# Training Executive Functions:

# Examining the Underlying Mechanisms for

# Effective Computerized Training Protocols

Publikationsbasierte Inaugural-Dissertation zur Erlangung der

Doktorwürde an der Fakultät für Humanwissenschaften

der Universität Regensburg

vorgelegt von

**Katrina Sabah**

Aus Shefa-'Amr, Israel

(Regensburg, 2020)

**Erstgutachterin**: Prof. Dr. Gesine Dreisbach

**Zweitgutachter**: Prof. Dr. Karl-Heinz Bäuml

**Acknowledgments**

True, every journey comes to an end, yet its endless. Pursuing my PhD was not only a mission of science but a challenge of life. Throughout this experience I have not only grew in knowledge and competence but found for me a second home. I was blessed with amazing inspiring colleagues, friends and new acquaintances who bestowed me with immense support, warmth and acceptances, transcending all barriers of language and culture.

At this opportunity, I would like to express my heartful and sincere gratitude to Prof. Gesine Dreisbach for the amazing opportunity to conduct my PhD under her supervision, all the granted support, time, understanding and wealth of shared knowledge and expertise. I am deeply thankful for our enriching and fruitful discussions as well as your influential guidance. I would also like to thank Prof. Nachshon Meiran for his outstanding support and mentoring, insightful commentaries and feedback that allowed me to broaden my horizons. Moreover, I thank my wonderful colleagues, especially Carmen and Thomas who supported and assisted me unconditionally from day one, Katrin, Kerstin, Anja, Vanessa, Johanna, Jonathan, Claudia and Felix who granted me so much warmth and support, you have been a great inspiration both personally and professionally. A special thanks to my research assistants, Leoni, Sophia and Berit for your professional and dedicated work. Also, I would like to thank the Deutsche Forschungsgemeinschaft (DFG) for the financial funding of this project.

My utmost gratitude and appreciation to my parents, Marwan and Hala, my sisters Reham and Karin, my grandmother and role model Efaf, amazing supportive aunts Hiam and Randa, and all my friends, who accompanied me every step of the way, always granting me so much love and support. Last but not least, I want to express my infinite appreciation to my beloved Thomas, for all of his continuous encouragement, understanding, unconditional love and patience.

## Preface

Are cognitive abilities modifiable? Can we improve critical functions like attention to better avoid distraction (i.e., reading while filtering out background noise), our capacity to inhibit maladaptive habitual tendencies (i.e., eating sweets when being on diet) or ability to flexibly switch between tasks (i.e., switching between English and German)? In our constantly and rapidly changing modern world, the idea of cognitive enhancement seems more appealing than ever. Indeed, the last decade has witnessed a revival of interest in the topic of cognitive training, both scientifically and commercially, perpetuating the idea of the "brain as muscle" that can be optimized through regular and repeated training. Consequently, the market has been flooded with variety of "brain fitness" apps, games and programs claiming to make us "smarter". How justifiable is this hype remains however a matter of controversy.

Especially relevant to the current thesis, is the topic of computerized cognitive training (CT) targeting Executive Functions (EFs). EFs, also referred to as cognitive control, are a critical subset of high-order cognitive skills that underlie intelligent goal directed behavior (Diamond, 2013; Miller & Cohen, 2001). They are critical to our physical and mental wellbeing, everyday functioning, learning and development, academic as well as vocational success (e.g., Alloway & Passolunghi, 2011; Cartwright, 2012; Cotrena et al., 2016; Diamond, 2013; Knowles et al., 2015; Miller et al., 2011; Morein-Zamir et al., 2016; Toll et al., 2011). Interest in EFs enhancement has reached its peak after several empirical observations, claiming to induce generalizable training effects to other untrained EF tasks and even to measures of fluid intelligence (GF; Jaeggi, Buschkuehl, Jonides, & Perrig, 2008; Karbach & Kray, 2009). Unfortunately, these observations failed to survive the test of replicability, with later studies and meta-analyses casting doubt on the effectivity of CT in inducing broad improvement in general cognitive abilities (Dougherty et al., 2016; Harrison et al., 2013; Melby-Lervåg et al., 2016; Pereg et al., 2013; Redick et al., 2013; Soveri et al., 2017; Thompson et al., 2013). Instead, the effects of CT seem rather specific, with improvements emerging solely on structurally similar tasks to the one trained on (Karbach & Verhaeghen, 2014; Schwaighofer, Fischer, & Bühner, 2015). Following a cycle of empirical inconsistencies and doubt, the current work turns back to examine the drawbacks of the currently applied training protocols, shedding light on possible underlying mechanisms for effective CT practices. Arriving into such understanding seems imperative for the future advancement of the field.

In the first part of this dissertation, I will commence by introducing and defining important terms, addressing as well relevant theoretical accounts to learning and transfer. Then I will turn to overview the state of affairs on cognitive enhancement, introducing the theoretical foundations of possible learning moderators in CT. Subsequently, through a series of three original studies, possible constrains of the so far applied training protocols will be explored, unraveling core principles for effective CT protocols. Finally, synthesis and discussion of the overall findings will be covered in the general discussion.

## CONTENT

# ABSTRACT

Research in the last decade has casted doubt on the trainability of EFs, showing rather very narrow transfer effects, limited to structurally similar tasks. Consequently, the current dissertation acknowledges the importance of contemplating on the possible caveats of the currently applied training protocols, exploring core underlying mechanisms for learning generalization in cognitive training. Therefore, in a series of two short-term task-switching training studies we tackled the role of "desired difficulty" conditions, first in **study 1**, by systematically manipulating variability in terms of content (tasks rules and stimuli were either fixed or changed across the blocks) and structure (fixed or random task sequence). Results showed that content but not structure variability counteracted the occurrence of transfer costs and promoted modest but significant near transfer gains. In **study 2,** we sought to expand this idea by examining the additional benefits of the interplay between content variability and learners' control (motivational factor) to promoting even wider transfer effects. Task demands were further enhanced by using bivalent stimuli. Here, voluntary vs. forced task-switching training were compared, under either varied or fixed content conditions. Content variability but not learners' control was yielded significant. Compared to **study 1**, even higher near transfer gains emerged in novel task switching, presumably due to the increased task demands. No evidence for far transfer effect on other flexibility measures (verbal fluency) were obtained. Last**,** in **study 3** we explored the role of abstract control policy, here WM gating policies, in CT. Using a context processing WM task, either input or output gating policy were trained. Transfer outcomes on distinct cognitive control tasks were assessed. Performance advantages on task switching following input gating policy training were revealed, providing evidence for the emergence of far transfer. No modulation for either input or output gating policies were found in a different context processing task, namely, the AX-continuous performance task. The results will be discussed in relation to the existing general

literature on learning and transfer, cognitive control and CT, offering new directions for future research.

# PART I -

# INTRODUCTION

The term Executive Functions (EFs) is widely used to denote a set of top-down effortful cognitive processes that are essential for successful goal-oriented behavior and emotion regulation. These mainly include the ability to overcome interference and distractibility by irrelevant information, to suppress prepotent response tendencies, to flexibly juggle between several cognitive tasks as well the mental management and short-term storage of information during task execution (Diamond, 2013; Miller & Cohen, 2001; Miyake et al., 2000). The work of EFs is considered critical for everyday functioning, coming into play even in seemingly simple tasks like switching to answer the doorbell when preparing a cup of coffee or when needing to suppress the urge to text-back while driving. Furthermore, they are extremely relevant for mental and physical health, school readiness and success, job realization, martial harmony and public safety (see Diamond, 2013 for a review). Consequently, its preservation, promotion and rehabilitation bare profound implications for both the individual and society, leading in turn to growing scientific and commercial interest in its modification. In fact, in one way or the other, we have all been acquainted with the concept of "brain training", transforming in the last decade into popular and economically prosperous trend.

Despite the evoked hype surrounding the modifiability of EFs, extensive research so far has failed to provide a solid evidence to the effectivity of CT procedures in promoting generalizable improvements in underlying trained ability. The current thesis as such attempts to shed light on the drawbacks of the currently applied training procedures and identify possible moderators of learning generalization.

Before closely addressing the relevant literature on CT, it is important to elaborate on key terms and theoretical accounts of EFs, moving to review and explain important theoretical frameworks to learning and transfer in general and to cognitive skills in specific. Finally, I will present the theoretical rationale behind the conducted studies.

# Understanding Executive Functions – A General Overview

The study of EFs or alternatively cognitive control can be traced back already to the mid of 19th century, following interest on frontal lobes functions and related lesions (e.g., Goldstein, 1944; Luria, 1966, 1969). The term EFs was explictly utlized for the first time by Pribram (1973, 1976) to address posterior mental proccess with the term “cognitive control” being consecutively introuduced by the work of Posner (1975; Posner & Snyder, 1975).

The groundwork for the study of EFs was first laid by attentional models of automatic and controlled processing, distinguishing between effortless inattentive and more deliberate attentionally demanding stimuli-triggered processes (Broadbent, 2004; Posner & Snyder, 1975; Schneider & Shiffrin, 1977). However such dichotomic conceptualization has been empirically challenged by later studies, rather suggesting that cognitive control operates on a continuum of automatic and controlled processes, influenced by the context in which it is executed and previous experience ( Anderson, 2018; Cohen, 2017). For instance, it has been shown that a task irrelevant feature such as context can become associated through contingency learning to a specific control mode that might be automatically triggered in novel but similar contexts (e.g., Fischer et al., 2008, 2014; Surrey et al., 2017). While the traditional early models consider automatic as inherently unconscious, several studies have shown for example that automatic response can be triggered by instructions due to establishment of Stimulus-Response (S-R) associations, even when not practiced or implemented before (Liefooghe et al., 2012; Meiran et al., 2017; Neumann & Klotz, 1994). Indeed, following years of massive research work on the topic, this simplistic and imprecise conceptualization of EFs underwent a drastic evolution (see Goldstein et al., 2014 for review of EFs definitions). Up-to-date, there is a wide agreemnt that EFs embody a broad set of higher-order PFC modulated processes that guide, monitor and regualte thoughts, actions, behaviour and emotions, nececary for everyday functioning and learning (Baggetta & Alexander, 2016).

Central to the understanding of EFs is the conterversy on whether EFs are a unitary or modulatory construct (Baddeley, 1996; Duncan, Johanson, Swales & Freer, 1997; Miyake et al., 2000; Norman and Shallice, 1986; Stuss & Alexander, 2000). On the one hand, unitary frameworks to EFs advocate for a higher order management system, responsible for information processing, coordination, control and storage. One of the earliest and most prominent examples is Baddeley's working memory (WM) model (1996; 2003), proposing a central executive system architecture that controls and coordinates the flow of information between its three sub-components (i.e., the phonological loop, viso-spatial sketchpad and episodic buffer). On the other hand, a more popular taxonomy for EFs is the modular approach, proposed by Miyake et al. (2000), advocating for both the unity and diversity of EFs. In line with this taxonomy, EFs are conceptualized as a set of separable yet inter-correlated executive processes, encompassing working-memory (WM) updating, behavioral inhibition, the ability to shift mental sets (task switching) in addition to a common EF ability (Miyake et al., 2000). The question of whether EFs are unitary or modular construct dictates as such the expected scope of learning generalization in CT. When embracing the unitary approach to EFs it is then presumed that training one process will result in improvements in general EF ability. In contrast, adapting a more synergetic approach, advocating for a separate yet interchangeable EFs, learning is thought to be domain specific, affecting only tasks that share common EF processes.

## The Three Musketeers: Inhibition, Updating and Task Switching

### *Inhibition*

Inhibition is defined as the ability to selectively attend information while ignoring irrelevant distractions and suppressing prepotent dominant responses. For example, one commonly used task to tap this ability in laboratory setting is the Stroop task (MacLeod, 1991; Stroop, 1935), in which color words (e.g., red) are printed with either congruent or incongruent font color.

The task requires to attend the words' font color while suppressing, distracting dominant information, namely the word's meaning. Other frequently utilized measures are the Simon (Hommel, 2011; Simon & Wolf, 1963), Flanker (Eriksen & Eriksen, 1974), Go-NoGo (Cragg & Nation, 2008), Stop-signal (Verbruggen & Logan, 2008) and antisaccade tasks (Hallett, 1978; Munoz & Everling, 2004). Inhibitory control processes have been shown to be facilitated via the anterior cingulate gyrus, orbitofrontal regions, left inferior frontal region as well as temporal and parietal areas (Bench et al., 1993; Bush et al., 1998; George et al., 1994; Kiefer et al., 1998; Larrue et al., 1994; Pardo et al., 1990; Taylor et al., 1997).

***Updating***

Updating or WM refers to the ability to monitor and code relevant incoming information, while continuously and dynamically modifying information held in WM, disposing of no-longer task related information in favor of updated relevant information (Miyake et al., 2000b; Morris & Jones, 1990). Updating is found to be strongly associated with the dorsolateral prefrontal cortex and frontal lobes (e.g., Chatham et al., 2011; Foster, Eskes, & Stuss, 1994; Frank, Loughry, & O'Reilly, 2001; Gardner, 1987; Jonides & Smith, 1997; Kammer et al., 1997) and is widely examined using the N-back paradigm (Kirchner, 1958; Owen et al., 2005) and the AX- Continuous Performance Task (AX-CPT ; Badre, 2012; D'Ardenne et al., 2012). As the latter will be utilized in study 3, I will shortly elaborate on its construction. Among other, the AX-CPT is used to investigate updating processes, assumed to be initiated through occurring contextual information (Badre, 2012; D'Ardenne et al., 2012). In this task, a sequence of letters is presented in each trial, with the first item determining whether a subsequent letter in the sequence (probe) is response relevant or not. Specifically, participants are required to make a target response whenever a X-probe is preceded by an A-cue. In all other conditions, that is, when a non-A cue (all other letters except A) is presented or when an A-cue is followed by a non-X probe (all other letters except X), a non-target response is solicited. Thus, in general, the task requires to update the entering information in each trial and maintain the cue in WM until response is given. Moreover, the cue allows for more efficient processing, determining whether a subsequent information (probe) needs to be additionally entered to WM or not. A more detailed account will be covered in later sections.

***Shifting***

Shifting or task switching denotes the ability to efficiently and flexibly alternate between multiple cognitive tasks, operations or task sets (Miyake et al., 2000; Monsell, 1996). The term task sets refers to the existing mental representations and cognitive process aligned with the demands of the task in hand (e.g., rules and relevant stimulus-response mappings; Dreisbach & Haider, 2008; Kiesel et al., 2010).

A popular and a valuable measure of mental flexibility is the task switching paradigm (Jersild, 1927; Rogers & Monsell, 1995; see Kiesel et al., 2010; Monsell, 2003 for reviews). In task switching, participants are typically required to perform two mental tasks, having to either repeat or switch between them. The common finding is that task switching is cognitively costly, inquiring behavioral costs both in latency and accuracy (e.g., Dreisbach, 2012; Kiesel et al., 2010; Monsell, 2003; Vandierendonck, Liefooghe and Verbruggen, 2010). These costs are echoed through the obtained *switching costs*, that is the difference in mean response times and accuracy rates between switch and repeat trials, and/or *mixing costs*, namely performance costs between single-task blocks (blocks in which only one task is performed) and mixed-tasks experimental blocks (Rogers & Monsell, 1995; Rubin & Meiran, 2005). The task switching literature introduces several variants of task switching, some of which were employed in current work(see Kiesel et al., 2010 for review). Relevant here is the distinction between predictable, also referred to as the alternating runs, and cued random task switching paradigms. In the standard predictable variant, tasks alternate in an anticipated manner on every second trial while in the cued version, a preceding or simultaneously presented cue announces which task needs to be attended. Stimuli can also be univalent or bivalent, that is, exclusively fitting to one task or affording both tasks, respectively. Another variant that will be also later addressed is the voluntary task switching (VTS), devised to investigate volitional underpinning of cognitive flexibility (Arrington & Logan, 2004, 2005). VTS allows participants to choose whether they want to repeat or switch a task, typically with the restriction to choose each task equally often and in a random order as if flipping a coin. On the neural level, several neuroimaging studies seemed to establish the involvement of lateral PFC areas and medial frontal activation in task switching (e.g., Dove, Pollmann, Schubert, Wiggins, & Yves Von Cramon, 2000; Rushworth, Hadland, Paus, & Sipila, 2002)

## Learning and Transfer of Cognitive Skills: Are EFs Trainable?

The last decade has witnessed an abundance of scientific efforts to explore modulatory factors and activities that might promote EF related processes, ranging from nutritional habits, physical activities, music, meditation to computerized cognitive training (e.g., Brunner et al., 2017; Gomez-Pinilla, 2011; Jaeggi et al., 2008; Kray et al., 2012; Malinowski & Shalamanova, 2017; Mandolesi et al., 2018). Of interest to this thesis is the immense excitement surrounding CT, governed by its potential in optimizing cognitive functions (for reviews see Lustig et al., 2009; Chein & Morrison, 2010). However, unlike envisioned, the actual effectivity of such practices remains unclear, with the current state of art presenting inconsistent evidence regarding the specify\generality of the induced learning effects and their durability (Dougherty et al., 2016; Harrison et al., 2013; Melby-Lervåg et al., 2016; Pereg et al., 2013; Redick et al., 2013; Soveri et al., 2017; Thompson et al., 2013).

To arrive into better understanding of the challenges facing cognitive enhancement studies, it is imperative to address first evidence on the trainability of EFs from the domains of physical exercise and video games, moving to prominent theories of learning and transfer in general and to EFs in specific. Subsequently, I will turn to overviewing the state-of-affairs on CT, exploring current pitfalls and possible moderators underlying effective training protocols.

## On the Trainability of EFs: Exercising with the Brain

The well-established interlink between physical fitness, brain plasticity and mental health has aroused considerable scientific interest in the application of varied physical exercise (PE) activities as means to improve cognitive functioning (Cotman & Berchtold, 2002; Erickson et al., 2011; Fernandes et al., 2017; Gomez-Pinilla & Hillman, 2013; Intlekofer & Cotman, 2013; Kennedy et al., 2016; Lista & Sorrentino, 2010; Pothier & Bherer, 2016). Such interventional practices include aerobic training (e.g., jogging and swimming), resistance training (e.g., weight-lifting, squats and push-ups) and even yoga, dance and Tai Chi (see Pothier & Bherer, 2016 for a review). In fact, recent meta-analysis studies among both older adults (>50) and children have provided a strong support for the benefits of PE to promoting EFs (Álvarez-Bueno et al., 2017; Northey et al., 2018). PE induced improvements have been also observed in learning and memory processes, attention and academic achievement in addition to arising benefits in mitigating and preventing age related decline in EFs and dementia risks (Colcombe & Kramer, 2003; Donnelly et al., 2016; Hollamby et al., 2017; Kramer et al., 1999; Lees & Hopkins, 2013; Ludyga et al., 2016; Winter et al., 2007). PE effects have also been captured at the structural levels of the brain, leading for instance to increases in brain volume and greater white matter integrity (Chaddock-Heyman et al., 2018; Colcombe et al., 2006; Svatkova et al., 2015). The positive effects of PE on brain health has been primarily associated to increased cerebral blood flow and oxygenation during physical effort as well as epigenetic changes like in acetylation and methylation, critical for regulating synaptic plasticity, learning and memory (Betik & Hepple, 2008; Fernandes et al., 2017; Olin et al., 2011; Pothier & Bherer, 2016). Interestingly, there has been some arising claims on the possible additional benefits of content-varied, multimodal as well as conjoint physical and CT practices to producing wider and longer-term retainable improvement effects in cognition (Demirakca et al., 2016; Erickson et al., 2011).

## Playing with the Brain: The Benefits of Video Games to Cognitive Enhancement

The popularity of video games (VGs) in our modern and technological world has offered in the last years a very promising platform for understanding neuroplasticity and learning processes (Bavelier & Green, 2019; Boot, 2015). Strikingly, despite the raised criticism on the negative impacts of VGs on behavior, especially those with violent content, abundance of empirical evidence has suggested to its contribution to a wide array of cognitive functions, including EFs (Boot et al., 2008; Colzato et al., 2010; Granic et al., 2014; Green & Bavelier, 2007; Green et al., 2010; Green et al., 2012; Strobach et al., 2012). Especially auspicious, promoting the widest transfer effects, are action video games that are characterized by complex, engaging, challenging and perceptually rich experience (e.g., stimuli variability) along with high processing and response demands (Bavelier et al., 2012; Green & Bavelier, 2015). It is assumed that the constantly and rapidly alternating settings found in this genre facilitates what is referred to as 'learning to learn' skill, that is to flexibly adapt to novel situations and to acquire new skills quickly and efficiently (Bavelier et al., 2012; Cardoso-Leite et al., 2018; Green & Bavelier, 2012). Additional important feature of VGs is the continuous experience of reward that enhances motivation and arousal, supporting plasticity and learning (see Bavelier & Green, 2019 for review). This in turn has been supported by neuro-imaging studies, showing that playing VGs seems to be associated with striatal dopamine release as well as to reward-related structural increases in gray matter volume (cf. Lorenz et al., 2015). Directly related to that is the notion of autonomy in VGs, assumed to enhance motivation by satisfying the human basic need for choice (Bavelier & Green, 2019).

Moreover, VGs are also suggested to promote higher levels of abstraction, facilitating thus broader transfer effects (Bavelier et al., 2012).

## Learning and Transfer – Important Concepts and Theoretical Frameworks Introduced

“An individual understands the concept, skill, theory or domain of knowledge to the extent that he or she can apply it to a new situation” (Gardner, 1999, p. 118-119). For long, the concept of transfer, namely the ability to export and extend previously acquired knowledge to novel contexts has been central to education and cognitive psychology (Byrnes, 2008; Noack et al., 2009 2014). In fact, this extraordinary ability of the human brain to flexibly transfer previous experiences and knowledge to novel domains is one of the main markers of intelligent adaptive behavior (Cole et al., 2011, 2013). In what follows, I will introduce important concepts to the domain of skill acquisition and review some prominent learning theories and models that are relevant to the current research.

### *Behavioral Accounts to Learning and Transfer*

The study of transfer owes its foundation to the influential works of  Thorndike (1922; Woodworth & Thorndike, 1901), introducing the identical elements theory. This theory posits that the occurrence of transfer and its scope are bound to the degree of overlap in content features between training and transfer situations. For example, a guitarist is in fact able to play different musical compositions using the same underlying content elements, that is musical notes. This in turn brings us to an important taxonym of transfer, distinguishing mainly between near and far transfer (Barnett & Ceci, 2002). Typically, near transfer effects reflect training induced improvement in performance on a structurally similar task (e.g., solving novel subtraction problems on a math test) whereas far transfer effect refers to improvement on other structurally dissimilar tasks, (e.g., improvement on a math test following chess training). Returning to the introduced overlap principles of Thorndike (1922; see also Gobet & Simon, 1996; Simon & Chase, 1973), it is then assumed that while the occurrence of near transfer effects are more plausible and common, far transfer effects are less likely to occur (e.g., Li et al., 2008; Melby-Lervåg & Hulme, 2013; Ritchie et al., 2015; Sala & Gobet, 2017a, 2017b, 2019). This quite simplistic S-R approach of Thorndike was later extended by Singley & Anderson (1989), subordinating the occurrence and scope of transfer to the degree of shared task representation or what they refer to as *production rules*. Such production rules are suggested to encompass knowledge about the processes and abilities required to perform a task that are retrieved when a condition is satisfied. For instance, to write an email there are usually a sequence of steps to undertake, commencing with clicking on the compose function, moving to writing the address of the recipient, entering the subject in corresponding panel, composing the text to finally pressing the send button. As most email service platforms require the same underlying *procedural rules*, it is quite easy to alternate between using *Gmail* at home to using *Outlook* at work.

Other insights on transfer come from the domain of analogical learning, drawing attention to the role of schema abstraction, namely, the identification of structural analogies between task elements in learning generalization (Clement & Gentner, 1991; Gentner & Hoyos, 2017; Gick & Holyoak, 1983; Holyoak & Thagard, 1989). Accordingly, a higher level of abstraction is assumed to facilitate broader transfer effects (Ahissar & Hochstein, 2004; Dosher et al., 2013; Karni & Bertini, 1997). Such approach to transfer seems very relevant to the domain of CT, fitting nicely with EFs theories that emphasis the link between executive processes and abstraction, both relying to a great extent on the work of the PFC (Badre et al., 2010; Barbey et al., 2009; Cole et al., 2013; O'Reilly, 2010; Speed, 2010).

More closely related to the domain of CT is the primitive element theory, proposed by Taatgen (2013). This model extends Singley & Anderson (1989) identical productions theory, positing that learned task knowledge involves the learning of lower-level task specific (e.g., S-R mappings) and higher-level abstract processing rules (e.g., strategies). It is claimed that wider transfer can be obtained between dissimilar tasks when the new task structure allows for reutilization of a previously learned strategy that is more effective than the default behavior. This model posits that any occurring improvement in performance is attributed to skill development rather than changes in inherent ability. As such, it is argued that “cognitive training helps developing our representations and strategies for strong cognitive control, and improves the arsenal of skills available to deal with different control situations” (Taatgen, 2013, p. 22). Drawing on Braver's (2012) dual mechanisms of control, the author distinguishes between two main control strategies , reactive and proactive. Proactive control strategy refers to top-down preparatory activation and maintenance of task goals, elicited by task context (i.e., structure, instructions, rules and cues). In contrast, reactive control strategy refers to bottom-up altered control mode that is triggered by stimulus features. For example, the model predicts that as proactive strategy is usually associated with more efficient performance and entails the learning of more task-general knowledge, its transfer to new situations is more probable.

Alternative recent outtake on learning and transfer of cognitive control build upon principles of associative learning (Abrahamse et al., 2016). It is posited the learning of cognitive control involves the establishment of abstract associations between perceptual, motor and goal representations that are bound to specific contextual features. Once these features are identified, they can trigger the corresponding control mode. Thus, cognitive control is assumed to bound to context, triggered and restricted by it.

### *A Neuroscientific Approach to Learning and Transfer*

A neuroscientific framework to transfer of cognitive skills is founded on principles of neuronal overlap, attributing the occurrence and breadth of transfer to the degree of shared cortical regions' recruitment between the trained and transfer tasks: the higher the overlap in neuronal activation, the broader the transfer (e.g., Dahlin et al., 2008; Hazy et al., 2006; Jonides, 2004; Klingberg, 2010; Lustig et al., 2009; Olesen et al., 2004; Persson & Reuter-Lorenz, 2008; Thorell et al., 2009). Alternative to the near and far taxonym of transfer, it is suggested that the evaluation of transfer should be reconceptualized to denote changes in ability, with the scope of transfer ranging from narrow, broad to changes in general ability (c.f. Schmiedek et al., 2010). Other neuroscientific accounts posit that the effectiveness of CT depends on the induction of durable changes in relevant neuronal circuits, promoting brain plasticity (Lövdén et al., 2010, 2013). This is suggested to occur when training demands exceeds one's available cognitive resources, such us when introducing enhanced task difficulty conditions (Brehmer et al., 2014).

Taken together, while the above reviewed accounts to transfer differ in the general underlying theoretical venue, important commonalities stand out: (a) the notion of abstractness seems to be laid as the heart of transfer across learning theories and domains and (b) transfer occurrence depends on the degree of overlap in shared processes between learning and transfer situations, however with less agreement on the nature of such processes. As mentioned before, the conceptualization of "shared overlap" determines in fact the expected scope of transfer. For example, while assumed overlap in content elements predicts a very limited transfer (e.g., identical element theory), advocating rather for underlying common strategies\procedural rules predicts a wider transfer effects to a class of tasks that might benefit from its application.

## The Promise and Pitfalls of CT

Cognitive or "brain" training refers to practices that aim at maintaining or improving cognitive abilities such as memory, attention, speed of processing and higher-order executive control processes. The underlying fundaments of CT is anchored in the concept of neuroplasticity, namely the occurrence of structural and functional alternations in the brain, enabling flexible adjustment of behavior to changing demands in our environment (Kuwajima & Sawaguchi, 2010; Lövdén et al., 2010). Of extreme relevance is the compelling evidence that such plastic characteristic of the brain is not only a feature of the young developing brain, but rather continues to manifest in adulthood and even among populations suffering from neurological developmental disorders and brain lesions (Brehmer et al., 2007, 2012; Karbach & Kray, 2009; Kray et al., 2012; Sacco et al., 2011; Söderqvist et al., 2012). This in turn has encouraged to examine the potential of CT in allowing to mitigate age-related cognitive decline and psychopathology associated cognitive impairments (e.g., Ball et al., 2002; Buitenweg et al., 2012; Chein & Morrison, 2010; Klingberg, 2010; Kray et al., 2012; Lövdén et al., 2012; Lussier et al., 2012; Lustig et al., 2009; Willis et al., 2006).

Interest in cognitive enhancement reached its peak in 2008, following scientific reports suggesting that computerized WM training leads to generalizable gains in GF (i.e., far transfer; Jaeggi et al., 2008). In a later prominent study, evidence for the effectiveness of CT was documented also in the domain of task switching, showing evidence for both near and far transfer effects to other executive processes and GF (Karbach & Kray, 2009). However, the premature enthusiasm generated by these observations was then counteracted by several successive studies, failing to replicate these findings (e.g., Harrison et al., 2013; Pereg et al., 2013; Redick et al., 2013; Thompson et al., 2013). In fact, recent meta-analysis studies refute the existence of training-induced far transfer effects and consequent improvements in real-life (e.g., Dougherty, Hamovitz, & Tidwell, 2016; Melby-Lervåg, Redick, & Hulme, 2016; Soveri, Antfolk, Karlsson, Salo, & Laine, 2017). The inconsistencies between training studies and the limited generated transfer effects have been attributed amongst other to methodological rigors, such as the absence of adequate active control group, low statistical power and testing reliability, as well as methodological variations in the applied training protocols and sampling (Dougherty et al., 2016; Katz et al., 2018; Melby-Lervåg et al., 2016;

Noack et al., 2014; Soveri et al., 2017a; Strobach & Schubert, 2001). Despite these setbacks, the more reliable generated near-transfer effects documented in the relevant literature on CT seem to offer hope to the realm of cognitive enhancement (Karbach & Verhaeghen, 2014; Schwaighofer, Fischer, & Bühner, 2015).

At present, the topic of CT is faced with various critical open questions concerning the scope of produced improvements and underlying mechanisms modulating its outcomes. For example, new directions point to the importance of considering possible modulators such as interindividual differences in baseline cognitive abilities, personality and motivation, nutrition and genetic predisposition. These considerations for instance can allow us to better understand who benefits more from such procedures and why (for review see von Bastian & Oberauer, 2014). Additional avenues discuss determinants of learning and transfer, like task difficulty and adaptability, degree of overlap in cognitive process and structure between the trained and transfer task as well as novelty inclusion (e.g., Buitenweg et al., 2012; Green & Bavelier, 2008).

One central pitfall of the currently applied training procedures seems to be anchored in the repetitive nature of CT, facilitating instead automatization and task-specific learning that is limited to lower level stimulus-response mappings. In contrast, I argue that training variability is one critical underlying mechanism for overcoming training specificity, promoting wider transfer effects in CT. This idea is supported by many theoretical accounts to learning and transfer, such as the desired difficulties framework (Fissler et al., 2013; Schmidt & Bjork, 1992; Spiro et al., 1994). Moreover, I claim that the currently applied training protocols focus mainly on external features (e.g., used training tasks and stimuli, dosage, used control groups), overlooking the interplay of externally and internally guided behavior in skill acquisition (e.g., Jolles, van Buchem, Rombouts, & Crone, 2012; Morrison & Chein, 2011). As such, the current work will focus on examining the role of *learners' control* in producing more favorable learning experience. The rational for such investigation was based on suggestions pointing to the motivational gains of choice availability and advantages of self-deliberate and regulated practice to skill development (Ackerman, 1987; Anderson, 1982; Ericsson et al., 1993; Inzlicht et al., 2014, 2018; Kinzie, 1990; Muraven et al., 2006; Nakamura & Csikszentmihalyi, 2014; Navon & Gopher, 1979; Paas et al., 2005). The benefits of self-controlled practice might be also expected on account of the robust generation effect, referring to the found advantage in remembering self-generated information (Slamecka & Graf, 1978).

Despite the difference in their outtake on mechanisms of learning and transfer, the notion of abstraction seems to be the essence of most of the previously described learning doctrines ( eg., Anderson, 1983; Schmidt, 1975; Schmidt & Bjork, 1992; Taatgen, 2013). As previously argued, the ability to mentally abstract knowledge is inherent to adaptive intelligent behavior in general and to learning and transfer in specific (e.g., Cole et al., 2011, 2013; Ho et al., 2019; Ruge & Wolfensteller, 2010). For example, abstraction is essential to overcoming capacity limitation of the cognitive system, as it allows more efficient processing and management of information through the detection of regularities in our surrounding and its reutilization in similar novel contexts ( cf. Bhandari & Badre, 2018; Ho et al., 2019). As such, it is to be expected the notion of abstraction is central to any learning protocol, especially CT. Recently, it has been suggested that one form of higher-level abstract entity of task knowledge are control policies, namely, mental models that encompass required representations of task relevant facts, rules and structure dynamics (Bhandari et al., 2017; Bhandari & Badre, 2018; Duncan et al., 2008). Such control policies were also found to be modifiable through training and generalizable to similar novel contexts (Bhandari & Badre, 2018). These encouraging findings offer a new direction to pursue in the study of cognitive training.

# Exploring Possible Learning Moderators in Short-term CT

## The Desirability of Variability: The Case of Task Switching

The contribution of training variability to skill acquisition has been originally pinpointed by motor learning theories (Schmidt, 1975; Shea & Morgan, 1979). Schmidt (1975) was the first to argue that varying training conditions engages higher level of abstraction, allowing thus to identify transferable rules (i.e., schemas). Benefits of variability to transfer has been also attributed to the derived desirable challenge during leaning, encouraging enhanced processing and retention (Schmidt & Bjork, 1992). Counterintuitively, this *desired difficulty* approach to learning argues that hampering learning through conditions like variability enhances learning, resulting in better longer-term gains. Highly relevant to CT is the interplay between variability and novelty, with the latter being inherent to cognitive development and vitality, cortical plasticity as well as improved anticipatory regulation to future new contexts (Angevaren et al., 2007; Brown et al., 2003; Düzel et al., 2010; Eskes et al., 2010; Fritsch et al., 2005; van Praag et al., 2000).

Direct manipulation of variability in the domain of CT was previously carried out using the task switching paradigm (Karbach & Kray, 2009; Minear & Shah, 2008). In one study, Karbach and Kray (2009) manipulated content variability by requiring participants to switch between two task rules that either remained fixed or varied across the training blocks. The study compared the performance of both adults and children on near and far-transfer measures (WM, inhibition and general intelligence and). As indicated by the results, more favorable outcomes for varied training were obtained on near but not far transfer measures. However, the found gains in near transfer were limited to adults. As noted by the authors, one critical limitation to interpreting these mixed results is the conjoint manipulation of content variability and self-verbalization strategies, opening-up the question to whether the complexity of such combined training conditions might have impacted their results. In another task switching training study, variability was manipulated on the deeper structure level of the task, training participants on either predictable/fixed or random/varied task sequence. Additionally, to enhance content variability, four different task pairs were introduced during training: One task pair was utilized for the pretest and posttest and three other tasks were used for training. Pretest and posttest performance were examined using varied and fixed task sequence blocks. As a control, another group of participants worked through single-task blocks that included the same six tasks without engaging in task switching. Both predictable and random training conditions were found to reduce switching and mixing costs during training. However, transfer gains have been observed only when both practice and transfer had random task structure and solely in measures of mixing costs.

Taken together, the role of variability in CT remains unclear, requiring to systematically reconsider its contribution to learning and transfer. This investigation was approached through **study 1** in this dissertation. For this purpose, the task switching paradigm was used, allowing to easily manipulate variability both in terms of content (fixed vs. varied task rules and stimuli) and structure (fixed and varied task structure). In the fixed content condition (FC), participants were required to switch between the same two tasks across training whereas in the varied content condition (VC) two new task rules and stimuli were introduced in each experimental block. For structure manipulation, participants were trained on either a predictable or random task switching conditions. In the predictable variant of task switching (fixed condition), participants were required to switch tasks every second trial whereas in the random variant, tasks appeared in random sequence (see figure 1). The study employed a pre-post design, commencing with a bassline block, followed by seven training blocks and last by one fixed and one random novel task switching blocks, respectively.

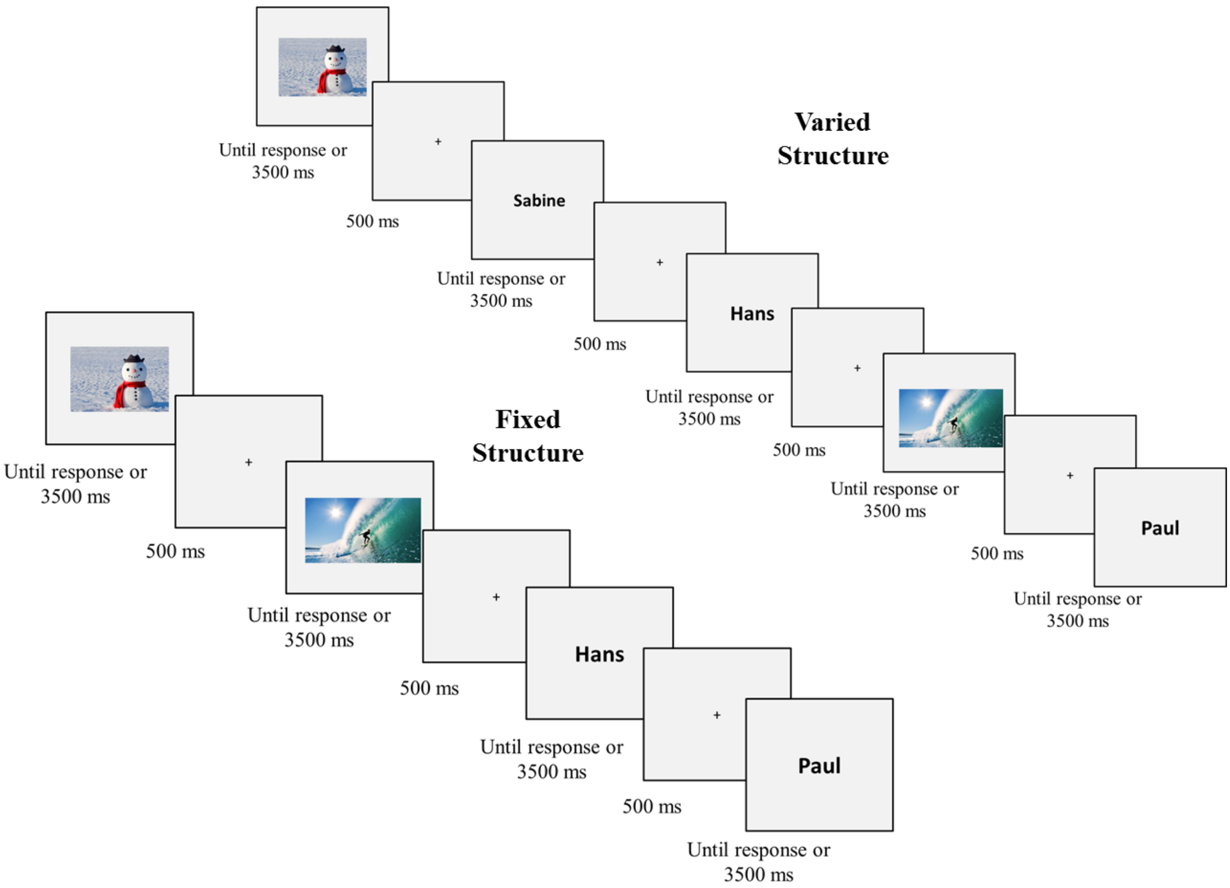



*Figure 1*. Example for fixed and varied task block structure. The task here requires to switch between two task rules, judging whether the presented pictures are summer or winter related (task rule 1) or whether the depicted names are male or female names. The lower panel shows the condition in which task rules are presented in a fixed order, alternating every second trial (task rule 1 – task rule 1-task rule 2-task rule 2). The upper panel shows an example of random alternations in task structure (task rule 1 – task rule 2-task rule 2-task rule 1 – task rule 2).

## Taking Command: Examining the Role of Learners' Control in Short-Term Task Switching Training

Despite existing evidence and theoretical models attesting the importance of intrinsic modulations of learning and transfer, factors such as motivation and individual differences have been for long considered as a liability in CT (Baldwin & Ford, 1988; Ruona et al., 2003; Haskell, 2004; Jolles et al., 2012; Morrison & Chein, 2011; Quiñones, 1995). However, in light of discouraging outcomes in CT along the past years, aspects pertaining to intrinsic characteristics, such baseline cognitive aptitude and engagement, seem to receive wider acknowledgment lately (Botvinick & Braver, 2015; Jaeggi et al., 2008, 2014; Katz et al., 2014; Mohammed et al., 2017). As such, the current work embarked on examining the possible benefits of learners' control, known to enhance motivation and engagement in learning, to promoting better transfer gains in CT.

Learners' control refers to a continuum of controllability over learning features such as determining sequence of presented information, pace and task selection. It is closely associated with autonomy, self-agency and choice availability, satisfying basic psychological and biological needs that underpin adaptive behavior, cognitive and emotion regulation, motivation and wellbeing (Bandura et al., 2003; Deci & Ryan, 2008; Gallagher, 2000; Leotti et al., 2010; Leotti & Delgado, 2011; Ryan & Deci, 2000; Shapiro et al., 1996). Hence, granting trainees the control over their own learning bares several motivational advantages necessary for effective learning, such as arousing higher task engagement, autonomy, perceived competence and self-efficacy (Becker & Dwyer, 1994; Bell & Kozlowski, 2008; Chiviacowsky, Wulf, Lewthwaite, et al., 2012; Deci & Ryan, 2008; Keith & Frese, 2005; McNevin et al., 2000; Ryan & Deci, 2000; Tafarodi et al., 1999).

Moreover, as human beings, we seem to have a natural tendency and preference for having a choice, with choice availability perceived as rewarding (affective gain), allowing in addition to mitigate negative emotions (Bown et al., 2003; Inesi et al., 2011; Leotti et al., 2010; Leotti & Delgado, 2011). Consecutively, this seems extremely relevant to CT when considering the costly and aversive nature of cognitive effort, highly engaged during EF training (Braver, 2012; Kool et al., 2010; Monsell, 2003; Westbrook et al., 2013). In addition, controllability over learning is suggested to enable self-regulated, strategic and flexible adaption of performance that enables more efficient deployment of effort and consequently gives rise to more favorable learning outcomes (Ackerman, 1987; Anderson, 1982; Inzlicht et al., 2014, 2018; Kinzie, 1990; Muraven et al., 2006; Nakamura & Csikszentmihalyi, 2014; Navon & Gopher, 1979; Paas et al., 2005).

Last, the idea to allow for learners' control during training coincides with the *deliberate practice* approach to expert behavior (Ericsson et al., 1993). Unlike the common assumption that "practice makes perfect", this framework posits that it is not repeated practice per se that underlies skill mastery but the process of engaging in self- initiated goal directed practice. These claims are supported by the observation that skill acquisition by itself necessitates only limited amount of practice, with individuals arriving into a performance asymptote quite rapidly without additional progress hereafter (i.e., automaticity; Anderson, 1982; Fitts & Posner, 1967). Accordingly, high inclination for seeking demanding tasks as well as engagement in self-monitoring processes is thought to be a key principle to overcoming automaticity, supporting continuous learning and improvement (Ericsson, 2006, 2008; Ericsson et al., 1993).

To examine the contribution of learners' control to learning and transfer in EF training, **Study 2** was designed. Again, the task switching paradigm was employed, allowing us to compare between two critical training conditions: VTS (Arrington & Logan, 2004, 2005) to that of forced task switching condition (FTS). The VTS variant is a valuable tool for examining volitional control (see Arrington et al., 2014 for review), in which participants freely decide whether to switch or repeat a task, typically with the instructed restriction to choose each task equally often and in a random order. In addition to switching and mixing costs, the task offers an additional measure of flexibility, namely the voluntary switching rate (VSR). Following a single training session of seven training blocks, near and far transfer effects were evaluated, comparing pre-post performance on novel task switching block and the verbal fluency task, another measure of cognitive flexibility that has a switching element ( e.g., Troyer, Moscovitch, & Winocur, 1997; Troyer, Moscovitch, Winocur, Alexander, & Stuss, 1998). Unlike study 1, here we used bivalent stimuli to increase task demands. As we were also interested in replicating the results of study1, variability (only content variability) was also manipulated, using here exactly the same fixed structure baseline and transfer blocks from study 1.

## Exploring the Role of WM Gating Policies in CT

As previously suggested, the occurrence of learning generalization to novel contexts is found to rely heavily on the human brain's ability to abstract knowledge (e.g., task rules) and to rapidly and flexibly exploit it across multiple unfamiliar contexts (e.g., Badre, Kayser, & D'Esposito, 2010; Cole, Etzel, Zacks, Schneider, & Braver, 2011; Cole, Laurent, & Stocco, 2013; Collins & Frank, 2013). One form of abstract knowledge, inherent for task execution, is internal control policies or task models that organize task related information like task rules , relevant facts, stimuli, responses and timing into adequate mental program (Bhandari & Badre, 2018; Duncan et al., 2008). Within the domain of WM, the construct of control policies can be embodied by gating mechanisms that guide the flow of information to and within WM (Chatham & Badre, 2015; O'Reilly & Frank, 2006; Todd, Niv, & Cohen, 2009). Accordingly, it is assumed that information can be selectively entered and updated through the operation of an input-gate while selective output-gate determines which representations should be utilized to influence behavior (Chatham & Badre, 2015; Hazy et al., 2007; O'Reilly & Frank, 2006; Todd et al., 2009).

Interestingly, a recent study has suggested that just like task rules, WM control policies (1) constitute an important abstract component of a task set that can be learned and transferred to similar novel task contexts and (2) are independent of lower level S-R mappings (Bhandari & Badre, 2018). Using a second order WM task, Bhandari & Badre (2018) trained participants on either a condition that promote input or output gating control mode (see Figure 2). In this task, participants see a sequence of three items, consisting of a number cue, a letter and a symbol. The task requires to respond to either the letter or symbol according to the presented cue. Participants were required to memorize two task rules through which the letters "A" and "G" were associated with the contextual cue "11", whereas the symbols "π" and ⨀ were associated with contextual item 53 (see figure 2(a)). Hence, whenever the cue "11" appears, participants need to respond to the letter. In contrast, whenever the cue "53" appears, a response to the symbol is required. For example, in a sequence composed of 11 → G → ⨀, the target item would be the letter G. Alternatively, in a sequence composed 53 →A→ π, the target item would be the symbol π. To encourage the utilization of input gating policies, a context-first processing condition (CF) was applied, in which the contextual item (here: the number cue) appeared first, followed by the two lower-order items, succesievely. Thus, the early appearnce of the cue enables the *selective entry* of the target item into WM. Conversly, in a context-last processing condition (CL), the contextual item (the number cue) appeard last in the sequenace, supporting the usage of out-put gating processes as it requires a *selective retrieval* of the relevant target item (see figure 2(b)). Parallel to the presentation of the last item, a response panel appeared on the lower part of the screen. On each side of the response panel, one letter and one symbol appeared. That way, depending on which side of the response panel the target item appeared, a left or right response-key had to be pressed. For example, in the presented upper CF trial design in figure 1(b), the contextual cue "11" signalizes that the response relevant item in this sequence is the letter "A". As the target letter "A" appears here on the left side of the response panel, a left key response was required. Following training with either the CF or CL, participants were transferred to either same or different task structure, resulting in four conditions (figure 2(c)). The outstanding finding was that experience with either the CL or CF conditions led to transfer of the trained gating policy to new contexts with the same ( e.g., CF -> CF) and different structure (e.g., CL-> CF).

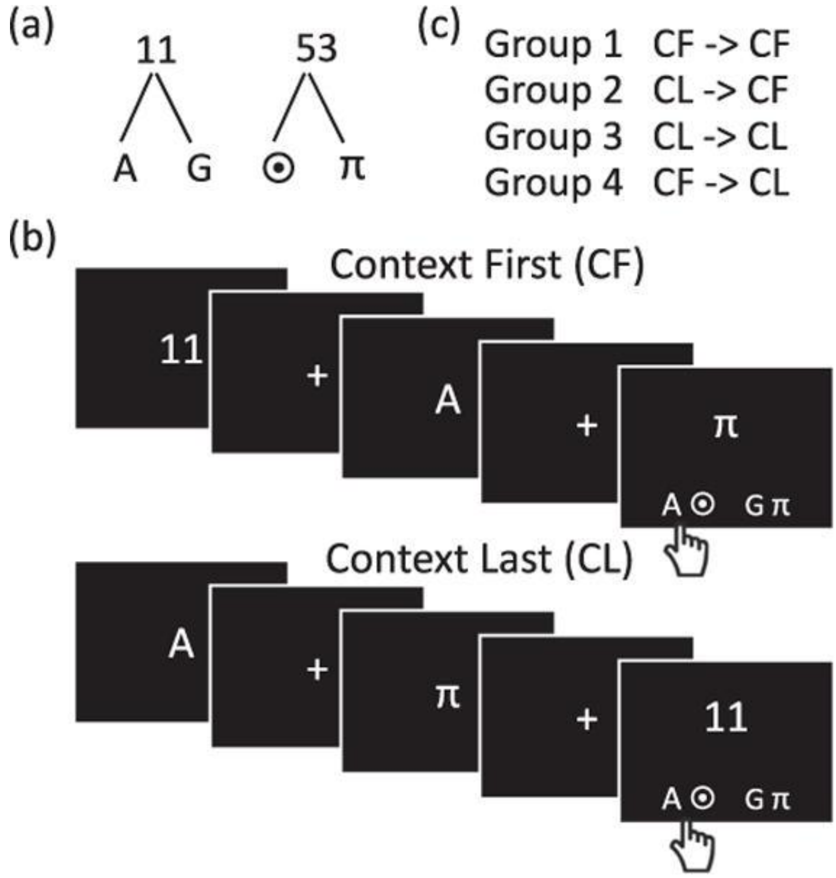



*Figure 2.* The second order WM-task and experimental design of experiment 1 as appearing in Bhandari & Badre (2018).

Following these encouraging results, in **study 3**, we attempted to expand these findings, investigating possible benefits of the exact same gating policy training to the domain of CT. Specifically, we aimed at examining whether the learning of gating policy might be transferred not only to similar context but also to other cognitive control tasks, in which such gating policies can improve performance. To do so, the same context-processing task as Bhandari & Badre (2018) was utilized for training, examining possible transfer effects to the cued task switching paradigm and AX-CPT paradigms, both suggsted to involve gating processes (Braver & Cohen, 2000; D'Ardenne et al., 2012b; Kessler, 2017; Kessler et al., 2017; Rougier & O'Reilly, 2002). As mentioned priviously, in the cued version of the task switching paradigm, participans are required to perfrom two tasks that share the same stimuli set (i.e., bivalent stimuli; Meiran, 2014). On a given trial, a cue announces which of the two tasks has to be carried out, resembling in fact the CF condition (input gating policy training). As learned input-gating control policy promotes enhanced proactive cue-processing and thus selective task selection, its succesful transfer to the context of task switching should result in improved performance on the latter. Also similar to the CF condition is the AX-CPT task, requiring to respond to a sequence of letters, making a target response when an A-cue is followed by an X-probe. As the AX sequence occues with a high frequency, the A-cue becomes highly predictive of the X-probe, encourging increased cue processing. The typical finding is that such high relience on a procative control mode results in higher error rates on trials in which the A-cue is not follwed by an X- probe (i.e., AY trials) but to less errors when the X-probe is not preceded by an A-cue (i.e. BX trials). An important observation is that such selective control mode evokes higher interference on BX trials due to the strong association between the X-probe and the target response (cf. Gonthier et al., 2016). From here, it was assumed that learning and transfer of selective output gating policies following CL training might consequently benefit performance on BX trials.

## Summary and Current Research

So far, the realm of cognitive enhancement in general and of EF training in specific is faced with numerous fundamental challenges, especially that of overcoming the problem of learning specificity. Years of research work, engendering dozens of studies and CT programs, seem to remain caught within an ongoing cycle of failed attempts to produce far-reaching transfer effects that go beyond the trained task (for recent reviews see Dougherty et al, 2016; Melby-Lervåg, Redick, & Hulme, 2016; Soveri, Antfolk, Karlsson, Salo, & Laine, 2017). As such, stepping back to reflect on and understand possible moderators underlying CT effectivity bares significant theoretical and empirical significance for its future.

First, we begin to explore the consequences of repetitive training procedures and benefits of variability inclusion. This idea draws on previous theoretical and empirical accounts to skills acquisition, highlighting the role of desired difficulty manipulations, such as variability, to learning and cognitive flexibility (Fissler et al., 2013; Schmidt & Bjork, 1992; Spiro et al., 1994). Up to date, the interlink between externally and internally guided intentions has not been well attended in the realm of cognitive enhancement, requiring thus deeper investigation (e.g., Jolles et al., 2012; Morrison & Chein, 2011). Here, we focus on the role of *learners' control* in producing more favorable learning experience. The rational for such investigation was based on suggestions pointing out to the motivational gains of choice availability and advantages of self-deliberate practice and self- regulated learning to skill development (Ackerman, 1987; Anderson, 1982; Ericsson et al., 1993; Inzlicht et al., 2014, 2018; Kinzie, 1990; Muraven et al., 2006; Nakamura & Csikszentmihalyi, 2014; Navon & Gopher, 1979; Paas et al., 2005). Last, abstraction is brought forward by several learning theories as core principle underlying the efficiency of the cognitive system to transport and reuse knowledge across contexts (e.g., Gick & Holyoak, 1983; Schmidt, 1975; Taatgen, 2013). New findings in the domain of cognitive control have suggested that abstract control policies, that is task general mental models, can be trained and generalized beyond the trained task, inducing performance gains in similar novel contexts that can benefit from their application (Bhandari et al., 2017). Consequently, we sought on expanding this idea to the domain of CT, examining whether such control policies can be trained and transferred to other dissimilar cognitive control tasks.

**In study 1**, the role of training variability in CT was approached within the task switching paradigm, allowing to manipulate content (fixed vs. varied task and stimuli) and structural variability (fixed vs. random task sequence). Here, we examined the occurrence of transfer to structurally similar (e.g., fixed structure training and transfer conditions) and dissimilar (e.g., fixed structure training condition to random structure transfer condition) untrained task switching.

**In study 2,** we attempted to examine whether granting learners' control over their own learning will produce more favorable learning outcomes, promoting wider transfer effects. The task switching paradigm was again utilized as it allowed us to compare voluntary vs forced task switching processes. Transfer performance was evaluated on forced novel task switching (near transfer) and on the verbal fluency task (far transfer). Study 2 served also as replication for study 1, manipulating in addition training variability (here only content variability). The additional benefits of enhanced task demands were also explored, utilizing as such bivalent stimuli to enhance between task interference.

**In study 3**, the role of WM control policies in CT were investigated, comparing the impact of input vs. output control polices on performance in other cognitive control tasks. For training, the second-order WM task was used, assigning participants to either a CF (input gating policy training) or CL (output gating policy training). Successively, transfer performance was evaluated on the task switching and AX-CPT tasks.

# PART II

# PEER-REVIEWED ARTICLES

**STUDY I**

# When Less Is More: Costs and Benefits of Varied vs. Fixed Content and Structure in Short Term Task Switching Training

Sabah, K., Dolk, T., Meiran, N., & Dreisbach, G. (2019). When less is more: Costs and benefits of varied vs. fixed content and structure in short-term task switching training. *Psychological Research, 83*(7), 1531-1542.

**Abstract**

Training variability has been brought forward as one possible moderator for wider scale transfer effects in cognitive training. However, little is known about which aspects of task variability are important for optimizing training outcomes. This study systematically examined the impact of variability in the different task components on outcome measures, here manipulating content (whether the task stimuli remained fixed or changed between blocks) and the deeper structural task configuration (task sequence: whether the task sequence was fixed or random). Short-term task switching training was implemented with one of four training variability conditions: fixed content\fixed structure; fixed content\ random structure; varied content\fixed structure and varied content\varied structure. The experiment consisted of a baseline block, seven training blocks (learning phase), followed by two transfer blocks, one with fixed and one with random task structure, respectively. In the learning phase, more rapid training gains were observed in the fixed content as compared to varied content. Interestingly, training with fixed content resulted in a trend for costs when transferred to a novel task switching context. In contrast, moderate transfer gains were noted in the varied content condition, manifested specifically on switch trials. These results suggest that task (content) variability is one of the means to improve positive transfer and avoid negative transfer. Additionally, and in agreement with the wide literature on training, this finding suggests that conditions that prevent training gains are in fact beneficial for learning generalization.

## Introduction

Cognitive enhancement has become a topic of great interest, transforming into a prosperous industrial sector, nourished by its assumed potential in enhancing cognitive plasticity and mitigating age-related cognitive decline and psychopathology associated impairments (for some early reviews see Chein & Morrison, 2010b; Lustig et al., 2009). Though notable improvement on the trained tasks and generalization (i.e., transfer) to other novel tasks has been documented on several training studies, recent meta-analytic reviews yield less optimistic conclusions regarding the effectiveness of cognitive training (CT, e.g., Dougherty et al., 2016; Melby-Lervåg et al., 2016; Soveri et al., 2017). This, in turn, brings us to an ongoing debate regarding the principles to design an optimal training protocol.

Prior work suggests that conditions that impair performance during training actually enhance the transfer of the trained skill to novel contexts, and the relevant means are predominantly related to introducing training variability (Buitenweg et al., 2012; Gopher et al., 1989; Karbach & Kray, 2009; Schmidt & Bjork, 1992). This claim is based on the premise that novelty (and training variability is one means to create novelty) enhances cognitive functions (e.g., Fritsch et al., 2005; Klusmann et al., 2010), prevents dementia and facilitates learning generalization (Fissler et al., 2013; Shawn Green & Bavelier, 2015). However, to our knowledge, few scientific studies have systematically examined which and how different aspects of variability impact learning and transfer in CT. As such, the current study embarks on a preliminary investigation into the contribution of variability across different task components to learning generalization following CT to similar contexts (i.e. near transfer). To this end, the task switching paradigm was utilized, allowing us to manipulate variability in terms of the introduced content (i.e. introduced stimuli and task rules) and variability in terms of the task's deeper structural configuration (i.e. the sequence of switch and repeat trials). In the following section, we review relevant literature on task-switching training.

**Training Executive Functions: The Case of Task-Switching**

Executive functions (EFs) can be roughly defined as a set of top-down processes that are considered as the groundwork for flexible, goal directed behavior. They enable adequate adjustment to novel demands of our constantly changing environment, withholding of prepotent behavioral tendencies and overcoming interference from irrelevant distracting information (Miyake et al., 2000). Here we focus on the ability to shift between tasks and mind-sets, or 'shifting ability' (e.g., Dreisbach, 2012; Kiesel et al., 2010a; Vandierendonck et al., 2010) that is arguably one of the three main EFs, along with working-memory updating and inhibition (Miyake et al., 2000).

Not surprisingly, task switching is one of the most widely targeted processes for cognitive enhancement studies, which have yielded promising outcomes. Specifically, these training benefits are reflected not only in task practice effects and switching ability on untrained similar tasks (i.e. near transfer) but also show generalization to other untrained processes of general fluid intelligence (Gf), working memory and inhibition across the different age spans (i.e., far transfer) (for review see Buitenweg et al., 2012; Karbach & Unger, 2014; Rueda et al., 2016). The relevance of task switching training in part is grounded in promising findings from developmental and clinical studies. For example, in Kramer, Hahn and Gopher's (1999) study, younger and older adults were trained on a task-switching paradigm. The study pointed to higher switch costs among older adults, but this age effect diminished due to training (see Buchler et al., 2008, for an analogical analogous finding). Beneficial outcomes for task switching training were also obtained among clinical populations. Children with attention deficits who were trained on task switching showed reduced switch costs after training as well as improvement on measures of inhibitory control and verbal working memory (Kray et al., 2012). However, despite these promising results, training outcomes targeting task switching as well as other EFs seem limited to in task-practice effects whereas the benefits of CT on near and far transfer measures have not been consistent (e.g., Dougherty et al., 2016; Lampit et al., 2014; Melby-Lervåg et al., 2016; Soveri et al., 2017). For instance, later studies failed to replicate the encouraging far transfer outcomes observed by Karbach and Kray (2009; see Kray & Fehér, 2017; Pereg et al., 2013). Consequently, recent studies have aimed to decipher the underlying mechanisms and training conditions that might lead to optimized training gains, bringing forward the notion of *variability* as possible moderator for training effectiveness (e.g., Karbach & Kray, 2009).

**Variability as a Mechanism for Transferrable Cognitive Training**

From an evolutionary/ecological perspective, it has been suggested that learning is beneficial especially in variable environments, because it promotes flexibility while stable environments promote rigid response patterns (e.g., DeWitt et al., 1998; Kakade & Dayan, 2002; Mery & Kawecki, 2004). Additionally, studies suggest that varied learning contexts facilitate rule-learning, a PFC-mediated ability that enables skill and knowledge transfer to new contexts (e.g., Cole et al., 2011; Gómez, 2002).

The significance of variability to cognitive flexibility can be further drawn from its interrelationship with novelty, the latter having a valuable role in cognitive development and vitality (Angevaren et al., 2007; Eskes et al., 2010; Fritsch et al., 2005). Moreover, it has been suggested that exposure to novelty is a main factor that allows improved anticipatory regulation to future new contexts and novelty exploration. Noting that such ability is one aspect that is hindered as a result of aging, novelty should also be addressed in cognitive training regimens, by ensuring high training variability (Düzel et al., 2010).

Training variability can be introduced on different task layers, for instance by manipulating *content* related features such as by including varied tasks and stimuli and\or *structural* features by varying task order (e.g., from predictable to unpredictable). This is based on the premise that slowing learning by means of varied training seems beneficial for learning generalization (Schmidt & Bjork, 1992). On the content level, it has been suggested that high content variability might allow the formation of a more flexible “schema” and more abstract rules. This in turn, might allow generalization to novel similar contexts (Cole et al., 2011; Wulf & Lee, 1993). For instance, in an explicit attempt to manipulate *content* variability, Karbach and Kray (2009) used task switching, comparing a fixed training condition that required participants to switch only between two task dimensions (transportation vs. number task) to a varied training condition that involved switching between different stimuli and response categories across the four experimental sessions (e.g., “transportation” vs. “number” task, “hobby” vs. “music” task). The study indicated that the more variable task switching paradigm enhanced near transfer effects among adults but not among children. Importantly, no difference between the fixed and variable groups was found on measures of far transfer. Variability manipulation on the level of task sequence is also implicated as a favorable condition for promoting transfer. Research in the field of perceptual and motor learning yielded positive evidence for better learning retention and transfer following random practice (Carnahan et al., 1990; Gabriele et al., 1987, 1989; Heitman et al., 2005; Sekiya et al., 1994; Shea et al., 1990; Shea & Zimny, 1983; Simon, 2007; Smith, 2002; Wulf & Lee, 1993; Wulf & Schmidt, 1988). A more closely related area is learning to perform in dual task conditions that is facilitated by randomly changing the priorities given to each task (Gopher, 1993; Gopher et al., 1989; Kramer et al., 1995; Larish et al., 1993). Extrapolating to task switching, this literature seems to suggest that predictable task order (e.g., alternating runs like AA-BB) would be less beneficial than random task sequence. One study addressed this issue directly. Specifically, for example, Minear & Shah, (2008) have employed a task switching training, comparing pretest-posttest performance on measures of mixing and switching costs between conditions on which task structure was predictable (i.e., alternating runs) vs. random. Additionally, to enhance variability, four different task pairs were introduced during training: One task pair was utilized for the pretest and posttest and three tasks were used for training. On both pretests and posttest, random and fixed task sequence blocks were administrated. For the control condition, participants were trained on single-task block that included the same tasks without engaging in task switching. The results point to training gains in both switching and mixing costs, following both predictable and random task switching training. However, transfer gains have been observed only from random task switching practice to the random transfer block and solely in measures of mixing costs.

Given the mixed results of the previous attempts, the current study acknowledges the importance to take a step back to disentangle the role of variability in cognitive training, by a factorial manipulation of two different forms of variability, commencing first with its impact on near transfer effects.The first manipulation involved content related features: fixed vs. varied tasks and stimuli (*content*, hereafter). Specifically, in the fixed content groups, participants were exposed to the same tasks and stimuli throughout the training blocks whereas in the varied content conditions, two new tasks and two new sets of stimuli were introduced on each experimental block. The second manipulation involved variability in one aspect of the task's structural features: whether the two tasks were ordered in a predictable manner vs. random task order. The factorial combination of these manipulations yielded four groups: (1) Fixed content/fixed structure; (2) Fixed content/varied structure; (3) Varied content/fixed structure, and (4) Varied content/varied structure condition. To assess training outcomes, baseline and post-test transfer measures were administered. In the post-training phase, four novel switching tasks (two novel tasks per block) were introduced, one block with the (same) fixed structure and another block with a random structure. As the study aims to pinpoint to the detrimental effects of repetition (practicing the same task repeatedly), a more conservative strategy of showing that repetition can be costly even in a short-term training was undertaken. Moreover, given unpublished evidence that maximal near-transfer effects do not necessarily require lengthy training (Meiran, Pereg & Shahar, 2015) and the ample of meta-analysis studies pointing to the absence of dosage modulating effects (Karbach & Verhaeghen, 2014; Karr et al., 2014; Melby-Lervåg & Hulme, 2013; Peng & Miller, 2016; Soveri et al., 2017), all training was restricted to one session.

When considering the variability manipulation, targeting both content and structure properties, two distinguishable levels of regularity are constructed, thus leading to two possible predictions:

1) Predictions for content: In the training phase (Block 2-8), better in-task practice gains for the fixed content vs. varied content conditions will be observed, as indicated by a decrease in response times on both switch and repeat trials. However, in the transfer blocks (Block 9 and 10), task switching performance in the fixed content group is expected to suffer once new tasks and stimuli are presented, as stimulus consistency in the training phase allows more bottom-up concrete form of learning, limited solely to the introduced stimulus and corresponding responses (Miller & Cohen, 2001).
2) Predictions for structure: In the training phase (Block 2-8), better in-task practice gains on both switch and repeat trails are predicted in the fixed structure conditions as compared to the varied structure conditions because structure consistency enables task preparation. This is in line with existing evidence that better performance on both repeat and switch trials is observed when foreknowledge is available about the task sequence as compared to random task switching conditions (e.g., Monsell et al., 2003; Sohn & Anderson, 2001). Presumably, even better training outcomes (on both switch and repeat trials) would be observed in the fixed structure/varied content condition.

Paradoxically, in the fixed structure condition, higher transfer costs will eventuate when transferred to a random task structure (Block 10; e.g., Pereg et al., 2013). This can be in part predicted by the possibility that an acquired verbalization strategy during training in the fixed order condition to prepare for the upcoming task (e.g., covert verbalization, cf. Goschke, 2000) might then result in performance costs when transferred to random task order in the transfer blocks (see also Karbach et al., 2010; Kray & Fehér, 2017). In contrast, in line with the suggestions from literature on practice, it is assumed that training with random structure would lead to higher transfer gains, possibly manifested on both repeat and switch trials. Optimal outcomes were predicted after training with varied content\varied structure condition. Possible advantage for variable over fixed (fixed) structure in task switching can in part be attributed to processing demand differences when confronted with predictable and unpredictable task switches. For example, it has been suggested that random task switching paradigms involves relaxed engagement of endogenous control, thus fostering more flexible forms of control whereas more rigid control patterns are observed in predictable task switching (Mayr & Kliegl, 2000; Stephen Monsell et al., 2003). In particular, predictable task switching conditions invoke more conservative manners of control, biasing task activation\inhibition to one task or the other, thus contributing to a higher switch cots and inability to flexibly adjust to unexpected events (Monsell et al., 2013; Goschke, 2000). In random task switching, a more flexible top-down control management of task bias seems to be at work, as suggested by the usually lower observed switch costs in such conditions (Andreadis & Quinlan, 2010).

## Method

### Participants

157 Regensburg University students (17 males and 124 females; $M_{age}$=22.14, $SD_{age}$=2.28) were randomly assigned to one of four experimental groups: (a) Fixed Content/Fixed Structure condition (FC/FS; N= 38); (b) Fixed Content/Varied Structure condition (FC/VS; N= 40); (c) Varied Content/ Fixed Structure condition (VC/FS; N=40) and (d) Varied Content/Varied Structure condition (VC/VS; N=39). Participants were compensated with either one-hour credit point as partial fulfilment of their studies' requirement (N= 33) or were paid 6€ (N=124). All participants reported having normal or corrected-to-normal vision and gave written consent prior to their participation in the study.

### Stimuli and Apparatus

All experimental tasks were programed in E-prime (Psychology Software Tools, Pittsburgh, PA, USA). The experiment was controlled by Dell computer with 19" flat screen.

**Training and transfer tasks - task switching**. For the purpose of the current study, a modified un-cued task-switching paradigm (employing univalent stimuli affording a single task) was utilized, encompassing solely mixed-task blocks. Participants were asked to switch between two task rules, by classifying either picture stimuli (Task Rule 1) or word stimuli (Task Rule 2) to a corresponding category. In total, 10 different task pairs were devised, each composed of two task rules, one for pictures and one for words, and they were labelled alphabetically (see Table 1). For each task rule, eight stimuli were used (four stimuli for each category) that were assigned to either a left response key (y) or right response key (m) on a QWERTZ-keyboard, depending on the respective category. The response keys were fixed across all tasks. For example, in Pair A, participants were instructed to indicate whether a presented set of pictures were summer- or winter-related (Task Rule 1) or whether the presented words denoted a female or male name (Task Rule 2). Summer-related pictures and female names were assigned to the right response key whereas winter related pictures and words denoting male names were assigned to the left response key. The stimuli in each category were exclusive to each task.[1] Pairs A-H served as the training tasks whereas Pairs I-J were the transfer tasks. The pictorial stimuli were sized 1.57” x 1.18” whereas the word stimuli were printed in 30px Calibri Light font.

[1] We used univalent stimuli and non-interfering task rules for two reasons: Given the complexity of the design we did not want to include another factor (i.e., task rule congruency). Moreover, if we had used bivalent stimuli, we would have needed an additional task cue at least for the group with varied structure which would have made the comparison between these groups more difficult. Note that there is broad evidence that univalent stimuli also produce reliable switch costs, especially when introduced with the corresponding task rule (e.g., Dreisbach et al., 2007; Dreisbach, 2012).

**Table 1**. Task rules used in the training and transfer blocks. The order of pairs B-H was counterbalanced across participants. In the fixed content groups, Pair A from baseline was also used in all experimental blocks. Pairs, I and J were the same for all groups.

| ***Pair*** | ***Task Rule 1 (Pictorial)*** | ***Task Rule 2 (Words)*** |
|---|---|---|
| **Pair A (Baseline, the same for all groups)** | Is it summer or winter related? | Is it a man's or woman's name? |
| **Pair B** | Is it sea or land transportation? | Can it be seen or heard? |
| **Pair C** | Is it vegetable or fruit? | Is it black or white material? |
| **Pair D** | Is it shoes or body parts? | Is it alcoholic or non-alcoholic drink? |
| **Pair E** | Is it mammalian or bird? | Is it old or new invention? |
| **Pair F** | Is it a cat or dog? | Is it located in Asia or Europa? |
| **Pair G** | Is it clothes or furniture? | Is it sweet or salty? |
| **Pair H** | Is it an electronic device or road sign? | Is it a hot or a cold meal? |
| **Pair I Fixed structure (same for all groups)** | Is it a musical or a sports instrument? | Is it a flower or tree? |
| **Pair J Varied structure (Same for all groups)** | Is it found in the kitchen or in the office? | Is it heavy or light? |

**Procedure**

Participants were randomly assigned to one of the four groups (FC/FS, FC/VS, VC/FS and VC/VS), attended a 45 minutes experimental session of one baseline block, seven training blocks and two transfer blocks. On the baseline block, all participants performed pair A with task sequence corresponding to the designated structure condition (e.g., participants assigned to VS condition performed a random task sequence). Consecutively, in the fixed content conditions, participants received the same pair of task rules (pair A) across the 8 training blocks while in the varied content conditions, new pairs of task rules (task pairs B-H; see Table 1) were introduced in each block. Moreover, in the fixed structure conditions, switching between task rules was predictable, occurring on every second trial (alternating runs: Rule 1 – Rule 1 – Rule 2 – Rule 2- …). In contrast, in the varied structure condition, switching between tasks rules occurred randomly, controlling for both switch rate (~ 50%) and stimulus appearance frequency.

In the transfer phase, all participants received new pairs of task rules in two separate blocks. The first testing block consisted of Pair I (see Table 2) with the fixed structure. In the second transfer block, Pair J with a random structure was used. Trial and block procedure remained the same as in the training blocks.

A block started with two instructional slides, followed by 8 practice trials. Thereafter, a block of 64 experimental trials started, ending with a feedback slide with the percentage of total correct responses and mean reaction time. On each trial, participants were presented with a fixation cross for 500 ms, followed by randomly selected stimulus that remained on screen either until a response was given or until 3,500 ms had elapsed. Feedback was only presented for errors or too slow reaction times (slower than 3,500 ms).

## Results

Four participants were excluded from analysis (one participant in the FC/FS condition, one participant in the FC/VS condition and two participants in VC/VS condition) due to exceptionally high error rate on either the baseline or transfer blocks (above 20% as compared to a mean error rate of the remaining sample of 4%). For reaction-time (RT) analysis, practice trials, trials deviating 3 SD from the groups mean in each block and trial type, erroneous trials, trials following an error as well as the first experimental trial of each block were discarded (11%). To look for potential initial differences between the training groups, 4X2 analysis of variance (ANOVA) was conducted just for the baseline block, with trial type (Repeat or Switch) as within-subjects factor and group (for this analysis, the between-participant independent variables content and structure were entered into the analysis as one group factor with four levels as between-subjects factor). The results revealed the typical switch cost pattern (Mean repeat= 567 ms; Mean Switch= 612 ms), $F(3, 149) = 162.55$, $p < .001$, with no significant difference between groups, $F(3, 149) = .753$, $p = .74$. Also, group did not interact with trial type, $F(3, 149) = .27$, $p = .85$. These results give legitimacy for the core analyses described below.

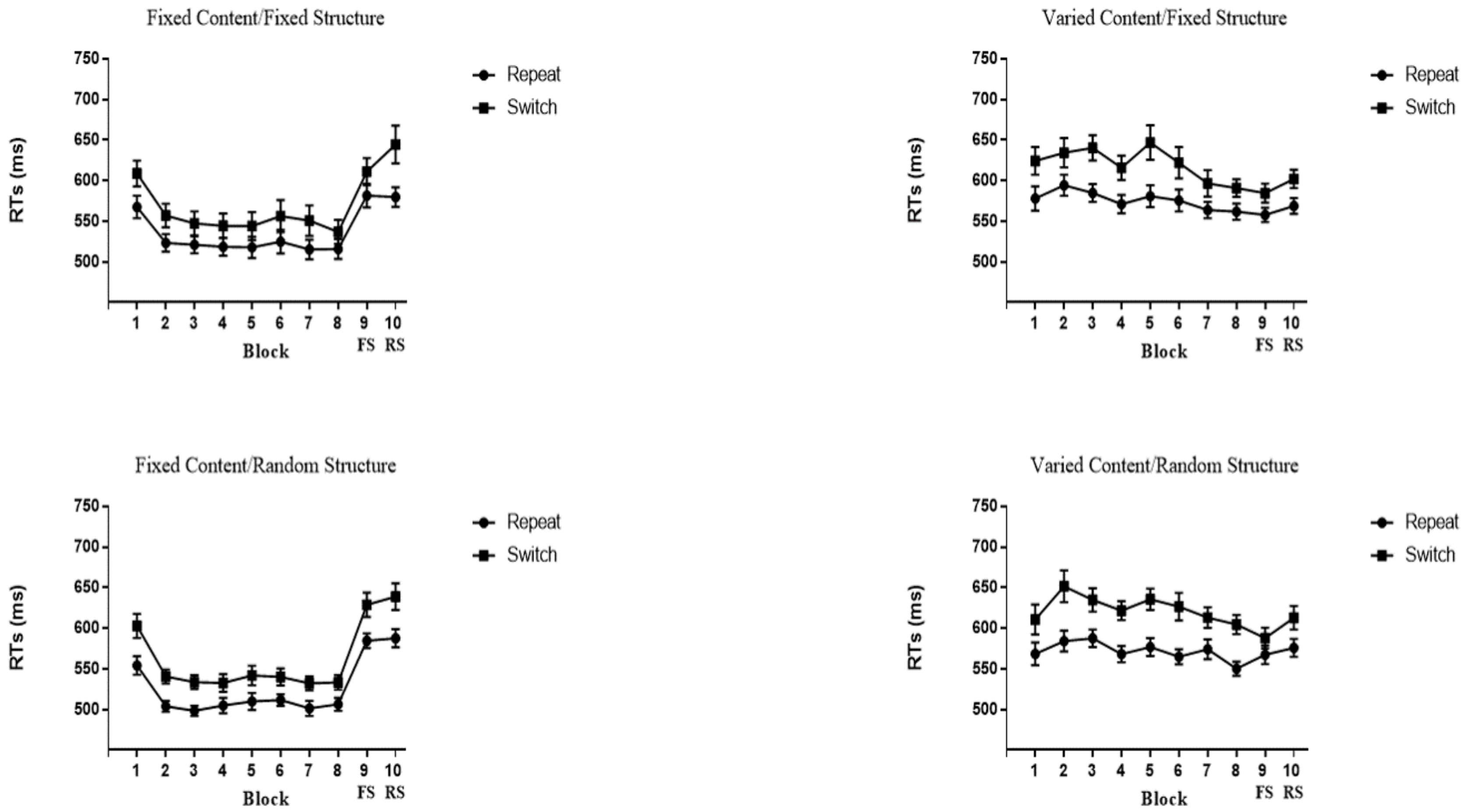



***Fig.1*** Mean RTs in ms as a function of trial type in blocks 1-10 in the four groups. Block 1 is the baseline block, Block 9 is the first transfer block with a fixed structure (FS), Block 10 the second transfer block with varied structure (VS). Error bars represent standard errors of the mean

**Training Performance (Blocks 1-8)**

Figure 1 presents mean RTs over all (training and transfer) blocks. To examine the unique contribution of each of the manipulated variability dimensions on training performance, a four-way analysis of variance was performed, with block (1-8) and trial type (repeat, switch) as within subject variables and content (varied/fixed) and structure (varied/fixed) as between subject factors. The results of this analysis are presented in Table 2. The results revealed a significant main effect for block, pointing to generally decreasing RTs from block 1 to 8 (589 ms vs. 550 ms). Likewise, a significant main effect was obtained for trial type, showing the typical switch costs (Mean repeat= 546 ms; Mean switch= 587 ms). Moreover, the between factor content was significant. Participants took generally longer to respond with varied content than with fixed content (Mean varied= 599 ms; Mean fixed= 534 ms). By contrast no significant main effect was found for the between factor structure (Mean varied= 563 ms; Mean fixed= 570 ms). Likewise, structure did not interact with any other factor (See Figure 1). The two-way interactions between block and trial type, block and content, trial type and content were further qualified by a higher order interaction between block, content and trial type. As can be seen in Figure 2, this interaction can be explained by the distinct switch cost pattern that was attained in the fixed vs. varied content condition with training progression. While a consistent reduction in switch costs was observed in the fixed content condition along the blocks, with switch costs being significantly lower in the last when compared to the baseline block, a fluctuating pattern was noted in the varied content condition. Furthermore, unlike the varied condition, a drastic decrease in switch costs is observed in the fixed condition already in the second block, suggesting content specific learning $F(1, 151) = 4.46$, $p < .05$, $\eta_p^2 = 0.03$ (See Figure 2).

**Table 2**. ANOVA results for RTs differences between baseline and transfer

| | ***Statistic*** | ***p* value** | **Effect Size ($\eta_p^2$)** |
|---|---|---|---|
| **Group** | $F(3, 149) = .40$ | .75 | .008 |
| **Trial Type** | $F(1, 149) = 206.81$ | <.001*** | .58 |
| **Block** | $F(2, 298) = 2.98$ | .05 | .02 |
| **Group X Block** | $F(6, 298) = 2.71$ | <.05* | .05 |
| **Trial Type X Group** | $F(3, 149) = 1.68$ | .17 | .03 |
| **Trial Type X Block** | $F(2, 298) = 6.31$ | <.01** | .04 |
| **Group X Block X Trial Type** | $F(6, 298) = 1.61$ | .14 | .03 |

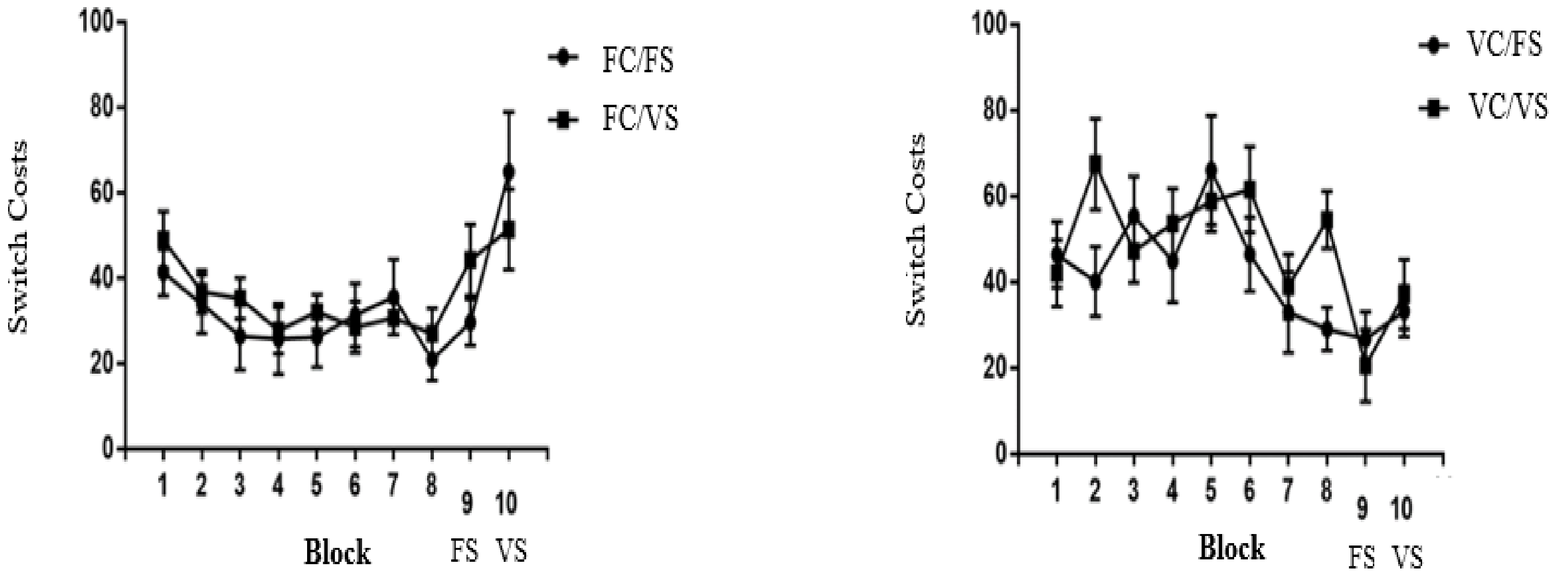



***Fig. 2*** Mean switch costs in the fixed content conditions (left panel) and varied content conditions (right panel) as a function of block. Error bars represent standard error of the mean.

**Transfer Costs and Gains**

To estimate transfer gains and/or costs, difference scores were calculated by subtracting RT values of the transfer blocks, (Block 9 and Block 10, respectively) from Baseline RTs (Block 1) for switch and repeat trial separately (see Table 3 for the respective mean RTs). That way, positive values will show transfer costs and negative values transfer gains. To assess the role of structure and content on performance differences in the transfer blocks in comparison to baseline performance, four-way analysis of variance was conducted, with block (9-10), corresponding to fixed vs. random task order) and trial type (repeat, switch) as within subject variable and content and structure (during training) as between subject factors (See table 4 for the full ANOVA table). As in the training phase, a significant main effect was found only for content but not for structure. Interestingly, in the transfer blocks, the varied content group showed transfer *gains*, as evidenced by a modest overall reduction in RTs (-13 ms) whereas in the fixed content group, overall transfer *costs* were found (24 ms). Additionally, a significant two-way interaction Content X Trial type was found:  In the varied content condition, transfer *gains* were higher for switch than for repeat trials and in the fixed content group the transfer *costs* were higher for switch than repeat trials (see Figure 3). A significant main effect was found for block, showing generally higher transfer costs in the second transfer block with random structure, 12.0 ms, as compared to the first transfer block, -1.3 ms, with fixed structure.

**Table 3**. ANOVA results for RT values in the training phase (Blocks 1-8)

| | ***Statistic*** | ***p* value** | **Effect Size ($\eta_p^2$)** |
|---|---|---|---|
| **Content** | $F(1, 149) = 36.15$ | $< .001^{***}$ | .19 |
| **Structure** | $F(1, 149) = .38$ | .54 | .002 |
| **Block** | $F(7, 1043) = 10.65$ | $< .001^{***}$ | .07 |
| **Trial Type** | $F(1, 149) = 321.72$ | $< .001^{***}$ | .68 |
| **Content*Structure** | $F(1, 149) = .32$ | .57 | .002 |
| **Block*Structure** | $F(7, 1043) = .19$ | .99 | .001 |
| **Block*Content** | $F(7, 1043) = 10.77$ | $< .001^{***}$ | .07 |
| **Trial Type*Block** | $F(7, 1043) = 2.2$ | $< .05^{*}$ | .01 |
| **Block*Content *Structure** | $F(7, 1043) = .56$ | .79 | .004 |
| **Trial Type*Structure** | $F(1, 149) = 1.51$ | .22 | .01 |
| **Trial Type*Content** | $F(1, 149) = 14.8$ | $< .001^{***}$ | .09 |
| **Trial Type*Content *Structure** | $F(1, 149) = .27$ | .60 | .01 |
| **Trial Type*Block*Content** | $F(7, 1043) = 2.95$ | $< .01^{**}$ | .02 |
| **Trial Type*Block*Structure** | $F(7, 1043) = 1.01$ | .43 | .007 |
| **Content *Structure *Block*Trial type** | $F(7, 1043) = 1.58$ | .14 | 0.01 |

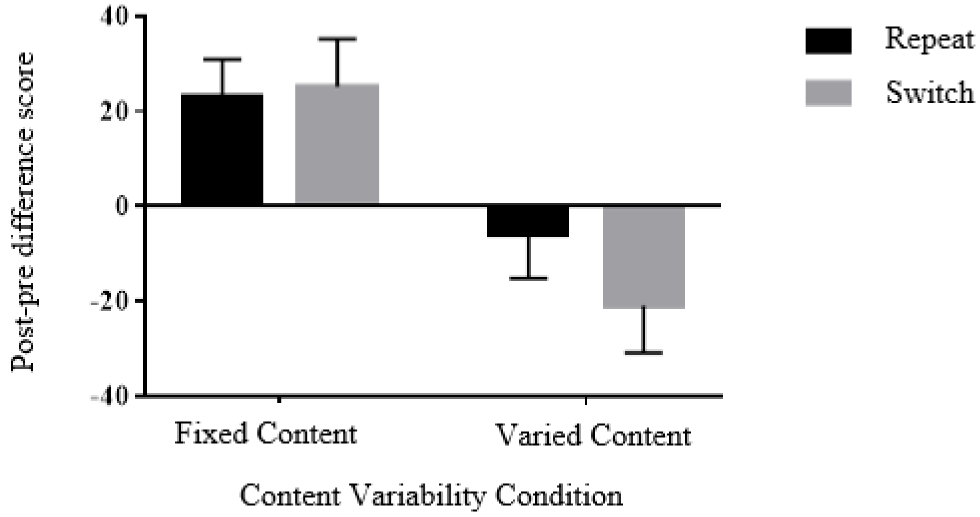



***Fig3.*** Transfer costs (positive values) and gains (negative values) in the fixed and varied content conditions as a function of trial type**.**

**Error Data.** Overall, participants made very few errors (4%). We analyzed these results with an ANOVA of Block X Trial type X Structure X Content that indicated just a main effect block, $F(9, 1341) = 2.85$, $\eta_p^2 = .02$. This effect shows that participants made slightly more errors in the training and transfer blocks when compared to baseline performance (Mean error rate in block 1: 3%, in blocks 8-10: 4% each). All other main effects and interactions were not significant (all $F < 1.65$, all $p > .09$). For a full table of mean error rates per block and condition, see supplementary material for study1. Additionally, it is worth noting that we did not observe any indication for speed accuracy trade-off in the critical RT findings.

## Discussion

Maximizing transfer effects is one of the major concerns of CT research. Yet, evidence for learning generalization following CT remains controversial. Thus, deciphering the underlying mechanisms that might promote learning generalization has valuable implications for the future of cognitive training.

In the general literature on practice, practice variability has been suggested to be a major moderator for training transfer. Nevertheless, regimented examination of the key aspects of variability how it can improve transfer effects in EF training remained limited. Accordingly, the current study examined different facets of variability in short-term task switching training. Specifically, we employed manipulations related to two possible task dimensions: task content and task sequence content and structure. (structure feature). Hence, two critical predictions were made regarding both

To manipulate content variability, participants responded to either the same stimuli repeated or varied them. To manipulate structural variability, participants trained with either fixed or random task sequences. Short-term training effects were evaluated by measuring training and transfer performance in the course of a single session. Following a baseline assessment, participants completed seven training blocks and two transfer blocks. The latter involved two novel tasks with fixed and random task sequence, respectively. We predicted that content/structure variability would result in a shallow learning curve in the *training phase* but better transfer. Our results show that in the *training phase*, significant main effect was found for content variability but not for structure variability. Specifically, participants in the varied content conditions showed slower RTs when compared to the fixed content condition and did not improve during the training phase. Importantly, significant three-way interaction was found between block, trial type and content condition. Whereas notable decrease in switch cost along the training blocks was obtained in the fixed content conditions, no noteworthy improvements in switch cost were observed in the varied content conditions. In *the transfer phase* a significant main effect was obtained only for content variability training, whereas there were no significant effects involving structure variability training. Interestingly, on novel tasks, **transfer gains** were noted in the varied content conditions, showing an overall reduction in RTs with a more pronounced acceleration on switch as compared to repeat trials. In contrast, **transfer costs** were observed in the fixed content conditions as reflected by general increase in RT, procuring slower RTs on switch as compared to repeat trials. Hereafter, we discuss the results for content and structure variability separately, addressing their impact on learning and transfer. Ultimately, the study implications for the realm of cognitive training are discussed.

As postulated, in the *training phase*, fixed content triggered more rapid learning and larger in-task improvement when compared to the varied content training condition. In the transfer phase however, undergoing training with fixed content conditions entailed performance costs as soon as novel tasks were introduced. This paradoxical learning-transfer outcome is in agreement with Schmidt and Bjork (1992), who emphasized a distinction between learning and performance. As pointed out by these authors, it seems that training conditions that facilitate rapid learning during practice hinder performance on consecutive novel tasks. These authors further proposed that practice variability is one means to boost retention and promote transfer either by means of enabling more abstract higher order learning that is not restricted to a set of S-R mapping and/or relaxing the process of task shielding occurring during task repetition (Dreisbach & Wenke, 2011; Miller & Cohen, 2001). Indeed, as we have shown, varied task content seems to at least reduce one core threat for cognitive training, namely negative transfer.

Contrary to our prediction, no significant effect was found for *task sequence variability* (structure feature), either in the training or in the transfer phase. Additionally, unlike Pereg et. al. (2013), the transition from a fixed structure composition during training to a random structure on the second transfer block did not generate any additional cost. This lack of any modulating effect of task sequence in the training phase is perplexing, because one would expect that introducing predictable task sequence would allow task preparation and would thus enhance learning. This is especially true when creating structure has been suggested to be incidentally acquired, even when it is not necessary (Collins & Frank, 2013; Koch, 2005; Stephen Monsell et al., 2003). One possible explanation for the results may relate to our utilization of univalent stimuli that can only be executed in one task. Such stimuli may lead participants to avoid higher-order structure learning, rather embracing a waiting strategy, relying on bottom-up task-cuing (stimulus priming). However, there is an alternative view that structure exploitation is a natural tendency in human cognition. Such a pattern enables rule abstraction and generalization, and it is found even in simple tasks that do not require it (Collins & Frank, 2013; Gershman & Niv, 2010). The present results cannot provide any definite answer as to what is the exact reason for the lack of structure-variability effects, and this remains a question for future research.

The aforementioned coupling of lack of observable learning in the training phase leading to improved transfer coincides with previous argumentations that disrupting learning can in fact enhance transfer to novel contexts (Lin et al., 2010; Shea & Morgan, 1979; Simon & Bjork, 2001). Consequently, our results call into question the validity of the widely used research practice in which the efficiency of training protocols is initially tested by training effects. A related approach is known as “correlated gains” in which practice efficiency is validated by establishing a correlation between learning gains and transfer gains (e.g., Baniqued et al., 2015; Zinke et al., 2012). Instead, in his valuable commentary, Seitz, (2017) addresses the criticality of reconceptualizing learning, taking into account its different facets and the conditions of its joint emergence, as inadequate conceptualizations result in failure to detect potential generalization.

Our additional attempt of unravelling the source of training costs and gains in the experimental conditions has yielded a noteworthy observation. As can be seen in Figure 3 (left panel), conjoint costs were found on both repeat and switch trials in the fixed content condition. In contrast, a rather specific gain was found on switch trials in the varied content condition (Fig. 3 right panel), driving in turn the main effect of content variability. Consequently, dissociating repeat and switch costs/gains seemed to be a differentiating marker for transfer outcomes even though no modulation on the level of switch costs was found. Such observation is significant, because in previous work the only outcome indices for task switching training evaluation were mixing and switching costs.

In line with Minear & Shah (2008), no indications for transfer effects have been found in terms of switching costs. Rather, we found moderate overall latency transfer gains with higher gains on switch trials when compared to repeat trials. This might fit with observations of previous studies, suggesting that switching costs seem less susceptible to training where training gains are more strongly pronounced on the general level of performance in the task-switching block. Such benefit would thus be reflected in mixing costs, i.e., the costs associated with being in a mixed task block as compared to when the block involves one task only (Pereg et al., 2013; Strobach, Liepelt, et al., 2012; Zinke et al., 2012). Nonetheless, we cannot rule out the possibility that a higher training dosage would have influenced switch costs too, especially given the claims that low training dosage is insufficient to induce “plastic changes” (Klingberg, 2010; Lövdén et al., 2010).

In sum, the current results directly support the notion of variability as a key factor that impacts the effectiveness of CT regimens, suggesting that “more can be less”. It further highlights the need for comprehensive examination of the conditions that encourage transfer that would enable designing effective CT regimens.

# STUDY II

## Enhancing Task-Demands Disrupts Learning but Enhances Transfer Gains in Short-Term Task Switching Training

Sabah, K., Dolk, T., Meiran, N. *& Dreisbach, G.* Enhancing task-demands disrupts learning but enhances transfer gains in short-term task-switching training. *Psychological Research* (2020). https://doi.org/10.1007/s00426-020-01335-y

### Abstract

Content variability was previously suggested to promote stronger learning effects in cognitive training whereas less variability incurred transfer costs (Sabah et al. 2018). Here, we expanded these findings by additionally examining the role of learners' control in short-term task-switching training by comparing voluntary task-switching to a yoked control forced task-switching condition. To this end, four training conditions were compared: (1) forced fixed content, (2) voluntary fixed content, (3) forced varied content, and (3) voluntary varied content. To further enhance task demands, bivalent stimuli were used during training. Participants completed baseline assessment commencing with task-switching and verbal fluency blocks, followed by seven training blocks and last by task-switching (near transfer) and verbal fluency (far transfer) blocks, respectively. For the baseline and transfer task-switching blocks, we used the exact same baseline and first transfer block from Sabah et al. (2018) employing univalent stimuli and alternating-runs task sequence. Our results pointed again to the contribution of content variability to task-switching performance. No indications for far transfer were observed. Allowing for learners' control was not found to produce additional transfer gains beyond content variability. A between-study comparison suggests that enhanced task demands, by means of bivalency, promoted higher transfer gains in the current study when compared to Sabah et al. (2018). Taken together, the current results provide further evidence to the beneficial impact of variability on training outcomes. The lack

of modulatory effect for learners' control is discussed in relation to possible methodological limitations.

## Introduction

Cognitive or “brain” training has evoked a heated debate regarding its effectiveness in inducing compelling and generalizable improvements in cognitive functions. In fact, recent meta-analyses show that there is no strong evidence for the transferability of training-related benefits to structurally different tasks (i.e., far transfer) or real-life situations (e.g., Dougherty, Hamovitz, & Tidwell, 2016; Melby-Lervåg, Redick, & Hulme, 2016; Soveri, Antfolk, Karlsson, Salo, & Laine, 2017). Nonetheless, consistent results support the occurrence of transfer to novel structurally similar tasks (i.e., near transfer; Karbach & Verhaeghen, 2014; Schwaighofer, Fischer, & Bühner, 2015). Consequently, and given the significant clinical and social implications of cognitive interventions, it seems warranted at this point to step back to reflect upon and examine the underlying mechanisms for Cognitive Training (CT) effectiveness. For example, recent attempts have introduced the notion of variability as a possible moderator for learning generalization (e.g., Karbach & Kray, 2009; Sabah, Dolk, Meiran, & Dreisbach, 2018). Findings indicate that the so far undertaken approach in CT studies of *doing more of the same* (i.e., task repetitiveness), seems to have transfer costs. That is, repetitive practices actually seem to perpetuate rigid behavioral patterns (Sabah et al., 2018).

Specifically, Sabah et al. (2018) observed that manipulating content variability in short-term task switching training (tasks and stimuli either changed in every block or remained the same throughout the training phase) counteracted the potentially deteriorating effects of repetitive training. Interestingly, a dissociation between learning and transfer has been revealed: Participants who practiced the same two tasks throughout training (i.e., fixed content condition) showed a steep learning curve but also showed significant transfer *costs* when confronted with two new tasks. Conversely, participants who received varying training tasks (i.e., varied content condition) showed a much flatter learning curve but critically smaller transfer *benefits* rather than costs. As such, we concluded that (1) training benefits are not a valid proxy for successful transfer, and (2) increased task demands during training prevent transfer costs. Here we aim to expand this line of research: First, we drew on these prior results as well as on the possible added value of higher task interference demands during training for transfer (Schmidt and Bjork, 1992). That is, unlike our previous study, in which univalent stimuli were used (a given stimulus was unequivocally associated with only one task), here we aimed to increase between task interference and thus task demands by always presenting two stimuli, one of each ask on a given trial. The idea is that this presentation mode would require top-down cognitive control, namely, knowing which task is currently required and would thus increase task engagement and reliance on cognitive control processes.

Moreover, and for the first time, we aimed at examining another possible moderator for determining the efficacy of cognitive training outcomes: *learners' control*. While so far the literature on cognitive training has focused on external features pertaining mostly to training design, less focus has been given to intrinsic features related to the trainee himself, such as motivation, cognitive abilities, beliefs, expectancies, and self-generated goals. Surprisingly, some of these factors like motivation have rather been treated as an undesirable confound (e.g., Jolles, van Buchem, Rombouts, & Crone, 2012; Morrison & Chein, 2011). This state of affairs is surprising given the empirical evidence and theoretical models linking the aforementioned internal states and individual differences to learning and transfer (e.g., Ackerman, 1987; Baldwin & Ford, 1988; Bürki, Ludwig, Chicherio, & de Ribaupierre, 2014; Quiñones, 1995; Ruona, Leimbach, Holton & Bates, 2002). We thus strived to investigate whether granting trainees control over their practice schedule would benefit learning. To this end, we used a task-switching paradigm, allowing us to manipulate training variability in terms of content (i.e., stimuli and task rules) as well as trainees' control over the task sequence. Training variability was achieved by using new task rules and stimuli in each training block (as compared to repeating the same task rules throughout the blocks) as in

Sabah et al. (2018). Trainees' control was manipulated by comparing the more standard instructed task-switching paradigm with the *voluntary* task-switching paradigm where participants have to choose themselves which of two available tasks to perform on each trial (Arrington & Logan, 2004, 2005).

**Passing the Torch: Considering Learners' Role in Cognitive Training**

The recognition that a learner is more than just a passive recipient but rather an active agent has long been central to learning and cognitive theories such as constructivism theories, cognitive flexibility theory and multiple intelligences theory (e.g., Gardner, 1987; Piaget, 1980; Spiro & Jehng, 1990; Vygotsky, 1986). These ideas have unsurprisingly inspired many instructional approaches (e.g., Bell & Kozlowski, 2008; Chiviacowsky, Wulf, Lewthwaite, & Campos, 2012; Mayer & Moreno, 2003).

Despite the remarkable body of literature on learners' control giving evidence to its contribution to learning outcomes across domains, the topic in the realm of CT remains underappreciated. This is quite intriguing when considering the fact that the most promising training outcomes with wider transfer effects are attributed to video gaming training (Al-Hashimi et al., 2013; Colzato et al., 2010; Shawn Green & Bavelier, 2003; Olfers & Band, 2018). After all, aside from the favorable environmental variability embedded within video gaming platforms, learners' control might also play an additional and critical component contributing to the beneficial training outcomes.

Why should learners' control be beneficial for cognitive training in the first place? In our understanding, possible benefits are grounded mainly on CT's interlink to the notion of desired difficulty – highlighting the paradox of mental effort (Bjork, 1994; Dougherty et al., 2016; Inzlicht, Shenhav, & Olivola, 2018; Schmidt & Bjork, 1992). According to this paradox, while engagement in highly demanding cognitive tasks appears to be costly and aversive, a certain amount of difficulty is actually desirable and promotes better long-term learning outcomes (Bjork & Bjork, 2009; Healy, Kole, & Bourne, 2014; Schneider, Healy, &

Bourne, 2002). This in turn seems very relevant to CT when considering the costly and aversive nature of cognitive effort, markedly manifested in training protocols, such as those targeting highly demanding processes of working memory (WM), inhibition of automatic tendencies and switching between tasks (Braver, 2012; Kool et al., 2010; Stephen Monsell, 2003; Westbrook et al., 2013). Hence, it is postulated that learners' control might allow individualized, strategic and flexible adaptation of effort allocation. This prevents depletion while at the same time maintaining a desired level of difficulty to avoid boredom, thereby allowing learning to occur (e.g., Ackerman, 1987; Inzlicht, Schmeichel, & Macrae, 2014; Kinzie, 1990; Muraven, Shmueli, & Burkley, 2006; Navon & Gopher, 1979; Paas, Tuovinen, Van Merriënboer, & Darabi, 2005). Similarly, it has been suggested that deliberate and self-initiated practice rather than merely repetitive extended practice underlies expert behavior (Ericsson et al., 1993). This claim is based on the observation that skill acquisition requires by itself only limited amount of practice with individuals reaching a performance asymptote quite rapidly without additional improvement hereafter (i.e., automaticity; Anderson, 1982; Fitts & Posner, 1967). In contrast, the "deliberate practice" framework emphasizes the role of high motivation for seeking demanding tasks as well as engagement in self-monitoring processes (e.g., error identification and correction) to overcoming automaticity and supporting progressive learning and improvement (Ericsson, 1992, 2006, 2008).

**Should I Stay or Should I Switch: Considering Voluntary Task-switching in Training Cognitive Flexibility**

Task-switching ability, widely considered as a marker of cognitive flexibility, is measured by the costs incurred in response times and accuracy when switching as compared to repeating cognitive tasks (for reviews, see Kiesel et al., 2010; Monsell, 2003; Vandierendonck, Liefooghe, & Verbruggen, 2010). Task-switching has also become central to cognitive enhancement studies (e.g., Karbach & Kray, 2009; Karbach, Mang, & Kray, 2010; Kray & Fehér, 2017; Minear & Shah, 2008). One advantage of the Task-switching paradigm is that it can help us gain a better understanding of the variables moderating training outcomes, such as training variability (Karbach & Kray, 2009; Minear & Shah, 2008; Sabah et al., 2018). Moreover, it allows to investigate an important additional moderator, learners' control. To allow for this, the voluntary Task-switching paradigm was used, enabling participants to voluntarily choose on any given trial which task they want to perform (Arrington & Logan, 2004). Moreover, given that participants themselves have to decide which task to execute on any given trial, the VTS paradigm engages participants in goal setting and thus in a relatively more active self- regulated processing (Arrington & Logan, 2004), which is arguably integral to learning and transfer.

As stated above, in our previous study (Sabah et al., 2018), content variability in task switching was shown to undermine the costly outcomes of repetitive training. Despite the observed improvement in task switching performance across the learning blocks, participants in the fixed content condition, produced transfer costs. In contrast, participants in the varied content condition seemed to have benefitted from content variability, however in the absence of improvement during learning. From here, this dissociation between learning and transfer performance falls in line with previous suggestions that advocate "desired difficulty" manipulations, such as content variability, to promote better learning generalization (Schmidt & Bjork, 1992).

Expanding our previous line of research, we strived to examine here whether (a) additional benefits would arise when increasing between task interference during training and allowing for learners' control in the varied content condition and, (b) whether negative transfer costs would be prevented in the fixed content condition by the same means (increased interference, allowing for learners' control). To this end, we ran a CT-task-switching study and manipulated content variability and whether the tasks were voluntarily chosen. We thus compared four conditions: (a) Voluntary varied content (voluntary VC), (b) forced varied content (forced VC), and (c) voluntary fixed content (voluntary FC), and (d) forced fixed content (forced FC). For the forced conditions, a yoked control procedure was followed[2]. Specifically, pre-post Task-switching performance was examined (near transfer measure), introducing untrained task stimuli and rules as well as a distinct task sequence (alternating runs, e.g., with Tasks A and B the sequence was AA-BB-AA…) on both the baseline and transfer blocks. Similarly, far transfer effects were examined using the verbal fluency task, a measure of cognitive flexibility that has a switching element (e.g., Troyer, Moscovitch, & Winocur, 1997; Troyer, Moscovitch, Winocur, Alexander, & Stuss, 1998). Specifically, we predicted the following:

1) For content variability manipulation, we expected to replicate and extend our previous findings, pointing to the advantage of content variability training over fixed content condition, reflected in better task-switching performance in near transfer coupled with less improvement during training (Sabah et al., 2018). The novelty here is that we also examined whether there would be far transfer effects seen in verbal fluency.
2) Allowing learners' control in Task-switching training was predicted to promote additional transfer benefits in the voluntary VC when compared to forced VC condition. Additionally, we aimed to explore whether the increased task demands due to increased task interference during training (bivalency) would diminish the transfer-costs in Task-switching performance which we observed before (Sabah et al., 2018) in the fixed-content group. To this end, the results of the current study will be compared to those obtained by Sabah et al. (2018).

Finally, even though not being part of our main question, the design allows to explore training effects on the voluntary switch rate as a function of varied vs. fixed content. Given

[2] Yoked control means that for every participant in the voluntary switching groups, we created a "forced twin" that received the exact same task sequence. That way we made sure that the respective groups only differ with respect to the voluntary aspect of task choice.

the evidence for bottom-up (e.g. Mayr & Bell, 2006) and context effects (Fröber & Dreisbach, 2017) on voluntary task-switching, one may predict higher switch rates when stimuli and tasks change in every block. On the other hand, given the literature on motivation and boredom one could predict the opposite, namely increased switch rates when stimuli and tasks never change (Inzlicht et al, 2014).

## Methods

### Participants

One hundred and sixty Regensburg University students (16 males; $M_{\text{age}}$ = 22.9, 95% CI [22, 23]) were compensated with either one-hour course credit ($n$ = 21) or were paid 6€ (6.89$; $n$ = 99). All participants reported having normal or corrected-to-normal vision and gave written consent prior to their participation in the study.

Apparatus

All experimental tasks were programed in E-prime (Psychology Software Tools, Pittsburgh, PA, USA). The experiment was controlled by Dell computer with 19" flat screen.

**Verbal fluency task (baseline and transfer)**. Stimulus presentation and response recording were computerized. Vocal responses were collected using an external voice recorder (TASCAM linear PCM recorder DR-05). The test began with a general instruction slide, which was followed by two test blocks. Participants were instructed to produce as many words that start with the target letter in 60s while avoiding proper names, same stem words, verb conjunctions or numbers. Participants were presented with two letters (either F, B or N, T), one in each block. We counterbalanced (between participants) the assignment of letter-pair to blocks (e.g., whether F-B were presented in Block 1and N-T in Block 2 or vice versa) and also counterbalanced the order of letters (e.g., F→B or B→F) within the block. (It is worth noting that the chosen letters were validated in German where each pair consisted of one hard and one easy item; see Schmidt et al., 2017). Each test block started with a screen asking participants to press the space-bar button when ready to perform the first task, followed by a visual and auditory presentation of the target letter for 1000 ms. A presentation of a one-minute sand clock followed, indicating the remaining time.

**Task-switching (baseline, transfer and training).** In total, nine different task pairs were employed, each composed of two task rules, one for pictures and one for words stimuli (See Table 1). The pictorial stimuli were sized 1.57” x 1.18” whereas the word stimuli were printed in 30px Calibri Light font. For each task rule, eight exclusive stimuli were used (four stimuli for each category) that were assigned to either a left response key (z or n) or right response key (x or m) on a QWERTZ-keyboard, depending on the respective category. The response key assignment to a given category was counterbalanced across participants. A modified version of the task-switching paradigm was used, including solely mixed blocks.

***Baseline and transfer***. In baseline and transfer we used a predictable task order of alternating runs (task sequence Picture-Picture-Word-Word… etc.), with univalent stimuli (when the task involved a picture, only a picture was presented, and when it involved a word, only a word was presented). We used the exact same baseline (Pair A) and transfer (Pair I) tasks as in Sabah et al (2018).

***Training***. The stimuli were bivalent (involving the simultaneous presentation of a picture and a word). For a given participant, stimuli pertaining to the one rule were constantly presented above and stimuli pertaining to the other rule were presented below the fixation cross (counterbalanced across participants). Whether the two tasks remained the same throughout training and whether participants could choose the tasks, was determined by the experimental group (see General Procedure).

In all, baseline, transfer and training, each task-switching block started with two instructional slides presenting the task rules, followed by eight practice trials. Thereafter, a block of 64 experimental trials started, ending with a feedback slide presenting the statistics for this block including percentage of correct responses, mean reaction time, and switch rate (in the voluntary group). In each trial, participants were asked to classify picture stimuli (Task

Rule 1) or word stimuli (Task Rule 2) to a corresponding rule. In the voluntary conditions, participants chose which task rule to execute. In the forced conditions, the required task rule (Picture/Word) was indicated by placing a rectangle around the relevant target stimulus. Stimuli remained on screen either until a response was given or until 3,500 ms had elapsed. After an inter-stimulus interval of 500 ms the next trial started. Feedback was only presented for errors or too slow reaction times (slower than 3,500 ms).

**Table 1**. Task rules used in the training and transfer blocks. The order of pairs B-H was counterbalanced across participants. In the fixed content groups, Pair A from baseline was also used in all experimental blocks. Pair I was the same for all groups.

| ***Pair*** | ***Task Rule 1 (Pictorial)*** | ***Task Rule 2 (Words)*** |
|---|---|---|
| **Pair A (Baseline, the same for all groups)** | Is it summer or winter related? | Is it a man’s or woman’s name? |
| **Pair B** | Is it sea or land transportation? | Can it be seen or heard? |
| **Pair C** | Is it vegetable or fruit? | Is it black or white material? |
| **Pair D** | Is it shoes or body parts? | Is it alcoholic or non-alcoholic drink? |
| **Pair E** | Is it mammalian or bird? | Is it old or new invention? |
| **Pair F** | Is it a cat or dog? | Is it located in Asia or Europa? |
| **Pair G** | Is it clothes or furniture? | Is it sweet or salty? |
| **Pair H** | Is it an electronic device or road sign? | Is it a hot or a cold meal? |
| **Pair I (same for all groups)** | Is it a musical or a sports instrument? | Is it a flower or tree? |

**General Procedure**

Participants were randomly assigned to one of four equal sized groups: (a) voluntary VC, (b) forced VC, (c) voluntary FC, and (d) forced FC. They attended a one-hour experimental session, starting with baseline: verbal fluency test block, followed by one baseline task-switching block (with univalent targets). Training consisted of seven task-switching blocks with bivalent targets. In the task-switching training blocks, participants in the VC conditions received two new task rules on each block whereas the same two task rules were performed across all blocks in the FC conditions (i.e., Pair A). In the voluntary switching conditions, participants were asked to freely choose which task to perform on a given trial, with the restriction to perform each task equally often and in random order as if “flipping a coin” (cf. Arrington & Logan, 2004). In the forced switching conditions, each participant was yoked to one of the individuals in either the voluntary FC or VC condition depending on group assignment, so it matched in task selection on each corresponding trial and switch rate. The session ended with one task-switching transfer block (univalent targets) followed by a verbal fluency transfer block.

## Results: Task-Switching

Data analysis was conducted following the protocol of our previous study (Sabah et al., 2018) to maintain a high comparability between the two studies. Thus, following the same exclusion criteria, participants with excessive error rates (above 20% as compared to 4% in the remaining sample) in either the task-switching baseline or transfer blocks were excluded from the analysis. Consequently, data from two participants in the forced FC group were discarded.

For response time (RT) analysis, practice trials, erroneous trials, trials following an error as well as the first experimental trial of each block were discarded (11%). For mean error rates, see Figure 1 and Figure 2 in supplementary material for study 2.

In addition, Bayes Factor (BF) analyses were carried out using JASP (JASP team, Version 0.11.1.0), contrasting H0 (no effect) with H1 which was specified using the default priors. We report $BF_{10}$ (advantage of H1 over H0) and $BF_{01}$ (advantage of H0 over H1). $BF_{10}$ for 2-way interaction effects was computed by dividing the $BF_{10}$ of a model with main effects and interaction by the $BF_{10}$ of a (respective) main-effect-only model. Similarly, $BF_{10}$ for triple interactions was computed by dividing the $BF_{10}$ of a full model including all the main effects, 2-way interactions and the triple interaction by the $BF_{10}$ of a similar model not including the triple interaction.

**Initial Differences between the Groups**

To look for potential initial differences between the training groups, 4 (Group: voluntary VC, forced VC and voluntary FC and forced FC, between participants) x 2 (Trial Type: repeat, switch, within participants) Frequentists and Bayesian analysis of variance (ANOVAs) were conducted on (a) RTs and (b) error rates of the baseline block.

**RTs.** The results revealed the typical switch cost pattern ($M_{repeat}$ = 612 ms, 95% CI [597, 628]; $M_{switch}$ = 764 ms, 95% CI [737, 791]), $F(1,154) = 245.64$, $p <.001$, $\eta p^2 = .62$, $BF_{10} > 100$, whereas no significant difference was found between groups, $F(3,154) = .48$, $p = .69$, $\eta p^2 = .01$, $BF_{10} = 0.05$ . Additionally, group did not interact with trial type, $F(3,154) = 1.04$, $p = .37$, $\eta_p^2 = .02$, $BF_{10} = 0.12$.

**Error rates.** Error rates were generally low ($M$ = .04; 95% CI [.03, .04]). The typical switch cost pattern was also revealed in error rates, with participants making more errors on switch ($M_{switch}$ = .04, 95% CI [.04, .05]) when compared to repeat trials ($M_{repeat}$ = .03, 95% CI [.02, .03]), $F(1,154) = 20.05$, $p <.001$, $\eta p^2 = .11$, $BF_{10} > 100$. Neither the main effect for group, $F(3,154)$ =.19, $p$ = .90, $\eta_p^2$ = .004, $BF_{10}$ = .06, nor the interaction between group and trial type reached significance , $F(3,154)$ = 1.28, $p$ = .28, $\eta_p^2$ = .02, $BF_{10}$ = 0.07.

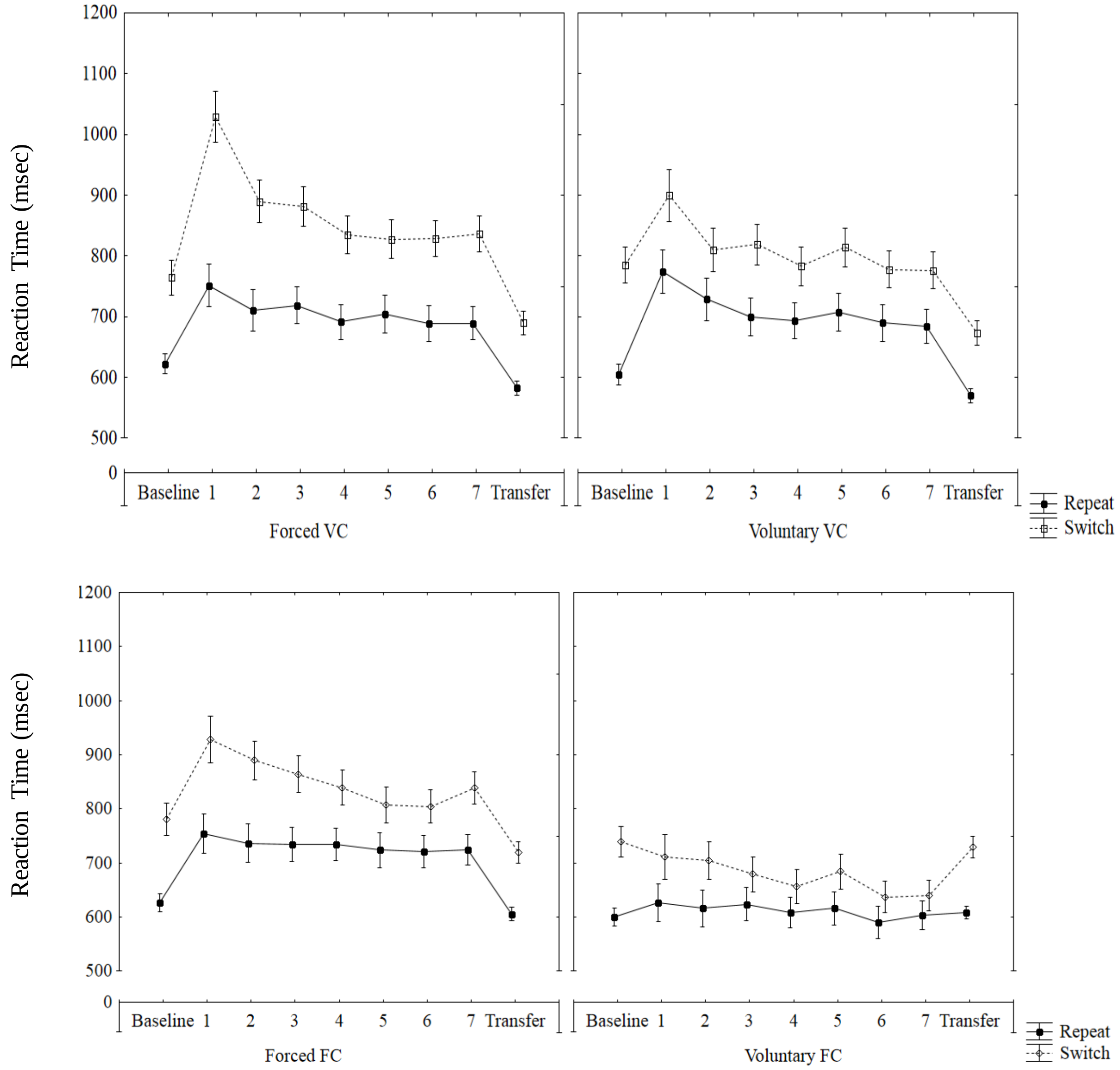



***Fig1***. Mean reaction time (RT) in ms as a function of trial type across the experimental blocks in the groups. Error bars represent standard error of the mean.

**Training Performance (Block 1-7)**

To analyze training performance, a four-way Frequentists and Bayesian ANOVA was performed with content (fixed vs. varied) and learners' control (Forced vs. VTS) as between-subject variables and block (1-7) and trial type (repeat, switch) as within-subject variables for both RTs and error data (see ANOVA table 2 and 3, respectively).

**Table 2**. Main effects and interaction of the Content X Learners' Control x Block (1-7) x Trial Type ANOVA (RTs).

| | ***Statistic*** | ***p* value** | **Effect Size ($\eta_p^2$)** | **$BF_{10}$** |
|---|---|---|---|---|
| **Content** | *F*(1, 142) = 4.34 | $< .05^{*}$ | .03 | 1.60 |
| **Learners' control** | *F*(1, 142) = 10.23 | $< .01^{**}$ | .07 | 17.50 |
| **Block** | *F*(6, 852) = 22.34 | $< .001^{***}$ | .14 | >100 |
| **Trial Type** | *F*(1, 142) = 273.96 | $<.001^{***}$ | .66 | >100 |
| **Content** x **Learners' control** | *F*(1, 142) = 4.43 | $< .05^{*}$ | .03 | 2.35 |
| **Trial type** x **Block** | *F*(6, 852) = 9.23 | $<.001^{***}$ | .13 | 59 |
| **Content** x **Block** | *F*(6, 852) = 2.935 | $< .01^{**}$ | .02 | 0.22 |
| **Learners' Control x Block** | *F*(6, 852) = 1.41 | .21 | .01 | < 0.01 |
| **Content** x **Trial Type** | *F*(1, 142) = 10.18 | $< .01^{**}$ | .07 | >100 |
| **Learners' Control** x **Trial Type** | *F*(1, 142) = 21.82 | $<.001^{***}$ | .13 | >100 |
| **Content** x **Learners' Control** x **Block** | *F*(6, 852) = 0.10 | .99 | .001 | < 0.01 |
| **Content** x **Learners' Control** x **Trial Type** | *F*(1, 142) = 0.09 | .77 | .001 | 0.20 |

| | | | | |
|---|---|---|---|---|
| **Content** x **Trial Type** x **Block** | $F(6, 852) = 1.10$ | .40 | .01 | < 0.01 |
| **Learners' Control** x **Trial Type** x **Block** | $F(6, 852) = 3.40$ | < .01** | .02 | 0.08 |
| **Content** x **Learners' Control** x **Trial Type** x **Block** | $F(6, 852) = 0.86$ | .53 | .06 | < 0.01 |

**Table 3**. Main effects and interaction of the Content x Learners' Control X Block (1-7) x Trial Type ANOVA (error rates)

| | ***Statistic*** | ***p* value** | **Effect Size ($\eta_p^2$)** | **$BF_{10}$** |
|---|---|---|---|---|
| **Content** | $F(1, 146) = 0.28$ | .60 | .001 | 0.12 |
| **Learners' Control** | $F(1, 146) = 0.14$ | .71 | .07 | 0.11 |
| **Block** | $F(6, 876) = 1.57$ | .15 | .01 | 0.004 |
| **Trial Type** | $F(1, 146) = 4.52$ | $< .05^{*}$ | .03 | 0.64 |
| **Trial Type** x **Block** | $F(6, 876) = 0.53$ | .78 | .004 | < 0.01 |
| **Content** x **Block** | $F(6, 876) = 2.34$ | $< .05^{*}$ | .02 | <0.01 |
| **Learners' Control** x **Block** | $F(6, 876) = 1.26$ | .27 | .01 | <0.01 |
| **Content** x **Trial Type** | $F(1, 146) = 0.01$ | .93 | .001 | 0.07 |
| **Learners' Control** x **Trial Type** | $F(1, 146) = 0.03$ | .85 | .001 | <0.01 |
| **Content** x **Learners' Control** x **Block** | $F(6, 876) = 0.59$ | .74 | .004 | <0.01 |
| **Content** x **Learners' Control** x **Trial Type** | $F(1, 146) = 2.69$ | .10 | .02 | <0.01 |
| **Content** x **Trial type** x **Block** | $F(6, 876) = 1.39$ | .21 | .01 | <0.01 |
| **Learners' Control** x **Trial Type** x **Block** | $F(6, 876) = 0.99$ | .43 | .01 | <0.01 |
| **Content** x **Learners' Control** x **Trial Type** x **Block** | $F(6, 876) = 0.57$ | .76 | .003 | <0.01 |

**RTs**. Statistics are depicted in Table 2. The results reveal a significant main effect for block, pointing to generally decreasing RTs from block 1 to block 7 ($M_{\text{Block1}}$ = 809 ms, 95% CI [773, 846]) vs. $M_{\text{Block8}}$ = 724 ms, 95% CI [698, 751]). Likewise, a significant main effect was obtained for trial type, showing the typical switch costs ($M_{\text{Repeat}}$ = 691 ms, 95% CI [663, 719]; $M_{\text{Switch}}$ = 803 ms, 95% CI [774, 833]). A significant main effect was found for content, where faster RTs were observed in the FC (*M* = 718 ms, 95% CI [678, 757]) when compared to the varied content condition (*M* = 776 ms, 95% CI [737, 816]). However, the Bayes Factor (BF) for content was inconclusive (i.e., representing "anecdotal evidence" for the alternative hypothesis). The main effect for learners' control also reached significance with participants being slower in the forced (*M* = 792 ms, 95% CI [753, 832]) as compared to the voluntary task-switching condition (*M* = 702 ms, 95% CI [663, 741]).

The interaction between trial type and block was significant, pointing to decreasing switch costs along the course of training: Significantly lower switch costs were observed in the last training block (Block 7; *M* = 87, 95% CI [68, 107]) when compared to the first training block (*M* = 163, 95% CI [136, 189]), $t(151) = 5.07$, $p < .001$, $d = .41$. Likewise, the interaction between content and trial type reached significance, with switch costs being higher in the VC (*M* = 134, 95% CI [114, 155]), when compared to FC groups (*M* = 89, 95% CI [69, 109]), $t(156) = 3.72$, $p < .001$, $d = .59$. Strong evidence for the alternative hypothesis is confirmed by the BF for the interactions of Trial Type x Block and Content x Trial Type.

The interaction between content and block was significant. An improvement in RTs was noted among both the FC and VC conditions, $t(77) = 4.20$, $p < .001$, $d = .40$, $t(79) = 5.11$, $p < .001$, $d = .57$, respectively. Participants in the VC condition, showed slower RTs in both the first and last training block, $t(156) = 2.8$, $p < .01$, $d = .23$, $t(156) = 2.01$, $p < .05$, $d = .32$, respectively. Also, a significant interaction between content and learners' control was found. In the VC condition, no significant difference in RTs was found between the forced and voluntary task-switching condition, $F(1,71) = .63$, $p = .43$, $\eta_p^2 = .01$. In contrast, in the FC condition, significantly slower RTs were observed in the forced when compared to the voluntary task-switching condition, $F(1,71) = 13.09$, $p < .01$, $\eta_p^2 = .16$. The two-way interactions Content x Block and Content x Learners' control should, however, be interpreted with caution, because the corresponding BF did not indicate sufficiently strong evidence.

Moreover, the two-way interaction between learners' control and trial type was further qualified by higher-order interaction between learners' control, trial type and block. As shown in Figure 2, in the first training block, higher switch costs were observed in the forced vs. voluntary task-switching condition, $t(150) = 4.87$ , $p < .001$, $d = .79$. While participants in the forced condition showed a decrease in switch costs with increasing training, no distinct pattern was found within the voluntary task-switching condition. Significant reductions in switch costs between the first and last training blocks were observed in both the forced and voluntary task-switching conditions, $t(74) = 4.74$, $p < .001$, $d = .55$ ; $t(76) = 2.39$ , $p < .05$; $d = .27$, respectively . In the last training block, significantly higher switch costs were obtained in the forced as compared to the voluntary task-switching condition, $t(148.16) = 3.14$ , $p < .001$, $d = .50$. The Bayesian analysis results were not aligned with the frequentist statistics, with BF suggesting a strong evidence for the two-way interaction Learners' Control x Trial Type but not for the three-way interaction Leaners' Control x Trial Type x Block.

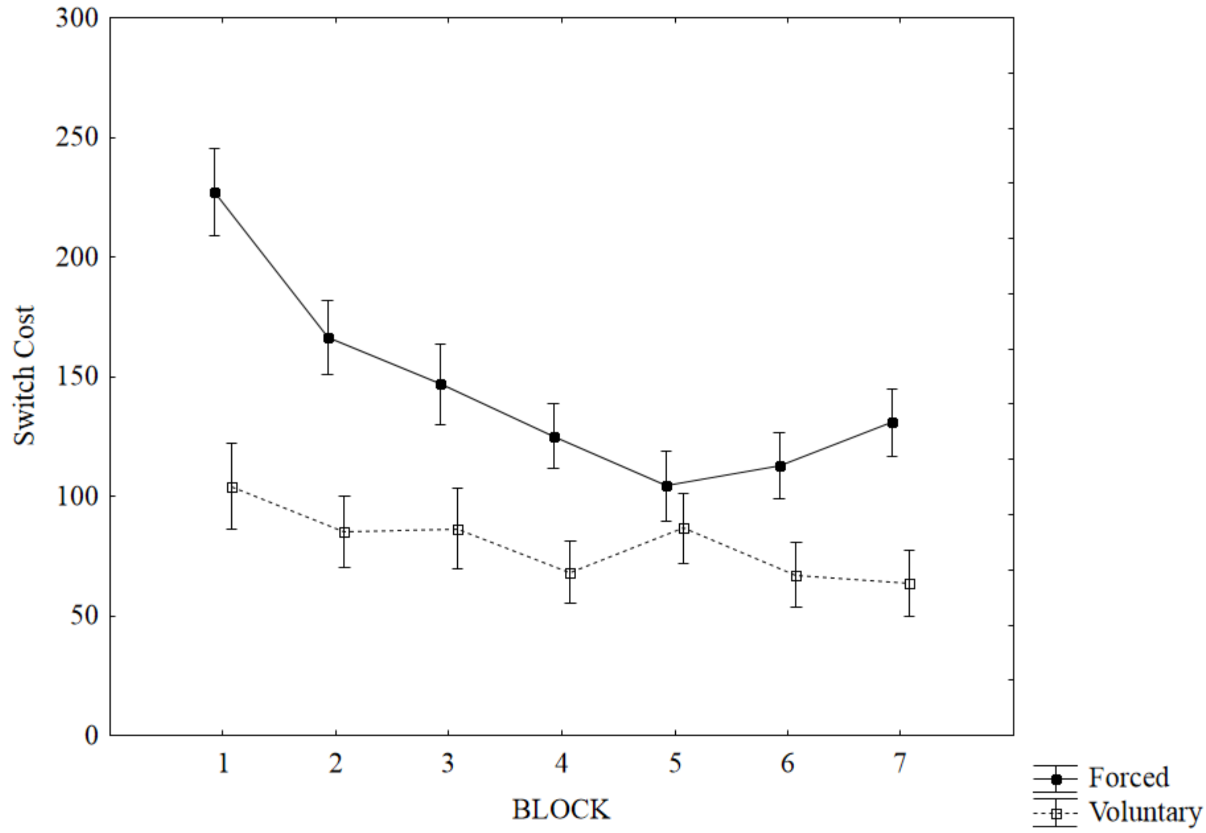



***Fig 2.*** Mean switch cost (in msec) as a function of Block and Condition (forced vs. voluntary) collapsed collapsed across content. Error bars represent standard error of the mean

The three way-interactions Content x Learners' Control x Trial Type and Content x Trial Type x Block as well as the four-way interaction Content x Learners' Control x Trial Type x Block did not reach significance. The corresponding Bayesian analyses in fact provided strong evidence for the null hypothesis.

Taken together, fixed content incurred smaller switch costs than varied content. In addition, switch costs were smaller in the voluntary task-switching conditions as compared to the forced switching conditions. A notable reduction in switch costs along the training blocks was observed solely in the forced condition. However, this latter effect was very small and not confirmed by the Bayesian analysis. Likewise, the interaction Block x Content replicated previous findings (Sabah et al., 2018) in showing steeper learning in the FC as compared to the VC groups. Note, though, that the effect was numerically small and its presence was not confirmed by the Bayesian analysis.

The results reveal a significant main effect for block, pointing to generally decreasing RTs from block 1 to block 7 ($M_{\text{Block1}}$ = 809 ms, 95% CI [773, 846]) vs. $M_{\text{Block8}}$ = 724 ms, 95% CI [698, 751]). Likewise, a significant main effect was obtained for trial type, showing the typical switch costs ($M_{\text{Repeat}}$ = 691 ms, 95% CI [663, 719]; $M_{\text{Switch}}$ = 803 ms, 95% CI [774, 833]). A significant main effect was found for content, where faster RTs were observed in the FC (*M* = 718 ms, 95% CI [678, 757]) when compared to the varied content condition (*M* = 776 ms, 95% CI [737, 816]). Moreover, the main effect for learners' control also reached significance with participants being slower in the forced (*M* = 792 ms, 95% CI [753, 832]) when compared to the voluntary task switching condition (*M* = 702 ms, 95% CI [663, 741]).

A significant interaction between content and learners' control was found. In the VC condition, no significant difference in RTs was found between the forced and voluntary task switching condition, $F(1,71) = .63$, $p = .43$, $\eta_p^2 = .01$. In contrast, in the FC condition, significantly slower RTs were observed in the forced when compared to the voluntary task switching condition, $F(1,71) = 13.09$, $p < .01$, $\eta_p^2 = .16$. Also, the interaction between trial type and block was found significant, pointing to decreasing switch costs along the course of training: Significantly lower switch costs were observed in the last training block (Block 7; *M* = 87, 95% CI [68, 107]) when compared to the first training block (*M* = 163, 95% CI [136, 189]), $t(151) = 5.07$ , $p < .001$, $d = .41$. Likewise, the interaction between content and block was significant. An improvement in RTs was noted among both the FC and VC conditions, $t(77) = 4.20$ , $p < .001$, $d = .40$, $t(79) = 5.11$ , $p < .001$, $d = .57$, respectively. Participants in the VC condition, showed slower RTs in both the first and last training block, $t(156) = 2.8$ , $p < .01$, $d = .23$, $t(156) = 2.01$ , $p < .05$, $d = .32$, respectively. The interaction between content and trial type reached significance, with switch costs being higher in the varied content (*M* = 134, 95% CI [114, 155]), when compared to fixed content (*M* = 89, 95% CI [69, 109]), $t(156)$ =

3.72 , $p < .001$, $d = .59$. Moreover, the two-way interaction between learners' control and trial type was further qualified by higher-order interaction between learners' control, trial type and block. As shown in Figure 2, in the first training block, higher switch costs were observed in the forced vs. voluntary task switching condition, $t(150) = 4.87$ , $p < .001$, $d = .79$. While participants in the forced condition showed a decrease in switch costs with increasing training, no distinct pattern was found within the voluntary task switching condition. Significant reduction in switch costs between the first and last training blocks were observed in both the forced and voluntary task switching conditions, $t(74) = 4.74$, $p < .001$, $d = .55$ ; $t(76) = 2.39$ , $p < .05$; $d = .27$, respectively . In the last training block, significantly higher switch costs were obtained in the forced as compared to the voluntary task switching condition, $t(148.16) = 3.14$ , $p < .001$, $d = .50$.

Overall, fixed content incurred smaller switch costs than varied content. Moreover, only with fixed content, switch costs were reduced over the course of training. Finally, higher switch costs emerged in the forced vs. voluntary task switching condition. Notable reduction in switch costs along the training blocks was observed solely in the forced condition. Interestingly, an effect for VTS training was limited to the FC condition, with overall slower RTs in the forced when compared to the voluntary condition.

**Error rates.** Overall, error rates were low ($M = .04$; 95% CI [.04, .05]). As shown by Table 3, the main effect for trial type reached significance. Participants made slightly more errors on switch ($M = .05$; 95% CI [.04, .05]) when compared to repeat trials ($M = .04$; 95% CI [.04, .05]). The interaction Block x Content was also significant. On the last training block, participants in the VC condition made less errors ($M = .03$; 95% CI [.03, .04]) when compared to the FC condition ($M = .05$; 95% CI [.04, .05]), $t(156) = 2.55$ , $p < .05$, $d = .56$. Neither the BF for the main effect trial type nor for the interaction Block x Content suggested strong evidence for the alternative hypothesis. All other effects did not reach significance with all corresponding $BF_{10}$ values providing strong evidence for the null hypothesis.

**Voluntary switch rate.** To examine possible differential learning features, switching rates in the VS groups were analyzed. To capture all attempted switches, erroneous trials were also included (cf. Arrington & Logan, 2004). To this end, a 2 x 7 mixed model Frequentists and Bayesian ANOVA were conducted with group as a between-subject variable (voluntary VC and voluntary FC) and block (block 1-7) as within-subject variable. The results brought up a significant main effect for group, pointing to higher switch rates (*M* = 53, 95% CI [49, 56]) in the FC group when compared to the voluntary VC group (*M* = 47, 95% CI [43, 50]), $F(1,78) = 6.66$, $p < .05$, $\eta_p^2 = .08$, $F(6, 468) = 16.06$, $p < .01$, $\eta_p^2 = .17$, $BF_{10} = 3.622$, respectively. In addition, the main effect for block reached significance, reflecting the continuous increase in switch rate with increasing training, $F(6, 468) = 16.06$, $p < .01$, $\eta_p^2 = .17$, $BF_{10} > 100$ (See figure 3). The interaction between block and content was not significant ($F < 1$, $p = 0.89$, $BF_{10} < 0.01$).

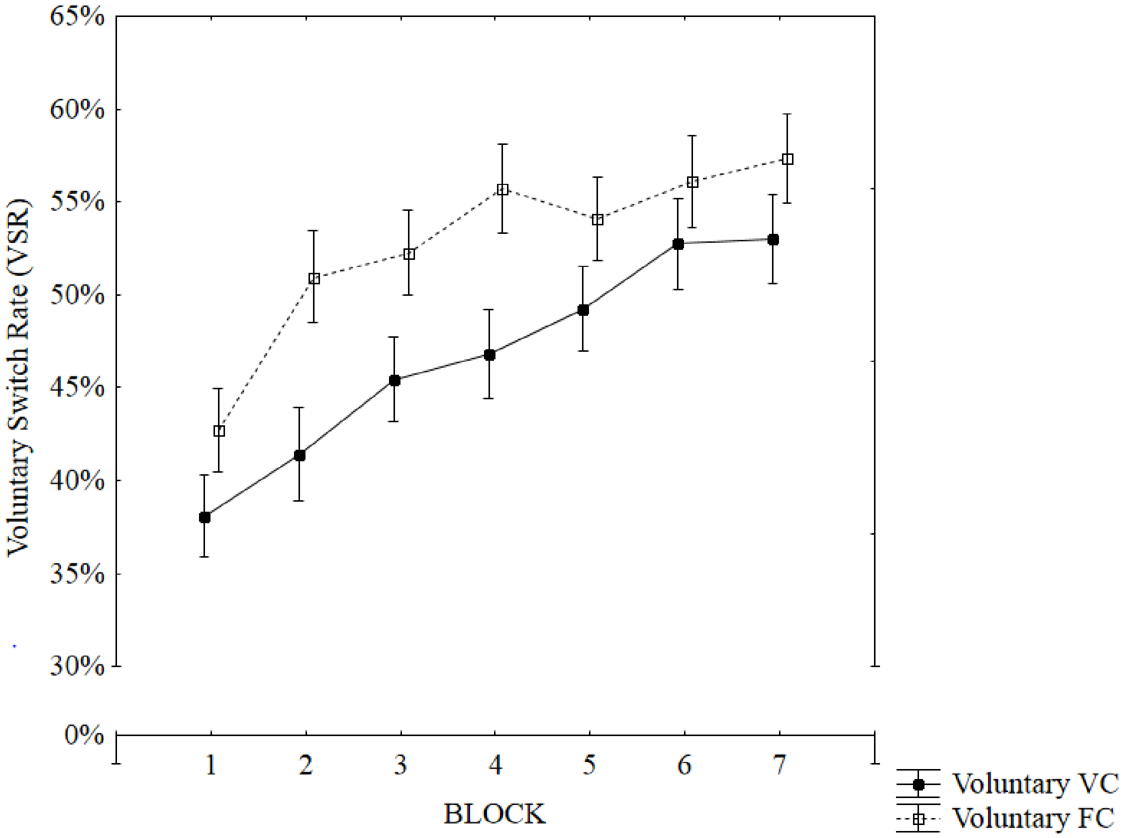



*Figure 3*. Mean Switch rates in the voluntary FC and VC conditions along the training blocks. Error bars represent standard error of the mean.

**Transfer Costs and Gains**

To investigate whether there is a difference in pre-post performance, 2 (Content: fixed, varied) x 2 (Learners' control: forced, voluntary) x 2 (Block: baseline, transfer block) x 2 (Trial type: repeat, switch) mixed model Frequentists and Bayesian ANOVAs were conducted on both RTs and error rates.

**RT**. As can be seen in Table 4, a significant main effect for block was found. Faster RTs were obtained on the transfer block (*M* = 648 ms, 95% CI [634, 662]) when compared to baseline (*M* = 688 ms, 95% CI [668, 708]). The typical main effect for trial type was also significant with slower RTs on switch (*M* = 735 ms, 95% CI [714, 756]) when compared to repeat (*M* = 602 ms, 95% CI [590, 613]). The corresponding BFs for the two aforementioned main effects indicate strong evidence for the alternative hypothesis.

The interaction between content and block was significant. As can be seen from Figure 4, participants in the VC condition show higher training gains (*M* = -63 ms, 95% CI [-86, -39]) in comparison to the FC condition (*M* = -17 ms, 95% CI [-41, 6.54]). However, the BF suggested only anecdotal evidence for the alternative hypothesis. No other effect reached significance.

In sum, the results point to a small but significant contribution of varied content training to inducing better transfer gains in task-switching performance.

**Error data**. Differences in error rates revealed the typical switch costs. In addition, the interaction between block and learners' control was significant (see Table 5). Participants in the voluntary task-switching condition seemed to show slightly higher error rates on the transfer block (*M* = .04, 95% CI [.04, .05]) when compared to the forced Task-switching condition (*M* =. 03, 95% CI [.02, .04]), $t(156) = 2.64$ , $p < .05$, $d = .28$.

**Table 4**. Main effects and interactions of the Content x Learners' Control x Block (Baseline vs. Transfer) x trial type ANOVA (RTs).

| | ***Statistic*** | ***p* value** | **Effect Size ($\eta_p^2$)** | **$BF_{10}$** |
|---|---|---|---|---|
| **Content** | $F(1, 154) = 0.41$ | .52 | .003 | 0.17 |
| **Learners' Control** | $F(1, 154) = 0.38$ | .54 | .001 | 0.16 |
| **Content x Learners' Control** | $F(1, 154) = 0.14$ | .71 | .001 | 0.21 |
| **Block** | $F(1, 154) = 22.57$ | <.001*** | .13 | >100 |
| **Block x Content** | $F(1, 154) = 7.37$ | <.01** | .04 | 2.53 |
| **Block x Learners' Control** | $F(1, 154) = 0.12$ | .72 | .001 | 0.12 |
| **Block x Content X Learners' Control** | $F(1, 154) = 1.63$ | .20 | .01 | 0.30 |
| **Trial Type** | $F(1, 154) = 326.66$ | <.001*** | .68 | >100 |
| **Trial Type x Content** | $F(1, 154) = 0.30$ | .59 | .002 | 0.14 |
| **Trial Type x Learners' Control** | $F(1, 154) = 0.42$ | .52 | .003 | 0.16 |
| **Trial Type x Content x Learners' Control** | $F(1, 154) = 0.93$ | .33 | .006 | 0.07 |
| **Block x Trial Type** | $F(1, 154) = 16.68$ | <.001*** | .10 | 2.98 |
| **Block x Trial Type x Content** | $F(1, 154) = 1.34$ | .25 | .01 | 0.22 |
| **Block x Trial Type x Learners' Control** | $F(1, 154) = 0.05$ | .82 | .001 | 0.17 |
| **Block x Trial Type x Content x Learners' Control** | $F(1, 154) = 1.73$ | .19 | .01 | 0.48 |

**Table 5**. Main effects and interactions of the Content x Learners' Control x Block (Baseline vs. Transfer) x trial type ANOVA (error rates).

| | ***Statistic*** | ***p* value** | **Effect Size ($\eta_p^2$)** | **$BF_{10}$** |
|---|---|---|---|---|
| **Content** | $F(1, 154) = 0.01$ | .91 | .001 | 0.12 |
| **Learners' control** | $F(1, 154) = 1.98$ | .16 | .01 | 0.29 |
| **Trial Type** | $F(1, 154) = 23.65$ | $<.001^{***}$ | .13 | >100 |
| **Block** | $F(1, 154) = 0.11$ | .74 | .001 | 0.09 |
| **Block x Content** | $F(1, 154) = 1.41$ | .24 | .01 | 0.27 |
| **Content x Learners' Control** | $F(1, 154) = 0.99$ | .32 | .006 | 0.23 |
| **Block x Learners' Control** | $F(1, 154) = 6.30$ | $< .05^{*}$ | .006 | 2.37 |
| **Block x Trial Type** | $F(1, 154) = 0.50$ | .48 | .003 | 0.72 |
| **Block x Content x Learners' Control** | $F(1, 154) = 0.84$ | .36 | .005 | <0.01 |
| **Trial Type x Content** | $F(1, 154) = 0.70$ | .40 | .004 | 0.18 |
| **Trial Type x Learners' Control** | $F(1, 154) = 0.70$ | .40 | .004 | 0.19 |
| **Trial Type x Content x Learners' Control** | $F(1, 154) = 0.80$ | .37 | .005 | 0.25 |
| **Block x Trial Type x Content** | $F(1, 154) = 0.52$ | .47 | .003 | 0.25 |
| **Block x Trial Type x Learners' Control** | $F(1, 154) = 0.20$ | .65 | .001 | 0.25 |
| **Block x Trial Type x Content x Learners' Control** | $F(1, 154) = 1.15$ | .28 | .007 | <0.01 |

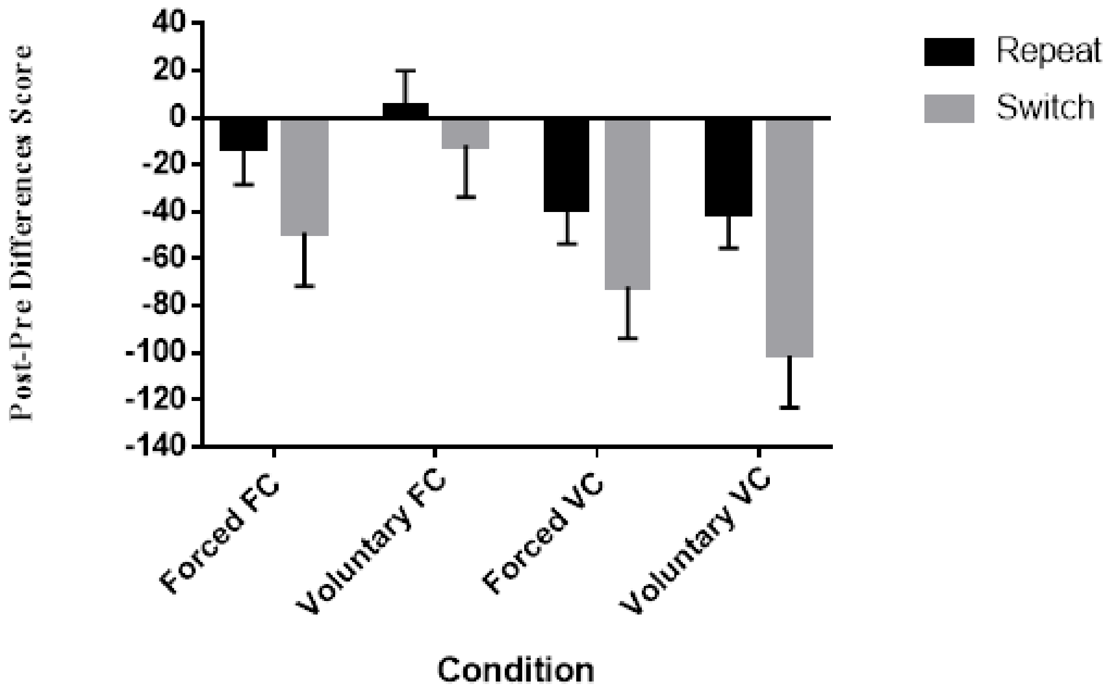



*Figure 4.* Pre-Post score differences in ms between the groups. Positive values show transfer costs and negative values show transfer gains. Scores are calculated as the difference between baseline and transfer block. Error bars represent standard errors of the mean.

**Comparison of Transfer Costs\Gains with Sabah et al (2018)**

An additional aim of the current study is to examine whether the previously observed effect for content variability (Sabah et al., 2018) replicates across studies. Moreover, we intended to explore whether enhanced task interference (the use of bivalent target stimuli in this study as opposed to univalent target stimuli in Sabah et al., 2018) might bear an additional benefit beyond content variability, diminishing the previously observed transfer costs following FC task-switching training condition. To this end, transfer costs and gains between this study and Sabah et al. (2018) were compared. Due to the discrepancies between studies, resulting from the utilization of VTS, only the forced conditions from the current study were considered for analysis. In addition, only the first transfer block from Sabah et al. (2018) was included in analysis, matching exactly the employed transfer block in the current study both in content and task sequence (AA-BB). It is noteworthy that the lack of random assignment between studies results in a possible confound and thus the results of the current set of analyses should be interpreted cautiously.

For the purpose of the current analysis, Study (Current study, Previous study) x Content (FC, VC) x Block (Baseline, Transfer) x Switch (Repeat, Switch) mixed model Frequentists and Bayesian ANOVAs were performed on RTs (See Table 6). A significant main effect for block was obtained, with faster RTs observed on the transfer (*M* = 620 ms, 95% CI [610, -640]) when compared to the baseline block (*M* = 642 ms, 95% CI [627, 657]). The main effect for study was also significant. Overall, slower RTs were observed in the current study (*M* = 673 ms, 95% CI [655, 691]) when compared to Sabah et al. (2018) (*M* = 589 ms, 95% CI [576, 601]). Moreover, the main effect for trial type was significant where faster RTs were obtained on repeat (*M* = 589 ms, 95% CI [580, 599]) as compared to switch trials (*M* = 672 ms, 95% CI [659, 686]).

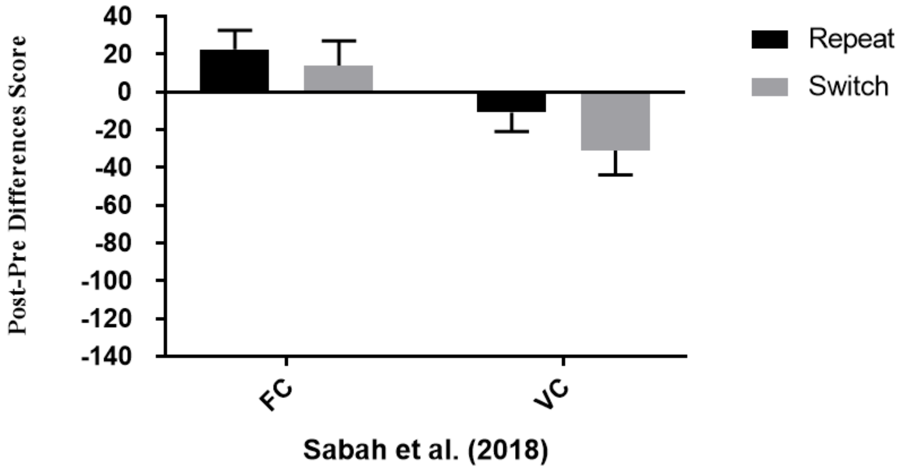
A significant two-way interaction was found between study and block with higher gains in the current study (*M* =-43 ms, 95% CI [-65, -21]) when compared to Sabah et al. (2018) (*M* = -1 ms, 95% CI [-17, 14]). Furthermore, the interaction between block and trial type reached significance (See Figure 5). Smaller switch costs were obtained in the transfer block as compared to the baseline block, $t(230) = 4.22$ , $p < .001$, $d = .27$. Importantly, the interaction between content and block was also significant, pointing to higher gains in the VC condition (*M* = -38 ms, 95% CI [-56, -19]) as compared to the FC condition (*M* = -6 ms, 95% CI [-25, 12]). This was further supported by the BF, indicating strong support for the alternative hypothesis. In addition, falling in line with the frequentist results, this interaction was not modulated by study, as indicated by the BF for the three-way interaction Study x

Content x Block. This last result means that H0 concerning lack of difference between the studies (in this regard) is ~32 times more probable than a difference between the studies, given the results (and equal priors for H0 and H1).

Overall, the benefit for content variability to Task-switching performance is successfully replicated, where across studies we see lower costs\higher transfer gains following VC training. Moreover, relative to Sabah et al. (2018), higher transfer gains emerged, possibly due to the utilization of bivalent target stimuli, enhancing task demands.

**Table 6**. Main effects and interactions of Study x Content x Block x Trial Type ANOVA (RTs).

| | ***Statistic*** | ***p* value** | **Effect Size ($\eta_p^2$)** | **$BF_{10}$** |
|---|---|---|---|---|
| **Study** | $F(1, 227) = 57.26$ | $< .001^{***}$ | .20 | >100 |
| **Content** | $F(1, 227) = 1.09$ | .30 | .005 | 0.20 |
| **Trial Type** | $F(1, 227) = 467.62$ | $< .001^{***}$ | .67 | >100 |
| **Block** | $F(1, 227) = 10.78$ | $< .01^{**}$ | .04 | 3.75 |
| **Block x Study** | $F(1, 227) = 9.49$ | $< .01^{**}$ | .04 | 56 |
| **Block x Trial Type** | $F(1, 227) = 21.45$ | $< .001^{***}$ | .09 | 1.11 |
| **Block x Content** | $F(1, 227) = 5.59$ | $< .05^{*}$ | .02 | 13.06 |
| **Study x Trial Type** | $F(1, 227) = 139.74$ | $< .001^{***}$ | .38 | >100 |
| **Study x Content** | $F(1, 227) = 0.13$ | .71 | .001 | 0.20 |
| **Content x Trial Type** | $F(1, 227) = 0.76$ | .38 | .003 | 0.02 |
| **Content x Block x Trial Type** | $F(1, 227) = 0.20$ | .65 | .001 | 0.17 |
| **Study x Content x Block** | $F(1, 227) = 0.38$ | .57 | .001 | 0.21 |
| **Study x Content x Trial Type** | $F(1, 227) = 0.004$ | .95 | .001 | 0.19 |
| **Study x Block x Trial Type** | $F(1, 227) = 3.71$ | .05 | .02 | 0.25 |
| **Study x Content x Block x Trial Type** | $F(1, 227) = 0.51$ | .47 | .002 | 0.26 |



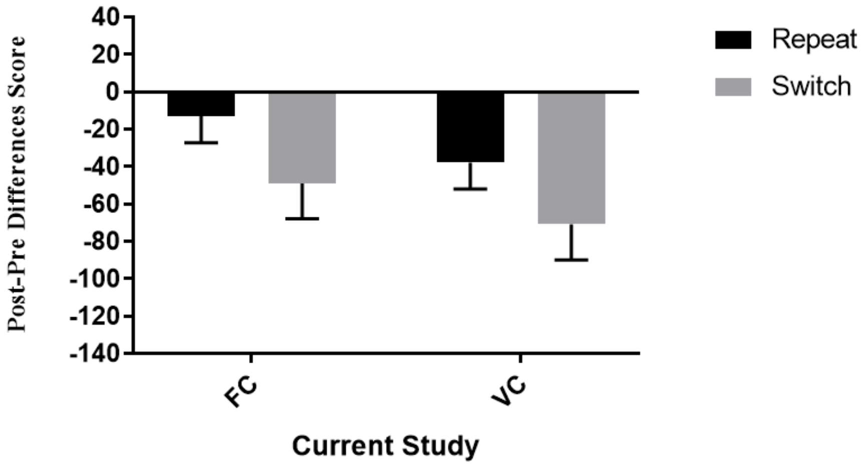




*Figure 5.* Comparison in transfer costs\gains (difference between baseline and transfer block) between Sabah et al. (2018) and the current study as a function of content variability and trial type. Note that the tasks and sequence in baseline and transfer-block were exactly the same in both studies. Error bars represent standard errors of the mean

**Training Outcomes on Verbal Fluency Measures**

To examine potential training modulation on a structurally dissimilar task of cognitive flexibility, here, verbal fluency, we first calculated a mean score for the total of generated words in the baseline and transfer block. To exclude initial difference between the groups, a one-way Frequentists and Bayesian ANOVAs were performed, pointing to no significant pre-existing difference, $F(3, 152) = 1.20$, $p = .311$, $\eta_p^2 = .02$, $BF_{10} =$ between the groups. Then, post-pre scores were calculated by subtracting the post from the pre-testing scores. Two-way Frequentists and Bayesian ANOVAs were performed on post-pre scores, entering content (fixed vs. varied) and learners' control (forced vs. voluntary) as between subject variables. No significant main effect was found for either content or learners' control, $F(1,152) =.13$, $p = .71$, $\eta_p^2 = .001$, $BF_{10} = 0.26$, $F(1,152) =.001$, $p = .97$, $\eta_p^2 = .001$, $BF_{10} = 0.27$. The scores were overall negative (M = -2.15), showing a general practice effect that was not further modulated by group (all $BF_{10} < 0.33$).

## Discussion

The current study attempted to examine the mutual contribution of variability and learners' control to training and transfer in short-term Task-switching training. To manipulate content variability, same or different task rules and stimuli were introduced during training. Learners' control was manipulated by applying either voluntary or forced Task-switching procedure. To enhance task demands during training, bivalent stimuli were used.

Three main findings stand out: First, we replicated the variability effect, found by Sabah et al. (2018), with content variability producing smaller practice effects yet higher transfer gains when compared to the FC condition. In contrast, learners' control did not induce additional beneficial effect on transfer beyond content variability. Lastly, we compared the present results to those of our former study, in which the exact same tasks during baseline and transfer were performed on univalent stimuli. This comparison showed that the current study yielded more pronounced transfer gains following VC training along with absent transfer costs after FC training. Thus, it is assumed that the enhanced control demands during training (usage of bivalent stimuli) underlie these more favorable outcomes. This latter result however is based on between study comparisons and therefore has to be treated with caution.

As expected, content variability is again found to promote better transfer outcomes in short-term Task-switching training. In line with Sabah et al (2018), disrupting learning by introducing practice variability seems to enhance transfer, with more pronounced benefit on switch when compared to repeat trials. Taken together, these results support the proclaimed notion of "desired difficulty", denoting the paradoxical nature of learning (Schmidt & Bjork, 1992). As such, it is postulated that creating challenging practice conditions can in fact facilitate deeper learning and retention yet withot any observable improvement during training. Despite the encourging pattern of near transfer gains (seen in Task-switching following VC training), no generlization effects were seen on the verbal fluency task. This in turn, falls in line with many recent indications that question the occurance of far transfer in CT (e.g., Dougherty, Hamovitz, & Tidwell, 2016; Melby-Lervåg, Redick, & Hulme, 2016; Soveri, Antfolk, Karlsson, Salo, & Laine, 2017).

With regard to learners' control, the resultts have failed to support our predictions. No additional transfer benefits beyond content variability were obtained in the voluntary when compared to the forced VC training condition. Consequently, the observed effect for learners' control in the trainig phase seems to merely reflect the different underlying cognitive process between the two procedures. Similar to Arrington and Logan (2005) our results revealed smaller switch costs in the voluntary when compared to the forced condition. The lack of modulating effect for learners' control on transfer is quite surprising when considering the existing litreature on learning and motivation, pointing to the contribtion of self-controlled practices to skill acquision across domains (e.g., Chiviacowsky, Wulf, Lewthwaite, et al., 2012; León, Núñez, & Liew, 2014; Sanli & Patterson, 2013). Hence, self-regulated practice has been suggested to underly effective learning, boosting key motivational componates, such as self-efficacy, higher task engagement and percieved competence (e.g., Bell & Kozlowski, 2008; Chiviacowsky, Wulf, & Lewthwaite, 2012; Deci & Ryan, 2008; Lewthwaite & Wulf, 2012; Ryan & Deci, 2000; Tafarodi, Milne, & Smith, 1999). In turn, the reason why we did not find any additional beneficial effect of learners' control might be due to the specific task instructions. That is, while participants were free to choose one of two tasks on each trial, they were also *told* to choose each task equally often but in a random order. This instruction might in fact have increased overall task demands rather than motivation. Furthermore, given that task demands were already high with varied content and bivalent stimuli, performance might have already reached ceiling. The overall higher transfer benefits and lower transfer costs as compared to Sabah et al. (2018) point to this direction.

Directly related to that, another aim of the current study was to explore whether enhancing task demands by utilizing bivalent stimuli might counteract the training costs following FC training condition (Sabah et al., 2018). As such, the results of the current study were compared to Sabah et al. (2018), excluding the voluntary conditions from analysis. The reason for this exclusion was to minimize the influence of excessive procedural variation between the studies when using VTS. As showed by the results, the effect for content variability was preserved across studies with higher training gains obtained here when compared to Sabah et al. (2018). In part, this falls in line with previous findings (Kray & Fehér, 2017), showing that enhanced interference demands in Task-switching (as a result of bivalency) leads to improved transfer effects. Nevertheless, unlike these authors, our results suggest that this advantageous outcome is not only restricted to older but also apparent among younger adults. Importantly, in contrast to Sabah et al (2018), no transfer costs in Task-switching performance emerged following FC training in the current study. This suggests on the one hand that higher task engagement by means of increased control demands might have prevented the occurrence of negative transfer. One the other hand, we cannot exclude the possibility of a failure to replicate Sabah et al.'s findings concerning costs. Lastly, it could also be possible that any observed differences between studies might be confounded by task structural differences (i.e., task sequence). In addition to content variability, Sabah et al (2018) introduced another variability manipulation on the deeper level of the task structural configuration, comparing fixed (i.e., alternating runs) with random task sequence. Conversely, in the current study, task sequence in the forced condition was determined by the choices of participants in the VTS conditions (i.e., by the yoking procedure), with task choices only approximating randomness. However, as task structure did not yield any notable effect in Sabah et al.'s (2018) study, such confounding effect seem quite implausible.

A noteworthy unexpected observation relates to the training effect on VSR in the FC and VC condition. Two lines of evidence would have suggested that varied content should increase the rate of voluntary task switching: Fröber and Dreisbach (2017) showed that frequent forced task switching increases cognitive flexibility and thus voluntary task switching (for a review see Dreisbach & Fröber, 2019). Additionally, Mayr and Bell (2006) had shown that single stimulus changes (from one trial to the next) invoke higher switch rates than stimulus repetitions. Both of these findings thus suggest that bottom up changes can motivate or otherwise cause voluntary task switching. However, VSR rates in the training blocks clearly point to the opposite direction. In fact, participants switched more often in the FC group and not in the VC group. It seems that at least during repetitive training of the same two tasks, participants tended to switch tasks more frequently, pointing perhaps to the possibility that switching serves as means to prevent boredom (e.g., Inzlicht et al., 2014; see also Jersild, 1927). Another interesting observation is the significant increase of VSR over the training blocks, a trend which was observed in both groups. Given that participants were asked to choose tasks equally often and in a random order (which would ideally result in a switch rate of 50%), this increase can in part be explained by the feedback (VSR in %) provided after the end of each block. However, participants in the FC condition had already reached the required 50% in Block 2 but still showed an increasing switch rate over the remaining blocks (see Fig. 2). This further speaks to the idea that participants in the FC may have avoided boredom. Alternatively, and not mutually exclusively, the VSR increase may be an instance of learned industriousness according to which effort is experienced as rewarding, and hence reinforces higher performance (Eisenberger, 1992). Future research is clearly needed to further disentangle the mechanisms underlying the differences in switch rates between content conditions

In sum, the current study provides additional support for the advantage of varied training regimes in short-term Task-switching training, with even more pronounced gains when coupled with increased task demands (i.e. bivalency). Although no notable impact for leaners' control on transfer was found, the (unpredicted) data pattern of VSR during practice (increasing VSR with increasing practice, higher VSR with fixed than varied content) points in interesting new directions. Future research may therefore address more directly the impact of boredom as an intrinsic modulator on task engagement and training outcome.

# STUDY III

## The Role of Working-Memory Gating Polices in Short-Term Cognitive Training

Sabah, K., Meiran, N. & Dreisbach, G. The Role of Working-Memory Gating Polices in Short-Term Cognitive Training. *Journal for Cognitive Enhancement* (In Review)

### Abstract

Internal working memory (WM) gating control polices have been suggested to constitute a critical components of task-sets that can be learned and transferred to very similar task contexts (Bhandari & Badre, 2018). Here we attempt to expand these findings, examining whether such control policies can be also trained and transferred to other untrained cognitive control tasks, namely to the task switching and AX-CPT. To this end, a context-processing WM task was used for training, allowing to manipulate either input (i.e., top-down selective entry of information into WM) - or output (i.e., bottom-up selective retrieval of WM) gating control policies by employing either a context-first (CF) or context-last (CL) task structure, respectively. In this task two contextual cues were each associated with two different stimuli. In CF condition, each trial began with a contextual cue, determining which of two subsequent stimuli is target relevant. In contrast, in the CL condition the contextual cue appeared last, preceded by a target and non-target stimuli successively. Participants completed a task switching baseline assessment, followed by one practice and six training blocks with the WM context-processing training task. After completing training, a task-switching and AX-CPT transfer blocks were administrated, respectively. As hypothesized, compared to CL training condition, CF training led to improved task-switching performance. However, contrary to our predictions, training type did not influence AX-CPT performance. Taken together, the current results provide further evidence that internal control policies are (a) inherent element of task-sets, also in task switching and (b) independent of S-R mappings. Importantly, our results

open a new venue for the realm of cognitive enhancement, pointing here for the first time to the potential of control policies training in promoting wider transfer effects.

## Introduction

Cognitive enhancement studies are faced with the challenge to produce transferable and durable learning effects to untrained structurally dissimilar contexts (i.e., far transfer) and real-life situations (Dougherty, Hamovitz, & Tidwell, 2016; Melby-Lervåg, Redick, & Hulme, 2016; Soveri, Antfolk, Karlsson, Salo, & Laine, 2017). Despite early encouraging results, the effectiveness of cognitive training (CT) remains disputable, with current training protocols showing at best rather limited generalization effects to very similar tasks (i.e., near transfer; Karbach & Verhaeghen, 2014; Schwaighofer, Fischer, & Bühner, 2015)

A central pitfall of current CTs seems to be anchored in their repetitive nature that may lead to automatization and task-specific learning, potentially incurring transfer costs (Sabah et al., 2018). In contrast, growing evidence suggests that the occurrence of learning generalization to novel contexts relies heavily on the human brain's ability to learn and represent abstract knowledge (e.g., task rules) and flexibly exploit this knowledge across multiple unfamiliar contexts, allowing rapid adjustment to new demands and situations (e.g., Badre et al., 2010; Cole et al., 2011, 2013; Collins & Frank, 2013; Dreisbach, 2012). Indirect evidence for the contribution of abstract task represention to learning and transfer emerges from CT studies advocating the importance of training variability (Gopher et al., 1989; Karbach & Kray, 2009; Sabah et al., 2018). For example, recent evidence suggests that the commonly undertaken approch of training "more of the same" promotes bottom-up learning, limited to the trained task (Sabah et al., 2018). In contrast, changing task information such as task rules and stimuli throughout training (i.e., content variability) was shown to promote transfer gains and to prevent negative transfer (costs), presumably by encourging the formation of abstarct task-rules (Karbach & Kray, 2009; Pereg et al., 2013b; Sabah et al., 2018; Shahar et al., 2018). Additional support for these claims comes from video game training studies, attributing the favourable transfer outcomes to variability in contextual information and to the related variability in cognitive processes offered (for review see Bavelier, Green, Pouget, & Schrater, 2012).

A form of abstract knowledge that is pertinent for task execution, are *internal control policies* or *task models – a* mental program that organizes task relevant information including rules, facts, stimuli, responses and timing in WM to control current behaviour (Bhandari & Badre, 2018; Duncan et al., 2008). Here, we aim to investigate more directly how the training of internal control policies may influence transfer to new tasks that might benefit from its application.

**Rules We Can't See or Hear: The Trainability and Transferability of Working Memory Gating Control Policies**

Internal control policies or task models are considered to encompass critical information for task execution such as facts, rules and task requirements, enabling real-time cognitive adjustments to task's dynamical structure (Bhandari & Badre, 2018; Bhandari & Duncan, 2014; Duncan et al., 2008). Within the domain of WM, the operation of such control policies can be embodied by gating mechanisms, which regulate the flow, updating and maintenance of information in alignment to task dynamics through the work of input and output gates (Chatham & Badre, 2015; Frank et al., 2001; Frank & Badre, 2012; O'Reilly & Frank, 2006; Todd et al., 2009). According to the gating framework, input gating selects which information is to be entered and updated in WM (top-down control) while output gating determines which information held in WM is response relevant. Recently, WM gating control policies were suggested to be trainable, supporting flexible behaviour and learning generalization (Bhandari & Badre, 2018). To train and compare between input and output gating policy training, Badre et al. (2018) employed a second-order context processing tasks (see figure 1).

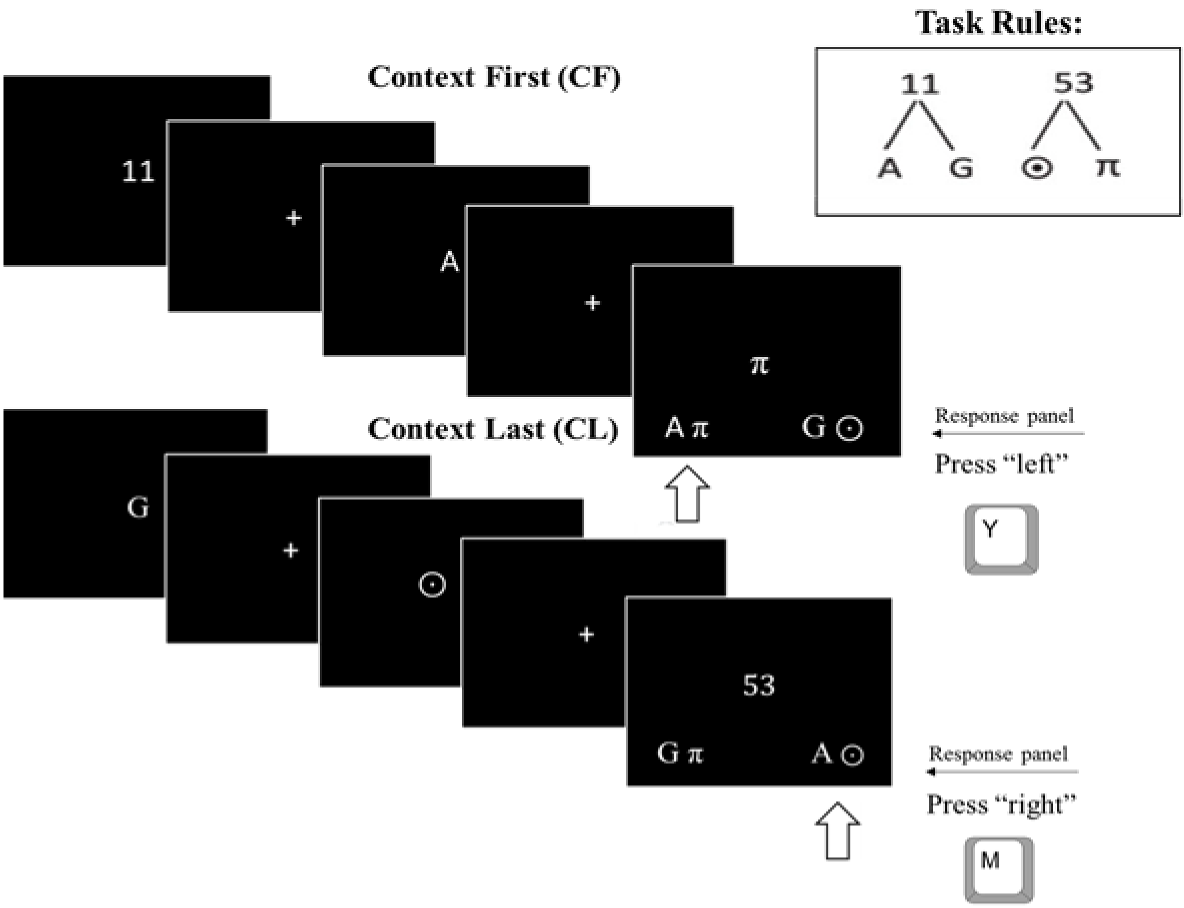



*Figure 1*. The second-order WM task rules and structure.

In this task, two contextual higher-order items (numbers) were each associated with two lower-order items. The cue 11 was associated with the letters A and G whereas the cue 53 was associated with the symbols ⊙ and π. Each trial presented a sequence of three items: a number cue, a letter and a symbol. Which of the two items (letter or symbol) was response relevant in a given sequence was determined by the number cue. Hence, whenever the cue "11" appears, participant need to respond to the letter. In contrast, whenever the cue "53" appears, a response to the symbol is required. To manipulate input and output gating policies, the number cue that discriminated the response relevant item either occurred first (context-first, CF) or last (context-last, CL) As such, the early appearance of the cue enables the selective entry of the target item into WM. In the given Context-First (CF) example, the first screen ("11") indicates that the response relevant item was a letter (figure 1, upper pannel). Response was determined in the last screen, here requiring a left-key response because the letter “A” appeared on the lower *left* side of the response panel. Conversly, in the CL condition the number cue appeard last in the sequence, supporting the usage of out-put gating processes, as it requires a selective retrieval of the relevant target item (figure 1, lower pannel). Here, the cue (53) appeared last after being preceded by the lower-order items G and ⨀. Here, the response relevant item was the symbol (⨀). Because the response-relevant item (⨀) appeared on the lower *right* side of the response panel, a right-key response is required. The outstanding finding in Bhandari & Badre (2018) was that experience with either the CL or CF conditions led to transfer of the trained gating policy to new contexts with the same ( e.g., CF -> CF) and different structure (e.g., CL-> CF).

The current study attempted to examine whether a similar short-term training in WM gating policies will produce a wider transfer effect to other cognitive control tasks sharing similar task dynamics. To this end, we used Bhandari and Badre’s task (Bhandari & Badre, 2018) for training, examining possible transfer effects to cued task switching and to a context processing paradigm (the AX-contious performance task AX-CPT).

**Examining the Contribition of WM Gating Policies to Task-Switching and AX-CPT Performance**

Task-switching (for reviews, see Kiesel et al., 2010; Monsell, 2003;Vandierendonck, Liefooghe, & Verbruggen, 2010) and AX-CPT (e.g., Braver & Cohen, 2000; Braver, Paxton, Locke, & Barch, 2009; Hefer & Dreisbach, 2016; 2017; Paxton, Barch, Racine, & Braver, 2008) are prominent paradigms to study cognitive control processes, underlying goal-directed and flexible behaviour (for reviews see Braver, 2012; Gratton, Cooper, Fabiani, Carter, & Karayanidis, 2018). Importantly, both the task-switching and AX-CPT paradigms were suggsted to involve gating processes (Braver & Cohen, 2000; D’Ardenne et al., 2012b; Kessler, 2017; Kessler et al., 2017; Rougier & O’Reilly, 2002), making them adequate transfer tasks for the current study.

The task switching paradigm is a widely used measure for cognitive flexibility and the main measure being the latency and accuracy rates when switching as compared to repeating tasks. A popular variant is the cued task-switching paradigm, in which a cue announces which of two tasks has to be executed in response to a bivalent stimulus (that in principle allows the application of both tasks ; Meiran, 2014). Cue-processing encourages proactive control (comparable to a CF condition) and thus eases the selection of the appropriate task. The AX-CPT is a context-processing task, applied for the study of WM processes and cognitive control dynamics. In this paradigm, a target response is required whenever an A-cue is followed by an X-probe, with AX sequences occurring with high frequency (70%), making the A cue highly predictive of the X probe. That way, the A-cue processing (comparable to a CF condition) encourages a proactive control mode leading to increased behavioural costs (higher error rates) when the A -cue is not followed by an X probe (i.e., AY trials) and to less errors when the X-probe is not preceded by an A (i.e. BX trials). Note that the typical assumption is that using a selective retrieval of contextual information is assumed to lead to higher interference on BX trials as the X- probe is strongly associated with a target-response (cf. Gonthier et al., 2016) .

Cued task switching and the AX-CPT thus share task dynamics with the second order WM task, used by Bhandari & Badre (2018). Namely they require hierarchical ta sk representation, in which response selection is bound to a higher-order contextual cue, the task cue or the A-cue, respectively (Braver & Barch, 2002). This structural similarity might facilitate transfer of cognitive control policies, here learned after exposure to the second-order WM task. For this purpose, a short-term WM gating policies training was applied, manipulating the type of trained gating policy by assigning participants to either a CF (input gating policy training) or a CL condition (output gating policy training). Task-switching performance was assessed prior and after training, utilizing a cued bivalent variation of the task-switching paradigm. Ultimately, participants were presented with an AX-CPT transfer block[3]. The following predictions were made:

1) For task-switching, higher transfer gains are expected to occur following CF as compared to CL training, reflected in higher reduction in RTs, both for task switches and task repetitions. There is a long-lasting debate on whether task switches and task repetitions profit to the same extent from pre-cues (e.g. Dreisbach, Haider & Kluwe, 2002). Therefore, it cannot be predicted whether switch costs should also be reduced in the CF condition as compared to the CL condition. In any case, we hypothesized that a selective operation of input gating control policies should encourage a selective entry of information within WM by means of enhanced cue processing, allowing for advanced preparation. This is supported by line of research suggesting benefits of enhanced cue processing and preparation processes to task switching performance (e.g., Meiran, 1996; Savine & Braver, 2010; for review see Kiesel et al., 2010 ).
2) For the AX-CPT, CL training was presumed to promote selective output gating policies that promote enhanced reactive control mode, leading to lower errors rates on AY-trails in the CL condition and to higher error rates on the BX trials in comparison to the CF condition. Moreover, CF might increase usage of the A cue, thereby leading to higher AY errors as compared to the CL condition.

[3] We decided against an AX-CPT block prior training, because the AX-CPT itself can be seen as a paradigm that promotes proactive control and cue usage like the CF condition does (for a detailed review on time on task effects in the AX-CPT see Hefer & Dreisbach, 2020). For the same reason, the order of task switching and AX-CPT was not counterbalanced but AX-CPT always was presented last.

## Method

### Participants

Eighty Regensburg University students (16 males; $M_{age}$ = 21.96, $SD$ = 2.74) were compensated with either one-hour course credit or were paid 6€. All participants reported having normal or corrected-to-normal vision and gave written consent prior to their participation in the study[4].

### Apparatus and Task Design

All experimental tasks were programmed in E-prime (Psychology Software Tools, Pittsburgh, PA, USA). The experiment was controlled by Dell computer with 19" flat screen.

**The second order WM control task (Training)**. The task was adapted from Bhandari and Badre (2018) based on the work of Chatham, Frank, and Badre (2014). On each trial, participants were presented with three stimuli, appearing in sequential order (see figure 1). Each sequence was composed of a number cue (11 or 53), a letter (A or G) and a symbol (π or ⨀). The contextual cue (number) determined for each trial whether the letter or symbol (lower level items) was response relevant. In specific, participants were instructed to memorize two rules through which the number 11 was associated with the letters whereas the number 53 was associated with the symbols (Please see Figure 1). For example, in a sequence composed of 11 → G → ⨀, the response relevant item was the letter G whereas the symbol ⨀ was response irrelevant. Alternatively, in a sequence composed of 53→A→ π, the response relevant item was the symbol π and the letter A was response irrelevant. Simultaneously with the presentation of the last item in a sequence, a response panel appeared on the lower part of the screen. On each side of the response panel, two pairs of lower level items, each comprising a letter and a symbol appeared. Participants were asked to press either a left (y) or right (m) response key, depending on where the target appeared in the response panel. For example, in the sequence 11 → G → ⨀, "G" was the target. Hence, the required

[4] It is noteworthy that 11 participants were replaced during data collection phase following exceptionally overall high error-rate on either the training task (>30%; CF: n=2; CL: n=3) or testing tasks (>50%; Task switching: n=2; AX-CPT: n=4).

response was the (right/left) side on which “G” appeared. In the response panel, there was an equal chance of congruent and incongruent item arrangement. In a congruent arrangement, the target and irrelevant item which appeared in a sequence appeared together on the same side of the response panel, hence both associated with the same response key. For example, the arrangement in the Context-First (upper) panel of Figure 1 is congruent since the target “A” and irrelevant item “π” appeared together on the left side of the response panel, both affording a left-key response. In contrast, in an incongruent arrangement, the target and irrelevant item which appeared in a sequence were presented on opposing sides of the response panel, each associated with different response key. As such, the Context-Last example in Figure 1 (lower panel) depicts an incongruent arrangement as the target “⨀” and irrelevant item “G” are associated with opponent response-keys (the right and left response key respectively). The location of the lower level items in the response panel was randomized, each appearing equally often on either the left or right side of the screen, with half of the trials requiring a right/left target response. Which of the lower item appeared first in the sequence was also randomized and balanced. All stimuli were printed in white, on a black background. We used the same stimuli set as Bhandari & Badre (2018) , extracted from (https://osf.io/exyks/).

Training consisted of six blocks, preceded by a short practice block to familiarize participants with the task and assure that the instructions were understood. Each block started with four instruction screens, followed by 48 trials. Two possible task structures were introduced, depending on the group assignment (see general procedure). For the CF group, each trial started with the cue (“11 or “53”), followed successively by two lower-level items, one response-relevant and the other response irrelevant (one letter and one symbol). In contrast, for the CL group, the cue appeared last in the sequence.

The first two items in the sequence appeared always for 300 ms whereas presentation of the last item was terminated upon response within a window of 3000 ms. A fixation cross was presented between stimulus presentation (pseudo-randomly jittered between 600-1600 ms) and between trials (ITI; 500). In the practice block, feedback was provided following incorrect trails, presenting the German word “Falsch” [incorrect] printed in red in the center of the screen.

**Task-switching (Baseline and Transfer blocks).** We used a modified version of the task-switching paradigm, including only mixed-tasks blocks. As stimuli, we used bivalent picture stimuli (meaning that the stimuli were relevant for the two tasks) depicting animals and objects. The size of the pictures was 1.57” x 1.18”. Participants switched between two task rules. One task rule was to classify the animals/objects as fly/can’t fly (Rule 1). The other rule was to classify these stimuli as living or non/living (Rule 2). We used four stimuli all affording the two task-rules that were assigned to either a left response key (y) or right response key (m) on a QWERTZ-keyboard, depending on the respective category. The response key assignment was counterbalanced across participants.

In both, baseline and transfer, the task-switching block started with two instructional slides presenting the task rules, followed by eight practice trials and a block of 64 experimental trials. Each trial started with a fixation cross for 500 ms, followed by cue for 650 ms. The target stimulus was then presented, remaining on screen either until a response was given or until 3500 ms had elapsed. Feedback was only presented for errors or too slow reaction times (slower than 3500 ms).

**AX-CPT** (Transfer**).** This paradigm (Servan-Schreiber, Cohen, & Steingard, 1996) is utilized as a measure of context-dependent cognitive control processes in which the cue determines the relevant response to consecutive lower-level item (i.e., probe). A target response was required whenever the letter A appears as a cue, followed by the letter X (AX trials), occurring 70% of all trial. Three non-target trial conditions were introduced (10% each): (a) AY condition in which the "A" cue was followed by a Y-probe (Y- all letters other than X); (b) BX condition in which the "X" probe was preceded by a B-cue (B – all letters other than A) or BY condition (the cue and probe were neither the letters A nor X). The higher frequency of the AX trials results in a strong expectation for a target response following the A-Cue, leading to high error rate on AY trials.

For response collection, a left response key (y) and right response key (m) on a QWERTZ-keyboard were used. The assignment of the response key to target and non-target response was counterbalanced between participants. The letters were printed in 24px Calibri Light font.

The block started with three instructional slides followed by 120 experimental trials. Each trial started with a cue (300 ms), a delay of 1500 ms which was then followed by the probe (300 ms). Participants had 1300 ms to respond. A feedback was presented for too slow reaction times (slower that 1300). The trial ended with a blank screen (ITI; 1000 ms).

**General Procedure**

Participants were randomly assigned to one of two equal sized training groups: (a) CF condition and (b) CL condition. They attended a one-hour experimental session, starting with task-switching baseline block, followed by one practice block with the WM training task, six training blocks and subsequently with task- switching and AX-CPT transfer blocks, respectively.

## Results

Practice trials as well as the first experimental trial were excluded from analysis. In addition, for calculating mean RTs, erroneous trials, trials preceding an error and trials deviating 3 *SD*s from the individual participant's mean in each block and trial type were discarded (24%). Following data processing, one participant from the CL was excluded from analysis due to exceptionally high error rate (40%), leaving only seven analyzable trials in the switch condition for that participant. Thus, data from 39 participants entered analysis eventually.

To look for potential initial differences between the training groups, 2 x 2 analysis of variance (ANOVA) was conducted just for the baseline block on both RTs and error rates, with trial type (repeat or switch) as within-subjects variable and group (CF or CL) as a between-subjects variable. For the RT data, the results revealed the typical switch cost pattern, such that slower responses were obtained on task-switch ($M = 811$ ms, 95% CI [765, 857]) as compared to task-repeat trials ($M = 743$ ms, 95% CI [703, 784], $F(1, 77) = 26.75$, $p < .001$, $\eta_p^2 = .26$, $BF_{10} > 100$. Unexpectedly, the main effect group reached significance with the Bayes Factor (BF) favoring H1, $F(1, 76) = 6.25$, $p < .05$, $\eta_p^2 = .07$, $BF_{10} = 4.80$. Participants in the CF group showed overall slower RTs ($M = 832$, 95% CI [744, 891]) as compared to the CL group ($M = 723$, 95% CI [664, 782]). In contrast, the evidence for an interaction between group and trial type provided evidence in favor of H0, $F = 1.09$, $p = .30$, $BF_{10} = 0.32$.

No significant effects were obtained in error data (all $F < 2.23$, all $p > .13$). The BFs for trial and group were indecisive tending to favour H0, $BF_{10\ (Trial)} = 0.49$, $BF_{10\ (Group)} = .40$, whereas evidence for H0 was obtained for the interaction Group x Trial, $BF_{10} = 0.28$.

**Training Performance – Context Processing Task**

A 2 x 6 mixed factors ANOVA was performed with block as a within-subjects variable (2-7) and group (CF or CL) as a between-subjects variable for both RTs and error rates (See Table 1 and Figure 2).

As seen in Tables 1, the main effect for group was significant for both RTs and error data, pointing to generally faster RTs and lower error rates in the CF ($M_{\mathrm{RTs}}$ = 731, 95% CI [669, 794]; $M_{Err}$= .04, 95% CI [.02, .06]) as compared to the CL group ($M_{\mathrm{RTs}}$ = 1167, 95% CI [1103, 1231]; $M_{Err}$ = .08, 95% CI [.06, .10]), thus replicating the findings of Bhandari & Badre (2018). The BF for group was aligned with the frequentist analysis, favoring H1.

The main effect block was significant in the RT data only, indicating to a reduction in RTs from Block 2 ($M_{\mathrm{RTs}}$ = 967, 95% CI [916, 1017]) to Block 7 ($M_{\mathrm{RTs}}$ = 922, 95% CI [876, 968]). The BF for block in the RT data provided only anecdotal evidence for H1 while that for the error data provided evidence for H0. The two-way interaction Group x Block was neither significant in RT nor error data (see Figure 2). The respective BF was indecisive for RT but provided evidence for the H0 in the error data.

**Table 1**. Main effects and interaction of the Group X Block ANOVA in the context processing training task (RTs and Error rates)

| | | ***Statistic*** | ***p* value** | **Effect Size ($\eta_p^2$)** | **$BF_{10}$** |
|---|---|---|---|---|---|
| **RTs** | Group | F(1, 77) = 93.37 | < .001*** | .55 | >100 |
| | Block | F(5, 385) = 3.13 | < .01** | .04 | 1.08 |
| | Group x Block | F(5, 385) = 2.05 | = .07 | .03 | 0.32 |
| **Error Rates** | Group | *F*(1, 77) = 10.04 | < .01** | .11 | 15.17 |
| | Block | *F*(5, 385) = 0.86 | = .50 | .01 | 0.01 |
| | Group x Block | *F*(5, 385) = 0.84 | = . 52 | .01 | 0.04 |

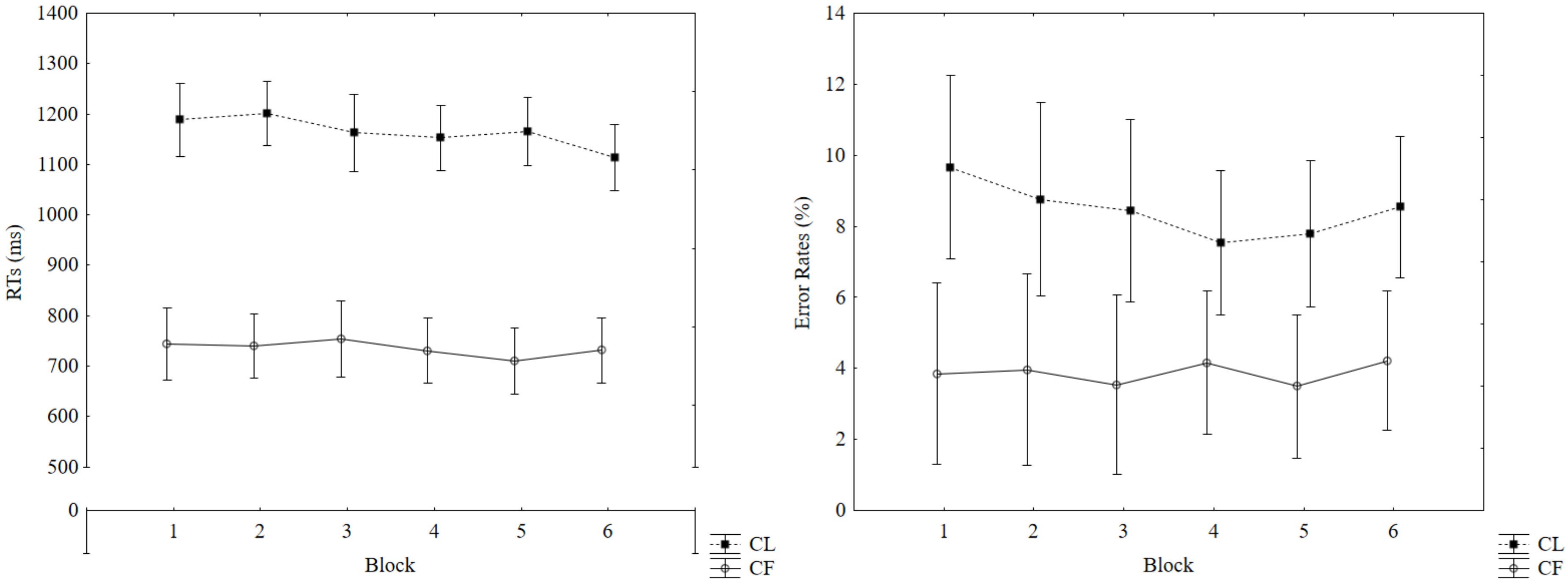



*Figure 2.* Mean RT in ms (left panel) and error rates in % (right panel) across the training blocks as a function of group. Error bars denote 95% confidence interval of the means.

**Transfer Performance – Task Switching**

To examine training effects on task switching performance, a 2 x 2 mixed factors ANOVA was conducted, with pre-test vs. post-test, trial type (repeat, switch) as within-subjects and group (CF, CL) as a between-subjects variable (for full Table of statistics, see Tables 2 and 3).

**Table 2**. Main effects and interaction of the Group X Block ANOVA in task-switching (RTs)

| | ***Statistic*** | ***p* value** | **Effect Size ($\eta_p^2$)** | **$BF_{10}$** |
|---|---|---|---|---|
| **Group** | $F(1, 77) = 2.93$ | 0.09 | .03 | 0.88 |
| **Block** | $F(1, 77) = 77.18$ | $< .001^{***}$ | .50 | >100 |
| **Trial Type** | $F(1, 77) = 29.82$ | $< .001^{***}$ | .28 | 24.01 |
| **Group x Block** | $F(1, 77) = 8.34$ | $< .01^{**}$ | .11 | >100 |
| **Trial Type x Block** | $F(1, 77) = 7.14$ | $< .01^{**}$ | .08 | 0.40 |
| **Trial Type x Group** | $F(1, 77) = 0.07$ | = . 79 | .001 | < 0.01 |
| **Trial Type x Block x Group** | $F(1, 77) = 6.76$ | $< .05^{*}$ | .08 | 0.56 |

**Table 3**. Main effects and interaction of the Group X Block ANOVA in task-switching (Error rates)

| | ***Statistic*** | ***p* value** | **Effect Size ($\eta_p^2$)** | **$BF_{10}$** |
|---|---|---|---|---|
| **Group** | $F(1, 77) = 1.51$ | 0.22 | .02 | 0.38 |
| **Block** | $F(1, 77) = 52.32$ | $< .001^{***}$ | .40 | >100 |
| **Trial Type** | $F(1, 77) = 8.04$ | $< .01^{**}$ | .09 | 1.77 |
| **Group x Block** | $F(1, 77) = 0.04$ | 0.84 | .001 | 0.16 |
| **Trial Type x Block** | $F(1, 77) = 0.31$ | = .57 | .004 | 0.18 |
| **Trial Type x Group** | $F(1, 77) = 0.71$ | = .40 | .01 | 0.24 |
| **Trial Type x Block x Group** | $F(1, 77) = 0.001$ | =.82 | .001 | 0.34 |

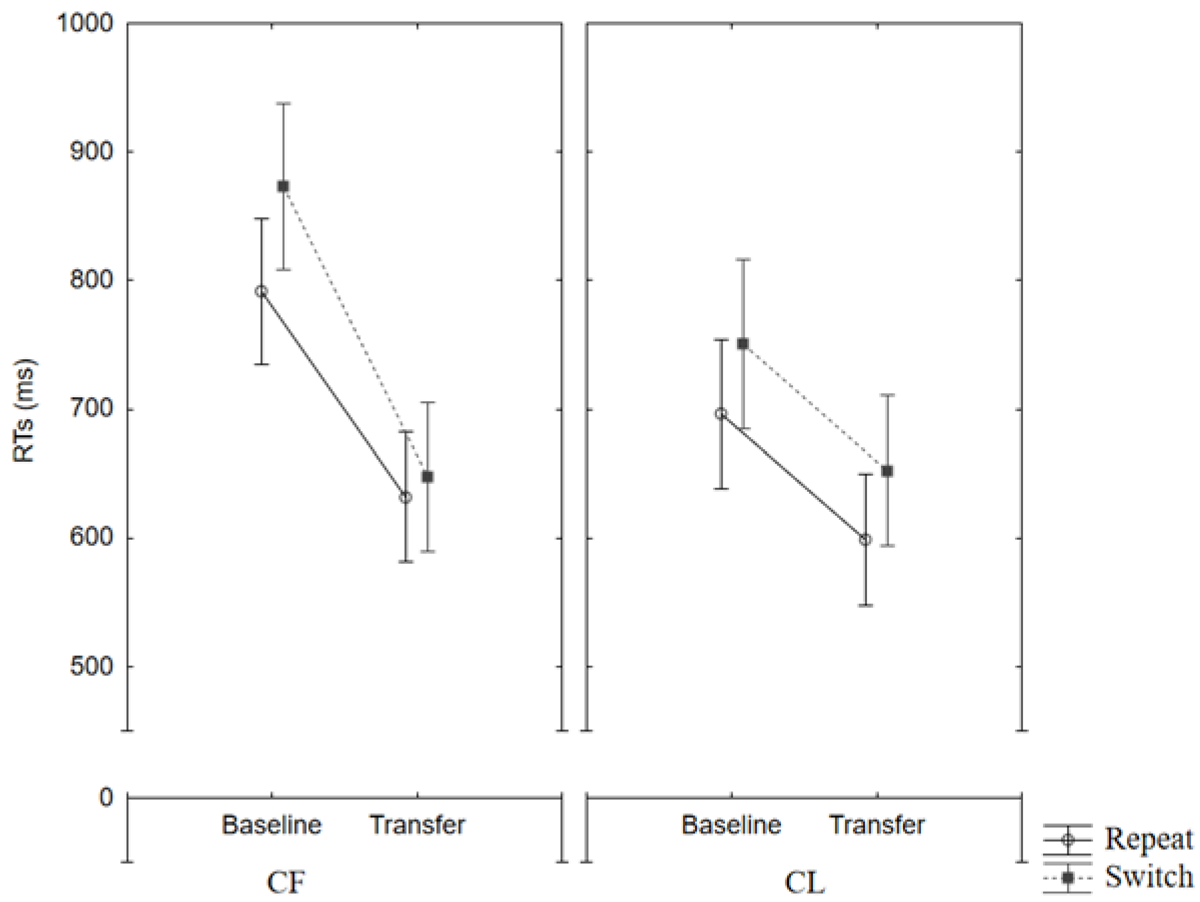



*Figure 3.* Mean RT in ms in baseline and transfer task-switching blocks in the CF (left panel) and CL condition (right panel). Error bars denote 95% confidence interval of the means.

**RTs.** As seen in Table 2, the main effect of block was significant, pointing to a reduction in RT from the baseline (*M* = 778 ms, 95% CI [736, 819]) to the transfer block (*M* = 633 ms, 95% CI [595, 670]). The BF provided very strong evidence for H1.

In addition, the main effect for trial type reached significance, denoting the typical switch costs, namely, slower RT on switch (*M* = 731 ms, 95% CI [691, 770]) as compared to repeat trials (*M* = 680 ms, 95% CI [645, 714]). This was further confirmed by Bayesian analysis, providing evidence in favor of H1. Conversely, the main effect of group did not reach significance, obtaining only anecdotal evidence for H0.

Importantly, the two-way interaction Group x Block was found to be significant. Despite the disadvantage in RT on the baseline block as compared to the CL group, higher reduction in RTs from baseline to the transfer block was found in the CF group ($M$ = -193 ms) as compared to the CL group ($M$ = -97 ms), $t(77)= 2.89$ , $p < .01$, $d = .65$. The BF provided very strong evidence for H1. The two-way interaction Group x Trial Type was not significant, finding a strong evidence for H0. A significant three-way interaction was found between group trial type and block (see Figure 3), indicating to a reduction in switch costs in the CF group, $t(39)= 3.50$ , $p < .01$, $d$ =.55, but not in the CL group ($p$= .64). In the transfer block, the CL group produced significantly higher switch costs as compared to the CF group, $t(77)= 2.07$, $p < .05$, $d$ =.46. However, the BF for the three-way interaction was indecisive.

Due to pre-existing differences between the groups in overall RT, we ran an additional analysis excluding participants from each group so that the slowest participants (as determined during pre-test) were ~equally slow in the two groups and the quickest participants were likewise ~equally quick, thus eliminating the initial group differences. In detail, we excluded participants in the CF whose RTs were higher than the $RT_{max}$ in the CL group (>1184 ms) and participants in the CL groups who responded faster than the $RT_{min}$ in the CF (< 559ms) (n=11; nine from the CL and two from the CF group). We then reanalyzed the trimmed data, the initial group differences were no longer significant and BF, albeit undecided, favored H0. Importantly, the statistical conclusions regarding a group by block interaction in task-switching remained unchanged (see Table S1 and S2 in supplementary material for the ANOVA results)[5].

Overall, the results indicate that CF training seems to lead to improved overall task switching performance as compared to CL training condition, indicating a transfer of learned

---

[5] ANCOVA analysis, inserting baseline RTs for repeat and switch trials as covariates, revealed a significant two-way interaction between group and trial type, $F(1, 75) = 6.86$, $p < .01$, $\eta p2 = .08$.

control policies to novel untrained contexts. Moreover, our data did not provide strong support for the reduction of switch costs in the CF group as compared to the CL group.

**Error rates.** The results point to significant main effect for block and very strong evidence for H1, indicating to a reduction in error rates from baseline (*M*= 0.10, 95% CI [0.08, 0.11]) to the transfer block (*M* = 0.04, 95% CI [0.03, 0.05]). Moreover, the main effect for trial type was also significant, pointing to typical switch costs, namely, higher error rates on switch (*M* = 0.08, 95% CI [0.06, 0.09]) compared to repeat trials (*M* = 0.06, 95% CI [0.05, 0.07]). The BF for trial was indecisive, tending to favor H1. No other effect reached significance. The found BF of group and that of the interaction Trial x Block x Group were indecisive, favoring H0 whereas the BFs for all two-way interaction provided strong evidence for H0.

**Transfer Performance – AX-CPT**

For RT analysis, the first trial as well as erroneous trials were excluded (5% of overall trials). A 4 x 2 mixed model ANOVA was performed on both RT and error rate, including condition as a within-subject independent variable (AX,AY,BX,BY) and group (CF,CL) as a between-subject independent variable (See Tables 4 and 5 for the ANOVA results).

**Table 4**. Main effects and interaction of the Group X Condition ANOVA in the AX-CPT block RTs)

| | ***Statistic*** | ***p* value** | **Effect Size ($\eta_p^2$)** | **$BF_{10}$** |
|---|---|---|---|---|
| **Group** | *F*(1, 77) = 0.65 | 0.42 | .01 | 0.26 |
| **Condition** | *F*(3, 231) = 125.10 | < .001*** | .61 | >100 |
| **Group x Condition** | *F*(3, 231) = 0.14 | 0.94 | .001 | 0.04 |

**Table 5**. Main effects and interaction of the Group X Condition ANOVA in the AX-CPT block Error rates)

| | ***Statistic*** | ***p* value** | **Effect Size ($\eta_p^2$)** | **$BF_{10}$** |
|---|---|---|---|---|
| **Group** | $F(1, 77) = 8.66$ | $< 0.01^{**}$ | .10 | 8.63 |
| **Condition** | $F(3, 231) = 26.93$ | $< .001^{***}$ | .26 | >100 |
| **Group x Condition** | $F(3, 231) = 0.09$ | 2.03 | .02 | 0.38 |

**RTs**. The results revealed the typical effect for condition, pointing to lower RT on AY (*M*= 493 ms, 95% CI [478, 0.508]) as compared to AX (*M*= 348 ms, 95% CI [335, 361]). All other effects were not significant, with results favoring H0 (All $F< 1$, $p> .45$, $BF_{10} < 0.26$).

**Error Rates**. The expected main effect for condition was significant, pointing to higher error rates on the AY (*M* = 0.23, 95% CI [0.17, 0.28]) as compared to AX (*M* = 0.12, 95% CI [0.06, 0.19). The main effect of group reached significance showing higher error rates in CF group (*M* = 0.25, 95% CI [0.17, 0.33]) as compared to CL group (*M* = 0.08, 95% CI [- 0.17, 0.16]). However, in contrast to our hypothesis, the two-way interaction Group x Condition did not reach significance, finding anecdotal support for H0.

## Discussion

The goal of the current study was to examine whether practicing WM gating control polices can lead to beneficial transfer to different cognitive control tasks that arguably involve similar control policies. To this end, we used Bhandari & Badre's (2018) second-order WM task and assigned participants to either an input-gating or output-gating policy training. Following training, transfer effects were assessed using the cued task-switching task and the AX-CPT task.

First, and in line with our hypothesis, CF structure training, more than CL structure training led to improvement in task switching performance, as evidenced in RT in both switch and repeat trials. Second, we did not find any effect of CL vs. CF training on performance in the AX-CPT task. There exists the possibility that this null effect reflects a methodological limitation which we were well aware of. Remember that the AX-CPT always occurred after task switching. This means that all participants had already worked through the cued task switching blocks where they experienced a condition involving CF. As a result, whatever group differences existed beforehand could have been eliminated.

Adhering to Bhandari and Badre (2018), we choose to interpret our findings within the working-memory gating frameowrk, attributing the advantage of the CF over CL training in task-switching to the learning and transfer of selective input-gating policies. Specifically, the early appearance of the cue in the CF condition encouraged participants to exploit this contextual information in order to optimize their performance through selective selection of information into WM. Successful transfer of such form of control policy to task switching produced performance gains, presumably by promoting advance preparation for the upcoming task, shown previously to benefit task switching (e.g., De Jong et al., 1999; Dreisbach et al., 2002; Meiran, 1996; Meiran & Chorev, 2005; Schuch & Koch, 2003). With respect to switch-costs, our results were less clear. The seemingly promising and novel switch cost reduction in the CF condition, as shown in the frequentist data analysis, was not supported by the Bayesian analysis. While such outcome can point to noise in our data, one cannot exclude the possibility that the absent Bayesian support for the alternative hypothesis is due to methodological limitation such as sample size or training dosage. Nonetheless, as argued by several authors, in the cued version of the task switching task, switch and repeat trials share preparatory processes (Dreisbach et al., 2002; Meiran et al., 2008; Shahar & Meiran, 2014; Sohn & Anderson, 2001).This is inherent in the unpredictable ordering of the task, requiring participants to know in advance the nature of the upcoming task (regardless if it repeats from the previous trial). These theories thus predict a benefit of CF training in both switch and repeat trials. With regard to training dosage, it remains less clear what is the optimal training dose for effective learning and promoting transfer effects. While some advocate for the importance of high training dose for transfer emergence, others suggest to the lack of any modulating effects for training dose on transfer (Brehmer et al., 2014; Jaeggi et al., 2008; Karbach & Verhaeghen, 2014a; Melby-Lervåg et al., 2016; Peng & Miller, 2016; Soveri et al., 2017a). In fact, recent studies suggest than transfer can actually occur even after single training sessions (Sabah et al., 2018; Shahar et al., 2018). This in turn seems to in line with existing evidence suggesting that the occurrence of skill acquisition per se requires only limited amount of practice with individuals reaching fast ceiling performance, developing automaticity (John R. Anderson, 1982; Logan, 1988).

More generally, our findings provide further support that internal control policies constitute a critical component of task switching and task-sets in general, which are independent from S-R associations. This in turn bares significant implications for the study of task switching, counteracting previous theoretical models speaking against the involvement of endogenous executive control processes (e.g., task reconfiguration upon switching and\or inhibition of previously activated task set) in cued task switching procedures, attributing switch costs to the benefits emerging on repeat trials due to mere cue priming effects (i.e., cue repetition; Logan & Bundesen, 2003; Schneider & Logan, 2005). Importantly and for the first time, we were able to show that the learning of control policies is not only transferable between very similar tasks (either CL or CF tasks; Bhandari & Badre, 2018) but also transfers to superficially dissimilar cognitive control tasks sharing similar task control dynamics. This in turn brings forward a new direction in cognitive training research, emphasizing the necessity to step back and reconsider the learning mechanisms of cognitive control. For example, a relevant and new theoretical contribution comes from recent studies, looking at the interaction between learning and cognitive control. This line of research points to the critical role of building-up and leveraging task-set structures extracted via contextual information in the service of learning and transfer of abstract policies that support cognitive control processes (Braun, Mehring, & Wolpert, 2010; Collins & Frank, 2013; Gershman, Blei, & Niv, 2010; Huys et al., 2015). Interestingly, such approaches draw among other on principles of categorial learning. Specifically, in their model, Collins and Frank (2013) propose that clustering via shared similarities between higher-order contextual features, that is how S-R contingences are conditioned by contexts, allows to identify applicable policies across unrelated contexts. Only recently, categorization-based learning has also been claimed to play an important role in the transfer problem, enhancing the frequency of spontaneous transfer (Kurtz & Honke, 2020). Others highlight the possibility that even abstract control settings such as flexibility can be learned and explained by way of associative learning (Abrahamse et al., 2016; Braem, 2017; Braem & Egner, 2018). As such form of learning seems to occur on higher hierarchical levels of abstraction, similar context training approaches might allow to promote wider transfer effects as compared to the currently applied training protocols, limited to specific task-rules and S-R association (e.g., Badre et al., 2010; Bhandari & Badre, 2018; Collins & Frank, 2013; Frank & Badre, 2012).

One possible noteworthy caveat of the current study might be the lack of control group (i.e., who did not undergo any control policy training) to decide whether it was really the CF training that improved and not the CL training that hampered task switching performance. However, this seems implausible here when considering that in both CF and CL groups, a reduction in overall RTs from baseline to transfer was observed. Additional downsize to consider is the absence of rest periods during training that might have led to fatigue, explaining as such the quite modest obtained learning effects. Instead, including rest periods have been shown to enhance cognition compared to non-rest conditions, which might have encouraged here a steeper learning curve and even stronger transfer effects (Steinborn & Huestegge, 2016) .

To conclude, our results support suggestions that internal control processes are an additional critical abstract entity constituting a task set that participants can learn through experience and reutilize across varied novel contexts (cf. Bhandari & Badre, 2018). For the first time, such control policies were shown to be transferable to novel untrained cognitive control task (i.e., far transfer), inducing performance gains. These results open a new venue for investigation for the domain of CT, allowing to better understand possible underlying mechanisms for its effectiveness.

# PART III

# GENERAL DISCUSSION

**Summary of Findings**

Following the wide controversy concerning the success of CT in producing generalizable improvements in cognitive ability, the current thesis endeavored on examining possible underlying mechanisms of generalizable training effects. Such investigation seems of extreme importance for the future advancement of cognitive enhancement domain.

**In study 1**, we examined the role of training variability in short-term task switching training. Content as well as structure variability were manipulated, resulting in four training conditions: FC/FS, FC/VS, VC/FS and VC/VC. A single training session was carried out, starting with a baseline block followed by seven training blocks and then with two task switching transfer blocks, one with FS and one with VS, respectively. Our findings supported the contribution of content but not structure training variability to transfer. A disassociation between training and transfer performance was noted. During training, notable improvement in task switching along the training blocks was observed among the FC but not the VC group. However, when transferred to new tasks, FC training seemed to induce transfer costs, with VC training producing transfer gains. Taken together, these findings (a) support the contribution of *desired difficulty* conditions, here content variability, to diminishing the costs of repetitive training and (b) suggest that learning performance is not necessarily a valid index for transfer occurrence (Schmidt & Bjork, 1992).

**In study 2**, we sought on expanding the results of our previous study, examining the additional benefits of enhanced task demands through the combined manipulation of content variability and increased task interference (i.e., bivalent stimuli utilization). Importantly, we examined the role of learners' control as an additional possible moderator of learning and transfer in CT. To this end, the task switching paradigm, manipulating (a) whether content remined fixed or varied across training and (b) whether participants were allowed to voluntarily switch\repeat a task or whether it was forced. A pre-post design was applied starting with a task switching and verbal fluency baseline blocks, followed by seven training blocks, task switching block (near transfer) and finally with verbal fluency block. To be able to compare between the two studies' results, we used the same baseline and transfer blocks as in study 1. As pointed out by our results, the content variability effect was replicated, failing however to show additional transfer benefits of learners' control beyond that of training variability. Interestingly, between-study comparison revealed an even higher transfer gains in study 2 when compared to study 1, modulated presumably by the enhanced task demands due to bivalent stimuli utilization.

**Study 3** draws on the previous findings of Bhandari & Badre (2018), suggesting that internal control policies, such as WM gating policies, are one critical aspect of task knowledge that can be learned and reutilized in novel similar contexts (near transfer). The study was conducted to expand these findings to the context of CT, assessing the possible contribution of WM gating policies to promoting wider transfer effects to other cognitive control tasks (far transfer). Similar to Bhandari & Badre (2018), the second order WM task was employed for training. Participants worked through a cued task switching block (bassline), followed by six training blocks with either a CF or CL task structure, affording the use of either input or output control policies respectively. Transfer was then assessed on the task switching and AX-CPT paradigm. When compared to CL training, CF task structure seemed to promote higher gains in task switching performance, due to transfer of selective input gating strategies. No impact of CL training was found. For the first time, we were able to show that WM control policies can be transferred to novel untrained cognitive control task (i.e., far transfer), promoting performance gains.

Taken together, the current work highlighted the role of *desirable difficulty* conditions such as [content] training variability in producing wider transfer gains. Enhanced task demands but not learners' control was found to promote even higher gains beyond that of training variability. For the first time, we showed that promoting abstraction on the higher-level of task knowledge through control policy training promotes far transfer effects, producing performance gains on untrained cognitive control tasks.

# New Direction to Reconceptualizing Effective CT

## Insights from Task Switching

The last decade has witnessed a huge revival of interest in cognitive enhancement, led by promising scientific evidence pointing to the success of WM and task switching training in promoting wide improvements in other untrained EF abilities and even GF. However, ample of consecutive attempts have failed to replicate these findings, showing only a very specific transfer effects in CT, resulting barely in near transfer effects to very similar tasks (see Lustig et al., 2009b; Melby-Lervåg et al., 2016; Melby-Lervåg & Hulme, 2013 for review). As such, stepping back to parse the underlying moderators of effective CT is necessary, offering new insights for future research.

### *Variability, effort and in-between*

So far, the realm of CT has been driven by *general-purpose* theoretical accounts to learning, assuming that improving one aspect of cognitive ability through training can promote general cognitive improvements (i.e., far transfer). Hence, the brain is approached as muscle that can be “shaped up” through repetitive and recurrent practice (Baumeister et al., 1998; Muraven & Baumeister, 2000; Simons et al., 2016). The current work sought to challenge this approach, arguing instead that this repetitiveness nature of CT leads instead to rigid and automatic behavioral patterns, limiting the occurrence of transfer (e.g., DeWitt, Sih & Wilson, 1998; Kakade & Dayan, 2002; Mery and Kawecki, 2004).

Accordingly, the finding of study 1 highlighted the incurred costs of “doing more of the same” approach, showing that training with fixed task rules and stimuli seemed to produce significant performance costs when transferred to novel task switching contexts (near transfer). In contrast, we gave solid evidence in both study 1 and 2 that *content variability* is a key underlying factor for preventing the occurrence of negative transfer and for promoting wider near transfer effects. These findings coincide with the learning principles proposed by Schmidt and Bjork (1992), emphasizing the importance of substantial but desirable effort manipulations to improving retention and generalization. This beneficial interplay between variability and effort to near transfer in CT is further suggested by the results of study 2, showing that the resulting increase in task demands due to bivalent stimuli utilization lead to even higher near transfer gains in varied content training and abolished the observed costs following fixed content training in study 1. These findings add to previous suggestions that engagement in effortful interference\conflict resolution processes during training is a key determinant for transfer occurrence (Anguera et al., 2013; Kray & Fehér, 2017). However, it is noteworthy that these assumptions are based on between-study comparisons and thus should be treated with caution, as we cannot exclude replication failure of the found costs in study 1. Aside from the residing favorable effort component to variability, we advocate to its role in (a) fostering higher-order abstract representations, transcending simple S-R associations and\or (b) enabling the relaxion of task shielding processes operating during repetitive task encounter (Dreisbach & Wenke, 2011; Miller & Cohen, 2001; Schmidt, 1975; Schmidt & Bjork, 1992).

In contrast to content, structure variability was not found to have any impact on near transfer outcomes in task switching training in study 1. First, taking into account the observed advantages of the preparatory processes afforded through task sequence foreknowledge to improving task switching performance, it is intriguing that no benefit for the fixed over the random structure was observed during learning (e.g., Monsell et al., 2003; Sohn & Carlson, 2000). Second, the absence of any benefits of the random task structure to near transfer in task switching seems to contradict theoretical accounts, advocating for the advantages of interleaved (random) over blocked (fixed) training schedules to enhancing retention and transfer (Schmidt & Bjork, 1992; Shea & Morgan, 1979). Last, unlike previous results, transfer from fixed structure training to the random task switching block didn't seem to incur any additional costs (Pereg et al., 2013). Taken together, this lack of modulating effect to task structure seems astonishing, especially when considering the suggested natural tendency of the human brain to create and learn abstract structures to benefit future behavior (Collins & Frank, 2013; Koch, 2005 Monsell et al., 2003). From here, this null effect of structure brings out possible methodological limitation in study 1, namely the use of univalent stimuli. In turn, this might lead participants to favor a less demanding waiting strategy, relying on bottom-up task-cuing (stimulus priming). This seems even more plausible when considering the more favorable transfer outcomes of using bivalent stimuli in study 2.

As we focused solely on near transfer outcomes in study 1, we wanted among other to further examine whether the favorable content variability effects in study 1 will replicate and extend also to measures of far transfer effects, namely verbal fluency. While the combination of training variability and increased task interference were found to promote wider near transfer effects in study 2, no indication to the occurrence of far transfer effects to another untrained measures of cognitive flexibility (i.e., verbal fluency) were obtained.  These results adjoin to large body of evidence casting dout on the occurance of far transfer in CT (e.g., Dougherty et al., 2016; Melby-Lervåg et al., 2016; Soveri et al., 2017). However, despite the scarce evidence for far transfer effects in CT, one cannot exclude that the failure to induce broader transfer effect beyond the trained task emerges from methodological rigors and the nature of the currently applied training protocols. For example, many of the existing training protocols target specific EF processes (i.e., process-based), applying one training task that taps this ability. Thus, it remains unclear whether this is sufficient to induce general improvement in the underlying targeted process, as it might promote superficial task-specific strategies, or whether variability in the utilized training tasks, not only task rules and stimuli, is necessitated. This can explain to some extent the more favorable transfer outcomes of video-game training, which is not only characterized by rich sensory experience but also engages varied spectrum of cognitive abilities (Bavelier et al., 2012; Green & Bavelier, 2012; Green et al., 2016). Another pressing matter to the notion of far transfer, is training dosage. While some findings support contribution of lengthy training to transfer, others speak against any interdependence between training dose and transfer (e.g., Soveri et al., 2017; Weicker et al., 2016). As such, the optimal training dose for wider transfer outcomes remains undetermined. Moreover, in study 2 we suggested that enhancing task demands seems beneficial for obtaining higher transfer gains, but it remains unclear what is the amount of effort required to produce maximal transfer effects, that is how do we obtain the suggested optimal mismatch between the individual available resources and task demands to induce plastic changes that allow for wider transfer effects (Lövdén et al., 2010)?

### ***Learners' Control: Food for Thought***

In contrary to our expectations, allowing for learners' control in task switching training was not found to modulate training outcomes. Despite the many documented motivational merits of learners' control in skill acquisition, no further advantages for voluntary over forced task switching training to transfer were observed (Bell & Kozlowski, 2008; Chiviacowsky, Wulf, Lewthwaite, et al., 2012; Deci & Ryan, 2008; León et al., 2014; Sanli & Patterson, 2013; Tafarodi et al., 1999). While our findings failed to present any evidence for the motivational benefits of learners' control, several concerns need to be taken in to account when interpreting these null effects. First, learners' control was manipulated in combination with training variability and task demands, thus it could be the case that a longer training was required to detect any additional benefits of the formers beyond those of the later. This in turn seems plausible when considering previous claims that motivational manipulations seem ineffective under short-term training conditions (Katz et al., 2014). Second, it is possible that by restricting participants freedom through the specific instructions to choose each task equally often and in a random order, we have increased task demands and not motivation. What could also point to this direction is the observation that learners' control seemed to modulate learning performance in the fixed but not varied content group. Moreover, as suggested by the overall higher transfer gains and reduced transfer costs in study 2 compared to study1, training was already highly demanding due to content variability and increased interference, which might have led participants to reach ceiling.

Taken together, in light of the above raised concerns, further research is required to clarify whether leaners' control might play a role in modulating training outcomes in CT, addressing the limitations of our study.  It would be also of great interest to examine other stronger manipulations of controllability such learning context, for example examining transfer outcomes in home-based training, allowing participants even more control over their learning process. In fact, there have been some preliminary suggestions to the utility of investigating self-paced home-based training to gauging the scope and limitations of transfer in CT (Payne & Stine-Morrow, 2017). Last, due to the so far scarce available knowledge on intrinsic underpinnings of effective CT, a deeper and more systematic exploration of individual differences and motivational influences on transfer is required.

***The Paradox of Learning: Lesson Learned***

An important outcome of study 1 and 2 is the found dissociation between training and transfer, emphasizing the necessity to distinguish between transient performance changes during practice and meaningful learning, that produces longer-term changes in behavior (retention) and transfer (Schmidt & Bjork, 1992). As suggested by our findings, disrupting learning during training by means of variability and enhanced task demands, seemed to promote higher transfer gains, despite the absence of any notable improvements during training *(*Schmidt & Bjork, 1992). These add to ample of empirical documentations, pointing out that training performance is not a reliable indicator of learning and transfer emergence (see Soderstrom & Bjork, 2015 for review). In fact, it is suggested that those very conditions that disrupt learning the most might lead often to the most optimal learning and transfer to novel contexts (Lin et al., 2010; Schmidt & Bjork, 1992; Simon & Bjork, 2001; Soderstrom & Bjork, 2015). As such, our results bring out the problematics of the widely applied research practices, relying on training effects as a measure of training effectiveness (see also Tidwell et al., 2014). For example, one such popular method is the correlated gains approach, in which training and transfer difference scores are correlated as proxy for training effectiveness (e.g., Baniqued et al., 2015; Zinke et al., 2012). Instead, and in line with the valuable commentary by Seitz (2017), our results call for a reconceptualization of learning, addressing its different facets and the conditions of its joint emergence. Hence, arriving into such understanding is a prerequisite for designing effective training and to better gauge the occurrence and breadth of transfer.

***Gauging Training Effects in Task Switching:***

To date, task switching training studies have relied on switch and mix costs as the sole parameters for evaluating training effectiveness. With regard to transfer, findings have been intermixed, with some studies pointing to a reduction in pre-post performance on both these measures while others finding specific reduction limited to one type of costs (Karbach & Kray, 2009; Minear & Shah, 2008; Zhao et al., 2020). In both study 1 and 2, no transfer gains were obtained in switch costs, showing instead to a reduction in overall latency from baseline to transfer in the varied content conditions. Therefore, this tends to point to improvement in global task switching performance, mirrored typically by mixing costs (Pereg et al., 2013; Strobach, Liepelt, Schubert & Kiesel, 2011; Zinke et al., 2012). On the other hand, we introduced yet another measure of transfer performance, namely pre-post score differences for repeat and switch trials, revealing a more pronounced reduction in latency that was specific to switch trials. An additional interesting venue to explore in future studies would be to evaluate possible transfer gains in VTS. Such examination will offer yet another training efficiency measure by examining possible increases in VSR following training, indexing increased flexibility (Arrington & Logan, 2004).

## Open Sesame: The Role of Gating Policies in CT

Throughout this dissertation, we continually highlighted the value of abstract knowledge representations to intelligent behavior in general and learning and transfer in specific. While in study 1 and 2 this interlink was indirectly addressed through the notion of variability, study 3 attempted to explicitly explore this matter by focusing on one critical aspect of abstract task knowledge, namely internal control policies. Previously, the trainability and learnability of control polices has been demonstrated within the domain of WM, captured through higher-order gating control mechanisms (Bhandari & Badre, 2018). Expanding this idea to the domain of CT, we provided further evidence that gating control policies are in fact trainable, constituting a critical component of task knowledge that is independent from S-R associations (Bhandari & Badre, 2018). Importantly and for the first time we showed that such knowledge can be reutilized to benefit performance on other distinct cognitive control tasks, here task switching, by exploiting regularities in task structure. As suggested by our results, training of selective input-gating control policies (CF condition) seemed to promote more efficient task preparation through enhanced cue processing, resulting in overall latency gains in task switching (e.g., De Jong et al., 1999; Dreisbach et al., 2002; Meiran, 1996; Meiran & Chorev, 2005; Schuch & Koch, 2003). Remember that in both the CF condition and task switching, a higher-order contextual information (i.e., cue) determines which task/stimuli are response relevant, thus allowing for more efficient selection and entry of information into WM. Less conclusive were however the results concerning switch costs, as the found gains in the frequentist data were not confirmed by Bayesian inference, thus possibly signaling to noise in our data. Nonetheless, the lack of support for the alternative hypothesis can also be related to possible methodological rigors such as sample size or training dosage. This can also explain the absence of any advantageous modulation for output over input gating policy training in the AX-CPT paradigm.

One fully cognizant additional limitation was the possible emergence of sequence effects due to the constant presentation of the AX-CPT after the task switching transfer block, with the later encouraging rather the employment of proactive input gating policies. As the nature of the AX-CPT itself further fosters such control policy or control mode (see Hefer & Dreisbach, 2020), it is not that surprising that we did not find an effect of the respective training conditions. If anything, the null effect in the AX-CPT together with the CF transfer effect in task switching suggest that control policies can be flexibly learned and applied to different task and context conditions. Such account is consistent with the findings of Bhandari & Badre (2018), showing that participants who executed a CF transfer block immediately after CF block after being previously trained on CL structure (i.e., CL → CF → CF) performed initially better than those exposed to only CL training structure (i.e., CL→CF). Alternatively, it could be the case that any indication for transfer of selective out-put gating might be observed only on the initial trails of the AX-CPT as with longer experience with the task, participants are encouraged to embrace a more proactive control mode. Unfortunately, such an analysis was not possible in the current study as the current design of the AX-CPT block didn't ensure a balanced distribution of the different conditions (i.e., AX, AY, BX, BY) within different trial bins.

Taken together our results bring up valuable new insights to the domain of CT, opening promising venues for future investigation. In specific, it highlights the importance of reassessing the interplay between cognitive control and learning processes, motivating generalizable cognitive control related skills. For example, particularly of interest are emerging hierarchical reinforcement learning accounts to cognitive control, pinpointing the role of policy abstraction in supporting flexible and adaptive cognitive control (see Bhandari et al., 2017 for a review). These suggest that learning and transfer of abstract control policies are facilitated in conditions that allow for hierarchical assemblance of task related contingencies, namely through the detection of abstract task structure, signaled by available contextual information (Collins et al., 2014; Collins & Frank, 2013; Frank & Badre, 2012). Alternatively, the acquisition of such abstract policies can be equally approached and investigated through the wider lens of associative learning (Abrahamse et al., 2016; Braem, 2017; Braem & Egner, 2018). Such understanding of cognitive control pave the way for a new and promising direction in CT, exploring further the potential of similar context training procedures to promoting wider transfer effects (e.g., Badre et al., 2010; Bhandari & Badre, 2018; Collins & Frank, 2013; Frank & Badre, 2012)

## Conclusion

Our findings challenge the “brain as a muscle” approach to cognitive enhancement, accentuating the incurred costs of the repetitive nature of the currently applied training protocols. In contrast, examined within the context of task switching (**study 1** and **2**), our results point to the benefits of *desired difficulty* manipulations, by means of content variability and enhanced task demands, to promoting more meaningful learning experience and thus higher transfer gains. Related to this was the observed dissociation between performance during training and transfer outcomes, warning against the common practices of utilizing training performance as an index for learning and transfer. Moreover, we “bring a fresh wind” to the domain of CT, offering a new promising avenue for tackling the problem of learning specificity in EF training. The results of **study *3*** provide further support to the role of abstract control policy learning in supporting adaptive and flexible behavior in distinct cognitive control tasks, suggesting to the emergence of far transfer. This in turn brings us to the importance of considering the joint mechanisms of learning and cognitive control that facilitates the build-up of such control policy repertoires and motivates its reutilization in novel contexts. Here we pinpoint to potential power of context in modulating learning of cognitive control related process, allowing to identify and leverage shared commonalities in task structure that facilitate the construction and transfer of such policies.

**References**


Abrahamse, E., Braem, S., Notebaert, W., & Verguts, T. (2016). Grounding cognitive control in associative learning. *Psychological Bulletin*, *142*(7), 693–728. https://doi.org/10.1037/bul0000047

Ackerman, P. L. (1987). Individual Differences in Skill Learning: An Integration of Psychometric and Information Processing Perspectives. In *Psychological Bulletin* (Vol. 102, Issue 1, pp. 3–27). https://doi.org/10.1037/0033-2909.102.1.3

Ahissar, M., & Hochstein, S. (2004). The reverse hierarchy theory of visual perceptual learning. *Trends in Cognitive Sciences*, *8*(10), 457–464. https://doi.org/10.1016/j.tics.2004.08.011

Al-Hashimi, O., Anguera, J. A., Rolle, C., Janowich, J., Kong, E., Gazzaley, A., Faraji, F., Johnston, E., Boccanfuso, J., Rintoul, J. L., & Larraburo, Y. (2013). Video game training enhances cognitive control in older adults. *Nature*, *501*(7465), 97–101. https://doi.org/10.1038/nature12486

Alloway, T. P., & Passolunghi, M. C. (2011). The relationship between working memory, IQ, and mathematical skills in children. *Learning and Individual Differences*, *21*(1), 133–137. https://doi.org/10.1016/j.lindif.2010.09.013

Álvarez-Bueno, C., Pesce, C., Cavero-Redondo, I., Sánchez-López, M., Martínez-Hortelano, J. A., & Martínez-Vizcaíno, V. (2017). The Effect of Physical Activity Interventions on Children’s Cognition and Metacognition: A Systematic Review and Meta-Analysis. In *Journal of the American Academy of Child and Adolescent Psychiatry*. https://doi.org/10.1016/j.jaac.2017.06.012

Anders Ericsson, K. (2008). Deliberate Practice and Acquisition of Expert Performance: A General Overview. *Academic Emergency Medicine*, *15*(11), 988–994. https://doi.org/10.1111/j.1553-2712.2008.00227.x

Anderson, B. A. (2018). Controlled information processing, automaticity, and the burden of proof. *Psychonomic Bulletin & Review*, *25*(5), 1814–1823. https://doi.org/10.3758/s13423-017-1412-7

Anderson, John R. (1982). Acquisition of cognitive skill. *Psychological Review*, *89*(4), 369–406. https://doi.org/10.1037/0033-295X.89.4.369

Anderson, John Robert. (1983). The architecture of cognition. In *The architecture of cognition.* (pp. xi, 345–xi, 345). Lawrence Erlbaum Associates, Inc.

Andreadis, N., & Quinlan, P. T. (2010). Task switching under predictable and unpredictable circumstances. *Attention, Perception, and Psychophysics*.

https://doi.org/10.3758/APP.72.7.1776

Angevaren, M., Vanhees, L., Wendel-Vos, W., Verhaar, H. J. j., Aufdemkampe, G., Aleman, A., & Verschuren, W. M. M. (2007). Intensity, but not duration, of physical activities is related to cognitive function. *European Journal of Cardiovascular Prevention & Rehabilitation*, *14*(6), 825–830. https://doi.org/10.1097/HJR.0b013e3282ef995b

Anguera, J. A., Boccanfuso, J., Rintoul, J. L., Al-Hashimi, O., Faraji, F., Janowich, J., Kong, E., Larraburo, Y., Rolle, C., Johnston, E., & Gazzaley, A. (2013). Video game training enhances cognitive control in older adults. *Nature*, *501*(7465), 97–101. https://doi.org/10.1038/nature12486

Arrington, C. M., & Logan, G. D. (2004). The cost of a voluntary task switch. *Psychological Science*, *15*(9), 610–615. https://doi.org/10.1111/j.0956-7976.2004.00728.x

Arrington, C. M., & Logan, G. D. (2005). Voluntary task switching: Chasing the elusive homunculus. In *Journal of Experimental Psychology: Learning Memory and Cognition* (Vol. 31, Issue 4, pp. 683–702). https://doi.org/10.1037/0278-7393.31.4.683

Arrington, C. M., Reiman, K. M., & Weaver, S. M. (2014). Voluntary task switching. In *Task switching and cognitive control.* (pp. 117–136). Oxford University Press. https://doi.org/10.1093/acprof:osobl/9780199921959.003.0006

Badre, D. (2012). Opening the gate to working memory. In *Proceedings of the National Academy of Sciences of the United States of America*. https://doi.org/10.1073/pnas.1216902109

Badre, D., Kayser, A. S., & D'Esposito, M. (2010). Frontal cortex and the discovery of abstract action rules. *Neuron*, *66*(2), 315–326. https://doi.org/10.1016/j.neuron.2010.03.025

Baggetta, P., & Alexander, P. A. (2016). Conceptualization and Operationalization of Executive Function. *Mind, Brain, and Education*, *10*(1), 10–33. https://doi.org/10.1111/mbe.12100

BALDWIN, T. T., & FORD, J. K. (1988). Transfer of Training: a Review and Directions for Future Research. *Personnel Psychology*, *41*(1), 63–105. https://doi.org/10.1111/j.1744-6570.1988.tb00632.x

Ball, K., Berch, D. B., Helmers, K. F., Jobe, J. B., Leveck, M. D., Marsiske, M., Morris, J. N., Rebok, G. W., Smith, D. M., Tennstedt, S. L., Unverzagt, F. W., & Willis, S. L. (2002). Effects of cognitive training interventions with older adults: A randomized controlled trial. *Journal of the American Medical Association*, *288*(18), 2271–2281. https://doi.org/10.1001/jama.288.18.2271

Bandura, A., Caprara, G. V., Barbaranelli, C., Gerbino, M., & Pastorelli, C. (2003). Role of Affective Self-Regulatory Efficacy in Diverse Spheres of Psychosocial Functioning. *Child Development*, *74*(3), 769–782. https://doi.org/10.1111/1467-8624.00567

Baniqued, P. L., Allen, C. M., Kranz, M. B., Johnson, K., Sipolins, A., Dickens, C., Ward, N., Geyer, A., & Kramer, A. F. (2015). Working Memory, Reasoning, and Task Switching Training: Transfer Effects, Limitations, and Great Expectations? *PLOS ONE*, *10*(11), e0142169. https://doi.org/10.1371/journal.pone.0142169

Barbey, A. K., Krueger, F., & Grafman, J. (2009). Structured event complexes in the medial prefrontal cortex support counterfactual representations for future planning. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *364*(1521), 1291–1300. https://doi.org/10.1098/rstb.2008.0315

Barnett, S. M., & Ceci, S. J. (2002). When and where do we apply what we learn? A taxonomy for far transfer. *Psychological Bulletin*, *128*(4), 612–637. https://doi.org/10.1037/0033-2909.128.4.612

Baumeister, R. F., Bratslavsky, E., Muraven, M., & Tice, D. M. (1998). Ego depletion: Is the active self a limited resource? In *Journal of Personality and Social Psychology* (Vol. 74, Issue 5, pp. 1252–1265). American Psychological Association. https://doi.org/10.1037/0022-3514.74.5.1252

Bavelier, D., & Green, C. S. (2019). Enhancing Attentional Control: Lessons from Action Video Games. In *Neuron*. https://doi.org/10.1016/j.neuron.2019.09.031

Bavelier, D., Green, C. S., Pouget, A., & Schrater, P. (2012). Brain Plasticity Through the Life Span: Learning to Learn and Action Video Games. *Annual Review of Neuroscience*, *35*(1), 391–416. https://doi.org/10.1146/annurev-neuro-060909-152832

Becker, D. A., & Dwyer, M. M. (1994). Using hypermedia to provide learner control. *Journal of Educational Multimedia and Hypermedia*, *3*, 155–172.

Bell, B. S., & Kozlowski, S. W. J. (2008). Active Learning: Effects of Core Training Design Elements on Self-Regulatory Processes, Learning, and Adaptability. *Journal of Applied Psychology*, *93*(2), 296–316. https://doi.org/10.1037/0021-9010.93.2.296

Bench, C. J., Frith, C. D., Grasby, P. M., Friston, K. J., Paulesu, E., Frackowiak, R. S. J., & Dolan, R. J. (1993). Investigations of the functional anatomy of attention using the stroop test. *Neuropsychologia*, *31*(9), 907–922. https://doi.org/10.1016/0028-3932(93)90147-R

Betik, A. C., & Hepple, R. T. (2008). Determinants of VO2 max decline with aging: An integrated perspective. In *Applied Physiology, Nutrition and Metabolism*. https://doi.org/10.1139/H07-174

Bhandari, A., & Badre, D. (2018). Learning and transfer of working memory gating policies. *Cognition*, *172*, 89–100. https://doi.org/10.1016/j.cognition.2017.12.001

Bhandari, A., Badre, D., & Frank, M. J. (2017). Learning Cognitive Control. In *The Wiley Handbook of Cognitive Control* (pp. 376–391). https://doi.org/10.1002/9781118920497.ch21

Bhandari, A., & Duncan, J. (2014). Goal neglect and knowledge chunking in the construction of novel behaviour. *Cognition*, *130*(1), 11–30. https://doi.org/10.1016/j.cognition.2013.08.013

Billard, C. (2017). Avant-propos: Les fonctions exécutives chez l'enfant... Où en est-on ? *ANAE - Approche Neuropsychologique Des Apprentissages Chez l'Enfant*, *29*(146), 13–15. https://doi.org/10.1146/annurev-psych-113011-143750

Boot, W. R. (2015). Video games as tools to achieve insight into cognitive processes. In *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2015.00003

Boot, W. R., Kramer, A. F., Simons, D. J., Fabiani, M., & Gratton, G. (2008). The effects of video game playing on attention, memory, and executive control. *Acta Psychologica*, *129*(3), 387–398. https://doi.org/10.1016/j.actpsy.2008.09.005

Botvinick, M., & Braver, T. (2015). Motivation and Cognitive Control: From Behavior to Neural Mechanism. *Annual Review of Psychology*, *66*(1), 83–113. https://doi.org/10.1146/annurev-psych-010814-015044

Bown, N. J., Read, D., & Summers, B. (2003). The Lure of Choice. *Journal of Behavioral Decision Making*, *16*(4), 297–308. https://doi.org/10.1002/bdm.447

Braem, S. (2017). Conditioning task switching behavior. *Cognition*, *166*, 272–276. https://doi.org/10.1016/j.cognition.2017.05.037

Braem, S., & Egner, T. (2018). Getting a Grip on Cognitive Flexibility. *Current Directions in Psychological Science*, *27*(6), 470–476. https://doi.org/10.1177/0963721418787475

Braver, T. S. (2012a). The variable nature of cognitive control: A dual mechanisms framework. In *Trends in Cognitive Sciences* (Vol. 16, Issue 2, pp. 106–113). https://doi.org/10.1016/j.tics.2011.12.010

Braver, T. S. (2012b). The variable nature of cognitive control: a dual mechanisms framework. *Trends in Cognitive Sciences*, *16*(2), 106–113. https://doi.org/10.1016/j.tics.2011.12.010

Braver, T. S., & Barch, D. M. (2002). A theory of cognitive control, aging cognition, and neuromodulation. *Neuroscience & Biobehavioral Reviews*, *26*(7), 809–817. https://doi.org/10.1016/S0149-7634(02)00067-2

Braver, T. S., & Cohen, J. D. (2000). On the Control of Control: The Role of Dopamine in Regulating Prefrontal Function and Working Memory. In *Control of Cognitive Processes* (Vol. 18, pp. 712–737). The MIT Press. https://doi.org/10.7551/mitpress/1481.003.0044

Braver, T. S., Paxton, J. L., Locke, H. S., & Barch, D. M. (2009). Flexible neural mechanisms of cognitive control within human prefrontal cortex. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(18), 7351–7356. https://doi.org/10.1073/pnas.0808187106

Brehmer, Y., Kalpouzos, G., Wenger, E., & Lövdén, M. (2014). Plasticity of brain and cognition in older adults. *Psychological Research*, *78*(6), 790–802. https://doi.org/10.1007/s00426-014-0587-z

Brehmer, Y., Li, S. C., Müller, V., Von Oertzen, T., & Lindenberger, U. (2007). Memory plasticity across the life span: Uncovering children's latent potential. *Developmental Psychology*, *43*(2), 465–478. https://doi.org/10.1037/0012-1649.43.2.465

Brehmer, Y., Westerberg, H., & Bäckman, L. (2012). Working-memory training in younger and older adults: Training gains, transfer, and maintenance. *Frontiers in Human Neuroscience*. https://doi.org/10.3389/fnhum.2012.00063

Broadbent, D. E. (2004). Perception and communication. In *Perception and communication.* Pergamon Press. https://doi.org/10.1037/10037-000

Brown, J., Cooper-Kuhn, C. M., Kempermann, G., Van Praag, H., Winkler, J., Gage, F. H., & Kuhn, H. G. (2003). Enriched environment and physical activity stimulate hippocampal but not olfactory bulb neurogenesis. *European Journal of Neuroscience*. https://doi.org/10.1046/j.1460-9568.2003.02647.x

Brunner, D., Abramovitch, A., & Etherton, J. (2017). A yoga program for cognitive enhancement. *PLoS ONE*, *12*(8). https://doi.org/10.1371/journal.pone.0182366

Buchler, N. G., Hoyer, W. J., & Cerella, J. (2008). Rules and more rules: The effects of multiple tasks, extensive training, and aging on task-switching performance. *Memory and Cognition*. https://doi.org/10.3758/MC.36.4.735

Buitenweg, J. I. V., Murre, J. M. J., & Ridderinkhof, K. R. (2012). Brain training in progress: a review of trainability in healthy seniors. *Frontiers in Human Neuroscience*, *6*. https://doi.org/10.3389/fnhum.2012.00183

Bürki, C. N., Ludwig, C., Chicherio, C., & de Ribaupierre, A. (2014). Individual differences in cognitive plasticity: an investigation of training curves in younger and older adults. *Psychological Research*, *78*(6), 821–835. https://doi.org/10.1007/s00426-014-0559-3

Bush, G., Whalen, P. J., Rosen, B. R., Jenike, M. A., McInerney, S. C., & Rauch, S. L.

(1998). The counting stroop: An interference task specialized for functional neuroimaging—validation study with functional MRI. *Human Brain Mapping*, *6*(4), 270–282. https://doi.org/10.1002/(sici)1097-0193(1998)6:4<270::aid-hbm6>3.3.co;2-h

Byrnes, J. P. (2008). Cognitive Development and Learning in Instructional Contexts. In *Cognitive Development and Learning in Instructional Contexts* (pp. 9–47).

Cardoso-Leite, P., Joessel, A., & Bavelier, D. (2018). Game Features for Cognitive Enhancements : Lessons from Action Video Games. In *Game Features for Cognitive Enhancements*.

Carnahan, H., Van Eerd, D. L., & Allard, F. (1990). A Note on the Relationship Between Task Requirements and the Contextual Interference Effect. *Journal of Motor Behavior*, *22*(1), 159–169. https://doi.org/10.1080/00222895.1990.10735507

Cartwright, K. B. (2012). Insights From Cognitive Neuroscience: The Importance of Executive Function for Early Reading Development and Education. *Early Education and Development*, *23*(1), 24–36. https://doi.org/10.1080/10409289.2011.615025

Chaddock-Heyman, L., Erickson, K. I., Kienzler, C., Drollette, E. S., Raine, L. B., Kao, S.-C., Bensken, J., Weisshappel, R., Castelli, D. M., Hillman, C. H., & Kramer, A. F. (2018). Physical Activity Increases White Matter Microstructure in Children. *Frontiers in Neuroscience*. https://doi.org/10.3389/fnins.2018.00950

Chatham, C. H., & Badre, D. (2015). Multiple gates on working memory. *Current Opinion in Behavioral Sciences*, *1*, 23–31. https://doi.org/10.1016/j.cobeha.2014.08.001

Chatham, C. H., Herd, S. A., Brant, A. M., Hazy, T. E., Miyake, A., O’Reilly, R., & Friedman, N. P. (2011). From an executive network to executive control: A computational model of the n-back task. *Journal of Cognitive Neuroscience*, *23*(11), 3598–3619. https://doi.org/10.1162/jocn_a_00047

Chein, J. M., & Morrison, A. B. (2010a). Expanding the mind’s workspace: Training and transfer effects with a complex working memory span task. *Psychonomic Bulletin and Review*, *17*(2), 193–199. https://doi.org/10.3758/PBR.17.2.193

Chein, J. M., & Morrison, A. B. (2010b). Expanding the mind’s workspace: Training and transfer effects with a complex working memory span task. *Psychonomic Bulletin and Review*. https://doi.org/10.3758/PBR.17.2.193

Chiviacowsky, S., Wulf, G., & Lewthwaite, R. (2012). Self-controlled learning: The importance of protecting perceptions of competence. *Frontiers in Psychology*, *3*(NOV). https://doi.org/10.3389/fpsyg.2012.00458

Chiviacowsky, S., Wulf, G., Lewthwaite, R., & Campos, T. (2012). Motor learning benefits of self-controlled practice in persons with Parkinson's disease. *Gait and Posture, 35*(4), 601–605. https://doi.org/10.1016/j.gaitpost.2011.12.003

Clement, C. A., & Gentner, D. (1991). Systematicity as a selection constraint in analogical mapping. *Cognitive Science, 15*(1), 89–132. https://doi.org/10.1016/0364-0213(91)80014-V

Cohen, J. D. (2017). The basics of cognitive control: Core constructs and current considerations. *The Wiley Handbook of Cognitive Control*. https://doi.org/10.1002/9781118920497.ch1

Colcombe, S. J., Erickson, K. I., Scalf, P. E., Kim, J. S., Prakash, R., McAuley, E., Elavsky, S., Marquez, D. X., Hu, L., & Kramer, A. F. (2006). Aerobic exercise training increases brain volume in aging humans. *Journals of Gerontology - Series A Biological Sciences and Medical Sciences*. https://doi.org/10.1093/gerona/61.11.1166

Colcombe, S., & Kramer, A. F. (2003). Fitness effects on the cognitive function of older adults: A meta-analytic study. *Psychological Science*. https://doi.org/10.1111/1467-9280.t01-1-01430

Cole, M. W., Etzel, J. A., Zacks, J. M., Schneider, W., & Braver, T. S. (2011). Rapid Transfer of Abstract Rules to Novel Contexts in Human Lateral Prefrontal Cortex. *Frontiers in Human Neuroscience, 5*. https://doi.org/10.3389/fnhum.2011.00142

Cole, M. W., Laurent, P., & Stocco, A. (2013). Rapid instructed task learning: A new window into the human brain's unique capacity for flexible cognitive control. In *Cognitive, Affective and Behavioral Neuroscience* (Vol. 13, Issue 1, pp. 1–22). https://doi.org/10.3758/s13415-012-0125-7

Collins, A. G. E., Cavanagh, J. F., & Frank, M. J. (2014). Human EEG uncovers latent generalizable rule structure during learning. *Journal of Neuroscience*, *34*(13), 4677–4685. https://doi.org/10.1523/JNEUROSCI.3900-13.2014

Collins, A. G. E., & Frank, M. J. (2013). Cognitive control over learning: Creating, clustering, and generalizing task-set structure. *Psychological Review*, *120*(1), 190–229. https://doi.org/10.1037/a0030852

Colzato, L. S., van Leeuwen, P. J. A., van den Wildenberg, W. P. M., & Hommel, B. (2010). DOOM'd to switch: Superior cognitive fl exibility in players of first person shooter games. *Frontiers in Psychology, APR*. https://doi.org/10.3389/fpsyg.2010.00008

Cotman, C. W., & Berchtold, N. C. (2002). Exercise: A behavioral intervention to enhance brain health and plasticity. In *Trends in Neurosciences*. https://doi.org/10.1016/S0166-2236(02)02143-4

Cotrena, C., Branco, L. D., Shansis, F. M., & Fonseca, R. P. (2016). Executive function impairments in depression and bipolar disorder: Association with functional impairment and quality of life. *Journal of Affective Disorders*. https://doi.org/10.1016/j.jad.2015.11.007

Cragg, L., & Nation, K. (2008). Go or no-go? Developmental improvements in the efficiency of response inhibition in mid-childhood. *Developmental Science*, *11*(6), 819–827. https://doi.org/10.1111/j.1467-7687.2008.00730.x

D'Ardenne, K., Eshel, N., Luka, J., Lenartowicz, A., Nystrom, L. E., & Cohen, J. D. (2012a). Role of prefrontal cortex and the midbrain dopamine system in working memory updating. *Proceedings of the National Academy of Sciences of the United States of America*. https://doi.org/10.1073/pnas.1116727109

D'Ardenne, K., Eshel, N., Luka, J., Lenartowicz, A., Nystrom, L. E., & Cohen, J. D. (2012b). Role of prefrontal cortex and the midbrain dopamine system in working memory updating. *Proceedings of the National Academy of Sciences*, *109*(49), 19900–19909. https://doi.org/10.1073/pnas.1116727109

Dahlin, E., Neely, A. S., Larsson, A., Bäckman, L., & Nyberg, L. (2008). Transfer of learning after updating training mediated by the striatum. *Science*, *320*(5882), 1510–1512. https://doi.org/10.1126/science.1155466

De Jong, R., Berendsen, E., & Cools, R. (1999). Goal neglect and inhibitory limitations: Dissociable causes of interference effects in conflict situations. *Acta Psychologica*, *101*(2–3), 379–394. https://doi.org/10.1016/s0001-6918(99)00012-8

Deci, E. L., & Ryan, R. M. (2008). Self-determination theory: A macrotheory of human motivation, development, and health. *Canadian Psychology*, *49*(3), 182–185. https://doi.org/10.1037/a0012801

Demirakca, T., Cardinale, V., Dehn, S., Ruf, M., & Ende, G. (2016). The exercising brain: Changes in functional connectivity induced by an integrated multimodal cognitive and whole-body coordination training. *Neural Plasticity*. https://doi.org/10.1155/2016/8240894

DeWitt, T. J., Sih, A., & Wilson, D. S. (1998). Costs and limits of phenotypic plasticity. *Trends in Ecology and Evolution*. https://doi.org/10.1016/S0169-5347(97)01274-3

Diamond, A. (2013). Executive Functions. *Annual Review of Psychology*. https://doi.org/10.1146/annurev-psych-113011-143750

Donnelly, J. E., Hillman, C. H., Castelli, D., Etnier, J. L., Lee, S., Tomporowski, P., Lambourne, K., & Szabo-Reed, A. N. (2016). Physical activity, fitness, cognitive function, and academic achievement in children: A systematic review. In *Medicine and Science in Sports and Exercise*. https://doi.org/10.1249/MSS.0000000000000901

Dosher, B. A., Jeter, P., Liu, J., & Lu, Z. L. (2013). An integrated reweighting theory of perceptual learning. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(33), 13678–13683. https://doi.org/10.1073/pnas.1312552110

Dougherty, M. R., Hamovitz, T., & Tidwell, J. W. (2016). Reevaluating the effectiveness of n-back training on transfer through the Bayesian lens: Support for the null. *Psychonomic Bulletin and Review*, *23*(1), 306–316. https://doi.org/10.3758/s13423-015-0865-9

Dove, A., Pollmann, S., Schubert, T., Wiggins, C. J., & Yves Von Cramon, D. (2000). Prefrontal cortex activation in task switching: An event-related fMRI study. *Cognitive Brain Research*, *9*(1), 103–109. https://doi.org/10.1016/S0926-6410(99)00029-4

Dreisbach, G. (2012). Mechanisms of Cognitive Control: The Functional Role of Task Rules. *Current Directions in Psychological Science*, *21*(4), 227–231. https://doi.org/10.1177/0963721412449830

Dreisbach, G., & Haider, H. (2008). That's what task sets are for: Shielding against irrelevant information. *Psychological Research*, *72*(4), 355–361. https://doi.org/10.1007/s00426-007-0131-5

Dreisbach, G., Haider, H., & Kluwe, R. H. (2002). Preparatory Processes in the Task-Switching Paradigm: Evidence from the Use of Probability Cues. *Journal of Experimental Psychology: Learning Memory and Cognition*, *28*(3), 468–483. https://doi.org/10.1037/0278-7393.28.3.468

Dreisbach, G., & Wenke, D. (2011). The Shielding Function of Task Sets and Its Relaxation During Task Switching. *Journal of Experimental Psychology: Learning Memory and Cognition*, *37*(6), 1540–1546. https://doi.org/10.1037/a0024077

Duncan, J., Parr, A., Woolgar, A., Thompson, R., Bright, P., Cox, S., Bishop, S., & Nimmo-Smith, I. (2008). Goal neglect and Spearman's g: Competing parts of a complex task. *Journal of Experimental Psychology: General*, *137*(1), 131–148. https://doi.org/10.1037/0096-3445.137.1.131

Düzel, E., Bunzeck, N., Guitart-Masip, M., & Düzel, S. (2010). NOvelty-related Motivation of Anticipation and exploration by Dopamine (NOMAD): Implications for healthy aging. In *Neuroscience and Biobehavioral Reviews* (Vol. 34, Issue 5, pp. 660–669). https://doi.org/10.1016/j.neubiorev.2009.08.006

E. A. Ruona, W., Leimbach, M., F. Holton III, E., & Bates, R. (2003). The relationship between learner utility reactions and predicted learning transfer among trainees.

*International Journal of Training and Development*, *6*(4), 218–228. https://doi.org/10.1111/1468-2419.00160

Erickson, K. I., Voss, M. W., Prakash, R. S., Basak, C., Szabo, A., Chaddock, L., Kim, J. S., Heo, S., Alves, H., White, S. M., Wojcicki, T. R., Mailey, E., Vieira, V. J., Martin, S. A., Pence, B. D., Woods, J. A., McAuley, E., & Kramer, A. F. (2011). Exercise training increases size of hippocampus and improves memory. *Proceedings of the National Academy of Sciences of the United States of America*. https://doi.org/10.1073/pnas.1015950108

Ericsson, K. A. (2006). The Influence of Experience and Deliberate Practice on the Development of Superior Expert Performance. In K. A. Ericsson, N. Charness, P. J. Feltovich, & R. R. Hoffman (Eds.), *The Cambridge Handbook of Expertise and Expert Performance* (pp. 683–704). Cambridge University Press. https://doi.org/10.1017/CBO9780511816796.038

Ericsson, K. A., Krampe, R. T., & Tesch-Römer, C. (1993). The role of deliberate practice in the acquisition of expert performance. *Psychological Review*. https://doi.org/10.1037/0033-295x.100.3.363

Eriksen, B. A., & Eriksen, C. W. (1974). Effects of noise letters upon the identification of a target letter in a nonsearch task. *Perception & Psychophysics*, *16*(1), 143–149. https://doi.org/10.3758/BF03203267

Eskes, G. A., Longman, S., Brown, A. D., McMorris, C. A., Langdon, K. D., Hogan, D. B., & Poulin, M. (2010). Contribution of Physical Fitness, Cerebrovascular Reserve and Cognitive Stimulation to Cognitive Function in Post-Menopausal Women. *Frontiers in Aging Neuroscience*, *2*(OCT). https://doi.org/10.3389/fnagi.2010.00137

Fernandes, J., Arida, R. M., & Gomez-Pinilla, F. (2017). Physical exercise as an epigenetic modulator of brain plasticity and cognition. In *Neuroscience and Biobehavioral Reviews*. https://doi.org/10.1016/j.neubiorev.2017.06.012

Fischer, R., Dreisbach, G., & Goschke, T. (2008). Context-Sensitive Adjustments of Cognitive Control: Conflict-Adaptation Effects Are Modulated by Processing Demands of the Ongoing Task. *Journal of Experimental Psychology: Learning Memory and Cognition*. https://doi.org/10.1037/0278-7393.34.3.712

Fischer, R., Gottschalk, C., & Dreisbach, G. (2014). Context-sensitive adjustment of cognitive control in dual-task performance. *Journal of Experimental Psychology: Learning Memory and Cognition*. https://doi.org/10.1037/a0034310

Fissler, P., Küster, O., Schlee, W., & Kolassa, I. T. (2013). Novelty interventions to enhance broad cognitive abilities and prevent dementia: Synergistic approaches for the facilitation of positive plastic change. In *Progress in Brain Research* (Vol. 207, pp. 403–434). https://doi.org/10.1016/B978-0-444-63327-9.00017-5

Fitts, P. M., & Posner, M. I. (1967). Human performance. In *Human performance.* Brooks/Cole.

Foster, J. K., Eskes, G. A., & Stuss, D. T. (1994). The cognitive neuropsychology of attention: A frontal lobe perspective. *Cognitive Neuropsychology*, *11*(2), 133–147. https://doi.org/10.1080/02643299408251971

Frank, M. J., & Badre, D. (2012). Mechanisms of hierarchical reinforcement learning in corticostriatal circuits 1: Computational analysis. *Cerebral Cortex*, *22*(3), 509–526. https://doi.org/10.1093/cercor/bhr114

FRANK, M. J., LOUGHRY, B., & O'REILLY, R. C. (2001). Interactions between frontal cortex and basal ganglia in working memory: A computational model. *Cognitive, Affective, & Behavioral Neuroscience*, *1*(2), 137–160. https://doi.org/10.3758/CABN.1.2.137

Fritsch, T., Smyth, K. A., Debanne, S. M., Petot, G. J., & Friedland, R. P. (2005). Participation in novelty-seeking leisure activities and Alzheimer's disease. *Journal of Geriatric Psychiatry and Neurology*, *18*(3), 134–141. https://doi.org/10.1177/0891988705277537

Gabriele, T. E., Hall, C. R., & Buckolz, E. E. (1987). Practice schedule effects on the acquisition and retention of a motor skill. *Human Movement Science*, *6*(1), 1–16. https://doi.org/https://doi.org/10.1016/0167-9457(87)90019-4

Gabriele, T. E., Hall, C. R., & Lee, T. D. (1989). Cognition in motor learning: Imagery effects on contextual interference. *Human Movement Science*, *8*(3), 227–245. https://doi.org/https://doi.org/10.1016/0167-9457(89)90008-0

Gallagher, S. (2000). Philosophical conceptions of the self: Implications for cognitive science. In *Trends in Cognitive Sciences*. https://doi.org/10.1016/S1364-6613(99)01417-5

Gardner, H. (1999). *The disciplined mind*. New York: Simon & Schuster.

Gardner, H. (1987). The theory of multiple intelligences. *Annals of Dyslexia*, *37*(1), 19–35. https://doi.org/10.1007/BF02648057

Gentner, D., & Hoyos, C. (2017). Analogy and Abstraction. *Topics in Cognitive Science*, *9*(3), 672–693. https://doi.org/10.1111/tops.12278

George, M. S., Ketter, T. A., Parekh, P. I., Rosinsky, N., Ring, H., Casey, B. J., Trimble, M. R., Horwitz, B., Herscovitch, P., & Post, R. M. (1994). Regional brain activity when selecting a response despite interference: An H215O PET study of the stroop and an emotional stroop. *Human Brain Mapping*, *1*(3), 194–209. https://doi.org/10.1002/hbm.460010305

Gershman, S. J., & Niv, Y. (2010). Learning latent structure: Carving nature at its joints. In *Current Opinion in Neurobiology*. https://doi.org/10.1016/j.conb.2010.02.008

Gick, M. L., & Holyoak, K. J. (1983). Schema induction and analogical transfer. *Cognitive Psychology*, *15*(1), 1–38. https://doi.org/10.1016/0010-0285(83)90002-6

Gobet, F., & Simon, H. A. (1996). Templates in chess memory: A mechanism for recalling several boards. *Cognitive Psychology*, *31*(1), 1–40. https://doi.org/10.1006/cogp.1996.0011

Goldstein, K. (1944). The Mental Changes Due to Frontal Lobe Damage. *Journal of Psychology: Interdisciplinary and Applied*, *17*(2), 187–208. https://doi.org/10.1080/00223980.1944.9917192

Gomez-Pinilla, F. (2011). Collaborative effects of diet and exercise on cognitive enhancement. *Nutrition and Health*, *20*(3–4), 165–170. https://doi.org/10.1177/026010601102000401

Gomez-Pinilla, F., & Hillman, C. (2013). The influence of exercise on cognitive abilities. *Comprehensive Physiology*. https://doi.org/10.1002/cphy.c110063

Gómez, R. L. (2002). Variability and Detection of Invariant Structure. *Psychological Science*, *13*(5), 431–436. https://doi.org/10.1111/1467-9280.00476

Gonthier, C., Macnamara, B. N., Chow, M., Conway, A. R. A., & Braver, T. S. (2016). Inducing Proactive Control Shifts in the AX-CPT. *Frontiers in Psychology*, *7*(NOV). https://doi.org/10.3389/fpsyg.2016.01822

Gopher, D. (1993). The skill of attention control: Acquisition and execution of attention strategies. In *Attention and performance 14:  Synergies in experimental psychology, artificial intelligence, and cognitive neuroscience.* (pp. 299–322). The MIT Press.

Gopher, D., Weil, M., & Siegel, D. (1989). Practice under changing priorities: An approach to the training of complex skills. *Acta Psychologica*, *71*(1–3), 147–177. https://doi.org/10.1016/0001-6918(89)90007-3

Goschke, T. (2000). Intentional reconfiguration and involuntary persistence in task set switching. *Attention and Performance*.

Granic, I., Lobel, A., & Engels, R. C. M. E. (2014). The benefits of playing video games. *American Psychologist*. https://doi.org/10.1037/a0034857

Gratton, G., Cooper, P., Fabiani, M., Carter, C. S., & Karayanidis, F. (2018). Dynamics of cognitive control: Theoretical bases, paradigms, and a view for the future. *Psychophysiology*, *55*(3), e13016. https://doi.org/10.1111/psyp.13016

Green, C. S., & Bavelier, D. (2007). Action-video-game experience alters the spatial resolution of vision: Research article. *Psychological Science*. https://doi.org/10.1111/j.1467-9280.2007.01853.x

Green, C. S., & Bavelier, D. (2008). Exercising your brain: A review of human brain plasticity and training-induced learning. *Psychology and Aging*, *23*(4), 692–701. https://doi.org/10.1037/a0014345

Green, C. Shawn, & Bavelier, D. (2003). Action video game modifies visual selective attention. *Nature*, *423*(6939), 534–537. https://doi.org/10.1038/nature01647

Green, C. Shawn, & Bavelier, D. (2015). Action video game training for cognitive enhancement. In *Current Opinion in Behavioral Sciences* (Vol. 4, pp. 103–108). https://doi.org/10.1016/j.cobeha.2015.04.012

Green, C. Shawn, Gorman, T., & Bavelier, D. (2016). Action Video-Game Training and Its Effects on Perception and Attentional Control. In *Cognitive Training* (pp. 107–116). Springer International Publishing. https://doi.org/10.1007/978-3-319-42662-4_10

Green, C. Shawn, Pouget, A., & Bavelier, D. (2010). Improved probabilistic inference as a general learning mechanism with action video games. *Current Biology*. https://doi.org/10.1016/j.cub.2010.07.040

Green, C.S., & Bavelier, D. (2012). Learning, Attentional Control, and Action Video Games. *Current Biology*, *22*(6), R197–R206. https://doi.org/10.1016/j.cub.2012.02.012

Hallett, P. E. (1978). Primary and secondary saccades to goals defined by instructions. *Vision Research*, *18*(10), 1279–1296. https://doi.org/10.1016/0042-6989(78)90218-3

Harrison, T. L., Shipstead, Z., Hicks, K. L., Hambrick, D. Z., Redick, T. S., & Engle, R. W. (2013). Working Memory Training May Increase Working Memory Capacity but Not Fluid Intelligence. *Psychological Science*. https://doi.org/10.1177/0956797613492984

Haskell, R. E. (2004). Transfer of Learning. In R. E. B. T.-T. of L. Haskell (Ed.), *Encyclopedia of Applied Psychology* (pp. 575–586). Academic Press. https://doi.org/10.1016/b0-12-657410-3/00834-5

Hazy, T. E., Frank, M. J., & O'Reilly, R. C. (2006). Banishing the homunculus: Making working memory work. *Neuroscience*, *139*(1), 105–118. https://doi.org/10.1016/j.neuroscience.2005.04.067

Hazy, Thomas E., Frank, M. J., & O'Reilly, R. C. (2007). Towards an executive without a homunculus: Computational models of the prefrontal cortex/basal ganglia system.

*Philosophical Transactions of the Royal Society B: Biological Sciences*, *362*(1485), 1601–1613. https://doi.org/10.1098/rstb.2007.2055

Healy, A. F., Kole, J. A., & Bourne, L. E. (2014). Training principles to advance expertise. In *Frontiers in Psychology* (Vol. 5, p. 131). https://doi.org/10.3389/fpsyg.2014.00131

Hefer, C., & Dreisbach, G. (2020). The volatile nature of positive affect effects: opposite effects of positive affect and time on task on proactive control. *Psychological Research*. https://doi.org/10.1007/s00426-018-1086-4

Heitman, R. J., Pugh, S. F., Kovaleski, J. E., Norell, P. M., & Vicory, J. R. (2005). Effects of specific versus variable practice on the retention and transfer of a continuous motor skill. *Perceptual and Motor Skills*. https://doi.org/10.2466/pms.100.3c.1107-1113

Ho, M. K., Abel, D., Griffiths, T. L., & Littman, M. L. (2019). The value of abstraction. In *Current Opinion in Behavioral Sciences* (Vol. 29, pp. 111–116). https://doi.org/10.1016/j.cobeha.2019.05.001

Hollamby, A., Davelaar, E. J., & Cadar, D. (2017). Increased physical fitness is associated with higher executive functioning in people with Dementia. *Frontiers in Public Health*. https://doi.org/10.3389/fpubh.2017.00346

Holyoak, K. J., & Thagard, P. (1989). Analogical mapping by constraint satisfaction. *Cognitive Science*, *13*(3), 295–355. https://doi.org/10.1016/0364-0213(89)90016-5

Hommel, B. (2011). The Simon effect as tool and heuristic. *Acta Psychologica*, *136*(2), 189–202. https://doi.org/10.1016/j.actpsy.2010.04.011

Inesi, M. E., Botti, S., Dubois, D., Rucker, D. D., & Galinsky, A. D. (2011). Power and choice: Their dynamic interplay in quenching the thirst for personal control. *Psychological Science*, *22*(8), 1042–1048. https://doi.org/10.1177/0956797611413936

Intlekofer, K. A., & Cotman, C. W. (2013). Exercise counteracts declining hippocampal function in aging and Alzheimer's disease. In *Neurobiology of Disease*. https://doi.org/10.1016/j.nbd.2012.06.011

Inzlicht, M., Schmeichel, B. J., & Macrae, C. N. (2014). Why self-control seems (but may not be) limited. In *Trends in Cognitive Sciences* (Vol. 18, Issue 3, pp. 127–133). https://doi.org/10.1016/j.tics.2013.12.009

Inzlicht, M., Shenhav, A., & Olivola, C. Y. (2018). The Effort Paradox: Effort Is Both Costly and Valued. In *Trends in Cognitive Sciences* (Vol. 22, Issue 4, pp. 337–349). https://doi.org/10.1016/j.tics.2018.01.007

Jaeggi, S. M., Buschkuehl, M., Jonides, J., & Perrig, W. J. (2008). Improving fluid intelligence with training on working memory. *Proceedings of the National Academy of*

*Sciences of the United States of America*. https://doi.org/10.1073/pnas.0801268105

Jaeggi, S. M., Buschkuehl, M., Shah, P., & Jonides, J. (2014). The role of individual differences in cognitive training and transfer. *Memory and Cognition*, *42*(3), 464–480. https://doi.org/10.3758/s13421-013-0364-z

Jolles, D. D., Van Buchem, M. A., Rombouts, S. A. R. B., & Crone, E. A. (2012). Practice effects in the developing brain: A pilot study. *Developmental Cognitive Neuroscience*, *2*(SUPPL. 1), S180–S191. https://doi.org/10.1016/j.dcn.2011.09.001

Jonides, J. (2004). How does practice makes perfect? In *Nature Neuroscience* (Vol. 7, Issue 1, pp. 10–11). https://doi.org/10.1038/nn0104-10

Jonides, J., & Smith, E. (1997). The architecture of working. In *Cognitive neuroscience* (p. 243).

Kakade, S., & Dayan, P. (2002). Dopamine: generalization and bonuses. *Neural Networks : The Official Journal of the International Neural Network Society*, *15*(4–6), 549–559. https://doi.org/10.1016/s0893-6080(02)00048-5

Kammer, T., Bellemann, M. E., Gückel, F., Brix, G., Gass, A., Schlemmer, H., & Spitzer, M. (1997). Functional MR imaging of the prefrontal cortex: Specific activation in a working memory task. *Magnetic Resonance Imaging*, *15*(8), 879–889. https://doi.org/https://doi.org/10.1016/S0730-725X(97)00021-0

Karbach, J., & Kray, J. (2009). How useful is executive control training? Age differences in near and far transfer of task-switching training. *Developmental Science*, *12*(6), 978–990. https://doi.org/10.1111/j.1467-7687.2009.00846.x

Karbach, J., Mang, S., & Kray, J. (2010). Transfer of task-switching training in older age: The role of verbal processes. *Psychology and Aging*, *25*(3), 677–683. https://doi.org/10.1037/a0019845

Karbach, J., & Unger, K. (2014). Executive control training from middle childhood to adolescence. In *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2014.00390

Karbach, J., & Verhaeghen, P. (2014). Making Working Memory Work. *Psychological Science*, *25*(11), 2027–2037. https://doi.org/10.1177/0956797614548725

Karni, A., & Bertini, G. (1997). Learning perceptual skills: Behavioral probes into adult cortical plasticity. *Current Opinion in Neurobiology*, *7*(4), 530–535. https://doi.org/10.1016/S0959-4388(97)80033-5

Karr, J. E., Areshenkoff, C. N., Rast, P., & Garcia-Barrera, M. A. (2014). An empirical comparison of the therapeutic benefits of physical exercise and cognitive training on the executive functions of older adults: A meta-analysis of controlled trials.

*Neuropsychology*, *28*(6), 829–845. https://doi.org/10.1037/neu0000101

Katz, B., Jaeggi, S., Buschkuehl, M., Stegman, A., & Shah, P. (2014). Differential effect of motivational features on training improvements in school-based cognitive training. *Frontiers in Human Neuroscience*, *8*(1 APR), 224. https://doi.org/10.3389/fnhum.2014.00242

Katz, B., Shah, P., & Meyer, D. E. (2018). How to play 20 questions with nature and lose: Reflections on 100 years of brain-training research. *Proceedings of the National Academy of Sciences*, *115*(40), 9897–9904. https://doi.org/10.1073/pnas.1617102114

Keith, N., & Frese, M. (2005). Self-regulation in error management training: Emotion control and metacognition as mediators of performance effects. In *Journal of Applied Psychology* (Vol. 90, Issue 4, pp. 677–691). https://doi.org/10.1037/0021-9010.90.4.677

Kennedy, G., Hardman, R. J., MacPherson, H., Scholey, A. B., & Pipingas, A. (2016). How Does Exercise Reduce the Rate of Age-Associated Cognitive Decline? A Review of Potential Mechanisms. In *Journal of Alzheimer's Disease*. https://doi.org/10.3233/JAD-160665

Kessler, Y. (2017). The Role of Working Memory Gating in Task Switching: A Procedural Version of the Reference-Back Paradigm. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.02260

Kessler, Y., Baruchin, L. J., & Bouhsira-Sabag, A. (2017). Working memory updating occurs independently of the need to maintain task-context: accounting for triggering updating in the AX-CPT paradigm. *Psychological Research*, *81*(1), 191–203. https://doi.org/10.1007/s00426-015-0717-2

Kiefer, M., Marzinzik, F., Weisbrod, M., Scherg, M., & Spitzer, M. (1998). The time course of brain activations during response inhibition: Evidence from event-related potentials in a go/no go task. *NeuroReport*, *9*(4), 765–770. https://doi.org/10.1097/00001756-199803090-00037

Kiesel, A., Steinhauser, M., Wendt, M., Falkenstein, M., Jost, K., Philipp, A. M., & Koch, I. (2010a). Control and interference in task switching-a review. *Psychological Bulletin*, *136*(5), 849–874. https://doi.org/10.1037/a0019842

Kiesel, A., Steinhauser, M., Wendt, M., Falkenstein, M., Jost, K., Philipp, A. M., & Koch, I. (2010b). Control and interference in task switching-a review. *Psychological Bulletin*, *136*(5), 849–874. https://doi.org/10.1037/a0019842

Kinzie, M. B. (1990). Requirements and benefits of effective interactive instruction: Learner control, self-regulation, and continuing motivation. *Educational Technology Research* *and Development*, *38*(1), 5–21. https://doi.org/10.1007/BF02298244

Kirchner, W. K. (1958). Age differences in short-term retention of rapidly changing information. *Journal of Experimental Psychology*, *55*(4), 352–358. https://doi.org/10.1037/h0043688

Klingberg, T. (2010). Training and plasticity of working memory. In *Trends in Cognitive Sciences* (Vol. 14, Issue 7, pp. 317–324). https://doi.org/10.1016/j.tics.2010.05.002

Klusmann, V., Evers, A., Schwarzer, R., Schlattmann, P., Reischies, F. M., Heuser, I., & Dimeo, F. C. (2010). Complex mental and physical activity in older women and cognitive performance: A 6-month randomized controlled trial. *Journals of Gerontology - Series A Biological Sciences and Medical Sciences*. https://doi.org/10.1093/gerona/glq053

Knowles, E. E. M., Weiser, M., David, A. S., Glahn, D. C., Davidson, M., & Reichenberg, A. (2015). The Puzzle of Processing Speed, Memory, and Executive Function Impairments in Schizophrenia: Fitting the Pieces Together. *Biological Psychiatry*, *78*(11), 786–793. https://doi.org/10.1016/j.biopsych.2015.01.018

Koch, I. (2005). Sequential task predictability in task switching. *Psychonomic Bulletin & Review*, *12*(1), 107–112. https://doi.org/10.3758/BF03196354

Kool, W., McGuire, J. T., Rosen, Z. B., & Botvinick, M. M. (2010). Decision Making and the Avoidance of Cognitive Demand. *Journal of Experimental Psychology: General*, *139*(4), 665–682. https://doi.org/10.1037/a0020198

Kramer, A. F., Hahn, S., Cohen, N. J., Banich, M. T., McAuley, E., Harrison, C. R., Chason, J., Vakil, E., Bardell, L., Boileau, R. A., & Colcombe, A. (1999). Ageing, fitness and neurocognitive function [7]. In *Nature*. https://doi.org/10.1038/22682

Kramer, Arthur F., Hahn, S., & Gopher, D. (1999). Task coordination and aging: explorations of executive control processes in the task switching paradigm. *Acta Psychologica*, *101*(2–3), 339–378. https://doi.org/10.1016/S0001-6918(99)00011-6

Kramer, Arthur F., Larish, J. F., & Strayer, D. L. (1995). Training for attentional control in dual task settings: A comparison of young and old adults. *Journal of Experimental Psychology: Applied*, *1*(1), 50–76. https://doi.org/10.1037/1076-898X.1.1.50

Kray, J., & Fehér, B. (2017). Age differences in the transfer and maintenance of practice-induced improvements in task switching: The impact of working-memory and inhibition demands. *Frontiers in Psychology*, *8*(MAR). https://doi.org/10.3389/fpsyg.2017.00410

Kray, J., Karbach, J., Haenig, S., & Freitag, C. (2012). Can Task-Switching Training Enhance Executive Control Functioning in Children with Attention Deficit/-Hyperactivity

Disorder? *Frontiers in Human Neuroscience*, *5*. https://doi.org/10.3389/fnhum.2011.00180

Kurtz, K. J., & Honke, G. (2020). Sorting out the problem of inert knowledge: Category construction to promote spontaneous transfer. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *46*(5), 803–821. https://doi.org/10.1037/xlm0000750

Kuwajima, M., & Sawaguchi, T. (2010). Similar prefrontal cortical activities between general fluid intelligence and visuospatial working memory tasks in preschool children as revealed by optical topography. *Experimental Brain Research*, *206*(4), 381–397. https://doi.org/10.1007/s00221-010-2415-z

Lampit, A., Hallock, H., & Valenzuela, M. (2014). Computerized Cognitive Training in Cognitively Healthy Older Adults: A Systematic Review and Meta-Analysis of Effect Modifiers. *PLoS Medicine*. https://doi.org/10.1371/journal.pmed.1001756

Lancaster, M. (1989). Summary for Policymakers. *Climate Change 2013 - The Physical Science Basis*, *53*, 1–30. https://doi.org/10.1017/CBO9781107415324.004

Laplane, D. (1992). Thought and language. *Behavioural Neurology*, *5*(1), 33–38. https://doi.org/10.3233/BEN-1992-5106

Larish, J., Kramer, A., DeAntona, J., & Strayer, D. (1993). Aging and Dual-Task Training. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *37*(2), 162–166. https://doi.org/10.1177/154193129303700201

Larrue, V., Celsis, P., Bès, A., & Marc-Vergnes, J. P. (1994). The functional anatomy of attention in humans: Cerebral blood flow changes induced by reading, naming, and the stroop effect. *Journal of Cerebral Blood Flow and Metabolism*, *14*(6), 958–962. https://doi.org/10.1038/jcbfm.1994.128

Lees, C., & Hopkins, J. (2013). Effect of aerobic exercise on cognition, academic achievement, and psychosocial function in children: A systematic review of randomized control trials. In *Preventing Chronic Disease*. https://doi.org/10.5888/pcd10.130010

León, J., Núñez, J. L., & Liew, J. (2014). Self-determination and STEM education: Effects of autonomy, motivation, and self-regulated learning on high school math achievement. *Learning and Individual Differences*, *43*, 156–163. https://doi.org/10.1016/j.lindif.2015.08.017

Leotti, L. A., & Delgado, M. R. (2011). The inherent reward of choice. *Psychological Science*, *22*(10), 1310–1318. https://doi.org/10.1177/0956797611417005

Leotti, L. A., Iyengar, S. S., & Ochsner, K. N. (2010). Born to choose: The origins and value of the need for control. In *Trends in Cognitive Sciences*.

https://doi.org/10.1016/j.tics.2010.08.001

Lesch, K.-P., Dreisbach, G., Hensch, T., Brocke, B., Goschke, T., & Müller, J. (2010). Dopamine and cognitive control: the prospect of monetary gains influences the balance between flexibility and stability in a set-shifting paradigm. *European Journal of Neuroscience*, *26*(12), 3661–3668. https://doi.org/10.1111/j.1460-9568.2007.05949.x

Lewthwaite R, & Wulf, G. (2012). Motor learning through a motivational lens. Skill acquisition in sport: Research; theory & practice. In *Skills Acquisition in Sport: Research, Theory and Practice*.

Li, S. C., Schmiedek, F., Huxhold, O., Röcke, C., Smith, J., & Lindenberger, U. (2008). Working Memory Plasticity in Old Age: Practice Gain, Transfer, and Maintenance. *Psychology and Aging*, *23*(4), 731–742. https://doi.org/10.1037/a0014343

Liefooghe, B., Wenke, D., & De Houwer, J. (2012). Instruction-based task-rule congruency effects. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *38*(5), 1325–1335. https://doi.org/10.1037/a0028148

Lin, C. H. J., Wu, A. D., Udompholkul, P., & Knowlton, B. J. (2010). Contextual Interference Effects in Sequence Learning for Young and Older Adults. *Psychology and Aging*, *25*(4), 929–939. https://doi.org/10.1037/a0020196

Lista, I., & Sorrentino, G. (2010). Biological mechanisms of physical activity in preventing cognitive decline. In *Cellular and Molecular Neurobiology*. https://doi.org/10.1007/s10571-009-9488-x

Logan, G. D. (1988). Toward an Instance Theory of Automatization. *Psychological Review*. https://doi.org/10.1037/0033-295X.95.4.492

Logan, G. D., & Bundesen, C. (2003). Clever Homunculus: Is There an Endogenous Act of Control in the Explicit Task-cuing Procedure? *Journal of Experimental Psychology: Human Perception and Performance*, *29*(3), 575–599. https://doi.org/10.1037/0096-1523.29.3.575

Lorenz, R. C., Gleich, T., Gallinat, J., & Kühn, S. (2015). Video game training and the reward system. *Frontiers in Human Neuroscience*. https://doi.org/10.3389/fnhum.2015.00040

Lövdén, M., Bäckman, L., Lindenberger, U., Schaefer, S., & Schmiedek, F. (2010). A Theoretical Framework for the Study of Adult Cognitive Plasticity. *Psychological Bulletin*, *136*(4), 659–676. https://doi.org/10.1037/a0020080

Lövdén, M., Brehmer, Y., Li, S. C., & Lindenberger, U. (2012). Training-induced compensation versus magnification of individual differences in memory performance. *Frontiers in Human Neuroscience*, *MAY 2012*.

https://doi.org/10.3389/fnhum.2012.00141

Lövdén, M., Wenger, E., Mårtensson, J., Lindenberger, U., & Bäckman, L. (2013). Structural brain plasticity in adult learning and development. In *Neuroscience and Biobehavioral Reviews*. https://doi.org/10.1016/j.neubiorev.2013.02.014

Ludyga, S., Gerber, M., Brand, S., Holsboer-Trachsler, E., & Pühse, U. (2016). Acute effects of moderate aerobic exercise on specific aspects of executive function in different age and fitness groups: A meta-analysis. *Psychophysiology*. https://doi.org/10.1111/psyp.12736

Lussier, M., Gagnon, C., & Bherer, L. (2012). An investigation of response and stimulus modality transfer effects after dual-task training in younger and older. *Frontiers in Human Neuroscience*, *MAY 2012*, 1–11. https://doi.org/10.3389/fnhum.2012.00129

Lustig, C., Shah, P., Seidler, R., & Reuter-Lorenz, P. A. (2009). Aging, training, and the brain: A review and future directions. *Neuropsychology Review*, *19*(4), 504–522. https://doi.org/10.1007/s11065-009-9119-9

M. Maki, P. (2002). Metacognition: Knowing about knowing. In *Electroencephalography and Clinical Neurophysiology* (Vol. 102, Issue 6, p. 519). https://doi.org/10.1016/s0013-4694(97)84006-4

MacLeod, C. M. (1991). Half a century of reseach on the stroop effect: An integrative review. *Psychological Bulletin*, *109*(2), 163–203. https://doi.org/10.1037/0033-2909.109.2.163

Malinowski, P., & Shalamanova, L. (2017). Meditation and Cognitive Ageing: the Role of Mindfulness Meditation in Building Cognitive Reserve. *Journal of Cognitive Enhancement*, *1*(2), 96–106. https://doi.org/10.1007/s41465-017-0022-7

Mandolesi, L., Polverino, A., Montuori, S., Foti, F., Ferraioli, G., Sorrentino, P., & Sorrentino, G. (2018). Effects of physical exercise on cognitive functioning and wellbeing: Biological and psychological benefits. In *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2018.00509

Mayer, R. E., & Moreno, R. (2003). Nine ways to reduce cognitive load in multimedia learning. *Educational Psychologist*, *38*(1), 43–52. https://doi.org/10.1207/S15326985EP3801_6

Mayr, U., & Kliegl, R. (2000). Task-Set Switching and Long-Term Memory Retrieval. *Journal of Experimental Psychology: Learning Memory and Cognition*. https://doi.org/10.1037/0278-7393.26.5.1124

McNevin, N. H., Wulf, G., & Carlson, C. (2000). Effects of attentional focus, self-control, and dyad training on motor learning: Implications for physical rehabilitation. In *Physical*

*Therapy* (Vol. 80, Issue 4, pp. 373–385). https://doi.org/10.1093/ptj/80.4.373

Meiran, N. (1996). Reconfiguration of processing mode prior to task performance. *Journal of Experimental Psychology: Learning Memory and Cognition*, *22*(6), 1423–1442. https://doi.org/10.1037/0278-7393.22.6.1423

Meiran, N. (2014). The task-cuing paradigm: A user's guide. In *Task switching and cognitive control.* (pp. 45–73). Oxford University Press. https://doi.org/10.1093/acprof:osobl/9780199921959.003.0003

Meiran, N., & Chorev, Z. (2005). Phasic alertness and the residual task-switching cost. *Experimental Psychology*. https://doi.org/10.1027/1618-3169.52.2.109

Meiran, N., Kessler, Y., & Adi-Japha, E. (2008). Control by action representation and input selection (CARIS): A theoretical framework for task switching. *Psychological Research*, *72*(5), 473–500. https://doi.org/10.1007/s00426-008-0136-8

Meiran, N., Liefooghe, B., & De Houwer, J. (2017). Powerful Instructions: Automaticity Without Practice. *Current Directions in Psychological Science*, *26*(6), 509–514. https://doi.org/10.1177/0963721417711638

Melby-Lervåg, M., & Hulme, C. (2013). Is working memory training effective? A meta-analytic review. In *Developmental psychology* (Vol. 49, Issue 2, pp. 270–291). https://doi.org/10.1037/a0028228

Melby-Lervåg, M., Redick, T. S., & Hulme, C. (2016). Working Memory Training Does Not Improve Performance on Measures of Intelligence or Other Measures of "Far Transfer": Evidence From a Meta-Analytic Review. *Perspectives on Psychological Science*, *11*(4), 512–534. https://doi.org/10.1177/1745691616635612

Mery, F., & Kawecki, T. J. (2004). An operating cost of learning in Drosophila melanogaster. *Animal Behaviour*. https://doi.org/10.1016/j.anbehav.2003.12.005

Miller, E. K., & Cohen, J. D. (2001). An Integrative Theory of Prefrontal Cortex Function. *Annual Review of Neuroscience*, *24*(1), 167–202. https://doi.org/10.1146/annurev.neuro.24.1.167

Miller, H. V., Barnes, J. C., & Beaver, K. M. (2011). Self-control and health outcomes in a nationally representative sample. *American Journal of Health Behavior*, *35*(1), 15–27. https://doi.org/10.5993/AJHB.35.1.2

Minear, M., & Shah, P. (2008). Training and transfer effects in task switching. *Memory and Cognition*, *36*(8), 1470–1483. https://doi.org/10.3758/MC.336.8.1470

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000a). The Unity and Diversity of Executive Functions and Their Contributions to

Complex “Frontal Lobe” Tasks: A Latent Variable Analysis. *Cognitive Psychology*, *41*(1), 49–100. https://doi.org/10.1006/cogp.1999.0734

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000b). The Unity and Diversity of Executive Functions and Their Contributions to Complex “Frontal Lobe” Tasks: A Latent Variable Analysis. *Cognitive Psychology*. https://doi.org/10.1006/cogp.1999.0734

Mohammed, S., Flores, L., Deveau, J., Cohen Hoffing, R., Phung, C., M. Parlett, C., Sheehan, E., Lee, D., Au, J., Buschkuehl, M., Zordan, V., Jaeggi, S. M., & R. Seitz, A. (2017). The Benefits and Challenges of Implementing Motivational Features to Boost Cognitive Training Outcome. *Journal of Cognitive Enhancement*, *1*(4), 491–507. https://doi.org/10.1007/s41465-017-0047-y

Monsell, S. (1996). Control of mental processes. *Unsolved Mysteries of the Mind: Tutorial Essays in Cognition.*, 93–148.

Monsell, Stephen. (2003). Task Switching Review. In *Trends in Cognitive Sciences* (Vol. 7, Issue 3, pp. 134–140). https://doi.org/10.1016/S1364-6613(03)00028-7

Monsell, Stephen, Sumner, P., & Waters, H. (2003). Task-set reconfiguration with predictable and unpredictable task switches. *Memory and Cognition*. https://doi.org/10.3758/BF03194391

Morein-Zamir, S., Voon, V., Dodds, C. M., Sule, A., Van Niekerk, J., Sahakian, B. J., & Robbins, T. W. (2016). Divergent subcortical activity for distinct executive functions: Stopping and shifting in obsessive compulsive disorder. *Psychological Medicine*, *46*(4), 829–840. https://doi.org/10.1017/S0033291715002330

Morris, N., & Jones, D. M. (1990). Memory updating in working memory: The role of the central executive. *British Journal of Psychology*, *81*(2), 111–121. https://doi.org/10.1111/j.2044-8295.1990.tb02349.x

Morrison, A. B., & Chein, J. M. (2011). Does working memory training work? the promise and challenges of enhancing cognition by training working memory. *Psychonomic Bulletin and Review*, *18*(1), 46–60. https://doi.org/10.3758/s13423-010-0034-0

Munoz, D. P., & Everling, S. (2004). Look away: The anti-saccade task and the voluntary control of eye movement. In *Nature Reviews Neuroscience* (Vol. 5, Issue 3, pp. 218–228). https://doi.org/10.1038/nrn1345

Muraven, M., & Baumeister, R. F. (2000). Self-Regulation and Depletion of Limited Resources: Does Self-Control Resemble a Muscle? *Psychological Bulletin*. https://doi.org/10.1037/0033-2909.126.2.247

Muraven, M., Shmueli, D., & Burkley, E. (2006). Conserving self-control strength. *Journal of Personality and Social Psychology*, *91*(3), 524–537. https://doi.org/10.1037/0022-3514.91.3.524

Nakamura, J., & Csikszentmihalyi, M. (2014). The concept of flow. In *Flow and the Foundations of Positive Psychology: The Collected Works of Mihaly Csikszentmihalyi* (pp. 239–263). https://doi.org/10.1007/978-94-017-9088-8_16

Navon, D., & Gopher, D. (1979). On the economy of the human-processing system. *Psychological Review*, *86*(3), 214–255. https://doi.org/10.1037/0033-295X.86.3.214

Neumann, O., & Klotz, W. (1994). Motor responses to nonreportable, masked stimuli: Where is the limit of direct parameter specification? In *Attention and performance 15: Conscious and nonconscious information processing.* (pp. 123–150). The MIT Press.

Noack, H., Lövdén, M., & Schmiedek, F. (2014). On the validity and generality of transfer effects in cognitive training research. *Psychological Research*, *78*(6), 773–789. https://doi.org/10.1007/s00426-014-0564-6

Noack, H., Lövdén, M., Schmiedek, F., & Lindenberger, U. (2009). Cognitive plasticity in adulthood and old age: Gauging the generality of cognitive intervention effects. In *Restorative Neurology and Neuroscience* (Vol. 27, Issue 5, pp. 435–453). https://doi.org/10.3233/RNN-2009-0496

Northey, J. M., Cherbuin, N., Pumpa, K. L., Smee, D. J., & Rattray, B. (2018). Exercise interventions for cognitive function in adults older than 50: A systematic review with meta-Analysis. In *British Journal of Sports Medicine*. https://doi.org/10.1136/bjsports-2016-096587

O'Reilly, R. C. (2010). The What and how of prefrontal cortical organization. *Trends in Neurosciences*, *33*(8), 355–361. https://doi.org/10.1016/j.tins.2010.05.002

O'Reilly, R. C., & Frank, M. J. (2006). Making Working Memory Work: A Computational Model of Learning in the Prefrontal Cortex and Basal Ganglia. *Neural Computation*, *18*(2), 283–328. https://doi.org/10.1162/089976606775093909

Olesen, P. J., Westerberg, H., & Klingberg, T. (2004). Increased prefrontal and parietal activity after training of working memory. *Nature Neuroscience*, *7*(1), 75–79. https://doi.org/10.1038/nn1165

Olfers, K. J. F., & Band, G. P. H. (2018). Game-based training of flexibility and attention improves task-switch performance: near and far transfer of cognitive training in an EEG study. *Psychological Research*, *82*(1), 186–202. https://doi.org/10.1007/s00426-017-0933-z

Olin, J. T., Dimmen, A. C., Subudhi, A. W., & Roach, R. C. (2011). Cerebral blood flow and oxygenation at maximal exercise: The effect of clamping carbon dioxide. *Respiratory Physiology and Neurobiology*. https://doi.org/10.1016/j.resp.2010.09.011

Owen, A. M., McMillan, K. M., Laird, A. R., & Bullmore, E. (2005). N-back working memory paradigm: A meta-analysis of normative functional neuroimaging studies. *Human Brain Mapping*, *25*(1), 46–59. https://doi.org/10.1002/hbm.20131

Paas, F., Tuovinen, J. E., Van Merriënboer, J. J. G., & Darabi, A. A. (2005). A motivational perspective on the relation between mental effort and performance: Optimizing learner involvement in instruction. *Educational Technology Research and Development*, *53*(3), 25–34. https://doi.org/10.1007/BF02504795

Pardo, J. V., Pardo, P. J., Janer, K. W., & Raichle, M. E. (1990). The anterior cingulate cortex mediates processing selection in the Stroop attentional conflict paradigm. *Proceedings of the National Academy of Sciences of the United States of America*, *87*(1), 256–259. https://doi.org/10.1073/pnas.87.1.256

Paxton, J. L., Barch, D. M., Racine, C. A., & Braver, T. S. (2008). Cognitive Control, Goal Maintenance, and Prefrontal Function in Healthy Aging. *Cerebral Cortex*, *18*(5), 1010–1028. https://doi.org/10.1093/cercor/bhm135

Payne, B. R., & Stine-Morrow, E. A. L. (2017). The Effects of Home-Based Cognitive Training on Verbal Working Memory and Language Comprehension in Older Adulthood. *Frontiers in Aging Neuroscience*, *9*, 256. https://doi.org/10.3389/fnagi.2017.00256

Peng, P., & Miller, A. C. (2016). Does attention training work? A selective meta-analysis to explore the effects of attention training and moderators. *Learning and Individual Differences*. https://doi.org/10.1016/j.lindif.2015.11.012

Pereg, M., Shahar, N., & Meiran, N. (2013a). Task switching training effects are mediated by working-memory management. *Intelligence*. https://doi.org/10.1016/j.intell.2013.06.009

Pereg, M., Shahar, N., & Meiran, N. (2013b). Task switching training effects are mediated by working-memory management. *Intelligence*, *41*(5), 467–478. https://doi.org/10.1016/j.intell.2013.06.009

Persson, J., & Reuter-Lorenz, P. A. (2008). Gaining control: Training executive function and far transfer of the ability to resolve interference. *Psychological Science*, *19*(9), 881–888. https://doi.org/10.1111/j.1467-9280.2008.02172.x

Piaget, J. (1980). The psychogenisis of knowledge and its epistemological significance. In *Language and learning* (pp. 23–34). https://doi.org/10.9790/7388-05616670

Posner, M. I., & Snyder, C. R. (1975). Attention and cognitive control. *Information Processing and Cognition: The Loyola Symposium.*

Pothier, K., & Bherer, L. (2016). Physical training. In *Cognitive Training: An Overview of Features and Applications*. https://doi.org/10.1007/978-3-319-42662-4_14

Pribram, K. H. (1973). The primate frontal cortex: Executive of the brain. In *Psychophysiology of the frontal lobes.* (pp. xii, 332–xii, 332). Academic Press.

Quiñones, M. A. (1995). Pretraining Context Effects: Training Assignment as Feedback. *Journal of Applied Psychology*, *80*(2), 226–238. https://doi.org/10.1037/0021-9010.80.2.226

Redick, T. S., Shipstead, Z., Harrison, T. L., Hicks, K. L., Fried, D. E., Hambrick, D. Z., Kane, M. J., & Engle, R. W. (2013a). No evidence of intelligence improvement after working memory training: A randomized, placebo-controlled study. *Journal of Experimental Psychology: General*. https://doi.org/10.1037/a0029082

Redick, T. S., Shipstead, Z., Harrison, T. L., Hicks, K. L., Fried, D. E., Hambrick, D. Z., Kane, M. J., & Engle, R. W. (2013b). No evidence of intelligence improvement after working memory training: A randomized, placebo-controlled study. *Journal of Experimental Psychology: General*, *142*(2), 359–379. https://doi.org/10.1037/a0029082

Ritchie, S. J., Bates, T. C., & Deary, I. J. (2015). Is education associated with improvements in general cognitive ability, or in specific skills? *Developmental Psychology*, *51*(5), 573–582. https://doi.org/10.1037/a0038981

Rogers, R. D., & Monsell, S. (1995). Costs of a predictible switch between simple cognitive tasks. *Journal of Experimental Psychology: General*, *124*(2), 207–231. https://doi.org/10.1037/0096-3445.124.2.207

Rougier, N. P., & O'Reilly, R. C. (2002). Learning representations in a gated prefrontal cortex model of dynamic task switching. *Cognitive Science*, *26*(4), 503–520. https://doi.org/10.1207/s15516709cog2604_4

Rubin, O., & Meiran, N. (2005). On the origins of the task mixing cost in the cuing task-switching paradigm. *Journal of Experimental Psychology: Learning Memory and Cognition*, *31*(6), 1477–1491. https://doi.org/10.1037/0278-7393.31.6.1477

Rueda, M. R., Cómbita, L. M., & Pozuelos, J. P. (2016). Childhood and Adolescence. In *Cognitive Training* (pp. 33–44). Springer International Publishing. https://doi.org/10.1007/978-3-319-42662-4_4

Ruge, H., & Wolfensteller, U. (2010). Rapid formation of pragmatic rule representations in the human brain during instruction-based learning. *Cerebral Cortex*, *20*(7), 1656–1667.

https://doi.org/10.1093/cercor/bhp228

Rushworth, M. F. S., Hadland, K. A., Paus, T., & Sipila, P. K. (2002). Role of the human medial frontal cortex in task switching: A combined fMRI and TMS study. *Journal of Neurophysiology*, *87*(5), 2577–2592. https://doi.org/10.1152/jn.2002.87.5.2577

Ryan, R. M., & Deci, E. L. (2000). Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions. *Contemporary Educational Psychology*, *25*(1), 54–67. https://doi.org/10.1006/ceps.1999.1020

Sabah, K., Dolk, T., Meiran, N., & Dreisbach, G. (2018). When less is more: costs and benefits of varied vs. fixed content and structure in short-term task switching training. *Psychological Research*, 1–12. https://doi.org/10.1007/s00426-018-1006-7

Sacco, K., Cauda, F., D'agata, F., Duca, S., Zettin, M., Virgilio, R., Nascimbeni, A., Belforte, G., Eula, G., Gastaldi, L., Appendino, S., & Geminiani, G. (2011). A combined robotic and cognitive training for locomotor rehabilitation: Evidences of cerebral functional reorganization in two chronic traumatic brain injured patients. *Frontiers in Human Neuroscience*. https://doi.org/10.3389/fnhum.2011.00146

Sala, G., & Gobet, F. (2017a). Does far transfer exist? Negative evidence from chess, music, and working memory training. *Current Directions in Psychological Science*, *26*(6), 515–520. https://doi.org/10.1177/0963721417712760

Sala, G., & Gobet, F. (2017b). When the music's over. Does music skill transfer to children's and young adolescents' cognitive and academic skills? A meta-analysis. In *Educational Research Review* (Vol. 20, pp. 55–67). https://doi.org/10.1016/j.edurev.2016.11.005

Sala, G., & Gobet, F. (2019). Cognitive Training Does Not Enhance General Cognition. In *Trends in Cognitive Sciences* (Vol. 23, Issue 1, pp. 9–20). https://doi.org/10.1016/j.tics.2018.10.004

Sanli, E. A., & Patterson, J. T. (2013). Learning Effects of Self-Controlled Practice Scheduling for Children and Adults: Are the Advantages Different? *Perceptual and Motor Skills*, *116*(3), 741–749. https://doi.org/10.2466/23.22.pms.116.3.741-749

Savine, A. C., & Braver, T. S. (2010). Motivated Cognitive Control: Reward Incentives Modulate Preparatory Neural Activity during Task-Switching. *Journal of Neuroscience*, *30*(31), 10294–10305. https://doi.org/10.1523/JNEUROSCI.2052-10.2010

Schmidt, R. A. (1975). A schema theory of discrete motor skill learning. *Psychological Review*, *82*(4), 225–260. https://doi.org/10.1037/h0076770

Schmidt, R. A., & Bjork, R. A. (1992). New Conceptualizations of Practice: Common Principles in Three Paradigms Suggest New Concepts for Training. *Psychological*

*Science*, *3*(4), 207–217. https://doi.org/10.1111/j.1467-9280.1992.tb00029.x

Schmiedek. (2010). Hundred days of cognitive training enhance broad cognitive abilities in adulthood: findings from the COGITO study. *Frontiers in Aging Neuroscience*, *2*(JUL). https://doi.org/10.3389/fnagi.2010.00027

Schneider, D. W., & Logan, G. D. (2005). Modeling Task Switching Without Switching Tasks: A Short-Term Priming Account of Explicitly Cued Performance. *Journal of Experimental Psychology: General*, *134*(3), 343–367. https://doi.org/10.1037/0096-3445.134.3.343

Schneider, V. I., Healy, A. F., & Bourne, L. E. (2002). What is learned under difficult conditions is hard to forget: Contextual interference effects in foreign vocabulary acquisition, retention, and transfer. *Journal of Memory and Language*, *46*(2), 419–440. https://doi.org/10.1006/jmla.2001.2813

Schneider, W., & Shiffrin, R. M. (1977). Controlled and automatic human information processing: I. Detection, search, and attention. *Psychological Review*, *84*(1), 1–66. https://doi.org/10.1037/0033-295X.84.1.1

Schuch, S., & Koch, I. (2003). The Role of Response Selection for Inhibition of Task Sets in Task Shifting. *Journal of Experimental Psychology: Human Perception and Performance*, *29*(1), 92–105. https://doi.org/10.1037/0096-1523.29.1.92

Schwaighofer, M., Fischer, F., & Bühner, M. (2015). Does Working Memory Training Transfer? A Meta-Analysis Including Training Conditions as Moderators. *Educational Psychologist*, *50*(2), 138–166. https://doi.org/10.1080/00461520.2015.1036274

Seitz, A. R. (2017). Generalizable Learning: Practice Makes Perfect — But at What? In *Current Biology*. https://doi.org/10.1016/j.cub.2017.01.064

Sekiya, H., Magill, R. A., Sidaway, B., & Anderson, D. I. (1994). The Contextual Interference Effect for Skill Variations from the Same and Different Generalized Motor Programs. *Research Quarterly for Exercise and Sport*, *65*(4), 330–338. https://doi.org/10.1080/02701367.1994.10607637

Shahar, N., & Meiran, N. (2014). Differential contribution of task conflicts to task switch cost and task mixing cost in alternating runs and cued task-switching: evidence from ex-Gaussian modeling of reaction time distributions. *Psychological Research*, *79*(2), 259–266. https://doi.org/10.1007/s00426-014-0569-1

Shahar, N., Pereg, M., Teodorescu, A. R., Moran, R., Karmon-Presser, A., & Meiran, N. (2018). Formation of abstract task representations: Exploring dosage and mechanisms of working memory training effects. *Cognition*, *181*, 151–159.

https://doi.org/10.1016/j.cognition.2018.08.007

Shapiro, D. H., Schwartz, C. E., & Astin, J. A. (1996). Controlling Ourselves, Controlling Our World: Psychology's Role in Understanding Positive and Negative Consequences of Seeking and Gaining Control. *American Psychologist*, *51*(12), 1213–1230. https://doi.org/10.1037/0003-066X.51.12.1213

Shawn Green, C., Sugarman, M. A., Medford, K., Klobusicky, E., & Bavelier, D. (2012). The effect of action video game experience on task-switching. *Computers in Human Behavior*, *28*(3), 984–994. https://doi.org/10.1016/j.chb.2011.12.020

Shea, C. H., Kohl, R., & Indermill, C. (1990). Contextual interference: Contributions of practice. *Acta Psychologica*, *73*(2), 145–157. https://doi.org/10.1016/0001-6918(90)90076-R

Shea, J. B., & Morgan, R. L. (1979). Contextual interference effects on the acquisition, retention, and transfer of a motor skill. *Journal of Experimental Psychology: Human Learning and Memory*, *5*(2), 179–187. https://doi.org/10.1037/0278-7393.5.2.179

Shea, J. B., & Zimny, S. T. (1983). Context Effects in Memory and Learning Movement Information. In *Advances in Psychology* (pp. 345–366). https://doi.org/10.1016/S0166-4115(08)61998-6

Simon, D. A. (2007). Contextual Interference Effects with Two Tasks. *Perceptual and Motor Skills*, *105*(1), 177–183. https://doi.org/10.2466/pms.105.1.177-183

Simon, D. A., & Bjork, R. A. (2001). Metacognition in Motor Learning. *Journal of Experimental Psychology: Learning Memory and Cognition*, *27*(4), 907–912. https://doi.org/10.1037/0278-7393.27.4.907

Simon, H. A., & Chase, W. G. (1973). Skill in chess. *American Scientist*, *61*(4), 394–403. https://doi.org/10.1007/978-1-4757-1968-0_18

Simon, J., & Wolf, J. D. (1963). Choice Reaction Time As A Function Of Angular Stimulus-Response Correspondence And Age. *Ergonomics*. https://doi.org/10.1080/00140136308930679

Simons, D. J., Boot, W. R., Charness, N., Gathercole, S. E., Chabris, C. F., Hambrick, D. Z., & Stine-Morrow, E. A. L. (2016). Do "Brain-Training" Programs Work? *Psychological Science in the Public Interest*, *17*(3), 103–186. https://doi.org/10.1177/1529100616661983

Singley, M. (1989). Referenceliste The study of transfer. In *The transfer of cognitive skill*.

Slamecka, N. J., & Graf, P. (1978). The generation effect: Delineation of a phenomenon. *Journal of Experimental Psychology: Human Learning & Memory*.

https://doi.org/10.1037/0278-7393.4.6.592

Smith, P. J. K. (2002). Task Duration in Contextual Interference. *Perceptual and Motor Skills*, *95*(3_suppl), 1155–1162. https://doi.org/10.2466/pms.2002.95.3f.1155

Söderqvist, S., Nutley, S. B., Ottersen, J., Grill, K. M., & Klingberg, T. (2012). Computerized training of non-verbal reasoning and working memory in children with intellectual disability. *Frontiers in Human Neuroscience*, *SEPTEMBER*. https://doi.org/10.3389/fnhum.2012.00271

Soderstrom, N. C., & Bjork, R. A. (2015). Learning Versus Performance: An Integrative Review. *Perspectives on Psychological Science*, *10*(2), 176–199. https://doi.org/10.1177/1745691615569000

Sohn, M. H., & Anderson, J. R. (2001). Task preparation and task repetition: Two-component model of task switching. *Journal of Experimental Psychology: General*, *130*(4), 764–778. https://doi.org/10.1037/0096-3445.130.4.764

Soveri, A., Antfolk, J., Karlsson, L., Salo, B., & Laine, M. (2017a). Working memory training revisited: A multi-level meta-analysis of n-back training studies. *Psychonomic Bulletin and Review*, *24*(4), 1077–1096. https://doi.org/10.3758/s13423-016-1217-0

Soveri, A., Antfolk, J., Karlsson, L., Salo, B., & Laine, M. (2017b). Working memory training revisited: A multi-level meta-analysis of n-back training studies. *Psychonomic Bulletin and Review*, *24*(4), 1077–1096. https://doi.org/10.3758/s13423-016-1217-0

Spector, Amos; Biederman, I. (1976). Mental Set and Mental Shift. *The American Journal of Psychology*, *89*(4), 669–679. https://doi.org/not indicated

Speed, A. (2010). Abstract relational categories, graded persistence, and prefrontal cortical representation. *Cognitive Neuroscience*. https://doi.org/10.1080/17588921003660728

Spiro, R. J., Coulson, R. L., Feltovich, P. J., & Anderson, D. K. (1994). Cognitive flexibility theory: Advanced knowledge acquisition in ill-structured domains. In *Theoretical models and processes of reading, 4th ed.* (pp. 602–615). International Reading Association.

Spiro, R. J., & Jehng, J.-C. (1990). Cognitive Flexibility and Hypertext: Theory and Technology for the Nonlinear and Multidemensional Traversal of Complex Subject Matter. In *Cognition, Education, and Multimedia: Exploring Ideas in High Technology* (pp. 163–205).

Steinborn, M. B., & Huestegge, L. (2016). A Walk Down the Lane Gives Wings to Your Brain. Restorative Benefits of Rest Breaks on Cognition and Self-Control. *Applied Cognitive Psychology*. https://doi.org/10.1002/acp.3255

Strobach, T., Frensch, P. A., & Schubert, T. (2012). Video game practice optimizes executive control skills in dual-task and task switching situations. *Acta Psychologica*, *140*(1), 13–24. https://doi.org/10.1016/j.actpsy.2012.02.001

Strobach, T., Liepelt, R., Schubert, T., & Kiesel, A. (2012). Task switching: Effects of practice on switch and mixing costs. *Psychological Research*, *76*(1), 74–83. https://doi.org/10.1007/s00426-011-0323-x

Strobach, T., & Schubert, T. (2001). Positive consequences of action-video game experience on human cognition: Potential benefits on a societal level. In *Epidemiology of Online Game Addiction* (Vol. 49, Issue 0, pp. 1–6).

Stroop, J. R. (1935). Studies of interference in serial verbal reactions. *Journal of Experimental Psychology*. https://doi.org/10.1037/h0054651

Surrey, C., Dreisbach, G., & Fischer, R. (2017). Context-specific adjustment of cognitive control: Transfer of adaptive control sets. *Quarterly Journal of Experimental Psychology*. https://doi.org/10.1080/17470218.2016.1239748

Svatkova, A., Mandl, R. C. W., Scheewe, T. W., Cahn, W., Kahn, R. S., & Hulshoff Pol, H. E. (2015). Physical Exercise Keeps the Brain Connected: Biking Increases White Matter Integrity in Patients with Schizophrenia and Healthy Controls. *Schizophrenia Bulletin*. https://doi.org/10.1093/schbul/sbv033

Taatgen, N. A. (2013). The nature and transfer of cognitive skills. *Psychological Review*, *120*(3), 439–471. https://doi.org/10.1037/a0033138

Tafarodi, R. W., Milne, A. B., & Smith, A. J. (1999). The confidence of choice: Evidence for an augmentation effect on self-perceived performance. *Personality and Social Psychology Bulletin*, *25*(11), 1405–1416. https://doi.org/10.1177/0146167299259006

Taylor, S. F., Kornblum, S., Lauber, E. J., Minoshima, S., & Koeppe, R. A. (1997). Isolation of specific interference processing in the stroop task: PET activation studies. *NeuroImage*, *6*(2), 81–92. https://doi.org/10.1006/nimg.1997.0285

Thompson, T. W., Waskom, M. L., Garel, K. L. A., Cardenas-Iniguez, C., Reynolds, G. O., Winter, R., Chang, P., Pollard, K., Lala, N., Alvarez, G. A., & Gabrieli, J. D. E. (2013a). Failure of Working Memory Training to Enhance Cognition or Intelligence. *PLoS ONE*. https://doi.org/10.1371/journal.pone.0063614

Thompson, T. W., Waskom, M. L., Garel, K. L. A., Cardenas-Iniguez, C., Reynolds, G. O., Winter, R., Chang, P., Pollard, K., Lala, N., Alvarez, G. A., & Gabrieli, J. D. E. (2013b). Failure of Working Memory Training to Enhance Cognition or Intelligence. *PLoS ONE*, *8*(5). https://doi.org/10.1371/journal.pone.0063614

Thorell, L. B., Lindqvist, S., Nutley, S. B., Bohlin, G., & Klingberg, T. (2009). Training and transfer effects of executive functions in preschool children. *Developmental Science, 12*(1), 106–113. https://doi.org/10.1111/j.1467-7687.2008.00745.x

Thorndike, E. L. (1922). The Effect of Changed Data upon Reasoning. *Journal of Experimental Psychology, 5*(1), 33–38. https://doi.org/10.1037/h0072415

Tidwell, J. W., Dougherty, M. R., Chrabaszcz, J. R., Thomas, R. P., & Mendoza, J. L. (2014). What counts as evidence for working memory training? Problems with correlated gains and dichotomization. *Psychonomic Bulletin and Review*, *21*(3), 620–628. https://doi.org/10.3758/s13423-013-0560-7

Todd, M. T., Niv, Y., & Cohen, J. D. (2009). Learning to use working memory in partially observable environments through dopaminergic reinforcement. *Advances in Neural Information Processing Systems 21 - Proceedings of the 2008 Conference*, 1689–1696.

Toll, S. W. M., van der Ven, S. H. G., Kroesbergen, E. H., & van Luit, J. E. H. (2011). Executive functions as predictors of math learning disabilities. *Journal of Learning Disabilities*, *44*(6), 521–532. https://doi.org/10.1177/0022219410387302

Troyer, A. K., Moscovitch, M., & Winocur, G. (1997). Clustering and switching as two components of verbal fluency: Evidence from younger and older healthy adults. *Neuropsychology*, *11*(1), 138–146. https://doi.org/10.1037/0894-4105.11.1.138

Troyer, A. K., Moscovitch, M., Winocur, G., Alexander, M. P., & Stuss, D. (1998). Clustering and switching on verbal fluency: The effects of focal frontal- and temporal-lobe lesions. *Neuropsychologia*, *36*(6), 499–504. https://doi.org/10.1016/S0028-3932(97)00152-8

van Praag, H., Kempermann, G., & Gage, F. H. (2000). Neural consequences of enviromental enrichment. *Nature Reviews Neuroscience*, *1*(3), 191–198. https://doi.org/10.1038/35044558

Vandierendonck, A., Liefooghe, B., & Verbruggen, F. (2010). Task Switching: Interplay of Reconfiguration and Interference Control. *Psychological Bulletin*, *136*(4), 601–626. https://doi.org/10.1037/a0019791

Verbruggen, F., & Logan, G. D. (2008). Response inhibition in the stop-signal paradigm. In *Trends in Cognitive Sciences* (Vol. 12, Issue 11, pp. 418–424). https://doi.org/10.1016/j.tics.2008.07.005

von Bastian, C. C., & Oberauer, K. (2014). Effects and mechanisms of working memory training: a review. In *Psychological Research*. https://doi.org/10.1007/s00426-013-0524-6

Weicker, J., Villringer, A., & Thöne-Otto, A. (2016). Can impaired working memory functioning be improved by training? A meta-analysis with a special focus on brain injured patients. *Neuropsychology*, *30*(2), 190–212. https://doi.org/10.1037/neu0000227

Westbrook, A., Kester, D., & Braver, T. S. (2013). What Is the Subjective Cost of Cognitive Effort? Load, Trait, and Aging Effects Revealed by Economic Preference. *PLoS ONE*, *8*(7). https://doi.org/10.1371/journal.pone.0068210

Willis, S. L., Tennstedt, S. L., Marsiske, M., Ball, K., Elias, J., Koepke, K. M., Morris, J. N., Rebok, G. W., Unverzagt, F. W., Stoddard, A. M., & Wright, E. (2006). Long-term effects of cognitive training on everyday functional outcomes in older adults. *Journal of the American Medical Association*, *296*(23), 2805–2814. https://doi.org/10.1001/jama.296.23.2805

Winter, B., Breitenstein, C., Mooren, F. C., Voelker, K., Fobker, M., Lechtermann, A., Krueger, K., Fromme, A., Korsukewitz, C., Floel, A., & Knecht, S. (2007). High impact running improves learning. *Neurobiology of Learning and Memory*. https://doi.org/10.1016/j.nlm.2006.11.003

Woodworth, R. S., & Thorndike, E. L. (1901). The influence of improvement in one mental function upon the efficiency of other functions. (I). *Psychological Review*, *8*(3), 247–261. https://doi.org/10.1037/h0074898

Wulf, G., & Lee, T. D. (1993). Contextual Interference in Movements of the Same Class: Differential Effects on Program and Parameter Learning. *Journal of Motor Behavior*, *25*(4), 254–263. https://doi.org/10.1080/00222895.1993.9941646

Wulf, G., & Schmidt, R. A. (1988). Variability in Practice. *Journal of Motor Behavior*, *20*(2), 133–149. https://doi.org/10.1080/00222895.1988.10735438

Zhao, X., Wang, H., & Maes, J. H. R. (2020). Training and transfer effects of extensive task-switching training in students. *Psychological Research*, *84*(2), 389–403. https://doi.org/10.1007/s00426-018-1059-7

Zinke, K., Einert, M., Pfennig, L., & Kliegel, M. (2012). Plasticity of executive control through task switching training in adolescents. *Frontiers in Human Neuroscience*, *MARCH 2012*. https://doi.org/10.3389/fnhum.2012.00041

# Supplementary Material – Study 1

## When Less Is More: Costs and Benefits of Varied vs. Fixed Content and Structure in Short Term Task Switching Training

Sabah, K., Dolk, T., Meiran, N., & Dreisbach, G. (2019). When less is more: costs and benefits of varied vs. fixed content and structure in short-term task switching training. *Psychological Research* **83,** 1531–1542 (2019). https://doi.org/10.1007/s00426-018-1006-7

**Table 1**. Mean error rates across the training and transfer blocks in the four training conditions

| | Training | | | | | | | | | | | | | | | | Transfer | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Condition** | **Block1** | | **Block 2** | | **Block 3** | | **Block 4** | | **Block 5** | | **Block 6** | | **Block 7** | | **Block 8** | | **Block 9** | | **Block 10** | |
| | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* |
| **FC/FS** | 0.04 | 0.02 | 0.04 | 0.03 | 0.04 | 0.03 | 0.04 | 0.03 | 0.04 | 0.03 | 0.04 | 0.03 | 0.03 | 0.02 | 0.04 | 0.03 | 0.04 | 0.03 | 0.03 | 0.02 |
| **FC/VS** | 0.03 | 0.02 | 0.03 | 0.02 | 0.03 | 0.03 | 0.04 | 0.03 | 0.03 | 0.02 | 0.04 | 0.03 | 0.04 | 0.03 | 0.04 | 0.03 | 0.04 | 0.03 | 0.04 | 0.03 |
| **VC/FS** | 0.04 | 0.04 | 0.04 | 0.05 | 0.04 | 0.04 | 0.04 | 0.03 | 0.05 | 0.04 | 0.05 | 0.03 | 0.05 | 0.04 | 0.05 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 |
| **VC/FS** | 0.03 | 0.02 | 0.03 | 0.02 | 0.04 | 0.02 | 0.04 | 0.03 | 0.05 | 0.03 | 0.04 | 0.03 | 0.05 | 0.04 | 0.05 | 0.06 | 0.04 | 0.04 | 0.05 | 0.04 |

# Supplementary Material – Study 2

## Enhancing Task-Demands Disrupts Learning but Enhances Transfer Gains in Short-Term Task Switching Training

Sabah, K., Dolk, T., Meiran, N. *et al.* Enhancing task-demands disrupts learning but enhances transfer gains in short-term task-switching training. *Psychological Research* (2020). https://doi.org/10.1007/s00426-020-01335-y

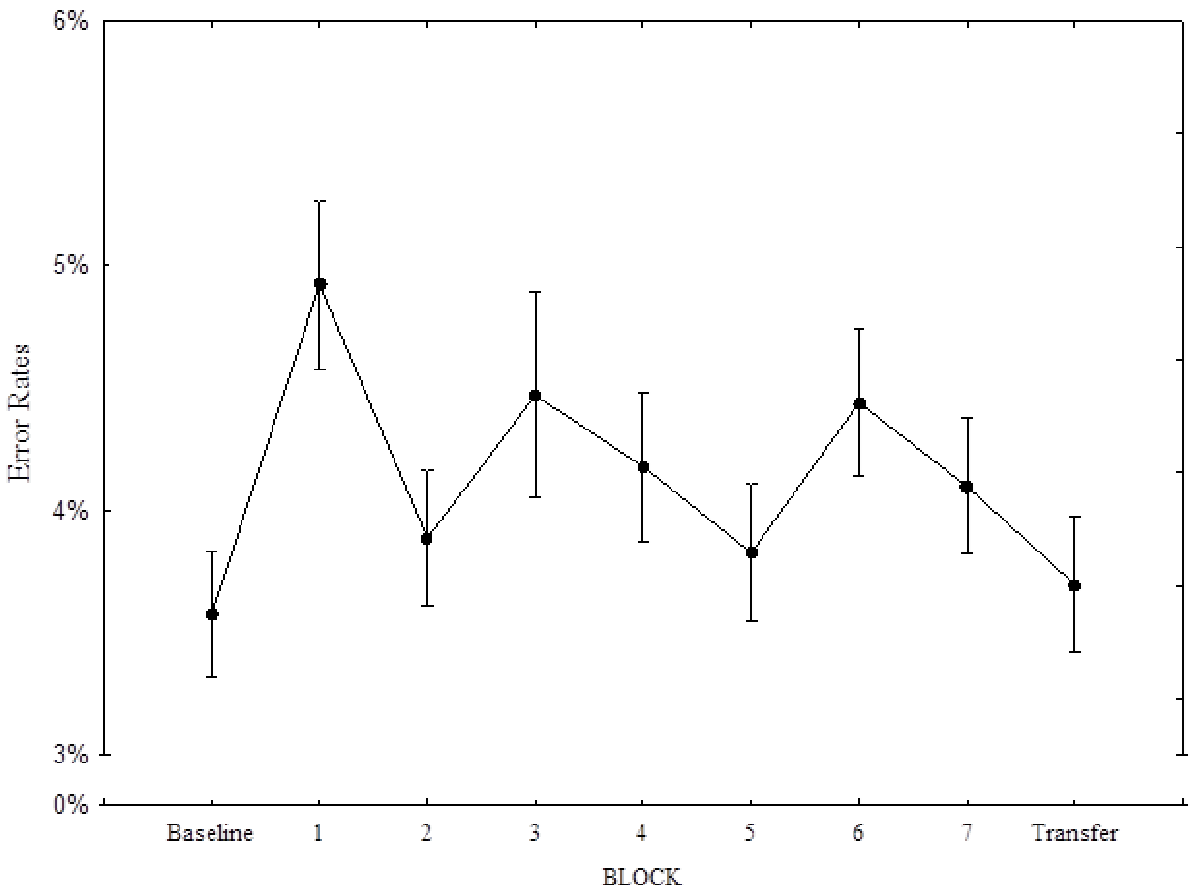



*Fig 1.* Mean error rates along the experimental blocks (collapsed across content and control conditions). Error bars represent standard errors of the mean.

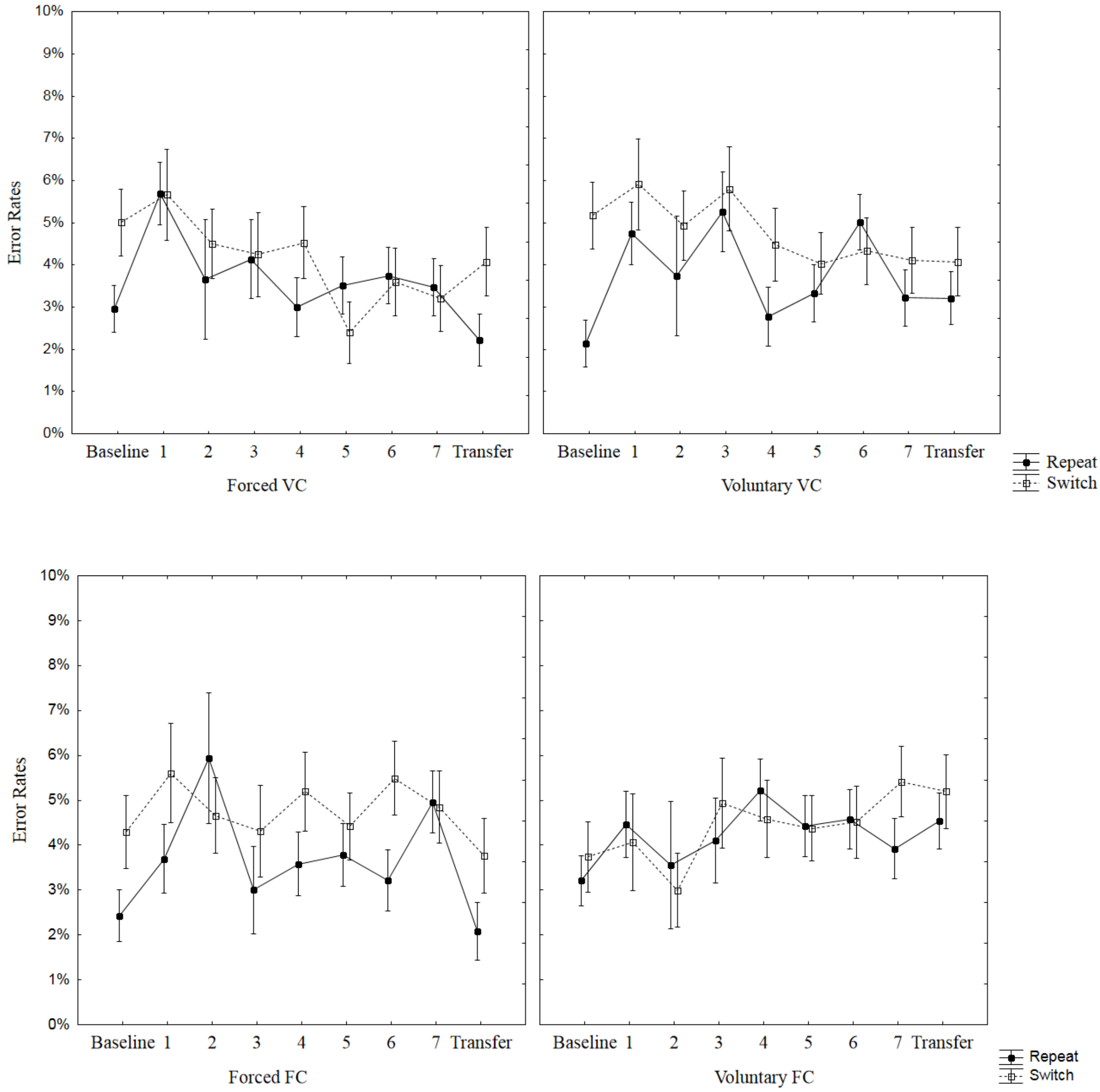



*Fig 2.* Mean error rates along the experimental blocks in the different groups. Error bars represent standard errors of the mean.