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at the Heinrich-Heine-University Düsseldorf

**Neural correlates of age-related differences
in dual-task performance**

Dissertation

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submitted by

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Le véritable voyage de découverte ne consiste pas
à chercher de nouveaux paysages,
mais à avoir de nouveaux yeux.
– Marcel Proust, *À la recherche du temps perdu*

Die wahre Entdeckungsreise besteht nicht darin,
neue Landschaften zu suchen,
sondern neue Augen zu haben.

The real voyage of discovery consists not
in seeking new landscapes,
but in having new eyes.

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Zusammenfassung

Die Bearbeitung von zwei Aufgaben gleichzeitig geht im Vergleich zu einzelnen Aufgaben mit Geschwindigkeits- und Genauigkeitsverlusten einher, insbesondere bei älteren Personen. In einer Gesellschaft, in der Menschen zunehmend mehrere Aufgaben gleichzeitig jonglieren, ist das Interesse an den zugrundeliegenden Mechanismen von Doppelaufgaben (DA)-Interferenz gestiegen. Dabei ist es wichtig zu verstehen, wie sich reaktionsbezogene Merkmale auf die negativen Folgen der DA auswirken, insbesondere in einer alternden Gesellschaft. Aus diesem Grund zielte diese Arbeit darauf ab, Altersunterschiede in den Verhaltens- (**Studie 1**) und neuronalen Korrelaten (**Studie 2**) der DA-Interferenz auf der Reaktionsebene zu analysieren und deren Zusammenhänge mit exekutiven Funktionen (EF) zu untersuchen. Wir induzierten Effektorbezogene DA-Interferenz durch zwei räumlich inkongruente manuelle Reaktionen basierend auf der Tonhöhe eines einzelnen auditiven Reizes. **Beide Studien** zeigten eine erhöhte Interferenz bei inkongruenten Reaktionen, insbesondere bei älteren Erwachsenen. Diese Interferenz zeigte asymmetrische Kosten zugunsten der anspruchsvolleren Aufgabe, was auf eine flexible Ressourcenallokation und strategische Priorisierung hindeutet. Ältere Erwachsene zeigten eine erhöhte Verwechslungsgefahr bei Reaktionen und Defizite bei der Interferenzabwehr. Unter Verwendung der funktionellen Magnetresonanztomografie zeigte **Studie 2**, dass DA mit reaktionsabhängiger Interferenz das domänengenerelle Multiple-Demand-Netzwerk (MDN) aktiviert. Die Aktivität innerhalb des MDN wurde jedoch nur minimal von individuellen Unterschieden in EF beeinflusst. Ältere Erwachsene zeigten eine nicht-kompensatorische Hyperaktivität im linken superioren frontalen Gyrus bei inkongruenten Reaktionen, während Arbeitsgedächtnisprozesse die rechte prämotorische und frontale Aktivität während DA modulierten. Mit einem Übergang von der Analyse von Gruppenmustern in Gehirn-Verhaltens-Assoziationen zur Vorhersage individueller kognitiver Leistung anhand von neurobildgebenden Daten betonte **Studie 3** die Herausforderung, EF aus individuellen strukturellen und funktionellen Charakteristika verschiedener Hirnnetzwerke vorherzusagen. Während morphometrische Daten bei älteren Erwachsenen vielversprechender waren, erwiesen sich Maße der funktionellen Hirnvariabilität als aussagekräftiger für junge Erwachsene. Darüber hinaus wurde die Bedeutung der globalen Hirnorganisation im Vergleich zu aufgabenbezogenen Netzwerken deutlich. In Zusammenfassung betonen diese Ergebnisse die altersbedingten Schwierigkeiten bei der Interferenzabwehr gleichzeitiger Aufgaben, die Rolle des MDN bei der Konfliktlösung in reaktionsinkongruenten DA und die Grenzen einzelner Hirnmetriken in der zuverlässigen Vorhersage von individuellen EF.

Summary

Performing two tasks concurrently or in close succession comes with costs in speed and accuracy compared to single tasks, especially in older individuals. In a society where people are increasingly accustomed to juggling several tasks simultaneously, interest in the underlying mechanisms of dual-task interference has increased. Thereby, it is crucial to understand how response characteristics affect the costs of dual-tasking, especially facing a rapidly aging society. For this reason, this work aimed to analyze age differences in behavioral (**Study 1**) and neural correlates (**Study 2**) of dual-task interference at the response level, and their associations with executive functioning (EF) abilities. We induced response-related dual-task interference by requiring participants to make two spatially incongruent manual responses depending on the pitch of a single auditory stimulus. **Both studies** revealed increased interference with incongruent responses, particularly in older adults. This interference showed asymmetric cost allocation, favoring the more demanding task, suggesting flexible resource allocation and strategic processing prioritization. In healthy aging, results emphasized increased response confusability and deficits in shielding tasks from interference. Utilizing functional magnetic resonance imaging, **Study 2** demonstrated that dual-tasking with response interference engaged the domain-general multiple-demand network (MDN). The activity within the MDN was only minimally affected by individual differences in EF performance. Older adults exhibited non-compensatory hyperactivity in the left superior frontal gyrus when confronted with incongruent responses, and working memory processes modulated their right premotor and frontal activity during dual-tasking. Transitioning from analyzing group-level patterns in brain-behavior associations to predicting individual cognitive performance based on neuroimaging data, **Study 3** highlighted the challenge of predicting individual EF abilities from structural and functional characteristics of different brain networks. While morphometric data showed promise in older adults, measures of functional brain variability proved more predictive for young adults. Moreover, the importance of the whole-brain organization became apparent compared to task-specific networks. In summary, these findings emphasize the age-related difficulties in shielding concurrent tasks, the involvement of the MDN in resolving response-related conflict during dual-tasking, and the limits of relying on single brain metrics as reliable predictors of EF abilities.

List of abbreviations

| Abbreviation | Definition |
|---------------------|--|
| ACC | Anterior cingulate cortex |
| aI | Anterior insula |
| BIS | Balanced integration score |
| BOLD | Blood-oxygen-level dependent |
| CRUNCH | Compensatory recruitment of neural circuits hypothesis |
| CV | Cross-validation |
| DECHA | Default-executive coupling hypothesis of aging |
| dIPFC | Dorsolateral prefrontal cortex |
| DMN | Default-mode network |
| dPMC | Dorsal premotor cortex |
| EF | Executive functioning |
| eMDN | Extended multiple demand network |
| fALFF | Fractional amplitude of low-frequency fluctuations |
| fMRI | Functional magnetic resonance imaging |
| GLM | General linear model |
| GMV | Gray-matter volume |
| gPPI | Generalized psychophysiological interaction |
| HAROLD | Hemispheric asymmetry reduction in older adults |
| IFJ | Inferior frontal junction |
| IFS | Inferior frontal sulcus |
| IPS | Intraparietal sulcus |
| MCC | Middle cingulate cortex |
| MFG | Middle frontal gyrus |
| MDN | Multiple-demand network |
| ML | Machine learning |
| MRI | Magnetic resonance imaging |
| PASA | Posterior-to-anterior shift with aging |

| | |
|----------------|---|
| preSMA | Pre-supplementary motor area |
| PRP | Psychological refractory period |
| ReHo | Regional homogeneity |
| rs-fMRI | Resting-state functional magnetic resonance imaging |
| RSFC | Resting-state functional connectivity |
| RT | Reaction time |
| SFG | Superior frontal gyrus |
| SOA | Stimulus onset asynchrony |
| STAC | Scaffolding theory of aging cognition |
| tb-fMRI | Task-based functional magnetic resonance imaging |
| WM | Working memory |

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1 Introduction

1.1 Multi-tasking and executive functioning

In our daily routines, we have grown accustomed to juggling multiple tasks simultaneously. Take, for instance, the widespread practice of answering a phone call while typing on the computer and browsing websites in parallel. Even in more mundane activities such as talking while driving, cooking a meal, or navigating the grocery store, we often find ourselves needing to manage various tasks concurrently. However, multi-tasking, or the ability to effectively manage two or more tasks simultaneously or in close succession, typically comes with a certain cost in performance compared to performing individual tasks in isolation, as reflected in speed and accuracy costs (Koch et al., 2018). Furthermore, this effect has been shown to be exacerbated with age (Koch et al., 2018; Verhaeghen et al., 2003).

With the growing societal interest in enhancing our cognitive abilities and adaptation requirements to an ever more technologically driven society, as well as an aging population, the study of dual-tasking and multi-tasking has become a topic of interest within several scientific fields, ranging from cognitive and clinical neurosciences to psychology, human-computer interaction, and education. This research is multi-faceted and dynamic, including various experimental paradigms and research questions. Classical multi-tasking studies use clearly defined and isolated stimuli and responses to study the mechanisms behind interference effects. Such paradigms, including dual-task settings, have been the experimental tasks most dominantly used in the field. Other studies have focused on the application dimension using paradigms that are closer to the cognitive demands of multi-tasking in the real world, such as driving and aircraft-control simulations, as well as combining gait or postural tasks with cognitive tasks (e.g., counting while walking or maintaining the balance while performing a memory task). Although dual-task settings reflect the lowest level of multi-tasking complexity, the combination of two simple tasks into a dual task allows for comparing performance in dual-tasking and single-task scenarios. This setup enables researchers to manipulate and isolate any experimental factor of the task to analyze and interpret underlying temporal dynamics and interference mechanisms. Such experiments have been instrumental in developing models that elucidate how humans process dual-task settings and the associated challenges. For instance, studies have delved into manipulating factors such as the inter-stimulus interval, stimulus

salience or order, stimulus–response (S-R) mappings, or stimulus and response modalities. However, an aspect overlooked in models of dual-task interference is the impact of effector or output characteristics. Consequently, this work focused on assessing dual-task interference by examining conflict between response codes, particularly spatial conflict arising from incongruent (spatially opposing) response codes.

Since performing multiple concurrent tasks requires people to act in an adaptive manner to accomplish the goal of each task, it is reasonable to assume that multi-tasking is related to executive functions (EF). The multi-dimensional construct of EF involves diverse higher-order cognitive functions responsible for goal-directed behavior and self-regulation (Diamond, 2013; Miyake et al., 2000; Miyake & Friedman, 2012), and it has been thoroughly investigated both at the behavioral and neural levels. One of the most well-known EF models has postulated three core subcomponents, including cognitive flexibility (i.e., shifting one's mental engagement between irrelevant and relevant task sets), working memory (WM; i.e., updating, monitoring, and maintaining incoming information according to the relevance of the task), and inhibitory control (i.e., deliberately suppressing automatic or prepotent responses when necessary and controlling one's attention from irrelevant information that can potentially cause interference) (Diamond, 2013; Miyake et al., 2000). Although dual-tasking was not identified as a fundamental component of the three-factor model, dual-tasking and other cognitive abilities (e.g., planning and verbal fluency) have been suggested to be closely associated with EF or a common higher-order cognitive control. Undoubtedly, dual-tasking engages multiple cognitive abilities intertwined with EF, as it involves maintaining the rules of two different task sets, shifting the attention between them, inhibiting dominant responses, and controlling the attention to suppress interference (Saylik et al., 2022; Szameitat & Brunel Students, 2022). More recently, Miyake and Friedman (2012; 2017) updated their classification and proposed a nested model with a unity-diversity EF framework, positing a common “unity factor” underlying all EFs (Friedman & Miyake, 2017; Miyake & Friedman, 2012). This factor encapsulates the shared variance between inhibition, updating, and shifting, while the “diversity factor” identifies specific processes representing distinct EF functions that branch from it. Notably, no unique inhibition factor remains after accounting for shared variance, indicating separate specific factors for updating and shifting. Thus, the nested model emphasizes shared cognitive processes across EFs with unique characteristics for each function. It is also a call to recognize that each aspect of a complex task contributes to our understanding of how individuals regulate their behavior and cognition.

Overall, this study aimed to elucidate associations between dual-task interference at the response level and EF, on the one hand, and brain functioning and connectivity, on the other, while assessing how these associations are modulated by healthy cognitive aging. The research field of dual-tasking and EF continues to evolve, driven by the need to understand the neural and behavioral mechanisms underlying higher-order cognitive-control processes and enhance human performance in an increasingly complex and interconnected world. Furthermore, this research may have practical implications for developing complex systems, such as designing interfaces, educational strategies, and clinical interventions aimed at optimizing human well-being in today's fast-paced, information-saturated world, as well as identifying early signs of frailty or disability in older adults and preventing an accelerated disease progression.

1.1.1 Theoretical accounts of dual-task interference

Several explanations within diverse theoretical frameworks have been proposed for dual-task performance deterioration (i.e., increased reaction times and error rates). Although dual-task costs have been mostly attributed to capacity limitations on the central (response selection) stage of task processing (Pashler, 1994; Schubert, 1999), there is still an ongoing debate about their specific source. Two overarching classes of models have been at the center of this debate to explain dual-task interference: The structural response selection bottleneck model (Pashler, 1984, 1994) and the central capacity-sharing model (Navon & Miller, 2002; Tombu & Jolicœur, 2003).

The response selection bottleneck model assumes that stimulus processing and response execution can operate in parallel for two concurrent tasks. However, the resources needed for the central response selection stage can only be allocated to a single task at once. Thus, two tasks with response selection stages overlapping in time need to be processed sequentially (De Jong, 1995; Pashler, 1994; Strobach et al., 2018). In other words, this class of models implies a passive and inflexible “first-come, first-served” serial task-order processing mechanism, in which the response for the second task can only be selected after the response selection for the first task has been completed. The assumption of a structural bottleneck was mainly inspired by the discoveries derived from the psychological refractory period (PRP) paradigm, the experimental set-up most widely used to assess dual-task performance. In the PRP paradigm, participants are asked to perform two-choice reaction tasks with variable temporal overlap (Pashler & Johnston, 1989; Schubert, 1999; Telford, 1931; Welford, 1952). The classical and replicated finding has been a prolongation of reaction times (RTs) in the second task with increasing temporal overlap, commonly referred to as stimulus onset asynchrony (SOA) (Hein

& Schubert, 2004; Pashler, 1994; Schubert, 1999). Meanwhile, RTs in the first task remain largely unaffected by the SOA manipulation. The increase of RT in the second task from long to shorter inter-stimulus intervals is commonly known as the PRP effect.

However, rigid structural bottleneck models have been challenged by alternative models, such as capacity-sharing models. This class of models argues that central processes required for each task's response selection can run in parallel when two tasks are dealt with concurrently, but only to a certain extent. This means that only a limited quantity of resources can be shared between two tasks, and this creates costs, as compared to devoting all resources to one task because central processing capacity is limited, but one major concern that has remained open is how many resources are devoted to either task (Koch et al., 2018; Navon & Miller, 2002; Pieczykolan & Huestegge, 2019; Tombu & Jolicœur, 2003). However, it is to be noted that the models discussed here are not mutually exclusive but represent processing modes among several mechanisms at work. Actually, a growing body of behavioral studies indicates that the specific task settings, task representations, and instructions, among other parameters, influence dual-task costs and may exert different interference mechanisms (Koch et al., 2018; Pieczykolan & Huestegge, 2018, 2019; Schumacher et al., 2018).

An extension of the capacity-sharing model has proposed to add a strategic resource allocation component, in which our cognitive system is perceived as flexible and capable of adapting to particular contextual and task demands (Fischer & Plessow, 2015; Hazeltine et al., 2006; Koch et al., 2018; Pieczykolan & Huestegge, 2019). For example, performing two concurrent tasks in a serial manner, rather than being a rigid default processing mechanism, may represent a strategic adaptation to avoid between-task interference or crosstalk (Logan & Gordon, 2001; Meyer & Kieras, 1997; Miller et al., 2009; Navon & Miller, 1987). In this context, crosstalk refers to the non-intentional information transmission between processing streams of different (sub)tasks, which becomes more likely if the tasks share physical features or conceptual dimensions, such as overlapping response alternatives (Navon & Miller, 1987). For example, the more "difficult" task, requiring more attentional resources, could be prioritized to overcome crosstalk.

Inspired by the more flexible processing models, studies have addressed the role other task characteristics may have on dual-task performance. To this end, experimental paradigms have been devised to manipulate factors such as stimulus and response modalities, task order presentation, or S-R mappings. One proposed paradigm to specifically study crosstalk at the effector level is the simultaneous-onset paradigm. This approach involves presenting stimuli for two tasks simultaneously or triggering two simultaneous responses using a single stimulus

with sufficient information for two concurrent task sets (Fagot & Pashler, 1992; Huestegge & Koch, 2010; Pieczykolan & Huestegge, 2014). For example, research has confirmed the existence of output cross-modality interference in dual-task scenarios (Huestegge & Koch, 2013; Koch et al., 2018; Pieczykolan & Huestegge, 2014, 2018). Additionally, employing the simultaneous-onset paradigm has revealed a response-modality dominance pattern, where saccades are prioritized over vocal responses, and vocal responses over manual responses (Huestegge & Koch, 2013). Nonetheless, the impact of other response properties, such as spatial conflict, on dual-task interference requires further characterization. Moreover, response-related crosstalk has been largely overlooked in cognitive neuroscientific and age-related dual-task research.

1.1.2 Neural correlates of dual-tasking and executive functioning

The field of cognitive neurosciences has profited from non-invasive neuroimaging techniques to investigate the neural correlates of different cognitive processes, such as inhibitory control, attentional processes, WM, or far less common, dual-tasking. Functional magnetic resonance imaging (fMRI) is one of the most popular neuroimaging techniques to map functional brain activity. This technique mainly detects changes linked to blood flow in different brain areas; more specifically, it detects changes in the relative levels of oxygenated and deoxygenated blood. Since it has been demonstrated that neuronal firing is coupled with an increased flow of oxygenated blood, the main contrast used in fMRI, the regional blood-oxygen-level dependent (BOLD) signal, is used as an indirect measure of neuronal activation and a proxy for regional functional brain activity. fMRI offers the advantage of being a non-invasive technique with a high spatial resolution despite a rather low temporal resolution.

Task-based fMRI (tb-fMRI) is a popular implementation of fMRI to localize the functional involvement of specific brain areas associated with cognitive processes; as such, it is an approach to explore brain-behavior associations. While a participant is presented with a series of stimuli or is instructed to perform a particular behavioral task, usually designed to isolate a specific cognitive process, inside the scanner, the BOLD signal changes are measured at regular intervals, and a time series of brain activity is created. Statistical analyses entail contrasting task-stimulated states and (baseline) control states to identify clusters or a network of brain areas that are significantly activated during the cognitive process of interest (Huettel et al., 2009). For example, researchers may contrast the BOLD signal during dual-task trials versus single-task trials to identify the brain regions functionally involved in dual-tasking. Besides regional brain activity, inter-regional communication between brain areas is pivotal for efficient

cognitive performance (Pessoa, 2014). In the domain of tb-fMRI, generalized psychophysiological interaction (gPPI) analysis is a method that models the functional synchronization between a predefined (seed) brain region and the rest of brain voxels depending on the experimental conditions or psychophysiological variables (McLaren et al., 2012; O'Reilly et al., 2012). Alternatively, resting-state fMRI (rs-fMRI) is a more recent task-free design in which spontaneous BOLD signal fluctuations are measured while the participant lies at rest in the scanner (with their eyes closed or fixated on a specific point) without performing any specific task (Biswal, 2012; Biswal et al., 1995). The intrinsic BOLD signal time series of rs-fMRI allows for studying resting-state functional connectivity (RSFC) obtained by computing the temporal correlation between time series in different brain regions. This measure goes beyond regional brain activity and is nowadays a proxy for functional synchronization and indirect coupling between different parts of the brain. The notions of regional brain activation and functional connectivity are not necessarily exclusive. For example, the brain can have highly specialized primary sensorimotor regions but, at the same time, require a distributed network comprised of distant regions for cognitive processes.

For a long time, the neuroscientific study of higher-order EF was only accessible via the observation of patients with brain lesions. Since most patients with frontal lobe damage presented deterioration in goal-directed and self-regulatory behavior, EFs were long assumed to be specifically related to frontal lobe development (Miyake et al., 2000). Further, with the advancements in functional neuroimaging technology, it became possible to corroborate that EF processes not only engage prefrontal brain areas, but that additional brain regions are recruited as well. A substantial number of functional neuroimaging studies have mapped brain areas and networks associated with different aspects of EF. However, the results can be quite heterogeneous depending on the specific task demands or EF subcomponents assessed in the scanner. By having a large body of fMRI results in the field of EF, it has been possible to perform meta-analyses, a statistical technique that integrates and analyzes the results of multiple fMRI studies to identify the convergence of brain activation patterns across different studies and subjects. Thus, meta-analyses provide a robust summary of brain functions associated with EF. Overall, research has found EF to be associated with distributed brain regions and networks covering, in particular, the inferior frontal sulcus (IFS), the bilateral anterior insula (aI), the pre-supplementary motor area, and the adjacent anterior cingulate cortex (preSMA/ACC), and the intraparietal sulcus (IPS) (Duncan, 2010). This set of regions has been collectively referred to as the multiple demand network (MDN), a network subserving multiple cognitive tasks, such as goal-directed behavior, working memory, vigilant attention, and inhibitory control (Cieslik

et al., 2015; Duncan, 2010; Langner & Eickhoff, 2013; Müller et al., 2015; Rottschy et al., 2012). Recently, an extended multiple-demand network (eMDN; Camilleri et al., 2018) has been proposed by performing task-dependent and task-independent functional connectivity analysis on seed regions that resulted from three different meta-analyses on working memory (Rottschy et al., 2012), inhibition (Cieslik et al., 2015) and vigilant attention (Langner & Eickhoff, 2013). The eMDN comprised three main groups of brain regions: A subcortical group (putamen and thalamus) mainly subserving sensorimotor processing, a group of potential organizers (bilateral preSMA/middle cingulate cortex [MCC], aI, IFS/middle frontal gyrus [MFG]), and a more heterogeneous task-dependent set of workers (IPS, inferior frontal junction [IFJ], dorsal premotor cortex [dPMC], left inferior temporal gyrus).

The neural substrates underlying dual-tasking performance have received comparatively less attention in neuroimaging studies, likely due to the relatively recent surge in interest in this multifaceted cognitive function, as well as the inherent complexities involved in conducting the experiments within the confines of an MRI scanner. For instance, the simultaneous recording of manual and saccadic responses can pose technical challenges when implementing such paradigms in an imaging environment. Moreover, the experimental paradigms can be highly diverse depending on the manipulated dual-task parameters but have often focused on multi-modal input-related interference or the PRP effect. Nevertheless, neuroimaging studies have consistently identified dual- and multi-tasking as associated with brain activations in a fronto-parietal network. This network comprises key regions, including the dorsolateral prefrontal cortex (dlPFC) and superior parietal regions, which play a role in detecting task changes, regulating concurrent processes to facilitate adaptive responses, and managing attention allocation across tasks, respectively (Al-Hashimi et al., 2015; Deprez et al., 2013; Hartley et al., 2011; Stelzel et al., 2006, 2008, 2009; Szameitat et al., 2006). Notably, a meta-analysis on dual-tasking with 26 studies found involvement of areas that overlap with the key regions of the MDN, including bilateral IFS/MFG, aI, dPMC, and IPS (Worringer et al., 2019). While meta-analyses provide the most robust spatial convergence of activity across studies, dual-task neuroimaging studies typically center on broad contrasts comparing dual-task versus single-task conditions, potentially overlooking nuanced cognitive processes and lacking the precision to isolate more specific dual-task interference mechanisms. Thus, further studies are needed to better understand specific dual-task processes. For example, an overlooked aspect has been the impact of effector characteristics on dual-task interference. Addressing this gap, Studies 1 and 2 in this work delved into dual-task interference at the response level, leveraging conflict induced by mutually incongruent spatial response codes. Employing a step-wise

analytical approach, we sought to isolate and disentangle the intricate stages involved in dual-task processing.

1.2 Healthy cognitive aging

In 2020, the WHO reported that the population of individuals aged 60 years and older surpassed the number of children younger than five years, and the sociodemographic transition towards an increasingly aging population continues to rise (Ritchie, 2019; World Health Organization, 2022). As individuals age, they commonly experience a range of health conditions and cognitive impairment. However, the extent and nature of these changes can vary widely from person to person. Therefore, it is imperative to thoroughly characterize these age-related cognitive changes, their underlying neural mechanisms, and their inter-individual variability to promote well-being and prevent disabilities in our aging population.

Cognitive aging encompasses not only deterioration but also some gains. Numerous aspects of information processing and executive functioning become less efficient, such as speed in information processing, attention, working memory, perception, and inhibitory control (Craik & Salthouse, 2008; Spreng & Turner, 2019). At the same time, other aspects of implicit memory and crystallized knowledge, such as vocabulary and semantic memory, tend to remain relatively stable as people age (Craik & Salthouse, 2008; Spreng & Turner, 2019). The theory of the semanticization of cognition integrates the decline of cognitive-control abilities and processing speed with the stability or increase in semantics or prior-knowledge representations during healthy aging (Park & Reuter-Lorenz, 2009; Spreng & Turner, 2019). Concurrently, healthy aging is accompanied by motor-related impairments, manifesting as a general slowing of motor performance and difficulties in motor coordination during physical activities, thereby increasing the susceptibility of older adults to falls.

1.2.1 Dual-tasking in advanced age

Older adults not only struggle with individual cognitive demands, but also show an overadditive impairment when carrying more than a single task at once. This exacerbates the detrimental behavioral effects of dual-tasking for them, as reflected in increased dual-task costs in speed and accuracy compared to young adults (Koch et al., 2018; Verhaeghen et al., 2003). The combined effect on speed and accuracy facets contradicts the assumption that age-related dual-task difficulties can be solely attributed to generalized cognitive slowing (Madden et al., 1992; Verhaeghen et al., 2003). Alternative explanations point towards the assumption of task-set differentiation difficulties in advanced age, meaning that older adults have difficulties

activating and differentiating two concurrent task sets; this was at least explored in task-switching scenarios (Mayr & Liebscher, 2001). Another theory proposes an impairment in task-set shielding or allocation of attentional resources, attributed to an inhibitory deficit, resulting in the decline of effectively managing attention distribution across various task sets and the disruption of parallel processing, especially with task ambiguity (Hartley, 2001; Hein & Schubert, 2004; Mayr, 2001; Mayr & Liebscher, 2001). These mechanisms align with the reduced-inhibition hypothesis, which suggests that older adults' increased distractibility and interference susceptibility during cognitive tasks result from a decline in the capacity to suppress task-irrelevant information (Hasher & Zacks, 1988). However, it differs from other theories in that it partially attributes this decline to a working memory overload. Despite the prevalence of these theories, their application to the context of dual-tasking remains unexplored, prompting Studies 1 and 2 to investigate age-related cognitive and neural mechanisms underlying dual-task decline under conditions of response-code conflict.

1.2.2 Neurocognitive models of healthy aging

Considering that cognitive processes rely on the anatomy and physiology of the brain, it is reasonable that the field of cognitive neurosciences has searched for links between the observed behavioral differences in aging and age-related changes in the integrity of brain structure and function (Craik & Salthouse, 2008). The diverse and complex pattern of age-related differences in brain-behavior associations has led to multiple dynamic neurocognitive models integrating age-specific neural and behavioral alterations.

Aging is typically accompanied by structural changes in the brain, often referred to as brain atrophy, manifesting in volumetric reduction, cortical thinning, and a decrease in white-matter integrity. Exaggerated brain atrophy has been identified as a neural biomarker and a risk factor for transitioning from typical to pathological aging (Craik & Salthouse, 2008; Spreng & Turner, 2019).

Functionally, it is common to find reduced but also increased brain activations among older people when performing different cognitive tasks or being at rest. However, the relationship between brain structure and function is still under debate and research. A common neurocognitive interpretation is that hypoactivations in certain brain regions reflect brain atrophy and cognitive deficits that come with age. On the other hand, hyperactivations have been explained by two largely popular competing but not necessarily mutually exclusive neurocognitive models: The compensatory hypothesis and the neural dedifferentiation hypothesis (Grady, 2012; Spreng & Turner, 2019). The compensatory hypothesis interprets age-

related brain hyperactivations, typically in prefrontal and contralateral regions, as a beneficial neural over-recruitment to counteract brain atrophy and cognitive decline and facilitate successful task performance. Conversely, the dedifferentiation hypothesis assumes a loss of neural specificity when performing a particular task. The dedifferentiation becomes evident through more diffuse and less efficient brain activation patterns, encompassing regions that are unrelated to the task, like more dispersed activations in visual regions. According to this model, hyperactivations should not correlate with enhanced task performance. These two mechanisms have been integrated into a model named compensatory recruitment of neural circuits hypothesis (CRUNCH; Reuter-Lorenz & Cappell, 2008), including the dependency of the neural resources according to the particular task demands. It proposes that since cognitive processing may become noisier and inputs may be gated more poorly with age, more cognitive control is required, but neural resources in older people may reach a limit at a lower demand level. This results in the utilization of compensatory neural circuits to maintain performance but also in a dysfunctional reduction of neural specificity for certain functions.

The prevalent finding of over-recruitment of prefrontal cortical areas, a brain region implicated in cognitive control and several cognitive tasks, in advanced age has been explained via two additional models: The hemispheric asymmetry reduction in older adults (HAROLD; Cabeza, 2002) and the posterior-to-anterior shift with aging (PASA; Davis et al., 2008; Grady et al., 1994). The HAROLD model suggests that as people age, hemispheric lateralization patterns during cognitive processing begin to decrease, especially in the prefrontal cortex. The theory was inspired by young adults showing highly lateralized prefrontal activity when performing, for example, cognitive tasks involving inhibitory control. In contrast, the HAROLD model suggests that older adults recruit both hemispheres more equally to manage demanding cognitive tasks and, thus, shift toward more symmetrical brain activation patterns. On the other hand, the PASA model proposes that older adults show a change in activation distribution when demands for cognitive-control processes increase from a decrease in posterior activation to increased engagement of anterior brain regions. In contrast, in young adults, posterior areas are more involved than anterior ones. These age differences could be reflected in a positive correlation between behavioral scores and increased frontal activity but a negative correlation with posterior areas among older adults.

Similar to the semanticization of cognition theory, the scaffolding theory of aging cognition (STAC; Park & Reuter-Lorenz, 2009) acknowledges that neurocognitive aging may not solely be characterized by cognitive decline but also by an ability to change and adapt according to the cognitive demands and to develop external support systems. According to this

model, besides developing compensatory mechanisms, older adults may engage in selective optimization methods of specific cognitive functions particularly relevant to them and which facilitate brain maintenance. The model additionally emphasizes that older adults' brains can still undergo neuroplastic processes, allowing them to learn new abilities and reorganize their neural architecture in response to new challenges. Finally, older people can also profit from enrichment and protective factors, such as using tools and strategies, modifying their environment, and engaging in social activities.

A more recent model, the default-executive coupling hypothesis of aging (DECHA; Turner & Spreng, 2015), incorporates knowledge from functional connectivity studies and different neurocognitive models. The DECHA model suggests a shift in the relationship between two distinct brain networks as individuals age: The default mode network (DMN) and the executive-related networks. The DMN is primarily active during rest and internally focused tasks and becomes suppressed during externally oriented tasks. It comprises the posterior cingulate cortex, precuneus, medial temporal lobes, and medial prefrontal areas (Raichle, 2015; Raichle et al., 2001). In contrast, increased activation in the executive-related networks has been linked to tasks increasing cognitive demands and requiring attention, working memory, cognitive control, and goal-directed thinking. Studies have often reported that in young adults, there is a certain level of anti-correlation between the DMN and executive networks, such that the latter becomes more active during executive tasks, and the former is suppressed. The model proposes a shift in the association between these two networks as people age, such that the strong anti-correlation observed in young adults becomes weaker in the older. As such, this shift involves transitioning to a decline in control processes, as indicated by less active prefrontal areas, as well as to a stronger dependence on prior knowledge, as indicated by less suppression of the DMN. The shift to a more positive coupling between the two networks is supposed to facilitate the semanticization of cognition.

Diving more particularly into the age-related differences in dual-tasking and cognitive control, neuroimaging studies also report increased prefrontal activation when comparing older and young participants (Clapp et al., 2011; Hartley et al., 2011; Ohsugi et al., 2013; Thönes et al., 2018). Regarding brain connectivity related to cognitive control, resting-state functional connectivity studies suggest that age-related decreases in the intrinsic coupling of right dlPFC and bilateral aI and preSMA may go along with a decline in cognitive action control (Langner et al., 2015), as these regions are associated with overcoming conflict in tasks with S-R incompatibility (Cieslik et al., 2010). However, the previous study centered on resting-state functional connectivity in association with cognitive control. In contrast, age differences in

brain activation, as well as task-related connectivity, have not yet been explored in dual-tasking, particularly in relation to response-code conflict or in conjunction with other cognitive domains, which will be the focus of Study 2.

After reviewing the established neurocognitive models of healthy aging, the diversity of theories highlights the challenge of integrating the changes across multiple cognitive domains, the associated neural processes, and the high inter-individual variability inherent in these processes. Nevertheless, they represent a diligent effort to incorporate findings from a constantly evolving research field. More recent directions suggest that studying various neuroimaging modalities within multivariate approaches may offer valuable insights for the understanding of the aging brain, as will be emphasized in Study 3.

1.3 Elucidating brain-behavior associations through inter-individual differences

The large body of neurocognitive models and their implied inter-individual differences make apparent the complexity of the human neural architecture and their associated behavioral and cognitive processes. Inter-individual variability refers to the differences in the expression of one or more behaviors or neural characteristics between individuals of a population. This heterogeneity should be considered when studying brain-behavior associations and developing neurocognitive models, as they can shed light on the mechanisms underlying cognitive functions, neurological conditions, and age-related changes.

In the cognitive domain, for example, some individuals excel in certain cognitive tasks while others may struggle. A myriad of factors could explain these differences, but one is that individuals can use diverse mechanisms and strategies to solve a given task. For example, when performing a cognitive task, some people may prioritize completing the task quickly but sacrifice accuracy. On the other hand, other people may prioritize accuracy when completing a task, but this may take them longer, increasing their reaction times (RT). This principle is referred to as the speed-accuracy trade-off, and it stands for a continuum of focus on speed or accuracy when solving a task (Liesefeld & Janczyk, 2019). In the context of dual-tasking, some participants may prioritize one task over another, allocating their attentional resources differently or planning a task solution differently. These differences in cognitive strategies may encompass variability in brain activation patterns or brain network recruitment, such as the multiple-demand network (Assem et al., 2020; Miller et al., 2012; Wen et al., 2020). For that reason, it becomes relevant, on the one hand, to use behavioral measures that account for different facets of task performance and, on the other hand, integrate diverse cognitive and

neural processes (e.g., regional activation and functional connectivity) when assessing brain-behavior associations (Breukelaar et al., 2018).

In healthy cognitive aging, significant inter-individual variability has also been observed across cognitive domains, including working memory, processing speed, attention, and inhibitory control. While certain people experience a faster decline in certain cognitive abilities, others maintain relatively stable cognitive functioning as they age (Tucker-Drob & Salthouse, 2011). Even within the same person, certain cognitive domains may remain unaffected while others are more susceptible to deterioration. In dual-task performance, variability in age-related detriments could be explained, on the one hand, by some older adults experiencing generalized slowing and higher susceptibility to response or task confusability linked to declining working memory. On the other hand, others may already be predisposed to distractions when processing stimuli, linked to attentional deficits. Alternatively, some older adults may resort to over-using top-down control, which, for example, can lead to an excessive resource allocation to central processes, ultimately harming overall performance. This mechanism has been termed the over-reliance on central attention in advanced age (Maquestiaux & Ruthruff, 2021). These cognitive differences are additionally accompanied by heterogeneity in brain development in interaction with the interplay of environmental factors, such as lifestyle. For example, variability in cognitive aging may be partially explained by differences in brain atrophy or network coupling but also by the availability of an external support system and daily cognitive stimulation. Certain neurocognitive models, such as the STAC model, acknowledge the adaptability and plasticity of the cognitive system and neural architecture.

A long-standing statistical method to study brain-behavior associations has been the general linear model (GLM), which involves modeling brain activity as a linear combination of explanatory variables, such as the different experimental conditions of a paradigm (Huettel et al., 2009). It is usually used to detect activity changes in brain regions that respond to experimental manipulations at the group level or to explore group differences in brain activity. Additionally, one can incorporate covariates into the models, such as other cognitive scores, to assess to what level other behavioral measures can explain the variance in brain activation underlying a specific experimental setting.

Another method that has gained significant attention in the field of neuroimaging over the last two decades is the prediction framework using machine learning (ML), particularly for its potential to draw individual-level inferences from multivariate neuroimaging data patterns (Habeck & Stern, 2010; Scheinost et al., 2019). A standard ML procedure consists of, first,

extracting the neuroimaging features per participant, such as brain region's volumes, mean time series, or FC correlation values between pairs of brain areas, which form the independent variables, predictors, or features. Then, multivariate ML models are iteratively trained to identify neuroimaging patterns that best predict a given phenotype. The dependent variable or target could be, for example, a task performance score or a neurological disease label. Thus, ML models are an approach that considers the multivariate nature of brain organization when mapping neuroimaging patterns onto individual phenotypical data. The technique primarily used in ML to evaluate the prediction effectiveness of a model is cross-validation (CV). CV involves splitting the available data into a train and test subset (Hastie et al., 2009). The model is trained on a given fraction of subsets, and a subset is withheld to test the model. A different testing subset is used in each iteration. This process is repeated several times, randomly splitting the sample into train and test subsets in each iteration to evaluate the generalizability and robustness of the model with unseen and independent datasets (Habeck & Stern, 2010; Scheinost et al., 2019). In this way, inter-individual variability in neuroimaging data is accounted for, as each individual's multivariate features are considered when predicting individual targets, such as a task performance score or disease label.

While a common approach in predictive studies is to use neuroimaging features from the whole brain, another approach has been selecting brain networks composed of delimited areas that functionally represent or are close to the cognitive domain under study (Heckner et al., 2023a; Nostro et al., 2018; Pläschke et al., 2017, 2020). This approach is inspired by the assumption that these networks should maximally represent the neural substrates of the cognitive process of interest, either based on group-level GLM analyses or meta-analytic studies. In addition, delimited networks can facilitate the interpretability of the underlying mechanisms in brain-behavior associations. However, these approaches have not been studied profoundly in the context of multi-tasking or executive functions. Furthermore, the field of predictions in neurosciences still faces methodological and theoretical challenges, mirrored by overall low behavioral prediction accuracies and generalizability.

1.4 Ethics protocols

Studies 1 and 2 were performed following the positive vote by the local ethics committee of the RWTH Aachen University Hospital (Study Registration Number: EK 188/10).

Study 3 used open-access data from the Enhanced Nathan Kline Institute – Rockland Sample (eNKI). The local ethics committee of the Heinrich-Heine University in Düsseldorf

approved the analysis of the data, and all methods were carried out following the relevant guidelines and regulations (Study Registration Number: 4039).

1.5 Aims of the thesis

This work was conceived with the goal of enhancing behavioral and neuroscientific dual-tasking models by analyzing interference mechanisms influenced by response-related characteristics. While previous studies have identified a response-modality dominance pattern in dual-tasking (Huestegge & Koch, 2013), further investigation is needed to understand the impact of other response properties, such as spatial conflict, on dual-task interference. Additionally, cognitive neuroscientific and age-related dual-task research has largely overlooked response-related crosstalk. Therefore, the overarching aim of this study was to elucidate associations between dual-task interference at the response level and EF, on the one hand, and brain functioning and connectivity, on the other, while assessing how these associations are modulated by healthy cognitive aging.

Prior research has suggested that response-related characteristics may affect dual-task interference, such as potential crosstalk resulting from spatially incongruent response codes. This effect has been previously reported under cross-modal, but not unimodal, dual-response demands (Huestegge & Koch, 2010; Pieczykolan & Huestegge, 2014). Within this conceptual framework, **Study 1** aimed to disentangle how spatial response-code conflict within the same response modality impacts dual-task performance at the behavioral level and how these effects vary between young and older adults. To achieve this, we developed a novel dual-task paradigm to ensure that dual-task interference remained unconfounded by factors such as stimulus or response modality, temporal task overlap, task order, and the number and relative location of response alternatives.

Once we confirmed that crosstalk between conflicting response codes contributes to dual-task interference, we moved forward to the neural level by implementing the aforementioned dual-task paradigm in the MRI scanner with young and older adults. Thus, **Study 2** is a neuroimaging study that comprehensively analyzes the neural correlates of response-related dual-task crosstalk and aging and addresses inter-individual variability in various cognitive domains. The study had multiple objectives: First, it aimed to investigate brain activity correlates of dual-task response-code conflict; second, it sought to examine activity modulations based on individual dual-task performance and cognitive abilities related to executive functioning; and third, it explored task-modulated functional connectivity within

the dual-task conflict network. Lastly, age-related differences were assessed across all previous aspects.

Building upon the findings of Study 1 and Study 2, which elucidated behavioral and neural correlates of response-related dual-task interference, I embarked on a third project, considering that dual-tasking can be conceived as closely related to several of the cognitive abilities that form the multi-dimensional construct of EF. Therefore, we examined how brain-behavior associations looked for other executive functions using different brain metrics within multiple networks. Furthermore, since healthy aging processes are heterogeneous and manifest differently in neuronal and behavioral measures, using a method that would account for inter-individual variability was relevant. Thus, **Study 3** employed an ML framework and aimed to predict EF abilities in young and older adults using structural (gray-matter volume [GMV]) and resting-state functional brain characteristics (resting-state functional connectivity [RSFC], regional homogeneity [ReHO], fractional amplitude of low-frequency fluctuations [fALFF]). These measurements were derived from EF-related, perceptuo-motor, and whole-brain networks. The study focused on three main aspects: First, determining whether differences in out-of-sample prediction accuracy could be attributed to a specific modality; second, assessing if predictions varied based on the network, age group, or task-demand levels; third, examining whether young and older adults differed in their predictability depending on the brain metric, network, or task-demand level. In essence, this final study assessed the robustness and age-sensitivity of predicting a set of EF abilities based on diverse neuroimaging characteristics that capture aspects of brain structure and function across distinct networks.

- 2 Response-code conflict in dual-task interference and its modulation by age, Paas Oliveros, L. K., Pieczykolan, A., Pläschke, R. N., Eickhoff, S. B., Langner, R., *Psychological Research*, 87(1), 260–280, (2023)**
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- 3 Brain functional characterization of response-code conflict in dual-tasking and its modulation by age, Paas Oliveros, L. K., Cieslik, E. C., Pieczykolan, A., Pläschke, R. N., Eickhoff, S. B., Langner, R., *Cerebral Cortex*, 33(18), 10155–10180, (2023)**
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- 4 Predicting executive functioning from brain networks: Modality specificity and age effects, Heckner, M. K., Cieslik, E. C., Paas Oliveros, L. K., Eickhoff, S. B., Patil, K. R., Langner, R., *Cerebral Cortex*, 33(22), 10997–11009, (2023)**
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5 Discussion

5.1 Summary of findings

This work investigated the relationship between response-related dual-task interference and executive functioning (EF) on the one hand, and brain functioning and connectivity on the other, while assessing their modulation by healthy cognitive aging. It comprises three independent research papers. **Study 1** is a behavioral investigation. It showed that the nature of the responses and age both have an impact on dual-task performance. Building upon these behavioral findings, **Study 2** investigated how dual-tasking and EF relate to neural activity and connectivity in young and older participants. It found that brain areas of the multiple-demand network (MDN) are recruited when solving response conflict in dual-tasking. Activity within the conflict-specific MDN shared limited variance with EF and its connectivity was not sensitive to dual-task conflict or age effects. Compared to young adults, older adults showed a different brain activation pattern when dealing with response-code conflict in dual-tasking, with non-compensatory hyperactivity in left superior frontal gyrus (SFG). Finally, **Study 3** used brain characteristics of various networks to predict individual EF performance in young and older adults. In general, we found limited predictive power. Regional morphometric brain measures proved more predictive for older adults, while functional within-subject brain variability showed greater predictive ability for young adults. In the following, I provide a detailed summary of these findings.

In **Study 1** and **Study 2**, we developed and implemented an auditory-manual single-stimulus onset paradigm to assess response-related dual-task interference unconfounded by other dual-task parameters. Here, young and older adults responded to high- or low-pitched tones through spatially mapped button presses with one or two hands concurrently. This paradigm allowed us to manipulate the spatial congruency between response codes in dual conditions and induce intra-modal response-code conflict by having two spatially opposing stimulus–response (S-R) mapping rules between hands (e.g., high pitch – low hand response combined with a high hand response). At the behavioral level, **Study 1** and **Study 2** showed that across age groups, spatially incongruent response codes elicited substantial mutual interference, as reflected via significantly higher dual-task costs in the response–response (R-R) incongruent condition compared to settings with dual congruent responses. In the R-R incongruent condition, a notable asymmetric cost allocation was identified, in which S-R

compatible responses exhibited higher dual-task costs than their S-R incompatible counterpart. The cost asymmetry was confirmed even after removing trials with strongly synchronized responses. Moreover, the response-related interference effect was accentuated with advanced age. It is to be noted that these effects were observed across all performance scores, including dual-task speed and accuracy costs, as well as costs on the balanced integration score (BIS) incorporated in Study 2. The BIS is a recently introduced behavioral score that accounts for potentially different speed–accuracy trade-offs (Liesefeld et al., 2015; Liesefeld & Janczyk, 2019). Thus, Study 2 represents a within-scanner replication of the behavioral findings of Study 1, confirming that crosstalk between conflicting response codes contributes to dual-task interference, an effect that is exacerbated with age.

At the neural level, **Study 2** allowed us to delineate brain areas associated with response-code conflict in dual-tasking and their age-related differences. By contrasting R-R incongruent vs. congruent trials through a GLM approach, we identified that response-code conflict was linked to the recruitment of a large fronto-parieto-insular network, covering substantial parts of the MDN, such as dPMC, preSMA, MCC, dlPFC, anterior insula, SPL, thalamus, and cerebellum (Camilleri et al., 2018; Duncan, 2010). Here, older adults, compared to young adults, showed non-compensatory hyperactivity in left SFG when dealing with response-code conflict in dual-tasking. Since dual-tasking involves other cognitive abilities that may vary among individuals, we conducted a covariance analysis to account for the inter-individual variability in brain activity within the response-code conflict network. Thus, the second aim of the study addressed how activity during response-code conflict was modulated by individual dual-task performance and cognitive abilities related to executive functioning. We found that enhanced dual-task performance went along with higher bilateral SMA and premotor recruitment, pointing towards a critical brain-behavior association for enhanced dual-task conflict resolution. When incorporating executive abilities, we found limited shared variance with the task-related network. Increased thalamic and caudate activity during response-code conflict was associated with higher cross-modal attentional and working memory performance, and reduced medial prefrontal activity during congruent trials went along with a faster cross-modal allocation of attention. In addition, increased right IPS activity was linked to improved global task-switching abilities. Assessing the age differences herein, older adults showed increased engagement of right PMC and MFG during dual-task conflict resolution to be positively associated with higher working memory capacity. The final objective of this study was to explore task-modulated functional connectivity between conflict-sensitive brain regions (i.e., right dPMC and SPL) and the dual-task conflict network and assess whether the

connectivity is affected by age. Study 2 showed that conflict-modulated connectivity was not sensitive to dual-task response-code conflict for either of the premotor or parietal seed regions or age-related effects.

Further, **Study 3** assessed the potential of structural (GMV) and functional (RSFC, ReHo, and fALFF) brain parameters within EF-related and EF-unrelated networks for predicting individual EF abilities in young and older adults. The nodes of the EF-related network were derived through the maximum conjunction of three meta-analytic studies on working memory (Rottschy et al., 2012), cognitive action regulation (Langner et al., 2018), and multi-tasking (Worringer et al., 2019). It is to be noted that, although not identical, this network resembles substantial brain areas of the MDN, as well as the response-code conflict network identified in Study 2. The EF-unrelated control networks included nodes from a perceptuo-motor and a whole-brain network (Heckner et al., 2021; Power et al., 2011). Finally, the predicted EF abilities covered low- and high-demand subtasks of working memory, inhibitory control, and cognitive flexibility. Using a CV approach within an ML framework, Study 3 showed prediction accuracies of individual EF abilities to be low to moderate for all modalities, networks, task-demand levels, and age groups, with explained variance not exceeding more than 6%. Focusing first on the brain modalities, fALFF and GMV reached the highest accuracies for predicting individual EF abilities, but the modality effect was age-dependent. In young adults, EF performance was predicted best by fALFF, a marker for functional within-subject brain variability. In contrast, in older adults, regional GMV, well linked to brain atrophy, was the brain metric that carried the strongest information. Study 3 is, additionally, a confirmation of the results reported in the previous companion paper (Heckner et al., 2023a). Both studies showed that across modalities, the EF-related network was not superior to the perceptuo-motor or even whole-brain networks when predicting individual executive abilities. Furthermore, predictions in each age group depended on the task difficulty level. In young adults, high-demand (vs. low-demand) EF abilities were best predicted. In comparison, the effect was reversed for older adults, for which low-demand (vs. high-demand) EF conditions were best predicted. The following sections will discuss and integrate the findings of the three studies.

5.2 Interpretation of findings

Across the history of cognitive neurosciences, one of the major aims of the field has been to understand common brain mechanisms underlying higher cognitive functions (Gazzaniga et al., 2018; Purves et al., 2018). One of the most prevalent approaches to

accomplish this objective involves utilizing neuroimaging methods to identify statistical similarities in brain structure and function across individuals linked to cognitive processes (Gazzaniga et al., 2018; Purves et al., 2012). Brain functional changes have been evaluated through manipulations imposed by various diverse cognitive tasks or experimental paradigms (Huettel et al., 2009; Soares et al., 2016). These findings have provided valuable insights for proposing mechanisms underlying the brain-behavior associations. However, it is crucial to emphasize that no average brain is responsible for performing a cognitive task in each individual (Braver et al., 2010; Finn et al., 2017). Instead, the specific cognitive strategies and neural mechanisms engaged during the solution of a particular task are likely to be heterogeneous among individuals. Furthermore, although a common activation pattern exists at the group level, each subject probably engages slightly different brain regions, as well as brain areas beyond the group-level pattern, when performing a given task. Thus, an ultimate and much more recent endeavor in the field has been to map cognitive processes within individual brains (Yeung et al., 2022). One of the predominant methods towards that goal has been implementing ML models, which account for and are sensitive to inter-individual differences, to predict and identify brain-behavior associations at the individual level (Poldrack et al., 2020; Scheinost et al., 2019; Yeung et al., 2022).

Considering these two overarching approaches in neuroimaging, one can see this work as, on the one hand, focusing on identifying common behavioral, cognitive, and neural patterns associated with dual-tasking across subjects, as well as assessing their age-related differences. Herein, we incorporated inter-individual differences in individual dual-task performance and EF abilities through covariance analyses. On the other hand, the last study sought to map brain characteristics to individual EF abilities with a framework sensitive to inter-individual differences in brain structure and function and their age-related differences.

5.2.1 Coping with response-code dual-task crosstalk and difficulties in healthy aging

A predominant model in the field of dual-task crosstalk has been the structural bottleneck model, which assumes a sequential response selection in dual-tasking, meaning that the response for the second task can only be selected after the response selection of the first or easier task has finalized (De Jong, 1995; Pashler, 1994; Strobach et al., 2018). Our findings are at odds with this model. Behaviorally, we found increased dual-task interference when two concurrent tasks with spatially opposing response codes had to be processed. However, most importantly, an atypical subtask order implied by the asymmetric cost allocation depending on the response compatibility towards the stimulus was observed, which is against a rigid serial

response selection strategy. As discussed in **Study 1** and **Study 2**, the underadditive cost asymmetry is more consistent with a rather flexible model, in which the cognitive system is capable of adapting to the specific task demands (Fischer & Plessow, 2015; Hazeltine et al., 2006; Koch et al., 2018; Pieczykolan & Huestegge, 2019). Our findings point towards a limited but strategic resource allocation according to task difficulty for preventing crosstalk in multiple-task scenarios, which has been previously reported in cross-modal scenarios (Huestegge & Koch, 2010; Pieczykolan & Huestegge, 2014; Weller et al., 2022). It appears likely that participants prioritize and allocate more processing resources toward the more demanding (incompatible) task, leaving the easier (compatible) response unattended (Hoffmann et al., 2020; Huestegge & Koch, 2010; Lehle & Hübner, 2009; Pieczykolan & Huestegge, 2014). For that reason, a large part of dual-task costs are conferred onto the easier but deprioritized task, while the more demanding task is shielded against crosstalk and suffers from lower dual-task costs. Alternatively, instead of engaging in an active and strategic resource allocation, a natural top-down bias may explain the increased attention toward the incompatible response, affecting task-set shielding (see Rusconi et al., 2006).

In addition to a flexible and possibly strategic resource allocation under dual-task conditions of response-code conflict, participants likely implemented a response grouping strategy, in which the first response is selected but held in until the second response has also been selected and is ready to be executed, presumably because it is easier to emit two responses simultaneously than in rapid succession (Fagot & Pashler, 1992; Pashler, 1994; Ulrich & Miller, 2008). The variability in cognitive strategies implemented within a cognitive task may differ between subjects, and, as suggested previously, the decision for a specific strategy might be made online within each trial (Miller & Ulrich, 2008).

A robust body of studies has reported that difficulties in dual-tasking are exacerbated with advanced age (Koch et al., 2018; Verhaeghen et al., 2003). However, the age-related deficits still need to be explored under dual-task settings with interference at the response level, unconfounded by other dual-task factors. The negative effects of incongruent response codes in older adults, observed across **Study 1** and **Study 2**, confirm that the ability to shield ambiguous task sets becomes compromised in older adults, particularly in situations where two mutually incongruent response codes need to be selected concurrently from otherwise highly similar task sets (Mayr, 2001; Mayr & Liebscher, 2001). These age-related dual-task differences do not underlie a difference in the speed–accuracy trade-off between age groups. However, the deficits can be partially explained by generalized slowing (Salthouse, 1996) or response grouping (Miller & Ulrich, 2008). Alternatively, older adults may experience an

inhibitory deficit, affecting their ability to control and manage their attentional resources across different tasks in multi-tasking scenarios. This could lead to interference and distraction between parallel processing streams and, ultimately, to response-code confusability (Hein & Schubert, 2004; Mayr, 2001; Mayr & Liebscher, 2001). Furthermore, older adults may voluntarily over-use attentional resources when confronted with demanding tasks, possibly attributed to an over-reliance on central attention with advanced age (Maquestiaux & Ruthruff, 2021), in this case, intending to improve performance and prevent dual-task crosstalk. Unfortunately, this overexerted top-down attention allocation, where not needed, could ultimately lead to reduced overall performance.

5.2.2 Mapping dual-task response-code conflict onto brain function and age-related differences

Through a step-wise analysis of the neuroimaging data of dual-tasking and age differences, it became possible to elucidate specific stages of the brain functional mechanisms involved in resolving dual-task response-code conflict and its modulation by age. Across subjects, dual-response execution, meaning simultaneously executing two congruent responses with a conjoint response selection process compared to single-hand reaction tasks, required increased input from motor, parietal, thalamic, and cerebellar areas, indicating that this aspect engages mainly brain processes involved in motor output and spatial transformations (Grefkes et al., 2004; Jäncke et al., 2000; Rizzolatti et al., 1998; van Dun et al., 2021). These findings are consistent with the literature, suggesting an upregulation of mainly motor areas during bimanual response execution (Jäncke et al., 2000; Nair et al., 2003; Swinnen & Gooijers, 2015). Additionally, dual-response execution was accompanied by reduced bilateral occipital and medial prefrontal activity, indicating an attentional shift away from the visual modality (Langner et al., 2011; Mozolic et al., 2008) and the downregulation of the task-negative DMN (Fox et al., 2005; Raichle et al., 2001) during an auditory-manual externally focused task. Behaviorally and neurally, this process appears to be well-preserved in age, since no differences were identified.

In the following step, we analyzed dual-tasking at large, meaning having two concurrent spatially incongruent mapping selections compared to single tasks. Dual-tasking showed to require, beyond motor-related areas, more top-down cognitive control by recruiting a large fronto-parieto-insular network covering regions of the extended MDN, involved in top-down executive control, as well as multi-tasking (Al-Hashimi et al., 2015; Camilleri et al., 2018; Duncan, 2010; Müller et al., 2015; Papegaaij et al., 2017; Worringer et al., 2019). As with dual-

response execution, global dual-tasking is consistently linked with visual processing disengagement and DMN suppression. In this case, age-related differences in brain functioning became apparent. When more demands were put on top-down cognitive control during dual-tasking, older adults showed hyperactivation in medial motor, cingulate and prefrontal areas, indicating increased difficulties in handling and coordinating incongruent dual-task sets (Goble et al., 2010; Swinnen & Gooijers, 2015) and inhibiting inadequate response tendencies (Botvinick et al., 2004; Cieslik et al., 2015; Corbetta & Shulman, 2002).

Ultimately, resolving response-code conflict in dual-tasking, meaning comparing two spatially incongruent mapping selections with a dual-response condition with a conjoint mapping selection, required additional top-down executive control via a more circumscribed but domain-general fronto-parieto-insular network (MDN) without additional primary motor recruitment nor reductions in brain activity. During dual-task response-code conflict resolution, besides other brain areas, right dPMC and SPL showed the strongest activation effect, presumably engaged in motor response preparation, for the former (Abe & Hanakawa, 2009; Genon et al., 2016; Worringer et al., 2019), and top-down attentional control shifting and spatial information processing, for the latter (Corbetta & Shulman, 2002; Grefkes et al., 2004; Langner et al., 2014). Furthermore, we found a critical brain-behavior association of dual-task response-related crosstalk effect when incorporating inter-individual variability in individual dual-task performance. Our results indicate that increased bilateral SMA and premotor activity is associated with enhanced conflict and interference resolution (Cieslik et al., 2010; Isherwood et al., 2021; Nachev et al., 2008) and accurate response preparation (Beurze et al., 2007; Genon et al., 2016) in demanding dual-task settings where spatially incongruent response codes need to be processed concurrently.

Interestingly, the activity within the conflict-sensitive MDN as a whole did not share general variance with executive functioning overall, as we only found limited overlap when introducing inter-individual variability in other EF abilities. For instance, only bilateral IPS and SPL conflict-sensitive activity shared variance with task-switching performance, emphasizing their relevance in effectively and flexibly allocating and maintaining spatial motor attentional resources across two concurrent task sets (Iacoboni, 2006; Rushworth et al., 2001; Saylik et al., 2022; Weiss et al., 2006; Worringer et al., 2019). Conversely, increased thalamic and caudate activity in the response-code conflict network was linked to enhanced cross-modal attentional and spatial working-memory performance. This suggests an attentional and task-rule maintenance requirement for resolving response-related interference between two tasks. It is worth noting that while these subcortical nuclei are part of the extended MDN (Camilleri et al.,

2018), they are densely packed brain regions associated with a wide range of cognitive functions (Boeken et al., 2022), including sensorimotor functions, movement regulation (Sommer, 2003), and higher-order cognitive functioning (Camilleri et al., 2018). However, contrary to our expectations, the activity of key MDN regions typically representative of cognitive control, such as lateral prefrontal areas and MCC, did not share variance between dual-task response-code conflict and executive functioning.

Regarding the impact of age on response-code conflict in dual-tasking, older adults demonstrated hyperactivation in a specific cluster in the left SFG when coping with conflicting response codes. This is consistent with previous literature reporting a potential compensatory over-recruitment of prefrontal resources to counteract age-related brain structural and functional decline and deficits in executive functioning (Reuter-Lorenz & Cappell, 2008; Seidler et al., 2010; Spreng & Turner, 2019). However, in our case, the left SFG hyperactivation did not indicate a compensatory mechanism because no positive association with dual-task performance was found. Instead, increased activity in right premotor and middle frontal areas during dual-task response-code conflict was linked with higher working memory capacity in older adults compared to young adults. Thus, these findings instead reflect a dedifferentiation pattern with more widespread activation and a loss of regional specificity in aging without any behavioral improvement, but also a potential inter-individual heterogeneity in strategies employed by older adults (Park et al., 2001; Voss et al., 2008). The mechanisms behind the increased behavioral dual-task costs in conditions with incongruent response codes among older adults may, thus, include a higher task-rule confusability or difficulty in maintaining the task sets (Hein & Schubert, 2004; Mayr, 2001; Mayr & Liebscher, 2001) for accurate dual-task processing and motor execution, which engages right premotor and frontal areas. Alternatively, similar to the theory of an over-reliance on central attention (Maquestiaux & Ruthruff, 2021), older adults may have put increased effort into maintaining the task rules more prominently to compensate for the cognitive deficits, e.g., reduced processing speed, that come with age, resulting, however, in an inefficient recruitment of neural resources in PMC and MFG, as indicated by higher dual-task costs. Additionally, the influence of spatial working memory on right premotor and middle frontal activity, coupled with the behavioral observation of generalized slowing in older adults, may indicate a tendency to be generally slower in distributing spatial motor attentional resources amidst conflicting mappings and sustaining task sets for optimal behavioral performance.

Finally, the lack of task-modulated connectivity changes during dual-task response-code conflict for either of the seed regions and the absence of any age differences reflect that

functional synchrony between conflict-sensitive brain areas is not pivotal for the efficient processing of simultaneous and conflicting mapping selection. In contrast, it is the level of activity within the MDN that emerges as a crucial component for coping with conflicting response codes in dual-tasking.

5.2.3 Mapping structural and functional brain characteristics onto individual executive performance

Based on the previous findings, it becomes evident that, across subjects, the general neural pattern for solving conflicting dual-task scenarios is to recruit the domain-general MDN instead of involving specific and delimited brain regions. Considering dual-tasking as part of the umbrella term of EF, our findings resonate well with the ample research literature associating EF with the MDN. However, the question arises whether different brain characteristics within such a network are informative to map their inter-individual characteristics onto each individual and identify each subject's unique cognitive performance level. The weak brain-behavior associations obtained in **Study 3** showed that predicting individual behavioral performance remains challenging, although the predictability levels are comparable to previous related research. Here, it is relevant to reiterate that, in contrast to Study 2 using tb-fMRI, the brain characteristics used to predict EF performance in this study were extracted from regional structural MRI (GMV) and task-unconstrained rs-fMRI (RSFC, ReHo, and fALFF), representing intrinsic functional measures.

On the one hand, since the whole-brain network achieved superior or similar prediction accuracies compared to the EF-related and perceptuo-motor networks, the relevance of global brain organizational properties in brain-behavior associations becomes apparent (Heckner et al., 2023a; Pläschke et al., 2020). The EF-related network was derived through the conjunction of meta-analytic studies using tb-fMRI on three core executive functions: Working memory (Rottschy et al., 2012), cognitive regulation (Langner et al., 2018), and multi-tasking (Worringer et al., 2019), and the obtained network covers substantial regions of the MDN. The network, thus, entails a highly reliable and robust convergence of brain areas associated with EF across the vast majority of studies and usually young subjects. Its superiority in predictability would have facilitated the interpretation of brain-behavior associations. Contrary to that assumption, it appears that the constrained network does not suffice to explain inter-individual differences in EF performance. On the other hand, the specific reason underlying the whole-brain network superiority in prediction accuracies still remains to be revealed. A potential reason is a larger feature space, as the whole-brain network includes significantly more

nodes than the task-specific one. Another reason is that the whole-brain network might include hubs or areas unspecific to EF but crucial for information exchange between brain networks, ultimately relevant for individual executive control (Heckner et al., 2023a). In any way, our results align with previous reports showing comparable or superior prediction accuracies based on whole-brain (vs. task-specific) networks (Kraljević et al., 2023; Pläschke et al., 2020).

Within the scope of overall low prediction accuracies, GMV and fALFF held a higher potential in predicting individual differences in EF performance when compared to the other modalities, and this potential is different between age groups. Individual EF performance in older adults was better explained by GMV, a measure that could reflect brain atrophy processes that come with advanced age. In contrast, young adults' individual EF performance was predicted better by fALFF, a measure of functional within-subject brain variability that may reflect their ability of cognitive adaptability to complex task demands (Uddin, 2020), as well as the flexibility and intrinsic variability to explore different functional network configurations for efficient task performance (Deco et al., 2011; Garrett et al., 2011). Furthermore, the overall better predictability of older (vs. young) adults' EF performance was not only modality-dependent but was also affected by the task difficulty level. In young adults, high-demanding EF tasks were most sensitive for capturing inter-individual differences in EF abilities. In contrast, in older adults, the low-demanding EF tasks were best predicted by the brain characteristics. This age-related predictability difference according to task difficulty is potentially explained by a compensatory mechanism (Reuter-Lorenz & Cappell, 2008), which would assume that older adults manage to recruit additional neural resources that suffice to compensate for performance in low-demanding conditions. However, a ceiling effect is reached so that the neural resources do not suffice to meet high-level task demands.

5.3 Navigating the limitations and charting the future path

Although this work offers new insights into dual-task interference at the response level, it is essential to note that the paradigm used in Study 1 and Study 2 tackles a specific and constricted process underlying dual-task interference. Further research is required to assess the relevance of output-related features interfering with dual-task abilities and their changes across ages within the context of a content-dependent central interference model. For example, studies could manipulate different dual-task parameters, such as having different response modalities in combination with different input systems, to investigate which combinations increase or decrease the probabilities of response-code confusability. To insert our findings into a broader perspective, it would be required to explore how our findings generalize using more

conventional task settings, considering input-output modality compatibility effects and different temporal overlaps. Within this context, a step-wise analysis of the neural mechanisms based on diverse task difficulty levels within an experimental paradigm, as exemplified in Study 2, offers the potential for more detailed insights into the specific brain mechanisms underlying complex cognitive processes. Likewise, using different behavioral scores that account for variability in cognitive performance, such as speed-accuracy trade-offs, will expand our knowledge of underlying cognitive mechanisms. This approach facilitates the interpretability of the findings and opens avenues for a more profound understanding of higher-order cognitive functions.

The GLM approach relies on within-sample consistent brain activations across subjects and aims to make population-level inferences based on the obtained brain-behavior associations. Since this approach is rather informative at the group-average level, it remains open to what extent individual brain activation and connectivity can explain differences in the individual's dual-task performance. Thus, a multivariate ML framework could be advantageous to validate our findings with unseen samples (i.e., out-of-sample predictions). However, it is relevant to note that univariate GLM and multivariate ML approaches should complement rather than contradict each other. At least, predicting individual EF abilities from different brain characteristics obtained from structural MRI and intrinsic rs-fMRI has proved challenging (Heckner et al., 2023b). New promising avenues in prediction studies entail featuring multi-modal neuroimaging data, such as combining rs- and tb-fMRI, structural and diffusion MRI, or different imaging techniques, such as magnetoencephalography, positron emission tomography, or functional near-infrared spectroscopy, with stacking frameworks to integrate multiple ML models (Engemann et al., 2020; Vaghari et al., 2022).

Recent research has shown that phenotypical prediction from functional connectivity during more constricted task settings (e.g., movie watching) may outperform prediction accuracies derived from rest (Finn & Bandettini, 2021; Greene et al., 2018; Kraljević et al., 2023). Since tasks modulate functional brain states, they may be informative for inter-individual differences in brain-behavior associations (Greene et al., 2018). Furthermore, functional and structural connectomes appear to carry different information related to cognition (Dhamala et al., 2021). Since structural brain measures (GMV) explained individual EF performance better in older adults, it may be advisable to test additional structural measures sensitive to brain atrophy in advanced age, such as structural connectivity.

Furthermore, meta-analytical networks derived from task-based fMRI offer robust and convergent nodes across most studies and subjects associated with a particular cognitive

process. However, when implementing those nodes in an ML framework, the inter-individual differences of brain characteristics are constrained to the alignment within the network nodes. In contrast, it has become increasingly recognized that the topography (e.g., size, shape, and position), subdivision, and connectivity patterns of single brain functional regions vary between individuals (Mueller et al., 2013). Recent studies have marked a promising research avenue being able to achieve better task-performance prediction accuracies from individualized resting-state networks, accounting for inter-individual variability in the functional organization of the brain, compared to group-level brain atlases (Kong et al., 2021; Li et al., 2019). For example, a future study may involve predicting individual dual-task performance from functional and structural connectomes in individualized task-specific and whole-brain networks.

Finally, given the studies' cross-sectional nature, it would be beneficial to use longitudinal designs to analyze intra-individual variability in brain and cognitive processes, considering both short-term fluctuations but also systemic changes over a more extended period of time, likely due to developmental and environmental factors that contribute to the age-related deficits.

5.4 Conclusions

This work sheds light on the complex relationships between brain activity and connectivity, inter-individual differences, and dual-task interference as part of executive functioning, as well as their modulation by healthy cognitive aging. Across subjects, the pattern of increased behavioral interference but asymmetric cost allocation with response-code conflict in dual-tasking corroborated a flexible allocation of attentional resources and a strategic prioritization of limited processing capacity, besides response grouping, which engaged substantial parts of the domain-general multiple-demand network. Within this response-code conflict network, thalamic and parietal activity was modulated by attentional, working-memory and task-switching abilities, but enhancing supplementary motor and premotor activity was shown to be crucial for efficient dual-task conflict resolution and response preparation. Task-modulated functional connectivity between conflict-sensitive regions, on the contrary, was not pivotal for efficiently processing incongruent dual-task mapping selections nor sensitive to age-related differences.

Older adults showed marked deficits in multiple-action control at the level of task-set shielding, with non-compensatory hyperactivity in left superior frontal gyrus. Our findings suggest higher response-code confusability and difficulties maintaining the task sets for accurate dual-task processing, which engage right premotor and frontal areas. In addition to

general slower distribution of spatial motor attentional resources, older adults may over-exert attentional and working memory resources to compensate for the cognitive and neural decline that come with age, resulting, however, in an inefficient recruitment of right premotor and frontal areas. Dual-task interference should be further studied using different response modalities, dual-task parameters, and conventional dual-task settings, as well as their modulation by age.

Although these group-level patterns offer new information about neural and cognitive mechanisms underlying dual-task interference processes, it remains challenging to predict individual executive function abilities from structural and functional brain metrics, at least considering structural (GMV) and intrinsic functional (RSFC, ReHo, and fALFF) brain metrics. The global organization of the whole brain carries relevant information for individual task performance, compared to task-delimited networks that are consistently activated across subjects. Nonetheless, measures of functional within-subject brain variability (fALFF) offer higher promise for predicting EF abilities in young adults, while structural brain metrics possibly reflecting brain atrophy processes (GMV) do so for older adults.

Our findings underscore the complexity of individual cognitive control, the involvement of the MDN in dual-task conflict resolution, and the challenges of using single brain metrics as reliable predictors of EF abilities. A holistic approach that combines different structural and functional metrics from individualized networks, accounting for the inter-individual variability in the topography and functional organization of the brain, may hold promise for improving predictions, especially in distinct age groups.

6 References

- Abe, M., & Hanakawa, T. (2009). Functional coupling underlying motor and cognitive functions of the dorsal premotor cortex. *Behavioural Brain Research*, *198*(1), 13–23.
<https://doi.org/10.1016/j.bbr.2008.10.046>
- Al-Hashimi, O., Zanto, T. P., & Gazzaley, A. (2015). Neural sources of performance decline during continuous multitasking. *Cortex*, *71*, 49–57. <https://doi.org/10.1016/j.cortex.2015.06.001>
- Assem, M., Blank, I. A., Mineroff, Z., Ademoğlu, A., & Fedorenko, E. (2020). Activity in the frontoparietal multiple-demand network is robustly associated with individual differences in working memory and fluid intelligence. *Cortex*, *131*, 1–16.
<https://doi.org/10.1016/j.cortex.2020.06.013>
- Beurze, S. M., de Lange, F. P., Toni, I., & Medendorp, W. P. (2007). Integration of Target and Effector Information in the Human Brain During Reach Planning. *Journal of Neurophysiology*, *97*(1), 188–199. <https://doi.org/10.1152/jn.00456.2006>
- Biswal, B. (2012). Resting state fMRI: A personal history. *NeuroImage*, *62*(2), 938–944.
<https://doi.org/10.1016/j.neuroimage.2012.01.090>
- Biswal, B., Zerrin Yetkin, F., Haughton, V. M., & Hyde, J. S. (1995). Functional connectivity in the motor cortex of resting human brain using echo-planar MRI. *Magnetic Resonance in Medicine*, *34*(4), 537–541. <https://doi.org/10.1002/mrm.1910340409>
- Boeken, O. J., Cieslik, E. C., Langner, R., & Markett, S. (2022). Characterizing functional modules in the human thalamus: Coactivation-based parcellation and systems-level functional decoding. *Brain Structure and Function*. <https://doi.org/10.1007/s00429-022-02603-w>
- Botvinick, M. M., Cohen, J. D., & Carter, C. S. (2004). Conflict monitoring and anterior cingulate cortex: An update. *Trends in Cognitive Sciences*, *8*(12), 539–546.
<https://doi.org/10.1016/j.tics.2004.10.003>
- Braver, T. S., Cole, M. W., & Yarkoni, T. (2010). Vive les differences! Individual variation in neural mechanisms of executive control. *Current Opinion in Neurobiology*, *20*(2), 242–250.
<https://doi.org/10.1016/j.conb.2010.03.002>
- Breukelaar, I. A., Williams, L. M., Antees, C., Grieve, S. M., Foster, S. L., Gomes, L., & Korgaonkar, M. S. (2018). Cognitive ability is associated with changes in the functional organization of the cognitive control brain network. *Human Brain Mapping*, *39*(12), 5028–5038.
<https://doi.org/10.1002/hbm.24342>
- Cabeza, R. (2002). Hemispheric asymmetry reduction in older adults: The HAROLD model. *Psychology and Aging*, *17*(1), 85–100. <https://doi.org/10.1037/0882-7974.17.1.85>
- Camilleri, J. A., Müller, V. I., Fox, P., Laird, A. R., Hoffstaedter, F., Kalenscher, T., & Eickhoff, S. B. (2018). Definition and characterization of an extended multiple-demand network.

- NeuroImage*, 165, 138–147. <https://doi.org/10.1016/j.neuroimage.2017.10.020>
- Cieslik, E. C., Mueller, V. I., Eickhoff, C. R., Langner, R., & Eickhoff, S. B. (2015). Three key regions for supervisory attentional control: Evidence from neuroimaging meta-analyses. *Neuroscience & Biobehavioral Reviews*, 48, 22–34. <https://doi.org/10.1016/j.neubiorev.2014.11.003>
- Cieslik, E. C., Zilles, K., Kurth, F., & Eickhoff, S. B. (2010). Dissociating Bottom-Up and Top-Down Processes in a Manual Stimulus–Response Compatibility Task. *Journal of Neurophysiology*, 104(3), 1472–1483. <https://doi.org/10.1152/jn.00261.2010>
- Clapp, W. C., Rubens, M. T., Sabharwal, J., & Gazzaley, A. (2011). Deficit in switching between functional brain networks underlies the impact of multitasking on working memory in older adults. *Proceedings of the National Academy of Sciences*, 108(17), 7212–7217. <https://doi.org/10.1073/pnas.1015297108>
- Corbetta, M., & Shulman, G. L. (2002). Control of goal-directed and stimulus-driven attention in the brain. *Nature Reviews Neuroscience*, 3(3), 201–215. <https://doi.org/10.1038/nrn755>
- Craik, F. I. M., & Salthouse, T. A. (2008). *The Handbook of Aging and Cognition*. Psychology Press.
- Davis, S. W., Dennis, N. A., Daselaar, S. M., Fleck, M. S., & Cabeza, R. (2008). Que PASA? The posterior-anterior shift in aging. *Cerebral Cortex*, 18(5), 1201–1209. <https://doi.org/10.1093/cercor/bhm155>
- De Jong, R. (1995). The Role of Preparation in Overlapping-task Performance. *The Quarterly Journal of Experimental Psychology*, 48(1), 2–25. <https://doi.org/10.1080/14640749508401372>
- Deco, G., Jirsa, V. K., & McIntosh, A. R. (2011). Emerging concepts for the dynamical organization of resting-state activity in the brain. *Nature Reviews Neuroscience*, 12(1), 43–56. <https://doi.org/10.1038/nrn2961>
- Deprez, S., Vandenbulcke, M., Peeters, R., Emsell, L., Amant, F., & Sunaert, S. (2013). The functional neuroanatomy of multitasking: Combining dual tasking with a short term memory task. *Neuropsychologia*, 51(11), 2251–2260. <https://doi.org/10.1016/j.neuropsychologia.2013.07.024>
- Dhamala, E., Jamison, K. W., Jaywant, A., Dennis, S., & Kuceyeski, A. (2021). Distinct functional and structural connections predict crystallised and fluid cognition in healthy adults. *Human Brain Mapping*, 42(10), 3102–3118. <https://doi.org/10.1002/hbm.25420>
- Diamond, A. (2013). Executive Functions. *Annual Review of Psychology*, 64(1), 135–168. <https://doi.org/10.1146/annurev-psych-113011-143750>
- Duncan, J. (2010). The multiple-demand (MD) system of the primate brain: Mental programs for intelligent behaviour. *Trends in Cognitive Sciences*, 14(4), 172–179. <https://doi.org/10.1016/j.tics.2010.01.004>
- Engemann, D. A., Kozynets, O., Sabbagh, D., Lemaître, G., Varoquaux, G., Liem, F., & Gramfort, A. (2020). Combining magnetoencephalography with magnetic resonance imaging enhances

- learning of surrogate-biomarkers. *eLife*, 9, e54055. <https://doi.org/10.7554/eLife.54055>
- Fagot, C., & Pashler, H. (1992). Making two responses to a single object: Implications for the central attentional bottleneck. *Journal of Experimental Psychology: Human Perception and Performance*, 18(4), 1058–1079. <https://doi.org/10.1037/0096-1523.18.4.1058>
- Finn, E. S., & Bandettini, P. A. (2021). Movie-watching outperforms rest for functional connectivity-based prediction of behavior. *NeuroImage*, 235, 117963. <https://doi.org/10.1016/j.neuroimage.2021.117963>
- Finn, E. S., Scheinost, D., Finn, D. M., Shen, X., Papademetris, X., & Constable, R. T. (2017). Can brain state be manipulated to emphasize individual differences in functional connectivity? *NeuroImage*, 160, 140–151. <https://doi.org/10.1016/j.neuroimage.2017.03.064>
- Fischer, R., & Plessow, F. (2015). Efficient multitasking: Parallel versus serial processing of multiple tasks. *Frontiers in Psychology*, 6(September), 1–11. <https://doi.org/10.3389/fpsyg.2015.01366>
- Fox, M. D., Snyder, A. Z., Vincent, J. L., Corbetta, M., Van Essen, D. C., & Raichle, M. E. (2005). The human brain is intrinsically organized into dynamic, anticorrelated functional networks. *Proceedings of the National Academy of Sciences*, 102(27), 9673–9678. <https://doi.org/10.1073/pnas.0504136102>
- Friedman, N. P., & Miyake, A. (2017). Unity and diversity of executive functions: Individual differences as a window on cognitive structure. *Cortex*, 86, 186–204. <https://doi.org/10.1016/j.cortex.2016.04.023>
- Garrett, D. D., Kovacevic, N., McIntosh, A. R., & Grady, C. L. (2011). The Importance of Being Variable. *Journal of Neuroscience*, 31(12), 4496–4503. <https://doi.org/10.1523/JNEUROSCI.5641-10.2011>
- Gazzaniga, M. S., Ivry, R. B., & Mangun, G. R. (2018). *Cognitive Neuroscience: The Biology of the Mind* (5th ed.). WW Norton & Co.
- Genon, S., Li, H., Fan, L., Müller, V. I., Cieslik, E. C., Hoffstaedter, F., Reid, A. T., Langner, R., Grefkes, C., Fox, P. T., Moebus, S., Caspers, S., Amunts, K., Jiang, T., & Eickhoff, S. B. (2016). The Right Dorsal Premotor Mosaic: Organization, Functions, and Connectivity. *Cerebral Cortex*, 27(3), 2095–2110. <https://doi.org/10.1093/cercor/bhw065>
- Goble, D. J., Coxon, J. P., Van Impe, A., De Vos, J., Wenderoth, N., & Swinnen, S. P. (2010). The neural control of bimanual movements in the elderly: Brain regions exhibiting age-related increases in activity, frequency-induced neural modulation, and task-specific compensatory recruitment. *Human Brain Mapping*, 31(8), 1281–1295. <https://doi.org/10.1002/hbm.20943>
- Grady, C. L. (2012). The cognitive neuroscience of ageing. *Nature Reviews Neuroscience*, 13(7), 491–505. <https://doi.org/10.1038/nrn3256>
- Grady, C. L., Maisog, J. M., Horwitz, B., Ungerleider, L. G., Mentis, M. J., Salerno, J. A., Pietrini, P., Wagner, E., & Haxby, J. V. (1994). Age-related changes in cortical blood flow activation during visual processing of faces and location. *The Journal of Neuroscience: The Official*

- Journal of the Society for Neuroscience*, 14(3 Pt 2), 1450–1462.
<https://doi.org/10.1523/JNEUROSCI.14-03-01450.1994>
- Greene, A. S., Gao, S., Scheinost, D., & Constable, R. T. (2018). Task-induced brain state manipulation improves prediction of individual traits. *Nature Communications*, 9, 2807.
<https://doi.org/10.1038/s41467-018-04920-3>
- Grefkes, C., Ritzl, A., Zilles, K., & Fink, G. R. (2004). Human medial intraparietal cortex subserves visuomotor coordinate transformation. *NeuroImage*, 23(4), 1494–1506.
<https://doi.org/10.1016/j.neuroimage.2004.08.031>
- Habeck, C., & Stern, Y. (2010). Multivariate Data Analysis for Neuroimaging Data: Overview and Application to Alzheimer’s Disease. *Cell Biochemistry and Biophysics*, 58(2), 53–67.
<https://doi.org/10.1007/s12013-010-9093-0>
- Hartley, A. A. (2001). Age differences in dual-task interference are localized to response-generation processes. *Psychology and Aging*, 16(1), 47–54. <https://doi.org/10.1037/0882-7974.16.1.47>
- Hartley, A. A., Jonides, J., & Sylvester, C.-Y. C. (2011). Dual-task processing in younger and older adults: Similarities and differences revealed by fMRI. *Brain and Cognition*, 75(3), 281–291.
<https://doi.org/10.1016/j.bandc.2011.01.004>
- Hasher, L., & Zacks, R. T. (1988). Working memory, comprehension, and aging: A review and a new view. In G. H. Bower (Ed.), *The Psychology of Learning and Motivation: Advances in Research and Theory* (Vol. 22, pp. 193–225). Academic Press. [https://doi.org/10.1016/S0079-7421\(08\)60041-9](https://doi.org/10.1016/S0079-7421(08)60041-9)
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning*. Springer.
<https://doi.org/10.1007/978-0-387-84858-7>
- Hazeltine, E., Ruthruff, E., & Remington, R. W. (2006). The role of input and output modality pairings in dual-task performance: Evidence for content-dependent central interference. *Cognitive Psychology*, 52(4), 291–345. <https://doi.org/10.1016/j.cogpsych.2005.11.001>
- Heckner, M. K., Cieslik, E. C., Küppers, V., Fox, P. T., Eickhoff, S. B., & Langner, R. (2021). Delineating visual, auditory and motor regions in the human brain with functional neuroimaging: A BrainMap-based meta-analytic synthesis. *Scientific Reports*, 11(1), 9942.
<https://doi.org/10.1038/s41598-021-88773-9>
- Heckner, M. K., Cieslik, E. C., Patil, K. R., Gell, M., Eickhoff, S. B., Hoffstädter, F., & Langner, R. (2023a). Predicting executive functioning from functional brain connectivity: Network specificity and age effects. *Cerebral Cortex*, 33(11), 6495–6507.
<https://doi.org/10.1093/cercor/bhac520>
- Heckner, M. K., Cieslik, E. C., Paas Oliveros, L. K., Eickhoff, S. B., Patil, K. R., & Langner, R. (2023b). Predicting executive functioning from brain networks: Modality specificity and age effects. *Cerebral Cortex*, 33(22), 10997–11009. <https://doi.org/10.1093/cercor/bhad338>
- Hein, G., & Schubert, T. (2004). Aging and Input Processing in Dual-Task Situations. *Psychology and*

- Aging*, 19(3), 416–432. <https://doi.org/10.1037/0882-7974.19.3.416>
- Hoffmann, M. A., Pieczykolan, A., Koch, I., & Huestegge, L. (2020). Two sources of task prioritization: The interplay of effector-based and task order-based capacity allocation in the PRP paradigm. *Attention, Perception, & Psychophysics*. <https://doi.org/10.3758/s13414-020-02071-6>
- Huestegge, L., & Koch, I. (2010). Crossmodal action selection: Evidence from dual-task compatibility. *Memory & Cognition*, 38(4), 493–501. <https://doi.org/10.3758/MC.38.4.493>
- Huestegge, L., & Koch, I. (2013). Constraints in task-set control: Modality dominance patterns among effector systems. *Journal of Experimental Psychology: General*, 142(3), 633–637. <https://doi.org/10.1037/a0030156>
- Huettel, S. A., Song, A. W., & McCarthy, G. (2009). *Functional Magnetic Resonance Imaging* (2nd ed.). Sinauer Associates, Inc.
- Iacoboni, M. (2006). Visuo-motor integration and control in the human posterior parietal cortex: Evidence from TMS and fMRI. *Neuropsychologia*, 44(13), 2691–2699. <https://doi.org/10.1016/j.neuropsychologia.2006.04.029>
- Isherwood, S. J. S., Keuken, M. C., Bazin, P. L., & Forstmann, B. U. (2021). Cortical and subcortical contributions to interference resolution and inhibition – An fMRI ALE meta-analysis. *Neuroscience & Biobehavioral Reviews*, 129, 245–260. <https://doi.org/10.1016/j.neubiorev.2021.07.021>
- Jäncke, L., Peters, M., Himmelbach, M., Nösselt, T., Shah, J., & Steinmetz, H. (2000). fMRI study of bimanual coordination. *Neuropsychologia*, 38(2), 164–174. [https://doi.org/10.1016/S0028-3932\(99\)00062-7](https://doi.org/10.1016/S0028-3932(99)00062-7)
- Koch, I., Poljac, E., Müller, H., & Kiesel, A. (2018). Cognitive structure, flexibility, and plasticity in human multitasking—An integrative review of dual-task and task-switching research. *Psychological Bulletin*, 144(6), 557–583. <https://doi.org/10.1037/bul0000144>
- Kong, R., Yang, Q., Gordon, E., Xue, A., Yan, X., Orban, C., Zuo, X.-N., Spreng, N., Ge, T., Holmes, A., Eickhoff, S., & Yeo, B. T. T. (2021). Individual-Specific Areal-Level Parcellations Improve Functional Connectivity Prediction of Behavior. *Cerebral Cortex*, 31(10), 4477–4500. <https://doi.org/10.1093/cercor/bhab101>
- Kraljević, N., Langner, R., Küppers, V., Raimondo, F., Patil, K. R., Eickhoff, S. B., & Müller, V. I. (2023). *Network and State Specificity in Connectivity-Based Predictions of Individual Behavior*. bioRxiv. <https://doi.org/10.1101/2023.05.11.540387>
- Langner, R., Cieslik, E. C., Behrwind, S. D., Roski, C., Caspers, S., Amunts, K., & Eickhoff, S. B. (2015). Aging and response conflict solution: Behavioural and functional connectivity changes. *Brain Structure and Function*, 220(3), 1739–1757. <https://doi.org/10.1007/s00429-014-0758-0>
- Langner, R., & Eickhoff, S. B. (2013). Sustaining attention to simple tasks: A meta-analytic review of

- the neural mechanisms of vigilant attention. *Psychological Bulletin*, *139*(4), 870–900.
<https://doi.org/10.1037/a0030694>
- Langner, R., Kellermann, T., Boers, F., Sturm, W., Willmes, K., & Eickhoff, S. B. (2011). Modality-Specific Perceptual Expectations Selectively Modulate Baseline Activity in Auditory, Somatosensory, and Visual Cortices. *Cerebral Cortex*, *21*(12), 2850–2862.
<https://doi.org/10.1093/cercor/bhr083>
- Langner, R., Leiberg, S., Hoffstaedter, F., & Eickhoff, S. B. (2018). Towards a human self-regulation system: Common and distinct neural signatures of emotional and behavioural control. *Neuroscience & Biobehavioral Reviews*, *90*(September 2017), 400–410.
<https://doi.org/10.1016/j.neubiorev.2018.04.022>
- Langner, R., Sternkopf, M. A., Kellermann, T. S., Grefkes, C., Kurth, F., Schneider, F., Zilles, K., & Eickhoff, S. B. (2014). Translating working memory into action: Behavioral and neural evidence for using motor representations in encoding visuo-spatial sequences. *Human Brain Mapping*, *35*(7), 3465–3484. <https://doi.org/10.1002/hbm.22415>
- Lehle, C., & Hübner, R. (2009). Strategic capacity sharing between two tasks: Evidence from tasks with the same and with different task sets. *Psychological Research*, *73*(5), 707–726.
<https://doi.org/10.1007/s00426-008-0162-6>
- Li, M., Wang, D., Ren, J., Langs, G., Stoecklein, S., Brennan, B. P., Lu, J., Chen, H., & Liu, H. (2019). Performing group-level functional image analyses based on homologous functional regions mapped in individuals. *PLOS Biology*, *17*(3), e2007032.
<https://doi.org/10.1371/journal.pbio.2007032>
- Liesefeld, H. R., Fu, X., & Zimmer, H. D. (2015). Fast and careless or careful and slow? Apparent holistic processing in mental rotation is explained by speed-accuracy trade-offs. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *41*(4), 1140–1151.
<https://doi.org/10.1037/xlm0000081>
- Liesefeld, H. R., & Janczyk, M. (2019). Combining speed and accuracy to control for speed-accuracy trade-offs(?). *Behavior Research Methods*, *51*(1), 40–60. <https://doi.org/10.3758/s13428-018-1076-x>
- Logan, G. D., & Gordon, R. D. (2001). Executive control of visual attention in dual-task situations. *Psychological Review*, *108*(2), 393–434. <https://doi.org/10.1037/0033-295X.108.2.393>
- Madden, D. J., Pierce, T. W., & Allen, P. A. (1992). Adult age differences in attentional allocation during memory search. *Psychology and Aging*, *7*(4), 594–601. <https://doi.org/10.1037/0882-7974.7.4.594>
- Maquestiaux, F., & Ruthruff, E. (2021). Testing the over-reliance on central attention (ORCA) hypothesis: Do older adults have difficulty automatizing especially easy tasks? *Journal of Experimental Psychology: General*. <https://doi.org/10.1037/xge0001020>
- Mayr, U. (2001). Age differences in the selection of mental sets: The role of inhibition, stimulus

- ambiguity, and response-set overlap. *Psychology and Aging*, *16*(1), 96–109.
<https://doi.org/10.1037/0882-7974.16.1.96>
- Mayr, U., & Liebscher, T. (2001). Is there an age deficit in the selection of mental sets? *European Journal of Cognitive Psychology*, *13*(1–2), 47–69.
<https://doi.org/10.1080/09541440042000214>
- McLaren, D. G., Ries, M. L., Xu, G., & Johnson, S. C. (2012). A generalized form of context-dependent psychophysiological interactions (gPPI): A comparison to standard approaches. *NeuroImage*, *61*(4), 1277–1286. <https://doi.org/10.1016/j.neuroimage.2012.03.068>
- Meyer, D. E., & Kieras, D. E. (1997). A computational theory of executive cognitive processes and multiple-task performance: Part I. Basic mechanisms. *Psychological Review*, *104*(1), 3–65.
<https://doi.org/10.1037/0033-295X.104.1.3>
- Miller, J., & Ulrich, R. (2008). Bimanual Response Grouping in Dual-Task Paradigms. *Quarterly Journal of Experimental Psychology*, *61*(7), 999–1019.
<https://doi.org/10.1080/17470210701434540>
- Miller, J., Ulrich, R., & Rolke, B. (2009). On the optimality of serial and parallel processing in the psychological refractory period paradigm: Effects of the distribution of stimulus onset asynchronies. *Cognitive Psychology*, *58*(3), 273–310.
<https://doi.org/10.1016/j.cogpsych.2006.08.003>
- Miller, M. B., Donovan, C.-L., Bennett, C. M., Aminoff, E. M., & Mayer, R. E. (2012). Individual differences in cognitive style and strategy predict similarities in the patterns of brain activity between individuals. *NeuroImage*, *59*(1), 83–93.
<https://doi.org/10.1016/j.neuroimage.2011.05.060>
- Miyake, A., & Friedman, N. P. (2012). The Nature and Organization of Individual Differences in Executive Functions: Four General Conclusions. *Current Directions in Psychological Science*, *21*(1), 8–14. <https://doi.org/10.1177/0963721411429458>
- Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The Unity and Diversity of Executive Functions and Their Contributions to Complex “Frontal Lobe” Tasks: A Latent Variable Analysis. *Cognitive Psychology*, *41*(1), 49–100.
<https://doi.org/10.1006/cogp.1999.0734>
- Mozolic, J. L., Joyner, D., Hugenschmidt, C. E., Peiffer, A. M., Kraft, R. A., Maldjian, J. A., & Laurienti, P. J. (2008). Cross-modal deactivations during modality-specific selective attention. *BMC Neurology*, *8*(1), 35. <https://doi.org/10.1186/1471-2377-8-35>
- Mueller, S., Wang, D., Fox, M. D., Yeo, B. T. T., Sepulcre, J., Sabuncu, M. R., Shafee, R., Lu, J., & Liu, H. (2013). Individual Variability in Functional Connectivity Architecture of the Human Brain. *Neuron*, *77*(3), 586–595. <https://doi.org/10.1016/j.neuron.2012.12.028>
- Müller, V. I., Langner, R., Cieslik, E. C., Rottschy, C., & Eickhoff, S. B. (2015). Interindividual differences in cognitive flexibility: Influence of gray matter volume, functional connectivity

- and trait impulsivity. *Brain Structure and Function*, 220(4), 2401–2414.
<https://doi.org/10.1007/s00429-014-0797-6>
- Nachev, P., Kennard, C., & Husain, M. (2008). Functional role of the supplementary and pre-supplementary motor areas. *Nature Reviews Neuroscience*, 9(11), 856–869.
<https://doi.org/10.1038/nrn2478>
- Nair, D. G., Purcott, K. L., Fuchs, A., Steinberg, F., & Kelso, J. A. S. (2003). Cortical and cerebellar activity of the human brain during imagined and executed unimanual and bimanual action sequences: A functional MRI study. *Cognitive Brain Research*, 15(3), 250–260.
[https://doi.org/10.1016/S0926-6410\(02\)00197-0](https://doi.org/10.1016/S0926-6410(02)00197-0)
- Navon, D., & Miller, J. (1987). Role of outcome conflict in dual-task interference. *Journal of Experimental Psychology: Human Perception and Performance*, 13(3), 435–448.
<https://doi.org/10.1037/0096-1523.13.3.435>
- Navon, D., & Miller, J. (2002). Queuing or Sharing? A Critical Evaluation of the Single-Bottleneck Notion. *Cognitive Psychology*, 44(3), 193–251. <https://doi.org/10.1006/cogp.2001.0767>
- Nostro, A. D., Müller, V. I., Varikuti, D. P., Pläsckke, R. N., Hoffstaedter, F., Langner, R., Patil, K. R., & Eickhoff, S. B. (2018). Predicting personality from network-based resting-state functional connectivity. *Brain Structure and Function*, 223(6), 2699–2719.
<https://doi.org/10.1007/s00429-018-1651-z>
- Ohsugi, H., Ohgi, S., Shigemori, K., & Schneider, E. B. (2013). Differences in dual-task performance and prefrontal cortex activation between younger and older adults. *BMC Neuroscience*, 14(1), 10. <https://doi.org/10.1186/1471-2202-14-10>
- O'Reilly, J. X., Woolrich, M. W., Behrens, T. E. J., Smith, S. M., & Johansen-Berg, H. (2012). Tools of the trade: Psychophysiological interactions and functional connectivity. *Social Cognitive and Affective Neuroscience*, 7(5), 604–609. <https://doi.org/10.1093/scan/nss055>
- Papegaaij, S., Hortobágyi, T., Godde, B., Kaan, W. A., Erhard, P., & Voelcker-Rehage, C. (2017). Neural correlates of motor-cognitive dual-tasking in young and old adults. *PLoS ONE*, 12(12), e0189025. <https://doi.org/10.1371/journal.pone.0189025>
- Park, D. C., Polk, T. A., Mikels, J. A., Taylor, S. F., & Marshuetz, C. (2001). Cerebral aging: Integration of brain and behavioral models of cognitive function. *Dialogues in Clinical Neuroscience*, 3(3), 151–165. <https://doi.org/10.31887/DCNS.2001.3.3/dcpark>
- Park, D. C., & Reuter-Lorenz, P. (2009). The Adaptive Brain: Aging and Neurocognitive Scaffolding. *Annual Review of Psychology*, 60(1), 173–196.
<https://doi.org/10.1146/annurev.psych.59.103006.093656>
- Pashler, H. (1984). Processing stages in overlapping tasks: Evidence for a central bottleneck. *Journal of Experimental Psychology: Human Perception and Performance*, 10(3), 358–377.
<https://doi.org/10.1037//0096-1523.10.3.358>
- Pashler, H. (1994). Dual-task interference in simple tasks: Data and theory. *Psychological Bulletin*,

- 116(2), 220–244. <https://doi.org/10.1037/0033-2909.116.2.220>
- Pashler, H., & Johnston, J. C. (1989). Chronometric Evidence for Central Postponement in Temporally Overlapping Tasks. *The Quarterly Journal of Experimental Psychology Section A*, 41(1), 19–45. <https://doi.org/10.1080/14640748908402351>
- Pessoa, L. (2014). Understanding brain networks and brain organization. *Physics of Life Reviews*, 11(3), 400–435. <https://doi.org/10.1016/j.plrev.2014.03.005>
- Pieczykolan, A., & Huestegge, L. (2014). Oculomotor dominance in multitasking: Mechanisms of conflict resolution in cross-modal action. *Journal of Vision*, 14(13), 1–17. <https://doi.org/10.1167/14.13.18>
- Pieczykolan, A., & Huestegge, L. (2018). Sources of interference in cross-modal action: Response selection, crosstalk, and general dual-execution costs. *Psychological Research*, 82(1), 109–120. <https://doi.org/10.1007/s00426-017-0923-1>
- Pieczykolan, A., & Huestegge, L. (2019). Action scheduling in multitasking: A multi-phase framework of response-order control. *Attention, Perception, and Psychophysics*. <https://doi.org/10.3758/s13414-018-01660-w>
- Pläsche, R. N., Cieslik, E. C., Müller, V. I., Hoffstaedter, F., Plachti, A., Varikuti, D. P., Goosses, M., Latz, A., Caspers, S., Jockwitz, C., Moebus, S., Gruber, O., Eickhoff, C. R., Reetz, K., Heller, J., Südmeyer, M., Mathys, C., Caspers, J., Grefkes, C., ... Eickhoff, S. B. (2017). On the integrity of functional brain networks in schizophrenia, Parkinson’s disease, and advanced age: Evidence from connectivity-based single-subject classification. *Human Brain Mapping*, 38(12), 5845–5858. <https://doi.org/10.1002/hbm.23763>
- Pläsche, R. N., Patil, K. R., Cieslik, E. C., Nostro, A. D., Varikuti, D. P., Plachti, A., Lösche, P., Hoffstaedter, F., Kalenscher, T., Langner, R., & Eickhoff, S. B. (2020). Age differences in predicting working memory performance from network-based functional connectivity. *Cortex*, 132, 441–459. <https://doi.org/10.1016/j.cortex.2020.08.012>
- Poldrack, R. A., Huckins, G., & Varoquaux, G. (2020). Establishment of Best Practices for Evidence for Prediction: A Review. *JAMA Psychiatry*, 77(5), 534. <https://doi.org/10.1001/jamapsychiatry.2019.3671>
- Power, J. D., Cohen, A. L., Nelson, S. M., Wig, G. S., Barnes, K. A., Church, J. A., Vogel, A. C., Laumann, T. O., Miezin, F. M., Schlaggar, B. L., & Petersen, S. E. (2011). Functional network organization of the human brain. *Neuron*, 72(4), 665–678. <https://doi.org/10.1016/j.neuron.2011.09.006>
- Purves, D., Augustine, G. J., Fitzpatrick, D., Hall, W. C., LaMantia, A.-S., Mooney, R. D., Platt, M. L., & White, L. E. (2018). *Neuroscience*. Sinauer Associates.
- Purves, D., LaBar, K. S., Platt, M. L., Woldorff, M., Cabeza, R., & Huettel, S. A. (2012). *Principles of Cognitive Neuroscience* (2nd ed.). Oxford University Press.
- Raichle, M. E. (2015). The brain’s default mode network. *Annual Review of Neuroscience*, 38, 433–

447. <https://doi.org/10.1146/annurev-neuro-071013-014030>
- Raichle, M. E., MacLeod, A. M., Snyder, A. Z., Powers, W. J., Gusnard, D. A., & Shulman, G. L. (2001). A default mode of brain function. *Proceedings of the National Academy of Sciences*, 98(2), 676–682. <https://doi.org/10.1073/pnas.98.2.676>
- Reuter-Lorenz, P. A., & Cappell, K. A. (2008). Neurocognitive Aging and the Compensation Hypothesis. *Current Directions in Psychological Science*, 17(3), 177–182. <https://doi.org/10.1111/j.1467-8721.2008.00570.x>
- Ritchie, H. (2019). The world population is changing: For the first time there are more people over 64 than children younger than 5. *Our World in Data*. <https://ourworldindata.org/population-aged-65-outnumber-children>
- Rizzolatti, G., Luppino, G., & Matelli, M. (1998). The organization of the cortical motor system: New concepts. *Electroencephalography and Clinical Neurophysiology*, 106(4), 283–296. [https://doi.org/10.1016/S0013-4694\(98\)00022-4](https://doi.org/10.1016/S0013-4694(98)00022-4)
- Rottschy, C., Langner, R., Dogan, I., Reetz, K., Laird, A. R., Schulz, J. B., Fox, P. T., & Eickhoff, S. B. (2012). Modelling neural correlates of working memory: A coordinate-based meta-analysis. *NeuroImage*, 60(1), 830–846. <https://doi.org/10.1016/j.neuroimage.2011.11.050>
- Rusconi, E., Kwan, B., Giordano, B. L., Umiltà, C., & Butterworth, B. (2006). Spatial representation of pitch height: The SMARC effect. *Cognition*, 99(2), 113–129. <https://doi.org/10.1016/j.cognition.2005.01.004>
- Rushworth, M. F. S., Ellison, A., & Walsh, V. (2001). Complementary localization and lateralization of orienting and motor attention. *Nature Neuroscience*, 4(6), 656–661. <https://doi.org/10.1038/88492>
- Salthouse, T. A. (1996). The processing-speed theory of adult age differences in cognition. *Psychological Review*, 103(3), 403–428. <https://doi.org/10.1037/0033-295X.103.3.403>
- Saylik, R., Williams, A. L., Murphy, R. A., & Szameitat, A. J. (2022). Characterising the unity and diversity of executive functions in a within-subject fMRI study. *Scientific Reports*, 12(1). <https://doi.org/10.1038/s41598-022-11433-z>
- Scheinost, D., Noble, S., Horien, C., Greene, A. S., Lake, E. Mr., Salehi, M., Gao, S., Shen, X., O'Connor, D., Barron, D. S., Yip, S. W., Rosenberg, M. D., & Constable, R. T. (2019). Ten simple rules for predictive modeling of individual differences in neuroimaging. *NeuroImage*, 193, 35–45. <https://doi.org/10.1016/j.neuroimage.2019.02.057>
- Schubert, T. (1999). Processing differences between simple and choice reactions affect bottleneck localization in overlapping tasks. *Journal of Experimental Psychology: Human Perception and Performance*, 25(2), 408–425. <https://doi.org/10.1037/0096-1523.25.2.408>
- Schumacher, E. H., Cookson, S. L., Smith, D. M., Nguyen, T. V. N., Sultan, Z., Reuben, K. E., & Hazeltine, E. (2018). Dual-Task Processing With Identical Stimulus and Response Sets: Assessing the Importance of Task Representation in Dual-Task Interference. *Frontiers in*

- Psychology*, 9(JUN), 1–7. <https://doi.org/10.3389/fpsyg.2018.01031>
- Seidler, R. D., Bernard, J. A., Burutolu, T. B., Fling, B. W., Gordon, M. T., Gwin, J. T., Kwak, Y., & Lipps, D. B. (2010). Motor control and aging: Links to age-related brain structural, functional, and biochemical effects. *Neuroscience and Biobehavioral Reviews*, 34(5), 721–733. <https://doi.org/10.1016/j.neubiorev.2009.10.005>
- Soares, J. M., Magalhães, R., Moreira, P. S., Sousa, A., Ganz, E., Sampaio, A., Alves, V., Marques, P., & Sousa, N. (2016). A Hitchhiker’s Guide to Functional Magnetic Resonance Imaging. *Frontiers in Neuroscience*, 10. <https://doi.org/10.3389/fnins.2016.00515>
- Sommer, M. A. (2003). The role of the thalamus in motor control. *Current Opinion in Neurobiology*, 13(6), 663–670. <https://doi.org/10.1016/j.conb.2003.10.014>
- Spreng, R. N., & Turner, G. R. (2019). The Shifting Architecture of Cognition and Brain Function in Older Adulthood. *Perspectives on Psychological Science*, 14(4), 523–542. <https://doi.org/10.1177/1745691619827511>
- Stelzel, C., Brandt, S. A., & Schubert, T. (2009). Neural mechanisms of concurrent stimulus processing in dual tasks. *NeuroImage*, 48(1), 237–248. <https://doi.org/10.1016/j.neuroimage.2009.06.064>
- Stelzel, C., Kraft, A., Brandt, S. A., & Schubert, T. (2008). Dissociable Neural Effects of Task Order Control and Task Set Maintenance during Dual-task Processing. *Journal of Cognitive Neuroscience*, 20(4), 613–628. <https://doi.org/10.1162/jocn.2008.20053>
- Stelzel, C., Schumacher, E. H., Schubert, T., & D’Esposito, M. (2006). The neural effect of stimulus-response modality compatibility on dual-task performance: An fMRI study. *Psychological Research*, 70(6), 514–525. <https://doi.org/10.1007/s00426-005-0013-7>
- Strobach, T., Hendrich, E., Kübler, S., Müller, H., & Schubert, T. (2018). Processing order in dual-task situations: The “first-come, first-served” principle and the impact of task order instructions. *Attention, Perception, & Psychophysics*, 80(7), 1785–1803. <https://doi.org/10.3758/s13414-018-1541-8>
- Swinnen, S. P., & Gooijers, J. (2015). Bimanual Coordination. In A. W. Toga (Ed.), *Brain Mapping: An Encyclopedic Reference* (Vol. 2, pp. 475–482). Academic Press: Elsevier. <https://doi.org/10.1016/B978-0-12-397025-1.00030-0>
- Szameitat, A. J. & Brunel Students. (2022). Inter-Individual Differences in Executive Functions Predict Multitasking Performance—Implications for the Central Attentional Bottleneck. *Frontiers in Psychology*, 13, 778966. <https://doi.org/10.3389/fpsyg.2022.778966>
- Szameitat, A. J., Lepsien, J., Von Cramon, D. Y., Sterr, A., & Schubert, T. (2006). Task-order coordination in dual-task performance and the lateral prefrontal cortex: An event-related fMRI study. *Psychological Research*, 70(6), 541–552. <https://doi.org/10.1007/s00426-005-0015-5>
- Telford, C. W. (1931). The refractory phase of voluntary and associative responses. *Journal of Experimental Psychology*, 14(1), 1–36. <https://doi.org/10.1037/h0073262>

- Thönes, S., Falkenstein, M., & Gajewski, P. D. (2018). Multitasking in aging: ERP correlates of dual-task costs in young versus low, intermediate, and high performing older adults. *Neuropsychologia*, *119*, 424–433. <https://doi.org/10.1016/j.neuropsychologia.2018.09.003>
- Tombu, M., & Jolicoeur, P. (2003). A central capacity sharing model of dual-task performance. *Journal of Experimental Psychology: Human Perception and Performance*, *29*(1), 3–18. <https://doi.org/10.1037/0096-1523.29.1.3>
- Tucker-Drob, E. M., & Salthouse, T. A. (2011). Individual differences in cognitive aging. In *The Wiley-Blackwell handbook of individual differences* (pp. 242–267). Wiley Blackwell. <https://doi.org/10.1002/9781444343120>
- Turner, G. R., & Spreng, R. N. (2015). Prefrontal Engagement and Reduced Default Network Suppression Co-occur and Are Dynamically Coupled in Older Adults: The Default-Executive Coupling Hypothesis of Aging. *Journal of Cognitive Neuroscience*, *27*(12), 2462–2476. https://doi.org/10.1162/jocn_a_00869
- Uddin, L. Q. (2020). Bring the Noise: Reconceptualizing Spontaneous Neural Activity. *Trends in Cognitive Sciences*, *24*(9), 734–746. <https://doi.org/10.1016/j.tics.2020.06.003>
- Ulrich, R., & Miller, J. (2008). Response grouping in the psychological refractory period (PRP) paradigm: Models and contamination effects. *Cognitive Psychology*, *57*(2), 75–121. <https://doi.org/10.1016/j.cogpsych.2007.06.004>
- Vaghari, D., Kabir, E., & Henson, R. N. (2022). Late combination shows that MEG adds to MRI in classifying MCI versus controls. *NeuroImage*, *252*, 119054. <https://doi.org/10.1016/j.neuroimage.2022.119054>
- van Dun, K., Brinkmann, P., Depestele, S., Verstraelen, S., & Meesen, R. (2021). Cerebellar Activation During Simple and Complex Bimanual Coordination: An Activation Likelihood Estimation (ALE) Meta-analysis. *The Cerebellum*, *21*(6), 987–1013. <https://doi.org/10.1007/s12311-021-01261-8>
- Verhaeghen, P., Steitz, D. W., Sliwinski, M. J., & Cerella, J. (2003). Aging and dual-task performance: A meta-analysis. *Psychology and Aging*, *18*(3), 443–460. <https://doi.org/10.1037/0882-7974.18.3.443>
- Voss, M. W., Erickson, K. I., Chaddock, L., Prakash, R. S., Colcombe, S. J., Morris, K. S., Doerksen, S., Hu, L., McAuley, E., & Kramer, A. F. (2008). Dedifferentiation in the visual cortex: An fMRI investigation of individual differences in older adults. *Brain Research*, *1244*, 121–131. <https://doi.org/10.1016/j.brainres.2008.09.051>
- Weiss, P. H., Rahbari, N. N., Lux, S., Pietrzyk, U., Noth, J., & Fink, G. R. (2006). Processing the spatial configuration of complex actions involves right posterior parietal cortex: An fMRI study with clinical implications. *Human Brain Mapping*, *27*(12), 1004–1014. <https://doi.org/10.1002/hbm.20239>
- Welford, A. T. (1952). The “psychological refractory period” and the timing of high-speed

- performance—A review and a theory. *British Journal of Psychology*, *43*, 2–19.
- Weller, L., Pieczykolan, A., & Huestegge, L. (2022). Response modalities and the cognitive architecture underlying action control: Intra-modal trumps cross-modal action coordination. *Cognition*, *225*, 105115. <https://doi.org/10.1016/j.cognition.2022.105115>
- Wen, T., Duncan, J., & Mitchell, D. J. (2020). Hierarchical Representation of Multistep Tasks in Multiple-Demand and Default Mode Networks. *Journal of Neuroscience*, *40*(40), 7724–7738. <https://doi.org/10.1523/JNEUROSCI.0594-20.2020>
- World Health Organization. (2022, October 1). *Ageing and health*. <https://www.who.int/news-room/fact-sheets/detail/ageing-and-health>
- Worringer, B., Langner, R., Koch, I., Eickhoff, S. B., Eickhoff, C. R., & Binkofski, F. C. (2019). Common and distinct neural correlates of dual-tasking and task-switching: A meta-analytic review and a neuro-cognitive processing model of human multitasking. *Brain Structure and Function*, *224*(5), 1845–1869. <https://doi.org/10.1007/s00429-019-01870-4>
- Yeung, A. W. K., More, S., Wu, J., & Eickhoff, S. B. (2022). Reporting details of neuroimaging studies on individual traits prediction: A literature survey. *NeuroImage*, *256*, 119275. <https://doi.org/10.1016/j.neuroimage.2022.119275>

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