered plan. There was an interaction between reward value and actual effort on mental energy replenishment [$F(1, 384) = 5.09$, $p = 0.025$, $\omega_p^2 = 0.010$]. In the high-reward condition, there was a significant effect of effort on mental energy replenishment [$F(1, 384) = 6.77$, $p = 0.010$, $\omega_p^2 = 0.015$]. More importantly, planned contrasts revealed that mental energy replenishment in the moderate effort condition ($M = 0.38$, $SD = 0.97$) was higher than in the low effort condition [$M = 0.08$, $SD = 0.91$; $t(384) = 1.93$, one-tailed test, $p = 0.027$, $\omega_p^2 = 0.007$] and the high effort condition [$M = -0.04$, $SD = 0.87$; $t(384) = 2.50$, one-tailed test, $p = 0.006$, $\omega_p^2 = 0.013$]. In the low-reward condition, there was no effect of effort [$F(1, 384) = 0.398$, $p = 0.528$]. Planned contrasts showed no difference in mental energy replenishment between the moderate effort ($M = 0.09$, $SD = 1.03$) and low effort ($M = 0.11$, $SD = 0.65$) condition [$t(384) = -0.14$, $p = 0.885$] or the moderate effort ($M = 0.09$, $SD = 1.03$) and high effort ($M = 0.25$, $SD = 1.20$) condition [$t(384) = -0.91$, $p = 0.363$]. These results are consistent with **Figure 2**.

Positive Affect, Felt Achievement, and Competence

Two-way ANOVAs revealed a main effect of effort on positive affect [$M_{\text{low effort}} = 4.99$, $M_{\text{moderate effort}} = 4.96$, $M_{\text{high effort}} = 4.45$; $F(2, 384) = 4.24$, $p = 0.015$, $\omega_p^2 = 0.017$] and a marginally significant main effect of effort on competence [$M_{\text{low effort}} = 5.97$, $M_{\text{moderate effort}} = 5.84$, $M_{\text{high effort}} = 5.58$; $F(2, 384) = 2.78$, $p = 0.063$, $\omega_p^2 = 0.009$]. Tukey *post-hoc* tests revealed that positive affect was lower in the high effort condition than in the low effort condition ($p = 0.019$, $d = 0.34$) and the moderate effort condition ($p = 0.030$, $d = 0.32$). Competence was lower in the high effort condition than that in the low effort condition ($p = 0.049$, $d = 0.30$). The lower ratings in the high effort condition could be driven by the fact that the task was much more effortful than what participants expected and thus was frustrating and made participants feel less competent. No other main effects or interactions were significant. In summary, the patterns of positive affect and competence cannot explain the interaction of reward value and effort on replenishment nor the quadratic effect we observed in the high-reward condition.

Discussion

Study 4 provides additional evidence that the amount of unexpected effort determines the amount of mental energy replenishment, provided the reward for engaging in the behavior is high. When unexpected effort was moderate, and the cost-benefit trade-off was favorable (i.e., the reward is high), there was mental energy replenishment. When there was no unexpected effort, there was no need to replenish mental energy. When unexpected effort was large, the cost-benefit trade-off was unfavorable and there was no mental energy replenishment. We contend that the lack of mental energy replenishment reflects an automatic strategy for using the mental energy deficit as a signal to take corrective action.

GENERAL DISCUSSION

We provide evidence for mental energy replenishment in an extrinsically motivated task. We show that when the effort expended in an extrinsically motivated task is significantly more than expected, and the actual the cost-benefit trade-off is favorable, mental energy is replenished at the completion of the task (see **Figure 2**). If the extrinsically motivated task does not provide a sufficient reward (studies 1–4; **Figure 2** B1, B2, and B3), or if unexpected effort is minimal (studies 3 and 4; **Figure 2** A1) or extreme (study 4; **Figure 2** A3), there will be marginal mental energy replenishment. Mental energy replenishment is a useful adjustment mechanism, so that energy deficits resulting from a conservative mental energy allocation system do not result in compromised performance on future tasks. Mental energy replenishment for extrinsically motivated tasks can also be useful when there is cumulative learning over time and it is difficult to anticipate the mental energy requirements of activities in the learning process. Learning is more likely to persist when rewarding learning is accompanied by mental energy replenishment.

Implications for the Management of Mental Energy Resources

We believe that mental energy replenishment subsequent to a rewarding, extrinsically motivated task is necessary for sustained, effective cognitive behavior. To understand why, consider what we know about mental energy management. First, people have a baseline level of mental energy (Shulmana et al., 2009). This baseline level of mental energy supports consciousness and cognition. Second, people can increase the baseline level of mental energy. Pre-task allocations of mental energy are sensitive to factors, such as anticipated demands and rewards of the upcoming task (Beedie and Lane, 2012; Kruglanski et al., 2012; Shenhav et al., 2013), so that people can engage in beneficial cognitive behaviors. Third, there are incentives to be conservative with mental energy allocation as mental effort is costly, both absolutely and from an opportunity cost perspective (Boksem and Tops, 2008; Kurzban et al., 2013; Goldfarb and Henik, 2014). This leads to mental energy deficits, especially when energy use exceeds energy allocation on consecutive tasks (Kanfer et al., 1994). Fourth, pre-task allocations of mental energy cannot address a cumulative deficit. Thus, an energy replenishment function is conceptually consistent with the prior literature on mental energy use. Replenishment is a necessary part of an effective mental energy management system.

Perhaps, the most curious characteristic of the mental energy replenishment system is its sensitivity to the cost-benefit trade-off of a completed task. As shown in **Figure 2**, there is no mental energy replenishment when the cost-benefit trade-off is unfavorable (i.e., A3, B2, and B3 in **Figure 2**). We argue that this is adaptive because a replenishment system that is insensitive to the efficiency of energy investment would continue to replenish mental energy, and prepare for the next task, regardless of task difficulty. If a person is in an unfamiliar environment that creates mental energy deficits, then it would be beneficial for the person to experience low energy (i.e., baseline mental effort should continue to drop) and disengage from the environment/task if the rewards do not justify the actual cognitive effort (Kanfer et al., 1994). In fact, this is exactly what happens when people experience low energy (Kurzban et al., 2013; Cardini and Freund, 2020). They disengage from the environment/task. When rewards are insufficient given the effort, there is no post-task energy replenishment and the resulting lack of energy leads to disengagement from subsequent tasks (Hopstaken et al., 2015).

In this sense, our research also speaks to the literature on the adaptive nature of mental energy levels (e.g., Kool et al., 2010; Kurniawan et al., 2011; Kurzban et al., 2013; Botvinick and Braver, 2015). A growing literature suggests that a lack of mental energy could be an adaptive signal of the need to abandon or change the course of the ongoing behavior, because the current behavioral strategy may not be the most appropriate (Boksem and Tops, 2008). Our research suggests that the replenishment of mental energy may well be a signal to continue the pursuit of other rewarding, extrinsically motivated tasks, rather than shifting task priorities away from “have-to” goals (e.g., work tasks) to “want-to” goals (e.g., leisure tasks; Robinson et al., 2010; Inzlicht and Schmeichel, 2012; Inzlicht et al., 2014).

Limitations

The research procedures used in this paper have limitations. First, the procedure relies on a single-item measure of mental energy. Cognitive resource levels are more commonly assessed by measuring repeated performance on a task, with decrements in performance indicating decreased cognitive resource levels (See et al., 1995). Our single-item measure likely reflects an indirect assessment of cognitive resource levels (e.g., a perception of changes in the difficulty of executing a repeated task), since a meta-cognitive assessment of actual cognitive resource levels is difficult.

Second, we used tasks for which a person can make fairly accurate assessments of cognitive resource demands, so that mental energy can be allocated pre-task and deficits can occur post-task. Assessments of resource demands are only relevant in situations where tasks demands are predictable. There are many situations where tasks are ambiguous owing to the complexity of the problem (Dörner and Funke, 2017). The problem solving space may be ambiguous, complex, uncertain, and volatile. In these types of domains, it is difficult to anticipate rewards associated with an outcome, anticipate mental energy requirements, allocate pre-task resources, and determine stopping points (e.g., task completion). Thus, it remains to be seen whether our results generalize to management of mental energy beyond the performance of simple, common tasks.

Third, our behavior-based evidence for mental energy replenishment is limited to a single study (study 2) that measures performance on an unfixed task (i.e., people perform a self-paced book-review task for as long as they like). The performance of unfixed tasks can be sensitive to any antecedent that increases the availability of mental energy. In addition to mental energy replenishment, our favored explanation, it is also possible that motivational factors influenced the supply of energy. The successful completion of an initial task (e.g., rewarding shopping task) could activate the trait grit (the motivation to complete tasks) and encourage a larger investment of energy in a subsequent task (e.g., reviewing books; Duckworth et al., 2007).

Conclusion

People need mental energy to complete cognitive tasks. In this research, we document a novel source of mental energy. Mental energy can be generated at the completion of an extrinsically motivated task, assuming the task created a mental energy deficit and the cost-benefit trade-off for the task was favorable. These results reflect the idea that engaging in high-reward activities can be self-sustaining, even if the activities are more difficult than expected. Future research can investigate additional factors that interact with unexpected effort and reward value to generate mental energy at task completion. An investigation of these issues will provide better insight into how people replenish mental energy throughout their day and, consequently, sustain productive behavior.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the University of Florida Institutional Review Boards. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

XW and CJ contributed to the study designs. XW collected and analyzed the data under the guidance of CJ. CJ drafted the manuscript. All authors contributed to conception of the studies and manuscript revision and approved the final manuscript for submission.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at https://www.frontiersin.org/articles/10.3389/fpsyg.2021.717414/full#supplementary-material

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What Can Neural Activity Tell Us About Cognitive Resources in Aging?

Chiara F. Tagliabue and Veronica Mazza*

Center for Mind/Brain Sciences (CIMeC) – University of Trento, Rovereto, Italy

A reduction in cognitive resources has been originally proposed to account for age-related decrements in several cognitive domains. According to this view, aging limits the pool of available cognitive supplies: Compared to younger adults, elderly exhaust the resources more rapidly as task difficulty increases, hence a dramatic performance drop. Neurophysiological indexes (e.g., BOLD response and EEG activity) may be instrumental to quantify the amount of such cognitive resources in the brain and to pinpoint the stage of stimulus processing where the decrement in age-related resources is evident. However, as we discuss in this mini-review, the most recent studies on the neurophysiological markers of age-related changes lack a consistent coupling between neural and behavioral effects, which casts doubt on the advantage of measuring neural indexes to study resource deployment in aging. For instance, in the working memory (WM) domain, recent cross-sectional studies found varying patterns of concurrent age-related brain activity, ranging from equivalent to reduced and increased activations of old with respect to younger adults. In an attempt to reconcile these seemingly inconsistent findings of brain-behavior coupling, we focus on the contribution of confounding sources of variability and propose ways to control for them. Finally, we suggest an alternative perspective to explain age-related effects that implies a qualitative (instead of or along with a quantitative) difference in the deployment of cognitive resources in aging.

Keywords: cognitive aging, cognitive resources, working memory, interindividual variability, aging trajectories, neural correlates, age-related brain activity change

Edited by:
Gesine Dreisbach,
University of Regensburg, Germany

Reviewed by:
Iris Wiegand,
Radboud University Nijmegen,
Netherlands
Alessia Rosi,
University of Pavia, Italy

****Correspondence:***
Chiara F. Tagliabue
chiara.tagliabue@unitn.it

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AGE-RELATED REDUCTION IN PROCESSING RESOURCES

A marked decline across several cognitive domains is a common feature of aging (Hedden and Gabrieli, 2004). To account for this performance reduction, the *processing resources* framework (Craik and Byrd, 1982; Salthouse, 1988, 1990) posits that aging implies a decline in the amount of available cognitive resources, in that older individuals exhaust them more rapidly than younger adults. According to this account, the performance drop, measured as task requests increase, occurs because old individuals consume processing resources already at low levels of cognitive demand. The age-related changes in working memory (WM) capacity, a hallmark of cognitive aging (Myerson et al., 2003), nicely fit with this perspective. Indeed, in simple short-term memory tasks (mainly tapping on storage capacity, e.g., forward digit span), old adults are negligibly compromised. However, compared to young, they become impaired in WM tasks requiring additional cognitive processing (namely, concurrent storage and manipulation of items, e.g., backward or complex digit span; see Bopp and Verhaeghen, 2005, for a review).

These effects may be interpreted within the processing resources framework: The reduced pool of cognitive resources in aging is sufficient for the elderly to efficiently perform in simple tasks (e.g., short-term memory tasks), but not when they have to face higher cognitive demands (e.g., in WM tasks), and thus, a greater performance decrement is visible. An interesting approach has been proposed to substantiate the hypothesis of age-related reduction in processing resources (thought to be responsible for the observed behavioral deficits): measuring the neural activity (e.g., BOLD response and M/EEG activity) during the execution of various tasks, and isolating specific indexes that mirror the hypothesized resource decrement (e.g., McEvoy et al., 2001; Mattay et al., 2006). This approach is beneficial for at least two reasons. First, it provides an additional (cerebral) measure to quantify the amount of available resources in the elderly; second, it individuates the specific neural and functional mechanism where age-related differences in processing deployment originate. As Salthouse (1988) originally suggested, the candidate neural index of cognitive resources should positively correlate with cognitive performance (i.e., the greater the cerebral recruitment, the better the performance) and negatively correlate with age (i.e., the older the participant, the more reduced the cerebral activity). However, finding a neural measure that satisfies these requirements has proven to be difficult in the field of aging research. Indeed, results obtained from cross-sectional studies highlight that a consistent coupling between neural and cognitive modulations is currently lacking, which complicates predictions on how the neural markers of cognitive resource deployment should be modulated by age. A review of the most recent (in the last 5 years) imaging studies (fMRI and M/EEG) on WM provides substantial examples of these non-unidirectional patterns of age-related brain activity. Indeed, WM has been proposed as an ideal domain to test for the presence of any age-related variation in cognitive resources, since it is defined by a limited capacity and is relevant to other cognitive domains (Salthouse, 1990). In the next section, we will briefly illustrate some of the most recent results (note, however, that similar conclusions can be drawn when also considering articles published earlier than 2016). As we will describe, linking brain and cognition in an attempt to quantify the amount of available processing resources in aging is far from being a straightforward research approach.

NEURAL INDEXES UNDERLYING COGNITIVE RESOURCE DEPLOYMENT IN AGING

fMRI and M/EEG studies investigating WM in young and older adults have used various tasks (e.g., verbal and visuo-spatial n-back, delayed match-to-sample, Corsi-Block Tapping, and Sternberg paradigm; see **Table 1** for further details on recent studies). Across these paradigms, elderly usually exhibit a reduction of WM capacity compared to young adults. However, such decrements in performance are mirrored by different patterns of brain activity.

TABLE 1 | Neuroimaging studies comparing young and older adults in WM tasks and published from 2016 onwards.

Article	Methodology	Task
Archer et al., 2018	fMRI	Spatial Addition Task
Bauer et al., 2018	fMRI	Modified version of Corsi-Block-Tapping test
Crowell et al., 2020	fMRI	Verbal WM manipulation task of consonant strings
Gallen et al., 2016	fMRI	Visual n-back task
Heinzel et al., 2017	fMRI	Numerical n-back task
Höller-Wallscheid et al., 2017	fMRI	Verbal, spatial and object-based delayed match-to-sample task
Jamadar, 2020	fMRI	Visuo-spatial sequence paradigm
Kennedy et al., 2017	fMRI	Numerical n-back task
Qin and Basak, 2020	fMRI	Modified 2n-back task with colored digits
Rieck et al., 2021	fMRI	Verbal n-back task
Vellage et al., 2016	fMRI	Visuo-spatial delayed match-to-sample task
Billig et al., 2020	EEG	Visual delayed match-to-sample task
Hou et al., 2018	EEG	Verbal n-back task
Lubitz et al., 2017	EEG	Spatial n-back task
Morrison et al., 2019	EEG	Numerical n-back task
Sghirripa et al., 2021	EEG	Sternberg task
Tagliabue et al., 2019, 2020	EEG	Visuo-spatial delayed match-to-sample task
Tran et al., 2016	EEG	Visuo-spatial delayed match-to-sample task
Leenders et al., 2018	MEG	Visuo-spatial delayed match-to-sample task
Proskovec et al., 2016	MEG	Sternberg task

To simplify result comparison, articles using dual-task or dual-task-like paradigms are not included.

Recent fMRI studies (Gallen et al., 2016; Heinzel et al., 2017; Kennedy et al., 2017; Archer et al., 2018; Bauer et al., 2018; Jamadar, 2020; Qin and Basak, 2020) show that the behavioral decrease in WM capacity of old adults is coupled with equal, increased, or reduced brain activation relative to younger adults. Moreover, different brain regions (or even different portions within the same region) show opposite patterns of age-related activity: While some of them are underrecruited, others appear overactive with respect to young. For instance, age-related decrement in WM performance can be accompanied by a reduced activation of task-related areas – middle frontal gyrus and bilateral precunei – together with increased activation of task-unrelated regions – cuneus, temporal gyrus, and cerebellum (Archer et al., 2018). In addition, at lower levels of task demand elderly can exhibit larger activations in frontal and parietal areas (Heinzel et al., 2017), but also reduced BOLD activity in frontal and temporal regions, with concurrent larger activation in the bilateral cuneus (Jamadar, 2020). Likewise, connectivity measures for easy task conditions indicate increased connectivity between lateral frontal areas and other networks with increasing age (Gallen et al., 2016), but no difference in connectivity strength between frontal and parietal regions (Heinzel et al., 2017).

Similar findings are observed when M/EEG studies are considered (Schwarzkopp et al., 2016; Tran et al., 2016; Lubitz et al., 2017; Morrison et al., 2019; Tagliabue et al., 2019, 2020): Taken together, the findings indicate that components reflecting attentional engagement and maintenance in WM may be enhanced, reduced or similar between age groups, even in the presence of marked behavioral differences. For instance, some EEG studies found decrements in older adults' WM with a concurrent less pronounced (Lubitz et al., 2017) or enhanced fronto-central P200 (Morrison et al., 2019), an ERP component reflecting deployment of attentional resources. Additionally, when individuals are presented with different memory loads, older adults might show either similar (Schwarzkopp et al., 2016; Tran et al., 2016) or reduced (Tagliabue et al., 2019, 2020) load-related modulations of the CDA, an ERP response indexing the amount of items maintained in the WM short-term storage.

To summarize, recent findings on aging highlight an apparent lack of a unidirectional coupling between brain and behavioral outcomes. The absence of a consistent brain-behavior pattern ultimately questions the possibility of formulating testable hypotheses on age-related effects at the neural level and, more generally, whether we can reliably interpret neural activity (being it BOLD signals, ERPs, neural oscillations, or functional connectivity) to infer the amount of deployed cognitive resources in aging. In the next section, we will consider potential sources of variability accounting for these different effects.

POTENTIAL SOURCES OF VARIABILITY ACCOUNTING FOR DIFFERENT AGE-RELATED PATTERNS OF RESOURCE DEPLOYMENT IN WORKING MEMORY

At least two sources of variability can account for the different brain-behavior associations in the WM domain. First, as previously mentioned, various cognitive tasks have been used to test WM functioning. Even if meant to assess the same cognitive function, different experimental paradigms can yield different results for at least two (partially related) main reasons. Different tasks might selectively engage different cognitive subcomponents (and their respective neural substrates), depending on their experimental structure (e.g., delayed match-to-sample paradigms tax more information maintenance and retrieval abilities, whereas n-back tasks rely more on information updating; see Daniel et al., 2016; Yaple et al., 2019) and type of material (verbal and visuo-spatial). Consequently, some tasks can intrinsically be more difficult than others. For instance, regarding the experimental structure, the overall accuracy in an n-back task is lower than in a Sternberg test (see Heinzel et al., 2016). With reference to stimulus material, elderly are usually more impaired with visuo-spatial than verbal items (Jenkins et al., 2000).

The second source of variability that may account for non-unidirectional age-related patterns is interindividual variability. Interindividual variability is prominent in aging (Lindenberger and von Oertzen, 2006) and may lead to optimal or less successful aging trajectories (Reuter-Lorenz and Park, 2010; Reuter-Lorenz and Park, 2014; Cabeza et al., 2018). Indeed, in some studies, the sample of older adults might include high-performing participants that can bias the group average performance toward one direction (and vice versa in the case of low-performing elderly). This heterogeneity in aging trajectories is largely due to age-related changes at multiple levels of neurobiological function and structure (Raz and Daugherty, 2018), in interaction with environmental factors (Daffner et al., 2011). Thus, interindividual variability in aging may underlie differences in the expression of brain activations (Cabeza et al., 2018). Specifically, preserving a good cognitive level at old age could be reflected by either a youth-like functioning brain (i.e., no age-related differences in brain activity; e.g. Pudas et al., 2013), an overactivation of some areas and/or supplementary engagement of an alternative set of brain networks (see Spreng et al., 2010 for a review) that might act as compensatory mechanisms to support the behavioral performance.

In the next section, we will consider possible solutions to minimize task-related variability and to better operationalize individual differences. Indeed, when sources of variability are (at least partially) accounted for, a more consistent pattern of age-related neural effects emerges, that can be more easily interpreted in the framework of cognitive resource deployment with a life span perspective.

HOW CAN COGNITIVE RESOURCES IN AGING BE MORE RELIABLY MEASURED THROUGH NEURAL INDEXES?

The use of various experimental paradigms to address the same cognitive function and individual differences are two major sources of variability that could explain the heterogeneity of findings in aging research. In particular, since individual differences are typically more prominent in older than young adults, they have been suggested to bias (e.g., by under- or over-estimating) the age-related differences observed in cross-sectional studies, where aging is implicitly treated as a uniform process (Schneider-Garces et al., 2010).

In an attempt to reduce the joint influence of task-related and interindividual variability, some studies (e.g., Höller-Wallscheid et al., 2017) have exploited procedures to equate the subjectively perceived difficulty of a specific task between age cohorts (and, in turn, across participants). These studies often apply titration procedures to match the difficulty level between young and older adults, namely, a stimulation "threshold" yielding the same accuracy value is chosen for each individual. WM studies using these procedures often find that elderly exhibit equal or increased neural activity (with reference to the compensation mechanism previously discussed) or similar load-related modulations (but see Billig et al., 2020). Indeed, recent fMRI studies with no age-related difference in accuracy found a similar modulation as a function of task demands in frontal and parietal areas between young and old adulthood (Höller-Wallscheid et al., 2017; Crowell et al., 2020), recruitment of a more extended network of areas (Vellage et al., 2016), and increased between-networks integration with increasing difficulty in the elderly (Crowell et al., 2020). In addition, M/EEG aging studies with individually titrated difficulty levels (Leenders et al., 2018) or no absolute difference in performance between age groups (Proskovec et al., 2016; Sghirripa et al., 2021) revealed that elderly showed greater increase in cortical excitability (as indexed by greater alpha power decrease; see Rihs et al., 2009) in both hemispheres (Leenders et al., 2018; Sghirripa et al., 2021) with respect to young participants (in which larger cortical excitability was instead specific to the hemisphere primarily processing targets, i.e., the contralateral hemisphere), or greater oscillatory activity in the alpha and beta bands in additional homologous frontal and parieto-occipital regions (Proskovec et al., 2016).

However, matching task difficulty between groups (likely selecting easier task conditions for the elderly) cancels out baseline differences in performance between age cohorts and (only) reveals (potential) age-related modulations of neural activity to attain the same accuracy level. In other words, this approach proves to be useful when the research focus is on within-subject effects (e.g., in the case of individual gains in training procedures), rather than on between-groups differences. Indeed, when difficulty-matching procedures are adopted, what remains to be explained is why older adults are deficient in their WM capacity (see Ramscar et al., 2014) from the very beginning (i.e., why they perceive the same subjective difficulty of younger adults at easier task levels).

When the research focus is on the comparison between different ages, two approaches can be adopted to overcome some of the limitations imposed by cross-sectional studies previously described. On one hand, dividing individuals (both young and old) in high and low performers may offer a less spurious estimate of age-related neural changes in the utilization of cognitive resources. For instance, in an EEG study by Daffner et al. (2011), low and high performers similarly allocated processing resources with increasing difficulty, regardless of age (see also Lubitz et al., 2017 and Morrison et al., 2019 for more recent EEG studies). Similarly, an fMRI study of Nagel et al. (2009) showed that, when considered altogether, elderly exhibited compromised brain responsivity compared to younger adults. Interestingly, when participants were instead split in high and low performers, the neural pattern of high-performing older adults resembled those of low-performing, equally accurate younger adults (see also Heinzel et al., 2017, Bauer et al., 2018 and Vaqué-Alcázar et al., 2020 for more recent fMRI studies).

A second approach to account for interindividual variability and overcome the drawbacks of cross-sectional studies consists of longitudinal investigations. Indeed, results obtained from cross-sectional studies might be biased by cohort effects related to preexisting generational differences (e.g., educational attainment; see Archer et al., 2018) that can "anticipate" age-related decrements (Rönnlund et al., 2005). Longitudinal studies allow researchers to (partially) isolate the effects due to aging from those linked to other experience-related variables (e.g., historical/social background). Notably, some discrepancies between cross-sectional and longitudinal studies have been found also in neural results. For instance, several cross-sectional studies documented over-recruitment of prefrontal areas in old compared to younger adults (e.g., Rajah and D'Esposito, 2005; Davis et al., 2008). However, some longitudinal studies (Nyberg et al., 2010; Rieckmann et al., 2017) reported an age-related reduction in frontal activity. More specifically, older adults defined as decliners (i.e., individuals with WM performance decline across time, as opposed to so-called maintainers) showed decreased recruitment of the prefrontal cortex (Rieckmann et al., 2017; Vaqué-Alcázar et al., 2020, 2021). To reduce the confound of cohort effects, it might be worth contemplating the administration of routine assessment of cognitive functions throughout an individual's life span.

CONCLUDING REMARKS

In a framework arguing for a reduction of processing resources in aging (Craik and Byrd, 1982; Salthouse, 1988, 1990), recent neuroimaging evidence in the domain of WM has not conveyed a unidirectional coupling between behavioral and neural data. However, apparent discrepancies can be reconciled if (at least) two sources of variability are controlled for, namely, task-related and interindividual differences. Indeed, when these factors are considered, two consistent findings emerge as: (1) elderly exhibit similar or augmented neural activity with respect to younger adults and (2) older low performers or longitudinal decliners engage task-related areas to a lesser extent than their more cognitively fit peers.

Taken together, results on age-related differences in brain activity prompt for a deeper understanding of these effects, especially in the case of neural over-recruitment in the elderly, which would ideally challenge the view of reduced processing resources in aging (Salthouse, 1988). In this respect, we suggest to enlarge the hypothesis space: Rather than having a *limited* pool of resources as originally postulated (Craik and Byrd, 1982; Salthouse, 1988, 1990), older individuals may use them in a *different* (sometimes less efficient) way compared to young adults. This interpretation would imply a shift from the original view that sees aging as a (quantitative) reduction of processing resources to a novel viewpoint considering a qualitative change, not necessarily a reduction, in resource allocation (**Figure 1**). Several pieces of evidence support this latter perspective. First, it is well documented that aging is characterized by increased susceptibility to distraction (e.g., Hasher and Zacks, 1988; Gazzaley et al., 2008) and broader attentional focusing (Greenwood and Parasuraman, 1999, 2004). These deficits are responsible for the inadvertent processing of irrelevant material, and this may result in the typical age-related WM capacity reduction (e.g., Jost et al., 2011; Tagliabue et al., 2019). Since WM storage has a limited capacity (Cowan, 2010), WM may become deficient because old adults tend to maintain both target and distracting items. Similarly, evidence of age-related reduced suppression of the default mode network (Raichle

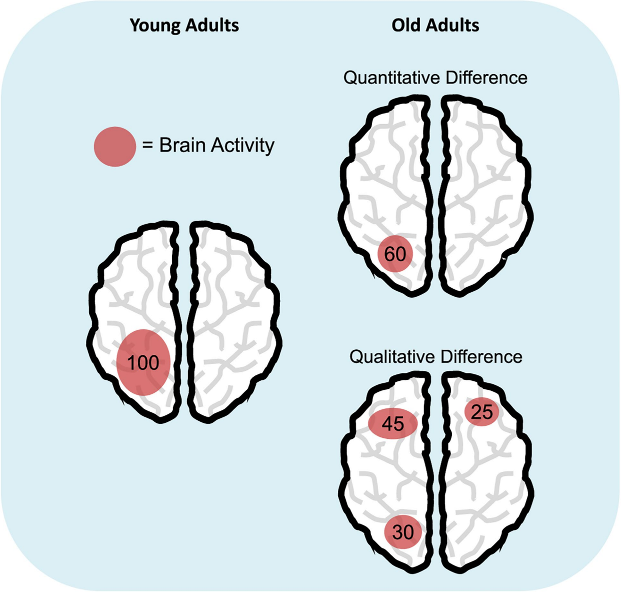

FIGURE 1 | Age-related differences in cognitive resource allocation. The schematic representations illustrate the hypothesis of quantitative (i.e., reduction; top right panel) versus qualitative difference (bottom right panel) in the deployment of cognitive resources in aging, compared to young adulthood (left panel). Numbers represent a hypothetical amount of engaged cognitive resources and how they are distributed during a specific task.

et al., 2001) during task execution has been linked to a deficit in cognitive control, which hampers efficient resource allocation to task-related areas with a consequent negative impact on WM performance in the elderly (Sambataro et al., 2010). Finally, the idea of an alternative use of processing resources would also be in line with the Compensation-Related Utilization of Neural Circuits Hypothesis (CRUNCH; Reuter-Lorenz and Cappell, 2008). CRUNCH states that, compared to younger adults, elderly recruit more neural resources (and exhaust them) at lower loads and are left without additional cognitive supplies when task demands further increase. A practical example of age-related qualitative changes in resource allocation might come from studies on the Posterior-Anterior Shift in Aging (PASA; Davis et al., 2008) research line: Elderly show increased engagement of frontal areas that correlates with reduced activity of posterior regions. Such activation pattern was suggested to reflect the involvement of high-order cognitive processes in response to deficits of posterior brain areas.

Some final considerations need to be addressed. Given that we focused our mini-review on the WM domain, our conclusions might not be generalized to other cognitive domains, even though age-related limitations in WM seem to account for age-related differences across different tasks (including memory – Baudouin et al., 2009 – and non-memory related domains – Van der Linden et al., 1999; Chen and Li, 2007; Borella et al., 2011). Moreover, while it would be desirable to obtain measures of general cognitive functioning to correlate with neural activations (e.g., Wiegand et al., 2018), such a unique and exhaustive performance index is not easy to choose or compute.

To conclude, on the basis of the recent findings discussed in this mini-review, we suggest that neural measures represent a powerful tool when investigating age-related differences in cognitive resource deployment, provided that some confounding factors are taken into account. Moreover, according to our view, a qualitative change in the deployment of cognitive resources instead or along with a quantitative reduction in the pool of available resources is an alternative hypothesis that deserves further consideration.

AUTHOR CONTRIBUTIONS

CT and VM equally contributed to conceptualization, literature overview, and writing of the manuscript. All authors contributed to the article and approved the submitted version.

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The Generation of Involuntary Mental Imagery in an Ecologically-Valid Task

Anthony G. Velasquez[1], *Adam Gazzaley*[2,3], *Heishiro Toyoda*[4], *David A. Ziegler*[2] and *Ezequiel Morsella*[1,2]*

[1] Department of Psychology, San Francisco State University, San Francisco, CA, United States, [2] Neuroscape, Department of Neurology, University of California, San Francisco, San Francisco, CA, United States, [3] Departments of Psychiatry and Physiology, University of California, San Francisco, San Francisco, CA, United States, [4] Toyota Collaborative Safety Research Center, Ann Arbor, MI, United States

Laboratory tasks (e.g., the flanker task) reveal that incidental stimuli (e.g., distractors) can reliably trigger involuntary conscious imagery. Can such involuntary effects, involving competing representations, arise during dual-task conditions? Another concern about these laboratory tasks is whether such effects arise in highly ecologically-valid conditions. For example, do these effects arise from tasks involving dynamic stimuli (e.g., simulations of semi-automated driving experiences)? The data from our experiment suggest that the answer to our two questions is yes. Subjects were presented with video footage of the kinds of events that one would observe if one were seated in the driver's seat of a semi-automated vehicle. Before being presented with this video footage, subjects had been trained to respond to street signs according to laboratory techniques that cause stimulus-elicited involuntary imagery. After training, in the Respond condition, subjects responded to the signs; in the Suppress condition, subjects were instructed to not respond to the signs in the video footage. Subjects in the Suppress condition reported involuntary imagery on a substantive proportion of the trials. Such involuntary effects arose even under dual-task conditions (while performing the *n*-back task or psychomotor vigilance task). The present laboratory task has implications for semi-automated driving, because the safe interaction between driver and vehicle requires that the communicative signals from vehicle to driver be effective at activating the appropriate cognitions and behavioral inclinations. In addition, our data from the dual-task conditions provide constraints for theoretical models of cognitive resources.

Keywords: involuntary imagery, unconscious processing, mental imagery, flanker task, semi-automated driving

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Bernhard Hommel,
University Hospital Carl Gustav Carus, Germany

Reviewed by:
Ben Bauer,
Trent University, Canada
Pilar Tejero Gimeno,
University of Valencia, Spain

***Correspondence:**
Ezequiel Morsella
morsella@sfsu.edu

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INTRODUCTION

In *response interference* paradigms such as the Stroop task[1] (Stroop, 1935) and the Eriksen flanker task (Eriksen and Eriksen, 1974), responses to a "target" stimulus are perturbed systematically by the incidental presence of "distractor" stimuli. In these tasks, interference, as indexed by error rates and response times (RTs), depends on the nature of the distractors. For example, in one variant of the flanker task (Eriksen and Schultz, 1979), subjects are first trained to press one button with one finger (e.g., the right index finger) when presented with the letter S or M, and to press another

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[1] In the Stroop task (Stroop, 1935), participants are instructed to name the color in which a word or string of letters is presented. Interference arises in the Incongruent condition, in which, for example, the word "BLUE" is presented in an incongruent color such as red (see review of the Stroop task in MacLeod and MacDonald, 2000).

button with another finger (e.g., the right middle finger) when presented with the letter P. After training, the subjects are instructed to respond to targets that are "flanked" by distractors. They are instructed to respond to the stimulus presented in the center of an array (e.g., SSPSS, SSMSS, SSSSS, targets underscored) and to disregard the flanking stimuli, which are the distractors. In the original flanker task, subjects were instructed to "respond only to the letter in [a] location and to ignore any and all other letters" (Eriksen and Eriksen, 1974, p. 144). The shortest response times are found when the distractors are identical to the target (Eriksen and Schultz, 1979; van Veen et al., 2001). Slower RTs are found when the distractors are associated with a response that is different from that of the target (*response interference* [RI]) than when the distractors are different in appearance but associated with the same response (*stimulus interference* [SI]; Eriksen and Schultz, 1979; van Veen et al., 2001; Ridderinkhof et al., 2021)[1].

Decades of research have focused on the behavioral effects of distractors in response interference paradigms. More recently, research has begun to focus on the subjective effects of these distractors. Regarding urges, for example, in "subjective" variants of the flanker task, "urges to err" are greater in the RI condition than in the SI condition or in a condition in which distractors are identical to the target (Morsella et al., 2009)[2]. Other effects in which distractors influence what enters consciousness involve, not urges, but the mental imagery (e.g., verbal imagery) that was associated with distractors during training (Bhangal et al., 2018; Bui et al., 2019; Cushing et al., 2019; Li et al., 2021). These effects reflect a kind of involuntary entry into consciousness (see also Scullin et al., 2021).

One concern regarding these subjective, distractor-elicited effects pertains to their ecological validity and robustness. Do these involuntary effects arise in real-world contexts in which the stimulus scene is complex and dynamic, for example, as occurs in driving? In real-world scenarios, critical objects are often not focal and not presented by themselves on a screen. Instead, these objects are nested within a complex field of view that is filled with other objects. Moreover, the field of view is usually, not static, but dynamic. A second question pertains to whether these involuntary effects are robust enough to arise under dual-task conditions, as when there is competition among mental representations. According to some theorists (Exner, 1879; Ach, 1905/1951; Woodworth, 1939; Neely, 1977; Gollwitzer, 1999; Hommel, 2000; Cohen-Kdoshay and Meiran, 2007, 2009), these involuntary effects should be detectable to some extent even during dual-task conditions. If this is the case, then theoretical accounts concerning cognitive resources must take such findings into account. We assume that the brain mechanisms that generate conscious mental imagery consume at least some cognitive/neural resources. These representations, as fleeting as they may be, are an achievement of sophisticated neural activity. It is interesting to consider that, when such imagery is the outcome of an automatic association, or of something akin to the "prepared reflex" (Ach, 1905/1951; discussed below), it might arise even under dual-task conditions. Theories concerning cognitive resources need to account for observations in which high-level cognitions, as in mental imagery, are unperturbed by, for example, dual-task conditions. More generally, theories concerning cognitive resources must account for the many findings concerning the prepared reflex, findings that suggest that the neural machinery is often unperturbed by secondary tasks.

Because of these concerns regarding subjective variants of response interference paradigms, we developed an experimental paradigm involving distractor stimuli that, though occurring in a complex, dynamic, and ecologically valid context, could still be (a) capable of yielding some involuntary imagery and (b) capable of being coupled with a secondary task (for dual-task conditions).

Introduction of the Navigation-Monitoring Task

Through extensive piloting ($n = 96$), we developed a new kind of response interference paradigm, the *navigation-monitoring task*, which features a new kind of stimulus set. Distractor stimuli (real street signs) were embedded in actual video footage of the kinds of events that one would observe if one were seated in the driver's seat of a semi-automated vehicle (**Figure 1**). The video portrayed, from a first-person perspective, the vehicle approaching intersections, slowing down, speeding up, entering garages, etc. The stimulus videos were developed by us from over 36 h of actual driving footage. Basing our experimental paradigm on semi-automated driving renders our project ecologically valid and applicable to real-world challenges involving emerging transport technologies.

In the paradigm, subjects are first trained to detect and respond to certain street signs (e.g., a crosswalk sign) using a training procedure (*optimal response-signaling*, discussed below) that is based on laboratory techniques known to induce stimulus-elicited involuntary imagery (e.g., Allen et al., 2013; Gollwitzer, 2014). In the critical condition (Suppress), subjects are instructed to perform the navigation task, during which they monitor the navigation of the vehicle (e.g., press a button whenever the vehicle turns or merges). When performing this task, subjects are instructed to *not* respond to the critical signs in any way and to also *not* think of the response that, during training, was associated with each sign. As in the subjective variants of the

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[1] Several theorists have attributed RI to the automatic, training-based activation of response codes by distractors (Eriksen and Schultz, 1979; Coles et al., 1985). The developers of the flanker task have explained this activation, which is mediated unconsciously, by appealing to the notion of "continuous flow" (Eriksen and Schultz, 1979), a notion that is based on observations of the basic neurophysiological characteristics of perceptual processing (Ganz, 1975). Continuous flow is similar to the notion of "cascade processing" in *parallel distributed processing* (PDP) models (McClelland, 1979). From the standpoint of continuous flow, once there is an association formed between percepts and response codes, then activation cannot help but flow from one stage of processing (e.g., the perceptual stage) to the next stage (e.g., motor preparation). Accordingly, psychophysiological research shows that, in a response interference task such as the flanker task, competition involves the simultaneous activation of the neural processes associated with the target-related responses and the distractor-related responses (DeSoto et al., 2001).

[2] These self-reported urges to make a mistake ("urges to err," for short) are measured after each trial by asking subjects, "How strong was your urge to make a mistake?" Subjects respond by using an 8-point scale, in which 1 signifies "almost no urge" and 8 signifies "extremely strong urge."

FIGURE 1 | Sample image, taken from a 24-s film clip.

flanker task (e.g., Morsella et al., 2009; Li et al., 2021), in this paradigm, experimenters can measure on a trial-by-trial basis the rates of involuntary imagery elicited by the distractors that are embedded in the video footage.

EXPERIMENT

Our primary aim was to assess whether involuntary imagery could be elicited by the distractors in our newly developed, navigation-monitoring task, a task that is complex, dynamic, and ecologically valid. We sought to obtain substantive evidence that these involuntary effects can occur involuntarily at a reliable, substantive rate (no fewer than one trial out of five trials; based on Bui et al., 2019), even though the stimuli are complex, dynamic, and ecologically valid. We also assessed whether the subject could respond to the visual stimuli we developed with a good level of engagement, one that does not yield floor or ceiling effects. In addition, we assessed whether these effects are robust enough to be detectable under dual-task conditions. To this end, we coupled our paradigm with two well-established tasks: the *n*-back task (Kirchner, 1958) and the *psychomotor vigilance task* (PVT; Dinges and Powell, 1985; Jung et al., 2011). One hypothesis is that the dual-task condition would interfere with the mechanisms that generate involuntary imagery (Cho et al., 2014), thereby decreasing substantively the proportion of trials in which such imagery occurs. Given the automatic nature of involuntary imagery, and based on the findings of a previous study (Cho et al., 2014), in which involuntary, stimulus-elicited imagery arose even while subjects performed a secondary task (humming in one's head but not aloud), we hypothesized that the secondary task would not decrease the rates of involuntary imagery substantively. We also took the opportunity to assess another manipulation: whether involuntary imagery still arises when the number of signals that are learned are, not three, but double that number, that is, six signals.

We employed a design that was 2 (Respond [to road signs] or Suppress [responses to road signs]) × 2 (three signals or six signals) × 3 (No Multi-Tasking, *n*-back, or PVT). (The third factor, Multi-Tasking, was the only factor that was held within-subjects; the other factors were between-subjects factors).

Prediction

We predicted that, despite the complex, ecologically-valid, and dynamic nature of the stimulus scene, and despite the dual-task conditions, these involuntary, stimulus-elicited effects on consciousness will be detectable (with the rate of detection being significantly above zero) and will occur at a reliable, substantive rate (no fewer than one trial out of five trials; based on Bui et al., 2019).

METHOD

Subjects

Eighty-four (21 per cell of the $2 \times 2 \times 3$ design) San Francisco State University students ($M_{\text{age}} = 20.24$, $SD_{\text{age}} = 4.54$, females $= 57$) participated in a 120-minute session for $20. The Institutional Review Board at San Francisco State University approved the involvement of human subjects in our project. Prior to participation in the study, all subjects provided written and verbal consent. The sample size ($n > 10$) was based on the effect size (Cohen's d [on raw proportions] $= 1.72$; Cohen's h [on raw proportions] $= 1.44$; Cohen's d [on arcsine transformations of the proportion data] $= 1.38$), *SD* (0.25), and other aspects of a previous project (Cho et al., 2016) that, similar to the present project, was designed to illuminate the boundary conditions of involuntary entry into consciousness. To determine the sample size, we used the program *G*Power 3* (Faul et al., 2007). The input parameters were: Cohen's $d = 1.72$, one sample t-test, tails = one, power = 0.95, and $\alpha = 0.05$. The output parameters were: noncentrality parameter = 4.21, critical $t = 2.02$, and actual power = 0.97.

Stimuli and Apparatus

The video stimuli were presented on a black background of a 50.8 cm Apple iMac computer monitor (Apple iMac 7, 1 A1224) with a viewing distance of ∼48 cm. Stimulus presentation and data collection were controlled by PsyScope software (Cohen et al., 1993). Subjects inputted their responses to questions and instructions by computer keyboard. All questions and instructions were presented in white or otherwise colored 44-point Arial font; all fonts were displayed on a black background. (The "Ready?" prompt was 40-point Arial font; the "rest time" prompt between the critical trials was 24-Arial font.)

We used an additional iMac keyboard as the input device for the button presses. Hence, the Apple iMac computer was connected to two keyboards. This secondary keyboard was not used by the subject for typing responses but only for responding to the signs. We covered the eight input keys with the overlays having the appropriate colors. Specifically, the tab key on the left of the standard keyboard served as the "Black key," and the / key served as the "White key," which was used during the multi-tasking conditions (explained below). We strove to preserve the spatial layout of a button box (Response Box; ioLab Systems; UK) that was used only during piloting. Thus, the remaining designated keys were as follows. Red = Z key; Orange = D key; Yellow = T; Green = U; Blue = K, Purple = period.

The video presented to subjects was actual footage of the kinds of events that one would observe if one were seated in the driver's seat of a semi-automated vehicle. The video portrayed, from a first-person perspective, the vehicle approaching intersections, slowing down, speeding up, etc. To have ecological validity, the footage retained the unexpected motions of the vehicle (e.g., when driving over a pothole) and unexpected visual phenomena (e.g., transient sun glare). Each video was composed of a series of short clips, some of which presented the critical, trained stimuli. The subject experienced the clips as a quasi-continuous movie of a vehicle navigating on roads and city streets. Most of the footage was of city streets, suburban neighborhoods, and highways in the cities of Burlingame, Oyster Point, South San Francisco, and San Francisco.

Each experimental session included the presentation of 60 critical clips, which included signs from the training session. The ∼120 min of final, color video footage that was presented to subjects was developed from over 36 h of raw footage obtained with an iPhone 6S camera mounted on the dashboard of a Lexus RX 350 (2014). The frame of the video clip was adjusted so that the hood of the vehicle would not be visible (**Figure 1**). The final footage that was selected had to satisfy many criteria, including that the clip presenting a sign did not present any of the other critical signs, that the weather conditions rendered the stimuli perceptible, and that the clip did not present any stimulus that would interfere with perceiving the critical sign or with responding to the critical sign.

Presented on a black background, each of the selected, final clips (33 cm wide × 18.5 cm high, with a viewing angle of 37.94° × 21.81°) was extensively video-edited, by hand tuning, through the software iMovie to increase the speed of the clip, increase contrast, decrease exposure, reduce brightness, increase the color saturation of the signs, and adjust other properties, so that all of the clips, though naturalistic and ecologically valid, were as uniform as possible.

The critical clips, which included the presentation of the trained signs, were composed of three parts. First, there was 20 s of footage in which none of the critical signs or control (untrained) signs were presented. After these 20 s, there was a one-second clip that presented footage of the vehicle driving toward a critical, trained sign or a control stimulus, with the signs appearing in their natural context (**Figure 1**). In these one-second segments, the sign stimuli were not ever occluded and were clearly perceptible. After the presentation of the stimulus, there were 3 s of extra footage. Because stimulus-elicited imagery could arise during this time, we avoided having novel, "attention-grabbing" stimuli presented during this span. Instead, we presented some of the uneventful footage taken from the 20 s of footage preceding the presentation of the sign. Subjects never saw the same entire critical clip twice, but they did sometimes see, more than once, footage taken from the same geographical region or, in very few cases, see, parts of a video sequence repeated in another critical clip. When developing the complex stimulus (the video footage), we strove for it to be ecologically valid and challenging, so that the detection of signs embedded in the footage would not be too easy or too difficult.

In each session, in addition to the 60 critical clips, subjects were presented with 60 "filler" clips, which, in terms of their content, resembled the critical clips in all respects but did not present any of the critical signs (i.e., the signs associated with training). These filler clips varied in duration, with most being 10, 16, or 20 s. This variability in duration was intended to diminish the predictability of the timing of the events composing the session.

In the training session (see details below), we presented only a single static frame of a real sign in its actual setting (**Figure 1**). This static image (a photograph) was culled from the raw footage. For the training session, there were 10 unique photographs per sign, and subjects never saw these stimuli again during the critical trials.

Procedures

The Navigation-Monitoring Task

Instructions were presented *via* computer screen. The first instruction to subjects was the following. "*You will see video taken from a vehicle that is driving. Press the black button when you see the vehicle turning left or right or merging left or right. That is, press the black button whenever the vehicle turns or whenever it merges to another lane. You will be doing this throughout the whole session. Press RETURN to continue.*"

Afterwards, subjects were instructed, "*At the beginning of each trial of the driving task, your hands must be in 'rest position,' which is having the palm of your right hand resting and having your left hand ready to press the black button. The experimenter can show you how to put your hands in this rest position. Press RETURN to practice this task.*" Subjects then viewed a 10-second clip in which the vehicle made a right turn. Subjects were instructed to press the black button as soon as they noticed the car turning or merging into another lane. This video footage was never presented again during the experimental session. The black button was actually a dummy button. During the experimental session, the experimenter made sure that subjects were pressing the dummy button during the task. We were not able determine the accuracy of each of these responses. The depressing of the black button did not cause any modification in the computer program or data output.

After this training event, subjects were told, "*For the upcoming task, you need to be familiar with the following street signs.*" Except for the Ambulance and Fire Truck signs, for each kind of sign, subjects were presented with an array of four versions of it (e.g., a Crosswalk sign depicting one person walking and a Crosswalk sign depicting two people walking). The signs presented in the arrays were not from photographs but were stylized, color diagrams, the kind of depiction that one would see in a driver's manual (**Figure 2**). Each array was presented for 5 s. The Ambulance signs and Fire Truck signs were presented by themselves (**Figure 3**).

Training Session

During training, subjects learned certain responses to the stimuli that would later be presented as distractor stimuli in the navigation-monitoring task. This was based on the procedures of subjective variants of the flanker task (e.g., Morsella et al., 2009; Li et al., 2021). As in the training for the flanker task, during the acquisition of these response codes, it is beneficial for the subject to experience the actual consequences of the self-generated action (Guthrie, 1935; Hommel, 2000, 2009; Hommel et al., 2001, 2016; Olsson and Phelps, 2004; Samaha et al., 2013; Chen et al., 2014). To maximize the effects of our training session, the instructions for performing the stimulus-elicited action were of the form, "If I encounter the situation *X*, then I will perform the response *Y*" (Gollwitzer, 2014). As Gollwitzer (2014) notes, "Whereas goal intentions merely specify a desired future behavior or outcome, the if-component of an implementation intention [prepared reflex] specifies when and where one wants to act on this goal (i.e., a certain situational cue), and the then-component of the implementation intention specifies the response that is to be initiated" (p. 306). Prior research (e.g., Gollwitzer, 2014), and our piloting, suggests that this is an effective way to induce involuntary, stimulus-elicited effects. The acquisition of the stimulus-response contingency through such verbal instructions, without extensive training, has been characterized as something akin to the acquisition of a "prepared reflex" (Exner, 1879; Ach, 1905/1951; Woodworth, 1939; Gollwitzer, 1999; Hommel, 2000; Cohen-Kdoshay and Meiran, 2009; Cole et al., 2013; Pereg and Meiran, 2019). The term reflects that the effects of this form of knowledge acquisition resemble, remarkably, those of involuntary stimulus-response links. The acquisition of these stimulus-response contingencies require very few trials (e.g., less than 10 trials). See recent review of the neural correlates of such a rapid form of learning (also called *Rapid Instructed Task Learning* [RITL] in Cole et al., 2013; Pereg and Meiran, 2019). Again, the involuntary effects resulting from this kind of learning are proposed to be robust enough to be detectable under dual-task conditions (Exner, 1879; Ach, 1905/1951; Woodworth, 1939; Gollwitzer, 1999; Hommel, 2000; Cohen-Kdoshay and Meiran, 2009; Cole et al., 2013; Pereg and Meiran, 2019).

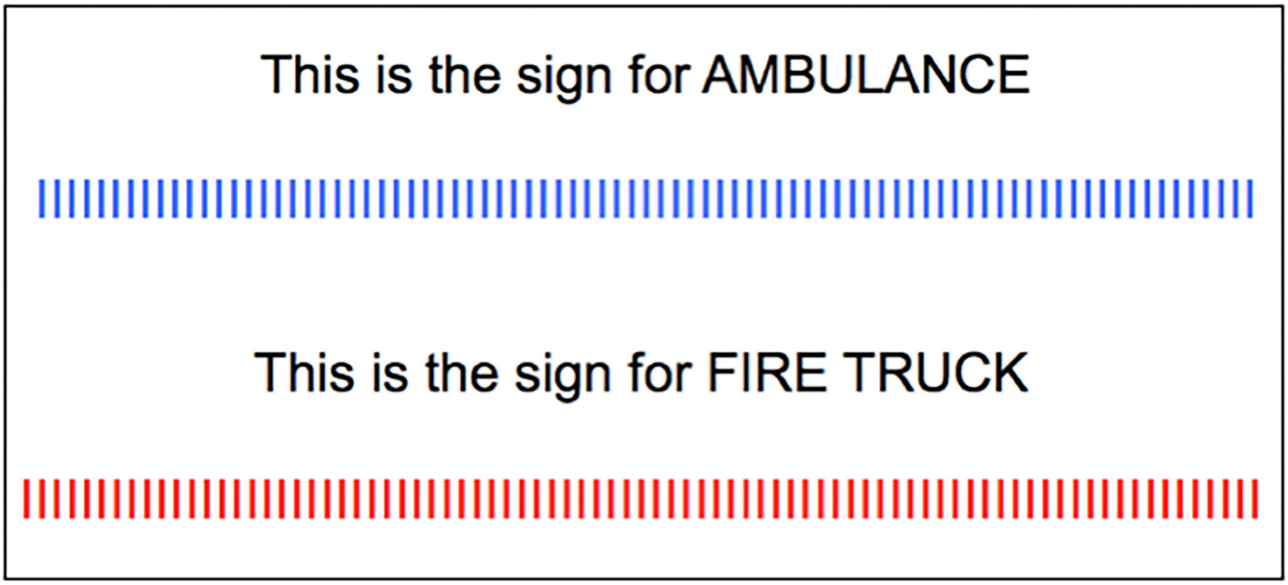
During stimulus-response acquisition (10 trials for each signal) for the experimental condition, subjects learned to associate certain stimuli/signals with certain specific responses. Training included (a) the actual experience of the action-effect following one's self-generated action, and (b) instructions in the form of "If I encounter the situation *X*, then I will perform the response *Y*," to induce a "prepared reflex" or "implementation intention" (Gollwitzer, 1999, 2014). When combined in one training session, these components could be construed as yielding an optimal form of stimulus-elicited, response-signaling (optimal response-signaling, for short).

For training, subjects learned to respond to the signs by virtue of the instructions presented below. Subjects were instructed to read these instructions aloud. After reading each set of instructions, subjects responded as instructed to a photograph that presented the sign for 3.5 s. They repeated this sequence of reading the instruction and responding to a stimulus ten times. The stimulus consisted of a single static frame of a real sign in its actual context. This static image (a photograph; **Figure 1**) was taken from the raw footage. There were 10 unique photographs per sign and subjects never saw these stimuli again during the critical trials. Using different stimuli on each of the 10 training trials diminishes the effects of stimulus-specific habituation (Bhangal et al., 2016) and also increases the likelihood of "stimulus generalization" across the entire stimulus class, so that training-based effects will arise for all school zones, for example.

For the crosswalk sign, the instructions were "*When you see a CROSSWALK sign, say 'Yellow Yield' aloud and press the YELLOW button. It is important that you respond as fast and as accurately as possible. Your hands must be in 'rest position.' Press G when you are ready to see the sign and respond to it.*" (See instructions for all signs in the **Appendix**).

In one condition, subjects were trained on only three signs of the six possible signs. The order of presentation of each of the three signs was random. Half of the subjects were trained in this way for Bike Lane, Speed Bump, and Fire Truck (Regimen 1). The other half of the subjects were trained in this way to respond to Crosswalk, Railroad Crossing, and Ambulance (Regimen 2). In each group of signs, there was one sign pertaining to an event that required for attention to be deployed to an upcoming event that would be occurring (usually) straight ahead, on the center of the road (Speed Bump and Railroad Crossing) and perpendicular to the direction of the vehicle; one sign that pertained to an event requiring also attention to be deployed to the right side of the road (Bike Lane and Crosswalk); and one event that pertained to sirens and emergency vehicles (Ambulance and Fire Truck;

FIGURE 2 | Sample stimulus signs.



This is the sign for AMBULANCE

This is the sign for FIRE TRUCK

FIGURE 3 | The manner in which subjects were presented with the Ambulance and Fire Truck signs. The Ambulance sign (presented in blue [top]) and the Fire Truck sign (presented in red [bottom]).

Figure 3). In short, each regimen contained one of each kind of sign.

Before the commencement of the critical trials, subjects read, "*You will now perform the driving task. Again, you will see video taken from a vehicle that is driving. Press the black button when you see the vehicle turning left or right, or merging left or right. That is, press the black button whenever the vehicle turns or merges into another lane. Respond as quickly and as accurately as you can.*" This was followed by a screen that presented, "Ready? Please be in 'rest position' and press the black button when ready?"

The 60 critical trials per session were presented as three blocks, with each block having 20 trials of randomly selected critical video clips. Each block was randomly coupled with one of the three Multi-Tasking conditions (each described below). Across the three blocks, each kind of sign (Bike Lane, Speed Bump, Crosswalk, Railroad Crossing, Ambulance, and Fire Truck) appeared 10 times. Within each block, the "embedded" signs (Bike Lane, Speed Bump, Crosswalk, and Railroad Crossing) appeared on 12 randomly selected trials of the 20 trials, and the unembedded signs (Ambulance and Fire Truck) appeared on eight randomly selected trials of the 20 trials. The subject never saw a given critical stimulus more than once.

The Suppress Condition

Before the critical trials of the Suppress condition, subjects ($n = 42$) were presented with the following. "*IMPORTANT: During the task, please DO NOT respond to any of the signs. Although you were presented with information about how to respond to the signs, you must NOT respond to any of the signs. Also, try to NOT think of the response you learned to any of the signs. However, if you do happen to think of the response to any of the signs in the video, then please report such thoughts when you are asked about them at the end of the given clip.*" After each trial of the Suppress condition, subjects reported about involuntary verbal imagery, based on instructions given before the beginning of the critical trials.[3]

Before the critical trials, subjects read, "*You are now ready to perform the task. There will be three blocks of trials, with each block taking around 15 min. IMPORTANT: If you have any questions about the task or about the nature of verbal imagery, please ask the experimenter. Press RETURN when ready to begin the task.*"

After each critical trial, subjects answered the following questions. ***1.*** *"Did you just experience any verbal imagery? That is, did you experience any verbal imagery during the last moments (that is, the last 5 sec) of the video? (Yes or No?),"* ***2.*** *"If you did experience any verbal imagery, please type the words you experienced,"* ***3.*** *"If you did experience verbal imagery, did the words come to mind immediately? (Yes or No?),"* ***4.*** *"During these last moments (5s) of the video clip, how strong was the urge to press a button?"* Subjects responded to the last question using an 8-point scale, in which 1 signified "almost no urge" and 8 signified "extremely strong urge" (based on Morsella et al., 2009).

The Respond Condition

Before the critical trials of the Respond condition, subjects ($n = 41$) received the following instructions. "*You will now perform the driving task. Again, you will see video taken from a vehicle that is driving. Press the black button when you see the vehicle turning left or right, or merging left or right. That is, press the black button whenever the vehicle turns or merges into another lane. Respond as quickly and as accurately as you can. IMPORTANT: During the task, please respond to the signs as instructed.*"

The experimenter clarified responses should consist of just the button presses and that the vocal responses were no longer necessary. The continued execution of the vocal responses would have introduced several practical and experimental-design problems, including that, over the course of the trials, the vocalizations would induce a form of training for the control signs.

Manipulations of Memoranda and of Multi-Tasking

For the between-subjects factor Memoranda, we manipulated the number of trained signals (3 or 6 signals). When the level of this factor was 3, we took the opportunity to compare the effects of trained signs (three in number) vs. untrained signs (three in number), which were not associated with any form of training.

For the within-subjects factor Multi-Tasking, in one of the experimental conditions, subjects performed, while carrying out the navigation-monitoring task, a second task that taxed cognitive control and working memory: An auditory version of the *n*-back (*2*-back) task (Kirchner, 1958) that presents sequences of numbers auditorily (Perlstein et al., 2003; based on Goncalves and Mansur, 2009). (All secondary tasks were auditory in nature, so that the stimuli would not occupy the visual buffer that was employed for the navigation-monitoring task; Baddeley, 2007). A *2*-back condition of the *n*-back task occurred on a block of 20 consecutive trials, with the total number of critical trials in the session being 60 trials. Each sequence occupied the span of the 24 s of the critical trials, with 3 s of silence between each of the six auditory stimuli (each auditory stimulus occupied 1 second of the 24 s span). Eight of the 20 trials presented "hit" trials, in which a heard number was heard before (the number heard before the previous number: e.g., 5 4 2 1 7 1, with 1 being the target). Targets were presented in the third, fourth, fifth, and sixth positions of the sequence. To report a hit, subjects used the "white key" (which was the / key on the keyboard). In the control trials ($n = 12$), there were no numbers repeated in the sequence in this way (e.g., 5 4 2 3 7 1). The 20 trials of the *n*-back were presented in random order. For various practical reasons (e.g., variable trial length), no *n*-back stimuli were presented during the filler trials. Before the block of trials, the subjects were presented with instructions for performing the auditory *2*-back (based on Perlstein et al., 2003; Goncalves and Mansur, 2009).

In another condition, which, too, consisted of a block of 20 consecutive trials, subjects performed a task that taxes sustained attention (a task based on the auditory version of the *psychomotor vigilance task* [PVT]; Dinges and Powell, 1985; Jung et al., 2011). For this task, subjects were instructed to, in addition to carrying out the many responses for the navigation-monitoring task, press a button as soon as they heard an auditory signal (a beep) during the 24 s of the critical trials. For various practical reasons (e.g., the variable lengths of the filler trials), no signals were presented during the filler trials. This auditory stimulus was presented only once per trial. The beep sounded at 5, 6, 6.5, 7, 8, 9, 10, 11, 12, 13, 14, 15, 15.5, 16, 17, 17.5, 18, 19, and 20 s.

For the sake of comparison, there was a block of 20 consecutive trials in which subjects performed the navigation-monitoring task without any secondary task (i.e., a "No Multi-Tasking" condition). The order of presentation of the three conditions composing the factor Multi-Tasking was fully counterbalanced across subjects. See **Figure 4** for a depiction of the sequence of events composing the experimental session. The data from one subject from the Respond condition were excluded from analysis because this subject performed only 20 trials of the 60 trials and was not following instructions.

Dependent Measures and Data Analysis Plan

The dependent measures of interest involved subjects' experience of involuntary imagery in the Suppress condition. The primary dependent measure was the mean proportion of trials in which subjects reported that they experienced involuntary imagery. We simply divided the number of trials in which there was imagery by the number of trials in that respective block of trials. For example, if *Subject 5* had imagery on 10 trials out of the 20 trials composing the PVT block, then the dependent

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[3] Subjects read the following instructions, which were based on Jantz et al. (2014). *"In this task, you will be asked to report about the occurrence of verbal imagery. 'Verbal imagery' refers to the following. Without saying it aloud, take a moment to imagine what the word 'HOUSE' sounds like. Take a moment to imagine what the word 'FLOWER' sounds like. You have just experienced an example of auditory verbal imagery. Another example of verbal imagery would be if you heard 'Mary had a little…' and then heard in your mind 'lamb'. The word 'lamb' would be a case of verbal imagery."*

On a second screen, it was further clarified that, *"Sometimes you experience verbal imagery, as when you are holding a number you just heard in mind long enough to dial it. Sometimes you don't experience verbal imagery. Verbal imagery is basically words heard only in your mind but not aloud, as when you quietly rehearse a poem or rehearse the words to a song. For this task, report only imagery that you are comfortable sharing with a stranger. If you do not understand what is meant by 'verbal imagery,' please contact the experimenter for further clarification."*

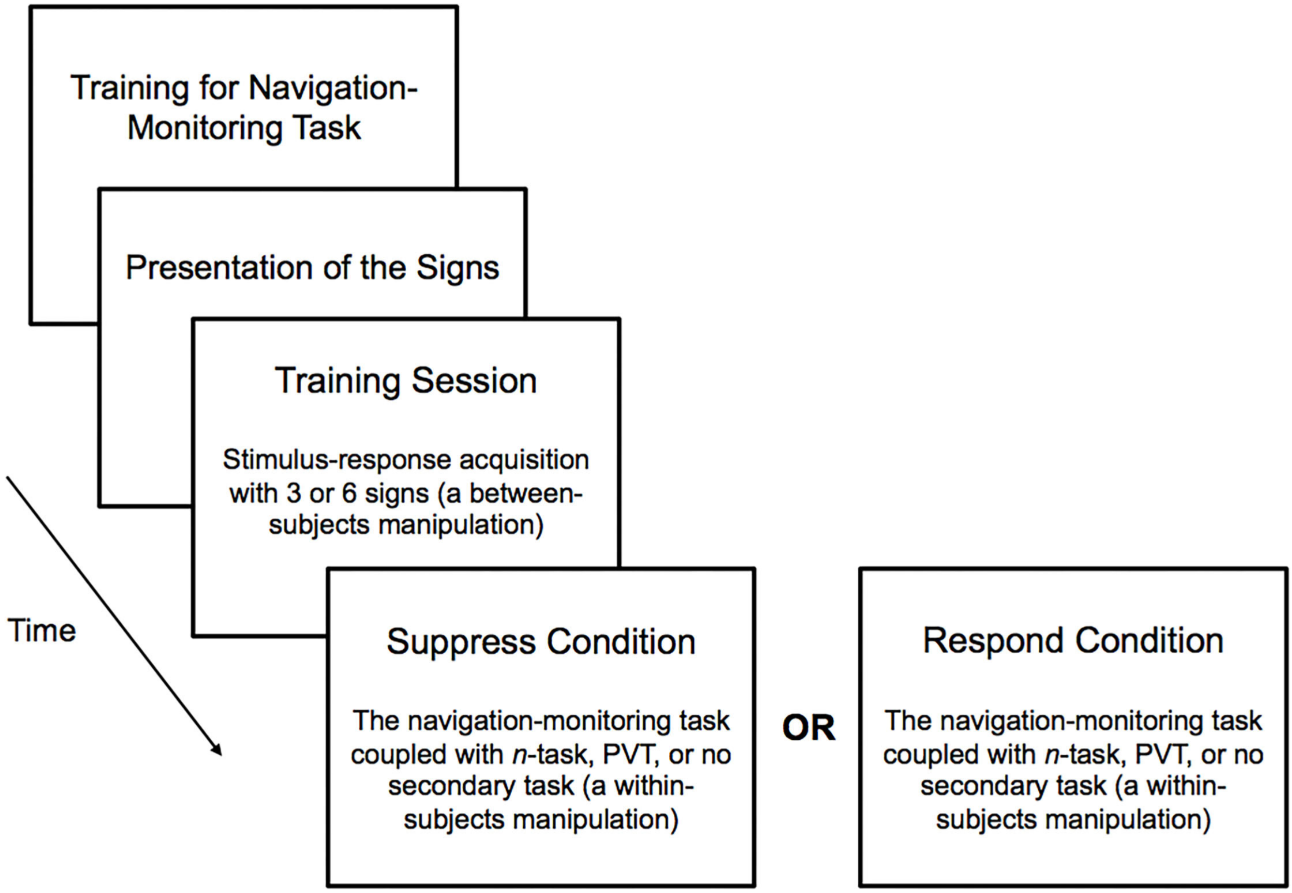

FIGURE 4 | Schematic depiction of sequence of events composing the experimental session.

measure for that condition, for that subject, would be 0.50. These proportions were treated as a continuous variable in the same manner that mean accuracy rates or mean error rates are treated as continuous variables. We conducted one-sample *t*-tests to assess whether these mean proportions were significantly different from zero. We also conducted an ANOVA to assess whether the memoranda manipulation (i.e., for three signs or six signs) and the three multi-tasking conditions had differential effects on the proportions of involuntary imagery. Because proportions are sometimes not normally distributed, we also performed these inferential statistics on the arcsine transformations of the proportion data. Arcsine transformations are often used to statistically normalize data that are in the form of proportions. All the significant effects presented below, concerning rates of involuntary imagery, were also found with arcsine transformations of the proportion data.

Another dependent measure was the mean proportion of trials in which subjects reported that the imagery was immediate. For this measure, we conducted an ANOVA to assess whether the two memoranda conditions and the three multi-tasking conditions had differential effects on the immediacy of the involuntary imagery.

Another dependent measure was subjects' trial-by-trial urges to err, which was based on an 8-point scale, in which 1 signified "almost no urge" and 8 signified "extremely strong urge." For this measure, we conducted an ANOVA to assess whether the two memoranda conditions and the three multi-tasking conditions had differential effects on the mean urges.

RESULTS

Involuntary Imagery

Computer malfunctions led to the loss of 37 (0.01%) of 2,520 trials in the Suppress condition. The mean removal of trials per subject was <1 trial ($M = 0.88$). These malfunctions caused some critical trials to appear more than once per session. Data from these repeated trials were removed from all analyses.

One aim of our analysis was to ascertain whether involuntary imagery arose in a substantive manner by the signs that were embedded in the video footage (e.g., the Speed Bump, Railroad Crossing, Crosswalk, and Bike Lane). Any effects in the Suppress condition are noteworthy because subjects were instructed to not respond to any of the signs. Despite the intentions of the subjects, involuntary imagery arose in response to the

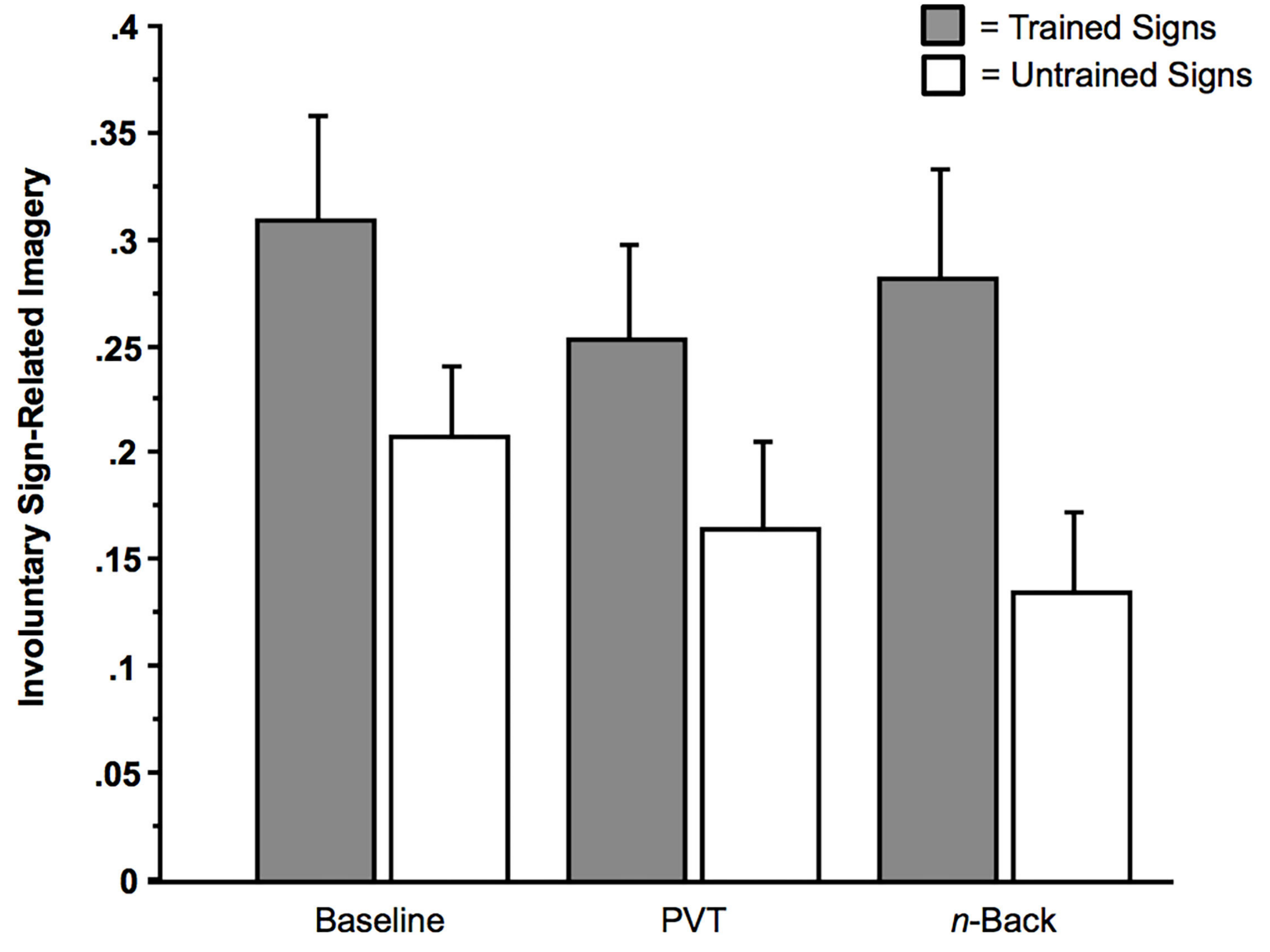

FIGURE 5 | Sign-related involuntary imagery as a function of Sign Type (Trained vs. Untrained [Control]) and Multi-Tasking (None [Baseline], Psychomotor Vigilance Task [PVT], or *n*-back). Error bars indicate *SE*s.

presentation of the street signs. This *involuntary sign-related imagery* was defined as the involuntary imagery of the color, name, or verbal associate of the sign (e.g., the "move" in "red move"). In response to the second question, there was involuntary imagery reported on a substantive proportion of the critical trials, as illustrated in the baseline, No Multi-Tasking condition ($M_{\text{Proportion of Trials}} = 0.31$ of 20 trials, $SD = 0.26$, $SE = 0.05$, Range = 0 to 0.90). This mean proportion was significantly different from zero, t (27) = 6.31, $p < 0.0001$ (Cohen's $h = 1.18$), as were the other two mean proportions from the trained-sign conditions, that is, the *n*-back condition ($M_{\text{Proportion of Trials}} = 0.28$ of 20 trials, $SD = 0.28$, $SE = 0.05$, Range = 0 to 0.83) and the PVT condition ($M_{\text{Proportion of Trials}} = 0.25$ of 20 trials, $SD = 0.23$, $SE = 0.04$, Range = 0 to 0.78), ts (27) > 5.37, ps < 0.001 (Cohen's $h = 1.12$ [*n*-back], Cohen's $h = 1.05$ [PVT]). The mean proportions presented in **Figure 5** that stemmed from the Untrained conditions, too, were significantly different from zero, ts (27) > 4.07, ps < 0.001.

Consistent with the hypothesis that these involuntary effects are robust enough to be detectable under dual-task conditions, the factor of Multi-Tasking (PVT, *n*-back, or None [baseline]) had no effect on the rate of occurrence of involuntary imagery. For example, as illustrated in **Figure 5**, in a 2 × 3 ANOVA with the within-subjects factor Sign Type (Trained or Untrained), and the within-subjects factor Multi-Tasking (None [Baseline], PVT, or *n*-back), there was only one main effect: a main effect of Sign Type on *involuntary sign-related imagery* (the color, name, or verbal associate of the sign), in which trained signs yielded more involuntary imagery than did untrained signs, $F(1, 27) = 12.64$, $p = 0.0014$ ($\eta_p^2 = 0.32$). There were no other significant main effects or interaction effects between the factors, Fs < 2.75, ps > 0.05.

The same results are found with the following analysis, in which, for the sake of thoroughness, we included the contrast between the two training regimens for the condition in which subjects were trained on only three signs. (Some subjects received training for the three signs of Bike lane, Speed Bump, and

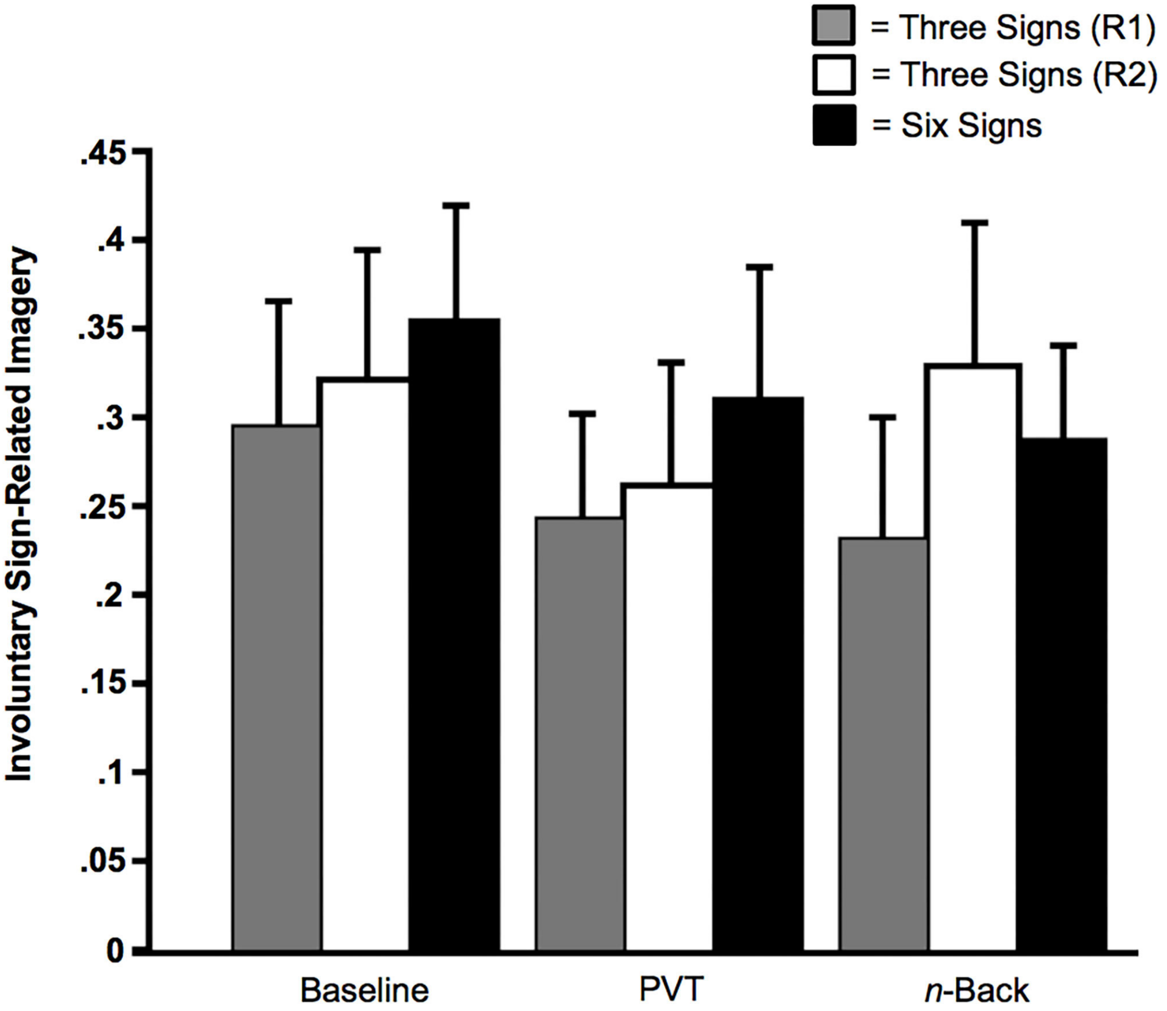

FIGURE 6 | Sign-related involuntary imagery as a function of Memoranda (three signals or six signals) and Multi-Tasking (None [Baseline], Psychomotor Vigilance Task [PVT], or *n*-back). The solid black bars indicate subjects who received training for all six signs. The gray bars indicate subjects who received training for the three signs of Bike Lane, Speed Bump, and Fire Truck (Regimen [R1]); the unfilled bars indicate subjects who received training for the signs of Crosswalk, Railroad Crossing, and Ambulance (Regimen 2 [R2]). Error bars indicate *SE*s.

Fire Truck [Regimen 1], while other subjects received training for the signs of Crosswalk, Railroad Crossing, and Ambulance [Regimen 2]). In this 2 × 2 × 3 ANOVA, with the within-subjects factor Sign Type (Trained or Untrained), the between-subjects factor Regimen (1 or 2), and the within-subjects factor Multi-Tasking (None [Baseline], PVT, or *n*-back), there was only one main effect: a main effect of Sign Type on *involuntary sign-related* imagery, in which trained signs yielded more involuntary imagery than did untrained signs, $F(1, 26) = 12.28$, $p = 0.002$ ($\eta_p^2 = 0.32$). There were no other significant main effects or interaction effects between the factors, $F\text{s} < 2.76$, $p\text{s} > 0.05$.[4]

Even when subjects were trained on six signs, there was involuntary sign-related imagery on a substantive proportion of the trials. This was the case for the baseline condition ($M_{\text{Proportion of Trials}} = 0.36$ of 20 trials, $SD = 0.24$, $SE = 0.06$, Range $= 0$ to 0.75), the PVT condition ($M_{\text{Proportion of Trials}} = 0.31$ of 20 trials, $SD = 0.27$, $SE = 0.07$, Range $= 0.05$ to 0.82), and the *n*-back condition ($M_{\text{Proportion of Trials}} = 0.29$ of 20 trials, $SD = 0.19$, $SE = 0.05$, Range $= 0$ to 0.70). Each of these three mean proportions was significantly different from zero, $t\text{s}\ (13) > 4.33$, $p\text{s} < 0.001$ (Cohen's $h_{\text{Baseline}} = 1.29$; $h_{\text{PVT}} = 1.18$; $h_{n\text{-back}} = 1.14$).

We conducted an ANOVA that excluded untrained signs and focused instead on the effects of Memoranda (three vs. six), along with the effects of Multi-Tasking. As illustrated in **Figure 6**, there was no significant effect of Multi-Tasking, $F(2, 78) = 2.81$, $p =$

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[4] The results of this analysis were complemented by the data that emerged from the first question after each critical trial, "*Did you just experience any verbal imagery? That is, did you experience any verbal imagery during the last moments (that is, the last five seconds) of the video? (Yes or No?).*" Again, there was only a main effect of Sign Type (Trained vs. Untrained), $F(1, 26) = 8.20$, $p = 0.008$ ($\eta_p^2 = 0.24$), and no other main effects or interaction effects, $F\text{s} < 2.00$, $p\text{s} > 0.14$.

TABLE 1 | Descriptive statistics for conditions of the suppress condition, including the psychomotor vigilance task (PVT): Means per condition with *SD*s presented in parentheses.

	Involuntary sign imagery*	**Immediacy**	**Urges to err**
Three signs trained			
Baseline	0.31 (0.26)	0.37 (0.29)	2.24 (1.67)
n-back	0.28 (0.28)	0.36 (0.30)	2.61 (1.81)
PVT	0.25 (0.23)	0.30 (0.27)	2.80 (1.91)
Six signs trained			
Baseline	0.36 (0.24)	0.41 (0.25)	2.56 (1.70)
n-back	0.29 (0.19)	0.36 (0.24)	2.91 (1.97)
PVT	0.31 (0.27)	0.38 (0.26)	2.94 (1.85)
Untrained signs			
Baseline	0.21 (0.17)	0.28 (0.21)	2.25 (1.69)
n-back	0.13 (0.20)	0.31 (0.30)	2.57 (1.89)
PVT	0.16 (0.21)	0.18 (0.21)	2.58 (1.77)

**For the involuntary sign imagery, each of the mean proportions is significantly different from zero, ps < 0.05. The same pattern of results is found with arcsine transformations of the proportions.*

0.07 ($\eta_p^2 = 0.07$), no effect of Memoranda, $F(2, 39) = 0.25$, $p = 0.78$ ($\eta_p^2 = 0.01$), and no interaction between the two factors, $F(4, 78) = 0.87$, $p = 0.49$ ($\eta_p^2 = 0.04$).

Perceived Immediacy

When subjects rated the immediacy with which the sign-related imagery was experienced, in response to the question, "*If you did experience verbal imagery, did the words come to mind immediately? (Yes or No?),*" there was only an effect of Sign Type (Trained or Untrained). In a 2 × 3 ANOVA with the within-subjects factor Sign Type (Trained or Untrained), and the within-subjects factor Multi-Tasking (None [Baseline], PVT, or *n*-back), there was only a main effect of Sign Type, $F(1, 27) = 6.51$, $p = 0.017$ ($\eta_p^2 = 0.19$), in which the involuntary imagery from trained signs was more likely to be perceived as immediate than that from untrained signs (**Figure 7**). There were no effects of Multi-tasking, Memoranda (six signals vs. three signals), or any interactions among these factors, $F\text{s} < 3.09$, $p\text{s} > 0.05$.

Action-Related Urges

We examined urges to press buttons during the Suppress condition, in response to the question, "*During these last moments (5s) of the video clip, how strong was the urge to press a button (8-point scale)?*" The only noteworthy effect is the following. In an ANOVA that excluded untrained signs and focused instead on the effects of Memoranda (three vs. six) and the effects of Multi-Tasking, there was an unpredicted effect of Multi-Tasking on these urges, $F(2, 78) = 3.77$, $p = 0.03$ ($\eta_p^2 = 0.09$). This effect, and what was observed regarding performance in the Respond condition (discussed next), will require further investigation. See **Table 1** for descriptive statistics for the conditions of the Suppress condition.

Behavioral Performance and Engagement in Secondary Tasks

Computer malfunctions and script errors led to the loss of 9 (0.004%) of 2,460 trials (from 41 subjects) in the Respond condition. The mean removal of trials per subject was < 1 trial ($M = 0.22$). These malfunctions caused some critical trials to appear more than once per session. Data from these repeated stimuli were removed from all analyses. Consistent with the data from the Suppress condition, subjects were sensitive to the trained signs. As revealed in **Figure 8**, accuracy was significantly above chance levels (with chance levels being 0.33 for the memory load of three signs and being 0.17 for the memory load of six signs), $t\text{s} > 2.88$, $p\text{s} < 0.014$. Moreover, consistent with the data from the Suppress condition, and as revealed in **Figure 8**, the factors of Memoranda (three signals vs. six signals) and of Multi-Tasking had no effect on the rate of responding to the trained signs, $F\text{s} < 2.40$, $p\text{s} > 0.10$. Moreover, these factors had no main effects or interaction effects on RTs, $F\text{s} < 3.24$, $p\text{s} \geq 0.05$.

As illustrated in **Figure 5**, involuntary sign-related imagery arose even when subjects were multi-tasking (i.e., concurrently performing the PVT or *n*-back). There is evidence that the subjects were indeed engaged in these secondary tasks. Regarding the *n*-back, subjects performed accurately (i.e., pressing the button when there was a repeated number and *not* pressing the button when there was no repeated number) on a proportion of 0.87 of the trials ($SD = 0.13$, Range = 0.45 to 1). Regarding the PVT, subjects correctly pressed the button in response to the sound of the beep on a proportion of 0.99 of the critical trials ($SD = 0.02$, Range = 0.90 to 1.00), with a mean response latency of 802.15 ms ($SD = 262.26$ ms, Range = 333.80 to 1,447.85 ms).

GENERAL DISCUSSION

In interference paradigms, distractors can activate urges, action dispositions, and mental imagery. Can such stimuli, when embedded in a dynamic and ecologically-valid stimulus scene, influence conscious processes in a similar manner? Specifically, can signs embedded in video footage of real street scenes trigger involuntary action-related imagery? The data from our project suggest that the answers to these questions is yes.

Our data reveal that involuntary imagery can arise in a substantive manner by stimuli (signs) that are embedded in dynamic video footage that has high ecological validity. It is noteworthy that such imagery arose despite the intentions of the subject, the complexity of the stimulus scene, and the minimal amount of training, which consisted of only 10 trials. The effect size of the involuntary imagery was comparable to that of other studies designed to illuminate the boundary conditions of such involuntary phenomena (e.g., Bui et al., 2019; Cushing et al., 2019). In addition, the data revealed that the task we developed is engaging at an informative level, with the task not being too easy (no ceiling effects) or too challenging (no floor effects).

One aim of the data analysis was to ascertain whether involuntary imagery arises in a predictable manner from the video clips we developed. The stimuli were developed from over

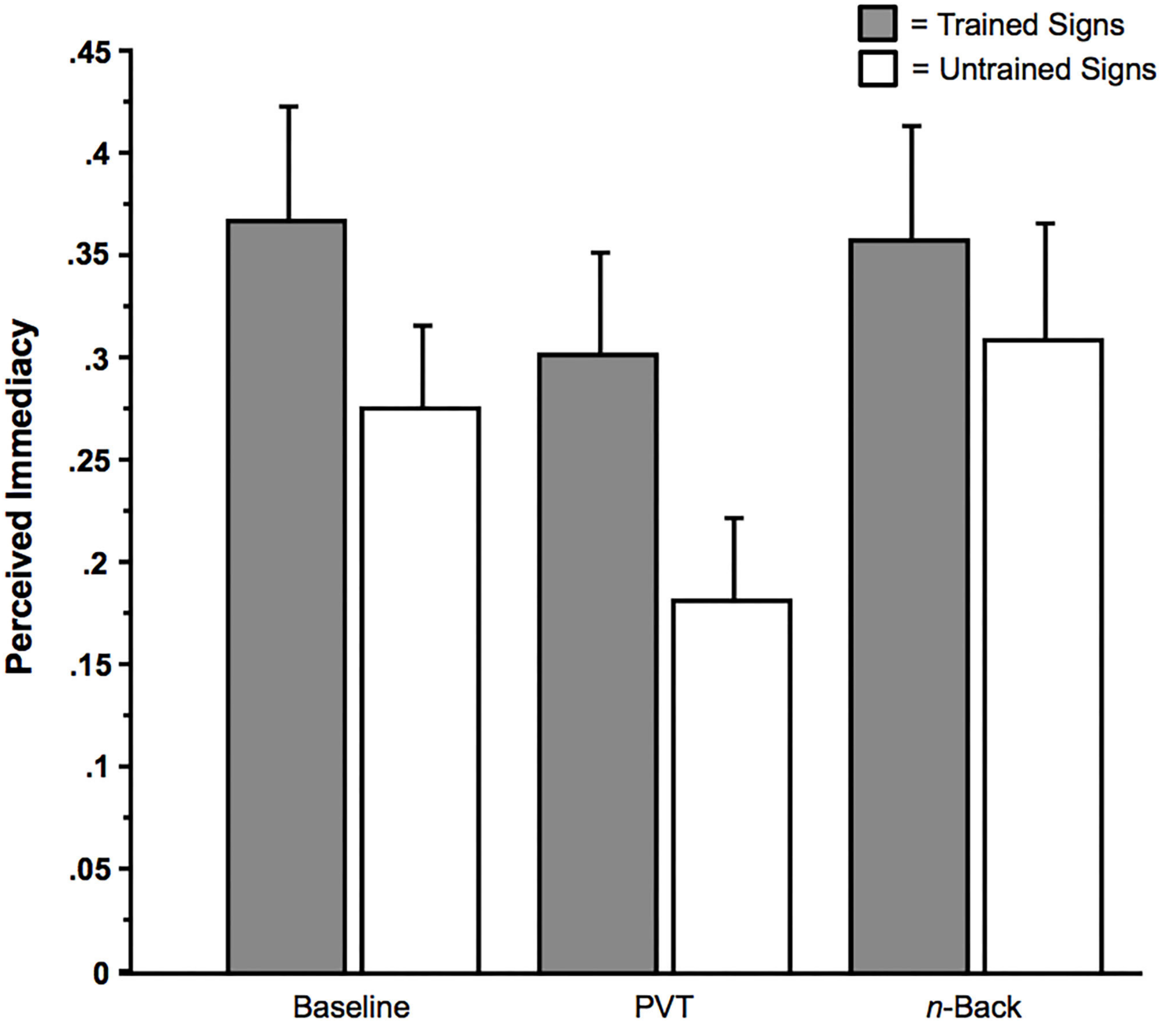

FIGURE 7 | Perceived immediacy of involuntary imagery as a function of Sign Type (Trained vs. Untrained [Control]) and Multi-Tasking (None [Baseline], Psychomotor Vigilance Task [PVT], or *n*-back). Error bars indicate *SE*s.

36 h of actual driving footage. These stimuli (i.e., the signs) that were embedded in the video footage were designed to appear within a dynamic and ecologically-valid context. Despite this and the intentions of the subjects, involuntary imagery arose in response to the signs on a substantive proportion of the trials ($M_{\text{Baseline Condition}} =$ 0.31 of 20 trials). This effect is noteworthy because subjects were instructed: "*IMPORTANT*: *During the task, please DO NOT respond to any of the signs… Also, try to NOT think of the response you learned to any of the signs.*"

The data support the hypothesis that these forms of involuntary imagery are robust and will arise even under different conditions of Memoranda (e.g., from the training of six critical signs instead of just three critical signs) and under conditions of multi-tasking (e.g., secondary tasks such as the PVT or *n*-back). Consistent with theorizing concerning the prepared reflex (Exner, 1879; Ach, 1905/1951; Woodworth, 1939; Gollwitzer, 1999; Hommel, 2000; Cohen-Kdoshay and Meiran, 2009; Cole et al., 2013; Pereg and Meiran, 2019), the manipulations of memoranda size and of multi-tasking did not seem to diminish substantively the rates of involuntary imagery. Theories concerning the nature of cognitive resources must take into account such an observation and also the more general notion of the prepared reflex, a mental act that seems to somehow be unaffected by the taxing of cognitive resources (Ach, 1905/1951; Gollwitzer, 1999; see Pereg and Meiran, 2019). It has been proposed that these effects, stemming from prepared reflexes, are often insuppressible and *motivation-independent* (Gollwitzer et al., 2009), requiring only the pre-stimulus activation of the appropriate action set (e.g., by external stimuli, task instructions, or prospective memory). The mental imagery experienced by our subjects, as fleeting as it might have been, is a case of high-level cognition, a phenomenon that requires at least some cognitive resources. Theories concerning cognitive resources need to account for observations in which such cognitions, and the kinds of cognitive effects trigged by prepared reflexes, are somehow unperturbed by, for example, dual-task conditions.

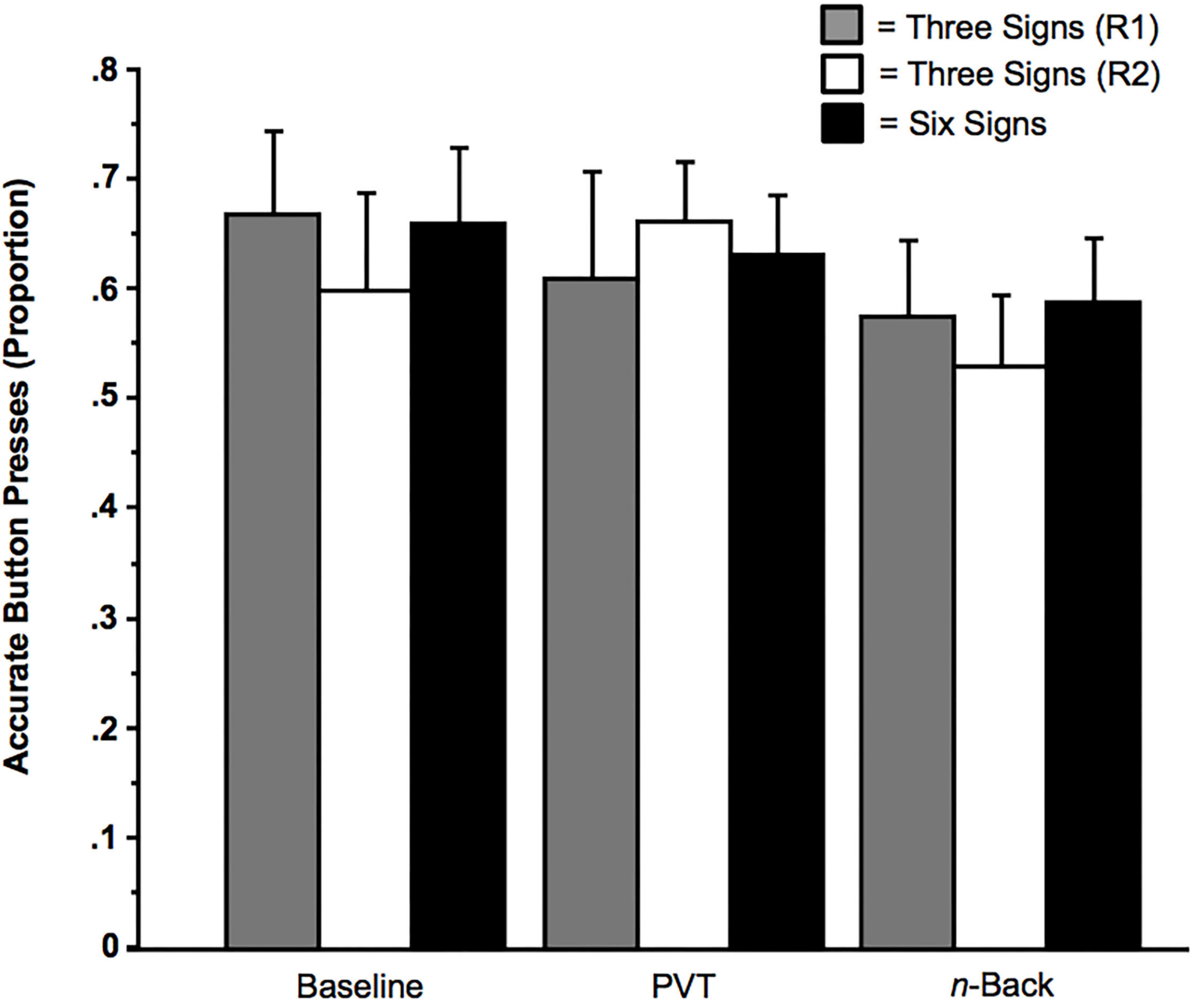

FIGURE 8 | Correct button press to presence of trained sign as a function of Memoranda (three signals or six signals) and Multi-Tasking (None [Baseline], Psychomotor Vigilance Task [PVT], or *n*-back). The solid black bars indicate subjects who received training for all six signs. The gray bars indicate subjects who received training for the three signs of Bike Lane, Speed Bump, and Fire Truck (Regimen [R1]); the unfilled bars indicate subjects who received training for the signs of Crosswalk, Railroad Crossing, and Ambulance (Regimen 2 [R2]). Error bars indicate *SE*s.

It is important to add that the data are based on subjects' self-reports of the conscious contents that were experienced after the presentation of the sign. Such self-reports, occurring moments after the experience of the relevant conscious experience, can be inaccurate as a result of (a) inaccurate memories of fleeting conscious contents (Block, 2007), or (b) subjects basing their reports on a strategy of how to comport oneself during an experiment (see discussion in Morsella et al., 2009). Given the conscientiousness of the subjects, as displayed, for example, in their accuracy rates on the two secondary tasks, we do not believe that subjects were confabulating or inaccurate about their introspections.

The present research has implications for the emerging technologies associated with semi-automated driving. The safe "intelligent interaction" between driver and vehicle requires that the communicative signals from vehicle to driver be as effective as possible at activating the appropriate cognitions, mental imagery, and behavioral inclinations (e.g., urges), even when (*a*) the driver is engaged in a secondary task and (*b*) such inclinations should *not* be expressed behaviorally in a particular context (e.g., because of the task set; Morsella et al., 2012). While monitoring the navigation of a semi-automated vehicle, a driver must remain sensitive to important signals and stimuli coming from outside of the vehicle (e.g., sirens and a school zone sign). The "stimulus control" exhibited by the trained signs in our project, which stemmed in part from the training session, provides a possible way in which these important signals could be more effective at influencing a driver's awareness and action selection. Thus, perhaps these initial data provide some evidence that a technique similar to that of our training session can benefit drivers' responses, especially in a scenario such as that of semi-automated driving, in which the driver is presented with more than a handful of signals and stimuli from both within the vehicle and from outside of the vehicle (Green et al., 1993).

To conclude, the distractor-elicited involuntary imagery that is observed in laboratory response interference paradigms does appear to arise in highly ecologically-valid conditions involving complex and dynamic stimuli (e.g., simulations of semi-automated driving experiences).

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

ETHICS STATEMENT

All studies involving human participants were reviewed and approved by Internal Review Committee, San Francisco State University, 1600 Holloway Ave, Administration 471, San Francisco, CA 94132. The participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

AV conducted the extensive piloting that was necessary for developing the experimental paradigm. AV was in charge of all the data collection. EM developed all the video stimuli. AV and EM conducted the data analyses and crafted the first, rough versions of the manuscript. HT provided critical feedback during each stage of the research process, from study designing to the writing of the manuscript. All authors contributed to the design of the study and the writing of the manuscript.

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Conflict of Interest: HT was employed by the company Toyota Motor North America, Inc.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

APPENDIX

For the crosswalk sign, the instructions were "*When you see a CROSSWALK sign, say 'Yellow Yield' aloud and press the YELLOW button. It is important that you respond as fast and as accurately as possible. Your hands must be in 'rest position.' Press G when you are ready to see the sign and respond to it.*"

For the bike lane sign, the instructions were "*When you see a BIKE LANE sign, say 'Green Scan' aloud and press the GREEN button. It is important that you respond as fast and as accurately as possible. Your hands must be in 'rest position.' Press G when you are ready to see the sign and respond to it.*"

For the speed bump sign, the instructions were "*When you see a SPEED BUMP sign, say 'Orange Slow' aloud and press the ORANGE button. It is important that you respond as fast and as accurately as possible. Your hands must be in 'rest position.' Press G when you are ready to see the sign and respond to it.*"

For the railroad crossing sign, the instructions were "*When you see a RAILROAD CROSSING sign, say 'Purple Pause' aloud and press the PURPLE button. It is important that you respond as fast and as accurately as possible. Your hands must be in 'rest position.' Press G when you are ready to see the sign and respond to it.*"

For the fire truck sign, the instructions were "*Red lines on the top of the screen indicate the presence of a fire truck. When you see the FIRE TRUCK sign, say 'Red Move' aloud and press the RED button. It is important that you respond as fast and as accurately as possible. Your hands must be in 'rest position.' Press G when you are ready to see the sign and respond to it.*"

For the ambulance sign, the instructions were "*Blue lines on the top of the screen indicate the presence of an ambulance. When you see the AMBULANCE sign, say 'Blue Hear' aloud and press the BLUE button. It is important that you respond as fast and as accurately as possible. Your hands must be in 'rest position.' Press G when you are ready to see the sign and respond to it.*"

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Time-Based Binding as a Solution to and a Limitation for Flexible Cognition

Mehdi Senoussi*†, Pieter Verbeke† and Tom Verguts

Department of Experimental Psychology, Ghent University, Ghent, Belgium

Why can't we keep as many items as we want in working memory? It has long been debated whether this resource limitation is a bug (a downside of our fallible biological system) or instead a feature (an optimal response to a computational problem). We propose that the resource limitation is a consequence of a useful feature. Specifically, we propose that flexible cognition requires time-based binding, and time-based binding necessarily limits the number of (bound) memoranda that can be stored simultaneously. Time-based binding is most naturally instantiated *via* neural oscillations, for which there exists ample experimental evidence. We report simulations that illustrate this theory and that relate it to empirical data. We also compare the theory to several other (feature and bug) resource theories.

Keywords: resources, binding, working memory, oscillations, modeling, simulations, cognitive flexibility

Edited by:
Gesine Dreisbach,
University of Regensburg, Germany

Reviewed by:
Ulrich Ansorge,
University of Vienna, Austria
Sebastian Musslick,
Brown University, United States

****Correspondence:***
Mehdi Senoussi
mehdi.senoussi@ugent.be

†These authors have contributed equally to this work and share first authorship

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INTRODUCTION

The existence of resource constraints on cognition is undebated: Just consider listening to a long list of grocery items to be fetched, and heading off to the supermarket without a piece of paper (or smartphone) to support your memory. What is debated, however, is the *nature* of these resource constraints. Of course, resource is a broad term that has been applied throughout psychology and neuroscience (e.g., Barlow, 1961). However, we will restrict our attention to theories with immediate implications for working memory (e.g., as in the supermarket example). With this delineation out of the way, we note that a long research tradition has empirically investigated the nature of resource constraints (Miller, 1956; Cowan, 2001; Bays and Husain, 2008; Oberauer and Lin, 2017) by positing a limited quantity of some sort, and then deriving predictions (perhaps supported by a formal model) with respect to behavioral data in the working memory domain. This is the "bug" approach mentioned in the abstract. However, in line with David Marr and the "feature" approach, we first consider what a computational perspective would stipulate for flexible cognition (Holroyd and Verguts, 2021). To be clear from the start, "computational" is often used as in "instantiated in a formal model"; this is not what we mean here. By computational, we refer to the computations that are required in tasks relying on flexible cognition (such as getting one's groceries, in the upcoming example). Our detour into flexible cognition lays the groundwork for our main thesis: The resource constraint is a consequence of the computational requirements to implement flexible cognition. Then, we consider the implementational perspective, and present some simulations to illustrate our theory, based on a recent oscillatory model of working memory

(Pina et al., 2018). Finally, we relate our theory to other (similar and different) proposals in the General Discussion section.

Role-Filler Binding

Cognition requires the flexible binding and unbinding of two or more elements. For example, an experimenter may instruct a subject to detect the red squares in a stream of stimuli, but ignore the blue squares and red triangles (Treisman and Gelade, 1980). More mundanely, a mother may ask her son to go to the store to buy a pack of gluten free pasta and 1 kg of apples. If he comes home with 1 kg of regular pasta and a pack of gluten free apples, he is likely to be sent back. As another example, acting appropriately in a restaurant requires binding the waiter role to the person running around with the drinks; this binding allows one to know how, what, and when to order. In a sense, cognitive life is built on binding.

A particularly important type of binding is that between roles to be filled and fillers of those roles (*role-filler binding*; Hummel, 2011). For example, suppose one wants to memorize that the fruit aisle is on the left of the dry food department in the supermarket. The roles are here "Left" and "Right"; the fillers are "fruit aisle" and "dry food department"; and the relevant role-filler bindings are (Left, fruit aisle) and (Right, dry food department). As an aside, these roles can be implemented *via* different types of representational codes, including verbal or spatial (Gevers et al., 2010; van Dijck and Fias, 2011); we currently remain agnostic about their nature. Consider as another example of role-filler binding, syntactic constructions such as the Subject—Verb—Object (SVO) type sentence. For example, in a sentence like "Tom buys pasta," the relevant role-filler bindings are (Subject, Tom), (Verb, buys), and (Object, pasta). Other syntactic constructions are possible to represent this information [e.g., (Buyer, Tom), (Object-bought, pasta)], but the syntactic structure doesn't matter for our argument, and we will stick to SVO constructions to explain our argument. We will discuss a few constraints on role-filler bindings in cognition, and how these constraints impose processing bounds on cognition.

Some sentences (such as "I love you") occur sufficiently frequently to be stored as a separate chunk in memory, independent from other information. There is indeed evidence that such (high-frequency) chunks are important in language (McCauley and Christiansen, 2014), and perhaps in cognition more generally. However, chunking is not a realistic possibility for coding SVO sentences in general. For example, if there are N possible fillers (Tom, buy, book, . . .) and three possible roles (Subject, Verb, Object), a systematic chunking approach confronts a combinatorial problem, as it would require storage of $3N^2$ chunks of knowledge. More importantly, a chunking approach does not easily lend itself to generalization (Marcus, 2001, 2018). If one learns something about books, generalization requires that this novel information generalizes to the statement "Tom buys a book" (Fodor and Pylyshyn, 1988). For example, even a rudimentary knowledge about books is enough to conclude that buying a book entails a very different process than buying a house. But if the proposition that "Tom buys a book" is stored as a separate chunk in memory, such generalization between propositions is not possible.

The solution to this generalization problem involves compositionality (Fodor and Pylyshyn, 1988): Storing all components (or building blocks, here, roles, and fillers) separately, in such a way that they can later enter into novel relations with other components. Applied to roles and fillers, this principle is also called *role-filler independence* (Hummel, 2011). Indeed, if one stores "book" information separately, the concept can later be independently enriched; and the novel information (e.g., that a book can be bought in bookstores, without the hassle and administration involved in buying a house) can thus be applied to instances like "Tom buys a house."

With role-filler independence, the memory requirements are much lighter than in a chunking approach. Consider **Figure 1**: Here, N fillers and 3 roles are represented, with a much lighter memory requirement of just $3 + N$ elements. Any specific sentence ("Tom buys a book") involves a combination of the corresponding roles and fillers.

If roles and fillers are stored independently, a next crucial property for flexible cognition is *dynamic role-filler binding* (Hummel, 2011). Specifically, it must be possible to rapidly bind and unbind roles and fillers in order to understand complex events in the real world. Consider hearing the story that Tom buys a book, then that Mehdi buys a bottle, and finally that Tom gives his book to Mehdi. In order to understand the three events and their logical relations, and in order to answer questions about the situation (Who currently owns two items?), it is important to initially bind Tom to Subject and book to Object; and then bind Mehdi to Subject (and unbind Tom and Subject) and bind bottle and Object (and unbind book and Object); and so on.

Synaptic Binding

It then remains to be explained how dynamic role-filler bindings are formed. One approach is to construct a synaptic connection between each (role, filler) pair for each sentence that is currently of relevance. We will call this a *synaptic binding* approach; presumably, a configuration of synapses stores the relevant information. Note that the term "synapse" can be interpreted either literally in the biological sense, or more metaphorically; the only functional requirement of a synapse for our purposes is that two memory elements are connected. It is the approach applied, for example, in neural network training algorithms (e.g., backpropagation; Rumelhart et al., 1986). Whereas originally thought to contribute mainly to long-term memory, recent work suggests that synaptic binding also supports working memory (the synaptic model of working memory; Mongillo et al., 2008; Stokes, 2015). However, this synaptic binding approach has its downsides. In particular, if synapses are not immediately removed after a sentence, interference will quickly occur. Consider again first representing that Tom buys a book, then that Mehdi buys a bottle, perhaps followed by some other purchases and exchanges of goods. In this case, roles and fillers will soon be saturated, connecting all roles with all fillers, and thus abolishing any meaning (see **Figure 1A** as an example). We will call this the unbinding problem of synaptic binding. Computationally, the problem manifests itself in catastrophic interference between partially overlapping tasks, which is a huge problem in neural networks (French, 1999), with several solutions being proposed

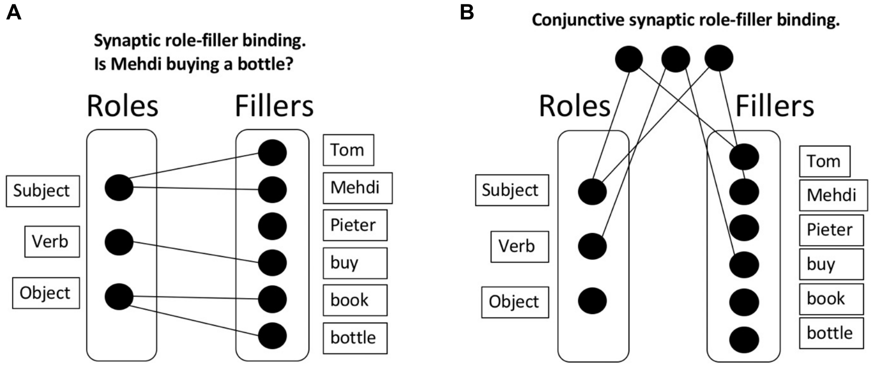

FIGURE 1 | Synaptic binding. **(A)** Synaptic role-filler binding. This approach allows to bind roles and fillers but has an important downside: After the presentation of multiple sentences, the roles and fillers are soon saturated, connecting all roles with all fillers. If synapses are not immediately removed, this approach will lead to interference; which we refer to as the unbinding problem. **(B)** Conjunctive synaptic role-filler binding. An alternative solution is to implement a set of "gates" that would, for instance, activate specific roles and fillers. Once activated, a gate would activate the corresponding (role or filler) elements. This approach has the same unbinding problem, and additionally presents a combinatorial problem: $3N^2$ gates must be created to store all possible bindings.

to overcome it (McClelland et al., 1995; Kirkpatrick et al., 2017; Verbeke and Verguts, 2019). Also biologically, it's not clear that the construction and destruction of biological synapses can occur at the time scale required for cognitive processing (Kasai et al., 2003; Caporale and Dan, 2008).

One could argue that the problem in the previous scenario derives from the direct synapses between roles and fillers. Thus, an alternative synaptic binding solution could be to implement a set of "gates" that filter out or activate specific roles and fillers. For example, there could be one gate for Tom, one for Mehdi, another for Subject, and so on. When the corresponding gates are activated, they in turn activate their corresponding (role or filler) elements. This approach would obviate the requirement of direct bindings between roles and fillers. However, in this approach, suppose each gate is selective for a specific role or filler; then appropriate (role, filler) pairs cannot be kept apart. Consider for example representing that Tom buys a book and Mehdi buys a bottle; in such a system, the interpreter of the system has no way to know whether the activated book belongs with Tom or with Mehdi. To solve this problem, one could suppose, instead, that there is a separate gate for each (role, filler) pair (**Figure 1B**). This approach could solve the problem of disambiguating different meanings. Because neurons are here dedicated to (role, filler) conjunctions, this falls under the more general conjunctive coding approach (Bouchacourt and Buschman, 2019). However, here the combinatorial problem ($3N^2$ gates must be created) and the unbinding problems appear again; furthermore, it's not clear how one can generalize information about (say) a filler to other (role, filler) pairs (Hummel, 2011). We conclude that a pure synaptic binding approach is likely insufficient to implement dynamic role-filler bindings at the time scale required in systematic cognition.

Time-Based Binding

Instead of synapses, one could consider using the time dimension to bind roles and fillers; we will call this a *time-based binding* approach. In particular, suppose that at time t, the role-filler pair (Subject, Tom) is active. However, a single time point doesn't leave enough time for processing; moreover, the system doesn't necessarily know when exactly the information will be of use in further task processing. It is thus useful to repeat the information for some period of time. Let's suppose that the binding is repeated at intervals of length d. Hence, at all times $A_1 = \{t, t + d, t + 2d, \ldots\}$ both elements of the (role, filler) pair (Subject, Tom) are active. Note that Subject and Tom are indeed joined by time only; there is no synaptic connection between them.

Besides representing (Subject, Tom), we also need to represent the pair (Verb, Buy). However, if the pair (Verb, Buy) were active at the same time as (Subject, Tom) (say, at time t) we run the risk of interference, as explained in the previous paragraph. We must thus represent it at some other time, say $t + e$. Just like for (Subject, Tom), we repeat the (Verb, Buy) pair at the same distance d so the two pairs maintain their temporal separation. Thus, we conclude that at times $A_2 = \{t + e, t + d + e, t + 2d + e, ..\}$ the pair (Verb, Buy) is active.[1] With a similar logic, at times $A_3 = \{t + 2e, t + d + 2e, t + 2d + 2e\}$ the pair (Object, Book) will be active.

Synaptic Learning on Time-Based Bindings

It is well known that a neural network training rule (such as backpropagation) can learn complex tasks *via* synaptic binding, especially if it has available appropriate (here, compositional) representations of the input space. We postulate that this allows an efficient combining of the synaptic and time-based approaches. Specifically, once a time-based binding system as sketched above is constructed, a synaptic learning rule operating on its representations can subsequently learn various tasks. For example, in the book-buying context, the training rule could learn to answer questions such as "Who bought a book?"; "Who owns a book?"; and so on. Or in an experiment context, relevant

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[1] Without loss of generalization, we can assume $e < d$.

mappings to be learned could be "Press the f key if you see a red square, the j key if you see a blue circle, and nothing otherwise."

Importantly, such a representational system with independent and dynamic role-filler pairs, allows for generalization. For example, if novel information is learned about, say, Tom, this novel information can be attached (by the learning rule) to the representation of Tom, and thus be immediately generalized to other contexts in which Tom may appear.

Moreover, during both learning and performance, it's very easy to delete old, no longer relevant information without leaving any trace to be erased: No synapses were created for binding, so none need be erased. It's straightforward to represent the fact that Tom buys a book, followed by the fact that Mehdi buys a bottle. Finally, it's relatively easy to construct new (role, filler) pairs *via* synchronizing "bursts" (Verguts, 2017; and see section "Discussion").

In summary, we propose that synaptic and time-based binding ideally complement each other for the purpose of flexible cognition. Time-based binding allows quickly constructing and destructing connections. In contrast, synaptic binding allows application of very powerful learning rules. In this way, advantages of both synaptic and time-based binding are exploited, and their respective disadvantages are mitigated.

A Resource Bound to Time-Based Binding

Despite its several advantages, there is a constraint to the time-based approach. Specifically, this system of representing information will only work if the elements of sets A_1, A_2, and A_3 [i.e., the timings of the different (role, filler) pairs] remain sufficiently separate (where "sufficient" depends on the level of precision required to robustly pass a message to a downstream neural area). Hence, such a system of representations can efficiently represent information [*via* dynamic (role, filler) bindings], and forget old, no longer relevant information. But it has an inherent constraint: It can only represent a limited number of elements at the same time.

Can we characterize this constraint more precisely? Note first that all distinct elements (or groups of bounded elements), referred to as items, should be activated once before any of them gets reactivated, otherwise, there is an ambiguity which set an item belongs to. For instance, if three items are presented in a specific order (item 1, item 2, item 3), and are activated at t, $t + e$, and $t + 2e$, then item 3 must be activated before item 1 gets reactivated. In other words, we require that $t + ne < t + d$, that is, $n < d / e$. Storage capacity n has thus an upper bound d/e, determined by the period (d) of each set, and the time (e) between elements. This bound cannot be made arbitrarily high: If d is too high,[2] the time between different elements [(role, filler) bindings] is too long, and the items cannot be simultaneously processed by a downstream neural area that must interpret the bindings. Imagine having to remember a grocery list with several minutes between the different items. Similarly, if e is too small, the separate elements cannot be disentangled from each other, either because of noise or because of the time scale of the downstream neural area. We propose that these factors together impose a bound on how many novel items agents can store simultaneously.

Note that the argument is purely computational: Any agent (biological or artificial) who is confronted with a task with the described requirements (simultaneous but systematic storing of possibly rapidly changing facts, using a single representational space), should use time-based binding; and as a result, he or she is subject to the constraints. The argument also clarifies when the bound applies and when it does not. It is perfectly possible to store thousands of facts *via* synaptic binding, as long as they do not require on-the-fly constructions and destructions of conjunctions of information. In other words, the resource bound applies to (non-synaptic) working memory, not to long-term memory.

SIMULATION

We next consider how a time-based binding system may be neurally implemented. To construct such a system for representing novel, on-the-fly constructions, one needs a periodic or oscillatory function [i.e., $f(X + c) = f(X)$ for some c and for all X)]. The simplest choice is perhaps a sinusoidal (sine or cosine) function, but this is not necessary.

Consistently, a long research tradition has suggested an important role of oscillatory functions (oscillations in short) for cognition in general, and for binding elements in memory in particular (Gray and Singer, 1989). It is well known that coupled excitatory and inhibitory neurons can easily be employed to generate oscillations (Wilson and Cowan, 1972; Gielen et al., 2010). The coupling parameters (synaptic weights) between excitatory and inhibitory neurons determine the characteristics of the oscillations, such as their phase, amplitude, and frequency.

To illustrate our argument, we used a recently proposed architecture of binding through oscillations to model working memory (Pina et al., 2018). This oscillatory neural network can bind and maintain elementary features (each represented by one node of the network) over time, while keeping different bindings apart. Each node of the network is composed of three components (a neural triplet, see **Figure 2A**). The three components are fast-excitatory (u, emulating AMPA synapses), slow-excitatory (n, emulating NMDA synapses), and inhibitory (v, emulating GABA synapses), respectively. The fast-excitatory—inhibitory pair constitutes a Wilson-Cowan type system (Wilson and Cowan, 1972). This pair exhibits limit cycle behavior (i.e., oscillations) and, as stated above, the characteristics of these oscillations (e.g., amplitude, frequency) can be controlled by changing the coupling weights between these components. Additionally, the slow excitatory component provides excitatory input to the inhibitory and fast excitatory components, thereby allowing bistability of the neural triplet (Lisman et al., 1998): an inactive state with low amplitude fluctuations, and an active state with persistent high amplitude oscillations. The left part of **Figure 2A** shows the connectivity between each component of a neural triplet; see **Appendix** for a full description of the differential equations defining each component's activity, and the

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[2] Note that the timescale of an upstream neural area may also impose an upper bound on d (there is a lower limit in frequencies produced by neural ensembles).

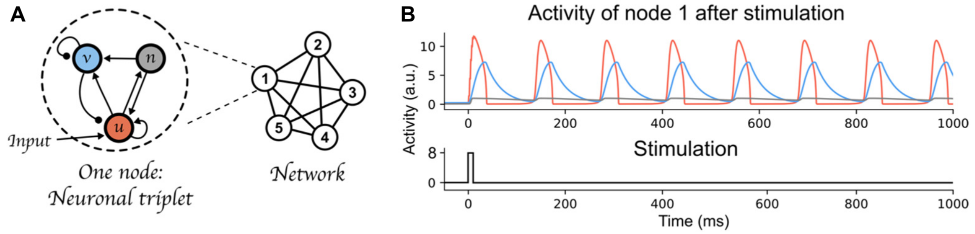

FIGURE 2 | Time-based binding network. **(A)** Each node of the network is a "neural triplet" composed of three components: A fast excitatory (u) neuron, an inhibitory (v) neuron, and a slow excitatory (n) neuron. Stimulation to a node affects unit u (as represented by the "Input" arrow). This architecture allows each node to start oscillating thanks to the excitatory-inhibitory pair of neurons (u and v, respectively), and maintain this oscillation through time (i.e., very slow decay) due to the slow excitatory neuron (n). When interconnected through excitatory-to-excitatory, and inhibitory-to-inhibitory connections, these nodes form a network that exhibits binding by phase and competition between active nodes or bound group of nodes. Synaptic weights are represented as lines between components or nodes: arrow ended lines represent excitatory connections, circle-ended lines represent inhibitory connections. **(B)** Top: Example of node 1 being activated by an input stimulation. The red curve represents the activity of the fast-excitatory neuron (u), the blue curve represents the activity of the inhibitory neuron (v), and the gray curve represents the activity of the slow-excitatory neuron (n). Bottom: stimulation time course.

value of each parameter including the weights between nodes of the network. We kept all parameter values equal to the main simulations in Pina et al. (2018), and only varied the inhibitory component's time scale (τ_i, Equation 2 in **Appendix**). This parameter defines the speed at which the inhibitory component's activity is updated. Varying τ_i allows to manipulate the oscillatory frequency of the nodes' active state. At the neurophysiological level, this parameter can be considered to reflect temporal aspects of the response function of GABA receptors. This response function, which can be thought of as a band-pass temporal filter on incoming inputs to the synapse (Robinson et al., 2004), has been shown to be affected by neuromodulators (e.g., noradrenaline Sillar et al., 2002), which provide a mechanism to control neural populations' dynamics (Berger et al., 2003; see also Shine et al., 2021 for a review on computational models of neuromodulatory systems). Moreover, in this model, nodes form a network (upper-right part of **Figure 2A**) in which all fast-excitatory components excite each other, and all inhibitory components inhibit each other (see bottom-right part of **Figure 2A**). This connectivity allows these nodes to form a network that exhibits binding by phase; that is, when the peak of two nodes coincide, within a certain temporal range that we will call a "binding window," they attract each other and align their peaks, forming a bound state. This network is further also characterized by competition between active nodes (or between groups of nodes that are bound together); i.e., when the peak of two nodes are separated by an interval outside of the binding window range, they will repel each other and remain active in an out-of-phase state. Due to the intrinsic attracting and repelling dynamics of this architecture, it can thus bind and maintain information to form distinct memories (a single active node, or bindings between nodes), while avoiding mixing them, through time-based binding. Each memory consists of one or multiple bound elementary features, each represented by a node. In line with the theory postulated above, a memory is activated only periodically (see **Figure 2B**).

The ability to concurrently store multiple items of information in this manner, relies on two important features. First, the elements of each item must be bound together. For instance, nodes representing the role "Subject" and the filler "Tom" are in synchrony. Second, to concurrently maintain multiple memories (e.g., Subject-Tom and Verb-Buy), the two nodes representing the Subject-Tom pair must remain out of synchrony with those representing the Verb-Buy pair (see units 1–2 and 3–4 in **Figure 3**). This mechanism entails that the number of distinct memories that can be maintained simultaneously without interference, is limited by the frequency of the oscillation. In doing so, this model exemplifies how capacity limits emerge as a property of a system using oscillatory mechanisms for binding, i.e., the time interval between two peaks of activated nodes (or groups of nodes).

One of the parameters that determines the memory capacity, is the oscillatory frequency of the network, which itself is determined by the τ parameters. To illustrate the effect of frequency, we changed the temporal scale of the inhibitory component (τ_i) of all nodes. In a first simulation (using $\tau_i = 32$),

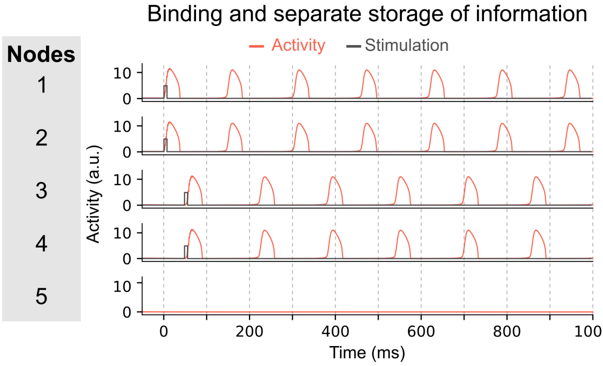

FIGURE 3 | Maintenance of two pairs of items in the network. In this network, pairs of nodes are activated simultaneously, i.e. nodes 1 and 2 at time 0 ms, and nodes 3 and 4 at time 50 ms. Due to the inter-node coupling, each node of a pair will oscillate in synchrony and can thus represent a bound multi-element memory. The other pair will oscillate out-of-phase with the first pair allowing to store each binding separately and to permit read-out of each multi-element memory by downstream areas.

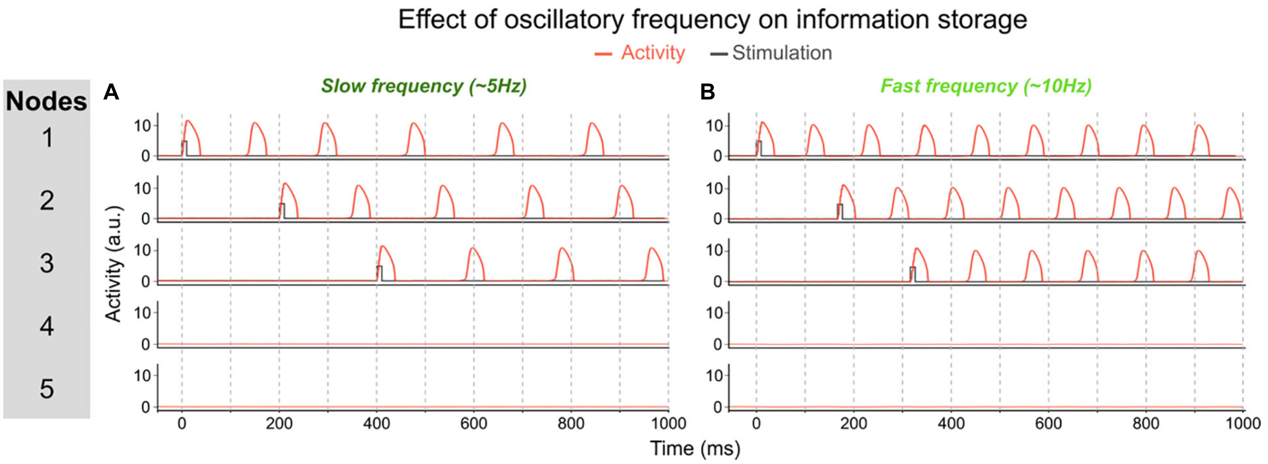

FIGURE 4 | Effect of oscillatory frequency on maximum number of maintained items. **(A)** In this network each activated node will oscillate at ~6 Hz (τ_i = 32). This allows to activate up to three units out-of-phase, i.e., three separately maintained memories. In this example, each node is activated sequentially and stays activated. **(B)** In this network, the inhibitory time scale (τ_i) has been decreased to 20 which increases the frequency of activated nodes to ˜10 Hz. This prevents three nodes to be activated out-of-phase because of the short time interval between the activity peaks of activated nodes to "store" a third memory. In this example, node 3 is activated after nodes 1 and 2. Node 3 then shifts its phase and aligns with node 1, thereby losing the distinct information represented by each of the three nodes. This faster network thus has a lower memory capacity.

each node oscillates at ∼6 Hz once activated. The network can maintain up to 3 memories out-of-phase (i.e., their activity periodically peaks but never at the same time, allowing a downstream area to read-out each memory independently, see **Figure 4A**). In this network, the memory capacity is thus 3. In a second simulation we decreased the temporal scale of inhibitory components to obtain a network in which nodes oscillate at a slower frequency (τ_i = 20). In this network, activated nodes will oscillate at a faster frequency of ∼10 Hz (see **Figure 4B**). When activating the first two nodes, they start oscillating out-of-phase, thereby maintaining 2 memories in the network. But when activating a third node, it will start competing with the first or second active node (depending on the exact timing of the stimulation of the third node). This competition will lead to one of three possible states: (1) the third node may not be able to sustain activation and this third memory will be lost; (2) the third node inhibits one of the other two nodes and the network will thus loose one of the previously stored memories; or (3) the third node synchronizes (or binds) with one of the activated nodes, thus creating a new bound memory. This last state is illustrated in **Figure 4B**. Each of these options shows that in this faster network, three distinct memories cannot be maintained concurrently, and therefore that a faster oscillatory frequency leads to a lower memory capacity.

GENERAL DISCUSSION

To sum up, we have argued that synaptic and time-based binding have complementary advantages for the implementation of flexible cognition. Time-based binding can be quick and literally leaves no traces behind; but it leads to a natural processing (or resource) bound. Instead, synaptic binding is slower, prone to interference, but it does not suffer from this processing bound. We illustrated this theory with simulations of a recent oscillatory model. In the General Discussion, we relate our proposal to resource (or "bug") theories, computational (or "feature") theories, and to earlier oscillation theories. We end by pointing out some empirical predictions.

Resource Theories

In the current section, we discuss three influential theories on the nature of working memory constraints and resources, key data that earlier literature interpreted as supporting the respective theories, and how our own perspective accounts for those data.

A long-standing *slots theory* holds that working memory consists of a fixed number of slots (with the proposed number varying from 1 to 7) (Miller, 1956; Cowan, 2001; Zhang and Luck, 2008); one can consider slots as a discrete resource. A key behavioral signature interpreted as favoring slots theory, is the observation of a fixed precision for memoranda held in working memory beyond the slots upper bound. To be more specific, Zhang and Luck asked their subjects to retain from 1 up to 6 colors presented on different locations on the screen in working memory. In the test phase, they subsequently queried which colors were accurately remembered (subjects indicated the colors by clicking on a color wheel). Fitting a mixture model on the behavioral data in the test phase, the authors observed that the precision (inverse variance) of memory was statistically similar for 3 and for 6 items. They interpreted this as meaning that the number of available slots was equal to around 3. Instead, the precision in working memory did increase from 1 to 3; the authors interpreted this as meaning that more than 1 slot can be devoted to the same object (e.g., an object represented by two slots will be represented more precisely than one represented by just a single slot). However, fine-grained experimental paradigms with continuous manipulations of the relevant features (e.g., color or physical location), have since then demonstrated that there is no abrupt non-linearity around 3 items (Ma et al., 2014). From the lowest set sizes on, when more items must be held in working memory, the representational precision of the remembered items gradually decreases. This data pattern was interpreted in terms of a *continuous resource theory* (often called resource theory in short), which holds there is a continuous but finite resource to be divided among the memoranda (Bays and Husain, 2008; Ma et al., 2014).

How to account for this data in a time-based binding perspective? We propose the following tentative theory. Suppose each neuron has a specific receptive field across some feature space (e.g., color space or Euclidean space). In the example, color- and location-sensitive neurons must bind to one another in order to represent the stimuli correctly. Suppose that there is a pool of neurons responding to specific colors and locations, in the color and Euclidean spaces, respectively. Suppose further that each neuron in one pool (e.g., responding to an active color) must be bound to at least one neuron from the other pool (responding to an active location) in order to influence downstream processing (i.e., be in working memory). Then, the precision will gradually decrease as more items must be retained: Indeed, more items retained means that less neuron pairs can be devoted to any specific item, given a finite period length of the oscillation. At first sight, it would seem that this theory predicts a hard bound at the maximal number of bindings that fit in a cycle, as in slots theory. However, given that several variables (including pool sizes, average receptive field, item location, period length, etc.), may vary from trial to trial, precision will also gradually decrease when additional items are in memory.

Another important behavioral signature is the occurrence of misbinding errors. This means that when (say) colors need to be remembered at specific locations, colors and locations may swap places in the participant's memory. The existence of misbinding errors is naturally in line with a binding account; if two features (say, location and color) are incorrectly bound in memory, a binding error at behavioral level automatically follows.

The existence of misbinding errors was originally interpreted in terms of a third influential perspective on the nature of cognitive constraints on working memory, namely *interference theory* (Oberauer and Lin, 2017). Interference theory is in line with a long tradition of computational modeling *via* synaptic binding, specifically in neural networks. Interference theory holds that the postulation of a (discrete or continuous) resource is not required.[3] Cognitive processing in a neural network already leads to massive processing limitations due to (catastrophic) interference, and the latter is sufficient to explain the behavioral-level processing impairments that arise in tasks requiring the maintenance of several items at the same time.

At the risk of being overly reconciliatory, it's worth pointing out that our time-based binding theory shares commonalities with each of the classical (discrete and continuous resources, interference) theories of working memory constraints. Like slots theory, it holds that just a fixed number of elements (here, bindings) can be maintained simultaneously. However, because the memoranda are bindings between neurons with variable parameters (cf. above), our perspective can predict, just like continuous resource theory, that there is no fixed bound at any number of items, and representational precision instead gradually decreases with more remembered items. Finally, binding elements together is rarely sufficient to solve actual tasks. The bindings must be read out by downstream task-specific processing modules. Such processing modules can most naturally be composed of standard neural networks, which implement synaptic binding, and are trained with gradient-based algorithms. The latter naturally also leads to similarities with interference theory.

Computational-Level Theories

Generally speaking, computational-level theories consider that humans and other agents act in such a way as to achieve some goal (Lieder and Griffiths, 2020). As applied to working memory constraints, it holds that working memory may not be bound by the scarcity of a discrete or continuous resource, but that its boundedness is an optimal response to its environment. The early selection-for-action theory, for example, held that working memory must subserve action in the world (discussed in Hommel et al., 2001); and because action must be integrated (one cannot, for example, prepare a gratin dauphinois and play a video game at the same time), some environmental features must be selected, and others ignored. A generalization of the selection-for-action theory is the selection-for-procedures theory proposed by Ansorge et al. (2021). These authors argued that the bottleneck for actions (i.e., very few and typically just one action can be carried out at the same time), also applies to the execution of procedures. Using their own example, drawing the correct conclusion from the premises "All bees are insects" and "All bumblebees are bees," requires that the relevant information is active at specific times, not all at the same time; thus to avoid drawing conclusions such as that all insects are bumblebees. The current theory is very much in line with this generalization of selection-for-action theory, and proposes a specific computational reason why time-sharing is beneficial (it keeps the number of synapses low), but, because time is one-dimensional, it introduces a processing bottleneck.

More recently, Musslick and Cohen (2021) have combined computational-level and interference theory (see previous paragraph) to explain why cognitive control appears to be limited. Their starting point is the dilemma between learning and processing efficiency in standard neural networks: Efficient learning requires overlapping (shared) representations between tasks, but at the same time such overlap impairs multitasking (i.e., simultaneously performing two or more tasks). When tasks share input or output features, multitasking is almost impossible in such neural networks. Their simulations demonstrate that, in standard neural networks, basically just one task can be performed at any time. Thus, the optimal agent chooses to carry out just one task at a time. In their perspective, the bound is an optimal choice, given the computations one has to do and

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[3] For completeness, it must also be mentioned that, in line with earlier work of Oberauer (2003) and Oberauer and Lin (2017) also included a focus of attention in their model; an extra storage component that can hold just a single item. One could think of this storage component as a single slot (discrete resource).

given the architecture that is available for doing so. In principle, all tasks could be carried out at the same time; but because of the massive interference this would engender, an optimal agent chooses to limit the number of simultaneously processed items. Alternatively, time-based bindings could allow to perform multiple tasks at the same time by attributing processing for different tasks at alternating oscillatory cycles. However, like bindings for working memory, also the number of tasks that one can alternate between is bounded by $n < d/e$. Moreover, such alternating task processing might decrease robustness of task representations when e is small or when noise enters the system. Hence, it would introduce a trade-off between cognitive stability (robust task processing supporting high performance) and cognitive flexibility (rapidly switching between different tasks).

Furthermore, it has been proposed that highly specialized separate representations might develop for high frequency tasks or stimuli (see also Musslick et al., 2020; and our discussion of high-frequency sentences in the Introduction). For instance, features of familiar faces are stored independently from other facial features (Landi et al., 2021). Hence, with more extensive learning synaptic bindings become more separated, decreasing the importance of time-based bindings.

Oscillation Theories

The interest in neural oscillations dates back at least to the theoretical work of von der Malsburg (von der Malsburg and Singer, 1988). Around the same time, Gray and Singer (1989) detected that neural spiking in cells in the visual cortex phase-lock to the gamma rhythm (50–90 Hz); especially for features that are perceived as belonging to the same object. This led to the "binding by synchrony" and later the "communication through coherence" (CTC) theory. According to CTC, neurons in different brain areas can be bound together by firing in the same gamma phase (or more generally, by firing in a consistent and appropriate gamma phase difference; Fries, 2015). In particular, neurons in distant areas with a consistent gamma phase difference would share information more efficiently. For example, suppose the peak of the gamma wave is the phase where information can be most efficiently sent to other neural areas; if two neurons in distant areas always fire at this phase of the wave (i.e., the peak), this coincidence can be read out by downstream areas, and thus the two neurons are functionally (but not physically) bound. The binding of these different-area gamma waves could be orchestrated by a slower theta (4–7 Hz) wave (Voloh and Womelsdorf, 2016; Verguts, 2017). Originally, this theory was proposed for the visual cortex, but has later been extended to cortical processing more generally. At this time, a massive amount of electrophysiological data supports (aspects of) the CTC theory (Womelsdorf et al., 2010), also in human cognitive control (Cavanagh and Frank, 2014), and in particular its relation with the slower theta wave (see also "Empirical predictions" section below).

In a second broad oscillation theory, Lisman and Jensen (2013) proposed that neural spikes that are locked to different gamma waves represent different pieces of information, where each gamma wave itself is locked to a different phase of the slower theta waves. This theory originates from findings observed in the hippocampus. In particular, the phenomenon of theta phase precession (O'Keefe and Recce, 1993) entails that as an animal proceeds in a cell's preferred location, the cell's spike firing time relative to theta phase moves earlier (processes) in time. From this observation, it was proposed that the time of spike firing relative to theta phase is informative for downstream areas. This is what we will call the theta-phase binding (TPB) theory. Lisman and Jensen (2013) generalized this theta phase precession theory by proposing that items in working memory (and, potentially, their presentation order) are stored by locking consecutive items in the list (each of them represented as neurons locked to gamma waves), to consecutive phases of theta (see also "Empirical predictions" section below). Regarding ordered sets, during an individual theta cycle, neurons representing each item of the sequence fire in a fixed temporal order (e.g., the order of presentation), thereby conserving the ordinal information of the sequence.

Clearly, CTC and TPB theories have some commonalities; and they can be combined in the same framework, as was already demonstrated by McLelland and VanRullen (2016). Specifically, in a two-layer neural network model, they demonstrated that inhibition in the higher layer only, would cause patterns similar to what CTC would predict; whereas inhibition in both lower and higher layers, would instead cause patterns more similar to TPB. Also, our own time-based binding theory combines elements of CTC and TPB. Like CTC, it proposes that binding elements together is crucial for cross-area communication. Also, like CTC, it proposes that such binding is efficiently implemented *via* time. Like TPB, it holds that different packages of bindings can each be locked to a phase of a slower wave.

We emphasized that role-filler independence is a crucial property of an efficient (learning) cognitive system; role-filler independence itself can be considered a special case of factorization or disentanglement, a major aspect of modern Artificial Intelligence systems (Higgins et al., 2017; Steenbrugge et al., 2018). Role-filler independence implies that the two constituents must be bound somehow, and we mentioned both synaptic and time-based approaches for achieving this. One synaptic approach to achieve role-filler independence was described by Kriete et al. (2013). These authors propose that the "address" of a filler would be gated into a "slot" relevant for a specific role that is encoded in the prefrontal cortex. In this way, roles and fillers remain separate (disentangled), but can still be combined when a filler is queried (e.g., who owns the book?). Finally, we note that, besides synapses and time, other binding schemes can be devised. For example, Akam and Kullmann (2010, 2014) proposed that also frequency could be used to bind elements together (as is also implemented in telecommunication systems). In general, any "labeling" of two or more elements would in principle be usable. Time and frequency happen to be the ones that are most naturally implemented *via* oscillations.

Empirical Predictions

Our perspective also leads to several empirical directions for future research. Ideally, empirical predictions are derived from a computational model (e.g., Senoussi et al., 2020b). However, whereas the current model can be used to illustrate theoretical concepts (as we did here), it is not ideal for deriving specific empirical predictions, because it lacks critical components to derive such predictions, such as a response interface. While the full model awaits further development, we already point out more general predictions in the remainder of this section.

One interesting direction is to look at evidence for oscillations in behavioral measures. Recent literature has started to do just that by using dense temporal sampling paradigms in which the time interval between two events (e.g., a cue and a target) is varied across trials, allowing to estimate a time course of behavioral performance. For instance, Landau and Fries (2012) asked their subjects to pay attention to two horizontally lateralized gratings and notify the appearance of a brief contrast decrease. Spectral analysis (e.g., using Fast-Fourier Transform) of time-course of the accuracy data, obtained *via* a dense temporal sampling paradigm, revealed that attention fluctuated at theta frequency between the two gratings. Several other studies have replicated this finding (e.g., Fiebelkorn et al., 2013; Dugué et al., 2016; Senoussi et al., 2019; Michel et al., 2021; see Kienitz et al., 2021 for a review), and additionally expanded the study of oscillations in behavioral performance to the field of working memory (Peters et al., 2020; Pomper and Ansorge, 2021). Of importance, although the findings on fluctuations in attentional sampling might be interpreted as reflecting a different role of oscillations than the one that is proposed in this article, we believe that these potential roles share a core function supported by oscillations, namely to avoid interference. Fiebelkorn and Kastner (2019) proposed that across one cycle of a theta oscillation, there is an alternation between sensory information sampling (e.g., at a spatial location) and motor processes associated with shifting the focus of attention (e.g., to another location or object). They argue that this temporal isolation of distinct processes (i.e., sensory and motor) allows to resolve potential conflicts between sampling and shifting functions by organizing them temporally. This is in line with the role of oscillation we consider in the current article which is to avoid the massive interference that parallel processing in neural networks may naturally yield. Altogether, and irrespective of the specific role attributed to oscillations, this rapidly growing body of literature provides converging evidence that oscillatory processes are central to behavioral performance in a wide range of cognitive functions, in which they provide both a mechanism to sample or bind information, as well as a capacity limit of these functions.

In the field of working memory, predictions from the TPB theory have received support from several studies. According to the TPB theory, theta oscillations originating from medial temporal lobe and basal forebrain structures (e.g., hippocampus, septum) are hypothesized to support the maintenance of the ordinal information in an item sequence in working memory (Lisman and Jensen, 2013): the phase of theta oscillations structures the activation of distinct neural populations oscillating at gamma frequency, each representing an item of the maintained sequence. This theory thus predicts that a lower frequency of theta oscillations, leading to longer periods in which items could be nested, would lead to higher working memory capacity. Some studies have confirmed this prediction empirically by showing that higher working memory loads led to a reduction of theta frequency (Axmacher et al., 2010; Kosciessa et al., 2020). Moreover, a recent study causally tested this prediction using transcranial alternating current stimulation (tACS; Wolinski et al., 2018) and showed that stimulating a fronto-parietal network at a slow theta frequency (i.e., 4 Hz) led to higher working memory capacity than stimulating at a faster theta frequency (i.e., 7 Hz). These studies confirm some predictions from the TPB theory as applied to working memory; and thus, they strengthen the view proposed in this article that oscillatory frequency modulates capacity limits in working memory, thereby constituting a factor limiting cognitive resources. Finally, we note that TPB naturally accounts for contiguity effects (i.e., if item n from a sequence in a free recall paradigm is recalled, then contiguous items at locations n - 1 and n + 1 are likely to be recalled next; Healey et al., 2019); and particularly the asymmetric nature of contiguity effects (the item at location n + 1 is more likely to be recalled than the item at location n - 1). Indeed, in TPB, items are preferentially "replayed" in the order in which they appeared, and this has been observed empirically (Reddy et al., 2015, 2021; Kok et al., 2017; Blom et al., 2020; Senoussi et al., 2020a). However, a long list of benchmark phenomena relating to the contiguity effect have been reported (e.g., 34 phenomena by Healey et al., 2019), and we do not claim that we can explain them all based on time-based binding; nor, indeed, that time-based binding is responsible for all of them. In fact, the reader will recall that we propose that time-based and synaptic processes necessarily co-exist for the construction of (episodic) memories. It will remain a future challenge to disentangle which of the two processes accounts for which phenomenon.

A related body of work has investigated the role of theta oscillations generated by the anterior cingulate cortex (ACC) in cognitive control processes (Cavanagh and Frank, 2014). Several studies have shown that these frontal theta oscillations are elicited when control is needed, i.e., during conflict or in preparation of a difficult task (Cavanagh and Frank, 2014), and allow to coordinate distant neural populations to create task-relevant functional networks through synchronization (Bressler et al., 1993; Varela et al., 2001; Palva et al., 2005; Canolty et al., 2006; Voloh and Womelsdorf, 2016). This theta-rhythmic process has been shown to support successful task performance (Voloh et al., 2015) and to support the instantiation of task rules (Womelsdorf et al., 2010). Critically, the frequency of these oscillations has recently been proposed to shift in response to task demands. Indeed, a recent study proposed that theta frequency balances reliable instantiation of task rules and the rapid gating of sensory and motor information relevant for the task at hand (Senoussi et al., 2020b). They showed that this shift is observable both in oscillation of behavioral performance (using a dense behavioral sampling paradigm) and electrophysiological data, and that the magnitude of this shift correlates with inter-individual differences in task performance (Senoussi et al., 2020b). Other studies have also reported the involvement of different low-frequency bands during top-down control processes, especially in hierarchical task implementation

(Cooper et al., 2019; de Vries et al., 2020; Riddle et al., 2020; Formica et al., 2021). Together, these results open interesting avenue for future research on the conventional frequency limits of oscillations supporting cognitive control (usually attributed to the theta band) and more generally on the nature of the constraints controlling and limiting frequency shifts in neural oscillations. Future studies investigating the causes and consequences of frequency shifts in neural oscillations supporting cognitive control, for instance through neuromodulatory systems (Sara, 2015; Silvetti et al., 2018), will undoubtedly provide valuable insights on the neural bases of cognitive resources and their limitations.

CONCLUSION

We proposed that neural oscillations are both a solution to and a problem for flexible cognition. They are a solution because they allow items to be bound "on the spot," leaving no synaptic traces that need to be erased afterward, thus causing minimal interference (a notorious problem in standard artificial intelligence). They are also a problem because of the natural bound this system imposes; in this sense (only), the theory could be considered a resource theory.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article and supplementary material, and the scripts to run the model and reproduce the simulations are available on this GitHub repository: https://github.com/mehdisenoussi/resources. Further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

MS, PV, and TV developed the model. MS and PV analyzed model simulations. All authors wrote the manuscript.

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APPENDIX

The activity of each neuron of a neural triplet (u, v, and n) are defined by this system of differential equations:

$$u_j' = -u_j + f\left(a_{ee}\cdot\tilde{u}_j - a_{ei}\cdot\tilde{v}_j + a_{en}\cdot\tilde{n}_j - \theta_e + s_j\,(t)\,\right) \tag{1}$$

$$\tau_i\cdot v_j' = -v_j + f\left(a_{ie}\cdot u_j - a_{ii}\cdot v_j + a_{in}\cdot n_j - \theta_i\right) \tag{2}$$

$$\tau_n\cdot n_j' = -n_j + a_n\cdot u_j^p\left(1 - n_j\right) \tag{3}$$

Where u_j, v_j, and n_j are the activity of the fast-excitatory, inhibitory and slow-excitatory components of node j, respectively. $s_j\,(t)$ is the input signal (i.e., stimulation). Intratriplet coupling strengths are denoted by *a* parameters. Temporal constants are denoted by τ, note that there is no temporal constant the fast-excitatory component (i.e., $\tau_e = 1$). The parameters' index *e* refers to the fast excitatory component, the index *i* to the inhibitory component, and the index *n* to the slow-excitatory component. The parameters' values are given in the table below:

Temporal constants		**Intratriplet coupling strengths**							**Thresholds**		**NMDA gain**
τ_i = 32 or 24	τ_n = 144	a_{ee} = 14	a_{ei} = 10	a_{ie} = 20	a_{en} = 4	a_{ii} = 8	a_{in} = 0.1	a_n = 2	θ_e = 6	θ_i = 5	*p* = 2

The function f(x) represents the firing rate (approximating a noisy-integrate-and-fire spiking neuron): $f(x) = \sqrt{\frac{x}{1-exp(-\beta\cdot\, x)}}$ where $\beta = 1$.

The interaction between nodes (i.e., neural triplets) is defined by this equation:

$$\tilde{\alpha}_j = \left(\alpha_j + c_z\sum_{k\neq j}\alpha_k\right)\left(1 + c_z(N-1)\right)^{-1} \tag{4}$$

Where α_j, denotes one of the three components of a triplet (i.e., u_j, v_j, or n_j). Intertriplet coupling strengths are denoted by *c* parameters. The parameters' values are given in the table below:

Intertriplet coupling strengths		**Number of nodes**
c_e = 0.001	c_{ei} = 0.03	N = 5

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BRIEF RESEARCH REPORT
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Add Bilingualism to the Mix: L2 Proficiency Modulates the Effect of Cognitive Reserve Proxies on Executive Performance in Healthy Aging

Federico Gallo[1,2]*, Joanna Kubiak[3] and Andriy Myachykov[1,3]

[1] Centre for Cognition and Decision Making, Higher School of Economics, Institute for Cognitive Neuroscience, Moscow, Russia, [2] Centre for Neurolinguistics and Psycholinguistics, Vita-Salute San Raffaele University, Milan, Italy, [3] Department of Psychology, Northumbria University, Newcastle upon Tyne, United Kingdom

We investigated the contribution of bilingual experience to the development of cognitive reserve (CR) when compared with other, traditionally more researched, CR proxies, in a sample of cognitively healthy senior (60 +) bilingual speakers. Participants performed in an online study where, in addition to a wide inventory of factors known to promote CR, we assessed several factors related to their second language (L2) use. In addition, participants' inhibitory executive control was measured via the Flanker Task. We used Structural Equation Modeling to derive a latent composite measure of CR informed by traditional CR proxies (i.e., occupational complexity, marital status, current and retrospective socio-economic status, physical exercise, perceived positive support, maximal educational attainment, frequency of leisure activities and extent of social network). We examined whether bilingualism may act as a mediator of the effects of such proxies on cognitive performance therefore assessing the unique contribution of dual language use to CR. First, our analyses revealed facilitatory effects of both L2 age of acquisition and L2 proficiency on the executive performance. Second, our analyses confirmed the moderating role of bilingual experience on the relationship between other factors known to promote CR and cognitive integrity, revealing a strong contribution by bilingualism to CR development. Our findings provide further support to the notion that bilingualism plays an important role in mitigating cognitive decline and promoting successful aging.

Keywords: bilingualism, cognitive aging, cognitive reserve, cognitive reserve proxies, executive functions

Edited by:
Bernhard Hommel,
University Hospital Carl Gustav Carus, Germany

Reviewed by:
Greg Poarch,
University of Groningen, Netherlands
Ramesh Kumar Mishra,
University of Hyderabad, India

****Correspondence:***
Federico Gallo
fgallo@hse.ru

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INTRODUCTION

A key concept when discussing prevention or mitigation of cognitive aging is that of cognitive reserve (CR; Stern et al., 2020). CR is defined as the discrepancy between the expected and observed levels of cognitive impairment, given the observed level of age-related neuropathology or brain disruption (Stern et al., 2020). In other words, CR is the individual ability to compensate for age-related neural deterioration and maintain optimal cognitive functioning. Many lifestyle factors have been suggested to promote successful aging by means of CR development (for a review see Cheng, 2016), and bilingualism has been implicated as one such factor (for a review see Gallo et al., 2020).

While evidence supporting the role of bilingualism as a CR promoter continues to accumulate (e.g., Gold et al., 2013a; Perani et al., 2017; Del Maschio et al., 2018), research on bilingualism-related benefits on cognitive aging seems to fail, up to this point, to dialogue with the research on more generally oriented CR factors. Importantly, bilingualism might play a unique role among the known CR proxies due to our knowledge of the route through which it affects aging, namely its putative beneficial role on executive functioning. Indeed, parallel activation of co-present linguistic systems has been extensively observed in the bilingual brain (e.g., Kroll et al., 2014). This simultaneous activation of competing information leads to a conflict, which must be successfully and rapidly resolved by the bilingual speaker. The cognitively effortful simultaneous management of two competing linguistic systems is governed by a *language control* device wired in a neural network that overlaps with the domain-general executive system (Abutalebi and Green, 2016). Thus, via this sustained control effort, bilingualism may act as a "cognitive gym" allowing daily training and strengthening of the executive control, both at the neural and the behavioral levels (Abutalebi and Green, 2016; Bialystok, 2017). This hypothesis is in line with training effects widely observed for other executive sub-systems, such as attention (Posner and Fan, 2008; Tang and Posner, 2009; Posner et al., 2015). Indeed, several investigations report that bilinguals outperform monolinguals in various executive functions tasks (for a review see Bialystok, 2017) and show increased structural density and functional efficiency in the executive network, relative to monolinguals (for a review see Li et al., 2014), across the lifespan. Given the fundamental role that executive functions play in the cognitive aging process (for a review see Reuter-Lorenz et al., 2021), the continuous executive training provided by bilingualism would end up supporting successful aging. Nonetheless, some degree of variability emerges in the literature when attempting to replicate such bilingualism-induced beneficial effects (see e.g., Paap et al., 2015). Such variability has been recently ascribed to the tendency of dichotomizing the spectrum of bilingual experience, i.e., favoring group comparisons between "bilinguals" and "monolinguals" over a detailed, continuous assessment of the individual bilingual experience (e.g., Luk and Bialystok, 2013; Surrain and Luk, 2019). To overcome this issue, in line with recent investigations (e.g., Hervais-Adelman et al., 2018; DeLuca et al., 2019; Gallo et al., 2021), here we operationalized bilingual experience continuously, for the first time to our knowledge in an investigation on senior individuals.

The abovementioned peculiar stance of bilingualism among CR-inducing factors, i.e., the extra insight into the cognitive domain acting as a relay for age-related beneficial effects, provides the ground to test bilingualism's role as a CR factor in a novel way, namely assessing the extent of bilingualism's contribution compared to those of other, traditionally more researched, CR proxies. To this end, here we investigated whether bilingualism may modulate the relationship between widely known CR proxies, namely physical exercise, education, occupational complexity, social network, and leisure activities (for a review see Cheng, 2016), and cognitive performance during senescence. Given the amount of available evidence on positive effects of bilingualism on executive functioning, a set of cognitive ability that is well-known to play a central part in the cognitive aging process (for a review see Luszcz and Lane, 2008), we expected to observe a modulation of such relationship, indicating a primary role of multiple language use in supporting successful aging and preventing age-related cognitive decline.

MATERIALS AND METHODS

Participants

64 healthy older adults (30 males; mean age = 64.7, SD ± 4.7) were recruited via social media platforms (e.g., Facebook) and through the research recruitment platform Prolific[1]. The Psytoolkit software was used for data collection (Stoet, 2010, 2016). Requirements to participate in the study included at-least-partial knowledge of a second language (L2) and being aged 60 or above. Participants were screened for the presence of psychiatric or neurological impairments and those with a history of such impairments were removed from the analysis, resulting in the exclusion of one subject who reported an active Major Depression diagnosis. Participants also underwent an adapted online version of the Mini-Mental State Examination (MMSE; Cockrell and Folstein, 2002), to further control for the possible presence of age-related cognitive impairment in the sample. No participants were removed due to insufficient MMSE performance. Of the 63 participants eligible for the study, 36 spoke various first languages (L1s) and English as an L2, while the other 27 spoke English as an L1 and various L2s. We included the 36 L2 English speakers in the core analyses, while the full sample was used for sensitivity analyses and derivation of CR index (see in detail below). Participants were informed that they could withdraw at any point of the study and that all of the provided data would remain anonymous. Further, each subject was warned about potentially sensitive questions. On questions deemed as potentially upsetting, the option "I don't know" was provided in order to allow participants to avoid answering. All participants provided informed consent to take part in the study.

Demographics, General Intelligence, and Language Profile Assessment

All participants underwent a comprehensive online questionnaire in the Qualtrics platform that investigated their profiles in the following dimensions:

- Socio-demographics: age, sex, ethnicity, nationality, marital status, highest educational attainment;
- Physical health: nutritional status and dietary habits, cardiovascular health, neurological health, psychological health, presence of diabetes;

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[1] www.prolific.co

- Occupation: current and retrospective employment status, type of longest occupation, satisfaction with professional life;
- Retrospective socioeconomic status: parents' occupation, presence of financial problems during upbringing;
- Social network: contact frequency with relatives, friends and neighbors;
- Leisure activities: participation frequency in different leisure activities;
- Physical exercise: frequency of low- and high-impact physical activities;
- Perceived positive support: level of satisfaction with the support received from contacts in (eventual) situations of need.

A separate section of the questionnaire investigated participants' language background, including questions regarding L2 exposure, L2 proficiency, and number of years passed since L2 acquisition (henceforth, L2 years, a reversal of the age of acquisition measure devised to produce effects in the same direction of L2 proficiency and L2 exposure), as well as number of languages spoken. The full questionnaire can be found in **Supplementary Material**. Participants also underwent a subset of the Raven's Standard Progressive Matrices for adults (Court and Raven, 1992) to assess their general intelligence, as well as the online Cambridge test for adult learners[2] to assess their proficiency in English.

Assessment of Executive Performance

To investigate participants' executive ability, we presented them with a Flanker Task (Fan et al., 2005), a task measuring inhibitory executive control. In this task, a fixation cross is presented at the center of the screen for 400 ms, followed by an array of five arrows pointing to the left or to the right for a maximum duration of 2,000 ms. Participants are required to indicate the direction of the central target arrow by pressing the corresponding arrow key on the PC keyboard as accurately and fast as possible. Targets appear surrounded by flankers pointing to the same direction (→→→→→) (i.e., congruent condition), to the opposite direction (←←←←←) (i.e., incongruent condition), or by neutral dashes (– – → – –) (i.e., neutral condition). While congruent trials facilitate target response, incongruent trials present conflicting visual information and thus require inhibitory executive control to suppress its impact on the target response execution, typically entailing lower accuracy and longer reaction times (RTs). The three trial types were presented in a pseudo-randomized order during two runs of 96 trials each (32 for each condition). Participants were familiarized with the task via a practice run of 24 pseudo-randomized trials. The rationale behind the choice of this task lies in the fact that it mimics closely instances of bilingual language control, by relying on cognitive mechanisms such as conflict monitoring, interference inhibition and response selection, which are routinely required from bilinguals to carry out successful communication (Green and Abutalebi, 2013). For this reason, the Flanker task (sometimes replaced by the analysis of the sole executive component of the ANT task; Fan et al., 2005) is typically used in research on the cognitive consequences of bilingualism (Luk et al., 2010; Abutalebi et al., 2012; Del Maschio et al., 2018). As an additional reason behind our decision, we aimed to obtain results comparable to those of our previous investigations on the relationship between bilingualism and cognitive reserve, which all deployed the Flanker task (e.g., Del Maschio et al., 2018; Gallo et al., 2021).

Statistical Analyses

We used generalized Structural Equation Modeling (gSEM) in STATA 17 (StataCorp, 2021) to derive a latent measure of CR combining the contribution of different traditional CR proxy variables to a latent CR variable. The model (see **Figure 1**) included contributions from occupational complexity, marital status, presence of financial difficulties during upbringing, physical exercise and perceived positive support, as well as educational attainment, frequency of leisure activities and extent of social network. Since the first five predictors were categorical, an ordinal logit family link was used. For the last three, continuous, predictors, a linear family link was used. The corresponding linear SEM (STATA 17 does not allow postestimation of goodness of fit indices in the generalized SEM framework with mixed continuous and categorical predictors) fit the data well (χ^2 of fitted vs. saturated model test = 18.879, df = 20, $p = 0.530$). Next, we predicted individual values of the CR latent variable, which was normally distributed with a mean of 0.

As per the Flanker data, we removed incorrect trials and false starts (i.e., RT < 100 ms), as well as outlier trials, namely trials with RTs falling beyond 3 SDs from the mean RT of each participant. Neutral trials were also discarded, since we focused on the conflict effect, a measure of inhibitory executive control calculated as the difference between RTs of congruent and incongruent trials.

The Impact of Bilingual Experience on Age-Related Cognitive Decline

We aimed to investigate whether bilingual experience, measured as a continuous variable on three dimensions, namely L2 proficiency, L2 exposure and L2 years, impacts executive performance in healthy aging. Nonetheless, data on L2 exposure presented too little variability, and thus had to be excluded from the analyses: 80% of the participants reported to speak their L2 on a daily basis, while the remaining 20% was distributed across the four categories of weekly, monthly, quarterly or more rarely (see **Figure 2** for the distributions of L2 proficiency and L2 years). To test our hypothesis, we used a by-trial linear mixed-effects approach, which made it impossible to compute the conflict effect in the traditional way, namely as the difference between average RTs in the congruent and incongruent conditions. Hence, since we were interested in the differential effect of bilingualism on incongruent trials, i.e., those tapping on executive inhibitory control, we inserted an interaction term by trial type for each of our predictors of interest. Our model thus included Flanker RTs as the dependent variable, L2 proficiency, L2 years (both in interaction with trial type) and trial type as predictors, age,

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[2] http://www.cambridgeenglish.org/test-your-english/general-english/

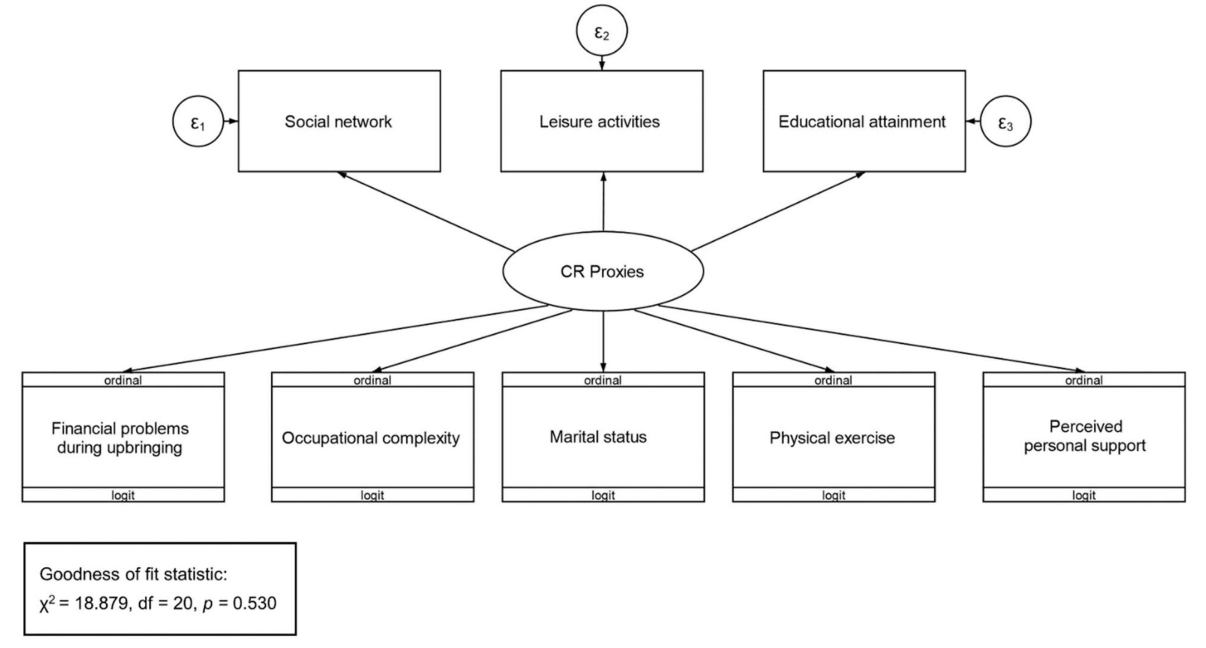

FIGURE 1 | Structure of the structural equation model (SEM) used to derive the CR Proxies latent variable.

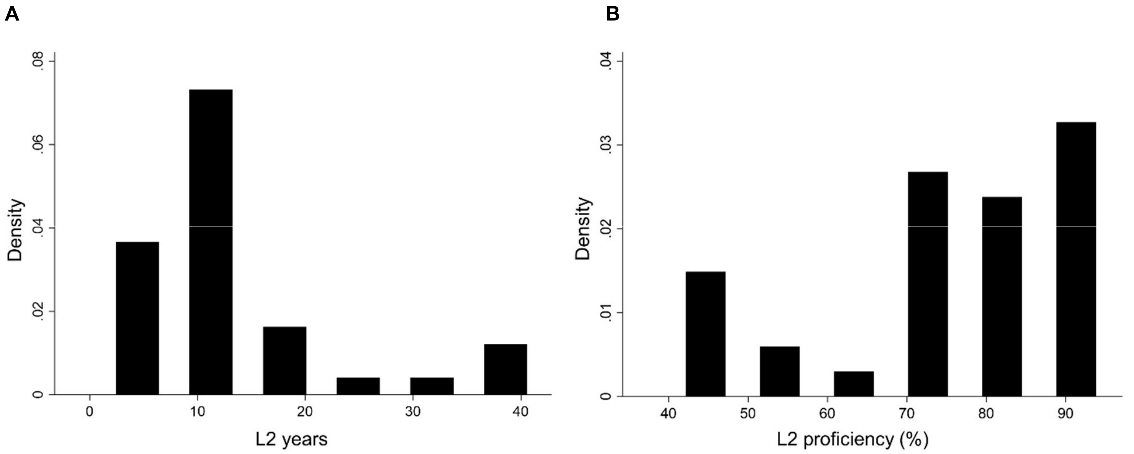

FIGURE 2 | Histograms of the distribution of **(A)** number of years passed since L2 was acquired (L2 years) and **(B)** L2 proficiency in the L2-English subsample.

sex and general intelligence as covariates, as well as random intercepts for participants and random slopes for trials.

The Impact of Bilingualism on the Relationship Between Cognitive Reserve Proxies and Cognitive Performance

Beside its consequences for cognitive performance *per se*, we aimed at testing whether bilingualism still exerted a beneficial effect on the cognitive aging trajectory when traditional CR proxies were also taken into account. Thus, we investigated whether L2 proficiency and L2 years modulate the well-known relationship between CR proxies and cognitive performance during senescence. To this end, we used a linear mixed-effects model including Flanker RTs as the dependent variable, three-way interactions between L2 proficiency, trial type and the CR proxies latent variable (henceforth, CR proxies) and L2 years, trial type and CR proxies, respectively, as predictors, age, sex and general intelligence as covariates, as well as random intercepts for participants and random slopes for trials.

Sensitivity Analyses

We additionally replicated the same set of statistical analyses in the whole sample of 63 individuals. The reason for this choice was two-fold: on the one hand, it allowed us to almost double our sample size, increasing statistical power; on the other, it allowed us to test whether the effects found for a sample of individuals sharing their L2 but differing in their native language also extend to individuals with a reverse linguistic profile, i.e., sharing their L1 but speaking different L2s. There was no significant difference in L2 proficiency or L2 years between the two subsamples.

RESULTS

The Impact of Bilingual Experience on Age-Related Cognitive Decline

The analysis revealed a significant effect of both L2 years ($\beta = -2.797$; $p < 0.001$) and L2 proficiency ($\beta = -9.045$; $p < 0.001$) on the executive performance of senior individuals, which differentially impacted congruent and incongruent trials. In particular, both variables beneficially affected the performance in the incongruent trials, but had no effect on the congruent trials, in line with the hypothesis that bilingualism enhances executive control abilities (see **Figure 3**). The beneficial impact of L2 proficiency was higher relative to that of L2 years.

The Impact of Bilingualism on the Relationship Between Cognitive Reserve Proxies and Cognitive Performance

We registered a significant three-way interaction between L2 proficiency, trial type, and CR proxies ($\beta = 45.276$; $p < 0.001$), while it only approached significance for L2 years ($\beta = 7.483$; $p = 0.092$), consistently with the previous analysis showing a stronger contribution by L2 proficiency. The interaction plot (see **Figure 4**) revealed that in the incongruent trials, for increasing levels of L2 proficiency: (i) executive performance levels increased, irrespectively of CR proxies; (ii) the relationship between higher scores of CR proxies and better executive performance was progressively mitigated, until disappearing at high levels of L2 proficiency. These results indicate a contribution of bilingualism to CR that spans beyond that of traditional CR proxies.

Sensitivity Analyses

Both L2 years ($\beta = -2.3$; $p < 0.001$) and L2 proficiency ($\beta = -5.723$; $p < 0.001$) showed a positive effect on RTs of incongruent trials of the Flanker Task. Moreover, L2 proficiency, but not L2 years, showed a significant interaction with trial type and CR proxies in the modulation analysis ($\beta = 45.124$; $p < 0.001$). Thus, the whole-sample sensitivity analyses confirmed our previous results.

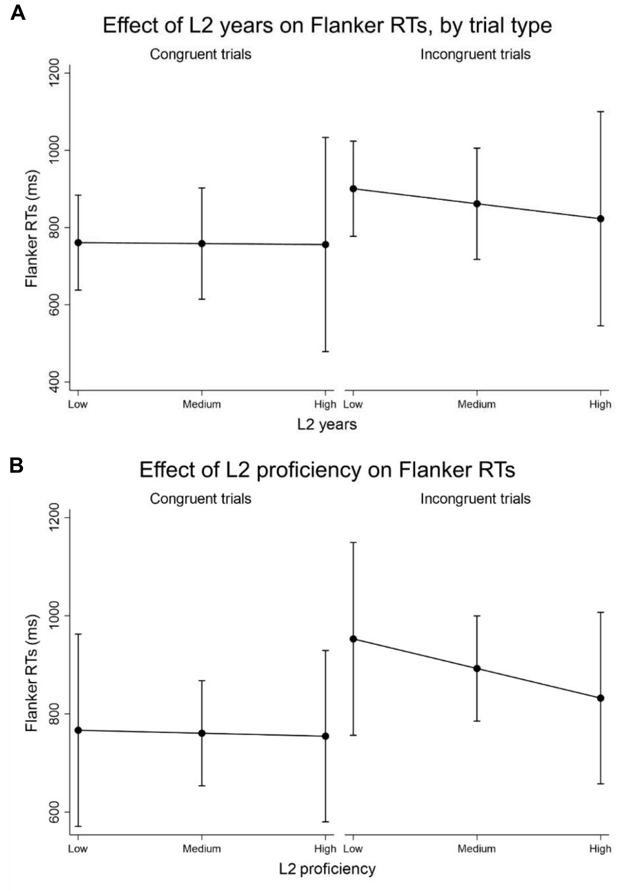

FIGURE 3 | (A) Interaction plot for the L2 years * trial type interaction predicting Flanker RTs (in ms). Increasing levels of time passed since acquiring L2 predict lower RTs, i.e., better inhibitory executive performance; **(B)** interaction plot for the L2 proficiency * trial type interaction predicting Flanker RTs (in ms). Increasing levels of L2 proficiency predict lower RTs, i.e., better inhibitory executive performance.

DISCUSSION

The study reported here investigated, for the first time to our knowledge, the effects of bilingualism on executive functioning during senescence operationalizing the bilingual experience as a continuous rather than a categorical variable. This approach, while in line with the general recent trend in bilingualism research (e.g., Hervais-Adelman et al., 2018; DeLuca et al., 2019; Del Maschio et al., 2020; Gallo et al., 2021), was yet to be applied to studies on senior individuals. A continuous assessment of the bilingual experience allows to draw a more detailed, individualized linguistic profile for a life experience that is intrinsically different for each individual, thus contributing to overcoming issues related with inconsistencies in methodological designs and results, which have been plaguing bilingualism research in recent years (Luk and Bialystok, 2013; Mishra, 2015; Surrain and Luk, 2019). Our approach revealed a beneficial effect of increasing L2 proficiency and amount of time passed since acquiring L2 on executive functioning in a sample of bilingual older adults. This result is in line with several previous investigations showing that bilingualism supports the maintenance of optimal executive performance during senescence (e.g., Bialystok et al., 2004; Gold et al., 2013b; Estanga et al., 2017; Del Maschio et al., 2018; Incera and McLennan, 2018). The rationale behind this effect would lie in the extra burden placed on bilinguals' executive control by the constant necessity to manage crosslinguistic interplay: mechanisms as response selection, interference inhibition, information updating

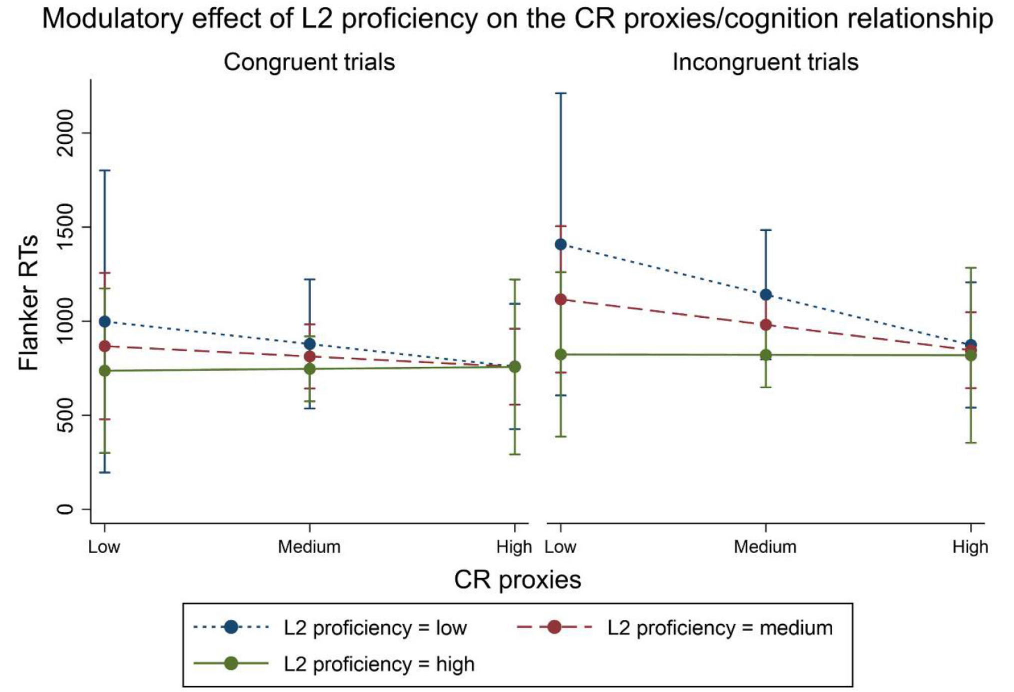

FIGURE 4 | Interaction plot for the L2proficiency*trial type*CR proxies interaction predicting Flanker RTs (in ms). Higher L2 proficiency entails lower RTs, i.e., better inhibitory executive performance. Increases in the CR proxies score predict lower incongruent RTs only at low levels of L2 proficiency. At increasing levels of L2 proficiency, variations of CR Proxies score do not affect executive performance.

and task-switching have been shown to be constantly active in the bilingual mind and brain during language processing (Abutalebi and Green, 2007; Green and Abutalebi, 2013). This training is thought to lead to ameliorations in bilinguals' executive network capacity, efficiency and flexibility (for a review see Kroll et al., 2015), namely the action mechanism of CR (Stern, 2009).

Indeed, our findings point to a primary role of bilingualism as a factor supporting CR development, at least in the executive domain. L2 proficiency appeared to modulate the widely known relationship between the most traditional CR proxies, namely level of occupational complexity, maximal educational attainment, social network size and frequency of leisure activities and physical exercise (for a review see Cheng, 2016), and cognition during senescence. For high levels of L2 proficiency, this relationship disappeared, leaving the stage to beneficial effects of bilingualism only, which continued to predict performance level. Our results, indicating a strong contribution of bilingualism to CR development, complement previous findings that dual language use mitigates the relationship between age-related gray (Del Maschio et al., 2018) and white (Gold et al., 2013a) matter deterioration and cognitive decline.

While our results are limited to the executive-function domain, it is key for future research to test whether these effects extend to other cognitive domains and to the cognitive aging trajectory in general. Given the primary role attributed to depletion of executive resources in the cognitive aging process (Davis et al., 2008; Luszcz and Lane, 2008), we hypothesize that bilingualism will prove beneficial for successful aging in general. This hypothesis is supported by evidence that multiple language use supports the maintenance of various non-executive abilities during senescence, such as episodic memory (Wodniecka et al., 2010; Ljungberg et al., 2013), working memory (Bialystok et al., 2014), semantic memory (Arce Rentería et al., 2019), and general intelligence (Bak et al., 2014). Obtaining further evidence is crucial to solidify the presence of bilingualism among widely accepted CR-supporting factors and thus capture the attention of policy makers to reinforce the implementation of bilingual programs. Moreover, although our results highlight a *general* contribution of bilingualism to executive functioning and cognitive reserve, which spans across different language pairs, it is important to direct future efforts toward illuminating the impact of L1-L2 linguistic distance, and other cross-linguistic differences, on the effects presented here. This might further inform policy makers' attempts to successfully design bilingual interventions and educational policies aimed at mitigating the aging trajectory at various stages of the lifespan.

Indeed, with average life expectancy constantly increasing, age-related cognitive decline is becoming a more and more central issue in our society. Dementia incidence is growing (World Health Organization, 2019), pharmacological solutions to age-related brain pathology are still unsatisfactory (Dyer et al., 2018) and healthcare expenditure dedicated to senior populations is increasingly burdening the public coffers of industrialized countries (Wimo et al., 2017). Thus, the quest for finding non-pharmacological, ecological ways to prevent cognitive aging such as, possibly, bilingualism, must be regarded as an utmost priority by the scientific community.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author/s.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Ethics Committee at Northumbria University. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

FG: study conception and design, data analysis, and interpretation. JK: data acquisition. AM: project supervision. All authors: drafting or revising the manuscript for intellectual content, approval of the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2022.780261/full#supplementary-material

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OPINION
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Trade-Off vs. Common Factor—Differentiating Resource-Based Explanations From Their Alternative

Christoph Naefgen and Robert Gaschler*

Abteilung Allgemeine Psychologie: Lernen, Motivation, Emotion, University of Hagen, Hagen, Germany

Keywords: cognitive resources, common factor, trade-off, intra-individual analyses, inter-individual and intra-individual differences

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****Correspondence:***
Christoph Naefgen
christoph.naefgen@fernuni-hagen.de

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It has long been appreciated that mechanistic explanations of cognition can be tested better when experiment-based studies are complemented with non-experimental studies. For instance, work on executive functions (e.g., Engle et al., 1999; Miyake et al., 2000; Friedman and Miyake, 2004; Oberauer, 2005; Schmiedek et al., 2007) has used between-person variability to more precisely identify candidate mechanisms that explain phenomena related to executive functioning. Notably, such approaches are often focused on analyzing between-person variability rather than on within-person variability. Yet, when seeking mechanistic explanations, cognitive psychologists usually want to know what causes a within-person effect or change (cf. Lewin, 1931; Hommel, 2020a,b), rather than what makes people different from one-another. To counteract risks of ecological fallacy, inquiries should therefore focus on describing and accounting for within-person variability rather than between-person variability. Within-person variability can present as effects of experimental conditions on the individual (rather than group-average effects; cf. Marciano and Yeshurun, 2017) or as spontaneous fluctuation (i.e., day-to-day variability).

Here we present a way of differentiating what we call cognitive resources and common factors from each other using within-person covariance patterns. While several research traditions in cognitive psychology already emphasize within-person variability as a notable phenomenon [e.g., early language development (van Geert and van Dijk, 2002), intermediate phenotypes of ADHD (Castellanos et al., 2005), affect (Eid and Diener, 1999)], we provide some elaboration on uses of within-person variability for readers coming from backgrounds where it usually is not as emphasized (i.e., experiment-based cognitive psychology). Even for those already generally familiar, the specific perspective we describe could be novel, as it focuses co-variation rather than measures of variability. The scope of this paper thus extends to research contexts where theories have a cognitive resource or a common factor as an element and the proposed method serves the purpose of constraining the plausible theory space or to test that aspect of already specified theories (some general areas where this could be useful are attention, executive functioning, dual-tasking).

We link the concept of a cognitive resource to that of a trade-off, signified by negative correlations between two measures on a within-person level of analysis, differentiating it from cases where a common factor is dominant, which results in positive within-person correlations. The two scenarios are described in the following segments and illustrated in **Figure 1**.

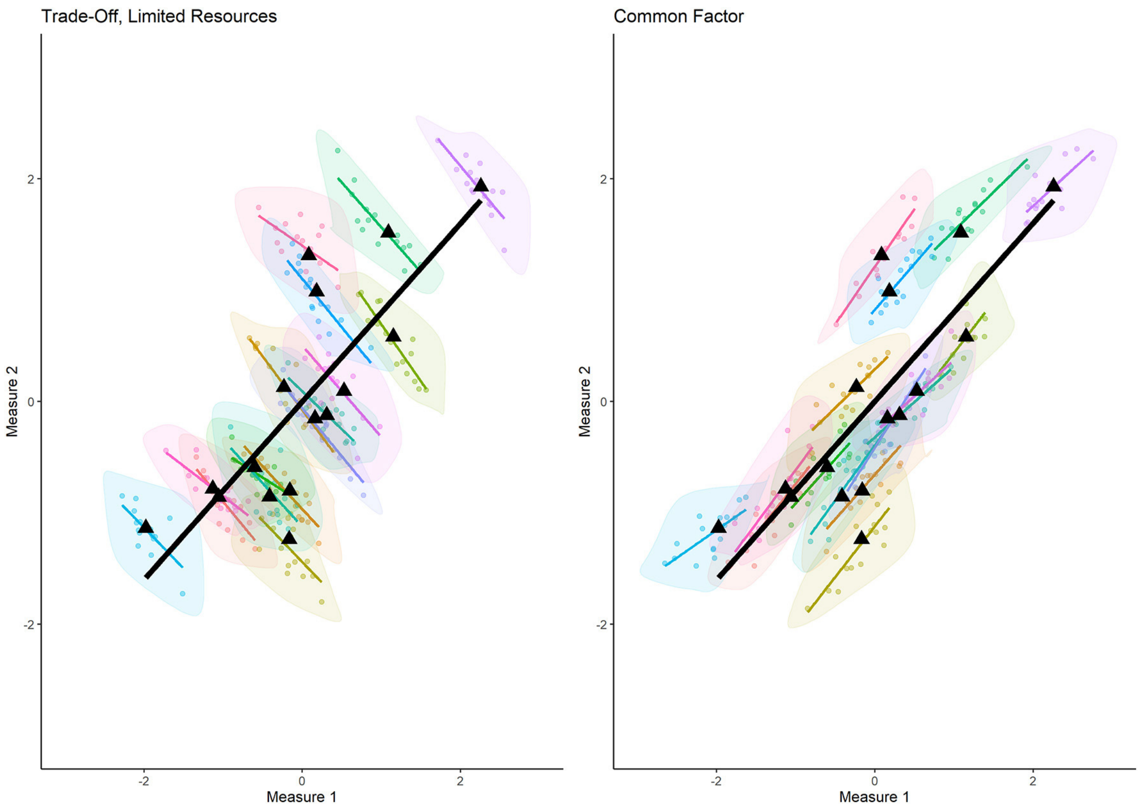

FIGURE 1 | Simulated data illustrating the two scenarios described in this opinion paper that can occur when investigating the correlations between two theoretically-linked measures on a within-person level. The different colors denote different "participants", the thin colorful lines illustrate the within-person correlations for each simulated participant. The black triangles are places in the mean values for the two measures for each participant and the thick black lines are the between-person correlations resulting out of these averaged values. In the left panel we illustrate what a trade-off scenario would look like and in the right panel what a common factor scenario would look like.

SHORT CHARACTERIZATION OF THE TWO VIEWS

Resource = Trade-Off = Negative Correlation

There are extreme cases where there is little doubt that cognitive processing is characterized by a trade-off. For instance, visual fixations are allocated to one *or* the other of two sufficiently distinct objects in space at a time (e.g., Eriksen and Yeh, 1985; Eriksen and St. James, 1986). Accordingly, allocating the processing of visual information at high acuity to one object necessarily precludes the other object from receiving such privileged processing. Furthermore, the literature on working memory suggests that only one object can be held in the narrow focus of attention in working memory (while approximately four objects can be held in the broad focus of attention) and that shifting the focus from one object held in working memory to another costs time and effort (e.g., Oberauer, 2002; Oberauer and Hein, 2012). This again indicates that granting privileged processing to one object implies withholding it from another object. Maniscalco et al. (2017) reported negative within-subject correlations of performance and metacognition in a vigilance task and used the negatively linked within-session changes to argue for a trade-off and a common resource. Similarly, Drury (1994) wrote about the speed-accuracy trade-off in industrial contexts and the negative correlation between speed and accuracy that appears when people perform resource-limited[1] tasks.

Common Factor = Positive Correlation

While a negative within-person correlation suggests the allocation of a limited resource, a positive correlation suggests a common factor. A common factor influences different tasks but is not *limitedly* allocated between the tasks. It can, for instance, be based on (1) a strategy that positively influences different tasks (cf. Gaschler et al., 2014) and is not "used up" when applied to a task), (2) differences in the substrate of the cognitions (e.g., faster overall neuronal transmission rates, Salthouse, 1992), but also (3) environmental factors (e.g., strength of a distraction affecting both tasks). In cognitive psychology, theories explaining cognitive functioning in different tasks by such a common factor are especially prominent in work on cognitive aging, a domain where experimental manipulation cannot be applied broadly and between-person differences as well as trajectories of change

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[1] Drury is referring to "task processing resources", not industrial resources, here.

within individuals are scrutinized. For instance, based on shared age-related variance across various measures of speed and attenuation of age-correlations after speed-variance is controlled for, Salthouse (1996) has argued that between-person differences and within-person change in the speed of basic processes are common factors behind cognitive aging. Slowing corrupts performance as relevant operations cannot be finished within the available time, products of cognitive processes cannot be combined as results of earlier processing are no longer available when later processes are finished. In a similar vein, based on simulations with neural networks on cognitive aging, Li et al. (cf. Li et al., 2000; Li, 2013; Li and Rieckmann, 2014) have argued for differences in the neural gain parameter as the one common cause of between-person and within-person differences in performance across different tasks.

An example of a common factor is Drury's (1994) observation that providing workers in aircraft inspection with well-defined boundaries to the search area can simultaneously increase speed and accuracy. Workers are thus not just shifted on the speed-accuracy curve in a trade-off manner but their performance benefits overall. As this illustrates, the common factor view is not limited to trait-like factors. This is very important for our argument, because otherwise the contrast we are proposing is not empirically identifiable, as the trade-offs would be visible within-person and the common factors would be visible only between-person. And while this is still possible in cases where a common factor only differs between persons but within each person remains perfectly stable and should be kept in mind, the methods we propose remains viable as long as the common factor has fluctuation in its strength.

On the within-person level, some variables of interest that have been shown to affect performance in tasks commonly used in cognitive psychology are the functioning of working memory, attentional control, motivation (e.g., Adam and deBettencourt, 2019 or Brose et al., 2012), as well as physiological fluctuations such as circadian rhythm, distribution of blood in the body, general stress, or availability of nutrition (e.g., Slaughter, 1901; Hasher et al., 1999). Within-person fluctuations have also been documented for goal-planning (e.g., Wiebe et al., 2018), and self-regulation (e.g., Berg et al., 2014). These variables can lead to positively correlated day-to-day changes in different performance measures.

One thing to mind is that while we use within-person correlations of measurements to illustrate our point, the theoretical conclusions are based on correlations of the underlying *constructs*. Capacity can be distributed to either increase speed or increase accuracy, but the measurement of accuracy can equally be measured in terms of percentage of correct responses or of percentages of errors. The main solutions here, in the spirit of the Research Topic's focus on mechanistic theories and specified cognitive structures, are having a solid theory of how the empirical measurements come about and an awareness that an approach like ours has neither the capacity nor the purpose of replacing good theories. A particularly difficult dynamic here is one in which the distribution of a cognitive resource is governed by a system that can be more or less efficient, that is, a common factor. For example, the action control system can be set to be more flexible or more stable (a cognitive resource, as the control system's balance can only lie in one place at a time) and shifting to flexibility improves task switch performance and worsens repetition performance (and vice versa), but metacontrol adaptivity (how efficient these shifts happen) is a common factor, as it increases the overall performance (cf. Mekern et al., 2019).

A constraint of this approach is that it is tailored to situations in which the amount of available cognitive resources is roughly fixed, at least within the time frame of data acquisition. Once a change in available resources is plausible, the logic we present here is not as easily applied anymore (for one example consider the "less is more" hypothesis of language acquisition, Newport, 1988, 1990, in which an increase in cognitive capacities between early childhood and adulthood leads to reduced language acquisition efficiency since they lead to change in "how" language stimuli are processed).

WITHIN-PERSON COVARIANCE AS CONSTRAINT ON POTENTIAL MECHANISMS

Studies of within-person variability can be used as a first step to constrain the search space for later experimental research to test mechanistic accounts. If it turns out that two measures are correlated negatively within participants (i.e., trade-off), this suggests that processes or representations overlap and are used competitively. An example that most experimental cognitive psychologists will be familiar with is the speed-accuracy trade-off (SAT), which is the phenomenon that for decision making systems the speed with which a decision is made negatively correlates with the accuracy with which the decision is made. Discovered relatively early in the history of modern psychology (Henmon, 1911, for a broader overview see Heitz, 2014), the SAT can, for cognitive psychologists, sometimes be more of a problem to be dealt with (e.g., Vandierendonck, 2018; Liesefeld and Janczyk, 2019), but it illustrates our point about trade-offs well: There seems to be some sort of limit on decision quality gained per time invested, which in accumulator models would be the velocity of evidence accumulation (see, e.g., Bogacz et al., 2010). Shifting toward speed at the cost of accuracy or vice versa results in a negative within-person correlation (Bakdash and Marusich, 2017). As such, the SAT is not only a confound adding noise to be controlled but also an epistemological signal to be used, as it indicates the presence of a cognitive resource.

As an example on the level of task representations, Schuck et al. (2015) used fMRT to track how redundant variants of representing a task as a color- vs. a spatial task were represented and found a negative coupling (space *or* color) rather than redundant coding in task-set relevant brain areas. In the applied domain this might mean that on some days people may approach a traffic light with a task-set strongly weighing color and on other days focusing on light position instead (cf. Overton and Brown, 1957, for a *between*-person difference perspective on this issue). Follow-up work can target active and passive mechanisms clearing redundant parts from task representations. Apart from task sets, trade-offs are also documented on the level of features.

A central aspect of the Theory of Event Coding (Hommel et al., 2001) is that features (such as the code "left") already used for an event file (such as planning a left arm movement) are less available when concurrently needed in a different task (i.e., recognizing a left-pointing arrow, Wühr and Müsseler, 2001).

In case of a positive correlation, candidates for a common factor can be tested. For instance, Brose et al. (2012) documented that days with lower working memory performance, were days with more negative affect and reduced control of attention, suggesting, to follow-up on the role of working memory in emotion regulation.

As mentioned, studies of within-person variability can not only be used to constrain first steps in constructing mechanistic theories, but also to test them. Some theories strongly linked to experimental work can make predictions on the covariance structure of task performance that can be tested in multi-session datasets that allow for day-to-day fluctuation. For instance, bottleneck-theories in dual-tasking (cf. Pashler, 1994; Tombu and Jolicœur, 2005) can be taken to suggest that measures of performance in the two tasks should correlate negatively within subjects.

Lastly, this approach can also be turned on its head to inform how to design environments in which there are multiple related concurrent tasks where good performance in one task is desired and in the other irrelevant. If it is established that a cognitive resource is divided among the tasks, then minimizing the amount of resources used by the irrelevant tasks is a design goal, while if a common factor pattern is established, no such precautions need to be taken. Cognitive load theory in the context of instructional design is an example of this logic: If a student is to learn a subject from teaching materials and needs to use a cognitive resource on both parsing the material and then processing the material, lowering the resource draw of the parsing component will free up resources for the processing component (Sweller et al., 1998).

DISTINGUISHING WITHIN- AND BETWEEN-PERSON CORRELATION

Correlative studies can help evaluate to what extent mechanisms implying a trade-off structure or mechanisms implying a common factor structure are relevant. Potential outcomes can be that there is evidence only for one or the other case, or that both mechanisms contributed (potentially with different weight). Importantly, to fully harvest the potential of correlative studies for constraining candidate mechanisms, the studies should not be limited to cross-sectional assessment of correlation.

An example involving typing might illustrate that correlations across persons are logically independent from correlations within person (Hamaker, 2012). In cross-sectional studies, the between-person correlation between the time needed for a typing task and error rate might be positive: Some people are good typists. They type quickly and accurately. In contrast, the within-person correlation obtained in a longitudinal study across many typing sessions might be negative: On occasions a person types faster, the error rate will be higher.

A small but growing body of research is now using intensive repeated measures, wherein participants complete tasks on many sessions, to examine within-person coupling of indicators of different cognitive processes. For example, Brose et al. (2012) studied within-person and between-person differences in working memory, control of attention, and affect in 101 young adults across 100 sessions. They obtained evidence for the common factor view (positive correlations), within- and between persons. They found that the same variables that predict between-person differences in working memory performance (cross-sectional correlations) also predict within-person (session-to-session) differences in working memory performance (longitudinal correlations). Given the logical independence of the within- and between-person variability, these results suggest that findings from prior studies of between-person differences that were at risk for ecological fallacy may be at least partially informative about within-person cognitive processes (Molenaar, 2004; Hamaker, 2012).

In summary, we think that the concept of a cognitive resource can be made epistemologically useful and empirically tractable by contrasting it with the concept of a common factor and identifying the two concepts with negative and positive within-person correlations on theoretically related measures. The epistemological use is primarily one of restricting the theoretical space within which mechanistic explanations are to be searched for, but also includes testing hypotheses.

AUTHOR CONTRIBUTIONS

CN wrote the first draft of the manuscript and created the figure. All authors wrote and revised sections of the manuscript and read and approved the submitted version.

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What Is Targeted When We Train Working Memory? Evidence From a Meta-Analysis of the Neural Correlates of Working Memory Training Using Activation Likelihood Estimation

Oshin Vartanian[1,2]*, Vladyslava Replete[1,3], Sidney Ann Saint[1,4], Quan Lam[1], Sarah Forbes[1,5], Monique E. Beaudoin[6], Tad T. Brunyé[7], David J. Bryant[1], Kathryn A. Feltman[8], Kristin J. Heaton[9], Richard A. McKinley[10], Jan B. F. Van Erp[11,12], Annika Vergin[13] and Annalise Whittaker[14]

[1] Defence Research and Development Canada, Toronto, ON, Canada, [2] Department of Psychology, University of Toronto, Toronto, ON, Canada, [3] Faculty of Medicine, Queen's University, Kingston, ON, Canada, [4] Department of Psychology, University of Waterloo, Waterloo, ON, Canada, [5] Department of Psychiatry, University of Manitoba, Winnipeg, MB, Canada, [6] Applied Research Laboratory for Intelligence and Security, University of Maryland, College Park, MD, United States, [7] U.S. Army DEVCOM Soldier Center, Natick, MA, United States, [8] U.S. Army Aeromedical Research Laboratory, Fort Rucker, AL, United States, [9] U.S. Army Research Institute of Environmental Medicine, Natick, MA, United States, [10] U.S. Air Force Research Laboratory, Wright-Patterson Air Force Base, Dayton, OH, United States, [11] Netherlands Organization for Applied Scientific Research (TNO), Soesterberg, Netherlands, [12] Department of Human Media Interaction, University of Twente, Enschede, Netherlands, [13] Bundeswehr Office for Defence Planning, Federal Ministry of Defence, Berlin, Germany, [14] Defence Science and Technology Laboratory, UK Ministry of Defence, Salisbury, United Kingdom

Edited by:
Bernhard Hommel,
University Hospital Carl Gustav Carus,
Germany

Reviewed by:
Claude Alain,
Rotman Research Institute (RRI),
Canada
Andy Wai Kan Yeung,
University of Hong Kong,
Hong Kong SAR, China

***Correspondence:**
Oshin Vartanian
oshin.vartanian@drdc-rddc.gc.ca

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Working memory (WM) is the system responsible for maintaining and manipulating information, in the face of ongoing distraction. In turn, WM span is perceived to be an individual-differences construct reflecting the limited capacity of this system. Recently, however, there has been some evidence to suggest that WM capacity can increase through training, raising the possibility that training can functionally alter the neural structures supporting WM. To address the hypothesis that the neural substrates underlying WM are targeted by training, we conducted a meta-analysis of functional magnetic resonance imaging (fMRI) studies of WM training using Activation Likelihood Estimation (ALE). Our results demonstrate that WM training is associated exclusively with decreases in blood oxygenation level-dependent (BOLD) responses in clusters within the fronto-parietal system that underlie WM, including the bilateral inferior parietal lobule (BA 39/40), middle (BA 9) and superior (BA 6) frontal gyri, and medial frontal gyrus bordering on the cingulate gyrus (BA 8/32). We discuss the various psychological and physiological mechanisms that could be responsible for the observed reductions in the BOLD signal in relation to WM training, and consider their implications for the construct of WM span as a limited resource.

Keywords: working memory span, training, cognitive resource, meta-analysis, executive functions

INTRODUCTION

Working memory (WM) is defined as "a multicomponent system for active maintenance of information in the face of ongoing processing and/or distraction" (Conway et al., 2005, p. 770). Most classic accounts of WM have conceptualized this system to be limited in *capacity*, reflecting the underlying notion that it represents a limited resource (e.g., Miller, 1956; Cowan, 2001; for a review, see Baddeley, 2003). Broadly speaking, a processing resource can be defined as "something that exists in limited supply and is responsible for the enhancing or enabling of certain cognitive processes" (Salthouse, 1990, p. 102). Within the construct of WM, *capacity* reflects individual differences in the limit of this system, indicating that people can process only a certain amount of content at any given time. Examining *why* WM capacity is limited remains an active area of research, with candidate processes (to be described further, below) including temporal decay, limitations in cognitive resources and mutual interference of WM representations, among others (see Oberauer et al., 2016).

In contrast to accounts which consider WM to be a resource-limited system which is only able to store and process a small, fixed number of items, some contemporary views have emphasized the flexibility with which information can be maintained and manipulated in WM. For example, Ma et al. (2014) reviewed a large body of behavioral and neuroimaging data to argue for alternative resource models that do not invoke a fixed limit on how many items can be stored in short-term memory (e.g., magical number 4, or magical number 7—plus or minus 2, etc.), but instead emphasize that WM capacity depends on the quality or precision with which items are processed. Such flexible resource models of WM assume that the internal representations of sensory stimuli are inherently noisy, and that this noise increases as the number of to-be-remembered items increases in memory (see Palmer, 1990; Wilken and Ma, 2004; Bays and Husain, 2008). In turn, the extent to which any given item is recalled with precision depends on the quantity of resources devoted to processing it: As this quantity increases, there is a corresponding decrease in the noise associated with the item in memory, and increased likelihood of precise recall. Consistent with such accounts, it has been shown that there is less precision in the recall of items from memory as the number of to-be-remembered items increases, and increased precision in recall as their salience or goal-relevance increases (Gorgoraptis et al., 2011). The upshot of this contemporary work is that even when resources are limited, there can be flexibility in their allocation as a function of context and goals, which can in turn impact quality as well as quantity of recall.

Behavioral Effects of Working Memory Training

Consistent with such flexible notions of information processing in WM, there has been great interest recently in improving WM capacity, skills, and performance *via* targeted training (see Klingberg, 2012). Indeed, several largescale meta-analyses and reviews of the behavioral literature have shown that WM training can lead to *near transfer*—defined as performance improvements on short-term and WM tasks that are similar to the trained task (Morrison and Chein, 2011; Melby-Lervåg and Hulme, 2013; Redick et al., 2015; Melby-Lervåg et al., 2016; see also Soveri et al., 2017). Evidence for near transfer suggests that WM training likely targets cognitive processes that are commonly shared by most short-term memory and WM tasks, such as maintenance and updating of information. In contrast, there is little or no reliable evidence to suggest that WM training can lead to *far transfer*—defined as observing performance benefits in outcome measures that are dissimilar to the trained task in terms of structure or surface features (Perkins and Salomon, 1994; but see Au et al., 2015). There could be many reasons why reliable evidence for far transfer has not been observed. One reason could be that the untrained tasks likely recruit other capabilities in addition to WM that must also be targeted by training for benefits to be observed in performance, including perhaps other executive functions (e.g., switching and inhibition). Another possibility might be that the gains observed in WM span are due to the development of strategies that are applicable to only certain tasks but not others, or at least not to the same extent (e.g., chunking). Finally, it could also be that WM training only leads to gains in some aspects of WM span but not others (see Shipstead et al., 2014), therefore limiting its broad utility. More generally, it is likely necessary to specify the dimensions along which far transfer can occur to optimize the goodness-of-fit between what is trained and the target tasks that it is meant to transfer to (see Barnett and Ceci, 2002).

Consistent with evidence that WM training can lead to near transfer, there are also findings to suggest that WM training can lead to gains in WM capacity. For example, Harrison et al. (2013) asked participants to complete a battery of near-, moderate-, and far-transfer tasks at baseline, followed by 20 sessions of training that consisted of one of following three conditions: Participants in the complex-span training condition completed adaptive versions of the operation-span and symmetry-span tasks during each session, whereas participants in the simple-span training condition completed two adaptive simple span tasks. In turn, the control condition consisted of participants who trained on an adaptive visual search task only. The same battery of near-, moderate-, and far-transfer tasks were completed after training. In terms of near transfer, the complex-span training group exhibited improvements on the rotation- and reading-span tasks, even though both contained different distractor tasks and different to-be-remembered items than the training tasks. Both the complex-span and simple-span training groups also showed improvement on the running-letter-span and running-spatial-span tasks. Because the same to-be-remembered stimuli were used for the training and running-span tasks, this improvement could be attributable to either an increase in WM capacity or learning of stimulus-specific strategies for remembering letters and matrix locations. In terms of moderate transfer, both the complex-span and simple-span training groups showed improvement on the secondary memory component of immediate free recall. In terms of far transfer, no group exhibited any gain in fluid intelligence. These results suggest that WM training can lead to improvement in WM span, although it is important to remember that one can observe such improvements without necessarily improving WM capacity at the construct level. This is because not all of the variance in WM span task performance reflects WM capacity, but can instead reflect other factors related to the performance (e.g., strategies, ability to chunk letters, and random error) (Kane et al., 2004; see Harrison et al., 2013) and beyond (e.g., stress, fatigue, and sleep loss). As such, when improvement in WM capacity is observed, care must be exercised in interpreting what has been targeted and improved by training (see also Vartanian et al., 2016, 2021).

Process Specificity and the Brain

Although researchers have begun to gain traction on some of the processes and mechanisms underlying behavioral performance improvements associated with WM training—including its possible moderators (see Jaeggi et al., 2014; Au et al., 2015)—relatively less is known about its neural correlates (see Buschkuehl et al., 2012). Nevertheless, a number of insights have begun to emerge based on the available literature. First, there is good reason to believe that whether transfer does or does not occur depends in part on *process specificity*—defined as the extent to which the specific cognitive process affected by the training task also underlies performance on the untrained task (Eriksson et al., 2016). Examples of such processes include the storage of information, suppression of distractors, and updating of information (see Flegal et al., 2019). Process specificity is important at the neural level because the greater the functional similarities between the trained and untrained tasks, the greater the likelihood that the sets of brain regions underlying those tasks will also overlap. In this sense, brain imaging studies are useful because they can reveal possible neural mechanisms whereby training-related improvements and transfer could occur (Klingberg, 2010; Buschkuehl et al., 2012).

For example, Dahlin et al. (2008) examined participants' brain activity using functional magnetic resonance imaging (fMRI) before and after a 5-week regimen of WM training. Neural data were obtained to assess training-related changes in brain activity. Training consisted of a letter memory task that focused specifically on updating of information in WM. The experimenters administered three tasks while participants underwent fMRI: The letter memory task, the *n*-back, and the Stroop task—the latter two being the transfer tasks. Importantly, both the letter memory task and the *n*-back task involved updating of information in WM, whereas the Stroop task did not. Not surprisingly, all three tasks engaged the well-established fronto-parietal WM system. In terms of the two transfer tasks, the investigators reasoned that if transfer hinges on a shared fronto-parietal network, then it should be observed for both the *n*-back task and the Stroop task—because both share activation in that region with the letter memory task. However, if transfer hinges specifically on updating of information in WM and is associated with shared activity in the striatal updating network, then it should be observed for the *n*-back task only. Indeed, the results supported the latter prediction, demonstrating that transfer occurs if the training task targets the same cognitive process and/or mechanism that underlies the transfer task—in this case updating of information in WM.

Increases and Decreases in Brain Activation

A second finding that has emerged from neuroimaging studies is that WM training can be correlated with both increases as well as decreases in brain activation, although the reasons behind this variability in the observed results are not well-understood. For example, in his early review of this literature Klingberg (2010) noted a pattern such that studies that involved short periods of WM training (<3 h) had been shown to result in decreased brain activity, whereas long periods of WM training had been shown to result in an admixture of both increased and decreased brain activity. Klingberg (2010) proposed that the decreases in activation could have occurred because of a number of different processes taking place, including strategy learning, priming during encoding, and time-on-task effects—all of which have been shown to be correlated with reductions in brain activation (see also Brouwer et al., 2014). In turn, during longer training regimens these reductions would be co-occurring with increases in WM capacity, which would in turn be correlated with activity in the intraparietal cortex, middle and superior frontal gyri, and the caudate nucleus. However, in their own review of largely the same literature on the neural effects of WM training, Buschkuehl et al. (2012) called for additional data to understand the impact of WM training on neural function. Specifically, they reviewed evidence from several studies to demonstrate that WM training was associated with decreases in brain activation in many fMRI studies, suggesting that perhaps brain function can become more efficient with increased practice and expertise. Given that brains are metabolically expensive, the ability to perform tasks to the same or improved level with less energy expenditure would represent a significant adaptive benefit.

Dahlin et al.'s (2009) review of the neuroimaging studies of WM training reached a conclusion quite similar to Buschkuehl et al. (2012) in attempting to interpret patterns of neural activation and deactivation. Namely, they noted that the central executive component of Baddeley's (1996) model of WM has been linked strongly to the fronto-parietal system.[1] Although greater activation in this system as a function of WM training can be attributed to either the recruitment of additional cortical units with practice or the strengthening of the blood oxygen level-dependent (BOLD) response within a specific region, a far more common observation is a reduction in activation in this system in association with WM training. Such reductions could mean that the task was initially difficult and required resources from the central executive, but with practice became less difficult or required less conscious thought and thus required fewer resources—and by extension less fronto-parietal involvement.

Interestingly, the opposite pattern was perceived in subcortical areas such as the basal ganglia where brain activation was far

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[1] It is important to note that some WM models such as Baddeley's include "slave" systems for processing modality-specific visual and auditory input, such as the visuospatial sketchpad and the phonological loop, respectively (see Van Erp et al., 2020). We are not making the argument here that such modality-specific systems do not engage the fronto-parietal system.

more likely to increase following WM training. Dahlin et al. (2009) argued that such increases in activation in subcortical areas could in turn reflect the strengthening of the specific skills in association with training (e.g., updating of information in WM). This two-pronged view suggests that during the early phases of learning the prefrontal cortex likely exercises cognitive control for the purpose of new rule and skill acquisition, whereas over time, when the previously novel rules and skills have been learned, the frontal lobes become less engaged and the acquired rules and skills are implemented by other neural systems (see Packard and Knowlton, 2002; Poldrack et al., 2005). Thus, Dahlin et al. (2009) interpreted "the decreased cortical activation as an indication of more automatized task performance following training, and the increased striatal activation as a change in the underlying skill" (p. 411). This interpretation is also consistent with the idea that rather than being a unitary construct, training can encompass the acquisition of new mental operations or shortcuts as well as reducing inefficiencies in existing processes. For example, Bryant and Niall (2020) characterized three approaches to cognitive optimization that are analogous—increasing the power of a cognitive capability, increasing the effect one can derive from an existing level of capacity, and providing external devices to perform cognitive tasks to reduce the need for using cognitive capabilities. Training might be viewed in a similar fashion—increasing the capacity of WM, making WM more efficient, or off-loading some functions of WM to other cognitive capacities. In turn, these effects can be associated with variations in the structures and directions of BOLD activity change in relation to WM training.

A fundamental problem when assessing this body of work concerns how to interpret the changes in the BOLD signal observed in relation to WM training. For example, in several cases to date, reductions in the BOLD signal due to training have been interpreted as reflecting increased efficiency of neural function. Poldrack (2015) has argued convincingly that such an interpretation is unjustified because a reduction in the BOLD signal does not necessarily mean that there is less energy expenditure for conducting the same task. Indeed, a reduction in the BOLD signal can be observed because a different set of cognitive processes and/or neural computations are being performed—neither of which means that there is reduced energy expenditure for the same amount of work. As noted by Poldrack (2015), one could argue for neural efficiency if the same neural computation were being performed with identical time and intensity, but with different metabolic expenditure due to factors such as amount of transmitter release, nature of neurovascular coupling, or the degree to which the neural computations draw on oxidative vs. non-oxidative metabolism. However, such inferences require information about metabolism at the cellular level, which the BOLD signal does not provide (Logothetis, 2008). Constantinidis and Klingberg (2016) came to a similar conclusion when interpreting the literature on the neuroscience of WM training, as the changes in brain activation could be due to many physiological factors including the number and/or the firing rate of the neurons during maintenance of representations in WM, among others. This prompted them to note that "A cautious interpretation is thus that these fMRI studies point to the areas of change but do not inform us about the underlying cellular mechanisms" (p. 444). Nevertheless, localizing where the changes occur and the direction in which they occur is a necessary first step for understanding the structures whose function is impacted by training, although subsequent research will be necessary to understand precisely why the changes have occurred, and the extent to which they reflect variations in metabolic expenditure at the cellular level.

Aims of Present Meta-Analysis

Our meta-analysis had three aims. The first aim was to reveal brain structures that are activated reliably across studies as a function of WM training. To this end, we employed the Activation Likelihood Estimation (ALE) approach, which is a widely adopted coordinate-based platform for the quantitative meta-analysis of neuroimaging data (Eickhoff et al., 2012). To address this aim, we specifically restricted our focus to studies that involved pre-test and post-test assessments of WM performance with fMRI, and training regimens involving a WM task. We are aware of three earlier meta-analyses of the literature on the neural bases of WM training, with different scopes and aims than ours. First, Li et al. (2015) investigated the neural correlates of WM training in healthy adults and patients with schizophrenia. Next, Salmi et al. (2018) investigated the neural correlates of WM training in healthy adults, but also included studies in which the target fMRI task was not necessarily a WM task (e.g., multitasking, divergent thinking, etc.). In turn, Pappa et al. (2020) focused exclusively on studies that utilized a WM updating task as the training task (rather than a maintenance task, etc.) to achieve greater homogeneity across studies in terms of the specific process that was being trained. All three meta-analyses included data from elderly samples. Although these meta-analyses have made valuable and important contributions to our understanding of the neural bases of WM training, we believe that the present meta-analysis fills a unique niche in the literature. First, we focused exclusively on samples of neurologically healthy adults having a mean age of <65 years, given the well-established finding that older adults display overactivation in functional brain imaging studies, likely as a compensatory mechanism against age-related decline in cognition (for review, see Reuter-Lorenz and Cappell, 2008; see also Cabeza et al., 2018; Tagliabue and Mazza, 2021). We reasoned that focusing on young-to-middle aged adults would reduce some of the heterogeneity in the findings due to the age-related differences in brain activation. Second, we focused exclusively on studies that has used a WM task both for training and for pre- and post-testing. The reason for this decision was to reduce heterogeneity in the tasks under consideration by focusing only on tasks that target WM function. We reasoned that by virtue of focusing on neurologically healthy non-senior adults who were trained and tested (pre- and post-training) exclusively on WM tasks, we would be in a position to examine whether training on any WM task can reliably impact brain function in regions of the brain that underlie WM in target tasks. Of particular interest were regions in the fronto-parietal network that have been consistently linked to performance and individual differences in this capacity (Wager and Smith, 2003; Owen et al., 2005; Darki and Klingberg, 2015), as well as subcortical systems such as the basal ganglia (Eriksson et al., 2016).

The second aim of our meta-analysis was to examine whether there are differences in brain regions that exhibit activation increases vs. decreases as a function of WM training (i.e., the directionality of training effects in the BOLD response). Indeed, one of the distinguishing features of individual studies to date has been the heterogeneity in the direction of change noted in brain activation following WM training, with some studies reporting exclusively increases or decreases in activations, whereas others have reported changes in both directions in different structures. As noted by Dahlin et al. (2009) in their review of this literature, the results "support the views that training does not result in a monotonic increase or decrease in neural activity. . ., and that training-related activation changes are not restricted to an isolated part of the brain. To better understand the neural reorganization that takes place after training, it is critical to identify neural networks underlying these activity changes" (p. 410). To address this second aim, we distinguished between foci that have shown increases vs. decreases in activation, aiming to highlight the reliability of the directionality of the differences in response to WM training. Notably, all three meta-analyses of WM training to date have revealed an admixture of activity increases and decreases in the brain (Li et al., 2015; Salmi et al., 2018; Pappa et al., 2020). We were keen to examine whether a similar pattern would arise when the scope was limited to neurologically healthy non-elderly adults who were trained and tested (pre- and post-training) exclusively on WM tasks.

The third aim of our meta-analysis focused not on the neural data, but instead on behavioral data collected in a subset of the fMRI studies under examination that had administered WM span tasks pre- and post-training. This is because from a theoretical perspective, we were particularly interested in the impact of WM training on WM span. Therefore, aside from conducting the meta-analysis of fMRI data to address the first two aims of the study, we also conducted a descriptive review of the subset of studies that had administered WM span tasks pre- and post-training to examine the reliability of transfer from WM training to WM span, and to examine whether there are specific features of training and testing that increase the likelihood of that transfer. This descriptive review was meant to supplement the core meta-analysis of the fMRI data by shedding light on factors that facilitate transfer from WM training to WM span, and what the implications might be for models of WM that treat WM span as a limited resource.

METHOD

Literature Search

The identification of articles relating to WM training was conducted by a series of Boolean searches of PsychINFO, PubMed, and Web of Science databases last updated in January 2022. The following keywords were used: "working memory training," "brain training," "cognitive training," "fMRI," and "PET." Furthermore, we examined review papers, past meta-analyses, and reference sections for additional studies. Our search yielded 341 references. These references were subsequently screened based on (a) article and journal title information, (b) abstract information, and (c) full-text evaluation (see **Figure 1**). Ultimately, this yielded 32 studies (reported in 31 unique publications) for the meta-analysis.

Selection Criteria

The articles were screened for neurologically healthy participants. In cases where a neurologically healthy control group was included as a comparison condition for a patient group, the data from the former group were included in the meta-analysis if separate results had been reported ($n = 2$), or by contacting the authors to obtain results only from the neurologically healthy control sub-group ($n = 1$). We focused exclusively on studies that reported data from samples with a mean age of <65 years. All articles included a WM training regimen, although the specific training task varied across studies. Furthermore, in each case the pre- and post-test measures were also WM tasks. In some cases, the pre- and post-test WM measures were identical to the WM training task, whereas in others it was a different WM task that was implemented for training vs. pre- and post-testing (**Table 1**).

All selected studies included neuroimaging data collected prior to and following WM training (i.e., pre- and post-test). In cases where post-test neuroimaging data were collected at two time points following the termination of WM training (e.g., immediately after training and again >1 month after training), we focused on the time point nearest to the termination of training (i.e., immediately after training). This allowed for a direct comparison of post-test data across studies using immediate vs. immediate *and* delayed methodologies, eliminating this potential confound. All the studies reported voxel-wise, whole brain data which reported foci in 3D coordinate space (i.e., not ROI analysis). In cases where the performance of an experimental group (i.e., WM training) was compared to a control group (i.e., active or passive control) at pre- and post-test time points, we selected the results of the Group × Time interaction effect for analysis. In cases where only the results of the training group were available/reported at pre- and post-test, we included in our analysis the coordinates associated with the simple main effect of training. In both cases above, if the authors reported results separately for different levels of difficulty of the same task (e.g., 3-back vs. 2-back for n-back at post-test compared to 1-back at pre-test), we selected the contrast that isolated the neural correlates of the more difficult level (i.e., 3-back at post-test compared to 1-back at pre-test rather than 2-back at post-test compared to 1-back at pre-test). In total, 31 articles that included 32 studies met the criteria and were included in the meta-analysis, including data from 813 participants and 385 foci (**Table 1**).

Activation Likelihood Estimation

ALE is a quantitative meta-analysis technique that compares activation likelihoods calculated from observed activation foci with a null distribution of randomly generated activation likelihoods. It pools peak activation coordinates across studies that have investigated an effect of interest (Laird et al., 2005). These coordinates must be spatially renormalized to a single template. For this meta-analysis, all coordinates were renormalized to MNI space using the icbm2tal transformation (Lancaster et al., 2007) implemented in the GingerALE 3.0.2

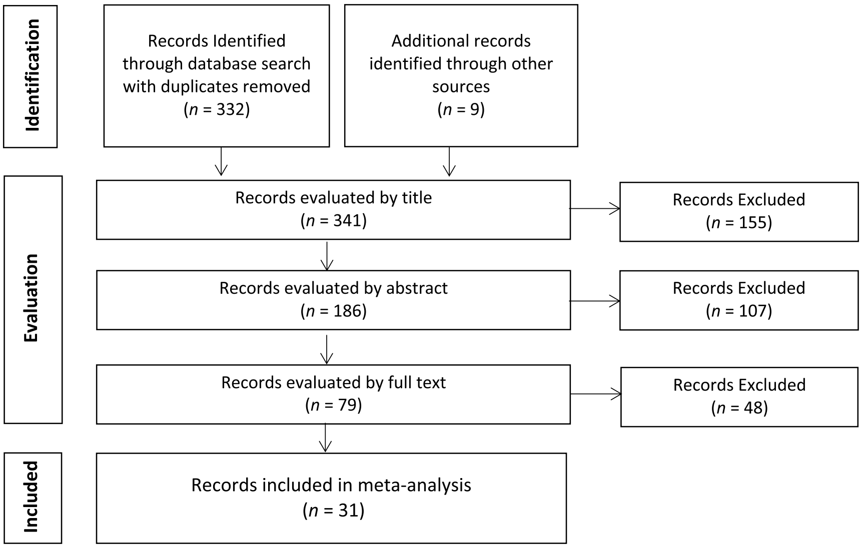

FIGURE 1 | Flow diagram for literature search.

toolbox (Research Imaging Center of the University of Texas Health Science Center, San Antonio, TX).[2] The resulting coordinates were used to generate "activation likelihoods" for each voxel in the brain. For each focus, ALE computes each voxel as a function of its distance from that focus using a three-dimensional Gaussian probability density function centered at its coordinates. This generates vectors of values for each voxel representing probabilities of belonging to a specific focus. These values are assumed to be independent such that the existence of one focus does not give information about whether another focus will occur. The vector values are combined with the addition rule for log-probabilities, yielding ALE statistics. Thus, the ALE statistic represents the probability of a certain voxel to belong to any of the included foci. Significance tests are conducted by comparing the ALE statistic in each voxel with a null distribution, generated *via* repeatedly calculating ALE statistics from randomly placed activation foci. This null distribution is then used to estimate the threshold based on a given cut-off. Finally, a cluster threshold (i.e., minimum spatial extent of significant contiguous clusters) can be applied. As recommended in Eickhoff et al. (2016), we conducted our analyses based on a cluster-level family-wise error (FWE) correction, which involves using an uncorrected cluster-forming threshold ($p < 0.001$) and employing a cluster-extent threshold ($p < 0.05$) that controls the chance of observing a cluster of that size if foci were randomly distributed—implemented in GingerALE 3.0.2 (Eickhoff et al., 2017). We used 1,000 thresholding permutations.[3]

RESULTS

Omnibus Analysis

The results of the omnibus analysis spanning all 32 studies revealed that WM training was associated with the involvement of the fronto-parietal system encompassing clusters in the left inferior parietal lobule (BA 40), right middle frontal gyrus (BA 9), and medial frontal gyrus bordering on the cingulate gyrus (BA 6/32) (**Figure 2** and **Table 2**).

Increases vs. Decreases in Activation

Next, we separated the 385 foci based on whether they had been reported as increases (176) or decreases (209) in activation in previous studies, and conducted the meta-analysis separately for each group of foci. The results demonstrated that WM training was associated with decreases in brain activation in clusters within the fronto-parietal system that underlie WM, encompassing the bilateral inferior parietal lobule (BA 39/40), middle (BA 9) and superior (BA 6) frontal gyrus, and medial frontal gyrus bordering on the cingulate gyrus (BA 8/32) (**Figure 2** and **Table 3**). In contrast, the analysis of foci which had exhibited increases in activation in previous studies did not reveal any cluster associated with WM training.[4]

Impact of Training on Working Memory Span: Behavioral Results

Of the 32 fMRI studies included in the present meta-analysis, we identified a subset of seven studies that had administered

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[2] http://brainmap.org

[3] Based on a largescale simulation of meta-analysis datasets using empirical parameters derived from the BrainMap database, Eickhoff et al. (2016) demonstrated that cluster-level family-wise error correction represents the most optimal statistical thresholding method, although voxel-wise family-wise error correction also represents an appropriate, but more conservative approach, to statistical thresholding. In turn, both uncorrected inference and correction for multiple comparisons using the false-discovery rate represent inappropriate methods.

[4] Note that it was not possible in ALE to directly conduct a contrast analysis involving foci that had exhibited activation decreases vs. foci that had exhibited activation increases because in the latter case no statistically significant results emerged.

TABLE 1 | List of 32 studies included in the meta-analysis.

Reference	Raw coordinates	Training task	Target task	Frequency (sessions)	Duration (min)
Aguirre et al., 2019	MNI	Adaptive n-back task	n-back task	4	60
Ando et al., 2007	Tal	Visuospatial WM	Visuospatial WM	105	?
Ando et al., 2009	Tal	Visuospatial WM	Visuospatial WM	210	?
Buschkuehl et al., 2014	MNI	Visuospatial n-back task	Visuospatial n-back task	7	20
Chang et al., 2017	Tal	Cogmed	2 back	20–25	30–40
Clark et al., 2017a	MNI	Lumosity visuospatial n-back task	Lumosity visuospatial n-back task	30	20
Dahlin et al., 2008 (Exp. 1)	MNI	Multimodal WM training	Letter memory, 3 back	15	45
Emch et al., 2019	MNI	Adaptive n-back task	n-back	32	?
Flegal et al., 2019	MNI	Adaptive visuospatial and visuo-verbal WM tasks	Visuospatial WM	10	50
Gaab et al., 2006	Tal	Pitch memory	Pitch memory	5	60
Garavan et al., 2000	Tal	Visuospatial WM	Visuospatial WM	1	32*
Jansma et al., 2001	Tal	Sternberg	Sternberg	1	45
Jolles et al., 2010	MNI	Verbal WM	Verbal WM	10.5	25
Kirschen et al., 2005	Tal	Verbal WM	Verbal WM	1	12
Koch et al., 2006	Tal	Sternberg	Sternberg	1	24*
Koch et al., 2007	Tal	Sternberg	Sternberg	1	24*
Landau et al., 2004	MNI	Face recognition task	Face recognition task	1	30
Miró-Padilla et al., 2018	MNI	Adaptive n-back task	n-back task	4	50
Miró-Padilla et al., 2020	MNI	Adaptive n-back task	Auditory, arithmetic WM	4	50
Moore et al., 2006	MNI	Simultaneous match to sample, delayed recognition, family placement, family discrimination	Match to sample	7	90
Olesen et al., 2004 (Exp. 1)	Tal	Visuospatial WM, backwards digit span, letter span	Visuospatial matching task	20–30	35–45
Olesen et al., 2004 (Exp. 2)	Tal	Visuospatial WM tasks: grid, grid rotation, 3D grid	Visuospatial matching task	25	35–45
Opitz et al., 2014	Tal	Adaptive n-back	Orthographic task (Chinese character learning)	14	40*
Ramsey et al., 2004	MNI	Verbal matching	Verbal matching	1	21
Sayala et al., 2006	Tal	Delayed object/spatial recognition	Delayed object/spatial recognition	1	30
Schneiders et al., 2011	Tal	Adaptive n-back	Visual n-back	8–10	50
Schneiders et al., 2012	Tal	Auditory adaptive n-back	Auditory and visual WM	8	50
Schweizer et al., 2013	MNI	Affective dual n-back	Affective dual n-back	18–20	20–30
Thompson et al., 2016	MNI	Adaptive n-back or multiple object tracking	Dual n-back	20	40*
van Raalten et al., 2008	MNI	Sternberg	Sternberg	1	25
Wagner et al., 2021	MNI	Dual n-back	Word order recognition task	40	30
Zimmer et al., 2012	MNI	Change Detection task	Change Detection task	12	?

WM, working memory; ?, not reported; Exp., experiment.
**To the best of our calculations based on reported data.*

WM span tasks before and after training. Importantly, those measures were not necessarily the tasks that were administered in the fMRI scanner before and after WM training, but were more commonly included as part of the larger set of neuropsychological measures to assess near and far transfer effects from WM training to other outcome measures. Nevertheless, a descriptive review of those studies is useful for examining the extent to which WM training can transfer to measures of WM span—both simple and complex. Measures of simple WM generally involve presenting participants with a list of to-be-remembered items (e.g., letters, digits, or words) which they must subsequently recall in the correct serial order (e.g., forward or backward) (see Unsworth and Engle, 2006). As such, span subscales from the Wechsler Adult Intelligence Scale—Revised (WAIS-R: Wechsler, 1981) can be considered measures of simple WM span. Chang et al. (2017) administered the WAIS-R Digit-Span and Spatial-Span tasks to participants in the adaptive or non-adaptive WM training groups before and after training. The results demonstrated a Group (Training vs. Control) × Time (pre- vs. post-training) interaction on both Digit Span and Spatial Span such that the

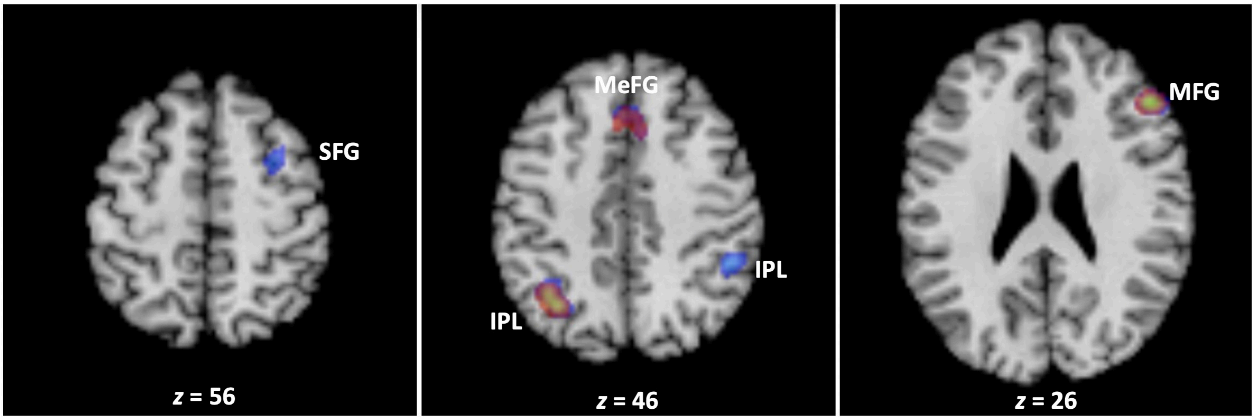

FIGURE 2 | The neural correlates of working memory training. Across all studies, working memory training engaged clusters encompassing the left inferior parietal lobule (BA 40), right middle frontal gyrus (BA 9), and medial frontal gyrus bordering on the cingulate gyrus (BA 6/32) (depicted in red). In turn, working memory training was associated with decreases in brain activation in clusters encompassing the bilateral inferior parietal lobule (BA 39/40), middle (BA 9), and superior (BA 6) frontal gyrus, and medial frontal gyrus bordering on the cingulate gyrus (BA 8/32) (depicted in blue) (see text, **Tables 2**, **3**). The transparencies of the activations are set to 50% to reveal three areas of overlap in the left inferior parietal lobule (BA 40), right middle frontal gyrus (BA 9), and medial frontal gyrus bordering on the cingulate gyrus (BA 6/32). IPL, inferior parietal lobule; MFG, middle frontal gyrus; SFG, superior frontal gyrus; MEFG, medial frontal gyrus.

TABLE 2 | The neural correlates of working memory training across all studies.

Area	BA	Center	Spatial extent of cluster	Size	Contributing studies
Inferior parietal lobule	39	−35, −59, 46	−42, −66, 40 to −28, −50, 52	1,936	Ramsey et al., 2004; Kirschen et al., 2005; Moore et al., 2006; van Raalten et al., 2008; Thompson et al., 2016; Miró-Padilla et al., 2018; Aguirre et al., 2019
Medial frontal gyrus	6/32	1, 25, 43	−8, 16, 38 to 10, 32, 48	1,880	Garavan et al., 2000; Moore et al., 2006; Sayala et al., 2006; Koch et al., 2007; Thompson et al., 2016; Miró-Padilla et al., 2018; Aguirre et al., 2019
Middle frontal gyrus	9	48, 33, 28	42, 26, 22 to 56, 38, 32	1,264	Olesen et al., 2004; Moore et al., 2006; Koch et al., 2007; Schneiders et al., 2011; Thompson et al., 2016; Aguirre et al., 2019

Number of studies = 32, number of participants = 813, number of foci = 385. The areas have been listed in order of decreasing cluster size.
BA, Brodmann Area; Size, cluster size in mm^3, coordinates are reported in MNI space.

(adaptive) WM training group registered significantly greater gains on both measures than did the non-adaptive control group. Olesen et al. (2004, Experiment 2) administered the WAIS-R Digit Span task to participants before and after a 5-week regimen of visuospatial WM training, observing significant post-training gains compared to baseline. Emch et al. (2019) administered the German version of the WAIS, the Hamburg-Wechsler-Intelligenztest für Erwachsene—Revision (HAWIE-R; Lutz et al., 1991) digit span sub-test (forward and backward versions) (Molz et al., 2010) to experimental and control participants before and after training. The HAWIE-R digit span sub-test requires one to repeat up to nine numbers in the same order as read aloud by the examiner (forward version), and afterward in reverse serial order (backward version). They observed a Group (Training vs. Control) × Time (pre- vs. post-training) interaction effect, such that there was a performance increase in the experimental group and a performance decrease in the control group. In contrast, Jolles et al. (2010) did not observe WM training-related gains in simple WM span as measured by the WAIS-R. Specifically, they administered the WAIS-R Digit Span task to participants who either trained on a WM task or were in a passive control condition before and after training, and did not observe a Group (Training vs. Control) × Time (pre- vs. post-training) interaction effect. Rather than administering the WAIS-R, Dahlin et al. (2008, Experiment 1) administered a different simple WM span measure referred to as "Letter Memory," which consisted of ten lists of serially presented letters (A-D) of varying length (7, 7, 9, 9, 11, 13, 9, 15, 13, 15). The task was to recall the last four letters as quickly as possible following the termination of the presentation. The results demonstrated a Group (Training vs. Control) × Time (pre- vs. post-training) interaction such that the (updating) WM training group registered significantly greater gains in Letter Memory than did the control group.

In turn, some of the studies administered measures of complex WM span before and after WM training. As noted by Unsworth and Engle (2006), like simple span tasks, complex span tasks also require participants to recall a set of to-be-remembered items in their correct, but in addition some form of processing activity is interleaved between the to-be-remembered items.

TABLE 3 | Clusters exhibiting reduced brain activation in relation to working memory training.

Area	BA	Center	Spatial extent of cluster	Size	Contributing studies
Inferior parietal lobule	39	−34, −58, 45	−42, −66, 38 to −26, −50, 52	1,888	Ramsey et al., 2004; van Raalten et al., 2008; Zimmer et al., 2012; Thompson et al., 2016; Miró-Padilla et al., 2018; Aguirre et al., 2019
Medial frontal gyrus	8/32	1, 27, 42	−8, 16, 38 to 8, 32, 46	1,448	Sayala et al., 2006; Koch et al., 2007; Thompson et al., 2016; Miró-Padilla et al., 2018; Aguirre et al., 2019
Superior frontal gyrus	6	29, 4, 56	24, −4, 50 to 34, 12, 66	1,352	Garavan et al., 2000a; Sayala et al., 2006; Schneiders et al., 2011; Miró-Padilla et al., 2018; Aguirre et al., 2019
Middle frontal gyrus	9	49, 33, 28	42, 26, 24 to 56, 38, 34	1,328	Olesen et al., 2004; Koch et al., 2007; Schneiders et al., 2011; Thompson et al., 2016; Aguirre et al., 2019
Inferior parietal lobule	40	48, −42, 44	42, −48, 38 to 56, −38, 48	960	Koch et al., 2006; Schneiders et al., 2011, 2012; Miró-Padilla et al., 2018

Number of studies = 25, number of participants = 648, number of foci = 209. The areas have been listed in order of decreasing cluster size.
BA, Brodmann Area; Size, cluster size in mm^3, coordinates are reported in MNI space.
Note that no cluster exhibited increased brain activation in relation to working memory training (see text).

For example, Clark et al. (2017a) administered the Automated Operation Span Task (AOSPAN: Unsworth et al., 2005) and the WAIS-R Digit Span task to their participants who were randomized to either the WM training or active control condition at pre- and post-test (see Clark et al., 2017b). The AOSPAN is "a complex measure of WM which requires participants to remember the sequential ordering of presented stimuli while carrying out simple mathematic problems as a distraction" (Clark et al., 2017b, p. 8). The Group (Training vs. Control) × Time (pre- vs. post-training) interaction was not observed for either outcome measure. In turn, Flegal et al. (2019) administered complex WM span measures involving verbal stimuli with the AOSPAN (Unsworth et al., 2005) and involving visual stimuli with a change localization (Gold et al., 2006) version of the Change Detection task (Luck and Vogel, 1997). Here, too, Group (Training vs. Control) × Time (pre- vs. post-training) interactions were not observed. However, it is important to note those two WM span tasks were selected specifically because they target the executive function of updating *without* changing the demand on WM capacity itself. For that reason, the fact that training-related improvements in WM updating performance did not transfer to complex WM span measures was not surprising.

DISCUSSION

This meta-analysis examined the neural correlates of WM training, with three aims in mind. Below, we will discuss the results with respect to each aim in a separate subsection.

General Neural System Sensitive to Working Memory Training

Based on a substantial body of evidence linking performance and individual differences in WM tasks to the fronto-parietal system, we had predicted that this system would be modulated by WM training across studies. This prediction was confirmed with respect to the omnibus analysis involving all studies (**Table 2** and **Figure 2**). As noted by Salmi et al. (2018) in their meta-analysis of a largely overlapping set of studies of WM training, "current brain imaging evidence does not provide evidence of areas that would be sensitive to learning *per se* but rather emphasizes the modulation of the core systems" (p. 117). It appears that the same inference can be drawn from the present meta-analysis, focused as it was on neurologically healthy non-senior adults that were tested and trained on WM tasks exclusively. There is evidence to show that the posterior cortices are the primary site where WM representations are stored and rehearsed, and that the frontal lobes become important contributors to the process when there is interference during a retention interval (Jonides et al., 2005), or a need for top-down regulation of stored content (Lara and Wallis, 2015). The present results suggest that WM training might have a modulatory effect, both on brain regions that store information as well as those that act on stored memory representations.

Interestingly, however, subcortical structures, such as those in the basal ganglia, did not exhibit involvement in WM training, despite the fact that they have been regularly engaged by WM tasks (Eriksson et al., 2016). This could perhaps be explained by the dissociation noted by Dahlin et al. (2009) regarding the involvement of the fronto-parietal system vs. subcortical regions in WM training. Namely, they noted that whereas the fronto-parietal system may play a more central role in the executive aspects of WM training, the subcortical regions may play a more critical role in the acquisition of skills during WM. Because many different types of tasks emphasizing different types of skills were employed for WM training across studies (**Table 1**), the variation in the specific skills targeted by training might have engaged different subcortical regions, thereby not coalescing in a shared subcortical region across studies. Indeed, there has even been some variation in previous meta-analyses of WM training studies in terms of the engagement of subcortical structures. For example, Li et al. (2015) did not report the reliable engagement of subcortical regions in WM training, whereas subcortical regions did emerge in the meta-analyses conducted by Salmi et al. (2018) and Pappa et al. (2020). Focusing strictly on WM updating studies, Pappa et al. (2020) reported consistent fronto-parietal activity decreases, but an admixture of activity increases and decreases in subcortical regions. Reviewing specific studies in the area, they noted that subcortical regions were more likely to be engaged if the training regimen had specifically involved a WM updating task than other varieties of WM tasks. As such, they argued that subcortical systems are more likely to be engaged by WM training if the task necessitates goal-directed flexibility—a hallmark of updating tasks. In support of this view, Pappa et al. (2020) reviewed theoretical frameworks according to which subcortical systems are hypothesized to play an important role in exhibiting goal-directed flexibility in behavior, in part *via* their interplay with the prefrontal cortex (Cools and D'Esposito, 2011; Nyberg and Eriksson, 2016). In turn, Salmi et al. (2018), who explored differences in the neural systems that support WM training vs. perceptual-motor learning, noted that the striatum was involved in both processes. This suggests that rather than making a unique contribution to WM *per se*, the striatum likely makes a domain-independent contribution to learning in both cases. Indeed, their analysis demonstrated that what distinguished WM training from perceptual-motor learning was the engagement of the dorsolateral and ventrolateral prefrontal cortex in the former process, although higher striatal and ventrolateral prefrontal activations coupled with lower activation in the dorsolateral prefrontal cortex were better predictors of transfer to other untrained WM tasks. Echoing Dahlin et al. (2008), these results suggest that "the functional roles of the transfer-related regions showing enhanced brain activity suggest that near transfer may not be based on modulation of core WM processes, but on the development of relatively task-specific skills" (Salmi et al., 2018, p. 119).

Increases vs. Decreases in Activation

When we examined the neural correlates of WM training separately for foci that had exhibited increases vs. decreases in fMRI studies, our results demonstrated that WM training is associated exclusively with decreases in brain activation in clusters within the fronto-parietal system that underlie WM, including bilateral inferior parietal lobule (BA 39/40), middle (BA 9) and superior (BA 6) frontal gyrus, and medial frontal gyrus bordering on the cingulate gyrus (BA 8/32). This observation was somewhat surprising, given that all three previous meta-analyses of WM training had revealed an admixture of activity increases and decreases in the brain (Li et al., 2015; Salmi et al., 2018; Pappa et al., 2020). There could be a few explanations for the divergence of our results with previous meta-analytic studies. First, we opted to focus exclusively on samples of neurologically healthy adults with mean age <65 years, given the well-established finding that older adults display overactivation in functional brain imaging studies, likely as a compensatory mechanism against age-related decline (Reuter-Lorenz and Cappell, 2008; see also Cabeza et al., 2018; Tagliabue and Mazza, 2021). We opted not to focus on the elderly to reduce that possible source of variability in our findings. It is possible that not including those studies may have impacted our findings, although there has been quite a bit of heterogeneity in findings involving the elderly as there have been reports of both increases (Kim et al., 2017; Takeuchi et al., 2020) as well as decreases (Brehmer et al., 2011; Heinzel et al., 2016) in brain activity in relation to WM training. An additional reason might be the choice of training and/or target tasks that formed the focus of our analysis. In terms of the former, it is possible that WM training tasks that target updating might facilitate increases in brain activity in regions that underlie learning of skills and strategies (Pappa et al., 2020). In turn, extending the pre- and post-training measures to tasks that measure other abilities aside from WM (e.g., multitasking and divergent thinking) might engage structures that exhibit increases in brain activity due to the cognitive requirements of those tasks (Salmi et al., 2018). Our findings combined with those of others suggests that even when the focus of the meta-analysis is largely on the same literature, the specific choice of studies can have a noticeable effect on findings, and should be taken into consideration when drawing inferences from the work.

One possible lens for interpreting the reductions observed in brain activation in relation to WM training is in terms of increased expertise. Specifically, it could be argued that repeated practice on the same task, especially in cases where the task was adaptive, likely resulted in greater proficiency in the maintenance and manipulation of information in WM, and that this greater proficiency (i.e., expertise) was reflected in reductions in the BOLD signal in the fronto-parietal WM network. Here we can ask whether expertise is reliably associated with reductions in neural activation across domains. Neumann et al. (2016) conducted an ALE meta-analysis exploring the neural correlates of cognitive expertise in several domains (mental calculation, chess, language, memory, and music without motor involvement), and found that compared to non-experts, experts were more likely to exhibit activation increases rather than decreases. It is important to note that in the studies analyzed by Neumann et al. (2016), persons needed to have had many years of training to qualify as true experts in a domain. It is therefore possible that short-term increases in skill acquisition might lead to reductions in brain activation, whereas true expertise that typically emerges following long-term engagement with domain-specific tasks eventually leads to increases in brain activation (see Klingberg, 2010). In addition to a focus on increases and decreases in brain activation, it is also important to note that in domains such as music, skill learning and expertise are associated not only with increases and decreases in brain activation but also with cortical reorganization, including the formation of new functional connections between brain regions (see Chang, 2014). Although the focus of the present meta-analysis has been on differences in the direction of activations, examining changes in the connectivity of large-scale brain systems and structures in relation to WM training can certainly add to our understanding of its neural bases.

Impact of Working Memory Training on Span

Although our focus was on the neuroanatomy of WM training, we were also interested in examining whether the studies reported transfer to measures of WM span. We reviewed the results separately for studies of simple vs. complex span, given that they draw on different processes (Unsworth and Engle, 2006). Seven studies from the identified subsample administered measures of simple WM span at pre- and post-test. In the case of three studies, WM training led to statistically significant gains in WM capacity (Olesen et al., 2004; Dahlin et al., 2008; Chang et al., 2017, Experiment 2). A common feature of the training regimens in all three studies was that the task was adaptive, meaning that the level of difficulty was adjusted automatically to maintain maximal cognitive exertion. In contrast, Jolles et al. (2010) and Clark et al. (2017b) who did not use an adaptive version of a WM task found no transfer effect to simple WM span. Finally, Emch et al. (2019) did find a statistically significant Group (Training vs. Control) × Time (pre- vs. post-training) interaction effect, but the interpretation of this effect is complicated by the fact that the performance increase in the experimental group was paired with a performance decrease in the control group. On balance, it seems that when the WM training task is adaptive, then there is a higher likelihood of transfer to simple WM span. In turn, when we switch to complex WM span, there is simply insufficient evidence to infer whether one can observe transfer or not. Specifically, Clark et al. (2017b) found no effect of training on AOSPAN. Furthermore, Flegal et al. (2019) found no effect of training on AOSPAN (Unsworth et al., 2005) or with a change localization (Gold et al., 2006) version of the Change Detection task (Luck and Vogel, 1997), although as noted earlier their focus during training was on WM updating rather than on expanding WM span itself. On balance, it would be prudent to conclude that more research is needed to determine whether WM training can transfer to complex WM span (see also Harrison et al., 2013).

Two additional points deserve attention here. First, as noted by Bryant and Niall (2020), training can impact performance in many ways, such as increasing the power of a cognitive capability, increasing the effect one can derive from an existing level of capacity, and providing external devices to perform cognitive tasks that reduce the need for using cognitive capabilities. In turn, not all of those training outcomes would be equally likely to impact WM capacity *per se*, such that one might observe improvements in WM performance that are not necessarily accompanied by gains in WM span. Second, as noted earlier, there is some evidence to suggest that WM training can lead to near transfer, but there is no such evidence regarding far transfer (Morrison and Chein, 2011; Melby-Lervåg and Hulme, 2013; Redick et al., 2015; Melby-Lervåg et al., 2016; see also Soveri et al., 2017). Although that specific question was not under investigation here, a similar picture emerged across the 32 studies included in our meta-analysis. Pappa et al. (2020) who examined that question formally by conducting a meta-analysis of the behavioral data associated with neuroimaging studies of WM updating found a moderate and statistically significant effect for near transfer (Hedge's $g = 0.63$), but a small and statistically non-significant effect for near transfer (Hedge's $g = 0.15$). These relatively weak transfer effects likely have a bearing on the neuroanatomy of WM training insofar as one might expect that more robust neural changes would accompany more robust behavioral/performance changes. As the size of this literature grows, it would be important to compare the impact of WM training for studies that report successful vs. unsuccessful near- and far-transfer effects.[5]

Working Memory Training and Cognitive Resources

Typically, reductions in brain activation in relation to WM training have been attributed to neural efficiency. However, as noted by Poldrack (2015), one could argue for neural efficiency only if the same neural computations were being performed with identical time and intensity, but with different metabolic expenditure. Unfortunately, due to our incomplete understanding of the cellular basis of the BOLD signal (Logothetis, 2008), coupled with the fact that we cannot rule out other factors with certainty (e.g., whether different set of cognitive processes and/or neural computations are being performed), we are not in a position to equate reductions in brain activation in relation to WM training within the fronto-parietal system to neural efficiency (Constantinidis and Klingberg, 2016). Nevertheless, it is prudent to consider the contribution of several candidate processes to this pattern of findings. First, it is possible that the observed pattern is driven by a shift from controlled to automatic processing (Shiffrin and Schneider, 1977). Specifically, it is well known that engagement with an initially novel task can be more effortful, whereas repeated engagement and familiarization with the same task can lead to greater levels of automaticity in task performance. This transition from controlled to automatic processing is captured by dual-process models of cognition that involve an interplay between effortful and automatic processing in the service of task performance (Evans and Over, 1996; Sloman, 1996; Kahneman and Frederick, 2002). In this sense, it is possible that the reduction in brain activation due to WM training could be due to greater automaticity in WM performance because of familiarization (see Chein and Schneider, 2005). Second, decreased brain activity could reflect increased specificity and precision for detecting stimuli—what has been referred to as *narrowing of tuning curves* (Rainer and Miller, 2000). As noted by Constantinidis and Klingberg (2016), a narrower tuning curve could be an indicator that fewer prefrontal or parietal neurons are necessary for coding a stimulus, which will be associated with a lower BOLD response. A third possibility is of course that fewer neurons are engaged for performing the same task post-training—a possibility that has not been tested directly in this domain.

Finally, what do the findings mean for our understanding of WM capacity as a *processing resource* (i.e., an entity that exists in limited supply and is responsible for the enhancing or enabling cognitive processes, Salthouse, 1990)? Historically, scholars who have considered the psychological reality of limited processing resources (or "mental energy") have typically also assumed that those resources have a physiological correlate (see Craik and Byrd, 1982). In this sense, one would expect that if WM training were to increase WM capacity, then there should be a corresponding change in activity in the neurological system

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[5] When using the most optimal thresholding method (i.e., cluster-level family-wise error correction), a minimum of 17 experiments is necessary to perform reliable and robust meta-analyses (Eickhoff et al., 2016).

that supports it. Although WM training leads to decreases in activation in the fronto-parietal system, it is not possible to infer that this reflects an increase in WM capacity *per se*. Not only is more research needed to examine how variations in the activity of the fronto-parietal system are related to variations in WM capacity measures, but it is also necessary to consider the broader context within which limited processing resources are measured. As noted by Navon (1984) in his classic criticism of resource models, "resource theory ascribes variability in performance of a task to the amount of some limited *internal input* dedicated to the task" (italics added, p. 217). However, we now know that performance on such tasks and our subjective assessments thereof (e.g., workload) are influenced by a host of contextual, environmental, and motivational factors that likely interact with those internal inputs dedicated to the task. In this sense, examining the neural correlates of constructs hypothesized to be limited by processing resources needs to be informed better by the assumptions that characterize their measurement.

CONCLUSION

Our meta-analysis demonstrated that WM training is associated with reduced activation in a set of regions that reside within the fronto-parietal system, including the bilateral inferior parietal lobule (BA 39/40), middle (BA 9) and superior (BA 6) frontal gyrus, and medial frontal gyrus bordering on the cingulate gyrus (BA 8/32) (**Figure 2** and **Table 3**). This pattern of findings suggests that WM training targets neural structures that are involved in the storage, rehearsal, and/or manipulation of mental representations within the core fronto-parietal system that supports WM. Importantly, due to our incomplete understanding of the cellular processes that underlie the BOLD signal, coupled with the fact that we cannot rule out other factors with certainty (e.g., whether different sets of cognitive processes and/or neural computations are being performed), it is not possible to isolate a specific mechanism that can explain the biological basis of the observed reduction in brain activation as a function of WM training. When viewed in the context of extant meta-analytic evidence suggesting that WM training reduces brain activation within the fronto-parietal system (Li et al., 2015; Salmi et al., 2018; Pappa et al., 2020), our results underscore the importance of developing paradigms to examine the biological basis of the observed effect, and thus lead to an improved understanding of what this finding means for resource models of WM.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

OV, VR, SF, and QL contributed to the conception and design of the study. VR, SF, QL, and SS organized the database. OV, VR, SF, QL, and SS performed the statistical analysis. OV wrote the first draft of the manuscript. All authors contributed to the refinement of the design, manuscript revision, read, and approved the submitted version.

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Restoration of Attention by Rest in a Multitasking World: Theory, Methodology, and Empirical Evidence

Frank Schumann[1]*, Michael B. Steinborn[2], Jens Kürten[2], Liyu Cao[3], Barbara Friederike Händel[2] and Lynn Huestegge[2]

[1] Mittweida University of Applied Sciences, Mittweida, Germany, [2] Department of Psychology, University of Würzburg, Würzburg, Germany, [3] Zhejiang University, Hangzhou, China

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Federal Institute for Occupational
Safety and Health, Germany

***Correspondence:**
Frank Schumann
schumann@hs-mittweida.de

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In this work, we evaluate the status of both theory and empirical evidence in the field of experimental rest-break research based on a framework that combines mental-chronometry and psychometric-measurement theory. To this end, we (1) provide a taxonomy of rest breaks according to which empirical studies can be classified (e.g., by differentiating between long, short, and micro-rest breaks based on context and temporal properties). Then, we (2) evaluate the theorizing in both the basic and applied fields of research and explain how popular concepts (e.g., ego depletion model, opportunity cost theory, attention restoration theory, action readiness, etc.) relate to each other in contemporary theoretical debates. Here, we highlight differences between all these models in the light of two symbolic categories, termed the resource-based and satiation-based model, including aspects related to the dynamics and the control (strategic or non-strategic) mechanisms at work. Based on a critical assessment of existing methodological and theoretical approaches, we finally (3) provide a set of guidelines for both theory building and future empirical approaches to the experimental study of rest breaks. We conclude that a psychometrically advanced and theoretically focused research of rest and recovery has the potential to finally provide a sound scientific basis to eventually mitigate the adverse effects of ever increasing task demands on performance and well-being in a multitasking world at work and leisure.

Keywords: rest breaks, attention restoration theory, cognitive resources, mental fatigue, ego depletion, multitasking, energy management, motivated cognition

Everyday wisdom tells us that multitasking is great in the kitchen when a cook is preparing several dishes at once, for example, the chicken to be ready at the same time as the rice, but it becomes worse when trying to schedule the work day (Salvucci and Taatgen, 2011, pp. 3–14). In fact, people's attentional capabilities are increasingly strained by environmental factors such as time pressure or multiple task demands (Levine, 1998), or even professional requirements (Strobach et al., 2015; Häusser and Mojzisch, 2017). Since multitasking demands preoccupy large parts of people's daily routines, the question of how to manage or to recover from the strain imposed by overload has become increasingly important, both for researchers and practitioners (Kaplan, 1995;

Kahneman et al., 1999; Proctor and Capaldi, 2008). However, despite a multitude of published papers, current research cannot provide answers to fundamental questions. Here we dramatize the position that both theory and methodology for studying the restoration of attention by rest is in a lacking condition at present. Formally, rest breaks are defined as temporal interruptions of an activity, serving the purpose of regenerating mental functions. Conceptually, there are three fundamental aspects that are connected to taking a break, depending on the particular context: to find distance, to change activity mode (e.g., from thinking to sensing), and to recover or regain energy levels (Kaplan and Kaplan, 1989; Colzato et al., 2012; Häusser and Mojzisch, 2017).

1. INTRODUCTION

In everyday language, rest breaks play an important role both at work and in active leisure time (Fritz and Sonnentag, 2006; Wendsche and Lohmann-Haislah, 2017). The metaphorical nature of everyday language already provides clues about an underlying hypothetical "mechanism" that people perceive as such in purely phenomenological terms. For example, people often talk about "*refueling*" their energy or "*recharging*" their batteries, which clearly implies a kind of resource that diminishes under strain and is restored through rest (Hobfoll, 1989; Kaplan, 1995; Fritz et al., 2011; Zacher et al., 2014). On the other hand, people often say *"I'm fed up with it,"* indicating a state of aversion to be reduced by taking some distance from the ongoing task (Lewin, 1928; Demerouti et al., 2001; Mojzisch and Schulz-Hardt, 2007; Kurzban et al., 2013). Therefore, rest-break structures in working life are firmly established by government law and specified by labor legislation. Although rest breaks in private life can be taken rather flexibly, even there a rhythmic structure can be observed, consisting of a change from strenuous activity to rest and vice versa (Tucker et al., 2003; Monk, 2005; Wendsche and Lohmann-Haislah, 2017). Because daily routines are similar for the majority of people, enabling similar experiences, hardly anyone would not agree with the proposal that breaks have a positive effect on feelings or mental performance (Poffenberger, 1928; Bills, 1943; Wyles et al., 2016). However, such an initial consensus would certainly not last long but maybe even turn into a point of contention if the question is taken further of how *exactly* rest affects cognition in a particular situation.

Though there are numerous proposals and theoretical notions in the scientific literature about how mental fatigue occurs, what demands create it, and how breaks regenerate or even restore it afterward (Strack and Deutsch, 2004; Fritz and Sonnentag, 2006; Wells and Matthews, 2015). Although it is obvious that the underlying mechanisms of rest and recovery might be completely different in the variety of contexts and time scales where strain and recovery take place, this aspect is not sufficiently distinguished in the empirical literature. On the other hand, most of the theoretical approaches are relatively similar in their base assumptions while focusing on rather specific contexts or making predictions about quite different units of observation (e.g., objective test performance vs. subjective ratings of feelings or motivation). They can be classified into two basic categories that clearly correspond to common everyday metaphors, which we will term here the "*resource model*" and the "*satiation model.*" The resource model covers all proposals that assume a hypothetical reservoir of energy, either perceived as such by an individual or indicated through performance, which depletes through work, is replenished by rest, and can be conserved to some degree by adopting strategy (Hobfoll, 1989). The satiation model covers those approaches that base their starting point on feelings that include a spectrum of aversive experiences capable of inhibiting ongoing task operations (Lewin, 1928; Watson et al., 1988; Thayer, 1989; Tellegen et al., 1999; Langner et al., 2010; Matthews, 2021).

The goal of this paper is threefold. First, the observable phenomena are to be ordered and classified, followed by a theoretical analysis of pauses and their effects on performance. Finally, empirical studies are discussed and methodological aspects elaborated on how pause effects can be meaningfully investigated by means of reliable performance-based experimental methods (Steinborn et al., 2018). Here we are focusing on experimental rest-break research, while considering field research (employing mostly correlational methods) with respect to similarities and differences in both the theorizing and methodological approaches. Since research on rest and recovery is a relatively broad and interdisciplinary field, relevant to many scientific domains including sports sciences, school psychology, work and occupational psychology, and cognitive-experimental psychology and neuroscience, it is rather impossible to organize the manuscript in the style of a classic meta-analysis, where study results are statistically aggregated to generate a quantitative estimate of an empirical phenomenon (e.g., the rest-break effect, etc.). Specifically, while it is viable to aggregate studies in well-defined work field situations, like the aftereffect of lunch breaks on performance (Monk, 2005), or the effects of shift-work on well-being (Kantermann et al., 2007, 2012), considering variations across studies as random factor, this is neither possible nor feasible in a purely experimental situation. This would actually reduce a rather complex research question to whether an effect exist or not (or what size an effect is on average) while ignoring crucial aspects of theorizing, design, and measurement methodology that is absolutely crucial for a deeper understanding of behavioral phenomena. Therefore, the present work aims at analyzing the problem at the level of theory, methodology, as well as psychometric measurement in the light of existing empirical evidence.

2. TAXONOMY OF REST-BREAK STRUCTURES

It is virtually impossible to theorize on the effect of rest breaks on mental function without considering the variety of contexts and time scales where breaks are relevant (Tucker et al., 2006; Helton and Russell, 2015; Wendsche and Lohmann-Haislah, 2017). In labor law, break systems are anchored and regulated by legislation. Work breaks are defined as the period of time specified in the company agreement during which employees'

TABLE 1 | Overview and description of paradigms and phenomena closely related to rest-break research.

	Type	Design and calculation	Assumption and description
1	Post-lunch dip	Pre-post comparison of performance before vs. after the main lunch break	- performance decline after lunch - glucose intake ≥ insulin response ≥ fatigue - digestion impose ("*dual-task*") interference - likely a part of diurnal rhythms
2	Time-of-day effect	Differential daytime performance curves as a function of work-break schedule	- evidence for both diurnal trends and fluctuation - empirical evidence is mixed and contradictory - lack of proper design in the majority of studies - difficulties of implementing proper controls - confounds: test-taker effects and practice
3	Incubation effect	Comparison of problem solving performance after resting vs. no-resting vs. interference	- improved problem solving after resting - latent processing during rest ≥ restructuring - the function of rest is to reduce fixation - can be conceived of as a rest-break paradigm
4	Memory consolidation	Comparison of memory recall after resting vs. interference	- relatively mixed empirical evidence - is an interference paradigm in a strict sense - rest = control, a proxy for "non-interference" - not a rest-break paradigm in the proper meaning
5	Restart-cost effect	Costs of re-starting mental set as a function of lengthening rest breaks (or unexpected task onset after long rest)	- concerns the detrimental effects of long intervals - benefits of rest turn into costs when too long - theoretical objective: aspects related to forgetting - has a more specific meaning in task-switch literature
6	Interruptions	Comparison of memory recall after interrupted vs. non-interrupted tasks	- evidence for increased recall of interrupted tasks - prerequisite: completable, purposeful tasks - use of intrinsically motivating task forms - examples: Hungarian cube, puzzles, etc.
7	Delays	Comparison of performance in a no-delay vs. predictable delay vs. non-predictable delay condition	- concerns "unwanted" delays during workflow - example: computer loading bar; CPU overload - aimed at simulating workflow interruptions - contextual semantics differ from rest-break studies

The types 1–2 are paradigmatic approaches to study daytime change and its compensation by rest in the context of work and leisure; the types 3–4 are not concerned with mechanisms of recovery but with latent processes of consolidation and representational restructuring. The types 5–7 address specific functions of inserted time intervals (e.g., forgetting as task set, motivation to complete a puzzle, annoying effects of computer loading bars or CPU overload, etc.).

work performance is suspended. Although statutory work breaks are primarily implemented for the purpose of taking meals, they also have a designated recreational function (Lombardi et al., 2014; Paech et al., 2014; Pylkkonen et al., 2015; Roach et al., 2016). During this time, employees are neither required to perform work nor to be ready to do so, and even more, they are free to decide where and how to spend this time. Work breaks can thus be spent both at the workplace and outside. In the conception of labor law, the break is a state of inactivity inserted into a work process, where inactivity also concerns the attitude toward the work performed in each case. Thus, inactivity is limited to the work process itself, so that any activities unrelated thereto, such as reading the newspaper, listening to music, or exercising, constitute a break activity. Scholz et al. (2017) conducted an experimental field study comparing different types of breaks and found that the exact type of break is of less relevance than the sole fact that a break takes place at all (see also Helton and Russell, 2015; Steinborn and Huestegge, 2016; Wendsche and Lohmann-Haislah, 2017).

By nature, rest breaks can be classified according to various aspects and dimensions, such as the time scale or context where rest is taken (see **Table 1**). An important aspect refers to the distinction between experimental rest-break research that typically takes place in the laboratory (using student-based participants) and the field-research approach that takes place within the facilities of a company (using employees as participants). Experimental studies typically manipulate critical experimental variables (e.g., duration, task, and content, etc.), field studies are often based on correlational methods. As a consequence, equally sounding theoretical concepts (e.g., ego depletion vs. burnout depletion) often differ in their exact meaning and likely address a rather different underlying mechanism, as compared to those addressed in experimental studies. Finally, field studies typically base their conclusions on self-report measures of mood or mental fatigue, obtained via questionnaire, or asking about the frequency of taking short breaks during the work day (Krajewski et al., 2010; Fritz et al., 2011; Zacher et al., 2014; Kim et al., 2017, 2018). In contrast, experimental studies are typically aimed at assessing performance differences (e.g., measuring the speed and accuracy of mental work) as evoked by the manipulation of critical experimental conditions. Some studies use a combined experimental-correlational approach in field settings, studying the effects of rest on workers' performance using laboratory tasks aimed to simulate the micro-case of the work process, though it is difficult to generalize (or transpose) the effect of rest on performance in a laboratory task on the real work process (Scholz et al., 2017, 2019).

Crucially, rest breaks must conceptually be distinguished from other types of interruption periods. For example, preparatory

TABLE 2 | Popular metaphors typically guiding theoretical predictions in the rest-break literature.

	Type	Metaphor and symbolic assumptions
1	Energetic-resource model	A hypothetical reservoir of resources is depleted through mental work (e.g., with time on task) and replenished during rest. The state of resource disposal is indicated by the decrease in performance speed in the task over time.
2	Strategic-resource model	Though resources are depleted during an ongoing sustained-attention task, they can be held in reserve or can be distributed in flexible ways. Thus, a straightforward relation of resource volume and performance over time is no longer assumed. Note: variants of strategic-resource models need further specification in order to be verifiable.
3	Ego depletion	Acts of self-control deplete resources and might potentially be replenished through periods of rest. The typical experimental arrangement goes as follows: Resources are depleted in task A and tested in a subsequent task B. In this way, ego depletion is concerned with the sequential transferability of a depleted across two subsequent tasks.
4	Satiation model	The critical variable relevant to performance is not a hypothetical volume of resources but the level of accumulated satiation that is experienced as aversive, thus considered the main driving force of behavior. Perceived satiation increases during repetitive work and dissipates during rest.
5	Reactive inhibition (Rasch model for speed tests)	Processing repetitive tasks yield a resistance gradient against further continuing with the ongoing action, conceived of as a distraction tendency. The inhibition gradient increases with prolonged task processing and leads to distraction (enforced rest) when reaching a critical threshold. This inhibition tendency thus increases monotonically during task processing and decreases during periods of (a) distraction or during (b) rest breaks.
6	Opportunity Costs	The term opportunity costs refers to the potential loss of a missed opportunity as a result of choosing one opportunity and foregoing another. These costs are indicated by the subjective experience of effort or aversion when proceeding with the ongoing task, but are relieved when the task is changed (that is, when alternatives are considered).
7	Attention Restoration Theory (ART)	Resources are claimed during the working hours of a day and replenished in the remaining free time and on weekends. Crucial is that recovery is not merely a function of time but depends on the context where rest takes place. Spending time in nature is assumed to be more beneficial than spending time in urban environments. In a strict way, ART is a psycho-sociological model but often misconstrued in the empirical literature.
8	Conservation of Resources Theory (CRT)	This is a psycho-hygienic model of stress prevention which is popular in the applied fields of rest-break research. In brief, the theory deals with how people perceive and estimate own resources including the costs of handling anticipated threats and challenges imposed by impending future events, and how people deal with uncertainty, respectively.

The models 1–3 employ a metaphor (resource volume) with a preconditioning parameter while the models 4–6 (satiation) make use of a delimiting parameter (thus both symbolic classes utilize a diametrically opposing metaphor to each other), though both metaphors make similar predictions. The models 7–8 are, in a strict sense, not performance models but theories about human wellbeing in the context of strain and recovery, though frequently referred to also by the experimental literature on mental fatigue and its recovery by rest breaks.

activities or waiting times in performance tests are typically not considered rest breaks, even when they are not overtly performed, such as monitoring or other kinds of watchkeeping activities (Warm and Alluisi, 1971; Steinborn and Langner, 2012; Ross et al., 2014). For example, Broadbent (1971) argued that rest break time is to be distinguished from preparatory time, though it might depend on the particular context whether individuals actually recruit rest intervals for preparation (Rabbitt and Vyas, 1980; Steinborn and Langner, 2012; Langner et al., 2018). More generally, all kinds of active waiting periods that require vigilance and where complete goal detachment is not possible are not to be considered resting time (Langner and Eickhoff, 2013; Thomson et al., 2016). In a practical sense, work breaks can be divided into work interruptions of different length as well as of different functions; from a cognitive-psychological point of view, however, the most meaningful is the division into three approximate time categories (or time zones, respectively): The long break (30–60 min) represents the break for meals and is the most relevant break in work contexts. The short break (3–10 min) is actually a form of break where the recreational aspect is paramount, and the majority of studies are actually addressing this kind of rest break. The last category concerns micro-breaks (<3 min), which are extremely brief pauses that mainly serve to reduce short-term overload of the cognitive system. While the study of long breaks is restricted to field approaches, the latter types are typically examined via experimental-design (Adams, 1954; Rickard et al., 2008; Ariga and Lieras, 2011; Helton and Russell, 2015; Ralph et al., 2016; Steinborn and Huestegge, 2016).

As already indicated, the *long break* is the most relevant break in the regular working life. It is an integral part of the classic 8-h workday and can only be investigated in this context (Chmiel et al., 1995; Folkard, 1997; Monk, 2005). It is neither possible nor feasible to manipulate critical experimental conditions in real-work contexts, such as to vary the break's length and content, so only the observation of those aspects that are naturally occurring during the workday remain suitable for investigation (Lombardi et al., 2014). Thus, the full-scale study of performance patterns over the entire workday is a classic domain of field research, often combined with a correlational approach (Meehl, 1967; Fritz and Sonnentag, 2005). Accordingly, the results of studies on time-of-day effects are also difficult to interpret, as numerous methodological artifacts can hardly be

TABLE 3 | Computation and meaning of the four essential contrasts in experimental rest-break designs.

	Type	Calculation and interpretation
1	Simple block comparison (relative block difference)	A baseline (no-rest) condition (A) serves to estimate the performance decrement over the testing period without rest breaks. A rests-break (B) condition serves to estimate the performance trajectory when rest is provided. Directly contrasting both yields a measure of the relative A–B block difference in performance, which provides a primitive measure of the overall benefit provided by rest, relative to a continuous condition.
2	Global rest-break effect (relative time change)	To obtain a measure of the "relative" change in performance over the testing period, the trajectory of performance (time-on-task gradient) for both A and B is contrasted. This gives an estimate of the relative change in the time-on-task effect in performance. In other words, it informs how the performance decrement is prevented by rest breaks, relative to when no rest break is given.
3	Local rest-break effect (before–after rest)	The local effect of rest on subsequent performance is obtained by contrasting the adjacent sections before and after the rest break (pre–post rest comparison). This gives an average estimate of the local benefit of rest that immediately occurs in the time series closely before and after taking a rest, irrespective of the time trajectory.
4	Differential effectiveness (early vs. late rest breaks)	To test the assumption that the effectiveness of a rest itself increases with testing time (i.e., with time on task), the local (pre–post) rest effect at different positions during the testing period is directly contrasted. A larger relative effect at late positions in empirical data would indicate that the immediate effect of rest increases over the testing period, in other words, that rest is more effective at late relative to early positions.

The type 1 is, in a strict sense, not interpretable (see Steinborn and Huestegge, 2016) but frequently used in the literature, thus presented here for reasons of completeness. Type 2 tells how rest compensates a potential performance decrement (the time-on-task effect). Type 3 concerns the local dynamics of recovery and thus provides a measure of how immediate recovery occurs directly after the break. Type 4 gives an indication of a change in the local effectiveness change of (early vs. late) rest breaks.

avoided (Roach et al., 2016; Riley et al., 2017). There are two relatively well-established effects that seem paradoxical at first glance but can be explained quite easily on closer inspection, (1) the time-of-day effect and the (2) post-lunch dip phenomenon. The *time-of-day effect* describes, according to mostly earlier studies, an increase in performance over the course of the day, at least better performance in the afternoon relative to morning times (Folkard, 1975; Roenneberg et al., 2003). More recent studies acknowledge the difficulty in studying daytime trajectories as there are many confounding variables that cannot be controlled easily. For example, because it is difficult to avoid the use of a repeated-measures design, daytime trajectory effects of performance are often superimposed by artifacts such as test-taker effects or practice gains (Folkard, 1975; Ballard, 1996; Dinges et al., 1997; Flehmig et al., 2007b; Lim and Dinges, 2008; Langner and Eickhoff, 2013; Basner et al., 2018; Steinborn et al., 2018).

In some way, the empirical finding of a *post-lunch dip* phenomenon contradicts the predictions implied by a resource–recovery model, as it refers to a decline (not an improvement) in performance immediately after (meal) breaks. It is also at odds with the predictions of prominent models connecting small declines in glucose levels during a task with decreased willpower and mental performance (Gailliot et al., 2007; Vadillo et al., 2016). To study lunchtime effects, one or more critical groups are typically compared with a control group each before and after the experimental variation (i.e., the break including the meal). In general, performance costs are found in the critical relative to the control group, and this effect is influenced by numerous factors. High calorie diet or high carbohydrate diet are the most important determinants of the effect, and even though there is a great heterogeneity with respect to the particular tasks and performance measures, empirical findings seem relatively robust (Bes et al., 2009; Reyner et al., 2012; Debus et al., 2014). Nevertheless, a detailed comparison of results across studies remains difficult because of the large differences in the use of tasks and performance metrics, as most of them hardly meet current psychometric standards (cf. Langner et al., 2010; Miller and Ulrich, 2013; Steinborn et al., 2018). Monk (2005) argues that there could be a habitual component in the post-lunch dip effect, since even without food intake there is often a small performance drop in the early afternoon, similar to the post-lunch phenomenon. However, the empirical evidence is rather unclear, as only a few studies have included such a condition.

The *short rest break* (3–10 min) and its effects on performance is typically studied via the experimental approach, typically with a clear focus on the underlying cognitive processes. Roughly speaking, the research approaches can be divided into three categories, corresponding to which three basic types of tasks are used. (1) Active sustained attention is mostly measured by means of speeded tests, sometimes termed continuous–performance tests, or mental–concentration tests (Krumm et al., 2008; Blotenberg and Schmidt-Atzert, 2019a,b). These tests require continuous processing and are highly demanding at a subjective level (Pieters, 1983, 1985; Van Breukelen et al., 1995; Mojzisch and Schulz-Hardt, 2007; Steinborn et al., 2018). Notably, this type of task is also relatively often used to experimentally induce a hypothetical mental state termed *ego depletion*, which is relatively popular among social psychologists (cf. Hagger et al., 2010; Vohs et al., 2021). Speeded self-paced tests typically exhibit the highest degree of test reliability, thus a high number of items can be administered per unit of time, enabling precise measurement (Van Breukelen et al., 1995; Steinborn et al., 2018). (2) A rather passive type of sustained attention (vigilance) is measured in a classical way with detection tasks, which require the individuals to keep track on watching for rarely presented targets, either in time or among distractors (Mackworth, 1948; Warm et al., 1974; Langner et al., 2011), which is less reliable because target items are spaced by an intertrial interval thus only a few (1–2) responses are registered per unit of time. More recent studies opted for the use of the psychomotor vigilance test (PVT), which requires speeded responses to a simple targets, spaced by long and variable waiting intervals. Research indicate that these interval are not perceived as a rest but to form expectations about temporal moments to which the participants are to give a speeded response (Wilkinson, 1959; Langner et al., 2010; Steinborn et al., 2016; Massar et al., 2018; Unsworth and Robison, 2019).

The basic design for studying short rest-break effects consists of the following components (cf. Steinborn and Huestegge, 2016): A baseline condition is used to propagate mental fatigue (e.g., a test of 20–40 min), which is compared to one or more experimental conditions where rest-breaks (of 1–5 min) are intercalated. Typically, not merely the group differences (Ariga and Lieras, 2011; Helton and Russell, 2015) but a differential time course in the rest condition as compared to the baseline condition is taken as indication that rest prevented fatigue from accumulating (see **Table 3**). It is important to note that the term "mental fatigue" is most often not used in a specific sense but rather referred to as an umbrella term (cf. Langner et al., 2010), and the test length to propagate fatigue should not exceed 60 min. This might seem counterintuitive at first glance, however, many early studies have administrated their individuals to perform tasks (mostly mental arithmetic) over longer periods of 4–8 h, showing a decline in performance after 30–60 min, which then leveled off at a low performance (e.g., Robinson and Bills, 1926; Manzer, 1927; Schubert, 1932; Bills, 1943). Typical research questions involve a comparison of different types of rest, for example, whether the rest is taken in an active (i.e., walking) or passive way (sitting) or in the same vs. changing environments, or with respect to the freedom of choosing how to spent the given time for rest (e.g., Ulrich et al., 1991; Korpela and Hartig, 1996; Ross et al., 2014; Steinborn and Huestegge, 2016; Basu et al., 2018; Pasanen et al., 2018; for theoretical considerations).

The *micro-break* effect refers to the phenomenon that even the shortest pause inserted during continuous cognitive activity typically yields significant performance gains, relative to a condition where no such pauses are given (Adams, 1954, 1955; Eysenck, 1965, 1969). Studies theorizing on micro-break effects can be divided into at least two categories with assumedly distinct underlying mechanisms. Studies on the so-called "reminiscence" effect typically use continuous–performance tests, and there are also studies where pauses are not conceptualized in terms of restoring energy but as brief intermission phases that serve coordinating mental structure during memorization (Bower and Springston, 1970). While the former is typically concerned with (motor-)learning effects (Adams, 1954; Rickard et al., 2008), studying performance gains as a function of rest, the latter is concerned with the accumulation of short-term fatigue, sometimes termed accumulated refractoriness, and its reduction through rest (Weaver, 1942; Bertelson and Joffe, 1963; Rasch, 1980). In a typical study, tasks were presented as a continuous series as is common in psychometric instruments of the speed-test type (Rasch, 1980; Steinborn et al., 2018). In such a situation, one can observe occasional "mental blockades" occurring during continuous task processing. Bills (1931, 1935) studied this phenomenon in numerous task forms such as addition, coding, or sorting, which are the most common classes of items in speed tests (Neubauer and Knorr, 1998; Flehmig et al., 2007a; Wühr and Ansorge, 2019). His analyses of individual responses showed that even after 5 min of uninterrupted work, mental blocks could be observed, which were defined as extremely slow reactions relative to the average. According to Bills, mental blockings can be conceived of as enforced (or system-generated) pauses, aimed for refractoriness to dissipate. If one would administrate smallest breaks preventively, by inserting distributed brief pauses, then the blocking phenomenon is typically reduced or absent (cf. Van Breukelen et al., 1995).

3. RELATED PHENOMENA

3.1 Incubation

As mentioned earlier, rest breaks are distinguished from other forms of intervals separating work periods in time (e.g., preparation, monitoring, etc.), and other type of activities that require the further maintenance of attention (Gillie and Broadbent, 1989; Goschke and Kuhl, 1993; Allport and Wylie, 2000). A characteristic of these aspects is that they be distinguished theoretically while the empirical test of prediction derived from theory depends on the quality of design and measurement precision. However, there are some related phenomena obtained in a paradigm similar to a rest-break situation (at least could be framed as such) but with an entirely different underlying mechanism. One example is the so-called incubation paradigm, where individuals are typically administered with a problem-solving task, with the solution being dependent on sudden insight that is often prevented due to fixation or when misdirected toward another pathway (e.g., Vul and Pashler, 2007; Bilalić et al., 2008; Sio and Ormerod, 2009). The incubation effect is demonstrated by comparing a condition where individuals are administered to take a rest, relative to an alternative (distracting) activity and a control (no-rest) condition. The outcome, relatively often shown, is that those participants (a) who took a rest during an incubation period performed better than (b) those who performed a task during this period, (c) relative to the baseline (no-rest) condition, though opposing findings have also been reported (Sio and Ormerod, 2009).

3.2 Episodic–Trace Consolidation

Another related line of research concerns studies on memory consolidation during nocturnal sleep, daytime napping, or other kinds of resting periods. The term memory consolidation refers to a category of processes considered to support the stabilizing of a memory trace after its initial acquisition. Importantly, psychological research is not so much concerned with low-level consolidation processes such as synaptic consolidation, which has clearly been shown to occur 1–2 h after initial learning. Instead, the focus is on cognitive consolidation, that is, on how mental representation are formed or restructured, and how episodic traces are finally transformed into abstract codes with flexible retrieval structures (Tulving and Thomson, 1973; Hintzman, 1974, 1986; Tulving and Watkins, 1975). Classically, memory consolidation is studied during sleep, though psychological research is more focused on shorter time scales, studying mnemonic consolidation after resting relative to an active-work condition (Wamsley, 2019; Martini and Sachse, 2020). The participants in such studies are typically required to memorize material, with recall performance being tested afterward at a later time point, under a relaxed condition (e.g., closed eyes, napping, etc.), relative to a distractor condition (e.g., mental work, watching videos, etc.). The theoretical prediction is that waking rest supports the consolidation of previously learned memory content, relative to an interference condition, though the empirical findings are rather mixed with this regard (Martini et al., 2019). While this line of research addresses the aspect of "resting" on memory consolidation, it is important to understand that the *de facto* research question in this field is not on how rest breaks restore attention, but more on the *benefit of non-interference (vs.* interference) on memory recall performance (Wamsley, 2019; Martini and Sachse, 2020).

3.3 Restart Costs

By definition, the term restart costs refer to a cost point that is incurred when the time taken for rest is too long, and in this way, it could be viewed as a non-beneficial effect of rest on performance. It is directly connected to the question of how long a rest break should be to achieve the best results, which has been debated already by earlier studies (Graf, 1922; Manzer, 1927; Poffenberger, 1928; Schubert, 1932; Barmack, 1939; Ross and Bricker, 1951). In the literature on rest-break research, this is studied by experimentally varying the rest-break length and to determine the functional relationship between rest length and recovery. In the specific literature on task-switching performance, the term restart costs is not in the same way conceived of as a rest break, but taken in the more restrictive sense as the relative costs of intercalated time intervals in task repetition relative to alternation trials (Allport and Wylie, 2000; Wylie and Allport, 2000). In this way, re-start costs in task-switching research are linked to aspects of forgetting, or other aspects of losing proper memories for the upcoming task (Altmann, 2002; Altmann and Gray, 2008; Kiesel et al., 2010; Vandierendonck et al., 2010; Vallesi et al., 2013). We therefore argue that the conception of re-start costs are in its specific form (as used in the task-switching literature) different from those studied in the rest-break literature. While the rest-break literature deals with the aspect of attentional replenishment, the task-switching literature is concerned with aspects of forgetting, and in this way, re-start costs are not the primary concern but a side-show phenomenon in the task-switching literature.

3.4 Interruptions

The concept of rest breaks exhibits some remarkable similarity with the concept of an interruption, which refers to a temporal interruption of an activity that is not necessarily needed, and neither wished, nor intended, and not expected as such at a certain time point during ongoing task performance. In the early literature that has its starting point in Lewin's (1928) field theory, it was shown that when individuals were interrupted during an ongoing task (stringing beads, solving puzzles, etc.), but were allowed to continue with other tasks, then the interrupted task was recalled more often than the uninterrupted ones (Zeigarnik, 1927). Even more so, if they were allowed to freely decide what do to at some point, the individuals tended to re-start and completing the interrupted tasks (Ovsiankina, 1928), which indicates that the memory for non-completed tasks tend to further persist in memory and thus guiding ongoing decisions (Gillie and Broadbent, 1989; Goschke and Kuhl, 1993; Einstein and McDaniel, 2005). Thus, the study of (completable) task interruptions like solving a puzzle is an interesting counterpoint to the study of rest breaks because it demonstrates the energizing effect of intrinsic motivation on cognitive persistence such that individuals are prevented to perceive a need for rest before completing a task such as a puzzle, or when they are given an objective (or purpose) to aim for Kruglanski et al. (2012), Suri et al. (2015), Krishna and Strack (2017), Steinborn et al. (2017).

3.5 Delays

While the theorizing in the rest–recovery model literature is focused on mechanisms of attentional replenishment, considering rest as to result in an improvement or at least stabilization of performance, the literature on delayed processing or unpredicted interruptions during ongoing action sometimes shows the opposite effect, as often a detrimental effect on performance is reported which is considered to originate from kinds of distraction. In fact, delays can severely interrupt workflow and may also result in affective responses, or emotional disturbances, such as increased distress, despite a measurable decrease in performance (Kohlisch and Kuhmann, 1997; Szameitat et al., 2009; Thomaschke and Haering, 2014). A crucial difference between the research on rest breaks and those on interruptions lies in the contextual semantics of situational prototypes where breaks or interruptions typically take place. By definition, rest breaks are studied in situation where rest is naturally indicated such as to counteract the time-on-task effect in sustained-attention and vigilance tasks. In contrast, interruptions are meant to disrupt the workflow and are typically infused in situations where they are unwanted. While people can clearly distinguish between both in everyday situations, it is difficult to determine the contextual semantics of everyday concepts in the artificial situation of a laboratory experiment. For example, the loading bar in computer games would unlikely be conceived of as a rest break, but when one attempts to study this situation in the laboratory experiment, it becomes difficult to distinguish (Suchotzki et al., 2017; Suchotzki and Gamer, 2018).

4. THEORIES OF THE REST-BREAK EFFECT

The starting scenario of a theory of pause effects consists of the observation that individuals show a decline in performance during the processing of continuous task forms already after a relatively short period of time (Nuechterlein et al., 1983; Caggiano and Parasuraman, 2004; Langner et al., 2010; Steinborn et al., 2016). Depending on the type of task form, this decline manifests itself in slower reactions, higher error rates, or stronger work fluctuations, but in any case in a reduced efficiency of work performance (Bills, 1935; Barmack, 1939; Craik, 1948; Rohmert, 1973a,b). By inserting a break condition, it is possible to test the extent to which this drop in performance is diminished or reversed (Steinborn and Huestegge, 2016). The so-called tester fatigue effect does not just occur after hours of prolonged mental work, but rather emerges quickly; according to Bills (1943) the first signs are already recognizable after 5 min. In aggregated performance characteristics, clear-cut effects are determined after 10–20 min (Bills, 1931, 1935). It reported from numerous studies that individuals in pure (non-speeded) detection tasks exhibit the primary performance drop in the detection rate within the first 20 min, which then levels off asymptotically at some point (Frankmann and Adams, 1962; Langner et al., 2011; Langner and Eickhoff, 2013; Thomson et al., 2016). When reaction time-based task forms are used, a similar pattern emerges in the form of slowed reaction times, but here the drop in performance is often superimposed (to varying degrees depending on the task form) by practice. Based on a study by Thomson et al. (2014), this aspect can be well explained: comparing the performance trajectories of two task forms (cf. Figures 1, 4, complex vs. easy task form), a seemingly "paradoxical" performance gain in the former but expected performance costs in the latter task are revealed. Yet, the self-reports clearly show an increased tendency toward mind wandering in both tasks, a typical indicator of decreasing attentional control (Smallwood and Schooler, 2006; Smallwood, 2013; Thomson et al., 2015, 2016).

Before theorizing on the potential mechanisms underlying the rest-break effect, the main types of models in the domain of sustained attention must be characterized and distinguished (see **Table 2**). They may be categorized along three dimensions, (1) the assumption of a volume of cognitive resources vs. a degree of experienced mental satiation, (2) the corresponding dynamics with which these resources are utilized, exhausted, and replenished, (3) and the extent of strategic control over the deployment of resources over time. In this context, it is difficult to assign taxonomically rigorous categories to the theoretical approaches published in the literature because they are sometimes not clearly articulated, contain inconsistencies or even contradictions in their propositional systems, or lack a specified measurement model (cf. Kahneman and Miller, 1986; Rothermund and Wentura, 2010; Greenwald, 2012; Stroebe and Strack, 2014; for a discussion). In particular, authors of empirical papers often argue in a way that consists of a diverse mixture of model predictions, everyday metaphors, and platitudes. The classic *resource-volume model* could be considered a standard model because it is straightforward, enables clear prediction, and is well suited as a starting position. The resource-volume model has its roots in Kahneman's energetic capacity model (Kahneman, 1973). While less concerned with how resources can be shared across tasks (Meyer and Kieras, 1997a,b; Tombu and Jolicoeur, 2003; Wickens, 2008), it focused more on the distribution of resources over time, which renders it particularly interesting from a rest-break perspective. Regarding the underlying dynamics, the basic assumption is that ongoing activity leads to a decrease in volume of resources, while pauses lead to an increase in volume (see following section for more details). The *satiation model*, in contrast, uses an entirely opposite metaphor. Here, continuous activity causes an increase in mental satiation, while taking breaks reduces the same (Mojzisch and Schulz-Hardt, 2007). The dynamics or momentum by which these parameters are drained and replenished is also an important parameter. Most current approaches implicitly assume a constant and slow decrease in resources over time, often (automatically) inferred from averaged performance curves in experimental conditions.

The third dimension concerns the degree of strategic control over the available resources (Van der Molen, 1996; Pashler, 1998; Sanders, 1998). The ideal norm of a *strategic-resource model* assumes a more or less flexible resource allocation over time. The perceived experiences of effort are considered the internal indicators that determine the momentary strategy, such that a feeling of "ease" indicates available energy while aversion indicates the need for rest and recuperation (Thayer, 1989; Matthews et al., 2002; Langner et al., 2010). Individuals seem to be able to anticipate effort in advance (in terms of an energetic cost point), which is often referred to as economic-strategic model (Humphreys and Revelle, 1984; Langner et al., 2010; Krishna and Strack, 2017). In contrast, a *non-strategic model* would be based on the assumption that individuals always work at maximum performance or at the individual performance peak. The presumption that individuals work at maximum effort is also an absolute prerequisite in the determination of test performance criteria in classical test theory (Miller and Ulrich, 2013; Steinborn et al., 2018). This is also tacitly presupposed in studies aimed to induce ego depletion, a concept referring to a hypothetical state of complete exhaustion of the resource volume or self-regulatory system. It is assumed that the processing of certain tasks over a defined period of time leads to a partial or complete reduction of the resource volume, that this can be measured by means of certain indicators, and that breaks lead to a replenishment of the resource volume. In this chapter, we evaluate theoretical-model approaches in the light of empirical evidence, but we must emphasize that these ostensibly "competing" model approaches should not be conceived of as alternative explanations, but rather as different cultures (Greenwald, 2012; Stroebe and Strack, 2014) in the empirical approach to the study of pause effects.

4.1 Energetic Capacity Model

The energetic capacity concept is one of the central elements in the research field of sustained attention and vigilance (Jennings and van der Molen, 2005; Langner and Eickhoff, 2013). The critical variable is the volume, which is decreased by cognitive work and recharged by breaks. In contrast to the computational concept of resources in dual-task research, the central issue here is not the allocation of a flexible resource to multiple forms of concurrent tasks, nor is it about the allocation of separate pools of resources to tasks with a need for a specific type of resources. Rather, the central issue revolves around the distribution of the capacity that can be provided by the resource over the time during which mental work is performed. In this respect, the energetic resource model rather corresponds to the metaphor of everyday language use (Greenwald et al., 1986; Kahneman, 2013, ch. 2): during intense mental work, the reservoir of mental resources is reduced or emptied, and it is recharged during breaks. The empirical indicator for the state of resource disposal is the decrease in performance in the task over time, measured with the respective characteristic values. The metaphor of an energy reservoir that is discharged and recharged by work or breaks is the core element of almost all theoretical approaches in this area. Differences often relate to the dynamics of these processes, the nature of the effect variables, and the weighting of additional variables such as self-reported motivation or psychophysiological parameters (Langner et al., 2010; Lim and Kwok, 2016; Steinborn and Huestegge, 2016).

Kaplan's (1995) attention-restoration theory is a highly regarded theoretical approach that (in a close definition) relates to long-term recovery. In a strict sense, it is a psycho-sociological theory that addresses the dynamics of recovery and stress in the context of the real world of work and leisure. An outstanding feature of this theory, relative to other accounts theorizing on rest and recovery, is that it holds clear implications for urban planning (Berman et al., 2008; Atchley et al., 2012; Anguluri and Narayanan, 2017; Pasanen et al., 2018). At its core, the model states that energetic resources are claimed by goal-directed work and restored in free time (during non-goal-directed activity). Yet, recovery is not only a function of spare time, as the model makes a distinction regarding the context where rest takes place. In other words, spending time in nature is assumed to be more beneficial than spending time in (typical) urban environments (but see Ouellette et al., 2005). According to this idea, natural environments are rich in what they term "gentle fascinations," that is, sensations that can be processed with effortless attention that is automatically directed by stimuli and not tied to goals (Kaplan, 1995; Berman et al., 2008; Kaplan and Berman, 2010). These include, for example, clouds moving across the sky, leaves rustling in a breeze, or water flowing over rocks in a stream. Critical to this approach is the theoretical distinction between reflective and automatic attentional control (cf. Strack and Deutsch, 2004; Krishna and Strack, 2017), albeit related to a more sociologically relevant context. There is also empirical support for his proposal showing that population satisfaction is higher in urbanized areas with green walkable parks than in areas without them, even when relevant variables are statistically controlled (cf. von Lindern et al., 2017, for an overview).

In the perspective of their analytical framework, Kaplan and Kaplan (1989) have identified four key principles of recuperation that can be generalized to the field of break research in general, (1) change of scenery, (2) conceptual distance, (3) fascination, (4) and extent of attracting involuntary engagement. Additionally, one more principle can – but rather indirectly – be extracted, (5) the slowing of pace (Levine, 1998; Hoffmann et al., 2021). In terms of break effects, it can be said that people recover well when they make a change from the work task to the break activity, when it offers sufficient distance from the work activity, when the break activity is beautiful or fascinating, and when it engages attention in a non-goal directed way. Finally, it is especially restful when time pressure is removed. Because these principles have high face validity, they have very often served as the basis for predicting rest-break effects in experimental studies. Despite this inspirational power, some methodological problems arise here. For example, it is unclear to what extent predictions can be transferred from large to small time domains. Related to this, many of the operationalizations chosen in "experimental" settings are questionable because of their reductionistic approach. The fundamental question here is whether reaction-time based performance is appropriate to test these principles (Miller and Ulrich, 2013). Therefore, the inspirational power of the theory consists mainly of its high generality, intuitive plausibility, and the logical consistency of its basic arguments (cf. Greenwald et al., 1986; Greenwald, 2012; Gray, 2017).

The recreational function of temporary slowing of behavior was already recognized by early authors, and is of high relevance in the current theorizing. For example, Bills (1943) already made the argument that during continuous speeded activity, the cognitive system can only operate at a maximum level of performance for a very limited time, until it experiences a transient depletion of the required resource pool, which then manifests itself in mental blocking. Bills (1943) argued that this phenomenon could be conceived of a type of pause enforced by the cognitive system, similar to the pause taken on a scheduled basis (cf. Jersild, 1926; Bertelson and Joffe, 1963). The finding that the frequency of exceptionally long responses increases after a prolonged period of uninterrupted processing (while there are typically no changes in the fastest responses) has often been used as evidence for this cognitive-energetic view (Sanders, 1998, ch. 9). Bertelson and Joffe (1963) generalized this principle of alternation of strain and recovery in continuous activities, arguing that performance in self-paced continuous tasks is heavily affected by the ability of an individual to regulate speed and accuracy for the purposeful completion of a task in such a way that it can be performed with optimal efficiency (Neubauer and Knorr, 1998; Stahl and Rammsayer, 2007; Steinborn et al., 2018). Following this view, numerous authors conceptualized "energetic regulation" a basic ability to attain and maintain a state of general optimal activation for upcoming demands, to set an optimal rhythm, and to maintain this rhythm over the duration of the demand.

4.2 Strategic Resource Model

One important aspect of research on rest concerns the rate of recovery from mental activity that takes place during breaks. Connected with this point, it is crucial to determine whether recovery potentially occurs (in a non-registered manner) during the active-task period itself. The early observation by Bills (1931) that periods of "enforced" rest take place during the task itself (and against the instruction to perform best) gives a clear indication that the answer is likely "yes." However, such an observation challenges the logic underlying a straightforward version of an energetic–capacity model, because differences between tasks or individual differences could be interpreted as differences in the employment of strategies (Pashler, 1998; Sanders, 1998). The question that follows is to what degree individuals have strategic control over the available resources to perform a task (Inzlicht et al., 2014, 2018). For example, individuals seem to be able to either delay (Kunde et al., 2004; Jentzsch and Leuthold, 2006) or to speed-up responses (Strayer and Kramer, 1994; Kleinsorge, 2001; Steinborn et al., 2017) when prompted to do so by proper cues, indicating that there is some flexibility in changing strategy. The strategic-resource idea emphasizes the allocation policy of resources, which refers to the basic principles underlying the distribution of capacity over the activity period. In other words, if one knows that there is a long way to go, one more likely allocates resources in a different way than if the way is expectedly short. Yet, it is difficult to exactly determine the strategies used in a task because there are not only differences between experimental conditions but also differences between individuals and, even more so, individuals might change their strategy over the task in a rather qualitative way, which complicates a straightforward interpretation of performance effects in the light of theory (Vandierendonck, 2017).

In fact, there is psychophysiological evidence for such a demand-adaptive mobilization of (physiological) capacity. A typical finding is that the courses of cardiovascular parameters are completely different in sprinters and long-distance runners, with the former showing an increase in heart rate from about 90 to 120 beats per minute immediately before the start of the race, while the latter showed no or only minor changes (e.g., Faulkner, 1964; Hilton, 1975; Inui, 1987; Baden et al., 2005). This is a remarkable finding in that this energetic mobilization occurs before the actual demand, implying anticipatory behavioral adaptation (cf. Requin et al., 1991; Jennings and van der Molen, 2005). It should be noted that the term "strategic" in this context does not strictly imply that the allocation policy results from reflective planning. Rather, it can also be "triggered" by experiences of effort (cf. Goschke and Kuhl, 1993; Koriat and Goldsmith, 1996; Strack and Deutsch, 2004; Mojzisch and Schulz-Hardt, 2007). More critical is the aspect of prevention, which is in contrast to a straightforward formulation of a resource model presupposing a functional relationship between performance and test length (i.e., the time-on-task effect). Many early authors stated that individuals may not always be completely focused, but that moments of rest occur in between, and that these moments of rest serve a regulatory function. Bills (1931, p. 244), for example, has contended that "*the rest afforded by these mental blocks maintains the objective performance of the individual at an average level.*" Therefore, one might wonder whether explicitly administered (micro-)breaks would reduce block frequency, and whether a specific distribution of such microscopic breaks might lead to an optimization of performance and performance stability (Leth-Steensen et al., 2000; Ballard, 2001; Flehmig et al., 2007a; Langner et al., 2010; Steinborn et al., 2010; Unsworth and McMillan, 2014).

Bertelson and Joffe (1963) gave their participants a continuous four-choice task that lasted for about 30 min and required them to press one of four keys assigned to one of four digits (1–4). Their result also suggests that mental blocks enforce a rest period to ensure efficient performance afterward. While mental blocks were always preceded by a slowdown in response and a deterioration in accuracy, both were followed by a sudden improvement. Unsworth and Robison (2019) examined exactly these unintentional pause structures in the psychomotor vigilance test (PVT). The task requires simple responses to targets which are separated from each other by a random interval separating trials from each other (Langner et al., 2010, 2011; Steinborn et al., 2016; Massar et al., 2018). Even here, where targets are separated in time, a similar pattern to that observed by Bertelson and Joffe (1963) emerged, likely because the individuals are engaged in monitoring the time flow until target occurrence (Miller and Schröter, 2002; Steinborn and Langner, 2011, 2012). Lapsing occurred more or less in a rather periodical way and was not related to the time position as given by the length of intervals. In some way, this confirms Broadbent's assumption that preparatory time (and any watchkeeping time in vigilance tasks) is not resting time but a rather arduous mental state of effortful engagement. Connected with this point, it has often been debated whether it is not the "rest" *per se* but the "change" in the nature of a current activity that leads to a recovery of mental functions. Helton and Russell (2015) have examined this particular aspect. The individuals were administered either with a baseline condition (no rest), a pure rest condition, and several "change" conditions, including typical mental operations (e.g., letter-matching task, etc.). As a result, performance was best for rest, worst for the continuous condition, while the other ("change") conditions were somewhere between the extremes, indicating that any change in a task cannot compete with having rest, which again means that rest is always the best option to recover (even though experimenters usually lack precise control over what exactly participants do when instructed to "simply rest").

The strategic model bears an important implication that is pertinent to pause research. From any straightforward formulation of a non-strategic model, the observation of a time-on-task decrement would indicate a decline or total depletion of resources (Baumeister et al., 1998; Hagger et al., 2010; Inzlicht and Schmeichel, 2012). In contrast, the strategic-resource model incorporates that individuals take preventive measures to either economize resource expenditure, or doing this rather impulsively, for example, when they suddenly experience effort (Thayer et al., 1994; Inzlicht et al., 2018; Hoffmann et al., 2021). Contemporary theorists such as Thayer (1989), Matthews (2021) proposed that it is the internal experience of states of the two aspects "energy" and "tension" that serves as the "tachometer" indicating whether to save or to spend effort to the task at hand. Such an approach automatically implies the question of how these indicators can be measured, either as emotions (experienced effort) or behavior (experienced lapsing), or a combination based on somatosensory experience and self-observation, arising from a stumbling of performance fluency at some point during the task (Kerr, 1973; Dreisbach and Fischer, 2011; Langner et al., 2011; Steinborn et al., 2016). In his pioneering work, Smallwood et al. (2004) introduced a technique where individuals are occasionally asked during the session whether they were still focused on the task or whether their thoughts were wandering elsewhere (on-task vs. off-task). Across numerous tasks and contexts, it was reliably found that individuals were far from being perfect as indicated by the proportion of "off-task" moments, typically increasing from about 20% to around 50% during a testing period, irrespective of whether task performance showed a decrement or not (e.g., due to practice effects), which is one of the reasons why only a few studies were able to show a correspondence between self-reports and the time-on-task effect in performance.

4.3 Psychological Satiation/Reactive Inhibition

Although the theory of mental satiation is a highly relevant framework with historical roots in the field theory of Kurt Lewin (1890–1947), it is surprisingly underrepresented today. In this perspective, the critical variable that is relevant to performance is not a hypothetical volume of an energetic reservoir (reduced by work and replenished by rest), but the level of accumulated mental satiation that is experienced and considered the main driving force of behavior (e.g., Mojzisch and Schulz-Hardt, 2007; Kruglanski et al., 2012, 2014; Kurzban et al., 2013; Häusser and Mojzisch, 2017; Krishna and Strack, 2017). The satiation model therefore utilizes a diametrically opposing metaphor when compared to the resource model. This becomes clear when one compares the two following everyday phrases. (1) *The engine runs until the fuel supply is exhausted*. (2) *The engine runs until it has run hot* (i.e., exceeded a critical temperature). In the first example we have a *preconditioning parameter while* in the second one we have a *delimiting parameter*, but despite that, both metaphors may allow for similar predictions. Continuous activity leads to an increase in mental satiation, while breaks lead to a decrease in the same. This implies that one could derive exactly the same predictions based on a resource model or the satiation model, which is why these approaches should not, in a strict sense, be contrasted as opposing theories. Rather, they represent separate cultures that, despite having a common essence, differ partially in experimental approach as well as in somewhat different weighting of key arguments (Greenwald et al., 1986; Greenwald, 2012). Studies on psychological satiation, for example, typically put strong emphasis on the aspect of subjective experience as well as on those variables that contribute to or influence experience.

Psychological satiation is a phenomenon that arises when an action is carried out frequently and in a repetitive manner, so that the activity, which might initially be perceived as neutral, is increasingly perceived as being aversive in the course of continuous repetition. This occurs mainly in task types that consist of homogeneous and repetitive forms which are not intrinsically motivating by themselves (Pieters, 1985; Donk and Hagemeister, 1994; Van Breukelen et al., 1995; Neubauer and Knorr, 1998; Steinborn et al., 2018). Typical tasks that are very well suited to induce satiation experimentally can be found in the classic psychometric instruments for measuring active forms of sustained attention, the so-called speed tests, sometimes also termed concentration tests. Lewin (1928) assumed that the persistent and excessive repetition of the very same action over and over again undermines the built-in tendency of any cognitive system to strive for a gain of information and the experience of agentic competence, whereby a resistance gradient develops against the further continuation of the same action, which is subjectively experienced as aversive. However, when individuals are instructed to continue the task over a longer period of time, an increasing conflict develops between two opposing tendencies that can only be resolved by exerting willpower. Although individuals experience aversion as a cause, Lewin considered it a perceivable indicator in terms of a phenomenological by-product of the internally created tendency (Robinson and Clore, 2002; Strack and Deutsch, 2004). More recently, Mojzisch and Schulz-Hardt (2007) have studied the determinants of mental satiation in various contexts, based on field theory. In one series of experiments, groups of individuals were instructed to complete speeded test of different workload levels over a period of 20–40 min, using a loaded mental addition test (Düker, 1949), and the subjective experience was assessed before and after the test. It was found that a high level of satiation developed particularly when the task did not allow for any resting by mind wandering, that is, when it was both occupying and repetitive.

Based on classic theorizing on accumulating mental satiation and the resulting distraction as well as on the compensatory function of rests, Van Breukelen et al. (1995) presented a psychometric model to characterize and predict performance and performance fluctuations during sustained mental work. In essence, it is posited that the averaged reaction times (typically RT mean) are composed of two components: responses emitted in the state of mental *focus* and those emitted in the state of *distraction*. The model is a generalization of earlier psychometric models of cumulative inhibition, which are based on broadly similar assumptions but different in their specific statistical parameters. The theoretical framework of the inhibition model is Hull's (1943) theory of reactive inhibition, and its implementation in the Rasch model for speed tests (Rasch, 1980; Pieters, 1985; Baghaei et al., 2019), which postulates that during ongoing monotonous processing, a kind of negative drive develops that forms an opposing gradient to the current goal orientation. In the context of performance testing, this can be seen as a "distraction tendency". The gradient increases as a function of the throughput processed and immediately leads to distraction when a certain threshold is reached. The inhibition tendency thus increases monotonically during task processing and decreases during periods of distraction or during rest breaks.

Some studies are particularly suited to highlight theoretically fruitful research approaches in this context. For example, Sanders and Hoogenboom (1970) presented their participants with a six-choice RT task characterized by a rapid pace (response-stimulus interval = 60 ms) with either a continuous work or a rest-pause condition. The digits 1–6 served as targets and were mapped to six separate buttons. Responses became faster on average in the rest-break condition, while they remained the same in the continuous work condition. Furthermore, a cumulative distribution function (CDF) analysis revealed that the two conditions did not differ in terms of the fastest, but only in terms of the slowest CDF percentiles. Sanders and Hoogenboom (1970) argued that this reflects that rest breaks proactively prevent the occurrence of mental blocks and in this way reduce performance variability. This interpretation is consistent with earlier suggestions (Jersild, 1926, p. 34). More recently, Steinborn and Huestegge (2016) examined the effect of rest on performance and experience as a function of the factors "rest," "demand," and "time on task." As a result, rest (vs. no rest) had beneficial effects on performance, which increased with time on task and was more pronounced for hard than for easy arithmetic. The CDF percentile analysis revealed that rest particularly reduced the frequency of dropouts and lapses. The pre–post assessment of experience revealed a differential pattern: while energy and engagement tended to decline, there was no effect of tension and distress. Taken together, these studies emphasize the importance of distributional analyses to draw relevant theoretical conclusions here.

4.4 Complicated Arguments in Current Theorizing

The majority of studies theorizes (in some or the other way) on grounds of resource models borrowed from the cognitive-experimental literature on multitasking research. An essential detail of particular models concerns the distinction of a variable vs. a fixed volume of capacity, with the former assuming a mobilization of capacity by immediate demand and the latter assuming an alternation or dynamic partial allocation of capacity between channels processing task-related vs. task-unrelated information. Another potentially important detail concerns the role of how feelings (before or during) task processing affect performance levels (e.g., energy, tension, motivation). The corresponding research traditions can be classified into three categories, (1) considering feelings as phenomenological by-products of cognition, (2) viewing them as a sort of "tachometer" of internal state indicating room for vigorous action or need for recuperation, or (3) as the underlying "cause" of the observed performance differences. Despite these pure categories, a transactional perspective would argue that while feelings may primarily have an indicator (tachometer) function, the mere act of reading out the internal state can by itself lead to distraction or conflict, similar to that in multitasking situations. Accordingly, an observed performance decline can actually be the result of distraction and self-referential processing (Wells and Matthews, 1996), or more precisely, from the act of monitoring and comparing actual values with an internal standard, and from subsequent evaluation or self-regulation (Carver and Scheier, 1990; Strack and Deutsch, 2004; Hewig et al., 2011; Krishna and Strack, 2017; Steinborn and Huestegge, 2020).

4.5 Mobilizing Capacity vs. Routing Channels

According to a mobilization model of sustained–attention performance, capacity is primarily demand-driven, which means that it is the immediate demands of the task that triggers capacity supply and not a deliberate decision. To a certain extent, it can be controlled at will, for example, when advance information is provided (Brown and Braver, 2005; Botvinick and Braver, 2015), or by a prompt (or reminder) to increase focus (Strayer and Kramer, 1994; Kleinsorge, 2001; Falkenstein et al., 2003; Steinborn et al., 2017), though it is impossible to control it precisely or to keep it steady. In a situation that emphasizes the aspect of "maintaining" performance levels over extended time periods, precise control would require a time-scheduled capacity threading between states of focusing and those of monitoring over the task period (cf. Craik, 1948; Humphreys and Revelle, 1984; Van Breukelen et al., 1995; Fernandez-Duque et al., 2000; Steinborn et al., 2017). This means that capacity varies over the duration of the task and thus can be characterized by a hypothetical ratio of utilized and spare capacity. According to Kahneman (1973), such variation is due to the fact that the allocation policy is not always set on focusing but sometimes sways capacity to other activities (monitoring or mind wandering), resulting in slower or even sluggish responses during these periods. Such a view of intermittent resource allocation to active operating vs. passive monitoring provides a natural way to explain the trial-to-trial response-speed variability that is commonly observed in reaction–time series (Flehmig et al., 2007a; Steinborn et al., 2016; Klein and Robinson, 2019).

A formal way to represent the aspect of performance fluctuation is to model data within the framework of the mixture-models type of speeded performance (Pieters, 1983, 1985; Miller, 2006; Schwarz and Miller, 2012). Basically, it is assumed that observed performance (i.e., reaction time) is composed of trials where the individual was under a state of focusing or a state of reduced focus (e.g., through non-registered rest, either enforced or taken). There are also many accounts that rather implicitly (and in a less formal way) refer to a similar idea without explicating the precise mechanisms of how exactly this is reflected in performance parameters (e.g., Humphreys and Revelle, 1984; Jensen, 1992; Leth-Steensen et al., 2000; Stuss et al., 2003; Robinson and Tamir, 2005; Flehmig et al., 2007a; Cheyne et al., 2009; Thomson et al., 2015). At a more sophisticated level, response variability is studied by analyzing the individual response-time distributions, often computed as a vincentized percentile function. Typically, reaction-time distributions tend to be leaning toward the right side (i.e., corresponding to the slower percentiles), in other words, to having a long tail toward the right. However, there is an important distinction that is often misunderstood in the literature. Precisely, to say that an experimental factor produced an effect on RT variability (i.e., to say it affects the ratio of focused vs. non-focused trials) requires that the factor has a selective effect on the slower percentiles of the distributive function that goes beyond mere scaling variability (De Jong et al., 1994; Miller, 2006; Steinborn et al., 2017), as would be indicated by the RT coefficient of variation (Flehmig et al., 2007a).

A capacity-mobilization model of sustained-attention performance can be characterized by some important key aspects: First, the hypothetical value of "capacity" is a latent (or theoretical) variable that is represented by the empirical indicator (or performance) variables, that is, in the speed of processing or the throughput of information processed per unit of time (Thorne, 2006; Szalma and Teo, 2012; Vandierendonck, 2017; Steinborn et al., 2018). Further, the mental resources devoted to continuous performance are essentially limited in two ways, (a) that the individuals punctually engage is only one mental activity, and (b) that they can maintain engagement for only a brief period. Task-relevant processing is referred to as utilized capacity and indicated by performance, while task-unrelated processing is referred to as spare capacity, which is the residual that can only be inferred indirectly (from the lack of optimal performance). The relation between both (i.e., the spare–utilized capacity ratio) varies across a sequence of trials, so that as individuals engage in task operations, spare capacity is reduced at the costs of utilized capacity, and vice versa, when they disengage from the task-relevant operation (i.e., microbreaks, either enforced or taken), utilized capacity is reduced at the cost of spare capacity (Steinborn and Huestegge, 2016, 2017, 2020). To know the dynamics of these alternation between spare and utilized capacity, it would be necessary to inspect not only the distributive function but also the time series of reaction times, separately for each individual. With this respect, only a very few studies examined this in greater detail (e.g., Kraepelin, 1902; Bills, 1931; Laming, 1979; Cheyne et al., 2011).

While a spare–utilized capacity model is both prudent and parsimonious in its base assumptions, more recent theoretical proposals seem to overstretch their structural basis, which generates a problem when it comes to using theory for deriving predictions. For example, Thomson et al. (2015) made an attempt to assume that an exactly equal amount of capacity alternates between two processes, one devoted to the task-related and the other reflecting task-unrelated processing (i.e., mindwandering), and over a series of trials, individuals are assumed to alternate between these two channels, while the capacity remains equal across all trials, thereby refuting any process of mobilization completely. According to this conception, performance is measured by standard parameters, while mindwandering occurs either by (passively) drifting off or by (actively) being on pause as assessed by self-report probes. The proportion of these conditions is assumed to change over time (i.e., the proportion of "off-task" conditions increases) which gives a measure of the amount of mindwandering, that is, not being on task. However, a problem here lies in a confusion of using natural language and theoretical formalism when speaking about performance effects. In natural language, one would agree that the brain does not consume more energy overall during phases of mental work as compared to alternating phases of mindwandering (but see Gailliot et al., 2007, for an opposing view). In the same vein, everyday language would link the term mobilization to changes in physiological activity, which is not addressed in the formulation of a spare–utilized capacity model. The problem is that any formal model that specifies capacity for alternative hypothetical processes (e.g., A = on-task; B = off-task) creates a problem in the formal structure in a way as the capacity budgeted for the on-task process is determined by the performance measures while those budgeted for the off-task process is indicated by the self-report probe trials. These self-reports give an indication that the individuals were not focused but absentminded, but they do not deliver an equivalent that allows to determine the capacity required during both alternating phases (Miller and Ulrich, 2013).

In summary, we argue that a formal model must be able to specify the degree of engagement of both the task-related and the task-unrelated process, and it must provide rules for determining the behavioral indications signaling this engagement. This is not possible in a model case where performance can be measured only for one task, while the other process (i.e., rest pauses, mindwandering, etc.) is indicated only indirectly, by the absence of a performance optimum (Van Breukelen et al., 1995; Miller and Ulrich, 2013). In order to be able to formulate a model that allows us to predict the direction or amount of capacity change during time on task, or afterward during rest breaks, it is crucial to link the theoretical variables to a connected measurement concept that specifies how the values of the model parameters are indicated by behavior and performance (most often performance speed and accuracy). Further, a measurement theory must also include a specification of performance characteristic trade-offs that presumably covary with the hypothetical state of mental fatigue (or overload, etc.). In most theoretical accounts, it is rather implicitly assumed (or simply presupposed) that both performance speed and accuracy deteriorate over time, indicating reduced mental efficiency, while pauses are assumed to restore mental efficiency. Empirically, it is often found that information processing slows down with no substantial effects on accuracy, and sometimes a speed–accuracy trade-off is observed (e.g., individuals become faster but more impulsive). Another aspect concerns the use of averaged performance parameters. Since mindwandering in continuous performance tasks is particularly evident in the slow percentiles of the reaction time distribution, it would be essential to additionally inspect time series data (Laming, 1979; Cheyne et al., 2009). In the field of rest-break research, these aspects are lacking, and in fact there are currently only a few studies that actually address these aspects in some or the other way (as outlined above).

5. METHODOLOGY, DESIGN, AND PSYCHOMETRIC MEASUREMENT

As aforementioned, there are numerous theoretical approaches, each of them highlighting different aspects of strain and recuperation, and each of them differing in the dynamics and time scale of these variables. In our assessment of the literature, there is a chaotic plentitude of theoretical proclamations available but hardly any testable model that would allow us to make straightforward predictions about performance effects. In view of this consideration, we worked toward evaluating the existing theoretical proposals with respect to their argument structure, completeness, and dialectical implicature. In our judgment, they can be characterized as historically grown research traditions, each with its own specific peculiarities, norms, and conventions, and each using reasonable conceptual metaphors at the underlying core (Ferguson and Heene, 2012; Greenwald, 2012; Proulx and Morey, 2021). Despite this, there are two practical questions for a researcher interested in studying mental fatigue and its restoration by rest breaks, that is, how to put all parts into relation, and, further, how to utilize the existing theoretical structure for deducing reasonable hypotheses. We argue that a proclaimed theoretical model is eligible only if it makes mechanistic (and falsifiable) predictions that are derived in a straightforward and non-ambivalent way, and further, a theoretical delineation must include a connected measurement model that specifies how the predicted effects of the experimental factors are reflected in performance measures. Finally, a theoretical proposal must waive any additional (specifying) assumptions if they on principle cannot be tested empirically, or are not accessible to measurement. In effect, a reduced and sharpened language when making predictions about performance effects would improve knowledge in the field by reducing redundancy and by creating a link between encapsulated subcultures, and would connect the knowledge and methodological repertoire between these separated fields of research (Ferguson and Heene, 2012). In the following, we will reflect on some of these issues in more detail.

5.1 The Experience–Performance Connection

As noted, all existing theoretical approaches can broadly be classified into two groups, which we term "*resource model*" and the "*satiation model*." According to the resource model, mental work leads to a decrease in the energetic reservoir, while rest breaks lead to an increase. According to the satiation model, mental work leads to an accumulation of satiation, but rest breaks lead to a reduction. In their simplest form, both model categories utilize a linear metaphor that is merely inversely poled (either as a permitting or delimiting condition). One particular difference lies in the emphasis on aspects of subjective experience. While the satiation model ties the loss of perceived intrinsic motivation to objectively measurable performance, the resource-model theorizes on the reduction of an energetic reservoir by mental work, and any reference to subjective experience is neither necessary nor mandatory. In fact, the proposal that experience and performance is connected or even causes each other is by no means trivial, at least it cannot automatically be taken as a presumption (Langner et al., 2010; Matthews, 2021). The literature is completely mixed in this regard. While a substantial number of studies reported a correspondence of pre-tested subjective state (e.g., energy, motivation, etc.) and subsequent performance, only a few were able to demonstrate a correspondence of the time course of these variables. For example, Thomson et al. (2014) showed a congruent temporal trajectory of self-reported mind-wandering tendencies and performance in one (relatively easy) task, while there was an opposing tendency of these measures in another (more complex) task. Clearly, the arrangement in one task was simpler and more repetitive than in the other one, providing fewer possibilities for procedural learning (e.g., Compton and Logan, 1991, see Figure 2; Healy et al., 2006).

5.2 Primary Measurement Artifacts

There are many aspects to be taken into consideration when conducting an experimental study on the effect of rest breaks on feelings and performance. Most of them relate to design, tasks, and performance measurement and are part of the basic knowledge repertoire of a skilled experimenter (Greenwald, 2012; Miller and Ulrich, 2013). But there is one aspect that pervades the entire research, the potentially concealing effects of test practice and item-specific learning (Flehmig et al., 2007b, 2010), which is difficult to control properly (Donk and Hagemeister, 1994; Hagemeister, 1994, 2007). Precisely, performance-based tests such as typing, cancelation, or mental-arithmetic are typically used as propagation tasks to induce ego depletion (Hagger et al., 2010; Vohs et al., 2021). These test forms are typically administered as self-paced versions thus requiring sustained-information transfer (Humphreys and Revelle, 1984; Steinborn et al., 2018), they are highly demanding, and most crucially, they achieve exceptional test–retest reliability, since many items can be processed per unit of time. Yet, it should be considered that the time-on-task effects on performance do not always produce a global response slowing, and further they are (to an unknown degree) subject to procedural learning. Finally, fatigue might affect these processes differently at different points in practice (Healy et al., 2004, 2006). Some authors opted for the use of simple tasks like the sustained-attention-to-response test (SART, Manly et al., 1999; Seli et al., 2013; Head and Helton, 2014), the psychomotor vigilance test (PVT) (PVT, Dinges et al., 1997; Steinborn et al., 2016; Unsworth and Robison, 2019), or even detection-based vigilance tests as measure of choice (Warm et al., 1974; Thomson et al., 2016). While these tasks are less susceptible to learning, due to their simplicity, the items in these tests are typically spaced in time so that a relatively low number of trials is obtained during testing as compared to self-paced tests, where each item follows after the previous one with no time in-between trials. Consequently, test–retest reliability has often been found to be a weakness of the former (vigilance tests) as compared to the latter (self-paced tests) if one considers the economy of testing (Miller and Ulrich, 2013; Steinborn et al., 2018).

5.3 Design Methodology

Many published studies actually suffer not merely from methodological weaknesses of aspects connected to measurement methodology, but also from inadequate (or incomplete) design issues. As noted, fundamental to the study of rest breaks is that several distinct effects of rest can be distinguished with a slightly different meaning of each of them, not to speak of the contextual effects that often change the dynamics of these effects, for instance, when testing effects of rest under sleep deprivation (Wilkinson, 1959; Sagaspe et al., 2006; Bratzke et al., 2009, 2012). This is not considered in most of the literature. Essentially, rest-break effects as obtained via an experimental design that contains a time-on-task condition can be divided into global and local difference effects (cf. Steinborn and Huestegge, 2016). In order to examine the global effect of rest on performance, the performance trajectory between the control (no-rest) condition and the critical (rest) condition is typically examined. This can be done by using a group-based design where the critical conditions are compared in terms of a between-subject comparison. The global benefit of rest is obtained as the relative difference in the time course of the performance curve (i.e., the slope of the time-on-task effect), as indicated by the relevant performance parameters.

The local-rest effect can (for obvious reasons) only be studied in the critical group (where rest-breaks are included). Here, the performance immediately before and after rest (i.e., the pre–post effect) of only the critical group is contrasted. This approach is formally equivalent to an analysis of trial sequences surrounding a critical event, such as errors (Brewer and Smith, 1984; Steinborn et al., 2012; Jonker et al., 2013), or attentional lapses (Bills, 1931; Bertelson and Joffe, 1963; Steinborn et al., 2016).

5.4 Psychometric Performance Measurement

While the effects of rest can basically be studied in any task form, speeded tests (e.g., mental arithmetic, letter cancelation, coding, etc.) are particularly suitable for performance measurement (cf. Van Breukelen et al., 1995). Since they require continuous work and because items are not spaced but rather compressed in time (items follow immediately after each other), they usually provide superior test reliability (Steinborn et al., 2018; Wühr and Ansorge, 2019). Individuals in these tasks are typically required to continuously respond to a series of successively presented targets, with each target following immediately after responding to the previous one, with no feedback given after errors. It should only be noted that individuals can efficiently detect any errors that they make, and they would even do so even when instructed to ignore them (Maylor and Rabbitt, 1995; Steinborn et al., 2012). One advantage is that they can be administered both as computerized versions of paper-and-pencil forms without changing the nature of the task (Van Breukelen et al., 1995; Steinborn et al., 2018). Since these tests offer the opportunity to simultaneously consider several performance aspects, they deliver some additional information about the working style. Typical measures are the speed, accuracy, and variability (Pieters, 1983, 1985; Flehmig et al., 2007a), or combined-efficiency indices (Thorne, 2006; Szalma and Teo, 2012). To summarize, a task must be applicable to experimentally study rest breaks, which means in the first place that it must put some strain on the individual, and it must allow for a reliable performance measurement. Although this may seem trivial, this condition is not met in the majority of empirical studies. However, without precise measurement, a sufficient number of trials, and adequate performance output variables, it will not be possible to derive correct theoretical conclusions from empirical results (Miller and Ulrich, 2013; Steinborn et al., 2018), and a proliferation of false conclusions would finally produce a chaotic plentitude of contradictory knowledge clusters rather than a systematic understanding of the underlying mechanisms of rest.

6. DETERMINERS OF REST-BREAK EFFECTS

Although it seems natural to review the empirical evidence in a certain field in the light of the critical factors determining the effect size including moderator variables, we found it impossible to do so in the field of rest-break research, for several reasons. First, the term rest is a bit of an umbrella term that has a bearing on several aspects differing in time and context (cf. Antonovsky, 1979; Kaplan and Kaplan, 1989). Further, and despite an evidently vast body of literature, the methodical approach is at the same time completely underdeveloped with respect to tasks and measures (Steinborn and Huestegge, 2016). That is, the majority of studies are extremely heterogeneous with regard to context, design and implementation of critical means and measures, and often suffer from the constraints and practicalities imposed by the adopted field approach (Meehl, 1967; Wendsche et al., 2016; Wendsche and Lohmann-Haislah, 2017; Scholz et al., 2019). Moreover, there are substantial methodological weaknesses and inadequacies of many reported studies in this domain, which relate to aspects such as the employment of arbitrary tasks and/or unreliable or unaudited performance measures, or simply an insufficient number of trials (Miller and Ulrich, 2013; Steinborn et al., 2018). Despite this, there are some crucial principles which are essential to consider when adopting the experimental approach to study rest breaks.

First, the response–stimulus interval is of importance, and effects of rest breaks are likely more pronounced when this interval is short than when it is long, or when a rhythmic pace is administered between them (Wilkinson, 1959, 1990; Sanabria et al., 2011; Steinborn and Langner, 2012). Second, if a study seeks to induce a depletion of resources by a task, it must critically be ensured that the individuals are working at full tilt when performing this task (Kleinsorge, 2001; Miller and Ulrich, 2013; Steinborn et al., 2017). In other words, the time trajectory of performance can only meaningfully be interpreted when it can be ensured that the individuals are not adopting preventive strategies of withholding performance. While this can more easily be achieved in laboratory studies, and can even be boosted by the presence of an experimenter or by reminding instructions to do best, this condition is typically lacking in many field studies (Scholz et al., 2019). A recent study of Johnson et al. (2019) that contains several flaws with respect to design and measurement might serve as an example to demonstrate this problem: In this study, one group of individuals was administered with a walking condition in a nature environment while the other was in an urban environment, with performance being tested afterward for both groups. The first problem here is that there is no pre-to-post measurement. This is suboptimal at the level of measurement and design, but can probably be compensated partly if the sample is large and comparable between groups. The second point concerns the use of a 30 min battery of several tests administered consecutively (i.e., after each other). This, however, is a severe flaw in the design rendering clear-cut interpretations difficult. *Why is this so?* Because each task of a battery of consecutive tests is affected by the preceding task which propagates depletion or fatigue (in unknown proportion) on the subsequent one, so that a test later in the sequence of the test battery is likely not affected by the walk (in nature vs. urban environment) but by the immediately preceding task of the test battery. Together, these issues were discussed only to exemplarily highlight the relevance of paying attention to a number of issues affecting research on rest break effects.

There are a number of fundamental questions that immediately come to mind when theorizing on the effect of rest on mental performance, which basically address the three key aspects length, distribution, and kind of content or activity, respectively. There are reoccurring themes that were already asked by even the earliest authors in the field (Manzer, 1927; Lewin, 1928; Wilkinson, 1959; Eysenck, 1969; Rohmert, 1973a), though it is difficult to give a universal answer to it: How long should a rest be to be effective? How should rest periods be spent? How restful is a change of task? On the basis of the literature, it is possible to summarize some general rules applicable to rest periods. For ordinary periods of 30–120 min of mental work using either speeded test paradigms or vigilance tasks, rest periods are optimal in the range of 3–10 min. It is certainly possible to reveal differences even within this range, but this may be dependent on specific design characteristics (Helton and Russell, 2012; Lim and Kwok, 2016; Lim et al., 2016). Longer periods are detrimental because the individual is at risk of losing the general mindset to perform at maximum level, and accordingly, will leave the individual in a rather unprepared (i.e., *restart cost effect*) state to resume the task optimally. Note again that the terminology in the restart-cost literature differs between experimental disciplines, or has a more specific meaning in other (sub)disciplines such as multitasking research (Wylie and Allport, 2000; Altmann, 2002; Janczyk et al., 2008; Kiesel et al., 2010; Vandierendonck et al., 2010).

Motivation or incentives are especially effective only if the individual is reminded of them during the task period simply because individuals tend to quickly forget initial task instructions over long testing periods (Altmann, 2002; Steinborn et al., 2017; Massar et al., 2018), or when the task itself has a game-like structure (Los et al., 2013), or has the "completable" property (Zeigarnik, 1927). A stronger focus and maintenance of high performance levels seem to tap more strongly into mental resources, thus yielding a stronger decline of performance with time. This, on the other hand, directly implies that lack of focus (or unwillingness to do best) can under some circumstances result in reduced or even absent time-on-task effects on performance, a potential problem that is especially important to keep in mind in the study of individual differences. For example, Lim et al. (2012) analyzed individual differences in the performance decline during the psychomotor vigilance task (PVT), with a focus on genetic polymorphisms related to attention deficit disorder (ADHD). Although the authors originally expected a more severe decline of performance in the vulnerable (vs. their counterparts) group, the results were in the opposite direction, simply because the individuals who were slow right from the start did not show the expected decline in performance over the testing period.

Most critically, monotonous work and work that is highly continuous requires the most frequent rest (Van Breukelen et al., 1995; Mojzisch and Schulz-Hardt, 2007; Häusser and Mojzisch, 2017). However, also in this context it might be stated that frequent (but relative brief) rest is more critical than longer rest. Further, the length and frequency of implanted rest breaks is of importance, too, and exactly this aspect was already considered by earlier studies. For example, Bills (1943, pp. 113–129) evaluated the body of empirical evidence of experimental studies at his time concluding that rest breaks should be brief (3–6 min) but frequent, and should not exceed 8 min in length. Bills argued that any increase beyond the optimal length could result in a decrease in basal activation level, or task-related activation level, respectively (Van Breukelen et al., 1995; Steinborn and Huestegge, 2016). Regarding the position in time during the testing period, the rest is more effective when given late during a test, relative to when given early, though there are only a few studies that examined this aspect via proper design (Ralph et al., 2016; Steinborn and Huestegge, 2016). How the rest period should be spent is certainly relevant, too. The satiation model would suggest that this primarily depends on whether the change task provides distance from the basic task, or whether some property of the situation (i.e., walking) naturally changes the attention policy (Cao and Händel, 2019). Yet, there are no metrics available to objectively determine the degree of similarity of tasks (Norman and Bobrow, 1975; Navon and Gopher, 1979; Meyer and Kieras, 1997a,b). Accordingly, the empirical evidence is rather unclear. Yet, a mere change in the task at hand is unlikely to be more effective than rest, since recuperation is most likely when the shift occurs from a performance-based activity to a period that provides sensations that can be processed with effortless attention that is not tied to goals (cf. Humphreys and Revelle, 1984; Kaplan, 1995; Greenwald and Gillmore, 1997; Mojzisch and Schulz-Hardt, 2007; Salvucci and Taatgen, 2008; Colzato et al., 2012; Kurzban et al., 2013; for theoretical viewpoints). As mentioned earlier, Helton and Russell (2012, 2015) pointed toward the difficulty to control for (micro-) rest periods between subsequent tasks, typically not registered as such, arguing that maximally "pure" rest is, in most cases, likely the best option as compared to a change in the task whatever the task is (e.g., Ariga and Lieras, 2011; Lim and Kwok, 2016; Steinborn and Huestegge, 2016).

7. CONCLUSION AND FUTURE DIRECTIONS

In the present paper, we aimed to present a structured overview of both theory and empirical findings related to effects of rest breaks. On the backdrop of this summary, we developed a set of recommendations that should be able to provide some guidance for future studies in the field. We are currently living in a world characterized by acceleration on many fronts, which yields ever-growing task and performance demands, often requiring the execution of multiple tasks at around the same time (Engelmann et al., 2011; Wörle et al., 2021). In this context, it appears essential for corresponding research fields to focus on ways which render life in a multitasking world more bearable (Colzato et al., 2021; Hoffmann et al., 2021; Hommel and Beste, 2021; Kärtner et al., 2021), and the study of rest as a means to foster both performance and well-being represents a core endeavor that should clearly be explored further, but ideally on a maximally advanced level with respect to both theory building and methodology. The present paper was written with this objective in mind. From an applied point of view, many responses to important questions are still in their infancy. For example, typical rest breaks in working environments have fundamentally changed in nature, as nowadays most people devote their spare time whenever possible to the use of social media and web content using their smartphones or computers, and media coverage of such phenomena often emphasizes potentially serious distraction effects accompanying such behavior (Charlton, 2009; Ralph et al., 2014; Scheiter et al., 2014; Steinborn and Huestegge, 2017). Again, such discussions call for a more rigorous analysis of differential effects of type of rest. Finally, we predict that more research will be devoted to study interindividual differences, for example, regarding the efficiency of certain types of rest or regarding individual differences in spending spare time in the first place.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

JK, LC, BF, and LH contributed to the supervision, discourse, debate, and theorizing. FS and MS contributed to the concept and writing the manuscript. All authors contributed to the article and approved the submitted version.

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HYPOTHESIS AND THEORY
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Resourceful Event-Predictive Inference: The Nature of Cognitive Effort

Martin V. Butz [1,2]*

[1] *Neuro-Cognitive Modeling Group, Department of Computer Science, University of Tübingen, Tubingen, Germany,*
[2] *Department of Psychology, Faculty of Science, University of Tübingen, Tubingen, Germany*

Pursuing a precise, focused train of thought requires cognitive effort. Even more effort is necessary when more alternatives need to be considered or when the imagined situation becomes more complex. Cognitive resources available to us limit the cognitive effort we can spend. In line with previous work, an information-theoretic, Bayesian brain approach to cognitive effort is pursued: to solve tasks in our environment, our brain needs to invest information, that is, negative entropy, to impose structure, or focus, away from a uniform structure or other task-incompatible, latent structures. To get a more complete formalization of cognitive effort, a resourceful event-predictive inference model (REPI) is introduced, which offers computational and algorithmic explanations about the latent structure of our generative models, the active inference dynamics that unfold within, and the cognitive effort required to steer the dynamics—to, for example, purposefully process sensory signals, decide on responses, and invoke their execution. REPI suggests that we invest cognitive resources to infer preparatory priors, activate responses, and anticipate action consequences. Due to our limited resources, though, the inference dynamics are prone to task-irrelevant distractions. For example, the task-irrelevant side of the imperative stimulus causes the Simon effect and, due to similar reasons, we fail to optimally switch between tasks. An actual model implementation simulates such task interactions and offers first estimates of the involved cognitive effort. The approach may be further studied and promises to offer deeper explanations about why we get quickly exhausted from multitasking, how we are influenced by irrelevant stimulus modalities, why we exhibit magnitude interference, and, during social interactions, why we often fail to take the perspective of others into account.

Keywords: grounded cognition, cognitive resources, cognitive effort, predictive coding, active inference, event-predictive cognition

Edited by:
Gesine Dreisbach,
University of Regensburg, Germany

Reviewed by:
Giovanni Pezzulo,
National Research Council (CNR), Italy
Alexandre Zénon,
UMR5287 Institut de Neurosciences Cognitives et Intégratives d'Aquitaine (INCIA), France

***Correspondence:**
Martin V. Butz
martin.butz@uni-tuebingen.de

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1. INTRODUCTION

Our cognitive abilities are limited. We are forgetful in so many ways, lazy, and often stuck with sub-optimal task solutions. Dual- or even multi-tasking is often extremely effortful and error-prone, unless one of the tasks can be done fully automatically. Why can't we do it? The answer is that our "cognitive resources" are limited, restricting the "cognitive effort" we can spend on the current tasks at hand. Some of us may be satisfied with such an answer. Clearly though, neither "cognitive" nor "resources" nor "effort" are really well-defined. This article attempts to scrutinize what "cognitive resources" and "cognitive effort" are.

Recent insights from cognitive science imply that our minds' thoughts—and thus our minds' mental content—while being awake, do not only cover the present itself, but also the past and future to varying extents (Buckner and Carroll, 2007; Butz et al., 2019, 2021; Stawarczyk et al., 2021). Meanwhile, these thoughts are structured in the form of event-predictive encodings (Rao and Ballard, 1999; Hommel et al., 2001; Zacks and Tversky, 2001; Zacks et al., 2007; Frings et al., 2020), giving rise to event-predictive cognition (EPCog, cf. Franklin et al., 2020; Zacks, 2020; Baldwin and Kosie, 2021; Butz et al., 2021; Kuperberg, 2021). EPCog essentially suggests that we hold thoughts about events, event progressions, and characteristics of the scenes within which these events unfold. When considering a particular event, we tend to temporally bind event-characterizing encodings of the entities, the interaction dynamics, and typical starting and ending conditions into an event-predictive attractor.

Meanwhile, we actively explore these events and progressions thereof by means of active inference (ActInf, cf. Friston, 2009; Friston et al., 2018), which formalizes (i) short-term state- and event-inference (inferring what is going on), (ii) goal-directed planning, reasoning, and behavioral control (inferring what to do), as well as (iii) longer-term, retrospective behavioral optimization and model learning (inferring useful memory structures). Derived from the free energy principle (Friston, 2009), ActInf, as a process theory, essentially formalizes the brain's effort to minimize the conjoint effort of brain and body to survive, that is, to maintain an inner, bodily-grounded balance, akin to a highly complex autopoietic system (Maturana and Varela, 1980; Butz, 2008; Friston et al., 2015b, 2018). In typical psychological paradigms, this effort may be closely related to a simple cost-benefit analysis to find solutions to particular tasks with minimum effort (Wang et al., 2021).

Given EPCog encodings, ActInf formalizes how these predictive encodings are dynamically activated and bound together. Current activation densities essentially encode the considered events and event progressions within partially defined scenes (Butz, 2016; Schrodt et al., 2017; Gumbsch et al., 2021a; Stegemann-Philipps and Butz, 2021; Achimova et al., 2022). As a result, ActInf offers a quantitative formalism to model the goal-oriented direction of attention, the dynamic maintenance of active working memory content, dynamic reasoning and decision making, and a purposeful selection, activation, and control of behavior (Gumbsch et al., 2021a,b). Conjoint with event-predictive cognition, ActInf flexibly binds components into Event-Gestalten, integrates them into scenes, projects them into potential futures, and controls their dynamic interactions in a goal-directed, homeostasis-oriented manner.

In accordance with these theories, cognitive effort may be formalized by means of a Resourceful Event-Predictive Inference (REPI) model. REPI is closely related to previous approaches that have equated cognitive effort with the information needed to change prior into posterior densities, given some source of information (Ortega and Braun, 2013; Genewein et al., 2015; Zenon et al., 2019). Beyond these previous approaches, though, REPI integrates event-predictive encoding structures into the formalism and offers an actual implementation of the inference dynamics. We thus can simulate several basic findings—such as the Simon effect and task switching costs—and offer suggestions for imminent model expansions. Moreover, we can measure the cognitive, task-oriented effort explicitly while the dynamics unfold. Dynamic processing in REPI is also similar to previous dynamic processing models, which did not explicitly relate the simualted processing dynamics to cognitive effort. For example, Steyvers et al. (2019) simulate dynamic task and response side densities. The model yields the basic task switching effect. Moreover, it can simulate training effects by increasing an adaption rate. Apart from the relation to cognitive effort, we simulate cognitive processing dynamics in the full processing pipeline, including stimulus and stimulus-bias estimation densities.

The remainder of this work details how this cognitive effort may be well-approximated by a mixture of computational-algorithmic processes, which control our thoughts. Thereby, the nature of the structures co-determines the resources needed to execute a particular task: the more compressed and readily available particular task-relevant structures are, the less cognitive resources will be required. In this paper, first more detailed background is provided on related work and on the main motivation for proposing REPI. Next, REPI is detailed on a computational level (Marr, 1982) and an algorithmic implementation is introduced. The system implementation generates behavioral results that yield the SIMON effect and task switching behavior. Other well-known psychological phenomena may be explained with REPI, including the STROOP, SNARC, and crossmodal interaction effects as well as cognitive limitations in social interactions. A final discussion concludes the work.

2. INFORMATION AS EFFORT

The perspective that our mind and body somewhat invest information to survive dates rather far back. From the very general perspective of thermodynamics and quantum mechanics, Schroedinger (1944) already proposed that life itself may be characterized as the active intake of negative entropy, thus counteracting disintegration. Only over the last decade, however, several researchers have started formalizing how exactly our brains may invest information as a resource to elicit self-motivated, goal-directed decisions and behavior (Ortega and Braun, 2013; Genewein et al., 2015; Zenon et al., 2019).

2.1. Computational Information Processing Effort

The perspective that planning, reasoning, decision making, and control requires information processing resources can be partially motivated by, but it can also partially explain, the concept of bounded rationality (Bratman, 1987; Friston et al., 2013; Lieder and Griffiths, 2020). Bounded rationality essentially emphasizes that limited cognitive capacities prevent us from thinking problems fully through, deeming our decisions sub-optimal (Simon, 1955). To save resources, we employ heuristics and often act habitually rather than in a deliberate, goal-directed manner, which leads to typical errors in our reasoning and decision making (Kahneman, 2003; Gigerenzer and Gaissmaier, 2011). Thus, sub-optimal behavior is caused by our limited information processing resources, which struggle to process more complex tasks optimally due to their higher demand of information processing resources.

Ortega and Braun (2013) proposed a free energy-based formalization of bounded rational decision making that is directly derived from thermodynamics. Decision making requires to steer distributions away from a prior distribution toward a decision-peaked distribution. Changing the distribution requires information processing resources (e.g., to solve a task), while its investment is rectified by the corresponding expected utility gain (e.g., actually solving the task). Genewein et al. (2015) enhanced this model by enabling it to selectively recruit (provided) hierarchical encodings to further minimize cognitive effort. For example, the group of food items or dangerous animals is recruited, subsuming the entities that match with a respective interaction class, leading to a more efficient decision making process.

Focusing only on the cost of cognition—implicitly assuming that the effort will be worth the while and thus maximum available effort will be spent—(Zenon et al., 2019) formalize an optimization model that consists of three summands: the mutual information I between (i) the expected and actually perceived state of the environment, (ii) the expected prior (preparatory) response and actual posterior response, given the actually perceived state, and (iii) the assumed context T dependent stimulus-response mapping vs. the actual posterior response. The formalism thus assumes independency between stimulus processing effort, task-dependent response effort, and context-dependent response effort. The authors then illustratively address inferences in the Strop task and also discuss the consequences in task switching and multitasking, which we will follow up upon below.

REPI enhances the model of Zenon et al. (2019) and Genewein et al. (2015) in that it assumes an inner, event-predictive, generative model, which contains distributed predictive encoding densities. In line with Ortega and Braun (2013) and Zenon et al. (2019), REPI equates cognitive effort with the focused activation of current mental content away from both residual, previous task priors and latent, habitual priors. The mental content, however, is made more explicit and the active inference dynamics as well as the involved effort is simulated as a process model.

2.2. Neuro-Physiological Basis

While this paper does not address the question how cognitive effort is actually spent in the brain from a neuro-physiological perspective, it may generally be assumed that evolution has designed our brains to generate flexible and highly adaptive behavior—including socially-interactive behavior—in a very resource-effective manner. Accordingly, neuro-physiological evidence is accumulating that synchronized and coordinated neural firing is indeed effortful. It appears that processing resources are dominantly determined by the effort to generate and transmit signals via biochemical dynamics and neural spikes (Laughlin, 2001; Sengupta et al., 2010). Accordingly, energy is required for the maintenance of a wakeful state, in which neurons communicate with each other across cortical and sub-cortical areas by selective, rhythmic synchronization and coordination (Engel et al., 2001; Bastos et al., 2015; Fries, 2015; Daume et al., 2017; Misselhorn et al., 2019).

These and related insights are in agreement with the perspective that cognitive effort is needed to counter uncertainty, which, in neuro-physiological terms, is closely related to focusing the mind by means of precise, coordinated neural and biochemical activities (Daume et al., 2017; Misselhorn et al., 2019). Most recent research has even linked such resource constraints to predictive coding theory, showing that resource-efficient encodings are predictive and develop in recurrent neural networks naturally, when the goal is to solve a particular tasks resource-efficiently (Ali et al., 2021).

In sum, it may be said that the current's mind focus with its neuro-physiological activities essentially constitutes current mental content, Thereby, the maintenance of a stronger processing focus and dynamic refocusing is effortful. In order to make the mental content more explicit on a computational and algorithmic level, though, the active inference principle conjoint with event-predictive cognition offer suggestions.

3. INFERENCE AND INFORMATION PROCESSING

To maximize adaptivity and flexibility, computational resources need to be directed toward those considerations that are, or may soon or suddenly become, behaviorally relevant (Butz et al., 2003; Butz, 2008; Butz and Pezzulo, 2008; Pezzulo et al., 2008). Various research strands have put forward that planning and reasoning may be viewed as inference processes, essentially subsuming model-free and model-based reinforcement learning, visual perception, and even social cognition (Rao and Ballard, 1999; Botvinick et al., 2009; Friston, 2009; Botvinick and Toussaint, 2012; Baker et al., 2017).

The involved perception, planning, and motor control mechanisms can be formalized by means of the active inference (ActInf) principle. Additionally, though, inference requires information processing resources, which is again intrinsically linked to ActInf.

3.1. Active Inference

ActInf essentially highlights that our brain predicts the future given its past experiences, even including its genetically-gathered experiences (Hohwy, 2013; Friston et al., 2015a; Clark, 2016). Importantly, though, our brain does not predict the future—or generate models of our environment—for its own sake. Rather, it does so for optimizing the generation of (highly adaptive) behavior, which is elicited to maintain and foster both internal homeostasis and model consistency (Friston et al., 2015b). As a result, the developing predictive encodings, which constitute our individual *latent* beliefs about the world, serve a self-motivated purpose. Together, our individual ActInf processes, which unfold within our individual predictive encoding structures, generate our individual current state of mind.

In relation to behavioral psychology, ActInf offers a formalization of the ideomotor principle: initial evolutionary-determined, reactive behavior becomes associated with its effects. Later, behavior is elicited by the desire to generate the associated effects again under different but related circumstances, leading to further learning (Hoffmann, 1993, 2003; Stock and Stock, 2004; Butz and Kutter, 2017). ActInf thus formalizes how internal generative structures inevitably reflect the (hidden) outside reality—or at least those components of reality that tend to affect the well-being and mere existence of the living being in question (Friston, 2009; Butz and Kutter, 2017).

The ActInf formalization subsumes three distinct, highly interactive inference processes:

1. Fast, prospective ActInf, which infers behavior from projections into the future, aiming at minimizing expected free energy, which quantifies both expected uncertainty as well as homeostasis.
2. Fast, retrospective inference to adapt current model activities to the gathered (attended-to) sensory information and the hidden causes, which (as the brain's generative model believes) seem to explain away the sensory information (including, for example, the behavior of others, physical objects, etc.).
3. Much slower, longer-term, consolidating inference, which refines, modifies, and extends the brain's generative model itself, that is, its internal predictive encoding structures. Due to the free energy formalization, the process will focus learning on those experienced aspects, episodes, events, and components thereof that appear relevant to decrease (future) free energy.

In the REPI model, we focus on simulating the first two processes, providing presumably learned predictive encoding structures as the available generative model.

Since the reminder of this work focuses on the inference of behavior and involved effort, a formalization of prospective ActInf will be useful. To do so, it is necessary to specify the to-be-minimized free energy (Friston et al., 2015b, 2018; Gumbsch et al., 2021a). Given a particular policy π, which generates actions a in the light of the current belief state b_t and system needs n_t considering a particular, possibly adaptive, temporal horizon $\tau = \{t, t+1, t+2, ..., t+T\}$ with depth T, the anticipated free energy when pursuing policy π can be written as:

$$\begin{aligned}\widehat{\mathbf{FE}}(\pi,\tau,b_t,n_t) = &\underbrace{\mathrm{KL}\Big[Q\big(o_\tau \mid b_t,\pi\big)\,||\,P\big(o_\tau \mid b_t,n_t\big)\Big]}_{\textbf{predicted divergence from desired states}} \\ &+ \underbrace{\mathrm{E}_{Q(b_\tau|b_t,\pi)}\Big[\mathrm{H}\big[P\big(o_\tau \mid b_\tau\big)\big]\Big]}_{\textbf{predicted uncertainty}},\end{aligned} \tag{1}$$

where prior densities are denoted by P while expected posterior densities are denoted by Q. The KL divergence is calculated as the expected divergence of posterior observation densities, when following policy π starting from belief state b_t, from the prior desired observation densities $P\big(o_\tau \mid b_t, n_t\big)$ over the temporal horizon τ. Meanwhile, predicted uncertainty quantifies the entropy H over expected future observations dependent on expected policy-dependent future belief states $\mathrm{E}_{Q(b_\tau|b_t,\pi)}$, when following policy π starting from belief state b_t.

Driven by the purpose to minimize free energy, and thus to maintain internal structure, Equation (1) essentially quantifies a payoff, which may be equated with the decrease in free energy compared to the possible development of free energy given inactivity.

3.2. Information Processing Cost

Meanwhile, though, invoking activities and focus will come at a cost, which has been equated with the change from a prior to a posterior distribution in terms of KL divergences (Ortega and Braun, 2013; Genewein et al., 2015; Zenon et al., 2019):

$$\mathscr{C}(P,Q) = \mathrm{KL}\left[Q(x|e)||P(x)\right], \tag{2}$$

which quantifies the investment cost of changing a prior probability density over some representational generally continuous space $x \in \mathbb{R}$ into a posterior distribution over this space given a source of evidence e.

When furthermore assuming a density E over these evidences—be they sensory information about body or environment or also internal model expectations or motor activity—a more accurate cost estimate takes the weighted mean over the possible evidences, yielding a form of mutual information:

$$\mathscr{C}(P,Q,E) = \sum_{e\in E} p(e)\mathrm{KL}\left[Q(x|e)||P(x)\right] = \mathrm{I}_Q(E,P). \tag{3}$$

According to this equation, the cognitive effort to direct behavior and thoughts toward desired states and away from expected observational uncertainty (cf. Equation 1) can be equated with the mutual information I_Q between the state-informative evidence density E, which we here assume to be discrete for simplicity reasons, and state estimation prior $P(x)$, given the conditional model Q, which maps evidence onto posterior state estimations.

The system then ideally finds the optimal behavioral policy π^* that minimizes anticipated cognitive costs, that is, information investment costs, and anticipated free energy. When the gain in free energy minimization is larger than the cognitive costs, the effort is worth its while. Effort costs and utility gains thus need to be well-balanced. Accordingly, a weighting factor has been introduced as a Lagrangian multiplier that factors the optimization cost into the expected utility gain (Ortega and Braun, 2013), allowing an adaption in how much cognitive investment is currently worth the while. This factor may essentially be related to the current cognitive resources available to an agent, which is related to inner homeostasis and thus intrinsically part of Equation 1. In the future, the fixed horizon in Equation 1 may thus be subsumed by a dynamic horizon that may optimally take planning costs and available resources into account (cf. Gumbsch et al. 2021a for a similar proposal). For now, a simplifying alternative to balancing the two aspects lies in focusing on solving one particular task and assuming that maximal available cognitive effort is spent on solving it at any current point in time. In this way, cognitive costs dominate behavioral and cognitive processing and decision making: the larger the needed density changes to process a task, the slower the behavioral decision making.

To summarize: there is compelling evidence that our brain is developing generative predictive model(s) by means of ActInf. Concurrently, the developing models enable ActInf to focus our computational resources on anticipated needs. Combined with information processing cost considerations, ActInf thus controls how computational resources are invested, considering the future in the light of the present, the current needs, and our so-far gained behavioral and model-predictive knowledge. It continuously adapts the currently active internal models in the light of the accumulating evidence, develops these models further over time, and determines current attentional dynamics, reasoning, decision making, and behavioral control by attempting to minimize expected free energy (Equation 1).

The biggest criticism on ActInf and the information cost formalization from the cognitive science side lies in the testability and falsifiability of the involved formalism. This is particularly the case because the involved generative model is not specified. Indeed, ActInf may play out not only during ontogenetic development and the hear-and-now, but even on evolutionary time-scales, creating particularly well-suited bodily properties (such as our hands), developmental pathways (such as our brains' modular structure), and consequent inductive learning biases (Pfeifer and Bongard, 2006; Butz and Kutter, 2017)—all influencing generative model development. We thus now scrutinize likely properties of the developing generative model.

4. EVENT-PREDICTIVE STRUCTURES

EPCog emphasizes that event-predictive encodings are particularly prominent in our brain, as suggested from various disciplinary and interdisciplinary perspectives (Butz et al., 2021). Coming from the developmental psychology side, for example, Dare Baldwin and Jessica Kosie emphasize that events are inferred from our sensorimotor experiences:

> "Events–the experiences we think we are having and recall having had—are constructed; they are not what actually occurs. What occurs is ongoing dynamic, multidimensional, sensory flow, which is somehow transformed via psychological processes into structured, describable, memorable units of experience." (p.79, Baldwin and Kosie, 2021)

In relation to ActInf, we appear to learn to construct progressively more abstract event-predictive structures in a self-motivated manner. Over time, we even learn to express some of these structures via language. From an evolutionary, cognitive effort-oriented perspective, it may be said that over the course of our lifetime our brain attempts to minimize its cognitive effort to life a "successful" life (ultimately from an evolutionary perspective Darwin 1859; Dawkins 1976). To succeed in our challenging social and cultural cooperative and competitive world, it appears that evolution has given our brains the tendency, or inductive learning bias, to compress our experiences into abstract, conceptual, symbolizable structures (Deacon, 1997; Butz and Kutter, 2017).

In behavioral psychological research, *event-files* have been characterized as behavioral units that commonly encode actions with their consequences, allowing the triggering of actions by their anticipated effects (Hommel et al., 2001). In more observation-oriented event segmentation studies, strong commonalities have been identified in segmenting movies into event units at various levels of granularity (Zacks and Tversky, 2001; Zacks et al., 2007). Meanwhile, memory research has shown that events are memorized as units of experience, while event boundaries characterize predictably unpredictable decisions, for example, of what a person is going to do next after having finished a particular (sub-)task (Baldwin and Kosie, 2021; Kuperberg, 2021). On the language level, events constitute a critical structural component not only in research on grammar and semantics, but also in studies on metaphors and analogies (Lakoff and Johnson, 1980; Gentner and Markman, 1998; Pietroski, 2000; Gehrke and McNally, 2019; Ünal et al., 2021). Encompassing cognitive theories have also used the event concept extensively, such as the theory of conceptual spaces and the geometry of meaning (Gärdenfors, 2000, 2014).

Recent more explicit theories on EPCog have proposed that events consist of multiple, event-characterizing components (Butz, 2016; Butz et al., 2021):

- actions as well as other forces, which dynamically influence the event dynamics;
- entities involved in the event including their roles (e.g., agent, recipient, tool) and other critical properties (e.g., agentiveness, material properties);
- spatiotemporal relations and dynamics between the involved entities while the event unfolds;
- when agents are involved, intentions that trigger particular behavior.

These components need to be flexibly bound into current events, which are then characterized and constituted by their components and their interactions. The required binding process appears to be biochemically effortful, as it requires the selective synchronization of various brain areas, effectively binding the involved components and spatiotemporal dynamics into event structures (Engel et al., 2001; Buckner and Carroll, 2007; Fries, 2015; Daume et al., 2017; Misselhorn et al., 2019; Frings et al., 2020; Stawarczyk et al., 2021).

Events can be closely related to scripts in traditional cognitive science. Moreover, research on schema structures is closely related. In these cases, though, mostly linear, well-ordered, and often fully symbolic structures were assumed. Events seem to be more flexible than this, as recently highlighted from various research perspectives (Elman and McRae, 2019; Baldwin and Kosie, 2021; Butz et al., 2021; Kuperberg, 2021; McRae et al., 2021). That is, the dynamic construction and activation of events can unfold in highly varying manners.

On the one hand, it is stimulated bottom-up by the outside environment while inferring the currently activated internal generative model. On the other hand, it is controlled top-down, driven by current and anticipated, task-oriented, bodily, motivational, and emotional needs. The dynamic and selective activations, driven by the ActInf principle, essentially correspond to the dynamic consideration of the following conceptual questions: Which behaviorally relevant entities are present and which events dynamically unfold in the outside environment? Which behavioral and other counterfactual alternatives should be considered? Which dynamical interaction consequences may be relevant?

To be able to encode more complex event and event progressions, scene embeddings offer additional support. The ActInf of critical scene-characterizing properties, in which currently considered events are embedded, may constitute a hallmark of our imagination. We all know this rather well when reading a fiction book. If the book is good and we are in the right mind set, our imagination creates (abstract) scenes and fills-in unmentioned aspects with most plausible components—augmenting the stories with deeper gist, background, intentions, and emotions. There is evidence that network activity dynamics unfold within a *default network*, which appears to both maintain an actual event-specific thought and coordinate switching dynamics between thoughts (Buckner and Carroll, 2007; Buckner et al., 2008; Stawarczyk et al., 2021). The REPI model, which we introduced in the following section, essentially mimics such dynamics on an admittedly still rather simple level.

5. RESOURCEFUL EVENT-PREDICTIVE INFERENCE

REPI integrates formalizations of cognitive effort and ActInf with the EPCog perspective. That is, REPI assumes that event-predictive ActInf strives to continuously maintain and infer the currently deemed relevant event-predictive encodings about, and interactions with, the outside environment. Moreover, ActInf controls anticipatory and reflective event dynamics as well as switches between events while accounting for the involved cognitive effort. Meanwhile, ActInf will tend to maintain multiple, possibly competitive, event hypotheses in parallel, for example, when facing a complex problem with a yet unknown problem solution or when pursuing task switching.

REPI equates cognitive effort with the effort to dynamically activate precise event-predictive encodings via active inference, including retrospective, prospective, alternative, and counterfactual encodings. The effort essentially lies in adapting internal activities and choosing behavioral activities for the minimization of both task-respective divergence and observational uncertainty. Meanwhile, theories of event-predictive cognition suggest that the involved activities are constituted by interactive, event predictive codes, which predict not only the unfolding stimulus dynamics but also each others' dynamics.

Because the adaptation processes fundamentally depend on the current availability of (event-) predictive encodings, a particular task will be solved the easier the more task-concrete encoding are available. Vice versa, the more unusual a particular task is, that is, the more incompatible required task responses are to the so-far learned predictive encodings, the harder it will be to inhibit the learned encodings and to activate current task-relevant components.

5.1. Preparation and Processing Information Effort

Considering the effort of focusing densities in relation to EPCog, it will be effortful to selectively activate precise event-predictions, or foci, away from previous foci as well as from uncertainty and general lethargy. That is, cognitive resources are needed both to activate new foci, to deactivate previous ones, and to invoke structure away from uncertainty, that is, away from a uniform distribution (maximal entropy).

Because the ease of activating particular densities will depend on the (i.e., learned) predictive encoding structures available, the more unusual a particular event is, the more effortful it will be to encode it. Similarly, the more unusual, unexpected, or counter-intuitive the binding of individual event components is, the more effortful the binding will be. Meanwhile, inhibiting competing events as well as considering multiple alternative events will be effortful. Even more effortful will be the successive activation or parallel maintenance of mutually inhibitory encodings, such as when a stimulus needs to be mapped first onto the right response side and then onto the left response side, due to a task switch.

Since considered events may be integrated into scenes, the complexity of and the prior knowledge about a considered scene will also play crucial roles. First, the ActInf of particular scene aspects and un-mentioned but event-relevant components for the production of coherent mental content will be effortful. The more common and well-known an encoded scene, the fewer cognitive resources will be needed to activate its compressed scene-characteristic event structures. The activation of scene-unusual, or even scene-contradictory, attributes will be resource-demanding, because their activation will be inhibited by the scene code. When alternative scenes need to be considered, their compatibility or logical temporal progression will influence the effort to maintain them in parallel.

For example, the entities and interactions necessary to prepare a cup of tea can be effectively encoded because we know all involved entities and interactions well. Its encoding is even less demanding, once we have developed an even more integrative event-predictive schema, which predicts the involved sub-events, entities and conditional event progressions a priori, for example, when considering "preparing a cup of tea" (Kuperberg, 2021). Similarly, much less cognitive effort is necessary when succeeding in processing a multitude of stimuli in an integrative, Gestalt-oriented manner—as is the case when, for example, recognizing a human figure walking in a point-light motion display (Johansson, 1973; Pavlova, 2012; Sadeghi et al., 2021).

In sum, the preparation and processing of actual events and event progressions within scenes can be assumed to be the more resource demanding:

1. the more individual entities are involved,

2. the more distinct their current spatial relations and dynamics are,
3. the more distinct their properties are,
4. the less typical or well-known the respective components and interactions are,
5. the more distinct (non-)agentive roles are involved, and
6. the fewer precise prior event-predictive encodings are available for activating the content.

The activation of a particular event will also depend on previous content activations: the more the current event differs from the previous one, the more effortful the switch. Moreover, the fewer this particular event switch has been experienced in the past, the more resource-demanding it will be, because it is less expectable.

5.2. Cognitive Effort When Processing (Successive) Tasks

When facing a concrete task, various components of cognitive effort are involved. During task preparation, suitable event-predictive task-specific priors away from previous posteriors, latent habitual priors, and uniform entropy need to be activated. These include priors on the expected, relevant sensory stimulus information, the expected mappings—or, more generally speaking, computations—needed to transform the stimulus into an appropriate response, as well as priors over potential responses. When processing a task-informative stimulus these priors will be adapted further. For example, in a priming task the prime may bias response tendencies. Similarly, when the stimulus informs about likely upcoming actual imperative stimuli or the upcoming task, stimulus priors, stimulus-response mapping priors, and response priors will be focused further.

When processing the task-imperative stimulus then, super-threshold activities need to be reached while inhibiting incompatible priors in perception, in competing task sets, and in the action choices. This principle is closely related to dynamic neural field theory (Schoener, 2020), where sub-threshold activities in an activation field correspond to preparatory, but also latent and residual, priors. When preparation is maximally effective, expected and fully prepared stimuli will be processed fastest and with least effort, and they will yield smallest response errors. Meanwhile, when a response is overly prepared, it may be executed prematurely, or incorrectly when the imperative stimulus does not conform to the expected stimulus. This has been, for example, studied in detail in go-nogo tasks.

In the following section, concrete examples of such encodings are provided and REPI is implemented as a dynamic processing model. Model simulations yield the Simon Effect and Task Switching costs. More detailed model evaluations are needed to further verify or falsify the ability of the architecture to model more intricate task switching observations. We end with a discussion that sketches-out the potential of REPI to model other psychological experiments and typical observable behavioral effects.

6. MODELING PSYCHOLOGICAL OBSERVATIONS

The combination of EPCog with ActInf makes rather direct predictions about task-specific cognitive effort and consequent behavioral phenomena. In particular, it has immediate implications for all behavioral paradigms where multiple, including latent, stimulus-response options need to be considered and selectively activated. According to the theoretical considerations, each task setup will lead to the activation of a particular, event-predictive state of mind. ActInf will attempt to focus the available cognitive resources on the task at hand, while prior, latent activities (such as habitual stimulus-response mappings) will maintain a base-level activity of general knowledge and behavioral response structures.

In relation to expected free energy (Equation 1), the preparation to solve a particular task may be equated with desired future observations $P\big(o_\tau \mid b_t, n_t\big)$, which essentially quantifies the focus on the current task set. Observations here can also include motor responses and their consequences, thus triggering response-effect compatibilities (Elsner and Hommel, 2001; Kunde, 2003). Moreover, they can include the pre-activation of particular, internal stimulus-response mappings as well as the inhibition of inappropriate ones. The higher the uncertainty in this future-concerning observation density, the more difficult it will be to trigger a task-appropriate action.

Meanwhile, the second summand in Equation (1) will maintain a general alertness, aiming at decreasing general uncertainty about the environment. This component may thus lead to the generation of task-irrelevant, epistemic actions, but also to the prior activation of latent stimulus-response mappings, which have proven to be useful to decrease uncertainty—such as reacting to a particular stimulus with an orientation reflex.

6.1. REPI Model Implementation

In order to explain the mentioned psychological behavioral phenomena not only qualitatively but quantitatively, we now introduce an actual algorithmic implementation of the REPI model. In this implementation, we focus on modeling standard tasks that elicit the Simon effect as well as task switching costs. **Figure 1** shows a sketch of the task-oriented REPI model implementation, where sensory information flows into the model from the left, task-informative information from the top, response tendencies are sent toward the right, while anticipated response consequences are sent back to the left.

In all these tasks, we assume a dynamic perceptual space $\mathcal{O}$, where at a point in time t prior densities are given by $P(\mathcal{O}_t)$ and posteriors by $Q(\mathcal{O}_t)$. Similarly, we denote the relevant task space by Ψ, with priors $P(\Psi_t)$ and posteriors $Q(\Psi_t)$. As an additional latent observational bias space, we model $\mathcal{B}$. Moreover, we model response side dynamics in $\mathcal{S}$ and the actual response dynamics in $\mathcal{R}$.

During a trial, these densities are dynamically adapted toward particular target values. In each iterative update step, all densities are adapted from priors to posteriors, which constitute the priors

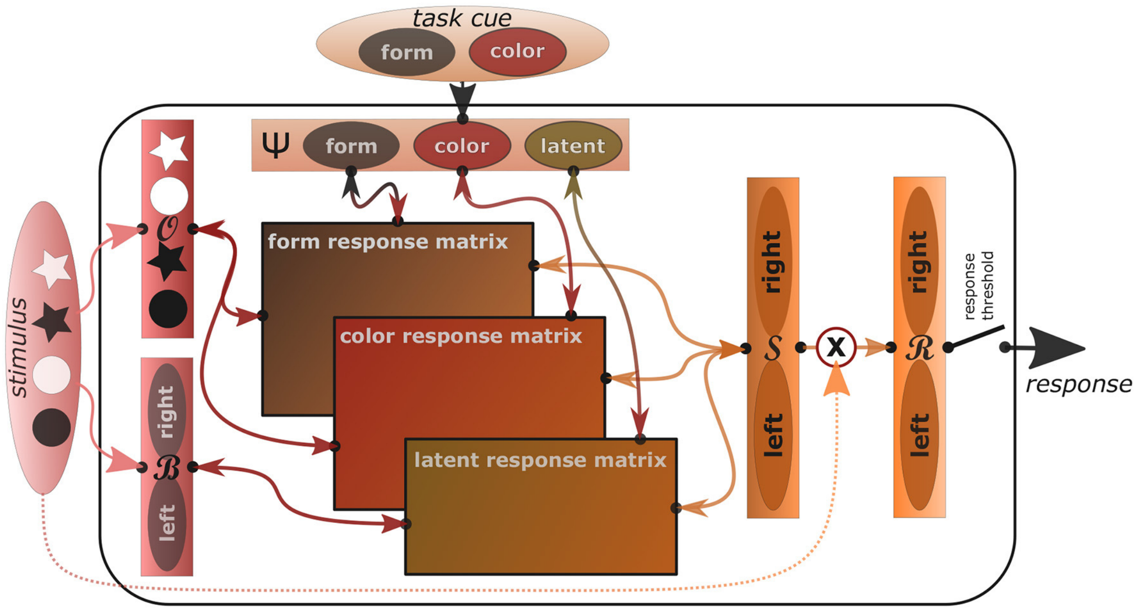

FIGURE 1 | The concrete REPI model implementation is able to mimic Simon and task switching effects. It consists of five main dynamics processing modules (slim rectangles), which simulate inferences of observation densities $\mathcal{O}$, observation bias densities $\mathcal{B}$, task set densities Ψ, response side densities $\mathcal{S}$, and actual response densities $\mathcal{R}$. The wide rectangles in the center correspond to task-specific mappings from stimuli to task-respective response sides. Form- and color-response matrices map the stimulus densities onto left/right responses mixing the output relative to the form and color task activity values of the task density, while the latent response matrix adds the stimulus bias density influence weighted by the latent task activity. A response threshold determines when the response is actually triggered. Activities are only passed into the response density $\mathcal{R}$ upon stimulus onset. To improve comprehensibility, a particular task switching scenario is shown exemplarily, where the two tasks correspond to a form and a color task and the stimuli include black and white stars and circles, which map to either a left or right response, dependent on the task.

in the next time step. The update is computed as follows:

$$Q(\mathcal{X}_t) \propto P(\mathcal{X}_t) + \alpha \epsilon_t G(\mathcal{X}_t), \tag{4}$$

where α denotes a rate factor, ϵ_t the currently available cognitive resources per time step (e.g., per second), $\mathcal{X} \in \{\mathcal{O}, \mathcal{B}, \Psi, \mathcal{S}, \mathcal{R}\}$ denotes the density that is adapted, and $G(\mathcal{X}_t)$ denotes the current targeted density, that is, the ideal goal state REPI strives for via active inference. In the simulations below we set the simulation speed to 10 ms per iteration and thus $\alpha = 0.01$, while we set the resource strength to $\epsilon = 6$.

When focusing on one particular task, the task density $P(\Psi)$ will strive to adapt toward a fully focused density, which would, for example, correspond to $(\Psi|\psi_t = 1) = [1, 0, \ldots, 0]$ in the case of a discrete one-hot encoding when focusing on the first task. While preparing for a particular task, or a set of tasks, the task densities will adapt to the average mixture of each possible task. Finally, to model a latent readiness to process stimuli habitually, a general latent readiness may be modeled with an offset factor λ, such that, for example, a maximal readiness for processing two equally probable tasks would correspond to:

$$G(\Psi|\psi_t \in \{1, 2\}) = \left[(1-\lambda)/2, (1-\lambda)/2, 0, \ldots, 0, \lambda\right], \tag{5}$$

where we assume additional dormant tasks in the middle with zero activity.

The observational density, which focuses on processing the imperative stimulus, will generate task-particular, top-down, goal-directed stimulus expectation densities $G(\mathcal{O}_t|P(\Psi_t))$ dependent on the current task density $Q(\Psi)$ during the stimulus preparatory phase. Once the stimulus is presented, though, processing will switch to bottom-up evidence accumulation by setting $G(\mathcal{O}_t|o_t)$ to, for example, a one-hot encoding of the discrete stimulus signal. While information fusion options may be included here, at the moment the implementation sets $G(\mathcal{O}_t)$ either to the top-down or the bottom-up observational goal, dependent on the current stimulus availability. Meanwhile, potential stimulus biases may be processed within the bias space $\mathcal{B}$, where no stimulus side bias corresponds to $G(\mathcal{B}_t) = [0.5, 0.5]$. The response side density is continuously updated task- and observation-estimate dependently. That is, $G(\mathcal{S}_t)$ is set to $P(\mathcal{S}|Q(\mathcal{O}_t), Q(\Psi_t))$, where the respective task sets are implemented by means of task-respective mapping matrices, which map individual objects to task-corresponding response sides. Finally, once a stimulus has been perceived, the actual response density is adapted away from a uniform response density toward the current processing side density, that is, $G(\mathcal{R}_t)$ is set to $Q(\mathcal{S}_t)$. The actual response is then triggered once a particular response threshold θ_r, which we typically set to 0.9, is reached.

Assuming, as specified above, that the full focus will lie on solving tasks during an experiment appropriately, the costs

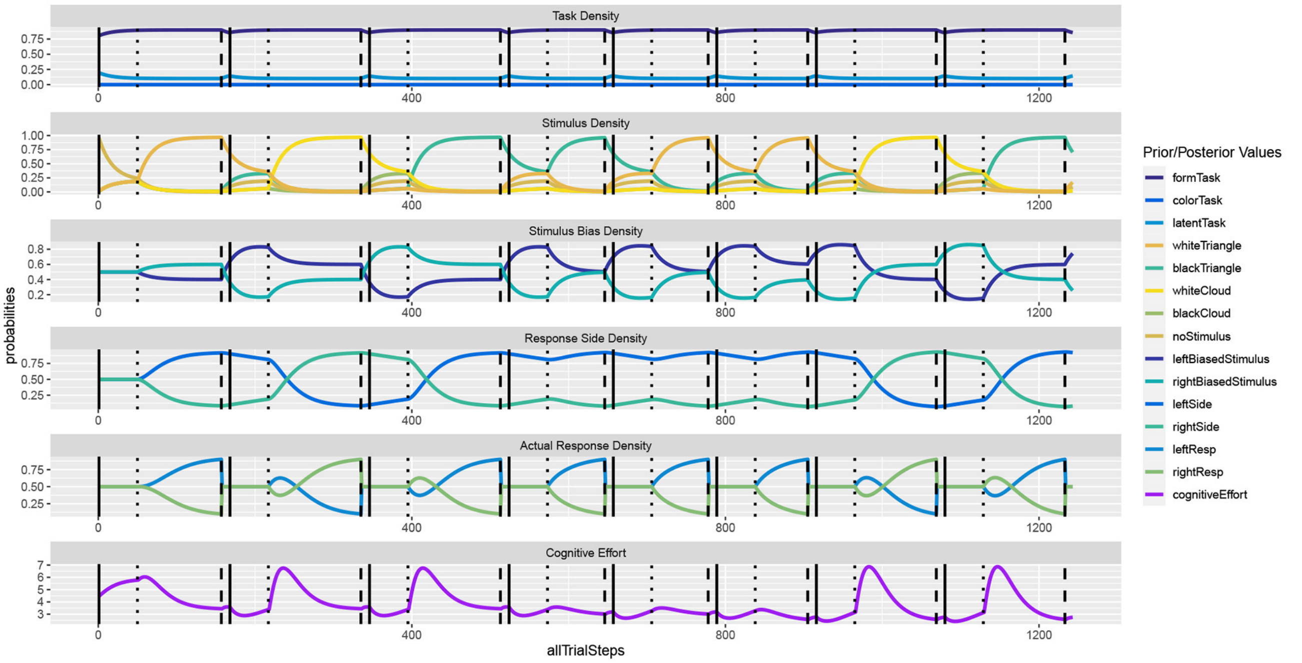

FIGURE 2 | In the **Simon effect**, the response dynamics are influenced by the side of the stimulus, besides the actual stimulus identity. The dynamics clearly show how REPI gets ready for the task once the fixation cross is shown (vertical solid bars). Once the imperative stimulus is shown (vertical dotted bars), response inference is activated and evidence for either response side accumulates. The response is triggered when a particular response threshold (set to 0.9) is reached (vertical dashed bars).

for solving a particular trial may then be quantified by the dynamically unfolding mutual information between current response tendencies and desired response tendencies given the beliefs in the current task and the current stimulus situation, that is:

$$\begin{aligned}\mathscr{C}(\text{task}) &= \mathscr{C}\left(P(\mathcal{S}_t), P(\Psi_t), P(\mathcal{O}_t)\right)\\ &= \sum_{\psi\in\Psi_t, o\in\mathcal{O}_t} p(\psi)p(o)\,\mathrm{KL}\left(Q(\mathcal{S}_t|\psi, o)||P(\mathcal{S}_t)\right)\\ &= \sum_{\psi\in\Psi_t, o\in\mathcal{O}_t} p(\psi)p(o)\,\mathrm{KL}\left(G(\mathcal{S}_t)||P(\mathcal{S}_t)\right)\\ &= \mathrm{I}(P(\Psi_t, \mathcal{O}_t); P(\mathcal{S}_t)). \qquad (6)\end{aligned}$$

In the future, several advancements in this cost computation and the distribution of cognitive resources are imaginable. These include (i) the computation and integration of costs based on mutual information in the other spaces, including the task and observational spaces, (ii) the adaptive, non-uniform, active-inference-driven distribution of computational resources over the considered density spaces, that is, adapting ϵ_t in Equation (4).

6.2. Modeling of the Simon Effect

The Simon effect characterizes the effect that participants respond to a stimulus faster with their ipsilateral than with their contralateral effector even when the position of the stimulus presentation is irrelevant for the actual task (Erlhagen and Schöner, 2002; Cho and Proctor, 2010). From the event-predictive ActInf perspective, paradigms that study the Simon effect essentially study the presence of latent, spatial stimulus-response mappings and their latent activity strength relative to the task-specific activities, participants attempt to focus on. The latent response mapping corresponds to an ipsilateral response to lateral stimuli, such as by an overt eye saccade, by a covert direction of attention, or by an actual manual interaction—where in the last case handedness plays an additional important role. For example, we respond to a visual stimulus by looking at it, by touching it (e.g., a power switch), avoiding it (e.g., an insect), or actively pursuing interactions with it (e.g., when washing our hands or grasping a mug). As a result, ipsilateral, stimulus-response mappings, which are predictive by nature, are latently active in our minds, facilitating many everyday interactions. In a particular experiment that elicits the Simon effect, though, these latent mappings get in the way and are hard to fully inhibit.

To model the dynamics and estimate the relative effort to solve individual trials, we ran REPI on a simulation of a typical Simon effect-eliciting task. We assumed that the task was to respond to the form of an object, ignoring its color as well as its location on the screen. Objects were simulated to be presented either centrally to the right or to the left of the center. The trial started with the presentation of a fixation cross, followed by the imperative stimulus 500 ms afterwards. The inter trial interval was set to 100 ms.

In our REPI implementation, we used the general setup shown in **Figure 1** focusing on the form task and leaving the latent activity active between a value of 0.1 and 0.2, dependent on if the fixation cross or the imperative stimulus are shown or not yet, respectively. Task cue and stimulus goal signals are set to 0.9 and 0.97, respectively assuming a latent task activity of 0.1 and a slim chance to perceive one of the other objects with a probability of 0.03, respectively[1].

Figure 2 shows the unfolding dynamics of the simulation over the first ten trials. Moreover, the dynamics of the costs, which focuses on solving the task quickly and correctly, are plotted. **Figure 3** shows the simulated reaction times as well as the resource investment determined over the time from the imperative stimulus until the response was triggered. The results clearly show the Simon effect: a stimulus that appears on the right or left is responded to faster with the compatible response side, while a stimulus in the center does not exhibit this influence. Moreover, response repetition benefits are visible, when the response side needs to be switched. The cost measurement $\mathscr{C}$ (cf. Equation 1) confirms that faster responses go hand-in-hand with smaller cognitive effort. Future work may also model the STROOP effect with similar principles. Here, an open question is whether modifications of the task priors will be enough to model the dominance of the word reading response in all its detail.

6.3. Modeling Task Switching

The task switching literature is full of additional insights on how quickly event-predictive encodings can be selectively engaged, disengaged, and inhibited. When comparing blocks with single and multiple tasks, parallel task processing costs as well as switching costs are assessed. These are needed to pre-activate the task-specific stimulus encodings and stimulus-response mappings as well as to switch between the distinct, task-specific encodings and mappings.

In contrast, mixed task blocks reveal the flexibility of the cognitive processes involved when switching between tasks (Kiesel et al., 2010; Koch et al., 2018; Frings et al., 2020). Task switching costs—that is, worse performance (typically measured in response times and response errors) when performing a different task in a subsequent trial vs. the same task—reveal that it is difficult to fully erase the task set that was relevant in the previous trial from memory. The robustness of this finding is stunning: it can be found in blocks with predictable task switches, cued switches, intermittent instructions, and even when task selection is mostly voluntary (Kiesel et al., 2010).

6.3.1. Model Results

To model the dynamics and estimate the relative effort to solve individual trials, we adapted the simulation and evaluated REPI in a typical task-switching experiment. We simulated mixed task blocks, where first a cue informed about the task of the trial. After a cue-stimulus interval (set to 100 ms if not stated differently below) the imperative stimulus appeared. After the reaction was executed by REPI, the response to cue interval, which we also set to 100 ms in the reported results, commenced. We leave the other settings identical to the Simon effect simulation, except for that all stimuli were simulated to be presented centrally yielding no latent response bias. A task switch occurred with a 50% chance[2].

Figure 4 shows the unfolding dynamics of the simulation for the first 10 trials. In contrast to the Simon task, we can now observe only indirect stimulus bias density dynamics, which stem from the response side activities. Moreover, we can observe how task switches delay decision making, as do response side switches.

Figure 5 shows simulated reaction times as well as the resource investment (cf. Equation 6). The results reveal the typical Task Switching effect as well as its decline when the response to the other task is compatible vs. when it is not. They also show that the task switching costs clearly decline with a longer cue-stimulus interval (Monsell, 2003; Altmann and Gray, 2008; Kiesel et al., 2010). Moreover, response repetition benefits are observed, which are particularly strong when the same object is presented. In comparison to the costs reported in the Simon effect simulation, it may come as a surprise that the costs for individual trials area actually slightly smaller on average. This may be the case because the costs currently only focus on the mutual information residing in the response side space. When the stimulus activities are directly set to the current value instead of dynamically adapted, the switching costs to not reverse when in the previous trial the other response side had to be chosen. This effect should be studied in further detail. When the stimulus is assumed to be processed instantly, in which case REPI acts very similar to the one in Steyvers et al. (2019), intricate interactions of the current trial situation with the previous response side disappear. Future research should further elaborate on the validity of these additional interactions. The put-forward REPI model would expect these influences, although their influences may not be as pronounced as the ones in the presented results. In fact, an instant perceptual processing essentially corresponds to very large update steps (i.e., large values of ϵ_t for the perceptual updates only; cf. Equation 4). Thus, REPI essentially subsumes the model in Steyvers et al. (2019), but, additionally, puts forward the relation to active inference, to event-predictive cognition, as well as to the involvement of cognitive effort and cognitive resources.

6.3.2. Task Switching and Multitasking Literature Relations

The typical task switch results are thus explained by REPI with its implementation of the event-predictive ActInf perspective. Each task requires the activation of a particular task set, which will be encoded by corresponding event-predictive encodings, that is, the prior activation of particular stimulus-response mappings. A response is then selected based on a sufficient activity threshold, which mimics accumulator or drift models (Ratcliff, 1978; Lewandowski, 2007) and is also related to dynamic neural field approaches (Schoener, 2020). Longer reaction times thus are generated when response alternatives still have larger

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[1] The Simon effect model implementation is available online as an interactive shiny app: https://cognitivemodeling.shinyapps.io/shinysimoneffectsimulation/. It allows explorations of critical model parameters, random trial order dynamics, and resulting, condition-dependent reaction time values.

[2] The task switching model implementation is available online as an interactive shiny app: https://cognitivemodeling.shinyapps.io/shinytaskswitchingsimulation/, which allows further explorations of additional effects of the model parameters and the simulation setup.

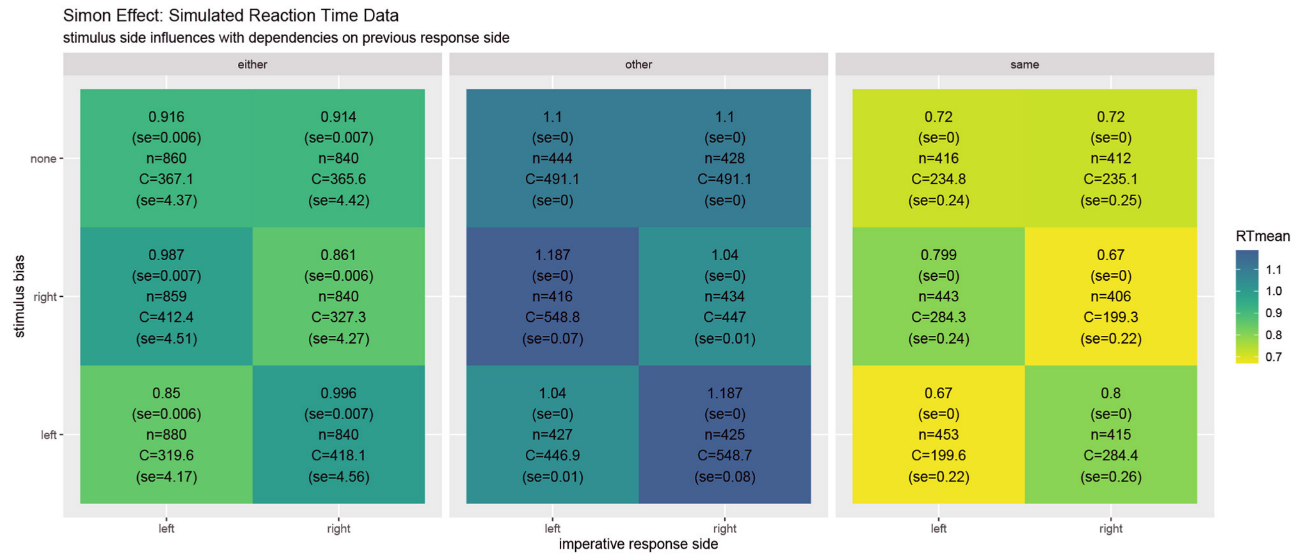

FIGURE 3 | In the **Simon effect**, the reaction times clearly depend on the stimulus bias, favoring ipsilateral responses. Besides the mean reaction times, the values report standard error, the number of condition-respective trials, and mean cognitive effort costs $\mathscr{C}$ (task) integrated over the time from the stimulus onset until the response.

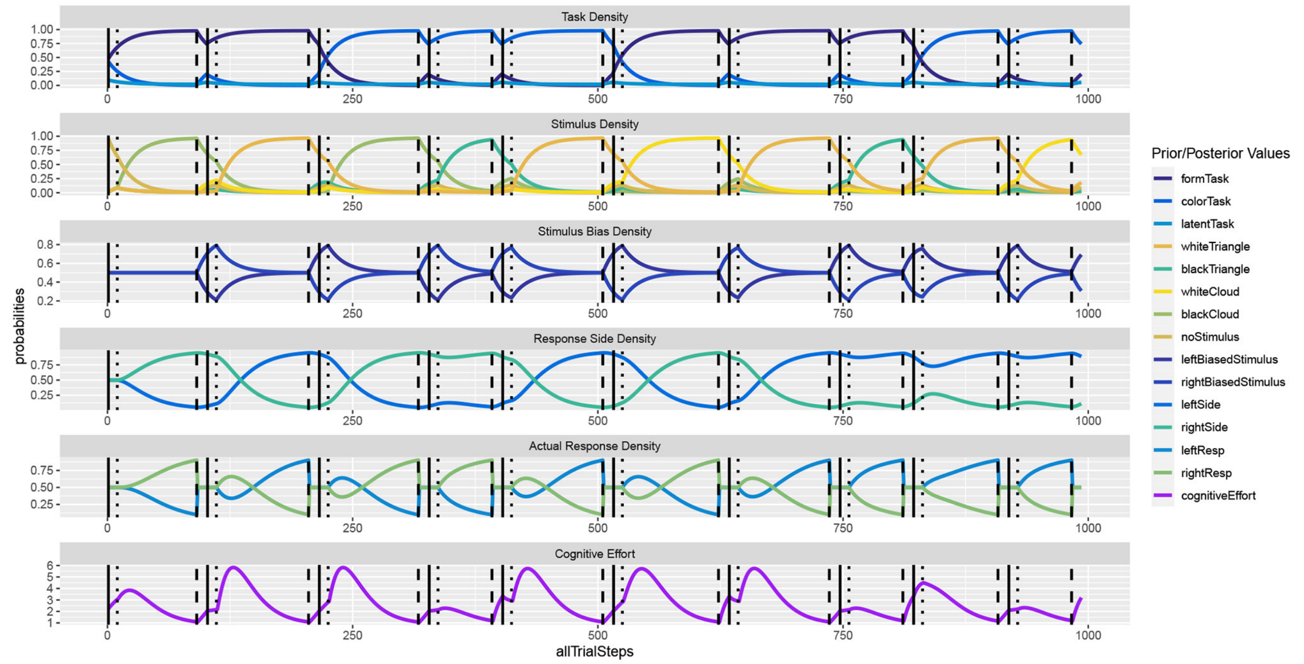

FIGURE 4 | In the **task switching** simulation, the response dynamics are indirectly influenced by the previous task as well as by the previous response. Once a response is executed, response side and action densities are set back to uniform.

prior activities from previous trials. Moreover, the activity of the same response in the previous trial yields response delays in the case of a task switch, because a now incorrect stimulus-response mapping is still co-activated.

Meanwhile, an independent congruency effect can be observed, which yields faster responses when the stimuli afford the same response in the case of either current task. Interestingly, the latter is much less dependent on preparation time. Both effects can be explained by the failure to fully suppress previous task activities, thus affecting response time. If it was possible to remove or normalize over the effects of the particular pairs of tasks, response time activities may be understood in even better manners. Generally, though, REPI simulates how competing task structures may elicit congruent or

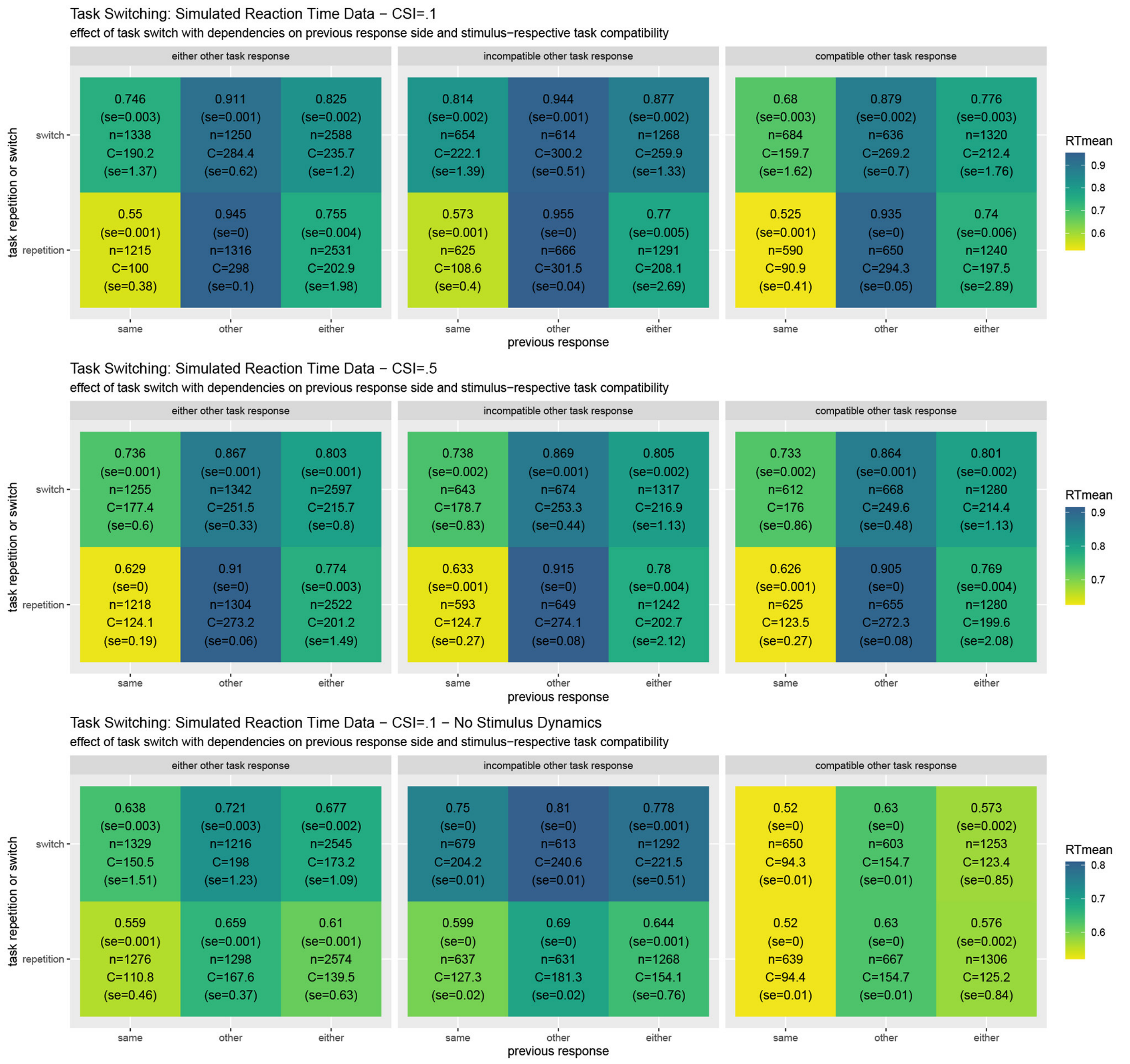

FIGURE 5 | Results of **task switching** simulations averaged over twenty experiments for the full REPI model with all dynamics simulating a cue-stimulus interval of 100 ms **(top row)**. When this interval is enhanced to 500 ms **(middle row)**, the task switching effect decreases, as is well-known from results in the task-switching literature. When the stimulus density is set directly to the actual stimulus value, the predicted response distributions undergo fewer dynamical interactions **(bottom row)**. The basic REPI simulation without further parameter optimization yields reaction times that depend on whether a task switch occurred (cf. "either" column in the left block). Additionally, a strong previous response side benefit is generated, yielding faster responses for the same response side. Moreover, the compatibility of the response to the other task in a trial plays an important role (center vs. right block of reaction times). When the stimulus is assumed to be processed instantly **(bottom row)**, the expected reversal of the task-switching effect in the case of the other previous response side disappears. Besides the mean reaction times, the numbers report standard error, the number of condition-respective trials, and mean cognitive effort costs $\mathscr{C}$(task) integrated over the time from the stimulus onset until the response.

incongruent stimulus-response mappings, causing the observable congruency effects.

In task-switching research, two-stage processing models have been developed, where the task selection and the actual response selection are analyzed separately (cf. Kiesel et al., 2010). Task selection corresponds to the effort to focus on one particular task while inhibiting all latent, incompatible mappings; that is, the adaption of prior task-set activities. This corresponds to the precision of the prior activation of desired observations, that is, sensory-to-motor mappings, in Equation (1), as well as additional latent activities (cf. **Figure 4**). Response selection then depends on the actual trial-specific stimulus as well as on the prior task set activities and competing activations. That is, response selection depends on both, the certainty which task should actually be performed and the certainty which response needs to be issued.

Moreover, given the imperative stimulus, the anticipation of the action consequences may include posterior self-evaluation attempts to maximize task-conform behavior (minimizing the KL divergence in Equation 1) while minimizing surprising consequences (minimizing expected entropy in Equation 1). These components are not included, yet, except after the actual response has been made. As a potential result, an imperative stimulus that is compatible with the other task but would require the opposite response in the other task will be particularly effortful to process, because the residual previous task activity leads to the prediction of an incorrect behavior, which needs to be avoided. Overall, larger uncertainties on both, although highly interactive, processing stages will thus yield response delays and larger errors.

Meanwhile, the refractory period to a full disengagement from the previous task will vary dependent on the complexity of the switch between tasks. Accordingly, preparation is faster the easier the switch. On the one hand side, switch training may facilitate switching between the involved, task-set characterizing predictive encodings. On the other hand, overlaps between the required perceptual stimulus processes and the relevant stimulus-response mappings will determine switching demands. If there is no overlap, switching will be rather easy. The higher the overlap, though, and the stronger the need to inhibit previously activated stimulus-response mappings, the higher the cognitive effort will be. When the task sets mutually inhibit each other, the switch of the task sets will be particularly effortful. This is the case because an even stronger change in the precision encoding is needed when the tasks overlap but demand incompatible responses. Task switching results have even shown that asymmetric tasks yield larger switch costs for switches to the easier task compared to switches to the harder task, suggesting that disengaging from inhibitions is more effortful than engaging into previously inhibited tasks (Kiesel et al., 2010). Further implementations of REPI may explore according effects.

7. FURTHER MODELING POTENTIAL

In the previous section we have successfully modeled the Simon effect and task switching behavior, the results of which generally conform to the literature and have correctly revealed larger task effort when an irrelevant stimulus bias interferes, when a task switch had to be processed, when the response side needed to be changed, and when the other task requires an incompatible response. We furthermore have discussed additional open questions and modeling challenges. Here, several other paradigms and behavioral psychological phenomena are addressed and discussed, which may be modeled with REPI in the near future, revealing possible further potential as well as potential limitations of the put-forward event-predictive inference approach.

7.1. Theory of Magnitude

The theory of magnitude (ATOM) (Walsh, 2003) suggests that space, time, and quantity are encoded by a common magnitude system. From the event-predictive inference perspective, the common encoding of magnitudes makes a lot of sense: in the real world, magnitudes are closely related across modalities. For example, a louder crashing noise is created by a stronger force or by a larger object or by taking a longer fall onto the ground. Similarly, numerously more objects will send more visual signals, will be heavier in sum, will take longer to swipe away, and will be more effortful to create, compared to fewer objects of the same type. Thus, over development, it seems highly likely that predictive encodings form that cross-correlate various magnitudes with each other, setting the stage for the discovery of ATOM.

One closely related, particularly well-studied paradigm addresses the SNARC effect: spatial-numerical associations of response codes. In this case, numbers have been shown to be spatially-distributed on a magnitude axis, leading from left to right in societies with left-to-right scripts, presumably because the reading and writing direction guides from the past into the future, determining a latent temporal axis in our minds. Given a particular task set then, particular sets of numbers will be pre-activated in our minds, leading to the SNARC effect: even if the number magnitude does not matter for the response itself (e.g., deciding between even and odd), smaller/larger numbers are responded to faster with a left/right response (Wood et al., 2008). This fact, however, depends on the numbers that are currently mentally active in working memory as well as their spatial grounding. Accordingly, a working memory-based account of the SNARC effect has been proposed (Abrahamse et al., 2016), which highlights the importance of currently active mappings between space and numbers. For example, imagining numbers on a clock face grounds the numbers seven to 11 left of the numbers one to five, while this grounding is reversed when imagining the number on a ruler (Baechtold et al., 1998).

From the event-predictive inference perspective, these prior spatial-numerical activations correspond to current predictive encoding activities, which temporarily and latently associate numbers with space. As a result, and in close correlation with the Simon effect, investigations concerning the SNARC effect, and various related effects concerning number processing (van Dijck and Fias, 2011; Lohmann et al., 2018; Cipora et al., 2020), essentially investigate the strength of latent and temporary associations between space and numbers as well as the activation of particular spatial axes, dependent on the task at hand. Further, much more detailed, modeling efforts by means of REPI may shed further light on the concrete encodings involved and their processing dynamics in the respective ATOM-related paradigms and particular experimental setups.

7.2. Crossmodal Concruencies

As a final example for behavioral psychological experiments, results from studies on crossmodal congruency may be explained in a similar manner. Related to the SNARC effect and the theory of magnitude, in crossmodal congruency paradigms typically irrelevant distractor stimuli in a somewhat irrelevant modality systematically interfere with stimulus processing in the response-relevant modality.

One prominent approach was originally motivated by single cell recording results in monkeys. Individual neurons were shown to encode peripersonal spaces, responding to stimuli touching or appearing close by a particular part of the hand or face (Fogassi et al., 1996; Maravita et al., 2003). From an event-predictive inference perspective, again this comes as no surprise. As discussed above, cross-modal associations occur very frequently in our world. Thus, latent predictive encodings can be expected to develop that associate these respective stimuli cross-modally as well as across respective frames of reference. In fact, the rubber hand illusion (Botvinick and Cohen, 1998) as well as the disappearing hand trick (Newport and Gilpin, 2011) fall in the same category, in which case the brain attempts to infer a consistent explanation for the multisensory or sensorimotor signals the participants focus on, leading to an adaption of internal body state estimations (Ehrenfeld and Butz, 2013; Butz et al., 2014). During a typical crossmodal congruency task, on the other hand, irrelevant stimuli close to response-relevant tactile stimuli will interfere with according responses (Spence et al., 2004), indicating that visual stimuli are mapped onto tactile perceptions a priori, because the two modalities typically offer compatible signals in the real world.

Interestingly, the more recently investigated anticipatory cross-modal congruency effect (Brozzoli et al., 2010; Belardinelli et al., 2018; Lohmann et al., 2019) shows that peripersonal space around the hand is projected onto a planned grasp even before the actual action execution commences. These results essentially indicate that event-predictive inference anticipates action results, pre-activating particular goal constellations and according multisensory mappings. Interestingly, as would be expected from the event-predictive ActInf perspective, when uncertainty is high while approaching the object, the focus should lie on controlling the actual arm movement, thus temporarily not yielding a significant anticipatory crossmodal-congruency effect (Lohmann et al., 2019). A first variational implementation of the effect can be found elsewhere (Weigert et al., 2021).

Earlier studies on simpler action-effect compatibilites also fall into the same category: the effect of an action and the latent or temporarily activated compatibility with the action code itself, can lead to anticipatory cross-modal interactions (Elsner and Hommel, 2001; Kunde, 2003). On the dynamic event encoding level, studies on rotations have shown yet again related predictive encoding interactions: the processing of a rotating tactile stimulus on the palm, for example, interferes with the active rotation of a visual stimulus in a dual task paradigm (Lohmann et al., 2017). Earlier, visual perception was shown to be biased by the rotating tactile stimulus (Butz et al., 2010), indicating shared temporal dynamic encodings across modalities. We believe that REPI may indeed be used to model all of these effects—although open questions include the stimulus design choices, the actual involved predictive encodings, as well as the exact means to process the anticipated horizon and its effect on actual stimulus processing dynamics.

7.3. Social Interactions With Other Agents

In our social realities, we experience scenes, and events within, often with a multitude of entities and other agents involved. These other agents have their own minds. Thus, to foster effective and adaptive interactions between these agents, it is beneficial to know something about the others' minds, that is, to develop a theory of mind (ToM) (Frith and Frith, 2005). When engaging in social interactions, then, ActInf may consider the ToM of others, including their perception of one's own mind and particularly one's own personality. Accordingly, building up scenes with a multitude of interaction-critical agents becomes effortful and can be strenuous. The more diverse agents (colleagues, friends, co-workers, team-members etc.) one is willing and able to consider, the more effort will be needed. Their parallel activation without between-agent interference (in one's mind), is *per se* strenuous because it is impossible to maintain too many distinct predictive densities simultaneously—particularly seeing that each set of events about another agent contains recursive agent events.

This recursiveness with respect to social interactions enables us to pursue rational social reasoning, as formulated in the rational speech act model (Frank and Goodman, 2012; Goodman and Frank, 2016). On the other hand, it also requires much more computational resources, as others need to be co-processed in one's own mind. Accordingly, a rather large corpus of studies suggests that our brains, particularly when acting under time pressure, have a very hard time to consider the perspective of others, failing to avoid, for example, undesired ambiguous situations during conversations (Ferreira and Dell, 2000; Ferreira, 2008). Due to the highly resource-demanding challenge to maintain the perspective of an interaction partner besides ones own perspective, we often sidestep this perspective taking problem by simply assuming that others have the same state of knowledge as we do. Nonetheless, when retrospectively interpreting ones own utterance and the observed actual behavioral response of the current conversation partner(s), we are able to inversely infer aspects of their motivations, intentions, and state of knowledge (Baker et al., 2017; Liu and Spelke, 2017; Achimova et al., 2022), enabling us to learn about others.

In sum, social interactions will require additional cognitive resources because effective and adaptive social interactions with particular others will need to activate our ToM about the other. Moreover, the more complex that social interaction and the more unusual the other(s); the more effortful the ActInf-based control of these interactions will be. It remains an open challenge to shed further light on the involved processes and resource demands by means of socially-extended REPI-like models.

8. CONCLUSIONS

This paper has put forward that cognitive effort unfolds in our brain on multiple levels of abstraction, within scenes, and event-respectively. During wakefulness, our state of mind essentially elaborates on the accumulating evidence about the outside environment, binding and integrating them into currently active, behavioral-relevant, generative models about—and possible interactions with—the environment. Meanwhile, we selectively probe the future to minimize anticipated uncertainty and deviations from expected internal homeostasis. Moreover, we consolidate our accumulated, event-oriented experiences into our episodic memory and, over time, into procedural and associative memory structures. All these aspects are effortful, because they require the selective, precise, coordinated activation of event-predictive encodings, the co-activation of alternatives, and selective consolidations.

The proposal is generally compatible with The Binding and Retrieval in Action Control (BRAC) proposal (Frings et al., 2020), which offers explanations for task switching and related tasks. BRAC suggests two main cognitive processes: stimulus-response-effect combinations are bound into event files for task preparation and execution. Meanwhile, related event files are retrieved from previous trials. Viewed from the introduced resourceful event-precictive inference perspective REPI, event files are constituted by sets of predictive encodings (Butz, 2016), which predict sensory perceptions, sensory-to-motor mappings, actual motor responses, and consequences thereof. Retrieval from previous trials corresponds to residual as well as latent, habitual predictive encoding activities. Beyond BRAC, though, the proposed ActInf-induced effort perspective offers a computational formalism how binding and retrieval are elicited. Moreover, it suggests that cognitive effort can be equated with changes in the event-predictive densities that focus our minds onto particular tasks while inhibiting previous activities as well as latent, habitual activities.

The put-forward resourceful event-predictive inference model REPI also offers a computational explanation why particularly multitasking and task-switching is cognitively effortful and strenuous. This is the case because the maintenance of multiple event schemata, that is, the maintenance of a more complex, multi-task-specific, predictive encoding density is more effortful. This is particularly the case, when multiple, independent alternatives need to be maintained and, even more so, when the alternatives need to activate mutually inhibitory predictive encodings. On top of that, it is not only the maintenance of complex densities, but also the fast switching between task-respective response mapping alternatives—be they explanations, counterfactual reasoning considerations, or simple task mappings. Such switches require the temporary stronger, selective activation of task-specific densities, while inhibiting those from the other concurrent tasks, whereby ActInf pushes toward accomplishing the switches back-and forth between them.

The REPI implementations of tasks that elicit the Simon effect as well as of task switching experiments underline the potential of the theoretical perspective and ask for further research efforts. REPI has essentially shown how computational resources may be distributed by means of ActInf within the developing, latent event-predictive structures. However, for now the effort was distributed equally over all modules, that is, ϵ_t in Equation (4) was constant and had the same value in all modules. Additionally, neither sequential expectation effects nor fatigue have been modeled, yet. Equation (4) allows for such adaptations and could certainly be modified further by modeling task-oriented focus following the general active inference principle. A related challenge lies in identifying and in learning the actual event-predictive structures that are maximally useful to improve task performance. Moreover, the neural mechanisms that enable the selective activation and maintenance of multiple present, past, future, and social considerations should be scrutinized further. As a final result, the put-forward event-predictive ActInf-induced perspective on cognitive effort may not only be able to explain and algorithmically model a multitude of results from psychological studies, but may also offer design and training suggestions to facilitate our interactions with our increasingly complex, diverse, social, digitalized world.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

The author confirms being the sole contributor of this work and has approved it for publication.

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