Understanding Cognitive Structure of Multitasking Behavior and Working Memory Training Effects

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Abstract

Multitasking behavior and working memory training are important topics in psychological science. The present thesis systematically investigated the underlying cognitive constructs of multitasking behavior and the cognitive strategies related to transfer effects of working memory training, which were described in two empirical studies.

In the first study, we examined the underlying cognitive constructs associated with the concept of multitasking behavior. Although prior investigations have revealed cognitive abilities to be important predictors of multitasking behavior, few studies have been conducted on the relation between executive functions (EFs) and multitasking behavior. In this regard, the current investigation explored the importance of EFs, working memory capacity (WMC), relational integration, and divided attention to multitasking behavior. A sample of 202 young adults completed a battery of EFs (shifting, updating, and inhibition), three WMC tests, three relational integration tests, two divided attention tests, and a multitasking scenario (Simultaneous Capacity). Our study provided several key findings. First, in direct replication attempts, we could replicate the multitasking behavior model (Bühner, König, Pick, & Krumm, 2006) and partially replicate the three-factor and nested factors EFs models (Friedman et al., 2016). Second, the regression analyses revealed that updating, inhibition, relational integration, and divided attention had strong contributions in explaining multitasking behavior variance, whereas shifting and WMC did not show any explanatory power beyond these constructs. Finally, using structural equation modeling, we found that the general EF ability representing variance common to shifting, updating, and inhibition highly overlapped with multitasking behavior. Our results are of value not only to shed light on the relevant cognitive correlates of multitasking behavior but also to position multitasking behavior in an established framework of cognitive abilities. Additionally, by providing strong empirical evidence in favor of cognitive constructs of multitasking behavior, this study builds the necessary groundwork for steering future research to elucidate the etiology of underlying relations between these specific cognitive correlates and multitasking behavior.

The second study inspected how transfer occurs on material-specific tasks, rather than other task types within the working memory training framework. Despite numerous attempts of using training interventions to increase WMC, the role of cognitive strategy in explaining the transfer effects is not yet experimentally investigated. We hypothesized that transfer would occur when a similar cognitive strategy is applied in solving both the trained and transfer tasks. According to this idea, we examined the strategic approach by directly using tasks that allow for specific strategies and tasks that do not. In particular, training with verbal and numerical materials should show transfer to figural (symbol) material, and the other way around. Additionally, differences between visual and verbal cognitive strategies could lead to differential transfer effects on working memory tasks. Eighty young adults received training on two working memory operations: storage and processing, and relational integration (derived from Oberauer, Süß, Wilhelm, & Weittman, 2003) with four different materials verbal/numerical/figural (pattern)/figural (symbol), and another 17 served as active control group and 8 as passive group. Before and after 12 days of adaptive training, performance on the storage and processing, and on the relational integration tasks was assessed. Linear-mixed effects modeling revealed four important findings. First, following training, there were reliable improvements on the performance of trained storage and processing, and relational integration tasks, compared to the active control group. However, such training did not generalize to measures of the same working memory operation with different materials in most cases. Second, the only transfer effect was observed between numerical and figural (symbol) material within relational integration tasks, thereby confirming our hypothesis. Third, no transfer was detected between storage and processing, and relational integration. Finally, there was no direct evidence supporting the influence of cognitive strategies (visual and verbal) on transfer effects.

Together, the present findings provide strong evidence for growing theories of multitasking behavior and working memory training, emphasizing the importance of cognitive underpinnings of multitasking behavior and specifying the efficacy of working memory intervention only on material-specific tasks, which may be emerged from the acquisition of task-specific cognitive strategies. Although the current investigation did not yet provide clear evidence about the strategic approach (i.e., internal information processing operations: visual and verbal), the combination of material-specific mechanisms with a general boost in the underlying cognitive strategies provides an important and interesting perspective for future work.

Zusammenfassung

Multitasking-Verhalten und Arbeitsgedächtnistrainings sind wichtige Themen in der psychologischen Forschung. In der vorliegenden Arbeit wurden im Rahmen von zwei empirischen Studien die dem Multitasking-Verhalten zugrunde liegenden kognitiven Konstrukte sowie die mit Transfereffekten in Arbeitsgedächtnistrainings assoziierten kognitiven Strategien systematisch untersucht.

In der ersten Studie wurden die dem Multitasking-Verhalten zugrunde liegenden kognitiven Konstrukte betrachtet. Obwohl frühere Untersuchungen einen wichtigen Beitrag kognitiver Fähigkeiten zu Multitasking-Verhalten aufzeigen konnten, wurden bisher nur wenige Studien über den Zusammenhang zwischen exekutiven Funktionen (EF) und Multitasking-Verhalten durchgeführt. Aus diesem Grund wurde in dieser Studie die Bedeutsamkeit von EF, Arbeitsgedächtniskapazität (AGK), Relational Integration und geteilte Aufmerksamkeit für Multitasking-Verhalten untersucht. Eine Stichprobe von 202 jungen Erwachsenen bearbeitete eine Aufgabenbatterie für EF (Shifting, Updating, Inhibition), drei AGK Aufgaben, drei Tests zu Relational Integration, zwei Tests zur geteilten Aufmerksamkeit und ein Szenario zu Multitasking (Simultankapazität). Die Hauptergebnisse der Studie lauten wie folgt: Erstens konnte das Modell zu Multitasking-Verhalten (Bühner, König, Pick & Krumm, 2006) direkt repliziert und das Drei-Faktoren-Modell sowie das Hierarchische-Faktoren-Modell (Friedman et al., 2016) zu EF teilweise repliziert werden. Zweitens konnte mit Regressionsanalysen gezeigt werden, dass Updating, Inhibition, Relational Integration und geteilte Aufmerksamkeit jeweils stark zur Erklärung der Varianz von Multitasking-Verhalten beitrug, während Shifting und AGK keinen Erklärungswert, zusätzlich zu den anderen Konstrukten, lieferte. Schließlich zeigte in einem Strukturgleichungsmodell ein allgemeiner Faktor zur Fähigkeit EF, der gemeinsame Varianz von Shifting, Updating und Inhibition beinhaltete, starke Überlappung mit Multitasking-Verhalten. Die Ergebnisse verdeutlichen nicht nur die relevanten kognitiven Korrelate von Multitasking-Verhalten, sondern ermöglichen es auch, Multitasking-Verhalten in einem anerkannten Framework kognitiver Fähigkeiten einzuordnen. Außerdem bildet die Studie, durch ihre starke empirische Evidenz zugunsten kognitiver Konstrukte von Multitasking-Verhalten, die notwendige Grundlage für die zukünftige Erforschung der Ätiologie zugrunde liegender Zusammenhänge zwischen spezifischen kognitiven Korrelaten und Multitasking-Verhalten.

In der zweiten Studie wurde untersucht, wie Transfer zwischen materialspezifischen Aufgaben im Gegensatz zu anderen Aufgabentypen, im Rahmen von Arbeitsgedächtnistrainings stattfindet. Trotz zahlreicher Versuche, AGK durch Trainingsmaßnahmen zu steigern, wurde die Rolle kognitiver Strategien bei der Erklärung des Transfereffekts bisher nicht experimentell untersucht. Es wurde die Hypothese aufgestellt, dass ein Transfer auftritt, wenn ähnliche kognitive Strategien sowohl bei der Lösung der Trainingsaufgabe als auch bei der Lösung der Transferaufgabe angewendet werden. Im Rahmen dieser Idee wurde der sogenannte strategische Ansatz dadurch untersucht, dass einerseits Aufgaben verwendet wurden, die spezifische Strategien erlauben und andererseits Aufgaben die dies nicht ermöglichen. Konkret sollte bei einem Training mit verbalem und numerischem Material Transfer zu figuralem (symbolischen) Material stattfinden und umgekehrt. Außerdem könnten Unterschiede zwischen visuellen und verbalen kognitiven Strategien zu differentiellen Transfereffekten bei Arbeitsgedächtnisaufgaben führen. Achtzig junge Erwachsene wurden in zwei Arbeitsgedächtnisfacetten trainiert: Speicherung/Verarbeitung und Relational Integration (angelehnt an Oberauer, Süß, Wilhelm & Weittman, 2003), mit vier verschiedenen Materialien: Verbal, numerisch, figural (Muster), figural (Symbole). Siebzehn weitere Probanden dienten als aktive und weitere acht als passive Kontrollgruppe. Vor und nach zwölf Tagen adaptiven Trainings wurde die Leistung in den Aufgaben Speicherung/Verarbeitung und Relational Integration erfasst. Gemischte lineare Modelle lieferten vier wichtige Erkenntnisse: Erstens zeigte die Trainingsgruppe im Vergleich zur aktiven Kontrollgruppe eine stabile Leistungsverbesserung in den trainierten Bereichen Speicherung/Verarbeitung und Relational Integration. Jedoch konnte ein solches Training in den meisten Fällen nicht auf Maße derselben Arbeitsgedächtnisfacette mit anderem Material generalisiert werden. Zweitens wurde der einzige Transfereffekt zwischen numerischem und figuralem (Symbole) Material innerhalb der Relational Integration Aufgabe beobachtet, was die Hypothese bestätigte. Drittens gab es keine direkte Evidenz für den Einfluss kognitiver Strategien (visuell und verbal) auf Transfereffekte.

Zusammenfassend liefern die vorliegenden Ergebnisse starke Evidenz für die wachsenden Theorien zu Multitasking-Verhalten und Arbeitsgedächtnistraining. Dabei wird vor allem die Wichtigkeit kognitiver Grundlagen von Multitasking-Verhalten betont sowie die ausschließliche Wirksamkeit von Arbeitsgedächtnisinterventionen bei materialspezifischen Aufgaben konkretisiert, die durch die Aneignung aufgabenspezifischer kognitiver Strategien zustande kommen könnte. Obwohl die vorliegende Untersuchung noch keine klare Evidenz für den strategischen Ansatz (d.h. internale Informationsverarbeitungstypen: visuell und verbal) liefern konnte, bietet die Kombination aus materialspezifischen Mechanismen und einer generellen Verbesserung in den zugrunde liegenden Strategien wichtige und interessante Perspektiven für zukünftige Forschung.

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List of Abbreviation

CIs	Confidence Intervals
CFI	Comparative Fit Index
EFs	Executive Functions
LRZ	Leibniz-Rechenzentrum der Bayerischen Akademie der Wissenschaften
NHST	Null Hypothesis Significance Testing
OLMT	Objektiver Leistungsmotivations-Test
RMSEA	Root Mean Squared Error of Approximation
SEM	Structural Equation Modeling
SIMKAP	Simultankapazität/Multi-tasking
SRMR	Standardized Root Square Residual
WM	Working Memory
WMC	Working Memory Capacity

Chapter One

General Introduction

Individuals differ in their cognitive abilities. The nature and origin of individual differences in cognition remain open to debate. One of the most impressive aspects of human behavior is the ability to execute multiple tasks simultaneously, which is referred as multitasking behavior. However, the question of the cognitive structure of multitasking behavior is still unresolved. Another eminent aspect of human cognition is working memory which shows positive manifold (positively correlated) with diverse cognitive processes. Although many investigations have expressed optimism and pessimism regarding working memory training, the cognitive mechanism underlying transfer of training to particular working memory task content has not been experimentally investigated so far. The main contribution of the present thesis is to investigate these questions by incorporating two studies. The first study, which is hereafter referred to Study 1 is on multitasking behavior and its related constructs. In this study, a broader approach was applied to investigate the importance of executive functions (EFs), working memory capacity (WMC), relational integration, and divided attention to conceptualize multitasking behavior. The second study, which is hereafter referred to Study 2 is on working memory training, concerning the role of cognitive strategies in the process of transfer.

In the following subsections, I first present the conceptual development of multitasking behavior and explain about its possible related cognitive constructs. Then the facets of working memory and a review on working memory training are discussed.

1.1 Conceptualization of Multitasking Behavior

Imagine a professor concentrates to write a book, while a phone call comes from the administrative office asking about the course curriculum – we perform such kind of multiple tasks very often in our everyday life. González and Mark (2004), for example, found that employees spend an average of only 3 minutes per task before switching to another task. The term ‘multitasking’ is originated in computer science (e.g., Kelman, Shah, & Smaalders, 1996), where it refers to managing equivalent processes. The research on multitasking behavior is not new. Dating back several decades to the development of the psychological refractory period (PRP) paradigm, a methodological breakthrough on the nature and limits of human multitasking was commenced to explain how to control the flow of information in executing two tasks concurrently (e.g., Telford, 1931; Welford, 1952). Later on, depending on the task demand, a broad account concerning the potential for processing bottlenecks was introduced which describes only one task can be processed at a time (e.g., Broadbent, 1958; Pashler, 1994). In this regard, Meyer and Kieras (1997) also proposed executive-process interactive control (EPIC) architecture for modelling human multiple task performance. Recently, Salvucci and Taatgen (2008) suggested an integrated theory of multitasking behavior, that implies the execution of multiple tasks threads, synchronised by a serial cognitive processor and allocated across multiple processing resources. In some situations, multitasking behavior seems to be difficult to handle (e.g., talking and writing), while in other situations, it seems not to need any effort (e.g., talking and cooking). Again, certain individuals are very good at performing efficiently in an environment taxing multitasking behavior, and others are not (Medeiros-Ward, Watson, & Strayer, 2015). Apparently, understanding cognitive abilities related to multitasking behavior is necessary.

1.1.1 Cognitive Constructs in Relation to Multitasking Behavior

Multitasking behavior depends on the human cognitive systems. In this regard, the processes of regulating thought and actions - EFs receive attention due to their strong relation to a wide range of cognitive and behavioral competencies (Chan, Shum, Toulopoulou, & Chen, 2008). Several theorists have posited the need for executive control capabilities in managing multiple tasks (e.g., Rubinstein, Meyer, & Evan, 2001). Burgess (2000) used the supervisory attentional system model of EFs (i.e., the higher-level mechanism that activates and inhibits the supporting and conflicting schemas; Norman & Shallice, 1986) to explain everyday multitasking performance, by incorporating several features: interleaving between discrete tasks with different characteristics, engagement in one task at a time, unexpected interruption, and no immediate feedback about performance. Consequently, it is justifiable to investigate the relation of EFs to multitasking behavior. Despite varied perspectives on EFs in the literature, for the present purpose, this study adopted the influential model of EFs, proposed by Miyake, Friedman, Emerson, Witzki, and Howerter (2000), which is later replicated by Friedman et al. (2016). The authors have explained EFs in terms of three often-postulated components: shifting between alternative mental sets, updating working memory, and inhibiting pre-potent or dominate responses. The zero-order correlations among these components and latent variable approaches indicate that EFs are multiple in nature, representing a general pattern of shared (i.e., unity) and distinct functions (i.e., diversity; Miyake et al., 2000), which is also consistent with the idea of McCloskey and Perkins (2013).

The notion of unity and diversity is confirmed by another latent variable approach, the nested factors/bifactor model (Friedman et al., 2016; Ito et al., 2015). In this model, EFs can be decomposed into three latent factors: common EF, unique shifting, and unique updating, but no unique inhibition factor is extracted. Common EF explains variance common to all domains (all EF tasks), whereas unique shifting and unique updating explain variance specific to individual domain (shifting and updating, respectively). Together, these findings raise the obvious question of how individual EF component relates to multitasking behavior.

Consistent with previous studies (Bühner, König, Pick, & Krumm, 2006, Redick et al., 2016), WMC (i.e., complex span task), relational integration, and divided attention were also taken into account in the present study to conceptualize multitasking behavior in a broader perspective. It is assumed that the relation between WMC and multitasking behavior is driven by the operation of multiple domain general cognitive processes that are required for the performance on tests designed to assess the capacity of working memory and multitasking behavior.

Moreover, another functional component of working memory is relational integration (i.e., coordinating single information to derive a concrete structure; Oberauer, Süß, Wilhelm, & Wittman, 2003), which might also require to handle multiple tasks. Working memory capacity and relational integration are not entirely the same: They share overlapping but different executive processes (Oberauer et al., 2003), thus, each of which might explain different aspects of the variance of multitasking behavior. Finally, WMC is the interplay between attention control and memory that governs the flow of information in the service of current goals (cf. Miyake & Shah, 1999). This stands to reason that attention capabilities, especially divided attention seems to be important for the explanation of differences in multitasking behavior. Additionally, divided attention allocates resources between different task-sets by splitting or rapid switching the focus of attention in the face of parallel processing of information (Parasuraman, 1998).

1.2 The Facets of Working Memory

To facilitate the understanding of the working memory training, a perspective of working memory is developed first. Working memory, also regarded as ‘the hub of cognition’ (Haberlandt, 1997, p. 212) enables individuals to temporarily retain goal-relevant information in a highly accessible state (Baddeley & Hitch, 1974). The use of working memory is quite ubiquitous in human thought. Jacobs (1887) was the first who devised the immediate memory span task. More than a century later, several psychologists contributed in psychometric advances with the development of different working memory models from various perspectives (for review, see Baddeley, 2012; Ma, Hussain, & Bays, 2014; Miyake & Shah, 1999). The current work focused on the facet model of working memory (Oberauer, Süß, Schulze, Wilhelm, & Wittman, 2000; Oberauer et al., 2003), which defines three working memory operations or facets: storage and processing, relational integration, and supervision. Storage and processing is described as “the retention of briefly presented new information over a period of time in which the information is no longer present” (Oberauer et al., 2003, p. 169). Relational integration refers to the ability “to build new relations between elements and to integrate relations into structures” (Oberauer et al., 2003, p. 169). Supervision involves “the monitoring of ongoing cognitive processes and actions, the selective activation of relevant representations and procedures, and the suppression of irrelevant, distracting ones” (Oberauer et al., 2003, p. 169). The relationships among the facets are replicated in several studies (Bühner, Krumm, & Pick, 2005; von Bastian & Oberauer, 2013): They share some common variances, but storage and processing and relational integration are highly correlated, and supervision is weakly related to these two factors. This is because supervision corresponds mainly to the shifting factor in the EFs model (Miyake et al., 2000). Therefore, the supervision factor is not considered in this study. Storage and processing, and relational integration facilitate a wide range of real-world cognitive tasks, such as intelligence (e.g., Bühner et al., 2005; Oberauer, Süß, Wilhelm, & Wittmann, 2008), problem solving (Bühner, Kröner, & Ziegler, 2008) or multitasking behavior (Bühner et al., 2006; Redick et al., 2016).

1.2.1 Review of Working Memory Training

The motivation behind working memory training is based on the suggestions that WMC can be enhanced through training, and the benefits of such training may transfer widely to other aspects of cognition. On account of process overlap theory (Kovavs & Conway, 2016), the transfer of cognitive training to other tasks is only possible if the cognitive processes of trained and transfer tasks overlap, which is also postulated by Schwaighofer, Fischer, and Bühner (2015). The transfer is said to be near if improvement is observed in structurally similar untrained tasks, and far if the training and transfer tasks are structurally dissimilar. Numerous brain training companies (Cogmed, Cognifit, Jungle Memory, Lumosity, Posit Science etc.) have been developed for the use in commercial purpose, claiming the power of brain training to improve a broad array of cognitive and everyday activities (for review, see Simons et al., 2016). However, independent of these companies, little or no evidence exists that reveals meaningful change in the performance of cognitive tasks, which differ from the trained task (e.g., Bühner, 2001; Guye & von Bastian, 2017; Linares, Borella, Lechuga, Carretti, & Pelegrina, 2018; Redick et al., 2013).

The efficacy of training interventions in terms of transfer effects has been criticized on several grounds. First, many studies included only no-contact control groups, which can confound potential expectancy effects with training induced improvement (Shipstead, Redick, & Engle, 2012; von Bastian & Oberauer, 2014). Second, the evidence supporting the far transfer effects largely stems from small scale studies (e.g., n = 15; Jaeggi, Buschkuehl, Jonides, & Perrig, 2008); while large scale studies generally found null effects (e.g., n = 116; Foster et al., 2017). Third, studies vary with regard to training conditions (e.g., training intensity, supervision, intervention type etc.; see Schwaighofer et al., 2015, for a meta-analysis). Fourth, the findings differ in terms of adaptive and non-adaptive training regimens, as adaptive training paradigm typically demands frequent updating (Morison & Chein, 2011), leading to substantial and sustained gain in working memory (Holmes, Gathercole, & Dunning, 2009). However, even several methodologically sound studies (claimed by the authors; e.g., Redick et al., 2013) suggested the presence of near transfer to untrained working memory task, and the absence of far transfer effects to other cognitive abilities. Notably, in the context of the facet model of working memory, neither storage and processing nor relational integration show broad transfer, but both constructs show near transfer effects (Hilbert et al., 2017; von Bastian, Langer, Jäncke, & Oberauer, 2013).

Critically, during storage and processing training, participants always need to build, maintain, and update the temporary item-context bindings (cf. Oberauer, Süß, Wilhelm, & Sander, 2007). Thus, it is expected that with improved storage and processing function, individuals are more likely to coordinate multiple relations and construct structural representation effectively. However, supporting Thorndike’s (1906) idea, Hilbert et al. (2017) found no transfer effect between storage and processing, and relational integration, although these constructs share common cognitive mechanism. It seems that training on a skill in a specific context does not improve one’s ability to execute that skill generally (e.g., training on estimating the area of triangles does not advance the ability to estimate the areas of circles). Therefore, the nature of training and the extent of transfer allow us to investigate the causal connection involved in transfer effects.

1.2.2 Cognitive Strategies Underlying Transfer Effects

As outlined by Jaeggi, Buschkuehl, Jonides, and Shah (2011), “future research should not investigate whether brain training works, but rather, it should continue to determine factors that moderate transfer” (p. 10085). Across literature, it is evident that working memory training (also called process-based training) has an advantage of promoting improvements in tasks similar or related to the trained task. The question is what the reason is behind it. The development of a cognitive strategy resulting from working memory training could explain the transfer effects on tasks closely related to working memory tasks (e.g., Sprenger et al., 2013). In line with the strategy mediation hypothesis (i.e., the use of effective strategies is associated with the performance of working memory; McNamara & Scott, 2001), von Bastian and Oberauer (2014) also suggested that training-related change can be achieved through enhancing working memory efficiency, as individual may acquire strategies during training. The cognitive strategies analyze the task characteristics and adapt according to its specific features (Lemaire, 2010), which could promote awareness of the cognitive processes involved in the training tasks. Therefore, the use of metacognitive self-regulation strategy is stimulated and has been shown to favour transfer effects (Cavallini et al., 2015).

Cognitive strategy refers to the individual differences in the way of organizing and processing information (Messick, 1984). Incoming information (such as number and letters) may be processed and represented predominantly either verbally or visually (Paivio, 1986; Rayner & Riding, 1997). According to the visualizer-verbalizer hypothesis, individuals differ in processing pictures (visualizer) and words (verbalizer) (Mayer & Massa, 2003). The visualizers are also subdivided into object and spatial visualizers: Object visualizers rely on pictures, while spatial visualizers rely on spatial materials (Höffler, Koć-Januchta, Leutner, 2016; Kozhevnikov, Kosslyn, & Shephard, 2005). The verbal encoding strategy (McNamara & Scott, 2001) or visual imagery strategy (Borella et al., 2017) is generally used to train participants, which leads to positive improvement on working memory performance. Apart from few studies, the strategy training studies are mostly conducted on elderly people, whose cognitive development is declined (e.g., Bailey, Dunloskey, & Hertzog, 2014; Borella, Carretti, Riboldi, & De Beni, 2010; Gross & Rebok, 2012), relative to young adults.

However, it is controversial whether the transfer of training relies on task-specific (i.e., material dependent) or process- specific (i.e., material independent) mechanisms. For example, Ericsson, Chase, and Faloon (1982) showed that training with numbers does not improve the recall of letters, although Hilbert, Nakagawa, Schuett, and Zihl (2014) found transfer between mirror-reversed letters and mirror-reversed numbers. It appears that skills acquired during training are tightly coupled to the stimuli, tasks, and responses that are required during transfer. Moreover, the mechanisms responsible for transfer of specific training are not necessarily the same in different working memory training paradigms. The issue of material-specific transfer effects has yet to be examined by incorporating self-reported cognitive strategy with task-specific training. We assumed that individual differences regarding cognitive strategies can result in favouring working memory training effects.

1.3 Empirical Studies

To address the above issues, the thesis focused on the following two studies:

The first study (*Multitasking behavior and its related constructs: Executive functions, working memory capacity, relational integration, and divided attention*) reported in this thesis investigated the underlying cognitive constructs associated with multitasking behavior. Considering the importance of replication and reproducibility towards progress in cumulative science, this work systemically attempted to directly replicate the well-established EFs models (Friedman et al., 2016) and multitasking behavior model (Bühner et al., 2006), and to relate these models to WMC, relational integration and divided attention in order to comprehend the concept of multitasking behavior. Two hundred and two participants completed measures of multitasking behavior, EFs (updating, shifting, and inhibition), WMC, and relational integration. Correlations, hierarchical regression analyses, confirmatory factor analyses, structural equation models, and relative weight analyses revealed relevant cognitive correlates of multitasking behavior.

In the second study (*Cognitive strategies and transfer effects between material- and operations-specific tasks within the working memory training framework*), the role of cognitive strategies in transfer of training with particular task contents to other working memory tasks was examined. One hundred and five participants were distributed into eight experimental groups, an active control group, and a passive group. The training regimen as well as working memory tasks at pre-and post-test were based on the facet model of working memory (Oberauer et al., 2003). The online training platform 'Arbeitsgedächtnis Training' (English: working memory training) was developed to train participants. Training was rigorous (12 sessions with a duration of 20 minutes each), and task difficulty was adaptive based on individual performance. Linear mixed-effects models were applied as a main analysis framework.

Although previous research has focused on the predictors of multitasking behavior and the training effects of working memory, detailed investigations are still necessary for furthering our understanding of individual differences in human cognition. The components of the PhD work - Study 1 and Study 2 are described in chapter two and three, respectively. Finally, I conclude with a general discussion including a summary of the two empirical studies, the integrated account of the two studies, and their possible future extensions. Study 1 is submitted to the *Cognition* journal, and Study 2 is going to be submitted to another international journal. In addition, the supplemental materials related to chapter two and three can be found in appendix A and B, respectively.

Chapter Two

Study 1

Multitasking Behavior and Its Related Constructs: Executive Functions, Relational Integration, Working Memory Capacity, and Divided Attention

Submitted to the *Cognition* journal: Himi, S. A., Bühner, M., Schwaighofer, M., Klapetek, A., & Hilbert, S. (2018). Multitasking behavior and its related constructs: Executive functions, relational integration, working memory capacity, and divided attention.

2.1 Introduction

Individuals differ in their ability to multitask, that is, simultaneously planning, performing, or supervising several tasks. Much of the variations in multitasking behavior are associated with the ability to allocate cognitive resources to the task sets (Meyer, Glass, Mueller, Seymour, & Kieras, 2001). Recently, cognitive constructs underlying multitasking behavior have been the subject of extensive research. Despite such endeavors, paradoxically a systematic approach is missing to examine which underlying cognitive constructs relate to the concept of multitasking behavior.

In this regard, promising cognitive correlates of multitasking behavior are executive functions (EFs), conceptualized as a set of goal-directed controlled mechanisms that carry out the dynamics of human cognition and action (e.g., Miyake & Friedman, 2012). Because EFs allow people to act in an adaptive manner in novel and complex situations (Lezak, Howieson, Bigler, & Tranel, 2012), namely performing multiple tasks concurrently, it seems logical to assume that EFs relate to multitasking behavior. Against this background, the specific aims of the current study are twofold. First, we attempted to determine whether we could replicate the multitasking behavior model proposed by Bühner, König, Pick, and Krumm (2006) and the EFs model, first suggested by Miyake, Friedman, Emerson, Witzki, and Howeter (2000), latter replicated by Friedman et al. (2016). Second, we intended to apply a broad model by combining EFs, working memory capacity (WMC; Kane et al., 2004), relational integration (Oberauer, Süß, Wilhelm, & Wittman, 2003), and divided attention models (Strum, 2008) to further illuminate cognitive correlates of multitasking behavior. The present work is an extension of previous studies conducted by Bühner, König, et al. (2006) and König, Bühner, and Mürling (2005). The main focus of the earlier works was to explore to what extent WMC, relational integration, and divided attention predict multitasking behavior. The research described here goes substantially beyond prior findings by including EFs in explaining multitasking behavior.

2.1.1 The Nature of Multitasking Behavior

Germane to the current work, it is important to point out that we were mainly concerned with multitasking ability, not multitasking activity, such as media multitasking (e.g., Ophir, Nass, & Wagner, 2009). Individuals engaging in higher levels of media multitasking have either worse multitasking ability (Sanbonmatsu, Strayer, Medeiros-Ward, & Watson, 2013) or shown no association with this ability (Alzahabi & Becker, 2013). Several studies show negative consequences of media multitasking with respect to mental health and EFs (e.g., van der Schuur, Baumgartner, Sumter, & Valkenburg, 2015). Yet, media multitasking relies on self-report questionnaire which is prone to response bias (Paulhus, 1991) and reflects the respondents' perception of their own multitasking experiences rather than their real multitasking behavior (e.g., Carrier, Cheever, Rosen, Benitez, & Chang, 2009; Lui & Wong, 2012). However, the ubiquitous requirement of multitasking ability is present in many workplaces for numerous occupations, including organization management (Mark, Gonzalez, & Harris, 2005; Sanderson, Bruk-Lee, Viswesvaran, Gutierrez, & Kantrowitz, 2013), medicine (Chisholm, Dornfeld, Nelson, & Cordell, 2001; Ferris & Sarter, 2011), and military/aviation (Loukopoulos, Dismukes, & Barshi, 2009).

Multitasking behavior has been studied from different perspectives with considerable differences regarding the scope of tasks used to measure this construct. Many of these investigations rely on tasks based on the simulation of specific work domain, such as military personnel (Synthetic Work Environment; Elsmore, 1994; Hambrick et al., 2011), flight controller (Multiattribute Task Battery; Comstock & Arnegard, 1992), or call center operator (Braun, Huettges, Timm, Wieland, & Willamowski, 2002; van der Horst, Klehe, & van Leeuwen, 2012). Other studies depend on classic laboratory tasks, for example, the dual coordination task (Logie, Cocchini, Della Sala, & Baddeley, 2004; Yee, Hunt, & Pellegrino, 1991), or the psychological refractory period procedure (Pashler, 1994). Moreover, few studies use neuro-psychological measures to assess multitasking behavior, such as the Greenwich Test (Burgess, Veitch, de Lacy Costello, & Shallice, 2000), or the Modified Six

Element Test (Siklos & Kerns, 2004). However, a large part of previous works has extensively restricted their multitasking measures to assess job specific content, or cognitive, perceptual, and motor resources in the controlled dual-task context, rather than adequately representing cognitive demands of multitasking in real-world.

Considering the insufficient approaches to measuring everyday-multitasking behavior, we employed the Simultankapazität/Multi-tasking test (SIMKAP; English: Simultaneous Capacity/Multitasking; Bratfisch & Hagman, 2011), which not only represents a generalized and standardized real-life scenario of multitasking (König et al., 2005), but also is conceptually relevant to other models of everyday multitasking (e.g., Burgess et al., 2000; Salvucci & Taatgen, 2008). SIMKAP requires a combination of multiple processes (e.g., perceptual speed, accuracy, or memory/intellectual ability) to interleave routine (i.e., identifying and marking certain combinations of stimuli in SIMKAP scenario) and problem-solving tasks in cohesive manner with changing circumstances. Hence, SIMKAP is able to capture individuals' dynamic aspects of behavior in the concurrent tasks environment and puts test takers in situations that are comparable to real-world multitasking. The multitasking behavior (SIMKAP) model was first introduced by König et al. (2005), defined through three aspects - speed, error, and question; and later replicated by Bühner, König, et al. (2006).

Building on the aforementioned studies, we attempted to replicate the model of Bühner, König, et al. (2006). For the present study, speed, error, and question can be defined, respectively, by performing multiple tasks quickly within a limited time, a cognitive mechanism that directs to perform multiple tasks accurately, and a conscious search for task-relevant information utilizing memory and mental resources. Therefore, it is plausible to assume that these aspects of multitasking behavior may have different underpinnings. We considered global multitasking behavior and its three aspects - speed, error, and question, as separate constructs related to various cognitive abilities.

In the following subsections, we first present a short review of the EFs model. Then we explain several cognitive constructs with respect to whether these constructs relate to multitasking behavior.

2.1.2 Miyake et al.'s (2000) Model of Executive Functions

One of the most well-known models of EFs has been proposed by Miyake et al. (2000). The authors postulated three core EFs: shifting, updating, and inhibition, which are guided by a unity and diversity framework (see Teuber, 1972). Miyake et al. (2000, p. 55) describe shifting as "the disengagement of an irrelevant task set and the subsequent active engagement of a relevant task set". The concept of shifting is closely linked to the notion of "task switching" (Monsell, 2003) or "supervision" (Oberauer, Süß, Schulze, Wilhelm, & Wittman, 2000; Oberauer et al., 2003). Updating entails "monitoring and coding incoming information for relevance to the task at hand and then appropriately revising the items held in working memory by replacing old, no longer relevant information with newer, more relevant information" (Miyake et al., 2000, p. 57). According to Miyake et al. (2000, p. 57), inhibition refers to the "ability to deliberately inhibit dominant, automatic, or prepotent responses when necessary". In their model, shifting, updating, and inhibition are related; but distinct at the level of latent variables.

Friedman and colleagues (e.g., Friedman et al., 2008, 2016; Ito et al., 2015) incorporated another model, named nested factors/bifactor model in which three EFs can be decomposed into three latent factors: common EF (i.e., general EF), unique updating, and unique shifting. According to Miyake and Friedman (2012), common EF accounts for the abilities required to perform successfully all types of EF tasks. Unique shifting concerns task flexibility in that it facilitates shifting between modes of responding according to new task demands, whereas unique updating accounts for retrieving information from long-term memory through filtering out redundant or irrelevant information (Miyake & Friedman, 2012). The assumption regarding the link between unique updating and long-term memory is akin to Unsworth and Engle's (2007a) notion of controlled search for information from long-term storage.

The present investigation is conducted to provide another jigsaw piece in the empirical study of EFs by attempting to replicate the three-factor (Friedman et al., 2016) and nested factors (Friedman et al., 2016) EFs models. At this point, it may be unclear why we decided to replicate these models in the first place. With regard to the three-factor EFs model, the reasons are threefold. First, the three-factor model has widely stimulated a great deal of scientific innovation (e.g., cited over 9707 times in October, 2018; as stated in Google scholar). Second, it is one of the most empirically supported factor models of EFs (Jewsbury, Bowden, & Strauss, 2015). Third, probably most importantly, there is no preregistered direct replication of the EFs model in the published literature. Although the EFs model (Miyake et al., 2000) has been replicated by diverse researchers, the specific cognitive architecture (factorial components) of EFs of the first model is not consistent across studies. This empirical inconsistency is largely rooted in methodology: 1) the use of different task sets for measuring the EF components (e.g., Brydges, Reid, Fox, & Anderson, 2012; Fisk & Sharp, 2004; Fournier-Vicente, Larigauderie, & Gaonac'h, 2008; Wiebe, Espy, & Charak, 2008); 2) the use of diverse samples (e.g., children [Duan, Wei, Wang, & Shi, 2010; van der Sluise, de Jong, & van der Leij, 2007], young adults [e.g., Friedman et al., 2016; Ito et al., 2015], or senior adults [Hedden & Yoon, 2006; Hull, Martin, Beier, Lane, & Hamilton, 2008]); 3) the use of insufficient indicators for each component (e.g., using single indicator for updating; Wu, Chan, Leung, Liu, Leung, & Ng, 2011).

Regarding the nested factors/bifactor EFs model, few studies have employed a hierarchical common EF factor model. These studies are either based on children (Engelhardt et al., 2016) or elderly (Lee et al., 2012), and have specified four EF factors, which are structurally different from the model favored by Friedman et al. (2016). No other researchers than Friedman et al. (2016), Ito et al. (2015), and Fleming, Heintzelman, and Bartholow (2016) have tried to replicate these two models using similar task sets in samples of young adults. Therefore, we designed the current study to address the issues of the aforementioned works. In our direct replication attempts, the selected tasks and procedures were as close as possible to the original study, as prescribed in the Replication Recipe (Brandt et al., 2014). Importantly, we administered the recently developed EF battery (Friedman et al., 2016; Ito et al., 2015), as this modified version is intended to elicit more individual differences in adults (Friedman et al., 2016).

2.1.3 Multitasking Behavior and Single Component of Executive Functions

The second main purpose of the study was how three core EFs might link to the concept of multitasking behavior. We considered the multifaceted model of EFs to more fully comprehend individual differences in multitasking behavior. Though there are some individual articles regarding the relations between multitasking and inhibitory control (Redick et al., 2016), shifting (Bühner, König, et al., 2006; Hambrick et al., 2011), and updating (Hambrick et al., 2011); to the best of our knowledge, this is the first study that investigated how multiple EFs, including individual domain ‘shifting, updating, and inhibition’, as well as general domain ‘common EF’ overlap with multitasking behavior. In addition, studies investigating the relationship between EFs and multitasking behavior have restricted their scope to a single working memory (WM) updating measure of EF (e.g., Mäntylä, 2013; Todorov, Missier, & Mäntylä, 2014), but multiple tasks for each EF component are needed to reduce the task-specific variance (Miyake et al., 2000; Schwaighofer, Bühner, & Fischer, 2017).

Theoretical accounts of these earlier literature indicate that executive control processes are needed to organize the flow of information while people encounter multitasking situations. From several investigations in clinical neuropsychology, it is apparent that individuals with pre-frontal dysfunction (EFs are often associated with prefrontal cortex) perform poorly when facing numerous tasks within a limited time (e.g., Dreher, Koechlin, Tierney, & Grafman, 2008; Law et al., 2004).

The single core EF has specific relevance for multitasking behavior. The term ‘shifting’ (operationalized as ‘task switching’) is frequently used to refer to multitasking (Monsell, 2003; Rubinstein, Meyer, & Evans, 2001). However, this equivalence has been doubted (Bühner, König, et al., 2006): The authors conclude that the cognitive mechanism required for shifting flexibly from one mind set to another differs from achieving two or more competing goals. In this regard, Miyake et al. (2000) also found no evidence of shifting in explaining multitasking behavior (measured with dual-task). Apparently, we can explain the variation across multitasking and task shifting scenarios from a mechanistic perspective. Task shifting requires explicit task-specific knowledge that dictates when task switching occurs (Kieras, Meyer, Ballas, & Lauber, 2000). In contrast, the concurrent tasks presentation (specific for multitasking behavior) is free from task-specific knowledge of when to switch between tasks (Pashler, 1994; Salvucci & Taatgen, 2008). For instance, a participant performing a classical shifting task (Friedman et al., 2016) has to classify the stimuli according to color or shape. The explicit cue indicates when the response must be performed. The tasks processing do not overlap, because the processes for one task are finished before beginning the next task (Arrington, Altmann, & Carr, 2003). Alternatively, a participant performing multitask has to execute several simultaneous tasks. No cue exists indicating when to perform and finish the tasks, thus performance of tasks may overlap in time and finish at different time (Salvucci & Taatgen, 2008). The distinct nature of these two constructs has also permeated to the study of their neural substrates: When performing two tasks simultaneously, as compared to performing them in succession, activation is located in the rostral anterior cingulate cortex. Switching between two tasks, relative to performing them simultaneously, activates the left lateral prefrontal cortex and the bilateral intra-parietal sulcus region (Deprez et al., 2013; Dreher & Grafman, 2003). However, recently Koch, Poljac, Müller, and Kiesel (2018) have integrated task switching (shifting) and dual-task in terms of the underlying cognitive mechanisms (i.e., cognitive bottlenecks, cognitive flexibility, and cognitive plasticity).

Another executive control process possibly related to multitasking behavior is updating. This can be justified by the analysis of demands posed by typical updating tasks. The essence of updating tasks is the requirement to actively manipulate relevant information in the memory, such as the letter memory task (Morris & Jones, 1990) in which people have to recall the last four from a changing list of letters. In other words, they must update their memory with new four letters. According to this view, multitasking behavior presumably requires updating to keep track of the current status of multiple ongoing tasks and to maintain interim results. The updating factor has not been exclusively studied in relation to multitasking behavior, with only a few exceptions: Hambrick et al. (2011), for example, related updating to multitasking behavior using a single updating task (digit *n*-back task). However, as mentioned earlier, it is important to use several tasks to measure single core EF. In addition, the updating construct is largely studied as WMC (measured with complex span tasks), because updating strongly overlaps with WMC due to underlying mechanism of storing information (Schmiedek, Hildebrandt, Lövdén, Wilhelm, & Lindenberger, 2009). However, several studies have cast doubt on their close relation (Jaeggi, Buschkuehl, Perrig, & Meier, 2010; Radvansky & Copland, 2001; Redick & Lindsey, 2013). To clarify this point, Ecker, Lewandowsky, and Oberauer (2014) stated that the ability to remove outdated information from memory is specific and unique to updating process (i.e., independent of WMC). On that premise, it is certain that the predictive relation between multitasking behavior and updating was not based on a proper measure of updating. This lack of literature motivates us to predict the involvement of updating in multitasking behavior. Hence, the present study intended to empirically separate WMC from updating on the construct level while predicting multitasking behavior. We used a broad set of updating tasks to test whether this construct contributes to the prediction of multitasking behavior over-and-above WMC.

Considering the processes involved in multitasking behavior as suggested by Gade and Koch (2012), multitasking may require inhibition (often termed attentional control) to decide which task is the relevant one in current ongoing tasks, while executing numerous tasks at the same time causing interference or response conflict. Two well-known multitasking paradigms provide a starting point for discussing the relationship between inhibition and multitasking behavior. First, the psychological refractory period paradigm (for review, see Pashler, 1994) proposes that when individuals maintain two independent task sets, each with its own stimulus-response assignments, the response to a second task is significantly slowed because the first task is being processed. Second, the prioritized processing paradigm (Miller & Durst, 2014, 2015) differs from the psychological refractory period paradigm in that it designates one task as the higher priority than the other one. The two tasks can be processed either incorporating the bottleneck assumption (Welford, 1967), where all processing capacities are allocated to one task; or resource allocation assumption (Navon & Miller, 2002), where processing capacities are shared between two tasks. Both paradigms, nonetheless, demonstrate that cognitive abilities to perform multitask simultaneously are limited because the tasks can interfere with each other. Inhibition supports to reduce this interference. Consequently, it appears more plausible to examine the role of the inhibitory process in multitasking behavior. Moreover, the neuroanatomical evidence also indicates the involvement of basal ganglia in both multitasking behavior and inhibition (Thoma, Koch, Heyder, Schwarz, & Daum, 2008), corroborating the presumed relation between these two cognitive constructs.

2.1.4 Multitasking Behavior and Common EF Ability

Perhaps the most obvious candidate for goal-oriented cognitive skill accompanying with multitasking behavior is the common EF, representing variance shared to shifting, updating, and inhibition. Common EF is the ability to actively maintain task goals in the face of interference, and thereby direct ongoing processes (Miyake & Friedman, 2012). In this regard, Gustavson, Miyake, Hewitt, and Friedman (2015) suggested that the common EF not only preserves goal-directed behaviors but also implements them accurately at the appropriate time, thus pointing towards an association with goal management ability. Additionally, Salvucci and Taatgen (2008, 2011) stressed that multitasking behavior is a consequence of multiple cognitive tasks where each task signifies a goal of task accomplishment. Therefore, we could essentially assume that common EF relates to multitasking behavior. However, to date no research exists on relation between multitasking behavior and common EF factor, derived from a multicomponent EFs model. As the unique updating and unique shifting factors are not explained elaborately (Miyake & Friedman, 2012), we did not have any specific assumption for their relationship with multitasking behavior. Nevertheless, unique shifting and common EF tend to show opposite patterns of correlations with other cognitive measures, whereas unique updating and common EF tend to show similar patterns of correlations (Friedman et al., 2008; Friedman & Miyake, 2017).

2.1.5 Multitasking Behavior, Working Memory Capacity, Relational Integration, and Divided Attention

In addition to relating the concept of multitasking behavior to EFs, WMC, relational integration, and divided attention also account for variance in multitasking behavior (Bühner, König, et al., 2006). Typically, in the realm of concurrent task environments, WMC (similar to "storage in the context of processing" in Oberauer et al., 2000, 2003) and multitasking behavior have been demonstrated as correlated psychological constructs (e.g., Ackerman & Beier, 2007; Colom, Martínez-Molina, Shih, & Santacreu, 2010; Hambrick, Oswald, Darowski, Rench, & Brou, 2010; Heathcote et al., 2014; König et al., 2005; Logie, Trawley, & Law, 2011; Morgan et al., 2013; Pollard & Courage, 2017; Redick et al., 2016). Working memory capacity can be measured through a variety of tasks that reflect different mechanisms of WM. In this study, we considered complex span tasks as measures of WMC. A strong relationship between complex span tasks and higher-order cognition (e.g., Kane, Conway, Hambrick, & Engle, 2007; McVay & Kane, 2012) has led researchers to propose that WMC is an important underpinning of multitasking behavior. In fact, due to the dual-task nature (storage and processing) of complex span task, Sanbonmatsu et al. (2013) used this task (i.e., operation span) as multitasking measure. Although diverse research literature confirms this relationship (e.g., Hambrick et al., 2010; Redick, 2016), recently using latent variable analysis, Redick et al. (2016) have found no significant direct path from WMC (measured with complex span tasks) to multitasking behavior. The capacity limit of WM and inhibition mediate the relationship between WMC and multitasking behavior (Redick et al., 2016). An inherent limitation of this study seems the use of 'absolute scores' (i.e., the sum of perfectly recalled items). However, Unsworth and Engle (2007b) suggested that the 'partial credit scores' (i.e., the proportion of correctly recalled items in each trial; for detail, see Conway et al., 2005; Redick et al., 2012) demonstrate higher correlations with criterion measures. In another study, using a partial credit score, Redick (2016) reported that WMC predicted multitasking behavior, even though a single measure of complex span task was used. The scoring system can affect the relationship between WMC and multitasking behavior, which is why we adopted partial credit scores, a psychometrically sound scoring procedure in the present investigation.

It is worth mentioning here that WMC, relational integration, and divided attention are interconnected constructs (Bühner, Krumm, & Pick, 2005). With respect to multitasking behavior, relational integration explains the variance of multitasking behavior above and beyond divided attention (Bühner, König, et al., 2006; König et al., 2005). Relational integration, which refers to the cognitive process of building a structural representation through integrating several events that are related to each other (Oberauer et al., 2003), might be crucial for multitasking behavior. While juggling the cognitive demands of numerous concurrent tasks, the environment has to be integrated so that the temporary binding between tasks can be established and maintained in WM accordingly. Further, we can reasonably expect that relational integration may be more fundamentally related to multitasking behavior than WMC and inhibition, since it has shown predictive power regardless of memory and executive control abilities (Chuderski, 2014).

On the contrary, it remains a controversial issue whether divided attention plays a role in predicting multitasking behavior: Bühner, König, et al. (2006), for example, found that divided attention can only explain a small amount of variance in multitasking behavior. However, Colom et al. (2010) and Thoma et al. (2008) considered the divided attention test as a measure of multitasking behavior, assuming divided attention and multitasking behavior are similar constructs. Therefore, to explore the divided attention – multitasking behavior relationship comprehensively, we assessed the divided attention construct using multiple tasks in contrast to Bühner, König, et al. (2006), who used single task.

2.1.6 Research Questions

Together, we address the following questions:

Research Question 1: Do the multitasking behavior model and the EFs models hold in our sample?

Research Question 2: Which cognitive abilities (the three core EFs, WMC, relational integration, and divided attention) show a unique contribution to the prediction of multitasking behavior and its three aspects (speed, error, and question)?

Research Question 3: To what extent does the common EF ability relate to multitasking behavior?

2.2 Methods

The research design including testing measures, and analyses plan were preregistered on the Open Science Framework. The preregistration and data are available at https://osf.io/tn6hp/?view_only=b7b162e880bf4c0b860605ad49f51a58

2.2.1 Participants

Two hundred and two younger adults (73.3% women, Mean age = 23.09 years, *SD* = 3.86 years, age range = 17-35 years) were recruited at the Ludwig-Maximilians University of Munich, the Fresenius University of Applied Sciences, Munich, and the Technical University of Munich. About three quarters of the participants were undergraduate students, and the rest of them had completed their Bachelor. All participants had normal or corrected-to-normal vision and hearing. After completion of the testing, the participants were rewarded with either a certificate of participation in an empirical study or a payment of €50 ($57.06).

2.2.2 Procedure

All participants gave their written informed consent prior to data collection. The study was conducted in two sessions on separate days within a period of one to two weeks, lasting about three hours each, including a ten-minutes break. The participants were tested either individually or in groups of maximally four persons in a university laboratory. All tasks were administered in the same order across participants to minimize subject-by-treatment interactions; and two tasks designed to measure the same EF were not presented successively (Friedman et al., 2016; Miyake et al., 2000). During the first session, the following tests were applied: 1. SIMKAP; 2. two divided attention tests: unimodal and crossmodal; 3. three working memory tasks: operation, symmetry, and reading span; 4. three relational integration tasks: numerical, verbal, and figural. The second session comprised the EF tasks: 1. stop signal; 2. nonverbal 2-back; 3. category switch; 4. antisaccade; 5. keep track; 6. color shape; 7. letter-memory; 8. number-letter; 9. nonverbal 3-back; and 10. Stroop. Most of the tests are in German, except the keep track, letter memory, and WMC tests which are in English. Being university students who are required to speak English fluently, none of the participants showed any problems with the English instructions.

2.2.3 Materials

The selection of indicators was undertaken considering the construct representation of each latent variable (Little, Lindenberger, & Nesselroade, 1999). Almost every latent variable comprised three indicators (e.g., verbal, numerical, and figural) to represent an adequate degree of heterogeneity (Humphreys, 1962) and factor identification (Velicer & Fava, 1998).

Multitasking behavior (SIMKAP; Bratfisch et al., 2003). The test consists of five subtests in which the first four represent the single (or routine) tasks phases, and the last subtest contains the multitasking phase. Subtests one to three require participants to compare numbers, letters, and figures between two windows (left and right side of the screen) and mark all the stimuli on the right which are crossed out on the left side of the screen. The implementation period lasts for three minutes per subtest.

The fourth subtest comprises 24 questions including eight logical-numerical (e.g., “Continue the numerical sequence: 3, 5, 7, 9, …….”), eight logical-verbal (e.g., “Which word differs from the others: bread, rice, egg, car?”), or eight arithmetic (e.g., “What is 4 times 6 divided by 2?”) questions. Twenty answers appear in a box on the lower part of the screen. Participants are instructed to select the right solution for each question from the response box. As soon as the response is registered, the next question is presented. This subtest takes approximately five minutes.

Figure 1 depicts the screenshot of the last subtest (multitasking phase). In this subtest, the first three subtests (numbers, letters, and figures) appear successively. While participants are working on these single or routine tasks (i.e., identifying and marking certain numbers, letters, and figures), they have to answer questions similar to those in the fourth subtest. Additionally, they must also answer few more new questions. These new types of questions require looking for information in a calendar (e.g. “Which evening are you meeting with your boss?”) or a telephone book (e.g., “What is Elizabeth Baur’s telephone number?”), or have to be answered with a specific time-delay using a clock which is running in the upper right corner of the screen (e.g., “When it is 1.25 on the timer, answer the following question …….”). Participants take eighteen minutes to complete this subtest.

During the fifth subtest, the computer automatically counts the number of correctly answered numbers, letters, and figures; the percentage of errors separately for numbers, letters, and figures; and the number of correctly answered questions. Each correct response adds one point, whereas one point is subtracted for each wrong response. Consistent with the previous study (Bühner, König, et al., 2006), three similar SIMKAP measures are used as dependent variables: speed (correct numbers, letters, and figures), error (percentage of errors concerning numbers, letters, and figures), and question (a total of 48 questions are randomly divided into three item-parcels, each containing 16 questions; and then the correctly answered questions of each parcel are summed and averaged). In addition, a global measure of multitasking behavior is calculated incorporating speed, error, and question, which serves as another dependent variable.

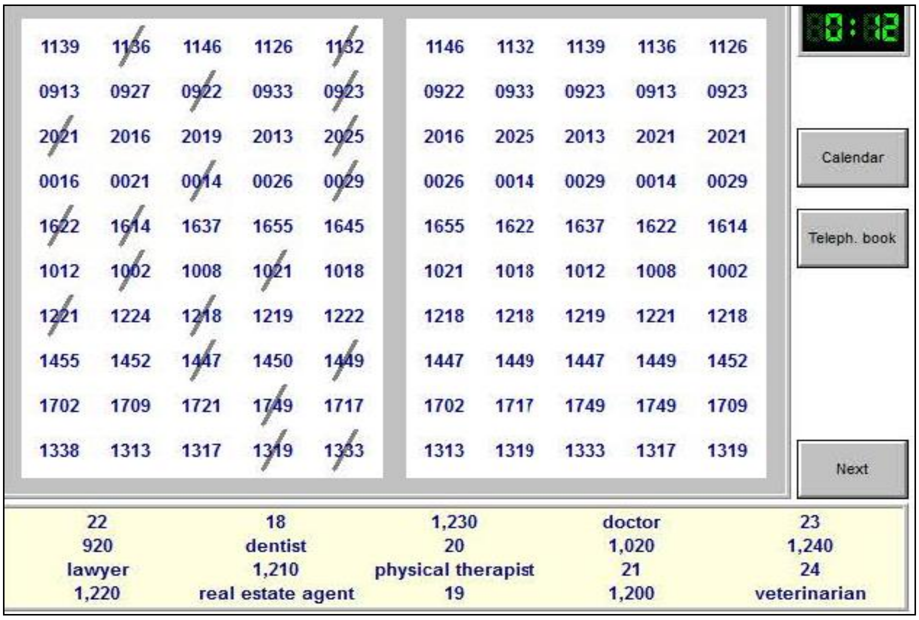


Figure 1. Screenshot of the English version of SIMKAP scenario (multitasking phase). In the SIMKAP, participant has to deal with the routine tasks (identifying and marking the numbers in the right window, which are crossed out in the left window) and the problem-solving tasks (answering the questions using calendar and telephone book) simultaneously.

Executive functions. We used three tasks each to measure shifting, updating, and inhibition. All tasks were exactly the same as employed by Friedman et al. (2016), excepting the following three tasks: the stop-signal, the nonverbal *n*-back, and the Stroop. Because of unavailability of the original task or ioLab USB button box, we could not administer the original ones. For this reason, we chose similar types of tasks (i.e., identical task requirements) from Vienna Test System (Kaiser, Aschenbrenner, Pfüller, Roesch-Ely, & Weisbrod, 2010; Schellig, Schuri, & Arendasy, 2011; Schuhfried, 2011), though the Stroop task slightly differed from the original task (relying on manual responses).

Shifting 1: Number-letter (adapted from Friedman et al., 2016). In this task, a pair of number-letter or letter-number (e.g., 9K) is presented in a 2 × 2 matrix. When the pair appears in the top half of the matrix, participants have to classify the number as odd or even; but when the pair appears in the bottom half of the matrix, they should classify the letter as vowel or consonant. Each pair is presented for 350 ms or until a response is registered. A 200 ms buzz sounds for wrong responses. Participants have to complete two single-rule blocks where the number-letter pairs are presented in top half followed by bottom half of the matrix (32 trials each, preceding by 12 practice trials and two warm-up trials). Then two predictable switch-blocks occur where the stimulus is presented in a clockwise pattern (64 trials each, preceding by 12 practice trials and four warm-up trials). Afterwards participants must perform two random-switch blocks where the stimulus location is randomly determined on each trial (64 trials each, preceding by 24 practice trials and four warm-up trials). Local switch cost is calculated as dependent variable: the difference between the mean reaction time (RT) of correct switch trials and the mean RT of correct repeat (no-switch) trials in random mixed blocks.

Shifting 2: Color-shape (adapted from Friedman et al., 2016). Participants need to classify the color (green vs. red) or the geometric shape (circle vs. triangle) of the target stimulus. The visual cue 'C' is presented for color and 'S' for shape judgement, each cue lasting for 350 ms on the screen. Afterwards, the target stimulus appears for 350 ms or until a response is registered. In color trials, participants are asked to press the 'D' key for green, and 'L' key for red using the standard keyboard; whereas in shape trials they have to press the 'D' key for circle and 'L' key for triangle. An error feedback (a 200 ms buzz) is given for wrong responses. Participants are required to complete two single-rule blocks with 24 test trials each, where the stimuli are presented for single tasks (color judgement followed by shape judgement, preceding by 12 practice trials and two warm-up trials); and two mixed-rule blocks with 56 test trials each, where the stimuli are presented randomly switching between color and shape judgement (preceding by 24 practice trials and four warm-up trials). Each of the single-rule blocks deals with same rule throughout the block, whereas the mixed-rule block deals with switching between two single rules in which half of the trials require switching tasks. The dependent variable is the local switch cost (the mean of correct $RT_{switch\ trials}$ – the mean of correct $RT_{repeat\ trials}$) in mixed-rule blocks.

Shifting 3: Category switch (adapted from Friedman et al., 2016). Participants are instructed to switch back and forth regarding the dimension of animacy (living or non-living) or size of the target stimulus (smaller or larger than a soccer ball). The visual cue is 'heart' for animacy or 'cross' for size judgement, and lasts for 350 ms on the screen. In animacy trials, participants are asked to press the 'D' key for non-living and 'L' key for living via a standard keyboard; whereas in size trials they have to press the two keys for small and big, respectively. A 200 ms buzz sounds as an error feedback. Participants need to complete two single-rule blocks with 32 trials each (animacy then size judgement, preceding by 12 practice trials and two warm-up trials), and two mixed-rule blocks with 64 trials each (switching randomly between animacy and size judgement, preceding by 24 practice trials and two warm-up trials). The local switch cost is calculated by subtracting the mean of correct $RT_{repeat\ trials}$ from the mean of correct $RT_{switch\ trials}$ in mixed-rule blocks.

Updating 1: Keep track (Friedman et al., 2016). Stimulus presentation is performed by Apple MacBook with PsyScope X Build 51 experimental software (Cohen, MacWhinney, Flatt, & Provost, 1993). A string of fifteen to twenty-five words concerning two to five target categories (relatives, countries, distances, colors, animals, and metals) appears on the screen every 2000 ms. Participants have to keep track the last example of each target category, and write these words on the answer sheet (see Appendix A1) after each trial. After practicing two trials (each contains two target categories), participants are instructed to perform 16 test trials, recalling a total of 56 words. Each of four trials appears with two, three, four, and five target categories in random order. Accuracy (i.e., the number of correct words divided by the total words) serves as dependent variable.

Updating 2: Letter memory (Friedman et al., 2016). Stimulus is displayed using Apple MacBook with PsyScope X Build 51 experimental software (Cohen et al., 1993). A list of consonants appears on the screen every 3000 ms. Participants have to continuously rehearse and remember the latest four consonants, adding the most recent letter and dropping the fifth letter back (e.g., "C … CF… CFH … CFHK … FHKP … HKPM … KPMD"). After each trial, participants are instructed to write the last four consonants in the correct serial order on the answer sheet (provided in Appendix A2). They must complete three practice trials and 12 test trials. Each of four test trials appears with sequence of nine, eleven, and thirteen consonants in random order. Accuracy (i.e., the proportion of correct trials) is used as dependent variable.

Updating 3: Nonverbal n-back (Schellig et al., 2011). In the nonverbal *n*-back task, abstract figures are displayed sequentially on the computer screen. After each trial, participants are asked to decide whether the current figure is identical with the previous figure that appeared 2 items (for 2-back condition) or 3 times (for 3-back condition) before. The 2-back and 3-back conditions are presented as separate tasks. There are 100 test trials for 2-back, and 140 test trials for the 3-back task. The proportion of correct responses are calculated separately for the 2-back and 3-back tasks, then these scores are arcsine transformed and z-scored. The dependent variable is the average of the z-scores across the 2-back and 3-back tasks.

Inhibition 1: Antisaccade (adapted from Friedman et al., 2016). The stimuli are displayed via Psychophysics Toolbox – 3 (Brainard, 1997; Pelli, 1997; see http://psychtoolbox.org/) running with Matlab (ver. R2016a, Mathworks Inc, Natick, MA). This task comprises one prosaccade block (18 trials) and three antisaccade blocks (36 trials each). There are 12 practice trials (preceded by two warm-up trials) before the prosaccade and the antisaccade blocks. Each trial starts with a central fixation dot (diameter: 0.3° of visual angle). After a random fixation interval between 1500 and 3500 ms, the fixation dot disappears and a saccade cue (a black square; edge length: 0.4° of visual angle) appears at 11° to the left or right of fixation. In prosaccade trials, participants are instructed to saccade towards the cue, while in antisaccade trials they have to saccade to the mirror-opposite position of the cue on the other display half. After a variable stimulus onset asynchrony (SOA; see below), the cue is replaced by a numeric target (a black digit between 1 and 9 inscribed in an imaginary square of 1.4° edge length). The target either appears at the same location of the cue (prosaccade trials) or at the mirror-opposite location (antisaccade trials) of the cue. It is masked by white noise after 150 ms. In prosaccade trials, the cue to target SOA is 183 ms. In antisaccade trials, the SOA is gradually reduced across the three blocks: 233 ms, 200 ms, and 183 ms, respectively. At the end of each trial, participants are asked to indicate the target identity by pressing a number button. The dependent variable is the proportion of correct target discrimination responses across three antisaccade blocks (a total of 108 trials).

Inhibition 2: Stop signal (Kaiser et al., 2010). In this task, the stimuli (arrows) are presented sequentially pointing to the left or right. Among 200 stimuli, 152 stimuli indicate to carry out motor responses (go trials) and the rest of stimuli appear with a pitch of 1000 Hz tone for duration of 100 ms (stop signal trials). In go trials, participants have to press the ‘5’ key for left pointing arrow and the ‘6’ key for right pointing arrow using the standard keyboard. In stop signal trials, the arrow appears with the tone and participants need to suppress their response. The delay between the onset of the go stimuli and the onset of the stop signal is adjusted by following staircase-tracking procedure (van den Wildenberg et al., 2006). Correct response to a stop trial determines to increase the next stop signal delay by 50 ms, and wrong response determines to decrease the delay by 50 ms. This procedure makes the task either difficult or easier so that the participant can respond correctly at least 50% of the trials. The delay ranges from 50 ms to 350 ms. The mean stop signal delay is subtracted from the median RT on go trials to obtain an estimate of stop signal reaction time (SSRT) as a dependent variable.

Inhibition 3: Stroop (Schuhfried, 2011; see also Stroop, 1935). This test comprises four conditions. In the reading-baseline condition, the color word written in grey font appears on the screen (RED, GREEN, YELLOW, or BLUE). Participants are instructed to press the appropriate color button for each word using a button box. In the naming-baseline condition, the color bar with one of the four colors is presented. Participants are required to name the color of the bars and respond accordingly. In the reading-interference condition, participants must read the color word and press the appropriate button disregarding the font color of the word. In the naming-interference condition, the word is written in different color, which acts as interference. Participants have to resist the dominant tendency to read the word and instead respond according to its font color. The dependent variable is the difference between the mean RT of naming-baseline and the mean RT of naming-interference condition, only RT for correct trials are considered.

Working memory capacity tests (Oswald, McAbee, Redick, & Hambrick, 2015). We used the shortened version of complex span tasks (operation, reading, and symmetry span) to assess WMC. Stimulus presentation and response collection are controlled by E-Prime 2 Professional software (Psychological Software Tools, Pittsburgh, PA).

Operation span. In each trial, participants have to solve a series of math problems by selecting ‘True’ or ‘False’, while remembering letters. Following each math problem, a letter is presented. After each math - letter sequence, participants are required to recall the letters in correct serial order. This task comprises six test trials preceding by three practice trials. Set size varies in length from 4 to 6 math - letter problems per trial. The partial-credit score serves as dependent variable.

Reading span. In each trial, participants should decide whether a series of sentences is meaningful or not by choosing ‘True’ or ‘False’, while remembering letters. Following a sentence presentation, a letter appears. After each sentence - letter sequence, participants have to recall the letters in correct serial order. This task comprises six test trials preceding by three practice trials. Set size varies in length from 4 to 6 sentence - letter problems per trial. The partial-credit score is used as dependent variable.

Symmetry span. In each trial, a set of patterns in an 8 × 8 matrix appears and participants have to decide whether the displayed pattern is symmetrical according to vertical axis. Following a pattern presentation, a red square appears in the 4 × 4 matrix. After each symmetry – square sequence, participants should recall the correct presentation order of red squares. Set size varies in length from 3 to 5 symmetry - square problems per trial. The dependent variable is the partial-credit score.

Relational integration tests (von Bastian & Oberauer, 2013). This test is written in Matlab (ver. R2016a, Mathworks Inc, Natick, MA), using the Psychophysics Toolbox - 3 (Brainard, 1997; Pelli, 1997; see http://psychtoolbox.org/). This test consists of three versions.

Numerical version. In this task, nine three-digit numbers are presented in a 3 × 3 matrix and one of the numbers is randomly replaced every 2000 ms. Participants have to respond when three identical last digits appear either in a row, column, or diagonal line. The task comprises a total of 112 trials including 15 practice trials. The dependent variable is the discriminability index (d′), reflecting sensitivity of target detection. It is computed by relating hit rate and false alarm rate (d′ = z (hit rate) – z (false alarm rate)), where z represents standardized scores.

Verbal version. Nine words in a 3 × 3 matrix are displayed and one word randomly changes every 2000 ms. Participants are asked to respond when three rhyming words are shown either in a row, column, or diagonal line within the matrix. Participants must complete 94 test trials proceeding by 17 practice trials. Discriminability index (d′) serves as dependent variable.

Figural version. Black dots in a 10 × 10 matrix are presented and two of twenty dots are replaced every 2000 ms. Participants are asked to respond when four black dots form a square. Participants must complete 108 trials including 23 practice trials. Discriminability index (d′) is used as dependent variable.

Divided attention tests (Strum, 2008). This test consists of two versions (unimodal and crossmodal).

Unimodal version. Participants have to monitor two visual stimulus presentation conditions (upper and lower channels), where a series of 260 stimuli (of which 65 are relevant) appears one after the other on the computer screen. Each stimulus consists of a pair of shapes (one square and one circle) and is presented for 1500 ms. Whenever the same shape (either square or circle) gets noticeably lighter twice in a row, participants should respond as quickly as possible. This change takes place every 500 ms. The dependent variable is the logarithmic mean RT of given responses.

Crossmodal version. Participants are required to monitor one visual and one auditory stimulus presentation conditions. A square appears at regular intervals on the screen and at the same time participants listen to a sound. Sometimes the square gets noticeably lighter, and sometimes the sound gets noticeably softer. Whenever the square gets noticeably lighter or the sound gets noticeably softer twice in a row, participants are asked to respond as quickly as possible. The presentation order of stimuli is determined randomly. The dependent variable is the logarithmic mean RT of given responses.

2.2.4 Statistical Analyses

Data trimming and transformation. For the purpose of the direct replication of the EFs models, we applied the same trimming and transformation procedures to improve normality, as explained in the original study (for a detailed description, see Friedman et al. 2016, p. 331). Regarding EF tasks, RT for error trials, RT below 200 ms, and RT that deviated from the median by more than 3.32 times the median absolute deviation were (Formula 3; Wilcox & Keselman, 2003) excluded for the three shifting and the Stroop tasks. In addition, RT for trials immediately following errors were omitted from all the shifting tasks. The accuracy scores of the nonverbal *n*-back task were arcsine transformed in order to stabilize the variances and linearize the relationship with other variables by stretching out the tails of the distribution of proportions (Cohen, Cohen, West, & Aiken, 2003).

For all tasks, observations falling beyond $\pm$3 *SD*s from the mean of each group were replaced by the values equal to $\pm$3 *SD*s from the mean, assuming 99.87% of the observations belonged to the normal distribution. This procedure made a difference of 1.9% of the values (maximum) for any task. Raw scores of the variables (except for the nonverbal *n*-back) were used for all analyses. Moreover, the scores (i.e., error aspect of multitasking behavior and all RT measures) were reversely coded so that higher scores expressed higher performance.

Data analyses. Germane to the preregistration of the current study, two approaches were adopted in analyzing the data, as recommended by Wagenmakers, Wetzels, Borsboom, van der Mass, and Kievit (2012): The first approach involved confirmatory pre-registered analyses in which we analyzed what we proposed to do during preregistration. We tested the multitasking behavior model and the three-factor EFs model using confirmatory factor analyses with maximum likelihood estimation. Furthermore, we intended to simultaneously evaluate the associations of EFs, WMC, relational integration, and divided attention with the performance of multitasking by applying structural equation modeling (SEM). However, this specific model estimation failed to converge, probably due to the presence of multicollinearity (as similar in Hambrick et al., 2010; Redick et al., 2016). To address this problem, we used the second approach, which involved exploratory unregistered analyses, guided by the previous research and theories that were not mentioned in the online preregistration document.

As suggested, we used a combination of fit indices to evaluate the models (Beauducel & Wittman, 2005). Therefore, the assessment of the global goodness-of-fit was based on a chi-square test (χ^2), the standardized root mean square residual (SRMR), the root mean squared error of approximation (RMSEA), and the comparative fit index (CFI). Values of SRMR $\leq$ .08, RMSEA $\leq$ .06, and CFI > .95 were taken as indication of adequate model fit (Hu & Bentler, 1999). We reported standardized loadings of each indicator on its corresponding latent factor. The χ^2 difference test ($\Delta\chi^2$) was used for model comparison. All models were estimated using Amos 24.

Because of multicollinearity, the variance of the coefficient estimates became extremely sensitive to minor changes in the model. We, therefore, decided to use multiple regression analyses to investigate how individual differences in EFs, WMC, relational integration, and divided attention relate to individual differences in multitasking behavior. The exploratory factor analysis (principal axis factoring) was applied to compute factor scores (more specifically, Bartlett scores) for all the variables; one factor was extracted in each analysis in an analogous manner described in earlier literature (Bühner, König, et al., 2006; König et al., 2005; Redick et al., 2016).[1] Multiple regression analyses were conducted using the open source statistical software R (R Development Core Team, 2015) with two additional packages ‘ppcor’ (Kim, 2015) for semi partial correlation and ‘boot’ (Canty & Ripley, 2016) for relative weight analyses. In the first step of regression analyses, the model of WMC, relational integration, and divided attention was established in order to be consistent with and to extend the prior work (Bühner, König, et al., 2006) in predicting multitasking behavior. In a second step, the three-factor EFs model entered the analyses, allowing us to determine

[1] Due to the occurrence of Heywood cases in the principal axis exploratory factor analysis, the estimation of the single factor multitasking behavior model with the variables speed, error, and question did not converge. Heywood cases may occur because of outlier, under identification, missing data, or structural misspecification (Kolenikov & Bollen, 2012). However, this is not the case for the present data set, as there was no outlier, missing data, or misspecification problem. Apparently, the residual covariance matrix may show negative variances due to empirical underidentification issue (Kenny, 1979) and result in Heywood cases. A plausible solution for the failure to converge might therefore be that the factor scores for multitasking behavior were calculated by following three steps: 1) The specified indicators of speed and question were entered together, and one construct (speed-question) was extracted, 2) The factor scores of error were created by separately entering its specified indicators, and 3) Using the factor scores of speed-question and error, the factor scores of multitasking behavior were created. Notably, from the theoretical perspective it is reasonable to load the indicators of speed and question on a single variable, as these two do not focus on the accuracy when responding the stimuli, but focus on responding as many stimuli as possible within a restricted period. Thus, conceptually speed and question measures are similar, but dissimilar with the error measure. Although this model is not identified in a maximum likelihood framework, we used principal axis factoring in which identification issue is not crucial.

whether it added a unique contribution to explain multitasking behavior above and beyond these previously known factors. In addition, as multicollinearity makes complexity in partitioning of variance among multiple correlated predictors, we also applied relative weight analyses (for a similar approach, see Redick et al., 2016), which explain the rank ordering of each predictor's proportionate contribution by partitioning R^2, in the presence of all other predictor variables (Tonidandel & LeBreton, 2011, 2015). Relative weight analyses examined the relative importance of WMC, relational integration, divided attention, shifting, updating, and inhibition to multitasking behavior. In all regression analyses, the following estimates were used: i) standardized regression weights (β), ii) squared zero-order correlations (r^2), iii) squared semi-partial correlations (r_p^2), iv) R^2 change (ΔR^2), v) raw relative weights (i.e., a measure of relative effect sizes; Tonidandel & LeBreton, 2015), and vi) rescaled relative weights (i.e., relative weights scaled as the percentage of explainable variance; Tonidandel & LeBreton, 2015).

2.3 Results

2.3.1 Preliminary Data Analyses and Task Correlations

Means, standard deviations, and reliability estimates for all measures are presented in Table 1. The range of skewness and kurtosis of the measures were acceptable. Reliability estimates were mostly high and consistent with the literature, with a few exceptions (i.e., the letter memory, the stop signal, and the symmetry span). Table 2 provides the correlations among the measures. Inspecting this zero-order correlation matrix, all the tasks that tapped the same latent factor seemed to be significantly correlated with each other, correlations ranging from low to high (r = .16 to r = .84); except the Stroop task. The Stroop task showed a significant correlation only with the category switch task (r = .18). Regarding EF tasks, the nine tasks tended to show significantly smaller (sometimes non-existent) correlations with each other indicating the unity and diversity framework of EFs (Ito et al., 2015; Salthouse, Atkinson, & Berish, 2003).

Table 1

Means, Standard Deviations (SD), and Reliability Estimates of the Sample.

Tests	Mean	*SD*	Skewness	Kurtosis	Reliability
SIMKAP aspects					
Speed					
Numbers	119.66	38.37	0.45	-0.42	.99[b]
Letters	113.65	35.30	0.86	0.51	.99[b]
Figures	136.13	46.35	0.61	0.16	.88[b]
Error					
Numbers	8.91	2.88	-1.34	1.77	-[f]
Letters	10.64	3.13	-1.38	2.51	-[f]
Figures	13.75	3.70	-1.28	2.08	-[f]
Question	32.94	7.89	-0.67	-0.20	.88[b]
Executive functions					
Shifting					
Number letter	457.88	157.64	-0.75	0.25	.89[c]
Color shape	828.06	275.50	-0.80	0.92	.92[c]
Category switch	592.94	186.20	-0.96	1.30	.83[c]
Updating					
Keep track	0.75	0.10	-0.68	0.20	.72[b]/.73[d]
Letter memory	0.69	0.19	-0.41	-0.37	.59[b]/.59[d]
Nonverbal *n*-back					
Nonverbal 2-back[a]	1.27	0.10	-0.37	0.73	.84 [b]
Nonverbal 3-back[a]	1.22	0.09	-0.36	0.11	.86 [b]
Inhibition					
Antisaccade	0.65	0.17	-0.62	0.03	.94[a]
Stop signal	165.93	55.48	0.60	0.25	.94[e]
Stroop	214.53	71.51	0.81	1.10	.87[e]
Working memory capacity					
Operation span	0.82	0.19	-1.39	1.56	.72[b]/.73[d]
Reading span	0.66	0.23	-0.66	-0.11	.73[b]/.73[d]
Symmetry span	0.65	0.20	-0.56	-0.03	.55[b]/.55[d]
Relational integration					
Numerical	2.43	0.73	-0.22	-0.13	.77[c]
Verbal	2.51	0.71	0.00	-0.31	.72[c]
Figural	2.48	0.42	-0.59	0.36	.59[c]
Divided attention					
Unimodal	481.60	151.06	-1.36	2.07	.96[b]
Crossmodal	492.11	171.42	-0.82	0.39	.96[b]

Note. The descriptive statistics were given after trimming $\pm$ 3*SD* (see text). Reliability estimates were calculated before trimming. The scores for multitasking error and all RT measures (in ms) were reversely codded. [a]Scores were arcsine transformed. [b]Cronbach’s Alpha. [c]Split-half reliability. [d] McDonald’s Omega. [e]Reliability for difference scores. [F]Could not be calculated.

Table 2

Correlation Matrix for All Task Performance.

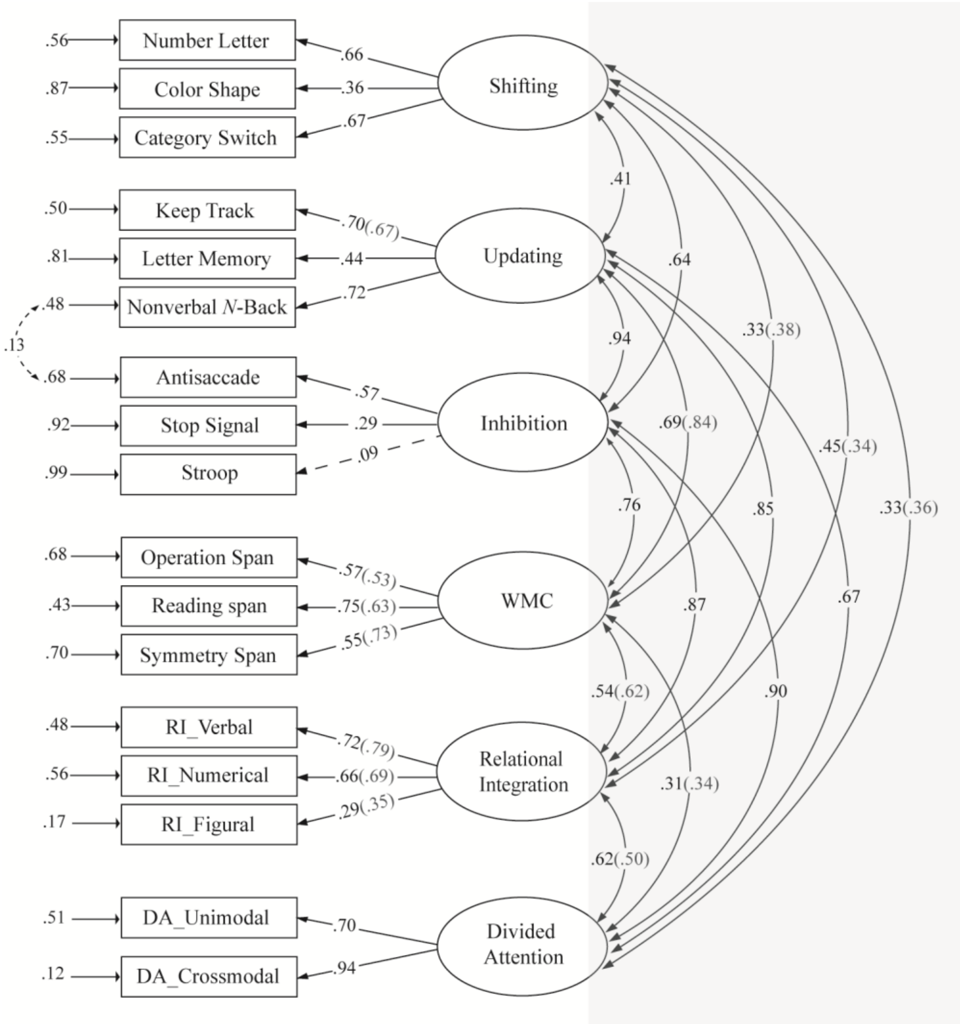
Measures	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1. Speed: Numbers																									
2. Speed: Letters	.77**																								
3. Speed: Figures	.80**	.84**																							
4. Error: Numbers	.15*	.05	.12																						
5. Error: Letters	.09	.11	.14	.53**																					
6. Error: Figures	.15*	.19**	.22**	.49**	.55**																				
7. Question (Parcel-1)	.48**	.44**	.41**	.29**	.37**	.36**																			
8. Question (Parcel-2)	.28**	.19**	.26**	.31**	.39**	.40**	.63**																		
9. Question (Parcel-3)	.46**	.43**	.38**	.29**	.33**	.34**	.63**	.57**																	
10. Number letter	.24**	.17*	.22**	.05	.07	.02	.18**	.20**	.25**																
11. Category switch	.21**	.14*	.22**	.10	.12	.12	.17*	.25**	.26**	.43**															
12. Color shape	.01	-.02	.01	.09	.02	.01	.03	.04	.15*	.24**	.28**														
13. Keep track	.29**	.30**	.34**	.46**	.39**	.40**	.46**	.40**	.37**	.24**	.19**	.19**													
14. Letter memory	.12	.16*	.16*	.25**	.18**	.27**	.29**	.22**	.21**	.04	-.00	.03	.40**												
15. Nonverbal *n*-back	.25**	.28**	.29**	.34**	.36**	.34**	.41**	.37**	.41**	.21**	.18**	.15*	.48**	.31**											
16. Antisaccade	.41**	.35**	.44**	.19**	.35**	.34**	.47**	.42**	.41**	.26**	.29**	-.01	.41**	.19**	.47**										
17. Stop signal	.15*	.13	.16*	.22**	.15*	.21**	.20**	.24**	.21**	.12	.11	-.02	.22**	.24**	.05	.16*									
18. Stroop	-.05	.00	.03	-.04	-.08	-.02	-.00	.03	-.03	.02	.18*	.03	.04	.07	.07	.01	.02								
19. Operation span	.17*	.18*	.24**	.14	.12	.25**	.29**	.31**	.28**	.18**	.20**	.01	.27**	.18*	.23**	.23**	.23**	.01							
20. Reading span	.23**	.28**	.29**	.26**	.22**	.30**	.24**	.27**	.31**	.19**	.14*	.07	.38**	.26**	.37**	.28**	.17*	.05	.45**						
21. Symmetry span	.14	.09	.18*	.13	.19**	.22**	.21**	.30**	.24**	.11	.06	.02	.22**	.17*	.32**	.31**	.18*	-.07	.30**	.40**					
22. RI_Figural	.22**	.13	.17*	.09	.04	.04	.17*	.14*	.17*	.10	.08	.05	.04	.12	.15*	.10	.08	.06	.09	.04	.05				
23. RI_Numerical	.35**	.29**	.32**	.30**	.26**	.31**	.44**	.46**	.38**	.27**	.18**	.24**	.42**	.22**	.42**	.34**	.13	-.03	.23**	.27**	.28**	.25**			
24. RI_Verbal	.38**	.40**	.42**	.31**	.33**	.33**	.42**	.36**	.45**	.18**	.21**	.04	.40**	.23**	.51**	.41**	.13	.04	.23**	.26**	.24**	.23**	.46**		.
25. DA_Unimodal	.30**	.26**	.34**	.27**	.34**	.34**	.36**	.39**	.41**	.14*	.13	.09	.39**	.10	.37**	.36**	.22**	.11	.30**	.16*	.20**	.08	.27**	.32**	
26. DA_Crossmodal	.32**	.31**	.36**	.26**	.37**	.35**	.45**	.45**	.38**	.27**	.18*	.03	.45**	.20**	.46**	.48**	.26**	.08	.23**	.18**	.14	.21**	.34**	.45**	.66**

Note. RI_Figural = relational integration_figural; RI_Numerical = relational integration_numerical; RI_Verbal = relational integration_verbal; DA_Unimodal = divided attention_unimodal; DA_Crossmodal = divided attention_crossmodal.
**p < . 01. *p < .05.

2.3.2 Confirmatory Factor Analysis: Correlated Factors Model

In the beginning of the analyses, motivated by the existing literature (Bühner et al., 2005; Redick et al., 2016) we examined how all basic cognitive abilities overlapped with one another. The EFs model was therefore extended by adding the models of WMC, relational integration, and divided attention (see Figure 2). The resulting model yielded excellent global fit, $\chi^2(103) = 138.47$, $p = .011$; CFI = .95; RMSEA = .04; SRMR = .05, and all factor loadings differed significantly from zero.[2] The model yielded information about the significant moderately high correlations between the latent constructs (ranged from $r = .31$ to $r = .94$), thereby revealing three significant contributions in the field: First, it replicated the measurement model of WMC, relational integration, divided attention, and shifting (Bühner et al., 2005). Because WMC was closely correlated with relational integration ($r = .54$), but weakly correlated with divided attention ($r = .31$) and shifting ($r = .33$). In line with previous finding, the highest correlation was found between relational integration and divided attention ($r = .62$). Second, consistent with prior demonstration, the present findings also confirmed the measurement model of two-factor WM (Redick et al., 2016), and showed that WMC and updating shared roughly 48% of their variance. Third, looking at the three EF components, inhibition was highly correlated with other cognitive abilities, compared to updating and shifting. Specifically, inhibition shared large amount of variance with WMC (58%), relational integration (76%), and divided attention (81%).

[2] Note that the residuals from the nonverbal *n*-back and the antisaccade task were allowed to correlate since both tasks share common cognitive mechanisms (similar to Friedman et al., 2016). However, the correlation was not significant.



$\chi^2(103) = 138.47$, $p = .011$; CFI = .95; RMSEA = .04; SRMR = .05

Figure 2. Correlated factors model with shifting, updating, inhibition, working memory capacity (WMC), relational integration, and divided attention. All significant paths ($p < .05$) are indicated by solid line. Non-significant paths are indicated by dotted lines. The proportion of residual variance of each indicator is calculated by subtracting the variance of the indicator from 1. The parameter estimates of the original models (Bühner et al., 2005; Redick et al., 2016) are depicted in parentheses (for indicators: the values in parentheses represent the estimates of identical tasks). RI_Verbal = relational integration_verbal; RI_Numerical = relational integration_numerical; RI_Figural = relational integration_figural; DA_Unimodal = divided attention_unimodal; DA_Crossmodal = divided attention_crossmodal.

2.3.3 Replication of the Multitasking Behavior Model

To test the replicability of the multitasking behavior model (Bühner, König, et al., 2006), we performed a confirmatory factor analysis and specifically compared the fit estimates between the original model and our model. Because of multicollinearity, we were not able to estimate the proposed multitasking behavior model represented by a hierarchical SEM, where three first-order factors (i.e., speed, error, and question) load on the second-order factor - multitasking behavior. Therefore, the first model (Figure 3) contained three aspects of multitasking behavior: speed, error, and question, which were correlated. The three-factor model revealed an acceptable overall model fit, $\chi^2(23) = 52.96$, $p < .001$; CFI = .97; RMSEA = .08; SRMR = .05. Factor loadings of all the indicators onto their respective latent variables were high (speed: $\lambda = .87$ to $\lambda = .92$; error: $\lambda = .68$ to $\lambda = .78$; question: $\lambda = .73$ to $\lambda = .84$), and significantly different from zero ($p < .001$). Correlations between the latent variables were low to moderate (speed and error = .20, error and question = .59, speed and question = .54). The 95% CIs for the correlations were [.06, .33] for the speed and error factors, [.49, .67] for the error and question, and [.43, .63] for the speed and question factors. A model comparison indicated that the three-factor model fitted significantly better than a single-factor model ($\Delta\chi^2(3) = 344.13$, $p < .001$) and two-factor models ($\Delta\chi^2(2) = 195.60$, $p < .001$; $\Delta\chi^2(2) = 195.43$, $p < .001$; $\Delta\chi^2(2) = 92.12$, $p < .001$). The correlated residuals between numerical speed and numerical error also held in our model. We deemed this correlation acceptable since both measures require the same numerical materials.

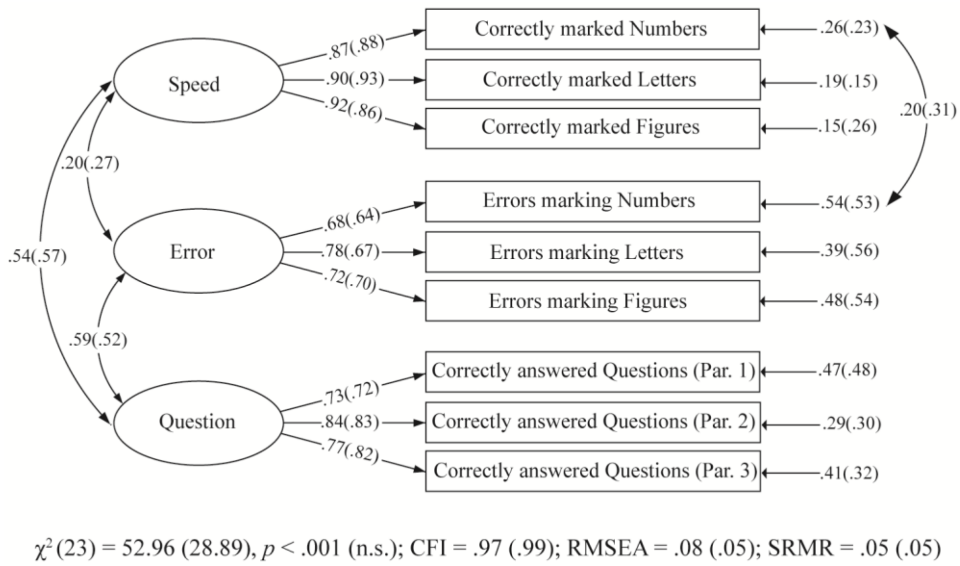


Figure 3. Replication of the multitasking behavior model. Numbers in brackets are the parameter estimates of the original model (Bühner, König, et al., 2006). The proportion of residual variance of each indicator is calculated by subtracting the variance of the indicator from 1. All parameters were statistically significant ($p < .001$).

2.3.4 Replication of the Executive Functions Models

Three-factor executive functions model. We tested the three-factor EFs model using a latent variable analysis as described by Friedman et al. (2016) and Miyake et al. (2000). The fit of the resulting three-factor model (Figure 4) was excellent, $\chi^2(23) = 39.37$, $p = .018$; CFI = .94; RMSEA = .06; SRMR = .05. All path coefficients from the indicators to the latent variables in this model were moderate to high (shifting: $\lambda = .36$ to $\lambda = .69$; updating: $\lambda = .48$ to $\lambda = .84$; inhibition: $\lambda = .30$ to $\lambda = .57$), and were all significant ($p < .001$), except the path from the Stroop to inhibition ($\lambda = .09$, $p > .05$). Correlations between the latent variables were also moderate to high (shifting and updating = .39, updating and inhibition = .83, shifting and inhibition = .60). The 95% CIs for the correlations were [.27, .50] for the shifting and updating factors, [.78, .87] for the updating and inhibition factors, and [.50, .68] for the shifting and inhibition factors. We also found significant correlation between the residuals of nonverbal *n*-back and the antisaccade tasks ($r = .29$), which was specified in the EFs model of Friedman et al. (2016). When we regressed all the indicators onto a single factor, the resulting model showed significant fit decrement, $\Delta\chi^2(3) = 46.52$, $p < .001$. Given the non-significant loading of the Stroop task onto inhibition and its lack of correlation with other two indicators (the antisaccade and the stop signal, see Table 2), we examined whether excluding the Stroop from the EFs model would change the pattern of parameter estimates considerably. The reduced model also fitted the data well, $\chi^2(16) = 30.85$, $p = .014$; CFI = .94; RMSEA = .07; SRMR = .05. Therefore, we dropped the Stroop task from all subsequent analyses.

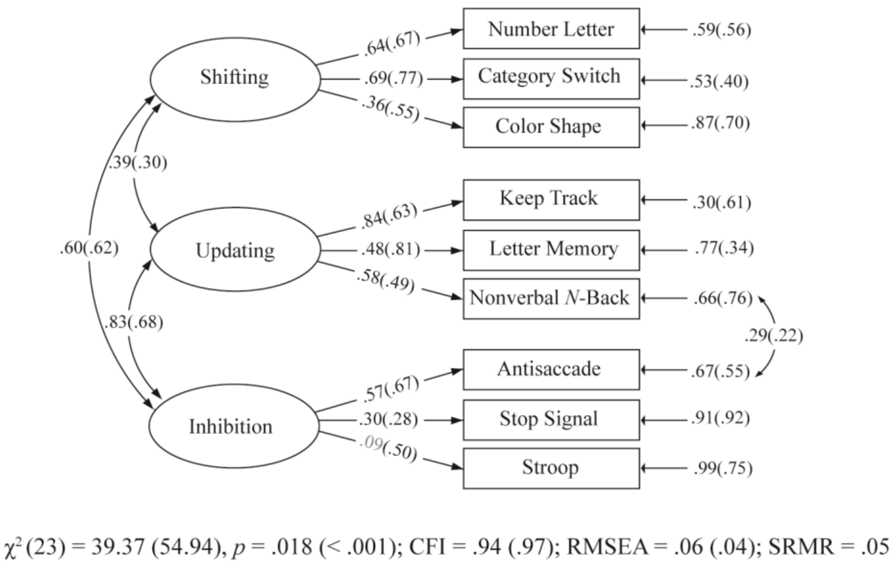
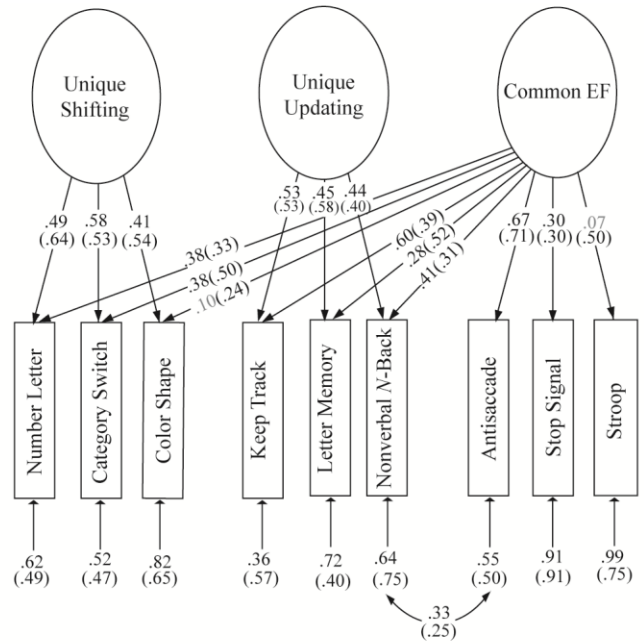


Figure 4. Replication of the three-factor EFs model. Numbers in brackets are the parameter estimates of the original model (Friedman et al., 2016). The proportion of residual variance of each indicator is calculated by subtracting the variance of the indicator from 1. All parameters were statistically significant ($p < .05$), except the parameter in grey color.

Nested factors executive functions model. We investigated whether the nested factors model of EFs (Friedman et al., 2016) replicated in our sample. In the nested factors model, all nine tasks directly loaded on common EF, and the shifting and updating tasks additionally loaded on nested factors constituting unique shifting and unique updating. As shown in Figure 5, the nested factors model revealed an acceptable model fit, $\chi^2(20) = 36.37$, $p = .014$; CFI =.94; RMSEA = .06; SRMR = .05. The factor loadings of the individual EF tasks onto common EF ranged from $\lambda = .28$ to $\lambda = .67$ and were significant at $p < .01$, except for the color-shape and the Stroop ($\lambda = .10$ and $\lambda = .07$, respectively) tasks. The indicators of unique shifting and unique updating also loaded significantly on the unique shifting ($\lambda = .41$ to $\lambda = .58$) and the unique updating ($\lambda = .44$ to $\lambda = .53$) factors, respectively. The correlated residual variance between the nonverbal *n*-back and the antisaccade ($r = .33$) was also significant. After the exclusion of the non-significant Stroop from our model, the reduced model also showed adequate fit, $\chi^2(13) = 27.39$, $p = .011$; CFI = .94; RMSEA = .07; SRMR = .05. Consequently, we omitted this task. However, the path from common EF to the color shape was retained as a non-significant indicator, because the color shape also loaded on unique shifting.

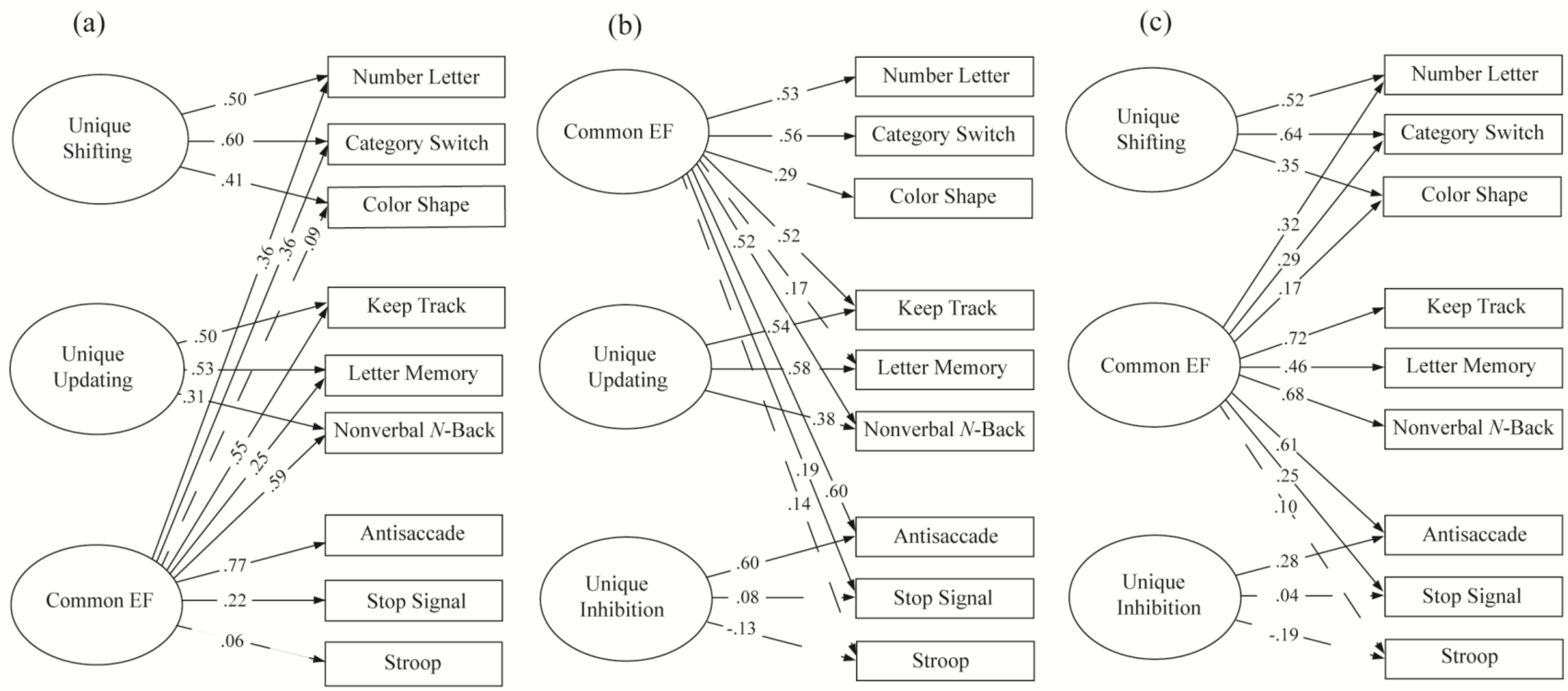
Critically, Friedman et al. (2016) have also claimed that common EF is isomorphic with inhibition, so we tested if our data supported this view. Therefore, a hierarchical model, in which each task loaded onto the three first-order EF factors (shifting, updating, or inhibition) and each first-order factor loaded onto a latent general factor of EFs (common EF) was tested, but resulted in a Heywood case (a standardized loading greater than 1.0) for the inhibition factor. Hence, we examined three alternative nested factors models: In the first model (Figure 6a), the manifest variables (the 9 EF tasks) loaded onto common EF (inhibition), and their specified latent variable (unique shifting and unique updating).[3] Similarly, in the second (Figure 6b) and third (Figure 6c) models, the nine EF tasks loaded onto common EF (shifting or updating, respectively) and their corresponding latent variables (unique updating and unique inhibition; or unique shifting and unique inhibition, respectively). The fit statistics for Figure 6a were χ^2 (21) = 40.39, p = .007; CFI = .92; RMSEA = .07; SRMR = .05; whereas the fit statistics for Figure 6b were χ^2 (21) = 70.79, p < .001; CFI = .80; RMSEA = .11; SRMR = .07; and for Figure 6c were χ^2(21) = 50.34, p < .001; CFI = .88; RMSEA = .08; SRMR = .06. Comparing the three resulting models, the model in which common EF emerged from inhibition (Figure 6a) showed excellent fit. Thus, the present results support earlier Friedman et al.’s (2016) conclusion that common EF can be equated with inhibition.

[3] Note that the Stroop task was retained for model identification and the correlated residual variance between the nonverbal *n*-back and antisaccade was dropped for alleviating the numerical problem in estimation.



$\chi^2(20) = 36.37$ (41.41), $p = .014$ (< .01); CFI = .94 (.98); RMSEA = .06 (.04); SRMR = .05

Figure 5. Replication of nested factors EFs model. Numbers in brackets are the parameter estimates of the original model (Friedman et al., 2016). The proportion of residual variance of each indicator is calculated by subtracting the variance of the indicator from 1. All parameters were statistically significant ($p < .05$), except the parameter in grey color.



$\chi^2(21) = 40.39$, $p = .007$
CFI = .92
RMSEA = .07
SRMR = .06

$\chi^2(21) = 70.79$, $p < .001$
CFI = .80
RMSEA = .11
SRMR = .07

$\chi^2(21) = 50.34$, $p < .001$
CFI = .88
RMSEA = .08
SRMR = .06

Figure 6. Comparison of nested factors EFs models. (a) Common EF emerged from inhibition, (b) Common EF emerged from shifting, (c) Common EF emerged from updating. All significant paths ($p < .05$) are indicated by solid line. Non-significant paths are indicated by dotted line.

2.3.5 Regression Analyses

We investigated the key theoretical question regarding the relations of EFs, WMC, relational integration, and divided attention with multitasking behavior through regression analyses. The correlations between the factor scores of all variables were significant (see Table 3).

Table 3

Correlations between the Factor Scores of the Variables.

Variables	1	2	3	4	5	6
1. Multitasking behavior						
2. WMC	$.43^{**}$					
3. Relational integration	$.59^{**}$	$.36^{**}$				
4. Divided attention	$.56^{**}$	$.27^{**}$	$.44^{**}$			
5. Shifting	$.25^{**}$	$.22^{**}$	$.30^{**}$	$.22^{**}$		
6. Updating	$.61^{**}$	$.46^{**}$	$.54^{**}$	$.50^{**}$	$.26^{**}$	
7. Inhibition	$.53^{**}$	$.38^{**}$	$.38^{**}$	$.47^{**}$	$.27^{**}$	$.46^{**}$

Note.. WMC = working memory capacity.
$^{**}p < .01$.

The results of the regression analyses are summarized in Table 4. The stepwise regression showed that the model of WMC, relational integration, and divided attention accounted for roughly 50% of variance in multitasking behavior, adding the three-factor EFs model to the regression equation an additional 6% of explained variance was produced for the criterion variable, ΔF (3, 195) = 9.14, $p < .001$. Concerning the prediction of multitasking speed, however, the EFs model did not provide a significant incremental proportion of variance. According to the squared semi partial correlation (r_p^2), relational integration accounted for the highest amount of unique variance (about 5%) in multitasking behavior. Divided attention and updating both explained about 3% of multitasking behavior variance uniquely, and inhibition accounted for 2%. On the other hand, WMC and shifting had no statistically significant contribution to multitasking behavior when all other factors were included in the model. Regarding the three multitasking aspects, relational integration explained nearly 5% of variance in both speed and question aspects, whereas updating accounted for 6% of variance in error aspect.

In the relative weight analyses, all the predictor variables contributed significantly, since none of the 95% CIs (not shown in Table 4) for the tests of significance included zero (or negative; Tonidandel & LeBreton, 2015), except the shifting variable. As depicted in Table 4, the results revealed that a weighted linear combination of relational integration and updating contributed mostly in explaining multitasking behavior (25.35% and 23.72% of variance, respectively). The remaining variance was accounted for by divided attention (20.54%), inhibition (17.63%), and WMC (10.40%). Consequently, the most important predictors of multitasking behavior turned out to be relational integration, updating, divided attention, and inhibition. Nevertheless, the rescaled weight results differed slightly in terms of three multitasking measures. Relational integration was the strongest predictor of speed and question aspects, while updating was the best predictor for the error aspect.

Critically, it is worth noting that using SEM, two additional analyses (provided in Appendix A3) were conducted to thoroughly comprehend the relevant predictors of multitasking behavior. First, we aimed at testing whether updating contributed to multitasking behavior because of its overlap with WMC, or whether it constituted an independent contribution. The result (Figure A1) showed that the model fitted well, $\chi^2(81) = 126.90$, $p = .001$, CFI = .97, RMSEA = .05, SRMR = .06; and updating uniquely accounted for 40% of variance in the criterion variable. Second, we estimated another model investigating the role of WMC, relational integration, and divided attention in multitasking behavior. The model (Figure A2) showed adequate model fit: $\chi^2(109) = 159.68$, $p = .001$, CFI = .97, RMSEA = .05, SRMR = .05. Relational integration highly overlapped with multitasking behavior, compared to WMC and divided attention.

Table 4

Multiple Regression and Relative Weight Analyses for Predicting Multitasking Behavior.

Variables	Standardized Coefficients (β)	Squared Zero-order Correlation (r^2)	Squared Semi-Partial Correlation (r_p^2)	ΔR^2	Raw Relative Weight	Rescaled Raw Relative Weight
Multitasking Behavior						
Step 1				$.50^{***}$		
WMC	$.21^{***}$	.18	$.04^{**}$		.10	19.74%
Relational integration	$.37^{***}$	.35	$.10^{***}$		.21	42.78%
Divided attention	$.34^{***}$	.31	$.09^{***}$		.19	37.48%
Step 2				$.06^{***}$		
WMC	.10	.18	.01		.06	10.40%
Relational integration	$.27^{***}$	.35	$.05^{**}$		.14	25.35%
Divided attention	$.21^{**}$	.31	$.03^{*}$		.11	20.54%
Shifting	-.01	.06	- .00		.01	2.35%
Updating	$.23^{***}$	.37	$.03^{*}$		.13	23.72%
Inhibition	$.19^{**}$	.28	$.02^{*}$		.10	17.63%
Speed						
Step 1				$.26^{***}$		
WMC	$.14^{*}$	.10	.02		.05	19.00%
Relational integration	$.31^{***}$	.20	$.07^{***}$		.13	49.88%
Divided attention	$.20^{**}$	.14	$.03^{*}$		.08	31.11%
Step 2				.02		
WMC	.09	.09	.01		.03	11.08%
Relational integration	$.27^{***}$	.20	$.05^{**}$		.09	33.30%
Divided attention	.14	.14	.01		.05	18.26%
Shifting	.05	.05	.00		.02	5.82%
Updating	.02	.13	.00		.03	11.74%
Inhibition	$.16^{*}$	.15	.02		.06	19.80%
Error						
Step 1				$.27^{***}$		
WMC	$.17^{**}$	.11	$.03^{*}$		.06	22.15%
Relational integration	$.22^{**}$	.17	$.04^{**}$		.09	34.17%
Divided attention	$.29^{***}$	.18	$.07^{***}$		.12	43.68%
Step 2				$.08^{***}$		
WMC	.07	.11	.00		.04	10.15%
Relational integration	.12	.17	.01		.06	16.77%
Divided attention	$.17^{*}$	.19	.02		.07	20.84%
Shifting	-.08	.02	-.00		.00	0.95%
Updating	$.33^{***}$	.28	$.06^{***}$		.13	36.86%
Inhibition	.11	.15	.01		.05	14.42%
Question						
Step 1				$.43^{***}$		
WMC	$.17^{**}$	.15	$.03^{*}$		.07	17.79%
Relational integration	$.37^{***}$	.32	$.10^{***}$		.20	45.85%
Divided attention	$.30^{***}$	.26	$.07^{***}$		.16	36.35%
Step 2				$.04^{**}$		
WMC	.09	.15	.00		.05	9.50%
Relational integration	$.29^{***}$	.32	$.05^{**}$		.13	28.26%
Divided attention	$.20^{**}$	.26	$.03^{*}$		.10	20.55%
Shifting	.05	.08	.00		.02	4.73%
Updating	$.15^{*}$	.28	.01		.09	18.73%
Inhibition	$.18^{**}$	.24	$.02^{*}$		.09	18.22%

Note: WMC = working memory capacity.
$^{***}p < .001$. $^{**}p < .01$. $^{*}p < .05$.

2.3.6 Structural Equation Models: Multitasking Behavior and Common EF Ability

To understand the nature of the relationship between multitasking behavior and common EF ability, we fitted a model comprising multitasking behavior, common EF, unique updating, and unique shifting, which was not included in the pre-registration. In order to do this, we tested a series of models (see Table 5 for the model fit statistics). In the initial model (Model A), the paths from the three constructs (common EF, unique updating, and unique shifting) to multitasking behavior were freely estimated. Considering Model A as a baseline model, we compared the relative fits of Model B (the path from unique shifting to multitasking behavior was constrained to 0), Model C (the path from unique updating to multitasking behavior was constrained to 0), Model D (the paths from unique shifting and unique updating to multitasking behavior were constrained to 0), Model E (the path from common EF to multitasking behavior was constrained to 0), Model F (the paths from unique updating and common EF to multitasking behavior were constrained to 0), and Model G (the paths from unique shifting and common EF to multitasking behavior were constrained to 0). As presented in Table 5, Model A showed equally well fit with Model B ($\Delta\chi^2(1) = 1.87$, $p > .05$), Model C ($\Delta\chi^2(1) = 0.55$, $p > .05$), and Model D ($\Delta\chi^2(2) = 3.71$, $p > .05$); but better fit than Model E ($\Delta\chi^2(1) = 85.87$, $p < .001$), Model F ($\Delta\chi^2(2) = 122.35$, $p < .001$), and Model G ($\Delta\chi^2(2) = 86.44$, $p < .001$). Nevertheless, the Model A, Model C, and Model D showed strong evidence of multicollinearity. To avoid this potential multicollinearity problem, we took Model B as our final model, which is depicted in Figure 7.[4] Indeed, the logic behind doing this was that when the path from unique shifting to multitasking behavior was estimated freely (Model A and Model C), it showed non-significance. Again, the shifting factor also proved to be an unimportant predictor of multitasking behavior in the above regression analyses and previous studies (Bühner, König, et al., 2006; Hambrick et al., 2011). However, common EF ability and unique updating accounted for 88% and 8% of multitasking behavior variance, respectively.

Critically, in support of the idea that the updating common to all EF tasks might have a potential role in predicting multitasking behavior, as updating contributed to all EF tasks (Figure 6c), we tested a model, which showed strong multicollinearity. However, when inhibition was merged with updating into one factor (similar to Klauer, Schmitz, Teige-

[4] Notably, in this model the correlated residual variances of the replication models (Bühner, König, et al., 2006; Friedman et al., 2016) were allowed. But correlated residual variance between the numerical speed and the numerical error was not significant.

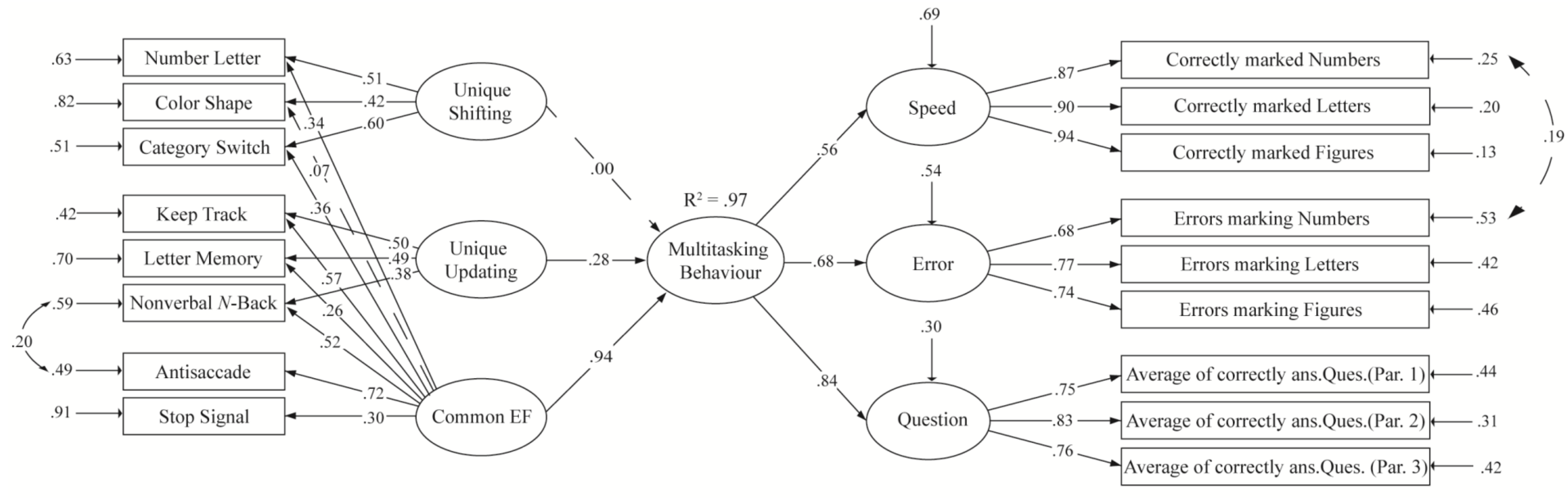
Mocigembe, & Voss, 2010), the loss in goodness of fit was not significant ($\Delta\chi^2(4) = 9.16$, $p > .05$) and the model fitted the data well (see Figure A3). It is worth noting that the indicators of inhibition mostly loaded on updating, and the correlation between updating and inhibition was very high (Figure 4). However, the model showed that the path coefficient for common updating predicting multitasking behavior was .97 ($p < .001$).

Table 5

Fit Statistics of Structural Equation Modeling (SEM).

Model	χ^2	*df*	CFI	RMSEA	SRMR
ComEF, UpdS, ShfS, and MB					
A. All paths to MB free	165.69	105	.96	.05	.06
B. SS-MB fix, US-MB free, ComEF-MB free	**167.56**	**106**	**.96**	**.05**	**.06**
C. US-MB fix, SS-MB free, ComEF-MB free	166.24	106	.97	.05	.06
D. SS-MB fix, US-MB fix, ComEF-MB free	169.40	107	.95	.05	.06
E. ComEF-MB fix, SS -MB free, US-MB free	251.56	106	.89	.08	.13
F. US-MB fix, ComEF-MB fix, SS-MB free	288.04	107	.87	.09	.18
G. SS-MB fix, ComEF-MB fix, US-MB free	252.13	107	.89	.08	.14

Note: We took model B as our final model which is printed in bold type. ComEF = common EF, US = update specific, SS = shifting specific, MB = multitasking bahavior, *df* = degrees of freedom, CFI = comparative fit index, RMSEA = root mean square error of approximation, SRMR = standardized root mean square residual.



$\chi^2(106) = 167.56$, $p < .001$; CFI = .96; RMSEA = .05; SRMR = .06

Figure 7. Structural equation modeling for common EF, unique updating, unique shifting, and multitasking behavior. All significant paths ($p < .05$) are indicated by solid lines. Non-significant paths are indicated by dotted lines. The proportion of residual variance of each indicator is calculated by subtracting the variance of the indicator from 1.

2.3.7 Factor Analysis of Basic Cognitive Abilities and Predicting Multitasking Behavior

As can be seen in Figure 2, the predictor variables were highly related, which points towards the strong multicollinearity we encountered during estimating the models with all available cognitive predictors of multitasking behavior. This issue led us to performing an exploratory factor analysis (maximum likelihood, oblimin rotation) incorporating all the variables (excluding the Stroop task) to order to examine the structure of the cognitive task sets and investigate the relations between the extracted factors and multitasking behavior. This model would be good basis for simultaneously examining the predictive power of several cognitive abilities in explaining multitasking behavior. However, the results favored the extraction of five factors (see Appendix A4), namely shifting, updating, WMC, relational integration (including *n*-back and antisaccade), and divided attention (including stop signal). Based on these factors, we retested the model (Figure 8) and this post hoc modified model showed a good fit, $\chi^2(256) = 350.05$, $p < .001$; CFI = .95; RMSEA = .04; SRMR = .06. All the factor loadings and correlation coefficients were significant ($p < .05$).[5] The relational integration factor (on which antisaccade and *n*-back significantly loaded) acted as the only significant predictor of multitasking behavior ($p < .001$).

[5] Note that the correlated residual variances of the replication model (Bühner, König, et al., 2006) was allowed.

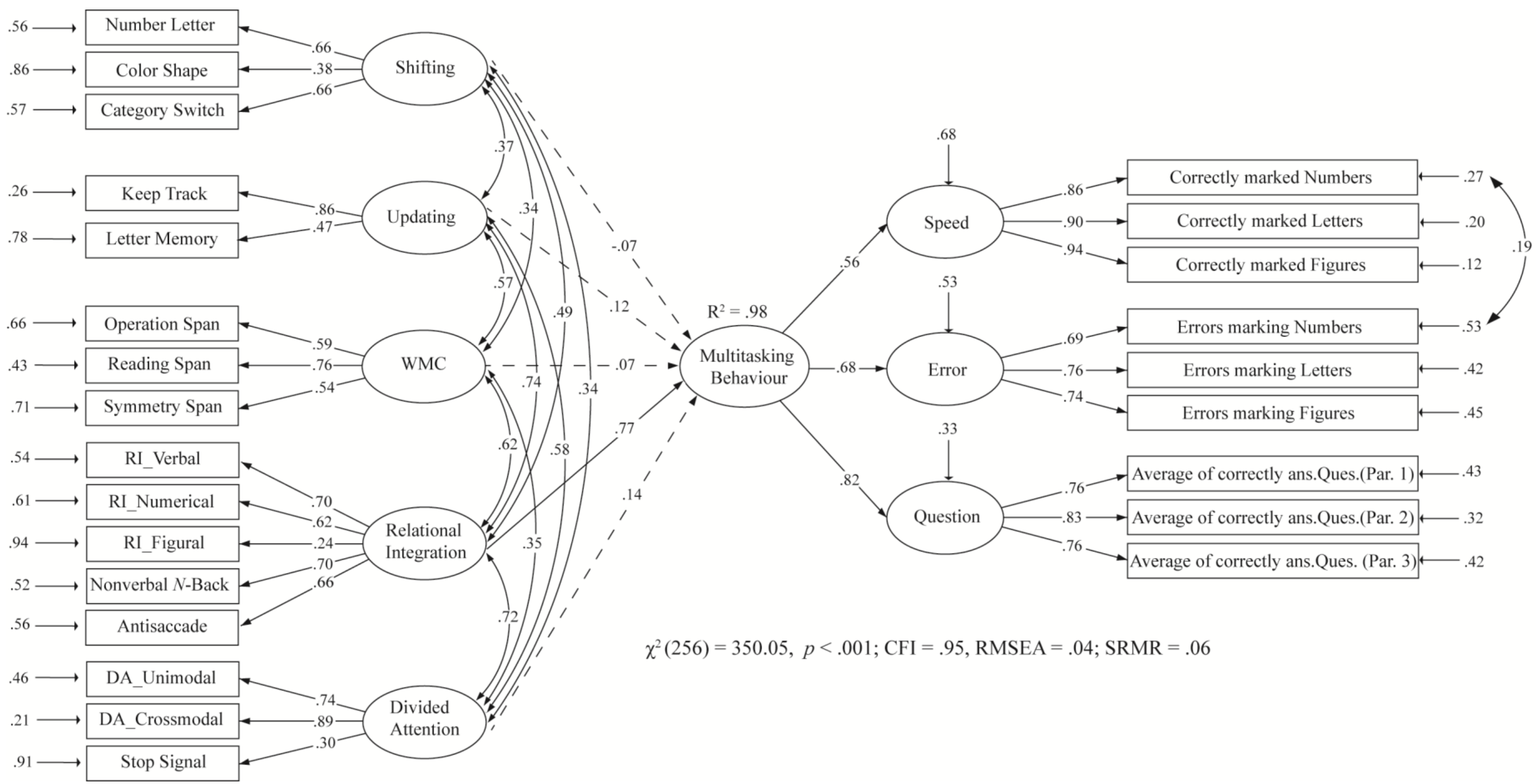


Figure 8. Structural equation modeling for basic cognitive abilities and multitasking behavior. All significant paths (p < .05) are indicated by solid lines. Non-significant paths are indicated by dotted lines. The proportion of residual variance of each indicator is calculated by subtracting the variance of the indicator from 1. WMC = working memory capacity; RI_Verbal= relational integration_verbal; RI_Numerical = relational integration_numerical; RI_Figural = relational integration_figural; DA_Unimodal = divided attention_unimodal; DA_Crossmodal = divided attention_crossmodal.

2.4 Discussion

The prevalent and longstanding interest to comprehend underlying cognitive influences that relate to multitasking behavior motivated this investigation. In particular, we aimed at testing whether proposed models of multitasking behavior and EFs hold, and consequently are useful to investigate the importance of EFs, WMC, relational integration, and divided attention to predict performance in multitasking environment. The updating, inhibition, relational integration, and divided attention proved to be important cognitive constructs in this regard.

2.4.1. The Relationship among Three Core Executive Functions, Working Memory Capacity, Relational Integration, and Divided Attention

Before explaining our main research questions, we began by illuminating the correlated factors model (Figure 2), which attempted to replicate the model of WMC, relational integration, divided attention, and shifting (Bühner et al., 2005) and the two-factor WM model (Redick et al., 2016). The replicated Bühner et al.'s (2005) model showed that WMC and relational integration were highly correlated, whereas shifting was moderately correlated with the factors WMC and relational integration, which is also in line with Bühner, Krumm, et al. (2006), and von Bastian and Oberauer (2013). These results also support the structure of WM identified by Oberauer et al. (2003; i.e., WMC, relational integration, and shifting). Conversely, divided attention shared differential variance concerning the WM model of Oberauer et al. (2003): a strong association with relational integration and moderate association with WMC (storage and processing) and shifting (supervision). Notably, both relational integration and divided attention tasks require responding to rapidly changing objects, which might have caused to the high correlation between these constructs (Bühner et al., 2005). Additionally, divided attention and WMC may be decomposed into a common pool of processing resources (Santangelo & Macaluso, 2013). The moderate correlation between divided attention and shifting indicates that divided attention is more oriented to engage people in splitting attention between tasks, instead of switching attention from one task to a completely different one.

Concerning the two-factor WM model by Redick et al. (2016), the correlation between WMC and updating was far from perfect, which is supported by the zero-order correlations among the measures of WMC and updating (ranging from r = .18 to r = .38). This result underlines that WMC and updating are distinguishable (but related) cognitive systems, and corresponds with the view of unity and diversity (Miyake et al., 2000). The shared variance across these two constructs may stem from the observation that WMC and updating both tap relational integration (Wilhelm, Hildebrandt, & Oberauer, 2013). It is worth to mention that in our model relational integration is strongly correlated with WMC (r = .54) and updating (r = .85).

Furthermore, the model also indicated that inhibition had the largest correlation with WMC, relational integration, and divided attention. Accordingly, this expands our finding (see Figure 6a), suggesting that inhibition is not only imperative to EFs, but also to many other cognitive abilities.

2.4.2 Replication Models (Research Question 1)

To provide the ground for the attempted direct replications, we followed the original protocol (Bühner, König, et al., 2006; Friedman et al., 2016) as closely as possible. The results from the confirmatory factor analyses clearly reflected the multitasking behavior model (Bühner, König, et al., 2006), and partially replicated the three-factor and nested factors EFs models (Friedman et al., 2016). Regarding the multitasking behavior model, all factor loadings were nearly equivalent to those of Bühner, König, et al. (2006; see Figure 3). In this model, the aspects speed and question were closely correlated; but error was strongly correlated with question and weakly with speed, according to earlier works (Bühner, König, et al., 2006; König et al., 2005). Thus, three aspects of multitasking behavior are related, but distinct. One might argue that speed, error, and question are not indicators of multitasking behavior, as these measures are extracted from a single multitasking scenario. However, we want to stress that multitasking behavior may not constitute a single process but may rather be divided into sub-processes - speed, error (accuracy), and question (memory search). It is therefore warranted to construct a latent variable out of these three different processes, even though they are derived from the same scenario.

Turning to the EFs models, although all parameter estimates were nearly in accordance with the original findings (Friedman et al., 2016), unlike prior work, the factor loading of the Stroop task onto inhibition turned out to be non-significant. The reason for this probably lies within the operationalization: the Stroop task used in this study was based on manual responses, rather than verbal responses, which were used in the study of Friedman et al. (2016). However, the variance of the Stroop task in our sample (σ^2 = 5113.68 ms) is comparable to that of the original study (σ^2 = 5476 ms, Friedman et al., 2016) and other studies which were conducted with university students (σ^2 = 4761 ms, Fleming et al., 2016; σ^2 = 4900 ms, Ito et al., 2015). Interestingly, in many studies the Stroop task is uncorrelated with other indicators of inhibition in order to form a latent variable (e.g., Hull et al., 2008; Krumm et al., 2009; Ren, Schweizer, Wang, Chu, & Gong, 2017; von Bastian et al., 2013), whereas Hull et al. (2008) and Ren et al. (2017) used nonverbal Stroop task (manual responses) on elderly and young people, respectively.

Specifically, in the three-factor EFs model, the loading of the letter memory onto the updating factor differed somewhat in its magnitude probably since its reliability turned out to be low. A possible reason for this is that the letter memory task used in this study differed from the original study, as participants had to silently rehearse the sequence of letters instead of rehearsing out load. Additionally, we found another non-significant loading of the color shape onto common EF in the nested factors EFs model (Figure 5), even though we used the exact task of the original study. The zero-order correlation matrix (see Table 2) showed the lack of significant correlation of the color shape with any of inhibition tasks, that are indicators of common EF (the correlations with the antisaccade, stop signal, and Stroop were -.01, -.02, .03). This difference may be caused by several factors: 1) sampling variability, that is two different samples may produce different estimates of effect size, even if they are drawn from a population with the same true effect (Stanley & Spence, 2014); and 2) the task impurity problem of EFs (Miyake et al., 2000): the switch cost of the color-shape task might reflect individual variation in other idiosyncratic requirements of the task, instead of capturing variation in inhibitory control processes (i.e., common EF).

In the three-factor EFs model (Figure 4), the correlations between the latent variables were moderate to high (ranging from r = .39 to r =.83), but far from perfect. Updating was correlated mostly with the inhibition factor and shifting was correlated weakly with the updating factor, in line with previous studies (Friedman et al., 2016). Above all, these features of EFs are strongly supported the general principle of unity and diversity of EFs (Miyake et al., 2000), which was also highlighted in several other studies (for review, see Friedman & Miyake, 2017). The strong overlap between the constructs updating and inhibition suggests that suppressing irrelevant information is important to update the relevant information, as the capacity of the WM is limited. In addition, shifting was highly related to inhibition. Indeed, the inhibitory process is thought to be involved in the process of task-set reconfiguration (i.e., switch cost; Friedman & Miyake, 2004; Koch, Gade, Schuch, & Phillip, 2010): for example, when people switch between two tasks, it is important to deactivate the competing task through inhibiting the irrelevant task set for dealing with the relevant one. On the contrary, regarding the moderate correlation between shifting and updating, a probable interpretation is that the shifting tasks require participants to respond to each stimulus after presenting the cue (while the previous responses are irrelevant), and updating requires maintaining representations of previous trials for comparing them to the current trial.

The evidence for diversity among three EF latent factors emerges from the pattern of relationship between the EF components and other cognitive abilities (Friedman & Miyake, 2017; Miyake et al., 2000), suggesting that each core EF demands unique cognitive mechanism that is not tapped by common EF ability. For instance, three EF components were differentially associated with multitasking behavior in this study.

The replicated nested factors model (see Figure 5) also supported the unity/diversity concept: Common EF reflected variance common to all EF tasks, representing the unitary notion of EF; whereas the remaining variance that was not captured by common EF was explained by unique shifting and unique updating, confirming the non-unitary notion of EF. The important aspect of this model is the absence of a unique inhibition factor (Friedman et al., 2016). To further elucidate this point, we tested alternative models and found that the model in which common EF emerged from inhibition (see Figure 6a) fitted the data well, compared to other two models in which common EF emerged from shifting (Figure 6b) and updating (Figure 6c). Notably, the confidence in Friedman et al.'s (2016) common EF explanation should be bolstered by the current findings: In light of these observations, we contend that inhibition seems to represent a broad range of cognitive processes at the behavioral level, namely memory representation, switching between mental sets, and withholding dominate responses (Hall & Fong, 2015; Zacks & Hasher, 1994). However, it is important to note that though the fit statistics of the model, in which common EF emerged from updating (Figure 6c) were not satisfactory, all significant path coefficients from common EF (i.e., common updating) to nine EF indicators (excepting the path from common EF to the Stroop task) demonstrated that updating and managing information are prerequisites for the EF tasks. Moreover, common updating captured the variance of the antisaccade and the stop signal tasks, where the stop signal did not load on inhibition. Even the variance of inhibition was also not significant. It seems that inhibition basically does not serve as a latent variable in this model. This is probably the reason why Karr et al. (2018) found that 11.11% of the studies on adult sample combined inhibition and updating together.

However, a closer inspection of the qualitative synthesis (Table B1) cast doubt on the factor structure of EFs, where we expanded the model beyond the evaluation of three EF factors by including other posited constructs (WMC, relational integration, and divided attention). Although we recruited a fairly large sample and used identical EFs test battery and scoring systems, the results did not identify a definitive measurement model of EFs in aggregate. Only the indicators of shifting loaded significantly on the latent shifting factor, but the *n*-back task and the indicators of inhibition either loaded on relational integration or divided attention, addressing the task impurity problem (Miyake et al., 2000) or "elusive nature" (Jurado & Rosselli, 2007, p. 213) of EFs. This post hoc account might help to explain how the model complexity depends on the underlying hypothesized structure of EFs, thereby leading to lack of convergence. Based on this empirical evidence, we agree with the suggestion of Karr et al. (2018), "researchers […] should also consider alternative models that may take a different approach to conceptualizing executive functions" (p. 31).

2.4.3 Cognitive Constructs Related to Multitasking Behavior (Research Question 2)

The central issue of this investigation was to identify the significant predictors of multitasking behavior. The results of the latent regression-based approach showed that the three core EFs differentially related to multitasking behavior. The inclusion of the three-factor EFs model (in addition to WMC, relational integration, and divided attention) led to a higher amount of explained variance in multitasking behavior than reported by Bühner, König, et al. (2006) and König et al. (2005). While the relation to shifting failed to reach significance, updating and inhibition showed a robust role in multitasking behavior. The current reports of close relations between updating, inhibition, and multitasking behavior are compatible with the findings of Redick et al. (2016). In fact, the updating factor accounted for more variance in multitasking behavior than the variance explained by inhibition. Importantly, it is evident that updating predicted multitasking behavior even when a method for isolating variance unique to updating (i.e., removal efficiency; Ecker et al., 2014) from the variance of general WMC was adopted (see Figure A1). These results further highlight the importance of updating in the current conception of multitasking behavior. Updating broadly involves inhibition to successfully disengage no-longer relevant information and to reduce interference in and around the focus of attention (Cowan, 2001; Oberauer, Süß, Wilhelm, & Sander, 2007). Thus, the overlapping variance of updating and inhibition seems to support the organization of memory and attention around relevant information through encoding little information strongly, rather than much information weakly, which in turn may facilitate to perform multiple tasks concurrently, as seen in Figure A3. Furthermore, the current results also provide differential information about the relations of updating and inhibition to multitasking aspects. Updating was predominantly related to multitasking error, while inhibition showed connection to multitasking speed and question. Indeed, errors in multitasking are known to emerge due to a lack of updating information (Bühner, König, et al., 2006). Regarding the association of the multitasking aspects speed and question with inhibition, a likely explanation is that ignoring the irrelevant stimuli is important to perform the routine tasks quickly and to utilize memory and mental abilities efficiently in problem solving tasks in the SIMKAP scenario.

Conversely, shifting did not add any significant explanatory power to the prediction of multitasking behavior and its three aspects, similar to the results reported by Bühner, König, et al. (2006) and Hambrick et al. (2011). This non-significant result possibly relates to the type of tasks used to operationalize the shifting construct. According to Jewsbury et al. (2015), the conceptualization of shifting tasks differs in terms of their scoring systems: switching between two-alternative choice RT scores (e.g. category switch; see Friedman et al., 2016), or accuracy scores (e.g., Wisconsin card sorting test; see Brydges et al., 2012; Hedden & Yoon, 2006). Our shifting tasks were based on RT difference scores, neglecting inter individual differences in switch accuracy. Therefore, the present finding suggests to further investigate the relation between multitasking behavior and shifting in a larger framework, especially using different methodologies and tasks (e.g., bin scores incorporating speed and accuracy of task switching; see Draheim, Hicks, & Engle, 2016).

Additionally, the results of multiple regression analyses suggest strong contributions of relational integration and divided attention towards the variance accounted for in multitasking behavior. However, our data did not provide a clear picture of the role of WMC on multitasking behavior and any of its three aspects. Notably, WMC was a significant predictor for multitasking behavior before including EF components in the regression equation. The predictive power of WMC may be subsumed under the overlapping variance between WMC and relational integration (Chuderski, 2014), divided attention (Colflesh & Conway, 2007), shifting (Redick, Calvo, Gay, & Engle, 2011), updating (Schmiedek et al., 2009), and inhibition (Kane et al., 2007). Another line of evidence for the relatively weak (or non-significant) role of WMC is possibly related to the task speed. For instance, Hambrick et al. (2010) found that WMC is a strong predictor of multitasking behavior when the pace of the tasks is relatively slow, but not when the pace is high. In the present study, the pace of the simultaneous task presentation demanded rapid responding. Further, when we modeled WMC, relational integration, divided attention, and multitasking behavior at the level of latent variables (see Figure A2), WMC also predicted multitasking behavior only minimally. An additional question of interest in this context is whether the processing component of WMC (i.e., the proportion of correct responses in processing tasks) is predictive for multitasking behavior, as suggested by Redick et al. (2016), and Unsworth, Redick, Heitz, Broadway, and Engle (2009). We used the factor scores of WMC processing component (ranging from r = .16 to r = .25) and found that processing did not significantly predict multitasking behavior, opposed to Colom et al. (2010). This finding suggests that the processing aspect of WMC might be independent of multitasking behavior. Processing component may be included under the global construct of mental speed (Oberauer et al., 2003).

Specifically, our study revealed that relational integration contributed mostly to multitasking behavior beyond other constructs (as seen in predicting fluid intelligence; Krumm et al., 2009). The unique mechanism of their relationship seems to lie in the relational thinking, which reflects the capacity to integrate cognitive relations of multiple tasks and creates a novel relational representation of how to work on these tasks. Critically, relational integration was related to multitasking behavior after controlling its overlapping variance with WMC, but it no longer predicted multitasking behavior once its overlap with inhibition was controlled for. This suggests that the driving force of the relational integration – multitasking behavior relationship may not depend on the sheer storage of information, but rather on the inhibitory control for representation and processing of relations. Additionally, relational integration accounted for multitasking speed and question (but not error), implying that the process of coordination between tasks specifically leads to faster performance and effective use of cognitive resources in problem solving tasks (Bühner, König, et al., 2006).

Notwithstanding, the finding regarding the relation between divided attention and multitasking behavior contradicts earlier observation (Bühner, König, et al., 2006) by highlighting the importance of attentional demand in concurrent task performance. Apparently, tasks used to measure divided attention typically assess interference control abilities through focusing relevant information (e.g., determining whether one of the stimuli noticeably changes two times in succession in a divided attention task) and ignoring irrelevant information at the same time. It seems that divided attention is inhibitory in nature at encoding and retrieving information (Kane & Engle, 2000). This conclusion has received support by the strong link between divided attention and inhibition (81% of shared variance; see Figure 2) in the present study. In this regard, the overall notion is compatible with the idea that multitasks (generally dual-task) require the cognitive control of attentional functioning (Logan & Gordon, 2001). Moreover, the application of the relative importance analysis revealed that divided attention could explain about 5.5% more variance in multitasking behavior after excluding inhibition. Further, divided attention showed a significant relation to error and question aspects of multitasking behavior, in line with the findings of König et al. (2005). These results indicate that the ability to rapidly divide attention permits people to be less error-prone and to solve problems efficiently in multitasking environment.

2.4.4 Multitasking Behavior and Common EF Ability (Research Question 3)

As hypothesized, the SEM with the common EF and multitasking behavior (Figure 7) revealed that common EF ability (i.e., goal management skill) explained a large and significant amount of variance in multitasking performance at the level of latent variables. Our finding implies that common EF provides domain-general support for multitasking behavior. On one hand, it reflects the ability to retain multiple task goals, especially when interference is present. On the other hand, it substantially assists to retrieve and activate relevant goals for coping with multitasking situation. Although we wanted to understand the relationship between multitasking behavior and common EF, the results also shed further light on the association between multitasking behavior and the unique updating factor. The significant path coefficient from unique updating to multitasking behavior (though minimally) adds to the growing understanding of the nature of unique updating ability. Common EF and unique updating jointly accounted for 97% of the multitasking behavior variance. One might assume that multitasking behavior and EFs are indeed identical constructs, but we attribute this finding to the certain configuration of EFs that can explain almost all variance in multitasking behavior, although these two constructs are conceptually different. Notably, a large amount of the estimated common variance might emerge from the correction for attenuation in the SEM, as suggested for WM and reasoning findings by Bühner, Krumm, Ziegler, and Pluecken (2006), who used SEM to investigate the interplay of WM and reasoning: An overestimation of correlation between latent variables goes along with low construct reliability (i.e., the proportion of variance in the latent variable explained by its indicator variables; see Hancock & Mueller, 2001), because lower construct reliability leads to higher measurement error, thereby resulting in stronger correction for attenuation. It is important to mention that EFs tasks have a reputation for capturing limited construct specific variance (Müller & Kerns, 2015). In this regard, the construct reliability of common EF, unique updating, and unique shifting in our model were .77, .45, and .53, respectively (calculated based on Hancock & Mueller, 2001, p. 202).

2.4.5 Limitations and Future Extensions

Despite the broad range of approaches undertaken here, the current research has some limitations that need to be mentioned. Notably, we limited our multitasking behavior model to a single SIMKAP scenario, which might collude the results with task-specific variance. However, the goal of the present study was to replicate the previous model (Bühner, König, et al., 2006) and expand earlier findings (Bühner, König, et al., 2006; König et al., 2005). Also, even though derived from a single scenario, multitasking ability was estimated based on three different measures, which made strong collusion less likely. Nevertheless, multiple measures of multitasking behavior (e.g., the Edinburgh Virtual Errands Test; Logie et al., 2011) could reduce the task-specific variance, and thereby provide an index of a more general multitasking ability in future.

In addition, the cognitive abilities involved in this study accounted for 56% of variance in multitasking behavior, which means 44% of variance remained yet to be explained. For example, although we included more basic cognitive functions, we did not consider fluid intelligence in our model. Previous researchers have focused on the role of fluid intelligence in multitasking behavior (Colom et al., 2010; Hambrick et al., 2010; Redick et al., 2016). However, one drawback of these studies is that crystalized intelligence (i.e., the ability to utilize learned knowledge from culture, education, and other experiences) is not incorporated, though it relates to fluid intelligence (Bühner, Krumm, et al., 2006; Carroll, 1993). Future investigations should accumulate such measures to fully understand the contribution of intelligence to multitasking behavior.

Further, the Stroop task used in the current study did not load on the inhibition factor. Therefore, we did not consider data of this task in further analyses. However, future work should examine whether the amount of multitasking behavior variance explained by the inhibition factor would be different after including an appropriate Stroop task (based on verbal responses).

Finally, our study indicates important cognitive abilities that explain multitasking behavior, but does not say why these abilities are related to multitasking behavior. In this regard, individual differences in EFs and WM reflect genetic or environmental influences, in which WM and EFs are primarily genetic in origin (Ando, Ono, & Wright, 2001; Friedman et al., 2008). Moreover, the communality between EFs and higher cognitive ability (e.g., intelligence) is influenced by genetic factor (Engelhardt et al., 2016). Therefore, exploring the etiology of the relations between cognitive abilities and multitasking behavior would provide further knowledge.

2.5 Conclusion

In the present study, we were able to replicate the multitasking behavior model, and partially replicate the EFs models. Applying these replication models, we found that individual differences in updating, inhibition, relational integration, and divided attention accounted for significant proportions of variance in multitasking behavior and its three aspects (speed, error, and question). Specifically, relational integration appeared to be essential cognitive abilities involved in multitasking behavior, compared to updating, inhibition and divided attention. However, these cognitive abilities were differentially related to the three aspects of multitasking behavior. In addition, the common EF ability accounted for large amount of variance in multitasking behavior. Finally, the exploratory analysis offers a tentative picture regarding the cognitive architecture of EFs, which is required to be cross-validated on independent sample. In conclusion, by providing strong empirical evidence in favor of cognitive correlates of multitasking behavior, this study thus builds the necessary groundwork for steering future research to elucidate the etiology of underlying relations between these specific cognitive correlates and multitasking behavior.

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Chapter Three

Study 2

Cognitive Strategies and Transfer Effects between Material- and Operation-specific Tasks within the Working Memory Training Framework

3.1 Introduction

Working memory, the ability to maintain limited information (Miller's 'magical number' seven, 1956; Cowan's four, 2001) in the face of interference, acts as a fundamental building block for higher cognitive functions and real-world behavior (Barrett, Tugade, & Engle, 2004). It stands to reason that training-related improvement in working memory can optimize an individual's constellation of complex cognition (e.g., Au et al., 2015; Brehmer, Westerberg, & Bäckman, 2012; Karbach & Verhaeghen, 2014; Spencer-Smith & Klingberg, 2015). However, this assumption has been controversial and argued that working memory training reliably improves performance on working memory tasks which are identical or closely related to the trained tasks (i.e., near transfer), rather than enhancing performance on distantly related tasks (i.e., far transfer) in diverse population: children (e.g., Ang, Lee, Cheam, Poon, & Koh, 2015), young adults (e.g., Clark, Lawlor-Savage, & Goghari, 2017; Harrison et al., 2013; Minear et al., 2016), and elderly (e.g., Borella, Carretti, Zanoni, Zavagnin, & De Beni, 2013). Sometimes, the working memory training even leads to worse performance on recognition memory tasks (relative to a passive control group; Matzen et al., 2016). These inconsistencies in the findings have been rooted on methodological differences: (1) small sample size (e.g., Melby-Lervåg, Redick, & Hulme, 2016; also see Cumming, 2011, for a review), (2) passive control group (Shipstead, Redick, & Engle, 2012; but see Colom et al., 2013), (3) various training regimens (e.g., simple span, *n*-back, or complex span tasks; Simons et al., 2016), (4) failure to account for baseline differences between trained and control group when calculating effect sizes (Melby-Lervåg & Hulme, 2016) in combination with the effects of publication bias (i.e., getting published only large and significant results), such as the file drawer problem or p-hacking (McCabe, Redick, & Engle, 2016; Melby-Lervåg, Redick, et al., 2016). In this regard, Sala and Gobet (2017) pointed out that the effect sizes are inversely associated with the quality of the study design.

Our focus is to critically examine the reasons of transfer on material-related tasks, instead of emphasizing the efficacy of an intervention. As suggested elsewhere (Redick et al., 2013), understanding the mechanisms responsible for transfer effect may require task-analytic training procedure in order to isolate the cognitive processes that are trained and improved. Few training accounts extensively differentiate between the stimulus materials for the training which may lead to transfer. In one study, for instance, Hilbert et al. (2017) incorporated verbal, numerical, and figural (pattern) materials for training two different working memory operations (i.e., storage and processing, and relational integration; derived from Oberauer, Süß, Wilhelm, & Weittman, 2003) and investigated the influence of training with these different materials in the same working memory tasks. The results demonstrated that transfer occurs between verbal and numerical materials, but not for figural material within the same operation. Why does training on verbal/numerical task not lead to transfer on figural task? In this context, it is important to understand the fundamental mechanism involved in the working memory training. Multiple studies acknowledge that transfer effects reflect stimulus-specific overlap between the trained and transfer tasks (e.g., Sprenger et al., 2013; von Bastian & Oberauer, 2013). Comblain (1994), for example, showed that training with verbal material (e.g., pictures of noun) can lead to improvement in numerical (digit) and verbal (letter) memory span task performance. The potential reason may be the acquisition of a cognitive strategy during training, which induces an increase in working memory efficiency (Foster et al., 2017; von Bastian & Oberauer, 2014). Against this background, a material-based systematic investigation is needed to examine the role of cognitive strategy for understanding how information is encoded and retrieved during training, which may yield transfer to trained or untrained task types.

3.1.1 Cognitive Strategies in Working Memory Training

A cognitive strategy is a mentally effortful and goal-directed process that enables people to organize information consciously or unconsciously for achieving a higher-level goal (Lemaire & Reder, 1999; Messick, 1984). The most prominent subdivision of using preferred cognitive strategies is made between visualization and verbalization (Paivio, 1986; Rayner & Riding, 1997). Eye-tracking studies also reveal that the visualizers and verbalizers differ in the way they represent pictorial and verbal information (e.g., Koc'-Januchata, Hoffler, Thoma, Precht, & Leutner, 2017). Visualization is a strategy whereby people tend to use internal imagery (mind’s eye) to construct a mental representation of the stimuli through grouping or associating semantically (Carrette, Borella, & De Beni, 2007), while verbalization refers to the use of inner speech mechanism to maintain verbally coded items through grouping or associating semantically (McNamara & Scott, 2001). Apparently, these two strategies correspond to the two working memory subsystems proposed by Baddeley and Hitch (1974), namely the visuospatial sketchpad and the phonological loop, respectively. In accordance with the strategy affordance hypothesis (Bailey, Dunlosky, & Kane, 2008), several studies have highlighted the working memory – cognitive strategy relationship, asserting that individual differences in strategy use mediate the relationship between working memory and other cognitive tasks when the same strategies are afforded by both tasks (e.g., Gonthier & Thomassin, 2015; Schelble, Therriault, & Miller, 2012). Thus, the strategies appear to be essential in reducing cognitive load for retrieving information from long term memory (Redifer, Therriault, Lee, & Schroeder, 2016), and reflect underlying mechanisms of cognitive abilities (Hertzog, Kramer, Wilson, & Lindenberger, 2008). As a consequence, individuals with a high working memory capacity use more elaborate and cognitively demanding memory strategies, which in turn lead to better performance on other high level cognitive tasks (Turley-Ames & Whitfield, 2003; Unsworth, 2016). Additionally, Gross and Rebok (2011) trained elderly people and found that cognitive strategy is not only related to memory performance, but also to everyday functioning. Relevant evidence also comes from Hilbert, Bühner, et al. (2015) who found that this task-specific cognitive strategy is predictive for a working memory task performance (measured with digit span backwards) and it can be adapted deliberately in order to perform the task at hand. Nevertheless, some authors have questioned the influence of strategy on predictive power of working memory, although the inherent limitation of these studies is either not to assess participants' strategy usage explicitly (St Clair-Thompson, 2007) or to control for cognitive strategy statistically (Dunlosky & Kane, 2007).

However, the use of cognitive strategy is recognized as domain-specific approach (Bailey, Dunlosky, & Hertzog, 2014). This is criticized by some authors, arguing that the domain-specific approach typically trains specific strategic process, and can improve cognitive performance on tasks that afford its use, without improving the core working memory capacity (e.g., Morrison & Chein, 2011). To refute this claim, Dunning and Holmes (2014), and Matzen et al. (2016) suggested that adaptive working memory training regimen (i.e., constantly changing demands of the tasks used in the training) might minimize this issue by boosting the accessibility of domain-general executive resources for a strategic deployment, which could be applicable to a wide variety of tasks.

To improve working memory performance, many researchers have used the strategy-based training (i.e., teaching participants a specific strategy) for children, adult and old people (e.g., Borella et al., 2017; McNamara & Scott, 2001; St Clair-Thompson, Stevens, Hunt, & Bolder, 2010; but see Dunning & Holmes, 2014). However, the strategy-based training perhaps yields no transfer to other memory tasks (see Schwaighofer, Fischer, & Bühner, 2015). Accordingly, it prevents us to clarify to what extent the result is obtained due to the participants spontaneous strategy usage. On the contrary, the self-reported cognitive strategy in which participants are not reminded to use a certain strategy, rather they are encouraged to provide information about their underlying strategic memory process (Woods et al., 2005). The advantages of using self-reported strategy are threefold. First, spontaneous cognitive strategy is unconsciously learned without knowing about what is being practiced within working memory training framework. Second, this kind of strategy usage at encoding increases the correct recall rate on working memory task (Dunlosky & Kane, 2007). Third, it would be crucial to understand how people generate strategies and apply them on certain tasks, which lead to training gains. Cognitive strategies either vary across individuals for the same task, or within the same individual across tasks (Morrison, Rosenbaum, Fair, & Chein, 2016).

To this end, we chose to study the self-reported strategic approach for examining transfer effects (near/nearest effect, the taxonomy of transfer distance; see Noack, Lövden, Schmiedek, & Lindenberger, 2009) on the working memory tasks. The cognitive strategy may be a critical factor for the resulting internal processing of information. For example, people strategically encode task-relevant information and create salient relationship between to-be-remembered information and information already held in long term memory (e.g., semantic knowledge or grouping), although not all cognitive strategies (e.g., mental imagery, sentence generation, rote repetition etc.) are effective in same way (Bailey et al., 2014). Additionally, Hilbert, Nakagawa, Puci, Zech, and Bühner (2015) showed that individuals relying on verbal processing strategies can be distinguished from those relying on visual strategies in working memory task (measured with digit span backward), which in turn may influence the amount of transfer to other working memory tasks. Evidence from the neuroimaging results suggests that the changes occur following training in the middle frontal gyrus (Olesen, Westerberg, & Klingberg, 2004), which is also responsible for verbal cognitive strategy (Hilbert, Bühner, et al., 2015), corroborating the presumed relation between cognitive strategies and training-related effects.

3.1.2 The Current Investigation

The main research question of the current investigation was to determine why working memory training leads to transfer to material-specific tasks but not to other task types. To our knowledge, no investigation has so far directly ascertained whether the use of cognitive strategies shows an influence on transfer of training with particular material to other working memory tasks. For this purpose, we developed a task-specific training regimen and examined the role of strategy by directly using tasks that allow for a particular strategy and tasks that do not. On the basis of Oberauer et al.'s (2003) work, we selected two working memory operations, namely storage and processing (i.e., complex span tasks) and relational integration (i.e., coordinating multiple information to build a mental structure). In the current investigation, we extended and further evaluated the findings regarding transfer effects between verbal and numerical materials within the same operation (Hilbert et al., 2017). It seems that transfer occurs because of same underlying cognitive strategy between trained and transfer tasks. In line with prior work, participants were trained in four different materials verbal/numerical/figural (pattern)/figural (symbol) within each operation. We hypothesized that training with verbal and numerical materials may lead to transfer to the task with figural (symbol) material within the same operation, and vice versa, if the same cognitive strategy is applied in solving both tasks. Additionally, we assumed that the use of cognitive strategies may explain the transfer effects: The use of a verbal strategy may be associated with the transfer of verbal, numerical, and figural (symbol) materials, whereas the use of a visual strategy is expected to relate to the transfer of figural (pattern) material.

To test our hypothesis, all participants were induced to use the verbal strategy by employing a figural (symbol) task, because symbols are concrete and easier to apply verbal strategy, compared to the position of the patterns in the matrix which are abstract and difficult to verbalize [e.g., figural (pattern) task]. The symbols used in this study were pronounced with one or two syllables in the German language. The storage and processing figural (symbol) task requires participants to memorize a string of symbols for serial recall followed by judging the arrows as upward or downward; while the relational integration figural (symbol) task requires participants to respond when three middle identical symbols appear in a row/column/diagonal in 3×3 matrix. Each participant was asked afterwards which strategy he or she used to perform each task. We limited the scope of our investigation to verbal stimulus material because there is evidence that visual representation in working memory is affected in a different manner than verbal representation: Following training, a significant increase in using verbal strategy is observed in performing untrained verbal tasks (Dunning & Holmes, 2014), whereas the use of visual strategy is found to be effective for the visuospatial working memory task (Paivio & Csapo, 1973). Importantly, encoding verbal or spatial information in working memory is not domain general fashion (as in Ginsburg, Archambeau, van Dijck, Chetail, & Gevers, 2017, Experiment 1, 2, 3; Zimmermann, von Bastian, Röcke, Martin, & Echen, 2016), thereby success in applying strategies is likely to depend on the context (Barnett & Ceci, 2002).

We also assessed transfer effects to tasks that are dissimilar to the training task but are theorized to reflect working memory: transfer from storage and processing training to gains in relational integration performance, and the other way around. Both the storage and processing, and relational integration tax attention control (i.e., ignoring irrelevant information; Himi, Bühner, Schwaighofer, Klapetek, & Hilbert, 2018), which can provide a rational for a potential transfer effect, although Hilbert et al. (2017), and von Bastian and Oberauer (2013) did not find any transfer between these two working memory operations. However, in contrast to previous study (Hilbert et al., 2017), the baseline scores for working memory tasks were taken into account in this study, as relying only on post-test differences can cause biased estimates (Melby-Lervåg, Redick, et al., 2016). Additionally, it might be important to check individual's baseline performance for understanding subsequent benefits from training.

Furthermore, studies investigating the role of cognitive strategy in working memory have so far restricted their scope to the storage and processing tasks. However, it would be interesting to examine the use of cognitive strategies in the relational integration tasks in order to understand how people detect a critical constellation by integrating single information. Finally, the digit span backwards task was applied to replicate the previous finding showing no difference in performances between visualizers and verbalizers (Hilbert, Nakagawa, et al., 2015), if the digits are presented optically or acoustically (single condition). Together, although a number of training studies have been published, we used a methodologically sound and well-defined study design (i.e., adequate sample size, adequate control groups: active control and passive groups, theory-based task selection, including pre-test, and random assignment of the participants), which is needed for providing a clear picture of what motivates transfer effects.

3.2 Methods

3.2.1 Participants

Participants were 105 university students (67.6% female), recruited from Ludwig Maximilians-University of Munich (*n* = 96) and University of Regensburg (*n* = 9). The median age was 22.0 years (1st quartile: 19.0 years; 3rd quartile: 26.0 years). About the half of the participants (51.4%) were the psychology students. They were randomly assigned to one of the 10 possible groups at the beginning of training: storage and processing verbal, storage and processing numerical, storage and processing figural (pattern), storage and processing figural (symbol), relational integration verbal, relational integration numerical, relational integration figural (pattern), relational integration figural (symbol), active control, and passive groups. In the beginning, 136 students participated in the pre-test session, 28 of them dropped out due to facing problems in installing the training program and 3 of them did not finish the training sessions, which left 105 participants who completed all the sessions. All participants reported normal or corrected-to-normal vision and no neurological problem. For their participation, they either received €35 or course credits. Only after the pre-test, participants were reinforced by being informed that if they improved their performance during the training sessions, they received additional €50.

3.2.2 Procedure

All participants provided written informed consent prior to the pre-test. The human research guidelines were followed, and anonymity and confidentiality were maintained. Neither the participant nor the experimenter was aware of group assignment. Participants had no precise knowledge about the purpose of the study. All of them were only informed that they would be assessed in different activities concerning their cognitive functioning. They were tested in a group of up to five people in a university laboratory. The study was conducted in two sessions (pre- and post-test) on separate days within approximately three weeks, and each session lasted about 1.5 hours (including a five-minute break). All the tasks were administered in the same order across participants to minimize subject-by-treatment interactions. During the pre-test session, the working memory tests were applied as follows: (i) four storage and processing tasks: verbal, numerical, figural (pattern), and figural (symbol); (ii) four relational integration tasks: verbal, numerical, figural (pattern), and figural (symbol). However, in the post-test session, these tasks were administered in reverse order.

The cognitive strategies questionnaire was administered in both sessions, and the digit span backwards task was applied in post-test session. Between the pre- and post-test sessions, the participants of the working memory training groups and the active control group had to train at home for 20 min on 12 consecutive days. Passive group did not receive any kind of training in this time interval. All the pre-post-test tasks and training tasks are in German.

3.2.3 Pre- and Post-tests

Participants completed the working memory tasks (adapted from Oberauer et al., 2003; von Bastian & Oberauer, 2013), which are written in Python 2.7 (see https://www.python.org). Manual responses are registered by a standard computer keyboard. We used same working memory tasks for pre- and post-tests.

Storage and processing. The storage and processing tasks with verbal, numerical, figural (pattern), and figural (symbol) materials require presenting a sequence of words/numbers/patterns/symbols to participants. The set sizes vary from 3 to 7 words and symbols, 4 to 8 numbers, and 2 to 4 patterns, which participants have to remember. Following these presentations, participants are required to complete processing tasks for 5 seconds which comprise materials of same content domain as used those in the memory tasks. In the verbal version, the processing tasks are to categorize the words as city and country, whereas for the numerical version the numbers are to classify as odd or even. Both figural (pattern) and figural (symbol) tasks contain the arrows which are needed to respond according to upward or downward. After several such tasks, participants should recall the words/numbers/patterns/ symbols in the order as they are originally presented. Each of the tasks comprises a total of 15 trials excluding 2 practice trials and takes about 12 min to 15 min to solve. The proportion of correctly recalled elements in each trial (i.e., partial credit score; cf. Conway et al., 2005) serves as dependent variable.

Relational integration. The relational integration tasks consist of four versions. For the verbal version, nine words in a 3 × 3 matrix are displayed and one word randomly changes every 2000 ms. Participants are asked to respond when three rhyming words are shown either in a row, column, or diagonal within the matrix. Participants must complete 111 test trials and 12 practice trials. The numerical version presents nine three-digit numbers in a 3 × 3 matrix in which one of the numbers is randomly replaced every 2000 ms. Participants have to respond when three identical last digits appear either in a row, column, or diagonal. The task comprises a total of 126 trials including 14 practice trials. The figural (pattern) version contains black dots in a 10 × 10 matrix and two of twenty black dots are replaced every 2000 ms. Participants are asked to respond when four black dots shape a square. They must complete 115 test trials and 14 practice trials. For the figural (symbol) version, nine sets of symbols (each set consists of three symbols) are presented in a 3 × 3 matrix and one of the symbols is randomly replaced every 2000 ms. Participants have to respond when three identical middle symbols appear either in a row, column, or diagonal. There is a total of 126 trials including 14 practice trials. The time limit is about 6 min for each task. The dependent variable is the discriminability index (d′), reflecting sensitivity of target detection. It is computed by relating hit rate and false alarm rate (d′ = z (hit rate) – z (false alarm rate)), where z indicates standardized scores.

Digit span backwards task. In the digit span backwards task, a series consisting of 4 to 7 digits are presented sequentially, which participants have to memorize in reverse order and write these digits on the answer sheet (see Appendix B1) after each trial. They perform 10 trials including 2 practice trials. The number of series correctly recalled is considered as dependent variable (maximum score 8).

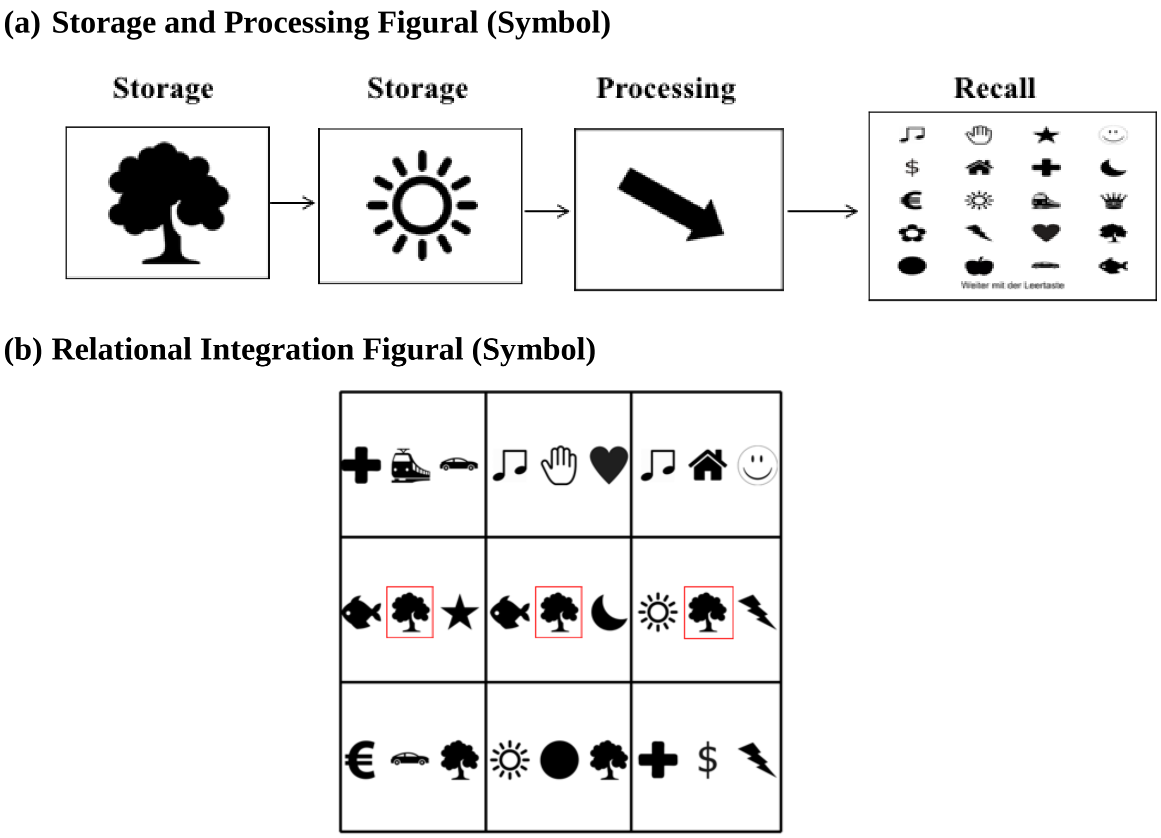

Figure 1. Overview of new working memory tasks used in the pre-post-test and training sessions. (a) Example item for storage and processing figural (symbol) task. (b) Example item for relational integration figural (symbol) task.

Assessment of cognitive strategies. A cognitive strategies questionnaire (provided in Appendix B2) is presented immediately after each of the working memory operation (storage and processing, and relational integration) at both pre- and post-test. Participants are required to indicate which cognitive strategies (i.e., verbalization, visualization, another strategy, and no strategy) they use to deal with words/numbers/patterns/symbols. In this questionnaire, visualization represents creating images of the stimuli in the head either grouping or applying personal association with the words; whereas verbalization denotes repeating the stimuli silently in head either grouping or applying personal association with the words. Afterward they are asked – “Which of the strategies - visual or verbal have you used more (Please respond even if the tendency is small)?”. They are also asked about an open-ended question regarding their applied strategies.

3.2.4 Working Memory Training

Participants in each working memory training group were trained with one of the working memory operations (storage and processing, and relational integration) related to one of the materials for 12 days. They were required to complete the task for 20 minutes each day, giving a total training dose of 4 hours spread over 2 to 3 weeks (with mean of 17.32 days). We developed the working memory training tasks based on the tasks of Oberauer et al. (2003), and von Bastian and Oberauer (2013). The stimuli of training task were different from the stimuli of pre- and post-test in order to minimize the recognition effect. The self-administered training was conducted at home via a Python 2.7 (see https://www.python.org) based freely accessible online platform, hosted by the Leibniz-Rechenzentrum der Bayerischen Akademie der Wissenschaften (LRZ; English: Leibniz Supercomputing Center of the Bavarian Academy of Sciences and Humanities) server (see Figure B1). The training program is mostly platform independent (Windows and Mac OS are supported) and can be installed on a local computer. To distribute it locally on a computer, a wrapper is written in Python 2.7 as well. Then smaller bootstrap and installation scripts are written in bash for the Mac OS version and batch for the Windows version. Several individuals can use the program parallelly at home by using different user names and passwords.

Data produced during the training are automatically uploaded and saved on a remote LRZ server, and can be exported as coma-separated raw data (.csv) files. Managing the files is done with a web interface system. When a participant starts the practice session, the data and settings (i.e., screen resolution, operating system, and time of access) are updated every time to verify the accuracy of the data with a Hash function. Performance based feedback is given after each session. The scoring procedures are as similar as the one used for pre- and post-test working memory tasks.

Adaptive algorithm. We followed the procedure of the adaptive training algorithm from the study of von Bastian and Oberauer (2013). According to this algorithm, in each session, the individual benchmark is established based on initial performance of the participant (the first 40% of trials). If participant outperforms the benchmark after another 40% of trials, the difficulty is increased; otherwise it remains at the same level and the participant gets 3 retries to exceed the benchmark. If he/she still does not succeed, a new benchmark is set. The task difficulty is decreased and he/she gets the task with the beginning difficulty level. Performance is continuously checked after each 40% of trials. The benchmark algorithm is set in-between 75% to 95% of accuracy for avoiding too low and too high individual benchmark. Each session starts with the same level of difficulty that participant has attained in the previous session. The level of difficulty is varied in terms of storage and processing, and relational integration tasks.

Adaptive storage and processing training tasks. In the case of the storage and processing task, difficulty is determined either by increasing the processing time duration (5s, 10s, and 15s) or increasing the number of recalled stimuli (e.g., from 3 to 10 for verbal and figural (symbol), from 4 to 11 for numerical, and from 2 to 5 for figural (pattern)). If participant performs better than benchmark, then either the processing duration or the number of elements is increased. For example, in the first session, the processing duration is 5s. If benchmark is outperformed, the number of elements is increased. However, if the benchmark is outperformed and the accuracy is below 75% or above 95%, then the task difficulty is adjusted according to what is changed before to control the floor or ceiling effect. For instance, the task starts with processing duration of 5s in the first session. If the benchmark is outperformed and accuracy is below 75%, then again, the processing time is changed. The long processing duration may be the reason for the accuracy to be too low (below 75%; floor effect). When the accuracy shows optimal range (i.e., between 75% and 95%), then both parameters again alternate.

Adaptive relational integration training tasks. The difficulty level for the relational integration task is adjusted across trials either by decreasing the time interval between changing elements (2.0 s, 1.5 s, 1.0 s, and 0.75 s) or increasing the number of changing elements (e.g., from 1 to 3 for verbal, numerical, and figural (symbol); from 2 to 5 for figural (pattern)). If the benchmark is outperformed, then time interval and the number of changing elements alternates. However, if the benchmark is outperformed and the accuracy is below 75% or above 95%, the two parameters do not alternate. The task difficulty is adjusted according to what is changed before for controlling floor or ceiling effect (similar procedure as the one described in the storage and processing tasks).

3.2.5 The Control Training

The active control group also attended the same number of sessions (12 days) and same time period (20 minutes) in each session, as the working memory training groups. During these sessions, participants completed the Objektiver Leistungsmotivations-Test (OLMT; English: objective achievement motivation test; Schmidt-Atzert, 2004), in which they must cover a specified course as quickly as possible by pressing two different keys: left and right ‘shift’ button (Figure B2). Each course is made up of 100 fields with red and green arrows. The arrows indicate which way the course goes and which key must be pressed in order to proceed. Green arrows point to the right direction, red arrows point to the left. This test should be independent from working memory tasks, as non-significant correlation with working memory is reported in the manual. The OLMT comprises three subtests containing particular motivational stimuli which directs the participant’s performance (i.e., motivation arising from the task itself, from setting personal goals, and from competition) and each subtest is made up of 10 identical runs which lasts for 10 seconds. The length of sequence covered by pressing the buttons in last three runs of the first subtest (i.e., task-related effort) is considered as dependent variable. After completing each run, the participants get feedback about their performance.

3.2.6 Statistical Analyses

Linear mixed-effects models. For each working memory task, we applied linear mixed-effects model to assess performance improvement after training. This analysis framework allows for both fixed effects (i.e., experimental conditions or predictors) and random effects (i.e., individuals in experimental conditions) parameters. Fixed effects describe the relationship between the criterion and predictor variables, whereas random effects explain the variability in sampling. The models were implemented using the “multilevel” (Bliese, 2016), the “lme4” (Bates, Maechler, Bolker, & Walker, 2015) and the “lmerTest” (Kuznetsova, Brockhoff, & Christensen, 2016) packages in the R programming language (R Development Core Team, 2015). We allowed for the random intercept term to vary across the subjects. The significance of predictors was determined using an alpha level of .05 (two-tailed).

To evaluate the training gains and transfer effects, we specified a fixed effect associated with a growth variable (representing the linear growth over time), which served as a single predictor and was included in the model as an interaction term with the group variable. The group variable was dummy coded, with the active control (OLMT) group as reference group, meaning that each of the working memory training groups and the passive group was coded 1 for each participant in the respective groups, and 0 for everyone else. The model also used dummy coding for the growth variable with 0 for the pre- and 1 for post-test. The difference in gain between pre- and post-test in each working memory training group, compared to the OLMT group was reflected by the regression weight of the interaction between the corresponding group dummy variable and the growth variable. The fixed intercept parameter represented the baseline mean in the OLMT group. Main effects of the group variable were not included in the model, as there was no reason to assume group differences at pre-test.

In a second group of models, we examined how training gains and transfer effects related to cognitive strategies (visual and verbal). In this regard, we specified the interaction of Time × Group × Strategy. We assessed the use of strategy in storage and processing, and relational integration tasks at pre- and post-test. Therefore, the entire analyses included a total of 16 models, with 2 strategies (pre and post) and 4 tasks for each working memory operation (i.e., storage and processing, and relational integration). It is important to mention that some training groups were dropped in some models during analyses, because these groups contained only one strategy (visual or verbal). Each of the models included a growth variable as well as a cognitive strategy variable (taking on a code of 0 for visualization and 1 for verbalization) at pre- and post-test, respectively. Both of the variables served as single predictors and were included in the model as an interaction term with each other. The fixed effect associated with the group variable was included only as an interaction term with the linear growth variable and the cognitive strategy variable. The resulting model, thus, represented the difference between verbalizers and visualizers in the difference in change between each working memory group and the OLMT group by the corresponding regression weight of the interaction between the strategy, the group variable and the growth variable. Additionally, the interaction of Time × Group was included in the models, which indicated the difference in change between each working memory training group and the OLMT group for visualizers.

Confirmatory factor analysis. To investigate the structure of the facet model of working memory, we performed a confirmatory factor analysis using the pre-test scores. The assessment of the global goodness-of-fit was based on a chi-square test (χ^2), the standardized root mean square residual (SRMR), the root mean squared error of approximation (RMSEA), and the comparative fit index (CFI). Values of SRMR $\leq .08$, RMSEA $\leq .06$, and CFI $> .95$ were taken as indication of adequate model fit (Hu & Bentler, 1999).

Power analysis. To compute statistical power, we performed several simulations using the "simr" package (Green & MacLeod, 2016). To detect a difference between trained group and active control group, corresponding to a small effect size ($f = 0.1$), the present study had a power of $1 - \beta < 0.80$ for all dependent variables. For storage and processing verbal, numerical, figural (pattern), and figural (symbol) tasks, the power were 0.60, 0.41, 0.75, and 0.58, respectively. For relational integration verbal, numerical, figural (pattern), and figural (symbol) tasks, the power were 0.40, 0.34, 0.35, and 0.40, respectively.

Additional analyses. All figures were generated in R using the package ggplot2 (Wickham, 2009). Fisher's exact tests were used to examine the differences between the frequency of using cognitive strategy at pre- and post-test. Two sample *t*-test was applied to compare the verbalizers and visualizers in the digit span backwards task.

Missing data. All participants completed 12 training sessions. However, due to the server being down, some training data were not saved online. One day's data was missing for five participants, two days for six participants, and three days for four participants. Consequently, we treated them as missing values and excluded them from the analyses, while calculating the mean training performance. If participants completed more than 12 training sessions, these additional sessions were also discarded from the analyses.

3.3 Results

3.3.1 The Facets of Working Memory

The current investigation was theoretically based on the facet model of working memory (Oberauer et al., 2003). The two-factor model (Figure 2) revealed an excellent overall model fit, $\chi^2(19) = 26.03$, $p = .130$; CFI = .95; RMSEA = .06; SRMR = .06. Factor loadings of all the indicators onto their respective latent variables were moderate to high (storage and processing: $\lambda = .51$ to $\lambda = .77$, relational integration: $\lambda = .39$ to $\lambda = .61$) and significantly different from zero ($p < .01$). Correlation between the latent variables was .52 (p

= .007). Notably, the new storage and processing figural (symbol) task highly loaded on storage and processing tasks.

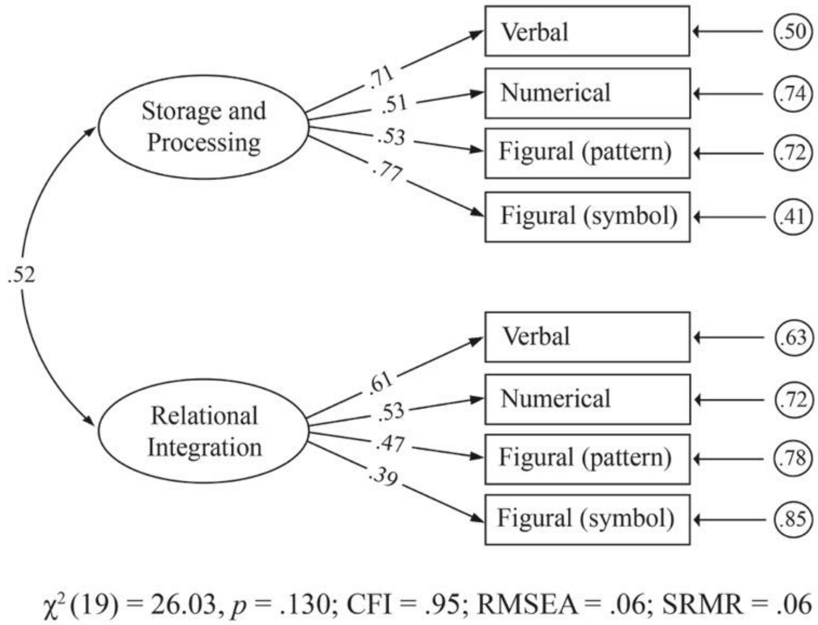

Figure 2. Measurement model representing the facet model of working memory. The proportion of residual variance of each indicator is calculated by subtracting the variance of the indicator from 1. All parameters were statistically significant ($p < .05$).

3.3.2 Training Performance

Figure 3 depicts the results of the mean performance achieved by the storage and processing, relational integration, and OLMT groups over the training period. The storage and processing, and relational integration both training groups showed different patterns of improvement with training. For the storage and processing groups (see Figure 3a), the performance somewhat improved for figural (pattern) and figural (symbol) groups, whereas the verbal group showed more or less consistent performance from the first to the last sessions. After the first session, the numerical group showed a decrease in the next four sessions, then started to increase from the sixth session onwards and regained the beginning level. With regard to the relational integration groups (Figure 3b), all the four training groups showed a decrease in performance with practice, although the slopes fluctuated in their steepness. The amount of mean performance decrease for the figural (pattern) was much less, compared to the other three. The performance decrease during training can be attributed to the adaptive algorithm of the tasks. The training graph for the OLMT group (Figure 3c) showed more or less steady increase with training.

Further, to assess whether performance improved with training, we also evaluated the training performance across 12 sessions via linear mixed-effects models in which sessions was considered as fixed-effect and participants as random-effect. The first training session acted as a reference category. The results revealed that the training sessions had a significant effect on training performance for six groups: storage and processing figural (pattern), $\chi^2(11) = 20.96$, $p = .034$; relational integration verbal, $\chi^2(11) = 66.82$, $p < .0001$; relational integration numerical, $\chi^2(11) = 69.88$, $p < .0001$; relational integration figural (pattern), $\chi^2(11) = 20.44$, $p = .03$; relational integration figural (symbol), $\chi^2(11) = 64.28$, $p < .0001$; OLMT, $\chi^2(11) = 81.26$, $p < .0001$. The regression parameters for the effect of sessions were negative for each of the relational integration groups, whereas these were positive for the storage processing figural (pattern) and the OLMT groups.

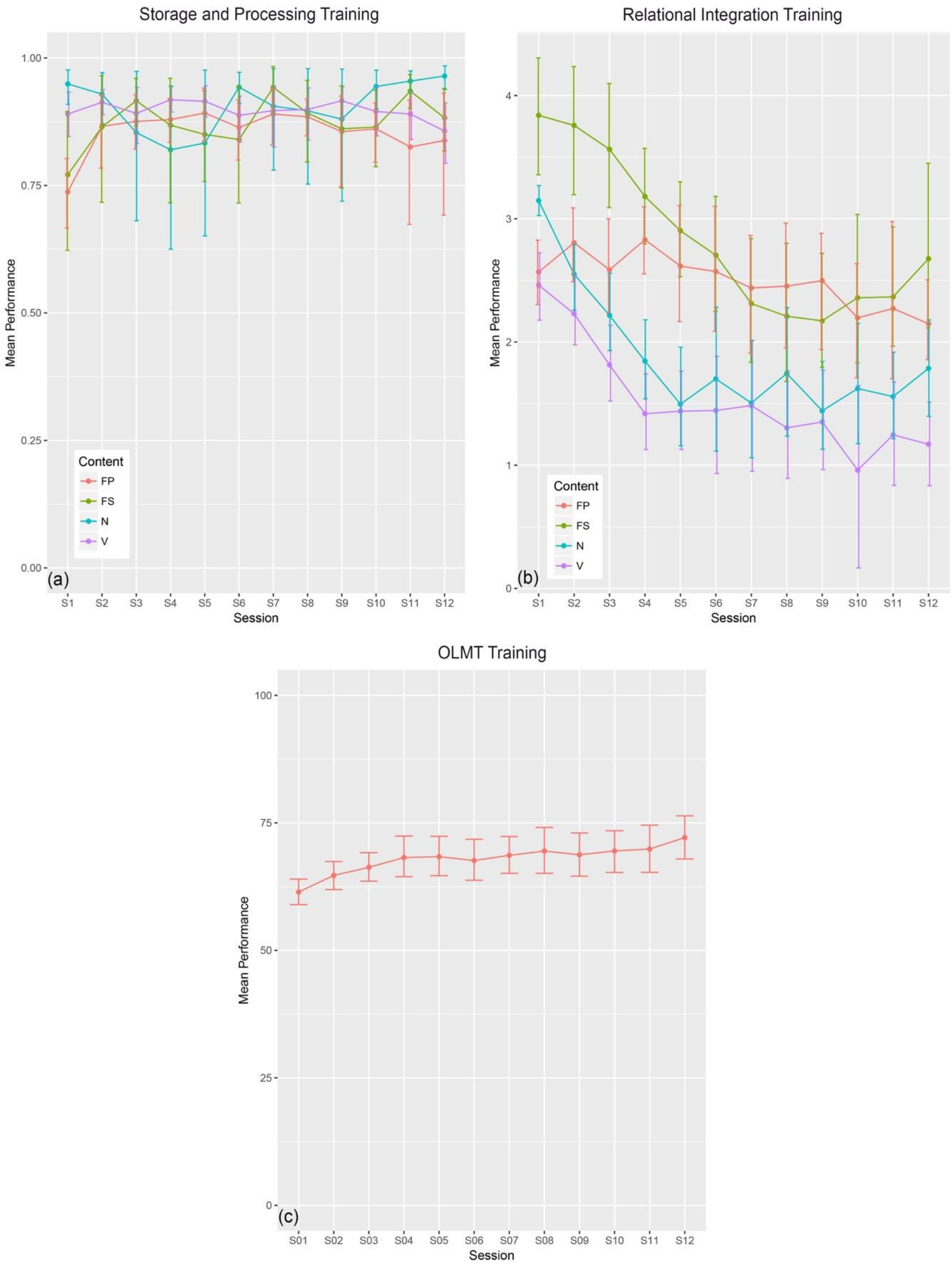

Figure 3. Training performance during 12 training sessions. Error bars represent 95% CIs. V = verbal; N = numerical; FP = figural (pattern); FS = figural (symbol). (a) Storage and Processing Training; (b) Relational Integration Training; (c) OLMT Training.

3.3.3 Training Gains and Transfer Effects

Descriptive statistics for pre- and post-test performance are presented in Table 1. To examine the training gains, we considered performance improvement in the corresponding working memory tasks for all training groups. Additionally, the near/nearest transfer effects to structurally similar (within operation) and structurally dissimilar working memory tasks (between operations) were examined. To investigate whether the training gains and transfer effects were achieved through training intervention, we estimated baseline group differences applying analysis of variances (ANOVA) using pre-test scores as dependent variables (see Table B1). There was no evidence for baseline differences among the groups in any task (*p*s >.05).

The mean working memory performances (including CIs) in the post-test for all groups are individually illustrated in Figure 4 and Figure 5. The graphical representations mimicked the results of the linear mixed-effects models for all eight working memory measures, which are depicted in Table 2A and Table 2B. With respect to the storage and processing groups, trained with figural (pattern) and figural (symbol) materials showed significant mean increase in their respective tasks, relative to the OLMT control group (b = 0.27, $p < .001$; b = 0.05, p = .024, respectively). However, the verbal and numerical trained groups did not show any significant change. Regarding the relational integration groups, all four training groups improved in the training tasks, compared to the OLMT group. Further inspection of the individual groups with the paired-sample *t*-tests, as outlined in Table 1 revealed that each training group also significantly improved at the post-test in some measures. Importantly, we found strong evidence for the absence of near/nearest transfer on structurally similar, but untrained working memory tasks. The only exception to this pattern was that relational integration numerical group showed a mean increase in relational integration figural (symbol) task in comparison with the OLMT group (b = 0.53, p = .039). Furthermore, regarding possible transfer to structurally dissimilar working memory tasks, the results clearly indicated no transfer effect between the two working memory operations, i.e., storage and processing, and relational integration. The OLMT group showed improvement from pre- to post-test in the storage and processing verbal, and figural (pattern) tasks, and in the relational integration verbal, numerical, and figural (pattern) tasks. The passive group, however, showed mean decrease on measures of storage and processing verbal and figural (pattern) materials while comparing to the OLMT group.

Critically, when we compared the working memory training groups with the passive group instead of the active control group, we found significant near transfer effects (see Table B2 and Table B3) on untrained and structurally dissimilar working memory tasks. For example, the storage and processing verbal, figural (pattern), and figural (symbol) groups showed improvement in other storage and processing tasks, even in relational integration tasks.

Table 1
Performance for the Transfer Tasks as a Function of Training Groups and Pre-Post-test.

		Storage and processing training groups				Relational integration training groups				Active Control	Passive
		Verbal	Numerical	Figural (Pattern)	Figural (Symbol)	Verbal	Numerical	Figural (Pattern)	Figural (Symbol)		
Sample Size		10	11	11	10	11	11	6	10	17	8
Drop out		3	2	4	6	5	2	4	4	1	0
Test											
Storage and Processing											
Verbal	Pre-test	0.78(0.12)	0.72(0.08)	0.69(0.14)	0.67(0.13)	0.73(0.12)	0.75(0.09)	0.75(0.10)	0.67(0.15)	0.73(0.10)	0.71(0.19)
	Post-test	**0.87(0.08)**	0.78(0.14)	**0.80(0.12)**	**0.76(0.11)**	**0.83(0.09)**	**0.85(0.09)**	**0.85(0.17)**	**0.76(0.20)**	**0.82(0.08)**	0.71(0.19)
Numerical	Pre-test	0.93(0.05)	0.96(0.02)	0.95(0.06)	0.95(0.05)	0.94(0.04)	0.95(0.05)	0.97(0.02)	0.94(0.06)	0.95(0.03)	0.97(0.01)
	Post-test	**0.95(0.04)**	**0.98(0.02)**	0.96(0.03)	0.96(0.05)	0.96(0.04)	0.96(0.04)	0.97(0.07)	0.94(0.06)	**0.96(0.03)**	0.97(0.04)
Figural (Pattern)	Pre-test	0.59(0.17)	0.56(0.17)	0.61(0.13)	0.54(0.16)	0.53(0.12)	0.61(0.13)	0.57(0.13)	0.55(0.10)	0.55(0.10)	**0.57(0.14)**
	Post-test	**0.69(0.17)**	0.60(0.18)	**0.94(0.04)**	**0.67(0.16)**	**0.62(0.11)**	**0.66(0.15)**	**0.67(0.15)**	**0.65(0.10)**	**0.63(0.09)**	0.52(0.19)
Figural (Symbol)	Pre-test	0.91(0.06)	0.85(0.10)	0.89(0.08)	0.86(0.10)	0.89(0.05)	0.89(0.05)	0.90(0.04)	0.87(0.09)	0.89(0.05)	**0.89(0.08)**
	Post-test	0.91(0.08)	**0.87(0.10)**	0.92(0.05)	**0.91(0.08)**	0.88(0.08)	0.90(0.07)	**0.94(0.03)**	**0.90(0.06)**	0.88(0.05)	0.85(0.07)
Relational Integration											
Verbal	Pre-test	2.59(0.66)	2.31(0.64)	2.20(.55)	2.46(0.74)	2.16(0.81)	2.38(.68)	2.34(0.48)	2.51(0.66)	2.26(0.42)	2.45(0.94)
	Post-test	2.71(0.61)	2.63(0.62)	2.42(.59)	2.82(0.81)	**3.08(0.80)**	**2.92(.73)**	**2.98(0.84)**	**3.01(0.53)**	**2.62(0.55)**	2.60(0.80)
Numerical	Pre-test	2.71(0.65)	2.69(0.65)	2.71(.40)	2.68(0.53)	2.32(1.35)	2.66(.65)	2.80(0.49)	2.90(0.60)	2.74(0.43)	2.12(1.18)
	Post-test	**3.01(0.55)**	2.82(0.66)	2.95(.63)	**2.96(0.45)**	**3.04(0.75)**	**3.63(.58)**	3.27(0.54)	**3.57(0.56)**	2.99(0.55)	2.80(0.48)
Figural (Pattern)	Pre-test	2.28(0.27)	2.34(0.51)	2.19(.23)	2.14(0.51)	2.09(0.45)	2.42(.53)	2.30(0.40)	2.43(0.30)	2.23(0.40)	2.33(0.29)
	Post-test	**2.60(0.40)**	2.57(0.30)	2.57(.48)	**2.45(0.47)**	**2.54(0.41)**	2.59(.40)	**2.96(0.36)**	2.70(0.31)	**2.49(0.41)**	2.45(0.47)
Figural (Symbol)	Pre-test	3.84(0.91)	3.63(0.72)	3.45(.72)	3.57(0.62)	3.92(0.41)	3.87(.55)	3.60(0.92)	3.63(0.92)	3.92(0.71)	3.52(1.04)
	Post-test	**4.23(0.47)**	3.92(0.65)	**4.16(.65)**	**4.09(0.39)**	**4.16(0.40)**	**4.22(.26)**	**4.30(0.29)**	**4.39(0.28)**	4.05(0.75)	**4.25(0.65)**
Digit Span Backwards		6.40(1.62)									

Note. Means (standard deviation) presented in bold are statistically different ($p < .05$) from means (standard deviation) at pre-test or post-test using a one-tailed paired samples *t*-tests.

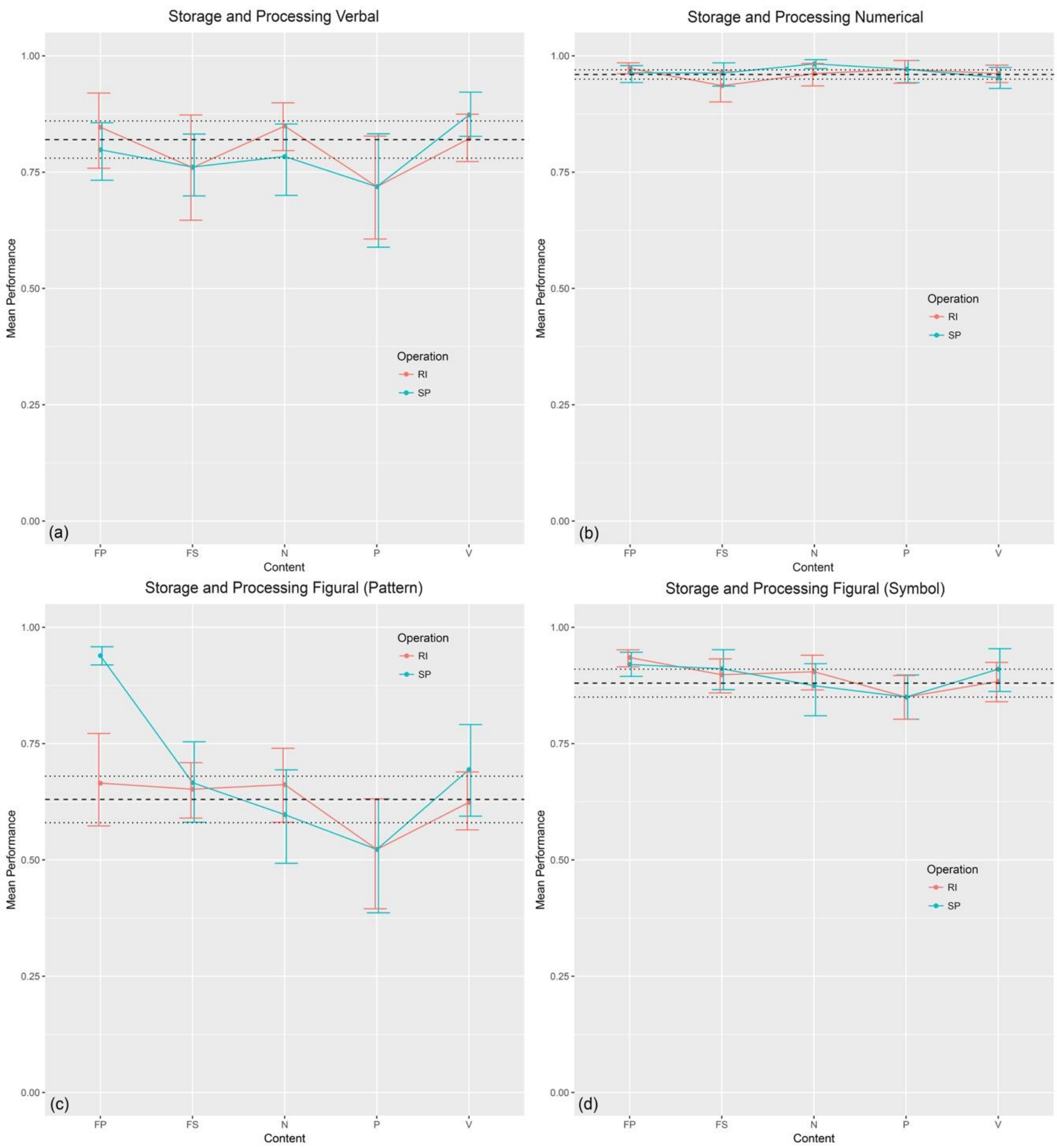

Figure 4. Post-test performances in trained and untrained tasks. Error bars represent 95% CIs; dashed horizontal line = mean performance of the active control group; dotted horizontal lines = error bar (95% CIs) for the active control group. SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural (symbol); P = passive. (a) Storage and Processing Verbal; (b) Storage and Processing Numerical; (c) Storage and Processing Figural (Pattern); (d) Storage and Processing Figural (Symbol).

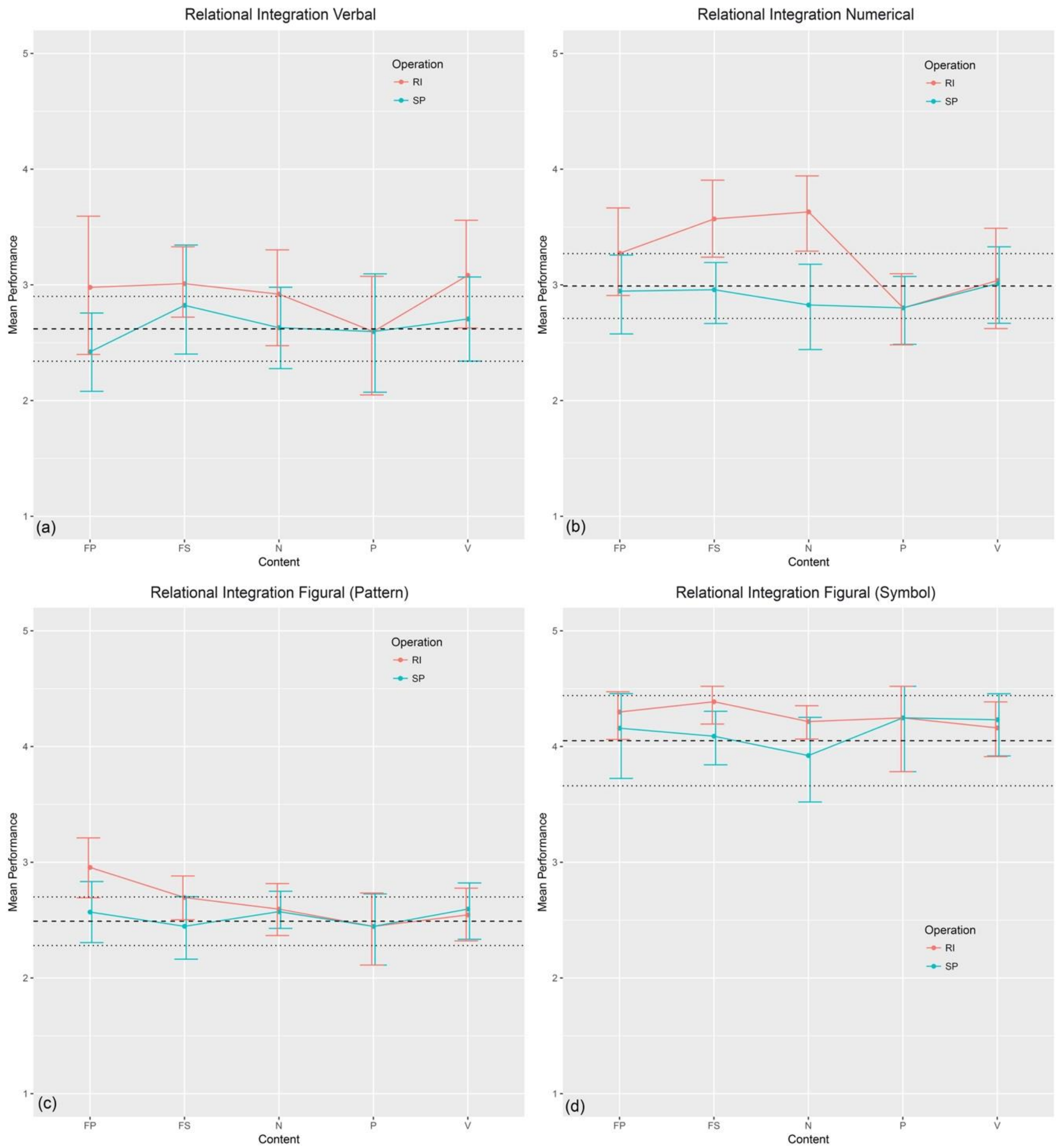

Figure 5. Post-test performances in trained and untrained tasks. Error bars represent 95% CIs; dashed horizontal line = mean performance of the active control group; dotted horizontal lines = error bar (95% CIs) for the active control group. SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural (symbol); P = passive. (a) Storage and Processing Verbal; (b) Storage and Processing Numerical; (c) Storage and Processing Figural (Pattern); (d) Storage and Processing Figural (Symbol).

Table 2A

Parameters Estimates from Linear Mixed-Effects Models for Storage and Processing Groups.

Covariates	Estimate	*SE*	*df*	*t*	*p*	Covariates	Estimate	*SE*	*df*	*t*	*p*
SP Verbal						**SP Figural (Pattern)**					
Intercept	**0.72**	**0.01**	**138.57**	**60.15**	**.000**	**Intercept**	**0.57**	**0.01**	**135.97**	**43.55**	**.000**
Control	**0.10**	**0.02**	**123.40**	**4.46**	**.000**	**Control**	**0.07**	**0.02**	**121.53**	**3.11**	**.002**
Control:SPV	0.01	0.04	130.70	0.42	.675	Control:SPV	0.04	0.04	127.93	1.00	.319
Control:SPN	-0.04	0.03	130.70	-1.08	.284	Control:SPN	-0.03	0.04	127.93	-0.94	.349
Control:SPFP	-0.00	0.03	130.70	-0.04	.965	**Control:SPFP**	**0.27**	**0.04**	**127.93**	**7.38**	**.000**
Control:SPFS	-0.02	0.04	130.70	-0.56	.579	Control:SPFS	0.05	0.04	127.93	1.36	.177
Control:RIV	-0.00	0.03	130.70	-0.08	.937	Control:RIV	0.01	0.04	127.93	0.36	.719
Control:RIN	0.01	0.03	130.70	0.33	.740	Control:RIN	-0.01	0.04	127.93	-0.14	.888
Control:RIFP	0.01	0.04	130.70	0.20	.843	Control:RIFP	0.02	0.04	127.93	0.56	.580
Control:RIFS	-0.01	0.04	130.70	-0.39	.696	Control:RIFS	0.03	0.04	127.93	0.68	.501
Control:Passive	**-0.09**	**0.04**	**130.70**	**-2.43**	**.017**	**Control:Passive**	**-0.12**	**0.04**	**127.93**	**-2.87**	**.005**
SP Numerical						**SP Figural (Symbol)**					
Intercept	**0.95**	**0.00**	**158.60**	**241.16**	**.000**	**Intercept**	**0.88**	**0.01**	**138.80**	**128.26**	**.000**
Control	0.01	0.01	139.80	1.37	.173	Control	-0.00	0.01	123.70	-0.25	.803
Control:SPV	0.00	0.01	152.40	0.07	.947	Control:SPV	0.01	0.02	131.00	0.73	.469
Control:SPN	0.01	0.01	152.40	1.20	.232	Control:SPN	0.02	0.02	131.00	1.05	.294
Control:SPFP	0.02	0.01	152.40	0.16	.874	Control:SPFP	0.04	0.02	131.00	1.81	.073
Control:SPFS	-0.00	0.01	152.40	-0.04	.968	**Control:SPFS**	**0.05**	**0.02**	**131.00**	**2.29**	**.024**
Control:RIV	0.00	0.01	152.40	0.27	.787	Control:RIV	-0.00	0.02	131.00	-0.03	.978
Control:RIN	-0.00	0.01	152.40	-0.12	.905	Control:RIN	0.02	0.02	131.00	1.15	.252
Control:RIFP	0.00	0.02	152.40	0.11	.914	Control:RIFP	0.04	0.02	131.00	1.71	.089
Control:RIFS	-0.02	0.01	152.40	-1.32	.188	Control:RIFS	0.03	0.02	131.00	1.51	.132
Control:Passive	-0.00	0.01	152.40	-0.12	.902	Control:Passive	-0.03	0.02	131.00	-1.56	.122

Note. SE = standard error; *df* = degrees of freedom; *t* = *t*-value; *p* = probability of committing type-I-error; Control = mean change between pre- and post-test in the active control group; Control:Group = difference in change between the working memory training group and the active control group; SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural (symbol); Covariates presented in bold are significantly different from zero.

Table 2B

Parameters Estimates from Linear Mixed-Effects Models for Relational integration Groups.

Covariates	Estimate	*SE*	*df*	*t*	*p*	Covariates	Estimate	*SE*	*df*	*t*	*p*
RI Verbal						**RI Figural (Pattern)**					
Intercept	**2.36**	**0.06**	**160.87**	**36.70**	**.000**	**Intercept**	**2.27**	**0.04**	**181.28**	**57.28**	**.000**
Control	**0.31**	**0.14**	**142.12**	**2.23**	**.028**	**Control**	**0.23**	**0.10**	**159.50**	**2.42**	**.017**
Control:SPV	-0.08	0.23	154.98	-0.37	.712	Control:SPV	0.09	0.15	178.13	0.57	.570
Control:SPN	-0.02	0.22	154.98	-0.08	.935	Control:SPN	0.05	0.15	178.13	0.31	.759
Control:SPFP	-0.17	0.22	154.98	-0.78	.439	Control:SPFP	0.09	0.15	178.13	0.62	.536
Control:SPFS	0.10	0.23	154.98	0.46	.648	Control:SPFS	-0.01	0.15	178.13	-0.10	.925
Control:RIV	**0.51**	**0.22**	**154.98**	**2.35**	**.020**	Control:RIV	0.10	0.15	178.13	0.67	.503
Control:RIN	0.24	0.22	154.98	1.08	.281	Control:RIN	0.04	0.15	178.13	0.28	.778
Control:RIFP	0.32	0.27	154.98	1.18	.240	**Control:RIFP**	**0.44**	**0.18**	**178.13**	**2.41**	**.017**
Control:RIFS	0.26	0.23	154.98	1.16	.247	Control:RIFS	0.14	0.15	178.13	0.91	.365
Control: Passive	-0.12	0.24	154.98	-0.49	.623	Control: Passive	-0.08	0.16	178.13	-0.49	.622
RI Numerical						**RI Figural (Symbol)**					
Intercept	**2.64**	**0.07**	**183.33**	**40.50**	**.000**	**Intercept**	**3.72**	**0.06**	**162.89**	**58.72**	**.000**
Control	**0.32**	**0.16**	**161.08**	**1.99**	**.047**	**Control**	0.23	0.14	143.44	1.62	.107
Control:SPV	0.03	0.25	180.51	0.10	.918	Control:SPV	0.22	0.23	157.23	0.99	.325
Control:SPN	-0.15	0.25	180.51	-0.62	.539	Control:SPN	0.02	0.22	157.23	0.09	.929
Control:SPFP	-0.04	0.25	180.51	-0.16	.873	Control:SPFP	0.34	0.22	157.23	1.56	.120
Control:SPFS	-0.02	0.25	180.51	-0.07	.948	Control:SPFS	0.22	0.23	157.23	0.95	.342
Control:RIV	0.17	0.25	180.51	0.68	.495	Control:RIV	0.12	0.22	157.23	0.53	.596
Control:RIN	**0.66**	**0.25**	**180.51**	**2.68**	**.008**	Control:RIN	0.20	0.22	157.23	0.90	.371
Control:RIFP	0.26	0.30	180.51	0.86	.389	Control:RIFP	0.41	0.27	157.23	1.52	.130
Control:RIFS	**0.53**	**0.25**	**180.51**	**2.08**	**.039**	**Control:RIFS**	**0.48**	**0.23**	**157.23**	**2.13**	**.035**
Control: Passive	-0.01	0.27	180.51	-0.02	.983	Control:Passive	0.40	0.24	157.23	1.64	.103

Note. SE = standard error; *df* = degrees of freedom; *t* = *t*-value; *p* = probability of committing type-I-error; Control = mean change between pre- and post-test in the active control group; Control:Group = difference in change between the working memory training group and the active control group; SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural (symbol); Covariates presented in bold are significantly different from zero.

3.3.4 Cognitive Strategies and Transfer Effects

In the next step of the analyses, we evaluated whether the use of verbal and visual strategies could explain the transfer of training. Table 3A and Table 3B show the parameter estimates of the interaction terms (Time × Group × Strategy) of the linear mixed-effects models. Note that the interaction terms of the models were reported because the difference between verbalizers and visualizers in the difference in change between working memory group and the OLMT group were of interest for the current study. A full report of all the parameter estimates is in the Appendix B6 (Table B4 to Table B11). Bonferroni-corrected alpha levels were reported where necessary. We did not include the passive group in this analysis. Two important findings stand out from these tables. First, we found null relation between the cognitive strategies and the training related gains on the trained tasks. Second, there was no evidence for the impact of cognitive strategies on the transfer effect between numerical and figural (symbol) materials within the relational integration tasks.

Table 3A *Cognitive Strategies as a Function of Transfer Effects for Storage and Processing Groups.*

Covariates	**Estimate**	***SE***	***df***	***t***	***p***	**Covariates**	**Estimate**	***SE***	***df***	***t***	***p***
SP Verbal						**SP Verbal**					
Control:SPV:SP_PreStrategy	0.04	0.10	107.74	0.34	.735	Control:SPV:SP_PostStrategy	-0.01	0.07	113.80	-0.08	.938
Control:SPN:SP_PreStrategy	-0.02	0.11	107.74	-0.19	.846	Control:SPN:SP_PostStrategy	-0.05	0.10	113.80	-0.46	.644
Control:SPFP:SP_PreStrategy	-0.01	0.10	107.74	-0.07	.946	Control:SPFP:SP_PostStrategy	-	-	-	-	-
Control:SPFS:SP_PreStrategy	0.11	0.11	107.74	1.02	.311	Control:SPFS:SP_PostStrategy	-	-	-	-	-
Control:RIV:SP_PreStrategy	0.04	0.12	107.74	0.36	.722	Control:RIV:SP_PostStrategy	0.00	0.08	113.80	-0.04	.969
Control:RIN:SP_PreStrategy	0.04	0.12	107.74	0.31	.759	Control:RIN:SP_PostStrategy	-	-	-	-	-
Control:RIFP:SP_PreStrategy	0.05	0.13	107.74	0.41	.680	Control:RIFP:SP_PostStrategy	0.04	0.10	113.80	0.35	.725
Control:RIFS:SP_PreStrategy	0.24	0.11	107.74	2.18	.031(.006)	Control:RIFS:SP_PostStrategy	-0.03	0.08	113.80	-0.43	.672
SP Numerical						**SP Numerical**					
Control:SPV:SP_PreStrategy	0.02	0.04	130.73	0.37	.709	Control:SPV:SP_PostStrategy	-0.02	0.03	126.80	-0.83	.406
Control:SPN:SP_PreStrategy	0.03	0.04	130.73	0.59	.560	Control:SPN:SP_PostStrategy	0.01	0.04	126.80	0.19	.849
Control:SPFP:SP_PreStrategy	0.05	0.04	130.73	1.11	.270	Control:SPFP:SP_PostStrategy	-	-	-	-	-
Control:SPFS:SP_PreStrategy	0.03	0.04	130.73	0.60	.551	Control:SPFS:SP_PostStrategy	-	-	-	-	-
Control:RIV:SP_PreStrategy	0.11	0.05	130.73	2.30	.023(.006)	Control:RIV:SP_PostStrategy	0.06	0.03	126.80	1.78	.077
Control:RIN:SP_PreStrategy	0.01	0.05	130.73	0.16	.875	Control:RIN:SP_PostStrategy	-	-	-	-	-
Control:RIFP:SP_PreStrategy	0.02	0.05	130.73	0.46	.645	Control:RIFP:SP_PostStrategy	-0.01	0.04	126.80	-0.29	.774
Control:RIFS:SP_PreStrategy	0.00	0.04	130.73	0.08	.934	Control:RIFS:SP_PostStrategy	0.06	0.03	126.80	1.97	.051
SP Figural (Pattern)						**SP Figural (Pattern)**					
Control:SPV:SP_PreStrategy	-0.06	0.12	111.38	-0.54	.593	Control:SPV:SP_PostStrategy	0.01	0.08	116.07	0.14	.890
Control:SPN:SP_PreStrategy	-0.08	0.12	111.38	-0.61	.543	Control:SPN:SP_PostStrategy	-0.07	0.11	116.07	-0.64	.522
Control:SPFP:SP_PreStrategy	-0.18	0.12	111.38	-1.50	.136	Control:SPFP:SP_PostStrategy	-	-	-	-	-
Control:SPFS:SP_PreStrategy	-0.05	0.12	111.38	-0.37	.712	Control:SPFS:SP_PostStrategy	-	-	-	-	-
Control:RIV:SP_PreStrategy	-0.18	0.14	111.38	-1.25	.213	Control:RIV:SP_PostStrategy	-0.03	0.09	116.07	-0.36	.720
Control:RIN:SP_PreStrategy	-0.02	0.14	111.38	-0.16	.877	Control:RIN:SP_PostStrategy	-	-	-	-	-
Control:RIFP:SP_PreStrategy	0.00	0.14	111.38	-0.03	.975	Control:RIFP:SP_PostStrategy	0.01	0.12	116.07	0.09	.926
Control:RIFS:SP_PreStrategy	-0.15	0.12	111.38	-1.23	.222	Control:RIFS:SP_PostStrategy	-0.01	0.09	116.07	-0.14	.890
SP Figural (Symbol)						**SP Figural (Symbol)**					
Control:SPV:SP_PreStrategy	-0.03	0.06	111.19	-0.52	.604	Control:SPV:SP_PostStrategy	0.04	0.04	116.55	0.94	.348
Control:SPN:SP_PreStrategy	-0.08	0.07	111.19	-1.23	.222	Control:SPN:SP_PostStrategy	0.03	0.06	116.55	0.57	.568
Control:SPFP:SP_PreStrategy	-0.09	0.06	111.19	-1.39	.168	Control:SPFP:SP_PostStrategy	-	-	-	-	-
Control:SPFS:SP_PreStrategy	0.01	0.07	111.19	0.09	.926	Control:SPFS:SP_PostStrategy	-	-	-	-	-
Control:RIV:SP_PreStrategy	-0.11	0.08	111.19	-1.41	.162	Control:RIV:SP_PostStrategy	-0.06	0.05	116.55	-1.21	.229
Control:RIN:SP_PreStrategy	-0.06	0.08	111.19	-0.79	.430	Control:RIN:SP_PostStrategy	-	-	-	-	-
Control:RIFP:SP_PreStrategy	-0.09	0.08	111.19	-1.09	.277	Control:RIFP:SP_PostStrategy	0.02	0.06	116.55	0.25	.805
Time:RIFS:SP_PreStrategy	-0.03	0.07	111.19	-0.47	.638	Control:RIFS:SP_PostStrategy	-0.04	0.05	116.55	-0.86	.390

Note. *SE* = standard error; *df* = degrees of freedom; t = t-value; *p* = probability of committing type-I-error; Control:Group:Strategy = difference between verbalizers and visualizers in the difference in change between the working memory training group and the active control group; SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural(symbol); PreStrategy = strategy usage at pre-test; PostStrategy = strategy usage at post-test. (-) denote the group that was dropped due to the rank deficient of fixed-effect model matrix; *p* values in bracket indicate corrected alpha levels after Bonferroni Correction.

Table 3B *Cognitive Strategies as a Function of Transfer Effects for Relational Integration Groups.*

Covariates	**Estimate**	***SE***	***df***	***t***	***p***	**Covariates**	**Estimate**	***SE***	***df***	***t***	***p***
RI Verbal						**RI Verbal**					
Control:SPV:RI_PreStrategy	0.54	0.73	139.01	0.74	.461	Control:SPV:RI_PostStrategy	-0.91	0.73	138.73	-1.24	.217
Control:SPN:RI_PreStrategy	-0.20	0.57	139.01	-0.35	.725	Control:SPN:RI_PostStrategy	0.39	0.61	138.73	0.64	.524
Control:SPFP:RI_PreStrategy	0.10	0.73	139.01	0.14	.889	Control:SPFP:RI_PostStrategy	-1.19	0.73	138.73	-1.63	.106
Control:SPFS:RI_PreStrategy	-0.25	0.58	139.01	-0.43	.671	Control:SPFS:RI_PostStrategy	0.39	0.56	138.73	0.70	.487
Control:RIV:RI_PreStrategy	-0.29	0.57	139.01	-0.50	.616	Control:RIV:RI_PostStrategy	-0.26	0.55	138.73	-0.47	.641
Control:RIN:RI_PreStrategy	-0.95	0.57	139.01	-1.65	.101	Control:RIN:RI_PostStrategy	-0.28	0.61	138.73	-0.45	.653
Control:RIFP:RI_PreStrategy	0.44	0.65	139.01	0.68	.496	Control:RIFP:RI_PostStrategy	0.42	0.65	138.73	0.65	.515
Control:RIFS:RI_PreStrategy	-	-	-	-	-	Control:RIFS:RI_PostStrategy	-0.07	0.62	138.73	-0.11	.914
RI Numerical						**RI Numerical**					
Control:SPV:RI_PreStrategy	-0.70	0.79	156.16	-0.89	.378	Control:SPV:RI_PostStrategy	1.07	0.80	159.75	1.33	.186
Control:SPN:RI_PreStrategy	-0.88	0.62	156.16	-1.42	.158	Control:SPN:RI_PostStrategy	0.15	0.67	159.75	0.23	.820
Control:SPFP:RI_PreStrategy	0.11	0.79	156.16	0.14	.892	Control:SPFP:RI_PostStrategy	0.22	0.80	159.75	0.28	.784
Control:SPFS:RI_PreStrategy	-0.57	0.62	156.16	-0.92	.360	Control:SPFS:RI_PostStrategy	0.87	0.61	159.75	1.42	.157
Control:RIV:RI_PreStrategy	-0.37	0.62	156.16	-0.61	.546	Control:RIV:RI_PostStrategy	0.34	0.60	159.75	0.57	.573
Control:RIN:RI_PreStrategy	-0.07	0.62	156.16	-0.12	.908	Control:RIN:RI_PostStrategy	-0.19	0.67	159.75	-0.28	.780
Control:RIFP:RI_PreStrategy	-0.27	0.70	156.16	-0.39	.700	Control:RIFP:RI_PostStrategy	0.71	0.71	159.75	1.00	.319
Control:RIFS:RI_PreStrategy	-	-	-	-	-	Control:RIFS:RI_PostStrategy	0.32	0.68	159.75	0.48	.636
RI Figural (Pattern)						**RI Figural (Pattern)**					
Control:SPV:RI_PreStrategy	-0.11	0.51	158.35	-0.22	.829	Control:SPV:RI_PostStrategy	0.11	0.51	155.35	0.22	.823
Control:SPN:RI_PreStrategy	-0.39	0.40	158.35	-0.96	.338	Control:SPN:RI_PostStrategy	-0.12	0.42	155.35	-0.28	.783
Control:SPFP:RI_PreStrategy	-0.15	0.51	158.35	-0.30	.762	Control:SPFP:RI_PostStrategy	0.29	0.51	155.35	0.57	.572
Control:SPFS:RI_PreStrategy	0.04	0.40	158.35	0.09	.927	Control:SPFS:RI_PostStrategy	-0.32	0.39	155.35	-0.82	.416
Control:RIV:RI_PreStrategy	-0.25	0.40	158.35	-0.63	.530	Control:RIV:RI_PostStrategy	-0.62	0.38	155.35	-1.63	.105
Control:RIN:RI_PreStrategy	0.04	0.40	158.35	0.11	.916	Control:RIN:RI_PostStrategy	-0.25	0.42	155.35	-0.60	.552
Control:RIFP:RI_PreStrategy	0.17	0.45	158.35	0.37	.709	Control:RIFP:RI_PostStrategy	0.05	0.45	155.35	0.11	.914
Control:RIFS:RI_PreStrategy	-	-	-	-	-	Control:RIFS:RI_PostStrategy	-0.34	0.43	155.35	-0.80	.425
RI Figural (Symbol)						**RI Figural (Symbol)**					
Control:SPV:RI_PreStrategy	-0.56	0.74	140.46	-0.76	.449	Control:SPV:RI_PostStrategy	-0.42	0.73	139.80	-0.57	.567
Control:SPN:RI_PreStrategy	-1.15	0.57	140.46	-2.00	.047(.006)	Control:SPN:RI_PostStrategy	-0.87	0.62	139.80	-1.42	.159
Control:SPFP:RI_PreStrategy	-0.38	0.73	140.46	-0.51	.608	Control:SPFP:RI_PostStrategy	-0.06	0.73	139.80	-0.08	.934
Control:SPFS:RI_PreStrategy	-0.77	0.58	140.46	-1.33	.186	Control:SPFS:RI_PostStrategy	-0.52	0.56	139.80	-0.92	.361
Control:RIV:RI_PreStrategy	-0.68	0.57	140.46	-1.18	.238	Control:RIV:RI_PostStrategy	-0.98	0.55	139.80	-1.79	.076
Control:RIN:RI_PreStrategy	-0.44	0.57	140.46	-0.77	.444	Control:RIN:RI_PostStrategy	-0.26	0.62	139.80	-0.42	.672
Control:RIFP:RI_PreStrategy	-0.38	0.65	140.46	-0.59	.557	Control:RIFP:RI_PostStrategy	-0.38	0.65	139.80	-0.59	.558
Control:RIFS:RI_PreStrategy	-	-	-	-	-	Control:RIFS:RI_PostStrategy	-0.35	0.62	139.80	-0.57	.570

Note. SE = standard error; *df* = degrees of freedom; t = t-value; *p* = probability of committing type-I-error; Control:Group:Strategy = difference between verbalizers and visualizers in the difference in change between the working memory training group and the active control group; SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural(symbol); PreStrategy = strategy usage at pre-test; PostStrategy = strategy usage at post-test. (-) denote the group that was dropped due to the rank deficient of fixed-effect model matrix; *p* values in bracket indicate corrected alpha levels after Bonferroni Correction.

3.3.5 Cognitive Strategies Survey

The frequency of using different cognitive strategies before and after training was analyzed by groups in a series of Fisher's exact tests (two tailed) to see whether participants change their strategies over time. Results revealed that there was no significant difference in the use of cognitive strategies between pre- and post-test for most measures and groups (provided in Table B12 and Table B13). Notably, the storage and processing figural (pattern) group significantly changed strategy after training (p < .001) in the trained task: About 91% of participants stated to have used visualization at pre-test, while they changed their strategies and used verbalization or a combination of both at post-test.

For storage and processing tasks, unsurprisingly, the dominated strategy was verbalization, reported by 89% of participants before training and 90% after training; for relational integration tasks it was visualization (85% at pre-training and 79% at post-training). Specifically, across all relational integration tasks, the strategy survey data indicated that about 12% (pre-training) and 9% (post-training) of participants stated that they used different (neither visual nor verbal) or additional strategies on certain tasks. These included: focusing on the potential combination of the stimuli, looking at the movement of the stimuli, expecting potential matches when two relevant elements appeared in the matrix, and giving attention to the relevant elements. Some participants did not report a clear strategy or simply reported that they used no strategy on certain tasks.

3.3.6 Digit Span Backwards Task Performance

To replicate the findings of Hilbert, Nakagawa, et al. (2015), we used the responses of cognitive strategies that participants reported to apply in storage and processing tasks at post-test and found no significant mean difference between visualizers and verbalizers in the digit span backwards task, t (103) = -0.17, p = .864. A point-biserial correlation (r_{pb}) between digit span backwards task and cognitive strategies revealed an insignificant relationship, r_{pb} = .02, p = .864. Thus, the present findings replicated the previous one.

3.4 Discussion

The overarching goal of the present study was to directly investigate the performances on working memory tasks that are closely related to the trained tasks in order to understand why transfer occurs especially on material-specific tasks, rather than on other types of tasks. We asked this question in two ways. First, within the tasks of the same operation (i.e., storage and processing or relational integration), do training with the verbal and numerical materials generalize to the new task with figural (symbol) material, and vice versa? Second, does the cognitive strategy account for the transfer effects of working memory training? Additionally, we also sought to examine whether the near transfer occurs between the two working memory domains (storage and processing, and relational integration). The present investigation yielded four important findings. First, we found consistent evidence of training gains on the tasks that were trained for most measures. Second, there was no evidence for transfer of training to measures of untrained structurally similar tasks within each working memory operation, with one exception of the transfer effect between relational integration numerical and figural (symbol) materials. Third, between the working memory operations, storage and processing, and relational integration did not show any transfer. Fourth, there was absence of evidence for the relation of cognitive strategy (visual or verbal) to transfer effect.

3.4.1 The Facets of Working Memory

Our study focused on the facet model of working memory (Oberauer et al., 2003). The confirmatory factor analysis of the two-factor model (Figure 2) represented that storage and processing, and relational integration were correlated but distinct, thus, replicating the original model. It is worth mentioning that the new storage and processing figural (symbol) task showed the highest loading on the storage and processing, suggesting that it taps simultaneous processing and storage demands, which are a hallmark of working memory. The figural (symbol) task differs from other storage and processing tasks in terms of retrieval of information - recall or recognition. This task requires participants to perform a recognition task in which they have to choose the correct order of symbols from the alternatives, whereas other storage and processing tasks involve to recall the words/numbers/patterns. The ability of recognition is an important determinant for storage and processing tasks (measured with complex span tasks; Lilienthal, Rose, Tamez, Myerson, & Hale, 2015). Moreover, the factor loading of another new task - relational integration figural (symbol) was also compatible with the other indicators of relational integration.

3.4.2 Training Performance

Over the course of 12 days training, the four storage and processing training groups showed a sketchier pattern of improvement, while the performance of the relational integration groups declined significantly. According to the linear mixed-effects models, the number of training sessions had a significant effect on training performances of the relational integration groups, the storage and processing figural (pattern) group, and the OLMT group, reflecting participant's capacity to adapt to the training circumstances. Notably, the figural (pattern) storage and processing group and the OLMT group showed improvements across sessions, compared to the first session. However, the adaptive algorithm of the training tasks would be the reason for such kind of performance decrement in the relational integration groups, as the level of difficulty of the training tasks was changed according to participant's performance. Specifically, the relational integration tasks became more difficult with decreasing the time interval between the switching stimuli or increasing the number of changing stimuli.

3.4.3 Training Gains

At first, consistent with previous literature on working memory training (e.g., Hilbert et al., 2017; Redick, Shipstead, Wiemers, Melby-Lervåg, & Hulme, 2015; von Bastian & Echen, 2016), the present results provided strong evidence regarding the improvement in the trained tasks (which is known as 'curse of specificity'; Green & Bavelier, 2012, p. 198), thus echoing the notion that working memory training does not advance general cognition beyond the tasks, which are actually being trained (Owen et al., 2010). Unexpectedly, however, the same training gains did not materialize for the storage and processing verbal and numerical measures. These inconsistent findings would be ascribed to the participant's already having a good baseline ability on these measures (Zinke et al., 2014). This is because the participants were university students and finished the standard education (*Abitur* in Germany), which could enhance their cognitive functioning and lead to the absence of benefit on the certain tasks. Another possible explanation could be that people frequently use verbal and numerical materials (e.g., reading comprehension, mathematical knowledge etc.) in everyday activities, thereby the verbal and numerical information processing systems are perhaps previously competent and have little room for improvement. It could also be the case that participants of the present study may need more sessions to show training gains. For example, the storage and processing groups showed variability in performing the storage and processing verbal task (Figure 4a), indicating that participants may require additional time to be efficient on that task. By contrast, in the storage processing numerical task, participants of all groups performed equally good (Figure 4b), reflecting ceiling level performance.

3.4.4 Material- and Operation-specific Transfer Effects

In stark contrast to the process overlap theory (Kovavs & Conway, 2016), no evidence was found for transfer of storage and processing training to untrained tasks, even when those tasks involved the same narrow ability, but used different stimuli materials. Also, the scarceness of transfer effects contradicts the prior work by our research group (Hilbert et al., 2017). Nevertheless, the prior work had the limitation of not including a baseline test, which can lead to biased effect sizes (Melby-Lervåg, Redick, et al., 2016), although the statistical power of the study was very high (80%) to detect a group difference, corresponding to a small effect size ($f < .1$). Given that a number of studies demonstrated transfer from complex span to other span-based measures (e.g., Harrison et al., 2013; Sprenger et al., 2013; von Bastian & Oberauer, 2013), it seems that our storage and processing tasks were not successful to detect any transfer effect after training, which is in line with Minear et al. (2016). Arguably, a particular relevant deviation may be occurred with the task of the present study: an unconventional task administration related to storage-processing tradeoff, which is further discussed below.

Contrary to the storage and processing groups, the only noteworthy transfer effect was observed within the tasks of relational integration. Training with numerical material resulted in better performance with figural (symbol) material, which supports our hypothesis that numerical and the figural (symbol) materials would be solved using same cognitive strategy. This substantial transfer suggests that training may promote highly task-specific strategies, which in turn enhance working memory resources (Dunning & Holmes, 2014; Soveri, Antfolk, Karlsson, Salo, & Laine, 2017; von Bastian & Oberauer, 2014), but the presence of strategies was not observed to account for this transfer effect (as discussed below). However, we did not find any other transfer effect within relational integration tasks.

Together, there are several potential explanations for the absence of transfer effects in storage and processing, and relational integration tasks. First, intensive practice on specific content [verbal/numerical/figural (pattern)/figural (symbol)] may not change underlying domain general gain in working memory capacity, which could subsequently yield non-significant transfer effect. In this regard, we should keep in mind that “the variance of the score gains, can have a radically different compositions than the variance of the scores themselves" (Hayes, Petrov, & Sederberg, 2015, p.9). More specifically, the latent variable analysis (Figure 2) revealed that the latent storage and processing factor accounted for between 26% and 56% of variance in its four manifest variables; and the relational integration explained between 15% and 39% of variance in its four indicators. This suggests that each of the single tasks possesses unique variances which are not explained by domain general storage and processing, and relational integration factors. Thus, this diversity pattern might be the case of lack of transfer to untrained tasks within the working memory operation. A recent meta-analysis concluded that isolated training with particular material may be restricted the training gains (Schwaighofer et al., 2015). Importantly, the benefit of relational integration numerical training on figural (symbol) task replicates the equivalent finding of previous studies (e.g., Lange & Süß, 2015; von Bastain & Eschen, 2016), even though our training regimen was embedded in narrow training context, and thus speaks against the core training condition, which have been postulated as an appropriate training regimen to produce transfer effects (Morrison & Chein, 2011).

Second, the theory of transfer (Barnett & Ceci, 2002) explains transfer as a function of the content of practiced elements (i.e., a specific stimuli) and the context in which practice and transfer occurs (i.e., a situation). In this regard, Maguire, Valentine, Wilding, and Kapur (2003) stressed the importance of context in applying cognitive strategies. It seems that transfer only takes place while the stimuli and the structure of the task interact. We can explain this issue more clearly by shedding light on the interference model of visual working memory (Oberauer & Lin, 2017): Retrieval of information is governed by the focus of attention representing the binding between the object's content and its context in which context serves as a cue and stimulates to access content. Although several studies claim process-specific improvement between training and transfer tasks, transfer of the training to other task modalities is hardly present (Healy, Wohldmann, Sutton, & Bourne Jr., 2006; Thorndike, 1906). Ericsson, Chase, and Faloon (1980), for instance, showed that practicing to remember digits is not effective in recalling letters.

Third, it is also possible that the absence of transfer effects was observe because of the lack of proper supervision (i.e., training under the supervision of a person) and low training intensity (i.e., the number of trials practiced in each session). According to Schwaighofer et al. (2015), supervision yields large mean effect sizes in lab-based training in comparison to home-based training. However, participants of this study were frequently contacted if they did not perform well or they missed their regular schedules of practice. With respect to training intensity, participants in the relational integration groups practiced more trials (on average 500 trials) in each session than those in the storage and processing groups (on average 50 trials), although the storage and processing tasks required more time to solve. This discrepancy may result in failure to detect any transfer effect in storage and processing tasks. Fourth, each of the training groups evinced improvement from pre- to post-test on several measures (paired samples *t*-test; see Table 1), but when comparing this with the OLMT control group, it turned into a non-significant effect. The OLMT group also outperformed on some working memory measures in post-test, which goes in line with practice-related improvement (Ackerman, Kanfer, & Calderwood, 2010). Apparently, the OLMT assesses processing speed (i.e., how many fields can be covered in 10s), which tends to be minimally related to working memory (Oberauer et al., 2003). Therefore, the comparison of working memory training groups with the OLMT group might underestimate the transfer effect (cf. von Bastian & Oberauer, 2014). Finally, the working memory intervention may suffer from publication bias – the positive transfer effects found in the previous studies could be overestimated (e.g., Simons et al., 2016). For example, the small study-effect contributes to low power, thus leading to biased effects (the so-called 'winner curse'; Bogg and Lasecki, 2015, p. 6).

Furthermore, the present results provided no convincing evidence for a near transfer across the facets: None of the storage and processing training conditions led to better performance in the relational integration tasks, and vice versa. This finding supports the previous studies (Hilbert et al., 2017; von Bastian & Oberauer, 2013). In the confirmatory factor analysis (Figure 2), the storage and processing, and relational integration factors shared about 27% of variance (i.e., $(.52)^2 = .27$), indicating that training may tap the remaining 73% of the variance, but not affect the shared variance (for a similar description, see Lange & Süß, 2015). Accordingly, even though storage and processing and relational integration are positively correlated, it is not necessarily the case that repeatedly practicing on specific measure reflects improvement in the common processes shared with other measure as well, as exemplified by Harrison et al. (2013): Making somebody heavier would not specify make him taller. In addition, the neural networks respond differently according to various working memory tasks (Rottschy et al., 2012), which might be another reason of the lack of transfer.

Closer inspection of the data showed that each of the storage and processing groups not only performed better on the trained tasks but also on the untrained tasks measuring storage and processing, and relational integration, compared to the passive group (Table B2 and Table B3), which opposes Coloms et al.'s (2013) suggestions regarding no difference in transfer results between passive and active control groups. Apparently, the working memory test scores were decreased from pre- to post-test in some measures for the passive group (see Table 1), which contributes to the Time × Group interaction being significant (Redick, 2015). Melby-Lervåg, Redick, et al. (2016) found a discrepancy with the effect size of .31 and .42 for verbal working memory and .28 and .51 for visuospatial working memory while comparing the active control group with the passive group, respectively. However, the relational integration groups did not reveal any transfer effect in this regard.

3.4.5 Cognitive Strategies Underlying Transfer Effects

We assumed that if there was any transfer effect, it could have occurred due to an underlying cognitive strategy which involved in solving trained and transfer tasks. However, we found no causal connection between visual/verbal cognitive strategies and transfer effects, specifically for the strong evidence of the training gains in the trained tasks and for the significant transfer between the relational integration numerical and figural (symbol) tasks. The training effects that we observed may be associated with the task-related anticipation, since participants practiced single type of task for a long time. Consequently, they might have expected to improve on tasks that are identical to those used at training, which is recognized as ‘stimuli-specific expertise’ (De Simoni & von Bastian, 2018). Yet, it is somehow puzzling that cognitive strategies could not explain these findings. The question is why we did not observe the influence of cognitive strategy on the transfer effects. The fact that using a cognitive strategy is demanding, as it stimulates an additional effort in the processing of the stimuli (Borella et al., 2014). Therefore, utilizing a strategy in the adaptive working memory training context (which is also challenging) might pose an additional burden on the cognitive system; or participants probably need more time to generate strategy which could relate to the transfer effects.

Another possibility is that participants were interviewed about their strategic approach by administering a questionnaire. Consequently, the language of the questionnaire could have prevented them to report their actual responses and restricted them in choosing only visual and verbal strategies, even though they might have developed their own strategies or used a specific approach in processing information or they might have applied a combination of strategies (visual and verbal; Kollöffel, 2012). Alternatively, they could have simply reported their preferred strategy, but Hilbert, Bühner et al. (2015) suggested that preference for using a visual or verbal cognitive style is not associated with task-specific cognitive strategies. Apart from that, participants' self-reported strategy may possibly undermine the role of strategic approach in understanding training gains, although it retains some advantages (as described in Introduction). The self-report measures have inherent weaknesses, such as potential discrepancies between participants subjective reports about the strategy and their actual behavior. Specifically, concerning the relationship between cognitive strategies and transfer effect, there are few studies reporting a lack of relationship between the self-report strategic approach and task performance in working memory training (Bellander et al., 2017; Minear et al., 2016; Redick et al., 2013). However, Minear et al. (2016) and Redick et al. (2013) only focused on participant's (young adults) acquisition of strategies for the training tasks, rather than focusing on the use of strategies for the post-test tasks after training. Additionally, cognitive strategies are covert in nature and cannot be assessed in a simple way (Joyner & Kurtz-Costes, 1997).

One important observation needs to be addressed in this regard: Our storage and processing and relational integration tasks are both experimenter-paced, not participant-paced, which stimulates to adopt memory strategies (Morrison et al., 2016; St Clair-Thompson, 2007). For example, in the storage and processing tasks, a sequence of stimuli is presented, after that the processing tasks (e.g., categorizing city or country in the verbal task) are automatically appeared for 5s, as we have fixed the processing time duration. Similarly, in relational integration, the time interval between the changing stimuli is restricted to 2s (e.g., changing words in 3 × 3 matrix). This contrasts with other working memory tasks (e.g., complex span tasks; Harrison et al., 2013; Sprenger et al., 2013), which require participants to operate the processing tasks on their own. They can spend some time on responding each trial (e.g., making a math judgement in the verbal span task), then proceed to the next. In this sense, participants of our study might have not been allowed to take additional time to implement elaborative or demanding strategies, rather they might have engaged in shallow types of strategic approaches (e.g., rote repetition, familiarity, focusing on graphical aspects etc.). The contribution of strategy to training effects can possibly be attributed to deep information processing, such as self-reference strategy (i.e., semantic connection with own life) or mnemonics strategy (i.e., chunking; for details, see McCabe et al., 2016). Alternatively, another speculation would be that those participants are more strategic, in accordance with the *strategy-as-cause* account (Bailey et al., 2008; Dunlosky & Kane, 2007), thereby performing worse in working memory tasks, which might have led to no transfer.

3.4.6 Cognitive Strategies Survey

From the analyses of Fisher's exact tests, it is clear that individuals in most of the groups did not significantly change their memory strategies after training, which contradicts Dunning and Holmes (2014). Possibly, the failure to detect transfer of training in the present study may be due to the lack of alteration of strategy over the course of training, because changes in memory strategy could have an impact on post training performance (Gross & Rebok, 2011; Matzen et al., 2013). This may also reflect how well training conveys the intended task-literacy per se. Nevertheless, it is worth noting that the storage and processing figural (pattern) group changed strategy during training. They reported having used visual strategy in pre-test, but later they reported a verbal strategy or combination of both strategies. It seems that participants used a verbal strategy to make the pattern meaningful by giving the name of the pattern (e.g., 'L' shaped or diagonal), indicating the importance of the verbal strategy in processing visual information (see Ginsburg et al., 2017, for a similar point). This notion is supported by the finding of significant training gains as seen in the storage and processing figural (pattern) task.

A corollary aim of the present study was also to address the contribution of cognitive strategies in performing relational integration tasks. According to the cognitive strategy survey, although most of the participants use a visual strategy, they also mentioned that they used another/additional strategies, such as paying attention to relevant information (e.g., determining whether the changing last digits are identical in row/column/diagonal in numerical task) and ignoring irrelevant information at the same time. This could mean either of two things: An attentional control mechanism is required to integrate interim mental representation (Himi et al., 2018), or the relevant specific features are bound together (Atkinson, Baddeley, & Allen, 2017). Probably, this is the reason of the absence of cognitive strategies (visual and verbal) in explaining the transfer effect between relational integration numerical and figural (pattern). Participants might have used other strategies, rather than visual and verbal strategies.

3.4.7 Comparing the Digit Span Backwards Task Performance of This Study with the Finding of Hilbert, Nakagawa, et al. (2015)

The result from *t*-test showed no difference in the mean performance on the digit span backwards task between the participants reported to have used visual and verbal strategies. Thus, the present finding replicates the previous finding of Hilbert, Nakagawa, et al. (2015), in which the authors found equivalent result in the single task condition (acoustically/optically). However, the task used in the present study differed from the original study, where participants had to write the digits (which were optically presented) on paper in reversed order instead of responding verbally.

3.4.8 Limitations and Future Prospects

An important limitation of our study is the small sample size, which may have dropped the value of the statistical power to detect any transfer effects as well as association between cognitive strategies and transfer effects. Low power not only reduces the likelihood of detecting a true effect, but also leads to a low positive predictive value and potential overestimation of the magnitude of the effect (Button et al., 2013). However, Cumming (2011) recommended to use precision analysis (the size of the CIs) instead of power analysis, as CI of a parameter indicate how close the estimated value is to the population value. Nevertheless, to achieve both sufficient power and increased precision, future interventions trying to induce transfer effects should strive for incorporating large scale samples. For example, based on an effect size of $f = 0.1$ for the storage and processing verbal task, a sample of 200 participants would be required in order to achieve a power of 0.8 with an alpha of .05.

Moreover, to address the strength of the transfer effects and the relationship between strategy and transfer effects, Bayesian multilevel models could be better equipped for further analysis. Bayesian methods differ from null hypothesis significance testing (NHST) in terms of whether the data is more compatible with null hypothesis (H_0) or an alternative hypothesis (H_1; Wagenmakers, 2007). Therefore, it would be informative to examine how much evidence the data provides in support of a training effect relative to the absence of this effect.

Another potential limitation is the degree of participants attrition (22.79%), although it did not differ among the ten groups, $\chi^2(9) = 9.97$, $p = .353$, and was lower than that in other training studies (e.g., 43.84% in Redick et al., 2013). However, this dropout rate may reflect individual differences in motivational and metacognitive aspects between finishers and abandoners. Anecdotally, some participants expressed that they got annoyed while encountering technical problems in installing the training program on their computer. Additionally, the metamemory framework of Nelson and Narens (1990) suggests that memory control processes contribute to application of effective strategies. However, we did not include any measures to explicitly assess participants' motivational and metamemory aspects such as self-efficacy, self-monitoring and stronger control over their memory processes etc.

However, these factors could play a role for better understanding on how working memory training promotes improvements.

Last, we employed a control group that actively engaged in a task which was non-adaptive (different from the working memory training groups). Therefore, participants in this group attended a specific task every session (without increasing difficulty level), which may have been monotonous. In this regard, Shipstead et al. (2012) recommended to use an adaptive task for the control group in order to minimize the treatment difference in terms of the rigor of practice. Additionally, Boot, Simons, Stothart, and Stutts (2013) emphasized that failure to match expectation between training and active control groups weakens causal inference. Nevertheless, we argue that each of three subtests of OLMT is built around a particular challenge (e.g., task-related effort, comparing performance with a superior opponent etc.) that contributes to motivating participants performance. During the OLMT training period, they also received constant feedback about the efforts they applied. Particularly, the steadily increasing training curve of the OLMT group (see Figure 3c) suggests that the current task was effective in motivating the participants.

3.5 Conclusion

To the best of our knowledge, our study can be regarded as the first step towards experimentally examining the cognitive strategy underlying transfer effects, which has been frequently mentioned in past research as a potential reason for the material-specific transfer. The present study not only provides strong evidence for the idea that training gains were achieved in the criterion tasks, but also presents an optimistic view by supporting our prediction regarding the transfer between the relational integration numerical and the new figural (symbol) materials. Although the present study does not provide clear evidence about the strategic approach that could account for the variation in training related improvement in working memory performance, it still advocates to conduct further research by including a large-scale sample. This may permit to fully evaluate the effects of training on performance of other working memory tasks and the strength of the relationship between cognitive strategies and working memory training effects.

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Chapter Four

General Discussion

The two empirical studies reported in this thesis investigated relevant cognitive abilities of individual differences in multitasking behavior and the mechanism of cognitive strategy underlying transfer effects of working memory training. The general discussion begins with a summary of the two empirical studies. Following these summaries, an integrated account of two studies is proposed. Finally, a conclusion is drawn and some specific recommendations for future research are made.

4.1 Summary of the Results of the two Studies

In Study 1 (*Multitasking behavior and its related constructs: Executive functions, working memory capacity, relational integration, and divided attention*), we inspected several important cognitive abilities that promote multitasking behavior. In previous investigations, WMC (measured with storage and processing; Oberauer et al., 2003), relational integration, and divided attention predict multitasking behavior (Bühner, König, et al., 2006; König et al., 2005). However, the relative importance of EFs in predicting multitasking behavior is yet unknown. Therefore, the present work attempted to directly replicate the well-established EFs model (Friedman et al., 2016) and to relate this model to WMC (measured with complex span task; Kane et al., 2004), relational integration and divided attention in order to comprehend the concept of multitasking behavior. For this reason, this research work goes substantially beyond prior works. We found that relational integration, divided attention, and individual EF components - updating and inhibition contributed in predicting multitasking behavior, but shifting and WMC did not show any significant role beyond these constructs. Notably, WMC could explain multitasking behavior, if EFs were not taken into account. It seems that the explanatory power of WMC might be subsumed under the overlapping variance between WMC and EFs. Further, the general EF component (common EF) accounted for 88% of variance in the criterion variable. Together, these findings provide a strong evidence for growing theories of multitasking behavior, emphasizing the importance of different cognitive abilities: Multitasking behavior requires to update the information in memory in the face of interference as well as integrate single information to build a relational structure of multiple tasks.

In study 2 (*Cognitive strategies and transfer effects between material- and operation-specific tasks within the working memory training framework*), we provided the first experimental evidence of the role of cognitive strategy in working memory transfer effects, given the rapidly expanding and evolving field of working memory training. Current state of knowledge suggests that transfer effects depend mostly on task-specific contents. However, the question of why working memory training leads to transfer on particular materials related to the trained or similar tasks, without transferring broadly to other working memory tasks is unclear. To unravel this question, a methodologically sound study was conducted. The current work focused on the facet model of working memory (Oberauer et al., 2003), which defines two working memory operations: storage and processing, and relational integration. Recently, Hilbert et al. (2017) found transfer between verbal and numerical materials within the same working memory operation. On the basis of this finding, we assumed that transfer occurs if a similar cognitive strategy is applied to solve trained and transfer tasks. Therefore, in the present study, we developed a figural (symbol) task, which is thought to be compatible with verbal or numerical tasks in terms of applying an identical strategy. We examined whether training with verbal and numerical materials could show transfer to figural (symbol) material, and vice versa. Additionally, the preferable cognitive strategies - visual and verbal might account for the occurrence of training-related transfer effects. For this purpose, 105 young adults were randomly assigned to one of ten groups: eight experimental groups, a passive, and an active control group. Four experimental groups were trained on storage and processing, and four groups on relational integration with verbal, numerical, figural (pattern), and figural (symbol) tasks. Results evinced significant pre- to post-test improvements in the criterion tasks (that were trained) for most measures, relative to the active control group. However, within working memory operation, the only transfer effect was that the relational integration numerical group outperformed the active control group on the relational integration figural (symbol) task, thus confirming our hypothesis. Yet, transfer across the working memory operations was absent. Additionally, none of the cognitive strategies (visual or verbal) was associated with the transfer effect between relational integration numerical and figural (symbol) tasks. Probably, the cognitive strategy that participants used to solve these two tasks is different from visual and verbal strategies. Finally, there was no convincing evidence for transfer of training to structurally different working memory tasks, despite significant improvement on almost all training tasks.

Thus, the results suggest that present working memory training is only effective to the task, which is trained - at best the task that is similar to the trained one, but not to general working memory capacity, indicating domain-specificity. Additionally, this study gives an impression of the involvement of cognitive strategy in transfer effect, although the relationship between them is not clear. Further investigation is recommended in this regard.

4.2 The Integrated Account of Multitasking Behavior and Working Memory Training in Psychological Science

The observation of overlapping variance among multitasking behavior, WMC (measured with complex span tasks), and relational integration gained from the first study could lead to surmise that boosting working memory ability (storage and processing, and relational integration) should lead to an increase in multitasking performance. The key feature of storage and processing training is to enhance the ability to update and maintain information while completing a secondary distractor task. The relational integration training, on the other hand, optimizes one’s capacity to coordinate single information elements into novel structure in working memory. Eventually, the essence of storage and processing tasks are dual-task in nature. Additionally, storage and processing, and relational integration both tap inhibitory control process (e.g., Himi et al., 2018; Kane et al., 2007), that is isomorphic with the general EF ability (Friedman & Miyake, 2017; Miyake & Friedman, 2012). Recent evidence also suggests that general EF is highly correlated with multitasking behavior (Himi et al., 2018). It seems that the importance of inhibition is the most central aspect for working memory, relational integration, and multitasking behavior: People who can organize attentional resources around goal-relevant tasks do well on executing multiple tasks simultaneously (e.g., positive manifold).

Considering the general features of storage and processing, and relational integration tasks, we suggest that working memory training may generalize to multitasking behavior, a proposal consistent with neuroanatomical evidence of the recruitment of prefrontal lobe in working memory training (Olesen et al., 2004) and improved multitasking performance (Dux et al., 2009). To test our proposition more directly, a complex adaptive training regimen (i.e., the interplay of basic cognitive functions; Schwaighofer et al., 2015) is needed to employ by incorporating storage and processing, and relational integration tasks. However, past working memory research (Foster et al., 2017; Redick et al., 2013), which demonstrated absence of transfer to multitasking behavior, was either based on complex span training task or dual n-back training task, differed from our proposed training regimen.

Furthermore, this training regimen seems to be equivalent to the multitasking scenario (e.g., SIMKAP), because multitasking behavior reflects strong demands on central information processing resources: Relevant task information has to be actively maintained in mind (tapping working memory), temporary binding between tasks has to be built (tapping relational integration), and irrelevant information has to be ignored (tapping inhibition). In this regard, De Simoni and von Bastian (2018) suggested that working memory training encourages to develop paradigm-specific-strategies. Additionally, the cognitive strategies produce training-related change on structurally similar untrained tasks (Laine, Fellman, Waris, & Nyman, 2018). On that premise, it is expected that the suggested training platform should reflect an increase in the availability of domain-general executive resources for such kind of strategic deployment, which in turn could yield transfer to multitasking behavior. Different organization, for instance, aviation corporations can arrange this kind training program to enhance their employees' multitasking ability.

4.3 Recommendations for Future Research

4.3.1 Study 1

Our study provided a robust empirical evidence in favor of cognitive correlates of multitasking behavior as well as its three components (speed, error, and question), which promotes an appropriate environment to enhance multitasking efficiency. Insights gained from this study may advance the organization settings as well as real-world contexts. Using the predictor variables of multitasking behavior, future work could be directed at understanding who is good at multitasking performance, and who is prone to multitasking failure, especially in contexts where a single error is very costly (e.g., aircraft pilot), or where speed in task performance might be more effective (e.g., call-center agents). In this regard, an important aspect which also needs to be taken into account in future studies is to distinguish this multitasking ability from multitasking activity - that is media multitasking (simultaneous use of media; Ophir et al., 2009), because media multitasking (contrary to multitasking ability) has a negative impact on cognitive functionings (e.g., van der Schuur et al., 2015). By contrast, job analyses highlight the relevance of multitasking ability for diverse job description in today's work environment (Kinney, Kung, Walvoord, & Shoemaker, 2010).

Although we examined individual differences in cognitive abilities related to multitasking behavior, we have not taken into account individual differences in personality characteristics. For example, studies on polychronicity (i.e., the preference for doing tasks concurrently) indicate significant association between personality traits and multitasking behavior (Sanderson et al., 2013), although König et al. (2005) suggested that working polychronically differs from performing well at doing tasks at the same time. However, it is quite obvious that processing multiple tasks simultaneously can impair affective control and increase stress (Offer & Schneider, 2011). Additionally, individual differences in impulsivity, and sensation seeking, and neuroticism are associated with multitasking behavior (König, Oberacher, & Kleinmann, 2010; Oswald, Hambrick, & Jones, 2007). Individuals high in impulsivity and sensation seeking, for instance, tend to show better multitasking performance (Sanbonmatsu et al., 2013). Also, Kirchberg, Roe, and Van Eerde (2015) found that polychronicity boosts individual's psychological well-being, and consequently improves performance. Therefore, to enlighten our understanding of multitasking behavior, we need to examine the relationship between individual differences in dispositional variables and multitasking behavior.

In addition, the evidence for the relationship between multitasking behavior and general EF ability gives an impression to the nature of multitasking behavior and goal management skill, although it is unclear how goal management ability fits in this picture. However, the present finding suggests that planning for goal accomplishment may act as an important determinant in performing multiple tasks simultaneously, which is also documented in previous studies (Burgess et al., 2000; Logie et al., 2011). Consequently, this study paves the way for arranging future goal-based interventions for people who have to do several tasks concurrently. For example, training people on how to plan and manage good goals may improve their ability to execute multitasks effectively.

A broad body of literature on developmental and aging psychology suggests that changes in cognition across the life span are considerably stable (e.g., Tucker-Drob & Briley, 2014), but multitasking behavior substantially changes over time (Kirchberg et al., 2015). Future research should investigate whether individual differences in multitasking behavior are stable across time, or if experience gained from across life span can contribute in this regard. Further, gender differences in multitasking behavior have been become an interesting topic in recent years. Hambrick et al. (2010) and Mäntylä (2013) showed that men outperform women, whereas Redick et al. (2016) found negligible gender differences in multitasking ability. Additionally, Mäntylä (2013) also suggested that gender variation depends on task specific constraints and strategies. In this regard, it would be informative if gender related differences in multitasking behavior is investigated using SIMKAP (which is assumed as a realistic task constraints).

4.3.2 Study 2

First of all, the sample size in study 2 was small, which led to low statistical power to detect any transfer effects as well as association between cognitive strategies and transfer effect in working memory training. A large sample size is required in this regard (as discussed in Chapter Three – Study 2). For this purpose, we plan to continue the present investigation and include a large-scale sample so that each group will contain at least 20 participants, as recommended in literature (e.g., Simmons, Nelson, & Simonsohn, 2011).

Second, our study relied on a single measure when assessing improvement of training performance, but multiple measures should be used to assess each outcome constructs (Shipstead et al., 2012; Simons et al., 2016). When transfer of training is measured via a single indicator, this may represent the possibility of improving the underlying ability, but it does not provide definitive evidence, because of the task impurity problem (Miyake et al., 2000). However, we were mainly interested in investigating why transfer occurs, rather than inspecting the effectiveness of working memory training on multiple measures. Additionally, we relied on tasks that produced transfer in prior work (Hilbert et al., 2017). However, to evaluate the success of the intervention, future work should aim to assess each construct of interest with multiple indicators in the current training regimen.

Additionally, the present result could not be generalized to population with potentially greater neural plasticity (i.e., the brain's ability to adapt), as we employed only young adults. Working memory training might be less effective in normally functioning adults compared to developing children, elderly, or disabled people. Bürki, Ludwig, Chicherio, & de Ribaupierre (2014) stressed the importance of considering individual differences in cognitive plasticity to understand training gain. Future research is needed to investigate the training effectiveness in a more representative sample. Notably, the aspects of training programs (e.g., the training intensity, location of training sessions, supervised training; e.g., Redick et al., 2015; Schwaighofer et al., 2015), and individual differences characteristics (e.g., initial cognitive ability, motivational factors, personality, alertness, genetic predispositions, culture, bonus structure; Boot, Simons, Stothart, & Stutts, 2013; Chooi & Thompson, 2012; Foster et al., 2017; Schubert, Strobach, & Karbach, 2014) could also contribute in training gains. However, Guye, De Simoni, and von Bastian (2017) reported that motivation and personality are unrelated to working memory training outcome, but individual differences in baseline abilities. Future intervention is needed to examine whether the impact of these factors can be strengthened the present findings.

Furthermore, gender differences in working memory and in strategy usage may have an influence on training gains, which could be included in the future experimental design. Men outperform women on figural working memory and perform equally well as women on verbal tasks (Lejbak, Crossley, & Vrbancic, 2011). In this regard, Wang and Carr (2014) proposed that the men who have better visual-spatial working memory ability select effective visual strategy than the women who have superior verbal working memory ability, resulting in the observed male advantage in the visual tasks. Taken together, the limited success of the present training study could possibly be improved if a broader range of factors is systematically ruled out.

4.4 Conclusion

Across the two studies, the present thesis offers a clear cognitive structural framework of multitasking behavior and working memory training effects. The results of the first study are applicable to practitioners and researchers interested in human factors, especially in assessing multitasking performance with realistic task constraints. The second study presents an optimistic view regarding the extent to which training on certain working memory tasks can improve performance on other related tasks, although the nature of the relationship between the training effects and cognitive strategies is not clear. However, the task-specific or domain-specific benefits suggest important practical implications for education and skill acquisition program to enhance particular cognitive or physical ability. Finally, our online training platform ‘Arbeitsgedächtnis Training’ can significantly contribute to scientific progress in conducting future working memory investigations.

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(Appendices follow)

Appendix A

Supplemental Materials – Study 1

Appendix A1

Keep track task – Answer sheet

Subject ID: __________________

Practice

A. _________ _________

B. _________ _________

Trials

1. _________ _________
2. _________ _________ _________ _________
3. _________ _________ _________ _________ _________
4. _________ _________ _________
5. _________ _________
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7. _________ _________ _________
8. _________ _________ _________ _________ _________
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12. _________ _________ _________ _________
13. _________ _________
14. _________ _________ _________ _________
15. _________ _________ _________
16. _________ _________ _________ _________ _________

Appendix A2

Letter memory task – Answer sheet

Subject ID___________________

Practice:

A. ____________
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B. ____________
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C. ______________
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Trials:

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Trials:

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12. ____________
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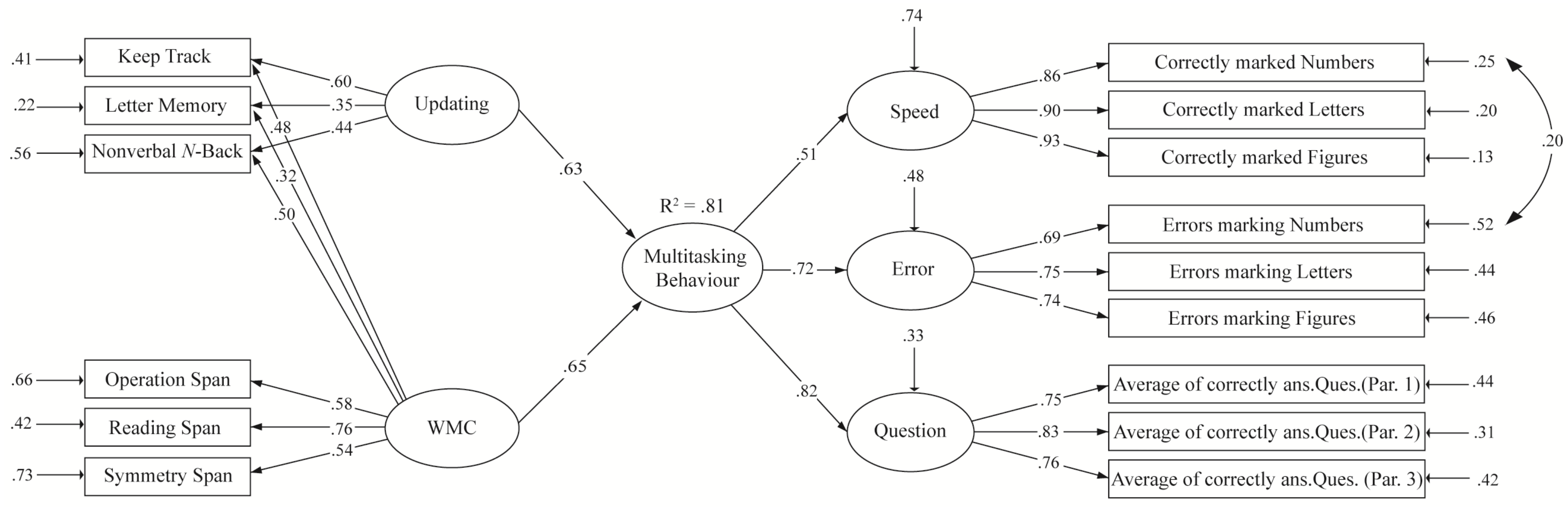
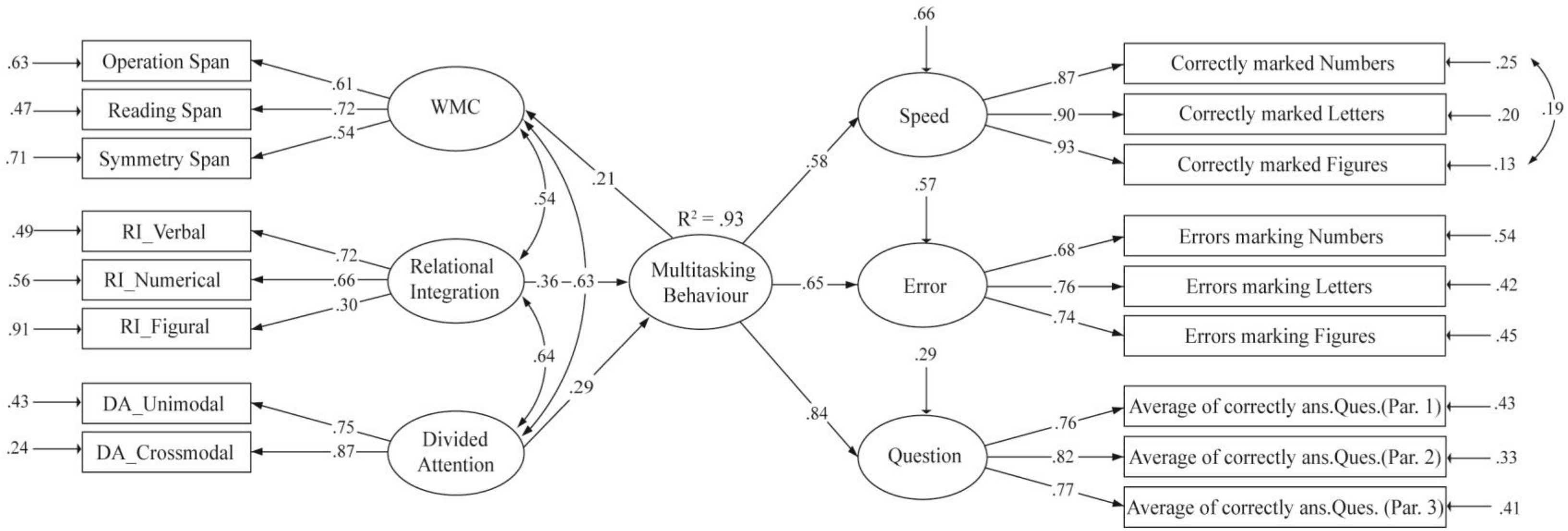
Appendix A3

Latent variable models for predicting multitasking behavior



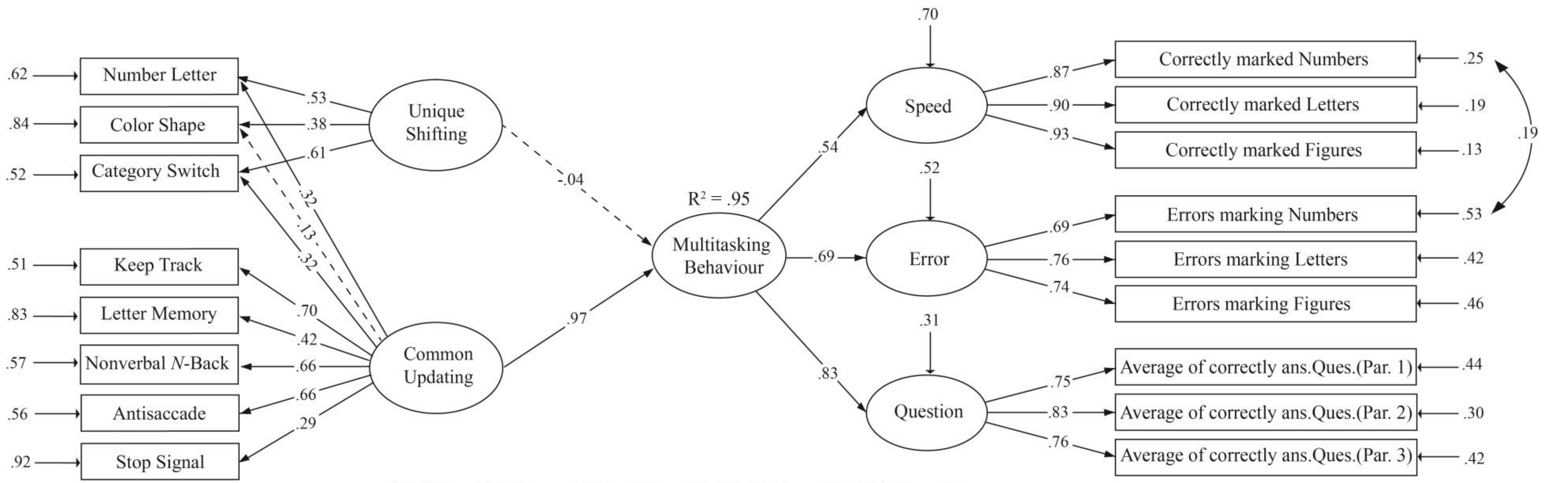
$\chi^2(81) = 126.90$, $p = .001$; CFI = .97; RMSEA = .05; SRMR = .06

Figure A1. Structural equation modeling for working memory capacity (WMC), updating, and multitasking behavior. All paths are significant at $p < .05$. The proportion of residual variance of each indicator is calculated by subtracting the variance of the indicator from 1.



$\chi^2(109) = 159.68$, $p = .001$; CFI = .97; RMSEA = .05; SRMR = .05

Figure A2. Structural equation modeling for working memory capacity (WMC), relational integration, divided attention, and multitasking behavior. RI_Figural = Relational Integration_Figural, RI_Numerical = Relational Integration_Numerical, RI_Verbal= Relational Integration_Verbal, DA_Unimodal = Divided Attention_Unimodal, DA_Crossmodal = Divided Attention_Crossmodal. All paths are significant at $p < .05$. The proportion of residual variance of each indicator is calculated by subtracting the variance of the indicator from 1.



$\chi^2(110) = 184.68$, $p < .001$; CFI = .95; RMSEA = .06; SRMR = .06

Figure A3. Structural equation modeling for common updating and multitasking behavior. All significant paths ($p < .05$) are indicated by solid lines. The proportion of residual variance of each indicator is calculated by subtracting the variance of the indicator from 1.

Appendix A4

Table A1

Factor Loadings for the Exploratory Factor Analysis of All Predictor Variables (N = 202).

	Factors				
Measures	1	2	3	4	5
Number letter	.56				
Color shape	.41				
Category switch	.72				
Keep track		.93			
Letter memory		.35			
Nonverbal *n*-back		.24		.53	
Antisaccade				.32	.22
Stop signal			.24		.26
Operation span			.63		
Reading span			.62		
Symmetry span			.55		
RI_Verbal				.53	
RI_Numarical		.21		.41	
RI_Figural				.30	
DA_Unimodal					.58
DA_Crossmodal					.91
			Correlation		
Factor 1	-				
Factor 2	.19	-			
Factor 3	.17	.38	-		
Factor 4	.26	.31	.27	-	
Factor 5	.20	.25	.34	.30	-

Note. The factor loadings less than .20 are not presented. RI_Verbal = relational integration_verbal; RI_Numerical = relational integration_numerical; RI_Figural= relational integration_figural; DA_Unimodal = divided attention_unimodal; DA_Crossmodal = divided attention_crossmodal.

Appendix B

Supplemental Materials – Study 2

Appendix B1

Digit span backwards task – Answer sheet

Subject Code: _______________

Please write the digits in reverse order.

Practice

A. _________ _________ _________

B. _________ _________ _________

Trials

1. _________ _________ _________ _________
2. _________ _________ _________ _________
3. _________ _________ _________ _________ _________
4. _________ _________ _________ _________ _________
5. _________ _________ _________ _________ _________ _________
6. _________ _________ _________ _________ _________ _________
7. _________ _________ _________ _________ _________ _________ _________
8. _________ _________ _________ _________ _________ _________ _________

Appendix B2

Fragebogen der kognitiven Strategien
(Cognitive strategies questionnaire)

Subject Code: ____________________

In dieser Doppelaufgabe:

1. Haben Sie beim Umgang mit den Wörtern eine der folgenden Strategien genutzt?

□ **Visualisieren** (Bildliches Vorstellen die Wörter im Kopf)

  □ Hierbei gruppieren von Wörter (haben Sie mehrere Wörter zu einer Gruppe verbunden?)

  □ Hierbei bilden persönlicher Assoziationen (haben Sie Wörter logisch oder semantisch verknüpft?)

□ **Verbalisieren** (Stilles Wiederholen die Wörter im Kopf)

  □ Hierbei gruppieren von Wörter (haben Sie mehrere Wörter zu einer Gruppe verbunden?)

  □ Hierbei bilden persönlicher Assoziationen (haben Sie Wörter logisch oder semantisch verknüpft?)

□ **Andere Strategie:** ____ □ **Keine**

2. Haben Sie beim Umgang mit den Zahlen eine der folgenden Strategien genutzt?

□ **Visualisieren** (Bildliches Vorstellen der Zahlen im Kopf)

  □ Hierbei gruppieren von Zahlen (haben Sie mehrere Zahlen zu einer Gruppe verbunden?)

  □ Hierbei bilden persönlicher Assoziationen (haben Sie Zahlen logisch oder semantisch verknüpft?)

□ **Verbalisieren** (Stilles Wiederholen der Zahlen im Kopf)

  □ Hierbei gruppieren von Zahlen (haben Sie mehrere Zahlen zu einer Gruppe verbunden?)

  □ Hierbei bilden persönlicher Assoziationen (haben Sie Zahlen logisch oder semantisch verknüpft?)

□ **Andere Strategie:** _____________________________________ □ **Keine**

3. Haben Sie beim Umgang mit den Mustern eine der folgenden Strategien genutzt?

□ **Visualisieren** (Bildliches Vorstellen das Muster im Kopf)

  □ Hierbei gruppieren von Muster (haben Sie mehrere Muster zu einer Gruppe verbunden?)

  □ Hierbei bilden persönlicher Assoziationen (haben Sie Muster logisch oder semantisch verknüpft?)

□ **Verbalisieren** (Stilles Wiederholen die Muster im Kopf)

  □ Hierbei gruppieren von Muster (haben Sie mehrere Muster zu einer Gruppe verbunden?)

  □ Hierbei bilden persönlicher Assoziationen (haben Sie Muster logisch oder semantisch verknüpft?)

□ **Andere Strategie:** ________________________________ □ **Kein**

4. Haben Sie beim Umgang mit den Symbole eine der folgenden Strategien genutzt?

□ **Visualisieren** (Bildliches Vorstellen das Symbol im Kopf)

□ Hierbei gruppieren von Symbol (haben Sie mehrere Symbole zu einer Gruppe verbunden?)

□ Hierbei bilden persönlicher Assoziationen (haben Sie Symbole logisch oder semantisch verknüpft?)

□ **Verbalisieren** (Stilles Wiederholen das Symbol im Kopf)

□ Hierbei gruppieren von Symbol (habe Sie mehrere Symbole zu einer Gruppe verbunden?)

□ Hierbei bilden persönlicher Assoziationen (haben Sie Symbole logisch oder semantisch verknüpft?)

□ **Andere Strategie:** ____ □ **Keine**

5. Welche der folgenden Strategie haben sie stärker angewendet?

□ Visualisieren oder □ Verbalisieren? (Bitte entscheiden Sie sich auch wenn die Tendenz gering ist)

6. Falls Sie eine bestimmte Strategie angewendet haben, beschreiben Sie bitte möglichst genau wie Sie dies getan haben.

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7. Wenn Sie eine der Auswahlmöglichkeiten nicht einordnen können, fragen Sie bitte die Versuchsleitung.

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Fragebogen der kognitiven Strategien

In dieser Relationale Integration Aufgabe:

1. Haben Sie beim Umgang mit den Wörtern (reimen) eine der folgenden Strategien genutzt?

□ **Visualisieren** (Bildliches Vorstellen die Wörter im Kopf)

  □ Hierbei gruppieren von Wörter (haben Sie mehrere Wörter zu einer Gruppe verbunden?)

  □ Hierbei bilden persönlicher Assoziationen (haben Sie Wörter logisch oder semantisch verknüpft?)

□ **Verbalisieren** (Stilles Wiederholen die Wörter im Kopf)

  □ Hierbei gruppieren von Wörter (haben Sie mehrere Wörter zu einer Gruppe verbunden?)

  □ Hierbei bilden persönlicher Assoziationen (haben Sie Wörter logisch oder semantisch verknüpft?)

□ **Andere Strategie:** ____ □ **Keine**

2. Haben Sie beim Umgang mit den Zahlen (identische) der folgenden Strategien genutzt?

□ **Visualisieren** (Bildliches Vorstellen der Zahlen im Kopf)

  □ Hierbei gruppieren von Zahlen (haben Sie mehrere Zahlen zu einer Gruppe verbunden?)

  □ Hierbei bilden persönlicher Assoziationen (haben Sie Zahlen logisch oder semantisch verknüpft?)

□ **Verbalisieren** (Stilles Wiederholen der Zahlen im Kopf)

  □ Hierbei gruppieren von Zahlen (haben Sie mehrere Zahlen zu einer Gruppe verbunden?)

  □ Hierbei bilden persönlicher Assoziationen (haben Sie Zahlen logisch oder semantisch verknüpft?)

□ **Andere Strategie:** ____ □ **Keine**

3. Haben Sie beim Umgang mit den Mustern (Quadrat bilden) eine der folgenden Strategien genutzt?

□ **Visualisieren** (Bildliches Vorstellen das Muster im Kopf)

  □ Hierbei gruppieren von Muster (haben Sie mehrere Muster zu einer Gruppe verbunden?)

  □ Hierbei bilden persönlicher Assoziationen (haben Sie Muster logisch oder semantisch verknüpft?)

□ **Verbalisieren** (Stilles Wiederholen die Muster im Kopf)

  □ Hierbei gruppieren von Muster (haben Sie mehrere Muster zu einer Gruppe verbunden?)

  □ Hierbei bilden persönlicher Assoziationen (haben Sie Muster logisch oder semantisch verknüpft?)

□ **Andere Strategie:** ___________________________________ □ **Keine**

4. Haben Sie beim Umgang mit den Symbolen (identische) eine der folgenden Strategien genutzt?

□ **Visualisieren** (Bildliches Vorstellen das Symbol im Kopf)

  □ Hierbei gruppieren von Symbol (haben Sie mehrere Symbole zu einer Gruppe verbunden?)

  □ Hierbei bilden persönlicher Assoziationen (haben Sie Symbole logisch oder semantisch verknüpft?)

□ **Verbalisieren** (Stilles Wiederholen das Symbol im Kopf)

  □ Hierbei gruppieren von Symbol (habe Sie mehrere Symbole zu einer Gruppe verbunden?)

  □ Hierbei bilden persönlicher Assoziationen (haben Sie Symbole logisch oder semantisch verknüpft?)

□ **Andere Strategie:** ____ □ **Keine**

5. Welche der folgenden Strategie haben sie stärker angewendet?

□ Visualisieren oder □ Verbalisieren? (Bitte entscheiden Sie sich auch wenn die Tendenz gering ist)

6. Falls Sie eine bestimmte Strategie angewendet haben, beschreiben Sie bitte möglichst genau wie Sie dies getan haben.

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7. Wenn Sie eine der Auswahlmöglichkeiten nicht einordnen können, fragen Sie bitte die Versuchsleitung.

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Appendix B3

Screenshot of the Training Programs

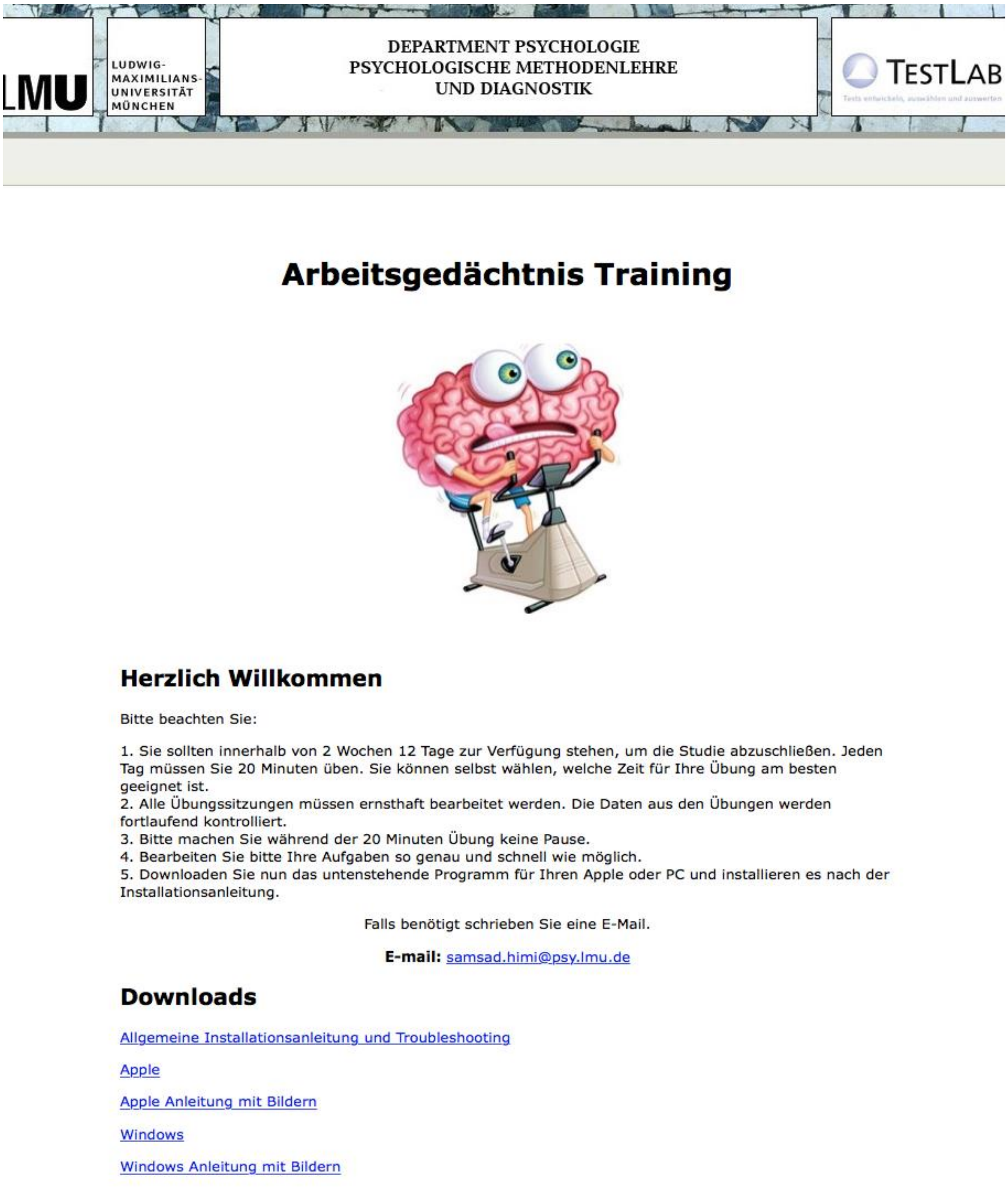

Figure B1. Screenshot of the online working memory training platform.

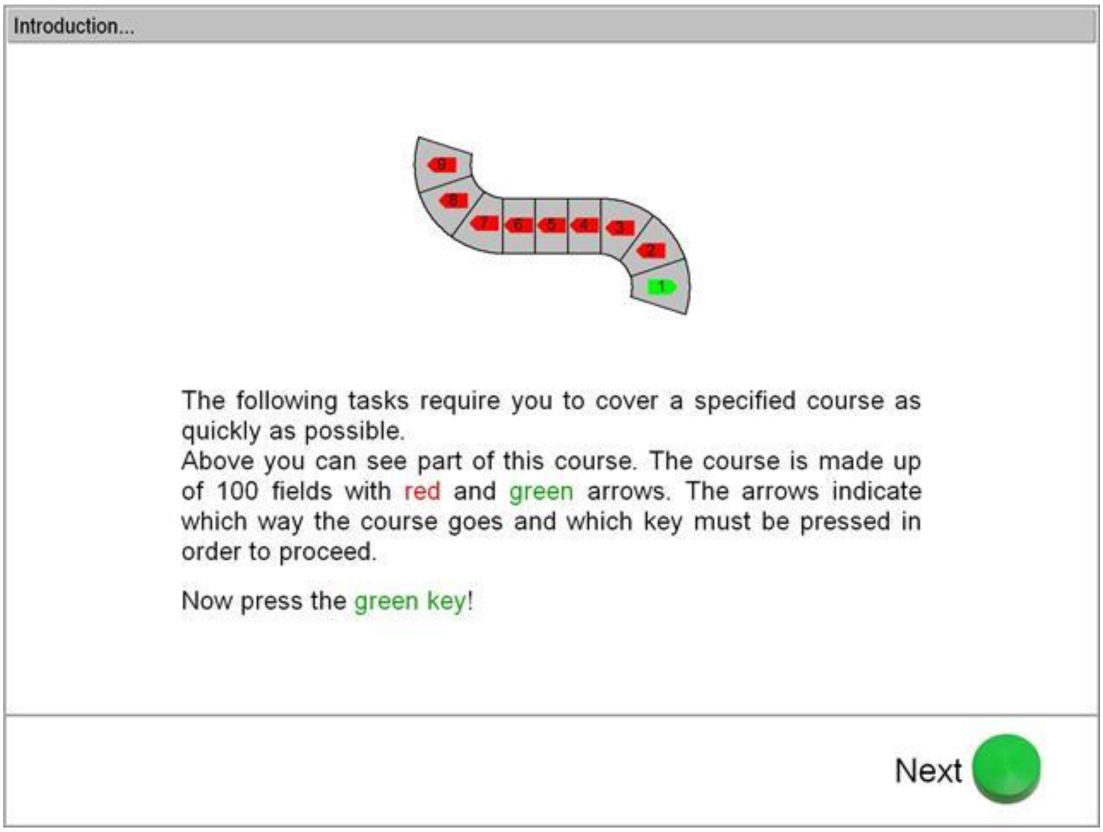

Figure B2. Screenshot of the the English version of OLMT training platform.

Appendix B4

Table B1

Significance Testing Results for Baseline Differences among the Groups.

Tasks	***F***	***df***	***p***
Storage and Processing Verbal	.968	9	.471
Storage and Processing Numerical	.765	9	.649
Storage and Processing Figural (Pattern)	.525	9	.853
Storage and Processing Figural (Symbol)	.688	9	.718
Relational Integration Verbal	.465	9	.895
Relational Integration Numerical	.910	9	.520
Relational Integration Figural (Pattern)	.845	9	.577
Relational Integration Figural (Symbol)	.617	9	.780

Note. *F* = *F*-value of the independent measures ANOVA; *df* = degrees of freedom; *p* = probability of committing type-I-error.

Appendix B5

Table B2

Parameters Estimates from Linear Mixed-Effects Models for Storage and Processing Groups.

Covariates	Estimate	*SE*	*df*	*t*	*p*	Covariates	Estimate	*SE*	*df*	*t*	*p*
SP Verbal						**SP Figural (Pattern)**					
Intercept	**.72**	**.01**	**115.30**	**52.57**	**.000**	**Intercept**	**0.56**	**0.014**	**110.75**	**38.43**	**.000**
Passive	**.01**	**.03**	**104.90**	0.18	.860	Passive	-0.04	0.03	100.77	-1.34	.182
Passive:SPV	**.10**	**.04**	**108.30**	**2.44**	**.016**	**Passive:SPV**	**0.15**	**0.04**	**103.42**	**3.42**	**.001**
Passive:SPN	**.06**	.04	108.30	1.29	.199	Passive:SPN	0.08	0.04	103.42	1.87	.063
Passive:SPFP	**.09**	**.04**	**108.30**	**2.12**	**.036**	**Passive:SPFP**	**0.38**	**0.04**	**103.42**	**8.78**	**.000**
Passive:SPFS	.07	.04	108.30	1.67	.099	**Passive:SPFS**	**0.16**	**0.04**	**103.42**	**3.76**	**.000**
Passive:RIV	**.09**	**.04**	**108.30**	**2.09**	**.039**	**Passive:RIV**	**0.12**	**0.04**	**103.42**	**2.98**	**.003**
Passive:RIN	**.10**	**.04**	**108.30**	**2.42**	**.017**	**Passive:RIN**	**0.10**	**0.04**	**103.42**	**2.51**	**.013**
Passive:RIFP	**.10**	**.05**	**108.30**	**2.02**	**.046**	**Passive:RIFP**	**0.13**	**0.05**	**103.42**	**2.77**	**.006**
Passive:RIFS	.08	.04	108.30	1.80	.075	Passive:RIFS	**0.14**	**0.04**	**103.42**	**3.18**	**.001**
SP Numerical						**SP Figural (Symbol)**					
Intercept	**0.95**	**0.00**	**134.00**	**210.83**	**0.00**	**Intercept**	**0.88**	**0.01**	**115.35**	**111.43**	**.000**
Passive	0.01	0.01	122.00	0.80	0.43	Passive	-0.03	0.01	104.96	-1.94	.054
Passive:SPV	0.00	0.02	128.00	0.13	0.90	**Passive:SPV**	0.04	0.02	108.32	1.92	.056
Passive:SPN	0.02	0.02	128.00	1.05	0.30	**Passive:SPN**	**0.05**	**0.02**	**108.32**	**2.22**	**.028**
Passive:SPFP	0.00	0.02	128.00	0.22	0.83	**Passive:SPFP**	**0.07**	**0.02**	**108.32**	**2.81**	**.005**
Passive:SPFS	0.00	0.02	128.00	0.06	0.95	**Passive:SPFS**	**0.08**	**0.02**	**108.32**	**3.19**	**.001**
Passive:RIV	0.01	0.02	128.00	0.30	0.76	Passive:RIV	0.03	0.02	108.32	1.35	.179
Passive:RIN	-0.00	0.02	128.00	0.00	1.00	**Passive:RIN**	**0.05**	**0.02**	**108.32**	**2.29**	**.023**
Passive:RIFP	0.00	0.02	128.00	0.18	0.86	**Passive:RIFP**	**0.07**	**0.02**	**108.32**	**2.62**	**.010**
Passive:RIFS	-0.02	0.02	128.00	-0.97	0.33	**Passive:RIFS**	**0.06**	**0.02**	**108.32**	**2.57**	**.010**

Note. *SE* = standard error; *df* = degrees of freedom; *t* = *t*-value; *p* = probability of committing type-I-error; Control = mean change between pre- and post-test in the passive group; Control:Group = difference in change between the working memory training group and the passive group; SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural (symbol); Covariates presented in bold are significantly different from zero.

Table B3

Parameters Estimates from Linear Mixed-Effects Models for Relational Integration Groups.

Covariates	Estimate	*SE*	*df*	*t*	*p*	Covariates	Estimate	*SE*	*df*	*t*	*p*
RI Verbal						**RI Figural (Pattern)**					
Intercept	**2.37**	**0.07**	**133.39**	**32.43**	**.000**	**Intercept**	**2.27**	**0.04**	**144.21**	**52.49**	**.000**
Passive	0.18	0.21	122.05	0.88	.382	Passive	0.14	0.13	132.35	1.06	.288
Passive:SPV	0.04	0.28	128.05	0.12	.901	Passive:SPV	0.17	0.17	140.30	0.97	.330
Passive:SPN	0.10	0.27	128.05	0.38	.706	Passive:SPN	0.12	0.17	140.30	0.73	.465
Passive:SPFP	-0.05	0.27	128.05	-0.18	.861	Passive:SPFP	0.18	0.17	140.30	1.07	.285
Passive:SPFS	0.22	0.28	128.05	0.80	.425	Passive:SPFS	0.08	0.17	140.30	0.46	.640
Passive:RIV	**0.64**	**0.27**	**128.05**	**2.34**	**.021**	Passive:RIV	0.20	0.17	140.30	1.15	.248
Passive:RIN	0.36	0.27	128.05	1.31	.193	Passive:RIN	0.11	0.17	140.30	0.67	.500
Passive:RIFP	0.44	0.32	128.05	1.38	.169	**Passive:RIFP**	**0.52**	**0.20**	**140.30**	**2.60**	**.010**
Passive:RIFS	0.38	0.28	128.05	1.37	.173	Passive:RIFS	0.21	0.17	140.30	1.20	.230
RI Numerical						**RI Figural (Symbol)**					
Intercept	**2.62**	**0.07**	**150.72**	**35.249**	**.000**	**Intercept**	**3.67**	**0.06**	**139.46**	**54.74**	**.000**
Passive	0.34	0.23	138.93	1.43	.153	**Passive**	**0.64**	**0.20**	**127.77**	**3.18**	**.001**
Passive:SPV	0.02	0.31	147.83	0.05	.959	Passive:SPV	-0.16	0.26	134.87	-0.61	.536
Passive:SPN	-0.16	0.30	147.83	-0.52	.598	Passive:SPN	-0.37	0.26	134.87	-1.43	.152
Passive:SPFP	-0.04	0.30	147.83	-0.16	.871	Passive:SPFP	-0.05	0.26	134.87	-0.22	.823
Passive:SPFS	-0.02	0.31	147.83	-0.08	.934	Passive:SPFS	-0.18	0.26	134.87	-0.68	.496
Passive:RIV	0.16	0.30	147.83	0.55	.583	Passive:RIV	-0.26	0.26	134.87	-1.03	.304
Passive:RIN	**0.65**	**0.30**	**147.83**	**2.12**	**.035**	Passive:RIN	-0.19	0.26	134.87	-0.72	.467
Passive:RIFP	0.24	0.35	147.83	0.69	.486	Passive:RIFP	0.01	0.30	134.87	0.04	.964
Passive:RIFS	0.51	0.31	147.83	1.63	.104	Passive:RIFS	0.08	0.26	134.87	0.32	.744

Note. *SE* = standard error; *df* = degrees of freedom; *t* = *t*-value; *p* = probability of committing type-I-error; Control = mean change between pre- and post-test in the passive group; Control:Group = difference in change between the working memory training group and the passive group; SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural (symbol); Covariates presented in bold are significantly different from zero.

Appendix B6

Table B4

Cognitive Strategies as a Function of Transfer Effects for Storage and Processing Groups.

Covariates	Estimate	*SE*	*df*	*t*	*p*	Covariates	Estimate	*SE*	*df*	*t*	*p*
SP Verbal						**SP Numerical**					
Intercept	**0.69**	**0.03**	**122.08**	**23.61**	**.000(.006)**	**Intercept**	**0.91**	**0.01**	**141.59**	**93.87**	**.000(.006)**
Control	0.16	0.08	105.38	1.96	.053	Control	0.06	0.03	126.03	1.63	.105
SP_PreStrategy	0.04	0.03	122.08	1.14	.258	**SP_PreStrategy**	**0.05**	**0.01**	**141.59**	**4.46**	**.000(.006)**
Control:SP_PreStrategy	-0.07	0.09	105.08	-0.83	.408	Control:SP_PreStrategy	-0.05	0.03	125.45	-1.37	.172
Control:SPV	-0.03	0.10	107.74	-0.26	.795	Control:SPV	-0.02	0.04	130.73	-0.42	.676
Control:SPN	-0.03	0.10	107.74	-0.27	.790	Control :SPN	-0.01	0.04	130.73	-0.19	.853
Control:SPFP	-0.01	0.10	107.74	-0.09	.926	Control:SPFP	-0.04	0.04	130.73	-0.94	.347
Control:SPFS	-0.12	0.10	107.74	-1.13	.260	Control:SPFS	-0.02	0.04	130.73	-0.61	.546
Control:RIV	-0.04	0.12	107.74	-0.38	.707	Control:RIV	-0.10	0.05	130.73	-2.12	.036(.006)
Control:RIN	-0.03	0.12	107.74	-0.21	.832	Control:RIN	-0.01	0.05	130.73	-0.20	.842
Control:RIFP	-0.04	0.12	107.74	-0.35	.724	Control:RIFP	-0.02	0.05	130.73	-0.42	.673
Control:RIFS	-0.21	0.10	107.74	-2.06	.042	Control:RIFS	-0.02	0.04	130.73	-0.61	.546
Control:SPV:SP_PreStrategy	0.04	0.10	107.74	0.34	.735	Control:SPV:SP_PreStrategy	0.02	0.04	130.73	0.37	.709
Control:SPN:SP_PreStrategy	-0.02	0.11	107.74	-0.19	.846	Control :SPN:SP_PreStrategy	0.03	0.04	130.73	0.59	.560
Control:SPFP:SP_PreStrategy	-0.01	0.10	107.74	-0.07	.946	Control:SPFP:SP_PreStrategy	0.05	0.04	130.73	1.11	.270
Control:SPFS:SP_PreStrategy	0.11	0.11	107.74	1.02	.311	Control:SPFS:SP_PreStrategy	0.03	0.04	130.73	0.60	.551
Control:RIV:SP_PreStrategy	0.04	0.12	107.74	0.36	.722	Control:RIV:SP_PreStrategy	0.11	0.05	130.73	2.30	.023(.006)
Control:RIN:SP_PreStrategy	0.04	0.12	107.74	0.31	.759	Control:RIN:SP_PreStrategy	0.01	0.05	130.73	0.16	.875
Control:RIFP:SP_PreStrategy	0.05	0.13	107.74	0.41	.680	Control:RIFP:SP_PreStrategy	0.02	0.05	130.73	0.46	.645
Control:RIFS:SP_PreStrategy	0.24	0.11	107.74	2.18	.031(.006)	Control:RIFS:SP_PreStrategy	0.00	0.04	130.73	0.08	.934

Note. *SE* = standard error; *df* = degrees of freedom; *t* = *t*-value; *p* = probability of committing type-I-error; Control = difference in change in the active control group for visualizers; Strategy = mean difference between verbalizers and visualizers in the active control group at pre-test; Control:Strategy = difference in change between verbalizers and visualizers in the active control group; Control:Group = difference in change between training group and active control group for visualizers; Control:Group:Strategy = difference between verbalizers and visualizers in the difference in change between the working memory training group and the active control group; SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural(symbol); PreStrategy = strategy usage at pre-test; *p* values in bracket indicate corrected alpha levels after Bonferroni correction; Covariates presented in bold are significantly different from zero.

Table B5

Cognitive Strategies as a Function of Transfer Effects for Storage and Processing Groups.

Covariates	Estimate	*SE*	*df*	*t*	*p*	Covariates	Estimate	*SE*	*df*	*t*	*p*
SP Figural (Pattern)						**SP Figural (Symbol)**					
Intercept	**0.52**	**0.03**	**125.29**	**16.18**	**.000(.006)**	**Intercept**	**0.86**	**0.02**	**125.12**	**48.99**	**.000(.006)**
Control	-0.05	0.10	108.75	-0.47	.639	Control	-0.05	0.05	108.56	-1.02	.312
SP_PreStrategy	0.05	0.04	125.29	1.41	.161	SP_PreStrategy	0.03	0.02	125.12	1.34	.183
Control:SP_PreStrategy	0.12	0.10	108.43	1.22	.225	Control:SP_PreStrategy	0.05	0.05	108.24	0.97	.333
Control:SPV	0.12	0.11	111.38	1.06	.293	Control:SPV	0.05	0.06	111.19	0.89	.377
Control:SPN	0.05	0.12	111.38	0.39	.701	Control:SPN	0.10	0.06	111.19	1.50	.136
Control:SPFP	**0.43**	**0.11**	**111.38**	**3.86**	**.000(.006)**	Control:SPFP	0.11	0.06	111.19	1.89	.061
Control:SPFS	0.11	0.12	111.38	0.91	.367	Control:SPFS	0.05	0.06	111.19	0.79	.434
Control:RIV	0.18	0.14	111.38	1.31	.194	Control:RIV	0.10	0.07	111.19	1.35	.179
Control:RIN	0.02	0.14	111.38	0.16	.874	Control:RIN	0.08	0.07	111.19	1.09	.280
Control:RIFP	0.04	0.14	111.38	0.33	.745	Control:RIFP	0.12	0.07	111.19	1.63	.106
Control:RIFS	0.17	0.12	111.38	1.42	.158	Control:RIFS	0.06	0.06	111.19	1.02	.311
Control:SPV:SP_PreStrategy	-0.06	0.12	111.38	-0.54	.593	Control:SPV:SP_PreStrategy	-0.03	0.06	111.19	-0.52	.604
Control:SPN:SP_PreStrategy	-0.08	0.12	111.38	-0.61	.543	Control:SPN:SP_PreStrategy	-0.08	0.07	111.19	-1.23	.222
Control:SPFP:SP_PreStrategy	-0.18	0.12	111.38	-1.50	.136	Control:SPFP:SP_PreStrategy	-0.09	0.06	111.19	-1.39	.168
Control:SPFS:SP_PreStrategy	-0.05	0.12	111.38	-0.37	.712	Control:SPFS:SP_PreStrategy	0.01	0.07	111.19	0.09	.926
Control:RIV:SP_PreStrategy	-0.18	0.14	111.38	-1.25	.213	Control:RIV:SP_PreStrategy	-0.11	0.08	111.19	-1.41	.162
Control:RIN:SP_PreStrategy	-0.02	0.14	111.38	-0.16	.877	Control:RIN:SP_PreStrategy	-0.06	0.08	111.19	-0.79	.430
Control:RIFP:SP_PreStrategy	0.00	0.14	111.38	-0.03	.975	Control:RIFP:SP_PreStrategy	-0.09	0.08	111.19	-1.09	.277
Control:RIFS:SP_PreStrategy	-0.15	0.12	111.38	-1.23	.222	Control:RIFS:SP_PreStrategy	-0.03	0.07	111.19	-0.47	.638

Note. *SE* = standard error; *df* = degrees of freedom; *t* = *t*-value; *p* = probability of committing type-I-error; Control = difference in change in the active control group for visualizers; Strategy = mean difference between verbalizers and visualizers in the active control group at pre-test; Control:Strategy = difference in change between verbalizers and visualizers in the active control group; Control:Group = difference in change between training group and active control group for visualizers; Control:Group:Strategy = difference between verbalizers and visualizers in the difference in change between the working memory training group and the active control group; SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural(symbol); PreStrategy = strategy usage at pre-test; *p* values in bracket indicate corrected alpha levels after Bonferroni correction; Covariates presented in bold are significantly different from zero.

Table B6

Cognitive Strategies as a Function of Transfer Effects for Storage and Processing Groups.

Covariates	Estimate	*SE*	*df*	*t*	*p*	Covariates	Estimate	*SE*	*df*	*t*	*p*
SP Verbal						**SP Numerical**					
Intercept	**0.74**	**0.03**	**125.19**	**24.52**	**.000(.006)**	**Intercept**	**0.95**	**0.01**	**136.70**	**89.19**	**.000(.006)**
Control	**0.12**	**0.04**	**98.67**	**3.25**	**.002(.006)**	Control	0.02	0.01	104.80	1.07	.288
SP_PostStrategy	-0.02	0.03	125.19	-0.75	.452	SP_PostStrategy	-0.00	0.01	136.70	-0.32	.750
Control:SP_PosStrategy	-0.03	0.04	101.88	-0.75	.458	Control:SP_PosStrategy	-0.00	0.02	109.40	-0.31	.760
Control:SPV	0.02	0.06	113.80	0.35	.725	Control:SPV	0.02	0.02	126.80	0.81	.421
Control:SPN	0.02	0.09	113.80	0.17	.865	Control:SPN	0.01	0.04	126.80	0.29	.771
Control:SPFP	0.01	0.04	113.80	0.35	.725	Control:SPFP	0.00	0.01	126.80	0.33	.740
Control:SPFS	-0.01	0.04	113.80	-0.15	.883	Control:SPFS	0.00	0.01	126.80	0.13	.897
Control:RIV	0.01	0.07	113.80	0.10	.921	Control:RIV	-0.04	0.03	126.80	-1.47	.144
Control:RIN	0.03	0.04	113.80	0.72	.476	Control:RIN	0.00	0.01	126.80	0.06	.950
Control:RIFP	-0.01	0.09	113.80	-0.15	.879	Control:RIFP	0.01	0.04	126.80	0.33	.741
Control:RIFS	0.02	0.07	113.80	0.28	.783	Control:RIFS	-0.06	0.03	126.80	-2.40	.018
Control:SPV:SP_PostStrategy	-0.01	0.07	113.80	-0.08	.938	Control:SPV:SP_PostStrategy	-0.02	0.03	126.80	-0.83	.406
Control:SPN:SP_PostStrategy	-0.05	0.10	113.80	-0.46	.644	Control:SPN:SP_PostStrategy	0.01	0.04	126.80	0.19	.849
Control:SPFP:SP_PostStrategy	-	-	-	-	-	Control:SPFP:SP_PostStrategy	-	-	-	-	-
Control:SPFS:SP_PostStrategy	-	-	-	-	-	Control:SPFS:SP_PostStrategy	-	-	-	-	-
Control:RIV:SP_PostStrategy	0.00	0.08	113.80	-0.04	.969	Control:RIV:SP_PostStrategy	0.06	0.03	126.80	1.78	.077
Control:RIN:SP_PostStrategy	-	-	-	-	-	Control:RIN:SP_PostStrategy	-	-	-	-	-
Control:RIFP:SP_PostStrategy	0.04	0.10	113.80	0.35	.725	Control:RIFP:SP_PostStrategy	-0.01	0.04	126.80	-0.29	.774
Control:RIFS:SP_PostStrategy	-0.03	0.08	113.80	-0.43	.672	Control:RIFS:SP_PostStrategy	0.06	0.03	126.80	1.97	.051

Note. SE = standard error; *df* = degrees of freedom; *t* = *t*-value; *p* = probability of committing type-I-error; Control = difference in change in the active control group for visualizers; Strategy = mean difference between verbalizers and visualizers in the active control group at pre-test; Control:Strategy = difference in change between verbalizers and visualizers in the active control group; Control:Group = difference in change between training group and active control group for visualizers; Control:Group:Strategy = difference between verbalizers and visualizers in the difference in change between the working memory training group and the active control group; SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural(symbol); PostStrategy = strategy usage at post-test; *p* values in bracket indicate corrected alpha levels after Bonferroni correction; Covariates presented in bold are significantly different from zero; (-) denote the group that was dropped due to the rank deficient of fixed-effect model matrix.

Table B7

Cognitive Strategies as a Function of Transfer Effects for Storage and Processing Groups.

Covariates	Estimate	*SE*	*df*	*t*	*p*	Covariates	Estimate	*SE*	*df*	*t*	*p*
SP Figural (Pattern)						**SP Figural (Symbol)**					
Intercept	**0.60**	**0.03**	**127.23**	**17.92**	**.000(.006)**	**Intercept**	**0.89**	**0.02**	**127.66**	**49.61**	**0.000(.006)**
Control	0.07	0.04	99.89	1.72	.089	Control	0.00	0.02	100.67	-0.09	.931
SP_PostStrategy	-0.04	0.04	127.23	-1.22	.225	SP_PostStrategy	-0.02	0.02	127.66	-0.80	.428
Control:SP_PosStrategy	-0.01	0.05	103.30	-0.12	.908	Control:SP_PosStrategy	0.00	0.03	104.039	-0.11	.914
Control:SPV	0.03	0.07	116.07	0.47	.640	Control:SPV	-0.01	0.04	116.55	-0.37	.709
Control:SPN	0.04	0.11	116.07	0.37	.716	Control:SPN	-0.01	0.06	116.55	-0.17	.867
Control:SPFP	**0.28**	**0.04**	**116.07**	**6.65**	**.000(.006)**	Control:SPFP	0.04	0.02	116.55	1.74	.084
Control:SPFS	0.06	0.04	116.07	1.34	.183	Control:SPFS	0.05	0.02	116.55	2.15	.033(.006)
Control:RIV	0.04	0.08	116.07	0.53	.596	Control:RIV	0.05	0.04	116.55	1.15	.252
Control:RIN	0.01	0.04	116.07	0.13	.899	Control:RIN	0.03	0.02	116.55	1.16	.249
Control:RIFP	0.02	0.11	116.07	0.19	.847	Control:RIFP	0.03	0.06	116.55	0.54	.588
Control:RIFS	0.04	0.08	116.07	0.48	.630	Control:RIFS	0.07	0.04	116.55	1.54	.126
Control:SPV:SP_PostStrategy	0.01	0.08	116.07	0.14	.890	Control:SPV:SP_PostStrategy	0.04	0.04	116.55	0.94	.348
Control:SPN:SP_PostStrategy	-0.07	0.11	116.07	-0.64	.522	Control:SPN:SP_PostStrategy	0.03	0.06	116.55	0.57	.568
Control:SPFP:SP_PostStrategy	-	-	-	-	-	Control:SPFP:SP_PostStrategy	-	-	-	-	-
Control:SPFS:SP_PostStrategy	-	-	-	-	-	Control:SPFS:SP_PostStrategy	-	-	-	-	-
Control:RIV:SP_PostStrategy	-0.03	0.09	116.07	-0.36	.720	Control:RIV:SP_PostStrategy	-0.06	0.05	116.55	-1.21	.229
Control:RIN:SP_PostStrategy	-	-	-	-	-	Control:RIN:SP_PostStrategy	-	-	-	-	-
Control:RIFP:SP_PostStrategy	0.01	0.12	116.07	0.09	.926	Control:RIFP:SP_PostStrategy	0.02	0.06	116.55	0.25	.805
Control:RIFS:SP_PostStrategy	-0.01	0.09	116.07	-0.14	.890	Control:RIFS:SP_PostStrategy	-0.04	0.05	116.55	-0.86	.390

Note. SE = standard error; *df* = degrees of freedom; *t* = *t*-value; *p* = probability of committing type-I-error; Control = difference in change in the active control group for visualizers; Strategy = mean difference between verbalizers and visualizers in the active control group at pre-test; Control:Strategy = difference in change between verbalizers and visualizers in the active control group; Control:Group = difference in change between training group and active control group for visualizers; Control:Group:Strategy = difference between verbalizers and visualizers in the difference in change between the working memory training group and the active control group; SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural(symbol); PostStrategy = strategy usage at post-test; *p* values in bracket indicate corrected alpha levels after Bonferroni correction; Covariates presented in bold are statistically significant; (-) denote the group that was dropped due to the rank deficient of fixed-effect model matrix.

Table B8

Cognitive Strategies as a Function of Transfer Effects for Relational Integration Groups.

Covariates	Estimate	*SE*	*df*	*t*	*p*	Covariates	Estimate	*SE*	*df*	*t*	*p*
RI Verbal						**RI Numerical**					
Intercept	**2.33**	**0.07**	**147.85**	**32.31**	**.000(.006)**	**Intercept**	**2.75**	**0.07**	**161.20**	**38.19**	**.000(.006)**
Control	0.31	0.15	124.45	2.03	.045	Control	0.19	0.17	134.67	1.17	.243
RI_PreStrategy	0.09	0.17	147.85	0.52	.602	RI_PreStrategy	-0.33	0.17	161.20	-1.97	.050
Control:RI_PreStrategy	0.08	0.44	129.55	0.19	.848	Control:RI_PreStrategy	0.69	0.47	142.39	1.46	.145
Control:SPV	-0.12	0.24	139.00	-0.51	.611	Control:SPV	0.10	0.26	156.16	0.41	.685
Control:SPN	0.02	0.25	139.00	0.08	.938	Control:SPN	0.02	0.27	156.16	0.06	.954
Control:SPFP	-0.18	0.23	139.00	-0.77	.442	Control:SPFP	-0.04	0.25	156.16	-0.15	.883
Control:SPFS	0.16	0.26	139.00	0.62	.535	Control:SPFS	0.07	0.28	156.16	0.25	.801
Control:RIV	0.57	0.25	139.00	2.29	.023(.006)	Control:RIV	0.20	0.27	156.16	0.74	.458
Control:RIN	0.48	0.25	139.00	1.93	.055	Control:RIN	0.61	0.27	156.16	2.28	.024(.006)
Control:RIFP	0.14	0.32	139.00	0.45	.653	Control:RIFP	0.25	0.34	156.16	0.73	.464
Control:RIFS	0.29	0.23	139.00	1.24	.216	Control:RIFS	0.58	0.25	156.16	2.34	.021(.006)
Control:SPV:RI_PreStrategy	0.54	0.73	139.00	0.74	.461	Control:SPV:RI_PreStrategy	-0.70	0.79	156.16	-0.89	.378
Control:SPN:RI_PreStrategy	-0.20	0.57	139.00	-0.35	.725	Control:SPN:RI_PreStrategy	-0.88	0.62	156.16	-1.42	.158
Control:SPFP:RI_PreStrategy	0.10	0.73	139.00	0.14	.889	Control:SPFP:RI_PreStrategy	0.11	0.79	156.16	0.14	.892
Control:SPFS:RI_PreStrategy	-0.25	0.58	139.00	-0.43	.671	Control:SPFS:RI_PreStrategy	-0.57	0.62	156.16	-0.92	.360
Control:RIV:RI_PreStrategy	-0.29	0.57	139.00	-0.50	.616	Control:RIV:RI_PreStrategy	-0.37	0.62	156.16	-0.61	.546
Control:RIN:RI_PreStrategy	-0.95	0.57	139.00	-1.65	.101	Control:RIN:RI_PreStrategy	-0.07	0.62	156.16	-0.12	.908
Control:RIFP:RI_PreStrategy	0.44	0.65	139.00	0.68	.496	Control:RIFP:RI_PreStrategy	-0.27	0.70	156.16	-0.39	.700
Control:RIFS:RI_PreStrategy	-	-	-	-	-	Control:RIFS:RI_PreStrategy	-	-	-	-	-

Note. SE = standard error; *df* = degrees of freedom; *t* = *t*-value; *p* = probability of committing type-I-error; Control = difference in change in the active control group for visualizers; Strategy = mean difference between verbalizers and visualizers in the active control group at pre-test; Control:Strategy = difference in change between verbalizers and visualizers in the active control group; Control:Group = difference in change between training group and active control group for visualizers; Control:Group:Strategy = difference between verbalizers and visualizers in the difference in change between the working memory training group and the active control group; SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural(symbol); PreStrategy = strategy usage at pre-test; *p* values in bracket indicate corrected alpha levels after Bonferroni correction; Covariates presented in bold are significantly different from zero; (-) denote the group that was dropped due to the rank deficient of fixed-effect model matrix.

Table B9

Cognitive Strategies as a Function of Transfer Effects for Relational Integration Groups.

Covariates	Estimate	*SE*	*df*	*t*	*p*	Covariates	Estimate	*SE*	*df*	*t*	*p*
RI Figural (Pattern)						**RI Figural (Symbol)**					
Intercept	**2.27**	**0.05**	**162.85**	**48.93**	**.000(.006)**	**Intercept**	**3.73**	**0.07**	**149.01**	**52.34**	**.000(.006)**
Control	0.21	0.11	137.64	1.96	.052	Control	0.16	0.15	124.87	1.07	.287
RI_PreStrategy	-0.06	0.11	162.85	-0.56	.577	RI_PreStrategy	-0.02	0.17	149.02	-0.12	.906
Control:RI_PreStrategy	0.20	0.31	145.15	0.65	.514	Control:RI_PreStrategy	0.55	0.44	130.33	1.27	.207
Control:SPV	0.10	0.17	158.35	0.62	.539	Control:SPV	0.29	0.24	140.46	1.19	.236
Control:SPN	0.13	0.17	158.35	0.75	.454	Control:SPN	0.24	0.25	140.46	0.96	.341
Control:SPFP	0.11	0.16	158.35	0.68	.501	Control:SPFP	0.37	0.23	140.46	1.61	.110
Control:SPFS	-0.06	0.18	158.35	-0.32	.750	Control:SPFS	0.33	0.26	140.46	1.28	.202
Control:RIV	0.14	0.17	158.35	0.80	.424	Control:RIV	0.22	0.25	140.46	0.88	.383
Control:RIN	0.01	0.17	158.35	0.07	.943	Control:RIN	0.23	0.25	140.46	0.93	.355
Control:RIFP	0.35	0.22	158.35	1.58	.116	Control:RIFP	0.41	0.32	140.46	1.27	.205
Control:RIFS	0.16	0.16	158.35	1.02	.310	Control:RIFS	0.53	0.23	140.46	2.31	.023(.006)
Control:SPV:RI_PreStrategy	-0.11	0.51	158.35	-0.22	.829	Control:SPV:RI_PreStrategy	-0.56	0.74	140.46	-0.76	.449
Control:SPN:RI_PreStrategy	-0.39	0.40	158.35	-0.96	.338	Control:SPN:RI_PreStrategy	-1.15	0.57	140.46	-2.00	.047(.006)
Control:SPFP:RI_PreStrategy	-0.15	0.51	158.35	-0.30	.762	Control:SPFP:RI_PreStrategy	-0.38	0.73	140.46	-0.51	.608
Control:SPFS:RI_PreStrategy	0.04	0.40	158.35	0.09	.927	Control:SPFS:RI_PreStrategy	-0.77	0.58	140.46	-1.33	.186
Control:RIV:RI_PreStrategy	-0.25	0.40	158.35	-0.63	.530	Control:RIV:RI_PreStrategy	-0.68	0.57	140.46	-1.18	.238
Control:RIN:RI_PreStrategy	0.04	0.40	158.35	0.11	.916	Control:RIN:RI_PreStrategy	-0.44	0.57	140.46	-0.77	.444
Control:RIFP:RI_PreStrategy	0.17	0.45	158.35	0.37	.709	Control:RIFP:RI_PreStrategy	-0.38	0.65	140.46	-0.59	.557
Control:RIFS:RI_PreStrategy	-	-	-	-	-	Control:RIFS:RI_PreStrategy	-	-	-	-	-

Note. SE = standard error; *df* = degrees of freedom; *t* = *t*-value; *p* = probability of committing type-I-error; Control = difference in change in the active control group for visualizers; Strategy = mean difference between verbalizers and visualizers in the active control group at pre-test; Control:Strategy = difference in change between verbalizers and visualizers in the active control group; Control:Group = difference in change between training group and active control group for visualizers; Control:Group:Strategy = difference between verbalizers and visualizers in the difference in change between the working memory training group and the active control group; SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural(symbol); PreStrategy = strategy usage at pre-test; *p* values in bracket indicate corrected alpha levels after Bonferroni correction; Covariates presented in bold are significantly different from zero; (-) denote the group that was dropped due to the rank deficient of fixed-effect model matrix.

Table B10

Cognitive Strategies as a Function of Transfer Effects for Relational Integration Groups.

Covariates	Estimate	*SE*	*df*	*t*	*p*	Covariates	Estimate	*SE*	*df*	*t*	*p*
RI Verbal						**RI Numerical**					
Intercept	**2.35**	**0.074**	**147.98**	**31.70**	**.000(.006)**	**Intercept**	**2.71**	**0.07**	**163.88**	**36.42**	**.000(.006)**
Control	0.29	0.15	123.12	1.93	.056	Control	0.33	0.17	135.05	1.97	.051
RI_PostStrategy	-0.02	0.15	147.98	-0.12	.906	RI_PostStrategy	-0.10	0.15	163.88	-0.68	.497
Control:RI_PostStrategy	0.16	0.43	130.71	0.37	.713	Control:RI_PostStrategy	-0.41	0.48	147.50	-0.86	.390
Control:SPV	0.03	0.24	138.73	0.11	.914	Control:SPV	-0.09	0.26	159.75	-0.35	.730
Control:SPN	-0.10	0.24	138.73	-0.40	.687	Control:SPN	-0.15	0.26	159.75	-0.58	.565
Control:SPFP	-0.06	0.23	138.73	-0.26	.793	Control:SPFP	-0.07	0.25	159.75	-0.29	.771
Control:SPFS	-0.20	0.32	138.73	-0.61	.541	Control:SPFS	-0.31	0.35	159.75	-0.88	.381
Control:RIV	0.58	0.27	138.73	2.10	.037(.006)	Control:RIV	0.16	0.30	159.75	0.54	.593
Control:RIN	0.28	0.24	138.73	1.19	.238	Control:RIN	0.72	0.26	159.75	2.76	.006(.006)
Control:RIFP	0.15	0.32	138.73	0.46	.646	Control:RIFP	0.13	0.35	159.75	0.38	.702
Control:RIFS	0.27	0.25	138.73	1.11	.269	Control:RIFS	0.51	0.27	159.75	1.89	.061
Control:SPV:RI_PostStrategy	-0.91	0.73	138.73	-1.24	.217	Control:SPV:RI_PostStrategy	1.07	0.80	159.75	1.33	.186
Control:SPN:RI_PostStrategy	0.39	0.61	138.73	0.64	.524	Control:SPN:RI_PostStrategy	0.15	0.67	159.75	0.23	.820
Control:SPFP:RI_PostStrategy	-1.18	0.73	138.73	-1.63	.106	Control:SPFP:RI_PostStrategy	0.22	0.80	159.75	0.28	.784
Control:SPFS:RI_PostStrategy	0.39	0.56	138.73	0.70	.487	Control:SPFS:RI_PostStrategy	0.87	0.61	159.75	1.42	.157
Control:RIV:RI_PostStrategy	-0.26	0.55	138.73	-0.47	.641	Control:RIV:RI_PostStrategy	0.34	0.60	159.75	0.57	.573
Control:RIN:RI_PostStrategy	-0.28	0.61	138.73	-0.45	.653	Control:RIN:RI_PostStrategy	-0.19	0.67	159.75	-0.28	.780
Control:RIFP:RI_PostStrategy	0.42	0.65	138.73	0.65	.515	Control:RIFP:RI_PostStrategy	0.71	0.71	159.75	1.00	.319
Control:RIFS:RI_PostStrategy	-0.07	0.62	138.73	-0.11	.914	Control:RIFS:RI_PostStrategy	0.32	0.68	159.75	0.48	.636

Note. SE = standard error; *df* = degrees of freedom; *t* = *t*-value; *p* = probability of committing type-I-error; Control = difference in change in the active control group for visualizers; Strategy = mean difference between verbalizers and visualizers in the active control group at pre-test; Control:Strategy = difference in change between verbalizers and visualizers in the active control group; Control:Group = difference in change between training group and active control group for visualizers; Control:Group:Strategy = difference between verbalizers and visualizers in the difference in change between the working memory training group and the active control group; SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural(symbol); PostStrategy = strategy usage at post-test; *p* values in bracket indicate corrected alpha levels after Bonferroni correction; Covariates presented in bold are significantly different from zero.

Table B11

Cognitive Strategies as a Function of Transfer Effects for Relational Integration Groups.

Covariates	Estimate	*SE*	*df*	*t*	*p*	Covariates	Estimate	*SE*	*df*	*t*	*p*
RI Figural (Pattern)						**RI Figural (Symbol)**					
Intercept	**2.28**	**0.05**	**160.66**	**47.74**	**.000(.006)**	**Intercept**	**3.75**	**0.07**	**148.82**	**50.76**	**.000(.006)**
Control	0.19	0.11	133.53	1.82	.071	Control	0.15	0.15	123.86	1.00	.319
RI_PostStrategy	-0.07	0.10	160.66	-0.66	.507	RI_PostStrategy	-0.09	0.15	148.82	-0.57	.567
Control:RI_PostStrategy	0.33	0.30	144.37	1.08	.280	Control:RI_PostStrategy	0.59	0.43	131.62	1.36	.177
Control:SPV	0.08	0.16	155.35	0.50	.621	Control:SPV	0.27	0.24	139.80	1.14	.258
Control:SPN	0.05	0.16	155.35	0.31	.757	Control:SPN	0.13	0.24	139.80	0.56	.579
Control:SPFP	0.07	0.16	155.35	0.46	.648	Control:SPFP	0.35	0.23	139.80	1.50	.137
Control:SPFS	0.04	0.22	155.35	0.17	.865	Control:SPFS	0.25	0.32	139.80	0.79	.434
Control:RIV	0.28	0.19	155.35	1.49	.138	Control:RIV	0.38	0.27	139.80	1.38	.169
Control:RIN	0.07	0.16	155.35	0.45	.656	Control:RIN	0.21	0.24	139.80	0.87	.387
Control:RIFP	0.36	0.22	155.35	1.66	.100	Control:RIFP	0.41	0.32	139.80	1.28	.203
Control:RIFS	0.19	0.17	155.35	1.10	.274	Control:RIFS	0.50	0.25	139.80	2.00	.047(.006)
Control:SPV:RI_PostStrategy	0.11	0.51	155.35	0.22	.823	Control:SPV:RI_PostStrategy	-0.42	0.73	139.80	-0.57	.567
Control:SPN:RI_PostStrategy	-0.12	0.42	155.35	-0.28	.783	Control:SPN:RI_PostStrategy	-0.87	0.62	139.80	-1.42	.159
Control:SPFP:RI_PostStrategy	0.29	0.51	155.35	0.57	.572	Control:SPFP:RI_PostStrategy	-0.06	0.73	139.80	-0.08	.934
Control:SPFS:RI_PostStrategy	-0.32	0.39	155.35	-0.82	.416	Control:SPFS:RI_PostStrategy	-0.52	0.56	139.80	-0.92	.361
Control:RIV:RI_PostStrategy	-0.62	0.38	155.35	-1.63	.105	Control:RIV:RI_PostStrategy	-0.98	0.55	139.80	-1.79	.076
Control:RIN:RI_PostStrategy	-0.25	0.42	155.35	-0.60	.552	Control:RIN:RI_PostStrategy	-0.26	0.62	139.80	-0.42	.672
Control:RIFP:RI_PostStrategy	0.05	0.45	155.35	0.11	.914	Control:RIFP:RI_PostStrategy	-0.38	0.65	139.80	-0.59	.558
Control:RIFS:RI_PostStrategy	-0.34	0.43	155.35	-0.80	.425	Control:RIFS:RI_PostStrategy	-0.35	0.62	139.80	-0.57	.570

Note. SE = standard error; *df* = degrees of freedom; *t* = *t*-value; *p* = probability of committing type-I-error; Control = difference in change in the active control group for visualizers; Strategy = mean difference between verbalizers and visualizers in the active control group at pre-test; Control:Strategy = difference in change between verbalizers and visualizers in the active control group; Control:Group = difference in change between training group and active control group for visualizers; Control:Group:Strategy = difference between verbalizers and visualizers in the difference in change between the working memory training group and the active control group; SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural(symbol); PostStrategy = strategy usage at post-test; *p* values in bracket indicate corrected alpha levels after Bonferroni correction; Covariates presented in bold are significantly different from zero.

Appendix B7

Table B12

Number of Participants (%) Using Different Strategies to Complete Working Memory Tasks at Pre- and Post-test.

Groups / **Tasks**	**Strategies**	**SPV**			**SPN**			**SPPF**			**SPFS**			**RIV**		
		Pre	**Post**	***p***	**Pre**	**Post**	***p***	**Pre**	**Post**	***p***	**Pre**	**Post**	***p***	**Pre**	**Post**	***p***
SPV	Visualize	10%			9.1%			9.1%			20.0%			18.2%	18.2%	
	Verbalize	40%	70%		72.7%	72.7%		63.6%	90.9%	.445	70.0%	90.0%		45.5%	54.5%	
	Both	50%	30%	.360	9.1%	27.3%	.589	27.3%	9.1%		10.0%	10.0%	.721	36.4%	27.3%	1.0
	Another				9.1%											
	None															
SPN	Visualize	10%			18.2%	9.1%		9.1%	9.1%							
	Verbalize	40%	70%		72.7%	81.8%		45.5%	72.7%	.489	80.0%	90.0%		90.9%	63.6%	
	Both	50%	30%	**.006**	9.1%	9.1%	1.0	45.5%	18.2%		20.0%	10.0%	1.00	9.1%	36.4%	.311
	Another															
	None															
SPFP	Visualize	60%	40%		63.6%	45.5%		90.9%	9.1%		60.0%	70.0%		45.5%	45.5%	
	Verbalize		30%		18.2%	18.2%	.906		36.4%		10.0%	10.0%		27.3%	18.2%	
	Both	40%	30%	.240	9.1%	27.3%			36.4%	**.000**	20.0%	10.0%	1.00	9.1%	18.2%	1.0
	Another								18.2%							
	None				9.1%	9.1%		9.1%			10.0%	10.0%		18.2%	18.2%	
SPFS	Visualize	20%	30%		9.1%	9.1%		27.3%	18.2%		40.0%			9.1%	9.1%	
	Verbalize	50%	20%		36.4%	63.6%		18.2%	54.5%	.161	50.0%	70.0%		45.5%	72.7%	
	Both	30%	50%	.523	45.5%	27.3%	.660	54.5%	18.2%		10.0%	30.0%	.162	45.5%	18.2%	.630
	Another				9.1%				9.1%							
	None															
RIV	Visualize	30%	40%		36.4%	27.3%		45.5%	18.2%		20.0%	10.0%		18.2%	9.1%	
	Verbalize	50%	50%		36.4%	36.4%		27.3%	72.7%		50.0%	60.0%		72.7%	72.7%	
	Both	10%		1.0		27.3%	.319			.162			1.0			.587
	Another	10%	10%		9.1%	9.1%		9.1%	9.1%		10.0%	20.0%			18.2%	
	None				18.2%			18.2%			20.0%	10.0%		9.1%		
RIN	Visualize	70%	50%		45.5%	72.7%		63.6%	81.8%		40.0%	20.0%		54.5%	54.5%	
	Verbalize	10%	20%		36.4%	9.1%		18.2%			20.0%	30.0%		36.4%	36.4%	
	Both		20%	.576			.701		9.1%	.578	10.0%	10.0%	.812		9.1%	
	Another	20%	10%		9.1%	9.1%		9.1%	9.1%		10.0%	30.0%		9.1%		
	None				9.1%	9.1%		9.1%			20.0%	10.0%				
RIFP	Visualize	90%	90%		81.8%	72.7%		90.9%	72.7%		50.0%	60.0%		90.9%	72.7%	
	Verbalize	10%	10%													
	Both			1.0		9.1%	.672		9.1%	.587	10.0%	10.0%	1.0		9.1%	.724
	Another				18.2%	9.1%					20.0%	20.0%			9.1%	
	None					9.1%		9.1%	18.2%		20.0%	10.0%		9.1%	9.1%	
RIFS	Visualize	50%	60%		63.6%	63.6%		81.8%	63.6%		40.0%	10.0%		81.8%	54.5%	
	Verbalize	10%			18.2%	9.1%					20.0%	50.0%		9.1%	18.2%	
	Both	20%	30%	1.0		9.1%	1.0		18.2%	.368		10.0%	.189		18.2%	**.046**
	Another	20%	10%		9.1%	9.1%		9.1%	18.2%		20.0%	30.0%			9.1%	
	None				9.1%	9.1%		9.1%			20.0%			9.1%		

Note. SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural (symbol); *p* = probability of committing type-I-error; *p* values in bold are significantly different from zero.

Table B13

Number of Participants (%) Using Different Strategies to Complete Working Memory Tasks at Pre- and Post-test.

Groups	**Strategies**	**RIN**			**RIFP**			**RIFS**			**OLMT**			**Passive**		
Tasks		**Pre**	**Post**	***p***	**Pre**	**Post**	***p***	**Pre**	**Post**	***p***	**Pre**	**Post**	***p***	**Pre**	**Post**	***p***
SPV	Visualize	18.2%			16.7%			30.0%	10.0%			17.6%			12.5%	
	Verbalize	81.8%	100%		50.0%	66.7%		70.0%	80.0%		70.6%	76.5%	.055	62.5%	75.0%	
	Both			.476	33.3%	33.3%	.748			.582	29.4%	5.9%		37.5%	12.5%	.569
	Another								10.0%							
	None															
SPN	Visualize	18.2%				16.7%			10.0%		11.8%	5.9%		25.0%	25.0%	
	Verbalize	72.7%	100%		83.3%	66.7%		90.0%	80.0%	1.0	88.2%	76.5%		37.5%	62.5%	
	Both	9.1%		.090	16.7%	16.7%	1.0	10.0%	10.0%			17.6%	.787	25.0%	12.5%	.804
	Another													12.5%		
	None															
SPFP	Visualize	90.9%	45.5%		33.3%	50.0%		80.0%	50.0%		47.1%	64.7%		75.0%	62.5%	
	Verbalize		45.5%		33.3%	16.7%		10.0%	40.0%		23.5%	17.6%		25.0%	12.5%	
	Both	9.1%	9.1%	**.035**	33.3%	16.7%	1.0	10.0%	10.0%	.443	17.6%	5.9%	.889			1.0
	Another										5.9%	5.9%			12.5%	
	None					16.7%					5.9%	5.9%			12.0%	
SPFS	Visualize		9.1%		16.7%	16.7%		20.0%			11.8%	41.2%		12.5%		
	Verbalize	81.8%	81.8%		83.3%	50.0%		50.0%	80.0%		70.6%	47.1%		50.0%	50.0%	
	Both	18.2%	9.1%	1.0		33.3%	.697	20.0%	20.0%	.406	17.6%	11.8%	.182	37.5%	37.5%	.326
	Another							10.0%							12.5%	
	None															
RIV	Visualize	18.2%						20.0%	20.0%		17.6%	35.3%		12.5%		
	Verbalize	63.6%	100%		83.3%	83.3%		40.0%	60.0%		52.9%	35.5%		50.0%	75.0%	
	Both			.09		16.7%	1.0	20.0%	20.0%	.596	5.9%	5.9%	.883	25.0%	12.5%	
	Another	18.2%						20.0%			11.8%	11.8%			12.5%	.765
	None				16.7%						11.8%	11.8%		12.5%		
RIN	Visualize	45.5%	54.5%			33.3%		70.0%	50.0%		52.9%	76.5%		50.0%	50.0%	
	Verbalize	18.2%	18.2%		50.0%	33.3%			50.0%		17.6%	5.9%		37.5%	12.5%	
	Both			1.0			.740			**.022**		5.9%	.429		25.0%	.521
	Another	27.3%	18.2%		16.7%	16.7%		20.0%			17.6%	5.9%		12.5%	12.5%	
	None	9.1%	9.1%		33.3%	16.7%		10.0%			11.8%	5.9%				
RIFP	Visualize	72.7%	100%		100%	100%		90.0%	100.0%		76.5%	94.1%		62.5%	100.0%	
	Verbalize															
	Both			.180			.473			1.0			.335			.200
	Another	18.2%						10.0%			5.9%			25.0%		
	None	9.1%									17.6%	5.9%		12.5%		
RIFS	Visualize	36.4%	45.5%		83.3%	50.0%		80.0%	90.0%		58.8%	58.8%		50.0%	50.0%	
	Verbalize	27.3%	27.3%						10.0%		5.9%	11.8%		12.5%	12.5%	
	Both			1.0		16.7%	.697			1.0		11.8%	.661	25.5%	25.0%	1.0
	Another	18.2%	18.2%			16.7%		10.0%			23.5%	11.8%		12.5%	12.5%	
	None	18.2%	9.1%		16.7%	16.7%		10.0%			11.8%	5.9%				

Note. SP = storage and processing; RI = relational integration; V = verbal; N = numerical; FP = figural (pattern); FS = figural (symbol); *p* = probability of committing type-I-error; *p* values in bold are significantly different from zero.